Erich-Christian Oerke
Roland Gerhards
Gunter Menz
Richard A. Sikora
Editors

Precision Crop Protection – the Challenge and Use of Heterogeneity

Springer

Precision Crop Protection - the Challenge and Use of Heterogeneity

Erich-Christian Oerke · Roland Gerhards ·
Gunter Menz · Richard A. Sikora
Editors

Precision Crop Protection - the Challenge and Use of Heterogeneity

Springer

Editors
Erich-Christian Oerke
University of Bonn
Institute of Crop Science
and Resource Conservation
Nussallee 9
53115 Bonn
Germany
ec-oerke@uni-bonn.de

Gunter Menz
University of Bonn
Department of Geography
Remote Sensing
Meckenheimer Allee 166
53115 Bonn
Germany
g.menz@geographie.uni-bonn.de

Roland Gerhards
University of Hohenheim
Department of Weed Sciences
Otto-Sanderstrasse 5
70599 Stuttgart
Germany
Roland.Gerhards@uni-hohenheim.de

Richard A. Sikora
University of Bonn
Institute of Crop Science
and Resource Conservation
Nussallee 9
53115 Bonn
Germany
rsikora@uni-bonn.de

ISBN 978-90-481-9276-2 e-ISBN 978-90-481-9277-9
DOI 10.1007/978-90-481-9277-9
Springer Dordrecht Heidelberg London New York

Library of Congress Control Number: 2010930514

Printed on acid-free paper

Springer is part of Springer Science+Business Media (www.springer.com)

Preface

A broad spectrum of weeds, animal pests and pathogens – collectively referred to here as pests – are known to cause considerable quantitative and qualitative losses in crop production worldwide. These yield-limiting biotic stress factors have to be appropriately managed in order to reduce their negative impact on the production of food, feed, fiber and fuel. The world's population is expected to expand to 9.1 billion by 2050. This growth in human population will require an increase in food production of up to 70% over present day production levels. A shift in agricultural production towards the use of biomass for energy and other types of renewable resources will dramatically increase the demand for plant based products. In order to meet this demand, crops have to be protected from pests in an effective, efficient and environmental friendly way. Management in most cases can be accomplished by a combination of mechanical, biological and/or chemical tools and other supportive technologies in integrated control programs.

Pests as well as abiotic stress conditions commonly are heterogeneous in time and space in a production field. In the past heterogeneities in soil, water and nutrient distribution affecting crop growth have been managed by dividing the agricultural area into small units with less heterogeneity. In modern large-scale farming, heterogeneity complicates targeted application of agricultural inputs such as pesticides and fertilizers. Heterogeneity often is ignored, because of the lack of appropriate technology to deal with it. Control options, such as the application of pesticides are applied uniformly across the field and can result in over- and under-dosing which in both cases is inefficient and uneconomical and can be an environmental burden.

Precision farming, including site-specific management (SSM), describes an agricultural management system using computerized information technologies (IT) – global navigation satellite systems (GNSS), geographic information systems, remote sensing devices, data management systems and telecommunications – for optimal use of nutrients, water, seed, pesticides and energy in heterogeneous field situations. Precision farming relies upon (I) intensive sensing of environmental conditions in the crop, (II) extensive data handling and processing, (III) use of decision support systems (DSS), and (IV) control of farm machinery (actuators) in the field (Fig. 1). Information from soil and/or crop maps or online information from remote sensing on soil status and crop growth is typically used in combination with GNSS

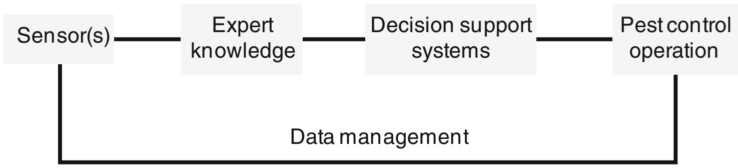

Fig. 1 Information technologies and data management for precision crop protection

data in order to optimize application and/or the timing of inputs to match the natural heterogeneity in the field.

Awareness of potential negative side-effects of agricultural practices on the environment has been a major driver of the concept of precision crop protection. Site-specific management means doing the right thing, at the right place and at the right time. Spatial and temporal variability of pests in the field is no longer ignored, but used in a systematic approach that minimizes the amount of pesticide applied by stipulating demand-oriented application without a reduction in the efficiency of crop protection and crop productivity.

Information technology is used to tailor crop protection activities to achieve effective control when and where needed by monitoring the crop during the crop cycle using DSS for site-specific decision making and by controlling the actuators during application of control options. Decision support systems are based on algorithms that simulate crop growth, the epidemic spread of pests in space and time and the final yield loss of the crop to be prevented by suitable control measures. Information from various spatial scales – plant, canopy or growing region – may be used to assess the variability of crop status.

Site-specific demand has to be assessed by detailed recording of spatial distribution and development of the pest groups and the evaluation of their potential economic impact on crop yield. This situation-specific, threshold-oriented and environmental friendly form of pest management requires large-scale and georeferenced monitoring of pests in the crop for precise timing and application of control measures. In addition to high capacities in data processing and exact regulation of actuators, innovative sensors are crucial for SSM as they generate the input information needed for decision making.

Sensing of heterogeneities in the field is the prerequisite for timely and spatially adjusted management. Recent developments in sensor technologies have led to a broadening of their capacity to detect pests and thereby improve application in crop protection practice. These sensors can be space-borne (satellite), air-borne (airplane, unmanned aerial vehicle) or ground-based (handheld, vehicle-mounted) and provide spatial information that has added value to conventional methods of soil and crop monitoring. Sensing and then reacting is linked by a powerful system of data management that includes DSS. The detection of within-field differences in crop status or growth conditions would enable a farmer to streamline input factors thereby optimizing his profit margin, while simultaneously improving the overall stability of the agro-ecosystem.

The pest groups that have to be monitored for precision crop protection differ greatly in size, patterns of incidence and epidemic spread within and between growth periods of the crops. Heterogeneity of weeds is often obvious and applications for site-specific control of weeds by targeted mechanical or chemical control have reached an advanced stage (Table 1). In contrast, the detection, identification and quantification of pests groups which are highly variable in space and time, is still in developmental stages.

A recent example for the use of information technologies for Integrated Pest Management on a national scale is the Pest Information Platform for Extension and Education (PIPE, http://sbr.ipmpipe.org/). This is a nationwide warning system to help USA soybean growers protect their crop against *Phakopsora pachyrhizi*, an invasive fungus causing Asian soybean rust (ASR). A website provides information for the detection and management of ASR as well as maps of confirmed ASR incidence across the USA and is an effective online warning system. The information is used by farmers and scientists that monitor and analyze disease spread in relation to environmental conditions in order to predict disease spread and to decide whether fungicide use is necessary or not. PIPE has created a high level of collaboration among governmental agencies, growers, agribusinesses, and scientists and has proven the suitability of IT in crop protection.

The assessment and management of arthropod pest and disease heterogeneity in crops is still a major challenge. Basic information is still required on: ground truth patterns of major air-borne diseases; epidemiology; spread and impact of latent infections; optimum time of spraying; (spectral) signatures of infected crops for the identification of diseases and arthropod pests; data handling for on-the-go applications. The influence of SSM on the epidemiology of the pest or multiples thereof over growing seasons also is required in order to evaluate the sustainability of site-specific control concepts.

Table 1 Current status of the control of various pest groups using precision crop protection technologies

Trait	Weeds	Nematodes	Insects	Pathogens
Size of organism [mm]	10–1,000	0.1–1	0.1–00	0.0001–1
Cycles per season	1	1–5	1–8 (?)	1–9 (?)
Mobility	Very low	Low	Low to high	High
Field heterogeneity	XX(X)	XX (X)	X(X)	X(-)
Detection	Individuals XX	Disease sympt. X(X)	Individuals, sympt. (X)	Disease sympt. (X)
Identification	XX	–	?	?
Quantification	XX	(X)	(X)	(X)
Prognosis/DSS	X(X)	X (X)		(X)
Data management	Off/on-line	Off-line		
Application technique	XX(X)	X	(X)	(?)

XX advanced stage; X first steps/moderate knowledge; ? not known/not feasible; - knowledge low

Future technical innovations, such as networked wireless sensors, meteorological sensors as well as nano-sensors for recording plant status, scattered over fields are expected to provide the farmer with site-specific data on crop and soil conditions. The detection, identification and quantification of infections on plants by high powered optical sensors should result in an objective and automated assessment of pests in the field. Automatic systems that use sensors and artificial intelligence to predict the needs of crops and respond accordingly in order to control the primary incidence of pests without human intervention (ambient intelligence) may be available in the foreseeable future.

Since 2001, a Research Training Group at the University of Bonn, Germany, entitled 'Use of Information Technologies for Precision Crop Protection' and funded by the German Research Foundation (DFG) is investigating the potential and limitations of SSM of weeds and pathogens. The Research Training Group organized a workshop on Precision Crop Protection as a post-conference meeting of the 2005 European Conference on Precision Agriculture in Uppsala, Sweden and in 2007 a scientific conference in Bonn, Germany. The number of active participants reflected both an increase in scientific interest in precision crop protection, as well as progress in developing appropriate strategies and tools for solving problems and developing suitable systems for field application.

This book reviews the state-of-the-art of research on precision crop protection and recent developments in the application of site-specific technologies for the practical management of weeds, arthropod pests, pathogens and nematodes with examples from the field. The chapters discuss a wide range of modern technologies that includes information on: (I) the biology and epidemiology of pests, (II) new sensor technologies, (III) application of sensors on different scales, (IV) sensor detection of pests in growing crops, (V) data management, (VI) impact of pest heterogeneity and (VII) precise mechanical and chemical pest control.

Examples for the use of precise application technologies are given for the management of weeds, arthropod pests and diseases which will enable growers to vary application timing, dosage and optimize pesticide mixtures or intensity of mechanical weeding according to the spatial and temporal variability of those pests. Sprayers and mechanical weeders controlled via computer terminals coupled to differential GNSS are described. In addition, decision algorithms developed for automatic regulation of application technology are presented that define the most effective and selective control measure at each site-specific location in a field.

The chapters in this book demonstrate that technologies for precision crop protection had an impact on IPM in the past and will continue to contribute significantly to improved plant health management. The technologies presented here will result in targeted pest control, lower pesticide residues, reduced environmental impact and lead to higher yields at a lower cost to the growers.

Bonn, Germany
January 2010

Erich-Christian Oerke
Roland Gerhards
Gunter Menz
Richard A. Sikora

Contents

Contributors

Vincent T.J.M. Achten PROBOTIQ, Kleefkruid 74, 5432 EE Cuijck, The Netherlands, vincent.achten@probotiq.com

Viacheslav I. Adamchuk Department of Biological Systems Engineering, University of Nebraska-Lincoln, Lincoln, NE 68583-0726, USA, vadamchuk2@unl.edu

Helmut Auweter Application Technology and Delivery, Crop Protection Division, BASF SE, D-67117 Limburgerhof, Germany, Helmut.Auweter@basf.com

Georg Bareth Department of Geography, University of Cologne, Köln D-50923, Germany, g.bareth@uni-koeln.de

Cedric Bravo Division of Mechatronics Biostatistics and Sensors (MeBioS), Katholieke Universiteit Leuven, Leuven 3001, Belgium, cedric.bravo@biw.kuleuven.be

Tito Caffi Istituto di Entomologia e Patologia vegetale, Università Cattolica del Sacro Cuore, I-29100 Piacenza, Italy, tito.caffi@unicatt.it

David E. Clay Plant Science Department, South Dakota State University, Brookings, SD 57007, USA, david_clay@sdstate.edu

Kevin Dalsted Engineering Resource Center, South Dakota State University, Brookings, SD 57007, USA, kevin_dalsted@sdstate.edu

Alexander Damm Remote Sensing Laboratories, University of Zurich, Zurich 8057, Switzerland, adamm@geo.uzh.ch

Karl-Heinz Dammer Engineering for Crop Production, Leibniz-Institute for Agricultural Engineering Potsdam-Bornim (ATB), D-14469 Potsdam, Germany, kdammer@atb-potsdam.de

Richard F. Davis Crop Protection and Management Research Unit, USDA-ARS, Tifton, GA 31793, USA, richard.davis@ars.usda.gov

Cedric Dieleman Global Formulation Development, Crop Protection Division, BASF SE, D-67117 Limburgerhof, Germany, Cedric.Dieleman@basf.com

Reiner Doluschitz Computer Applications and Business Management in Agriculture (410c), Department of Farm Management, University of Hohenheim, Stuttgart 70593, Germany, agrarinf@uni-hohenheim.de

Sharon K. Eggenberger Department of Plant Pathology, Iowa State University, Ames, IA 50011, USA, skp08@iastate.edu

Richard B. Ferguson Department of Agronomy and Horticulture, University of Nebraska-Lincoln, Lincoln, NE 68583-0724, USA, rferguson1@unl.edu

Jonas Franke RSS – Remote Sensing Solutions GmbH, Office Munich, München D-81667, Germany, franke@rssgmbh.de

Roland Gerhards Department of Weed Sciences (360b), University of Hohenheim, Stuttgart D-70599, Germany, gerhards@uni-hohenheim.de

Simona Giosuè Horta Srl, Università Cattolica del Sacro Cuore, I-29100 Piacenza, Italy, s.giosue@horta-srl.com

Hans W. Griepentrog Department of Agriculture and Ecology, Faculty of Life Sciences, University of Copenhagen, DK-2630 Taastrup, Denmark, hwg@life.ku.dk

Christoph Gutjahr Department of Weed Sciences (360b), University of Hohenheim, Stuttgart D-70599, Germany, cgutjahr@uni-hohenheim.de

William G. Henderson Clemson University – Edisto R.E.C., Blackville, SC 29817, USA, whende2@clemson.edu

Gary W. Hergert Panhandle Research and Extension Center, University of Nebraska-Lincoln, Scottsbluff, NE 69361-4939, USA, ghergert1@unl.edu

Joachim Hill Remote Sensing Department, Faculty of Geography/Geosciences, Trier University, Trier D-54286, Germany, hillj@uni-trier.de

Christian Hillnhütter Institute of Crop Science and Resource Conservation (INRES) – Phytomedicine, Bonn D-53115, Germany, chillnhu@uni-bonn.de; christian.hillnhuetter@gmx.de

Noha Holah Department of Plant Pathology, Iowa State University, Ames, IA 50011, USA, nholah@iastate.edu

Patrick Hostert Geomatics Lab, Humboldt-Universität zu Berlin, Berlin D-10099, Germany, patrick.hostert@geo.hu-berlin.de

Rasmus N. Jørgensen Institute of Agricultural Engineering, University of Southern Denmark, DK 5230 Odense M, Denmark, rasj@kbm.sdu.dk

Jeanette Jung Zentralstelle der Länder für EDV gestützte Entscheidungshilfen und Programme im Pflanzenschutz (ZEPP), D-55545 Bad Kreuznach, Germany, jung@zepp.info

Corné Kempenaar Wageningen UR – Plant Research International, 6700 AP Wageningen, The Netherlands, corne.kempenaar@wur.nl

Ahmad Khalilian Clemson University – Edisto R.E.C., Blackville, SC 29817, USA, akhlln@clemson.edu

Terrence L. Kirkpatrick Southwest Research and Extension Center, University of Arkansas, Hope, AR 71801, USA, tkirkpatrick@uaex.edu

Benno Kleinhenz Zentralstelle der Länder für EDV gestützte Entscheidungshilfen und Programme im Pflanzenschutz (ZEPP), D-55545 Bad Kreuznach, Germany, kleinhenz@zepp.info

Walter Kühbauch Crop Science Research Group, Institute of Crop Science and Resource Conservation, Bonn D-53115, Germany, w.kuehbauch@uni-bonn.de

Volker Kühnhold Institute for Crop Science and Resource Conservation (INRES) – Phytomedicine, University Bonn, Bonn 53115, Germany, volker.kuehnhold@bayercropscience.de

Martin Kunisch Association for Technology and Structures in Agriculture (KTBL), Bartningstrasse 49, D-64289 Darmstadt, Germany, m.kunisch@ktbl.de

Jürgen Langewald Crop Protection Division, Global Insecticide Research, BASF SE, D-67117 Limburgerhof, Germany, juergen.langewald@basf.com

Arie van der Lans Research Unit Flower Bulbs, Wageningen UR – Applied Plant Research, 2160 AB Lisse, The Netherlands, arie.vanderlans@wur.nl

Rick L. Lawrence Department of Land Resources and Environmental Sciences, Montana State University, Bozeman, MT 59717, USA, rickl@montana.edu

Ivar Lund Department of Industrial and Civil Engineering, Faculty of Engineering, University of Southern Denmark, DK-5230 Odense M, Denmark, ilu@ib.sdu.dk

H. Alastair McCartney Plant Pathology and Microbiology Department, Rothamsted Research, Harpenden AL5 2JQ, UK, zen966@zen.co.uk

Gunter Menz Remote Sensing Research Group, Department of Geography, University of Bonn, Bonn D-53115, Germany, g.menz@uni-bonn.de

Thorsten Mewes Center for Remote Sensing of Land Surfaces (ZFL), Bonn D-53113, Germany, tmewes@uni-bonn.de

Jean-Marie G.P. Michielsen Wageningen UR – Plant Research International, 6700 AP Wageningen, The Netherlands, jean-marie.michielsen@wur.nl

W. Scott Monfort Division of Agriculture, Lonoke Agricultural Center, University of Arkansas, Lonoke, AR 72012, USA, smonfort@uaex.edu

Dimitrios Moshou Agricultural Engineering Laboratory, Faculty of Agriculture, Aristotle University of Thessaloniki, Thessaloniki 275, Greece, dmoshou@auth.gr

John D. Mueller Clemson University – Edisto R.E.C., Blackville, SC 29817, USA, jmllr@clemson.edu

Forrest W. Nutter Jr. Department of Plant Pathology, Iowa State University, Ames, IA 50011, USA, fwn@iastate.edu

Roberto Oberti Department of Agricultural Engineering, Università degli Studi di Milano, Milano 20133, Italy, roberto.oberti@unimi.it

Erich-Christian Oerke Institute of Crop Science and Resource Conservation (INRES) – Phytomedicine, University of Bonn, Bonn D-53115, Germany, ec-oerke@uni-bonn.de

Akpona Okujeni Geomatics Lab, Humboldt-Universität zu Berlin, Berlin D-10099, Germany, akpona.okujeni@student.hu-berlin.de

Douglas R. Olsen Northern Great Plains Center for People and the Environment, University of North Dakota, Grand Forks, ND 58202-9011, USA, olsen@aero.und.edu

Brenda V. Ortiz Auburn University 204 Extension Hall, Auburn University, Auburn, AL 36849-5412, USA, bortiz@auburn.edu

Roland Pieruschka Institute of Chemistry and Dynamics of the Geosphere, ICG-3: Phytosphere, Forschungszentrum Jülich, Jülich D-52425, Germany, r.pieruschka@fz-juelich.de

Paolo Racca Zentralstelle der Länder für EDV gestützte Entscheidungshilfen und Programme im Pflanzenschutz (ZEPP), D-55545 Bad Kreuznach, Germany, racca@zepp.info

Herman Ramon Division of Mechatronics Biostatistics and Sensors (MeBioS), Katholieke Universiteit Leuven, Leuven 3001, Belgium, herman.ramon@biw.kuleuven.be

Uwe Rascher Institute of Chemistry and Dynamics of the Geosphere, ICG-3: Phytosphere, Forschungszentrum Jülich, Jülich D-52425, Germany, u.rascher@fz-juelich.de

Jesper Rasmussen Department of Agriculture and Ecology, Faculty of Life Sciences, University of Copenhagen, DK-2630 Taastrup, Denmark, jer@life.ku.dk

John J. Riggins Department of Entomology and Plant Pathology, Mississippi State University, Mississippi State, MS 39762, USA, jriggins@entomology.msstate.edu

Vittorio Rossi Istituto di Entomologia e Patologia vegetale, Università Cattolica del Sacro Cuore, I-29100 Piacenza, Italy, vittorio.rossi@unicatt.it

Arno Ruckelshausen Faculty of Engineering and Computer Science, University of Applied Sciences Osnabrück, D-49076 Osnabrueck, Germany, a.ruckelshausen@fh-osnabrueck.de

Victor Rueda-Ayala Department of Weed Sciences (360b), University of Hohenheim, D-70599 Stuttgart, Germany, victor.rueda.ayala@uni-hohenheim.de

Huub T.A.M. Schepers Wageningen UR – Applied Plant Research (AGV), 8200AK Lelystad, The Netherlands, huub.schepers@wur.nl

Anke Schickling Institute for Geophysics and Meterology, Universität Köln, Köln D-50937, Germany, a.schickling@fz-juelich.de

Jan Ole Schroers Association for Technology and Structures in Agriculture (KTBL), Bartningstrasse 49, D-64289 Darmstadt, Germany, j.schroers@ktbl.de

Peter Schulze Lammers Institut für Landtechnik, Technology of Crop Farming, D-53115 Bonn, Germany, lammers@uni-bonn.de

Astrid Schweizer Institute of Crop Science and Resource Conservation (INRES) – Phytomedicine, Bonn D-53115, Germany, astrid.schweizer@schwarzenbruch.de

George A. Seielstad Bay Area Environmental Research Institute, Missoula, MT 59808, USA, g.seielstad@nserc.und.edu

Richard A. Sikora Institute of Crop Science and Resource Conservation (INRES) – Phytomedicine, Bonn D-53115, Germany, rsikora@uni-bonn.de

Markus Sökefeld Department of Weed Science, Institute for Phytomedicine, University of Hohenheim, Stuttgart D-70599, Germany, markus.soekefeld@uni-hohenheim.de

Hein Stallinga Wageningen UR – Plant Research International, 6700 AP Wageningen, The Netherlands, hein.stallinga@wur.nl

Ulrike Steiner Institute of Crop Science and Resource Conservation (INRES) – Phytomedicine, University of Bonn, Bonn D-53115, Germany, u-steiner@uni-bonn.de

Antoine Stevens Department of Geography, University of Louvain, Louvain–La–Neuve, Belgium, antoine.stevens@uclouvain.be

Thomas Udelhoven Départment ‘Environnement et Agro-biotechnologies, Centre de Recherche Public Gabriel Lippmann, Belvaux L-4422, Luxembourg, udelhove@lippmann.lu

Jan C. van de Zande Wageningen UR – Plant Research International, 6700 AP Wageningen, The Netherlands, jan.vandezande@wur.nl

Sebastian van der Linden Geomatics Lab, Humboldt-Universität zu Berlin, Berlin D-10099, Germany, sebastian.linden@geo.hu-berlin.de

Maarten van Helden UMR Santé Végétale, University of Bordeaux, Gradignan cedex 33175, France, m-vanhelden@enitab.fr

Neil van Rij Cedara Department of Agriculture, Cedara Plant Disease Clinic, Cedara, South Africa, vanrij@kzndae.gov.za

Pleun van Velde Wageningen UR – Plant Research International, 6700 AP Wageningen, The Netherlands, pleun.vanvelde@wur.nl

Michael Vohland Remote Sensing Department, Faculty of Geography/Geosciences, Trier University, Trier D-54286, Germany, vohland@uni-trier.de

Jiri Vondricka Institut für Landtechnik, Technology of Crop Farming, D-53115 Bonn, Germany, vondricka@uni-bonn.de

Kerstin Voss Remote Sensing Research Group, Department of Geography, University of Bonn, Bonn D-53115, Germany, k.voss@geographie.uni-bonn.de

Martin Weis Department of Weed Science, Institute for Phytomedicine, University of Hohenheim, Stuttgart D-70599, Germany, martin.weis@uni-hohenheim.de

Jonathan S. West Plant Pathology and Microbiology Department, Rothamsted Research, Harpenden AL5 2JQ, UK, jon.west@bbsrc.ac.uk

Jeffrey L. Willers USDA-ARS Genetics and Precision Agriculture Unit, Mississippi State, MS 39762, USA, jeffrey.willers@ars.usda.gov

Thorsten Zeuner Zentralstelle der Länder für EDV gestützte Entscheidungshilfen und Programme im Pflanzenschutz (ZEPP), D-55545 Bad Kreuznach, Germany, zeuner@zepp.info

Xiaodong Zhang Northern Great Plains Center for People and the Environment, University of North Dakota, Grand Forks, ND 58202-9011, USA, zhang@aero.und.edu

Part I
Spatial and Temporal Heterogeneity of Crops, Pests, Diseases and Weeds – Causes and Implications

Chapter 1
Soil Heterogeneity and Crop Growth

Viacheslav I. Adamchuk, Richard B. Ferguson, and Gary W. Hergert

Abstract Producers around the world are considering the use of precision agriculture technologies. One of the key factors encouraging this development is the spatially varying performance of agricultural crops. In many instances, yield variability can be associated with differences in soil attributes across agricultural fields. Understanding and managing spatial variability in soils has become one of the main strategies to optimize crop production, based on local needs for fertilizer, lime, water and/or other crop production inputs. This chapter presents some basic concepts related to the formation of soil heterogeneity and discusses several ways agriculturists can account for spatial variability in soils through differentiated cultural practices and management.

1 Sources and Scales of Soil Heterogeneity

Since the last decade of the twentieth century, agriculturalists have become increasingly interested in using information-based agriculture for agronomically and/or economically optimized crop production systems (Sonka et al. 1997). One of the most obvious strategies is site-specific management, or, more generally, precision agriculture (Pierce and Nowak 1999), earlier termed farming by soil (Robert 1993). To see the reasons soil variability is linked with inconsistent crop performance, it is important to understand what causes even the best-managed agricultural fields to provide significantly different growing environments from one location to another (Webster 2000, McBratney et al. 2003).

The initial factors influencing variability in soils are related to five soil-forming characteristics: parent material, climate, topography, organisms (including vegetation) and time (Jenny 1941). These factors result in soils which are unique and varied on several scales – global, regional, among and within fields, down to the soil

V.I. Adamchuk (✉)
Department of Biological Systems Engineering, University of Nebraska-Lincoln, Lincoln, NE 68583-0726, USA
e-mail: vadamchuk2@unl.edu

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_1,

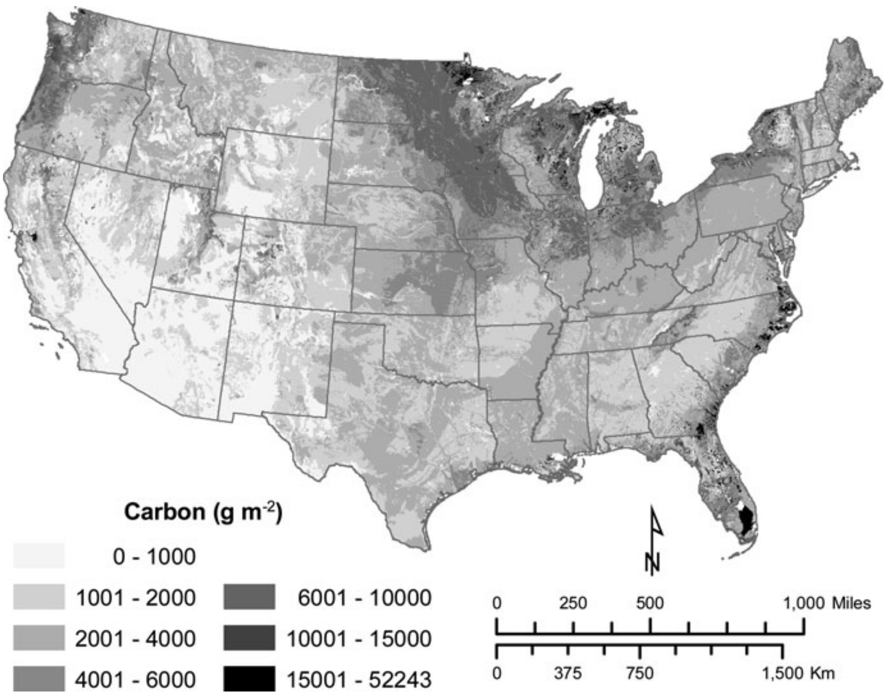

Fig. 1.1 Organic carbon in the top 1 m of soil throughout the contiguous United States provides an example of soil heterogeneity on a regional scale.
Source: United State Department of Agriculture Natural Resources Conservation Service, State Soil Geographic Database (STATSGO)

aggregates. These naturally occurring sources of variability dominate as primary influences on soil heterogeneity on global and regional scales. Figure 1.1 provides a good example, illustrating soil organic carbon in the top 1 m of soil across the continental United States. Soil organic carbon tends to be higher in regions with cool and/or wet climates, as well as in areas dominated by forest or prairie vegetation. It is lower in hot, dry regions.

On the field and sub-field scales, naturally occurring variability can remain quite significant, but historic management enters in as another important factor influencing variability. Figure 1.2 is an example of both natural and management factors affecting soil properties – in this case, soil color, which relates to soil organic matter and productivity in general. Located near the Platte River in central Nebraska, the field contains alluvial soils, with patterns associated with repeated flooding and deposition of sand and silt. The background aerial image obtained in the mid-1950s can be used to identify field areas with relatively light and dark soils, originating from both natural processes as well as management. Some patterns of darker soil are irregular or curved, resulting from silt deposition. Other patterns of darker soil are regular and linear, resulting from historic use of the land. In this case, the lighter-colored block in the eastern part of the image is an old field tilled and leveled

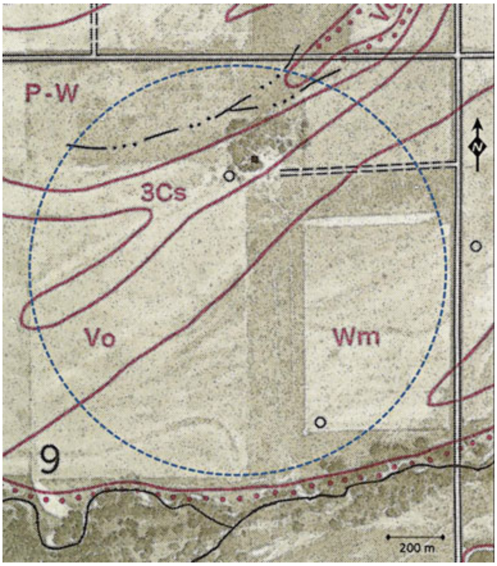

Fig. 1.2 Aerial image and soil series boundaries for a field in Hall County, Nebraska, USA. Vo = Volin silt loam; Wm = Wann loam; 3Cs = Cass fine sandy loam, deep; P-W = Platte-Wann complex.
Source: Hall County Nebraska Soil Survey, United States Dept. of Agriculture, January 1962. The *dashed line* represents the current field boundary

for furrow irrigation in the mid-1950s or earlier. The darker soil region surrounding this block was not tilled until the mid-1980s. Consequently, the portion of the field with a longer tillage history contains about half the soil organic matter of the more recently tilled soil. This image illustrates field boundaries which may be evident in patterns of crop growth many years later, when the entire field within the dashed outline is managed as one unit.

Applying soil amendments such as fertilizer and lime can also impact the heterogeneity of soil properties. The effects can be short-lived or persistent. Figure 1.3

Fig. 1.3 Aerial image of a furrow-irrigated maize field at V12 growth stage, Clay County, Nebraska, USA

illustrates both natural and management-induced patterns of crop nitrogen status. As nitrogen in soil is very dynamic, heterogeneity in soil's N supply is dynamic as well. Light areas within this field are deficient in crop nitrogen, while darker areas have an adequate supply of nitrogen to meet crop requirements at this growth stage. Irregular, curved patterns of N deficiency are associated with lower landscape positions in the field where water accumulated and caused denitrification. The regular, linear stripes across the field are the result of uneven nitrogen fertilizer application. Darker stripes received more fertilizer; lighter stripes received less. These regular patterns of uneven fertilizer application are more pronounced in lower/wetter areas of the field, where denitrification was greater.

Figure 1.4 is another example of management-influenced soil heterogeneity. Currently, this field is managed as a 60 ha center-pivot irrigated field. This field was subdivided into 11 smaller fields. At one time, a farmstead was located in the southwest corner of the field. Livestock manure was spread on the field nearest the farmstead. As a result, substantial immobile nutrients accumulated in places where the manure application rate exceeded the rate of crop nutrient removal. Colored dots in Fig. 1.4 represent soil phosphorus (P) measurements, with soil P concentrations in the southwest corner exceeding 100 mg kg^{-1}. Patterns of soil P concentration throughout the rest of the field are to some degree associated with soil series patterns. The Blendon soil series (Bed and BedA) are lower landscape position soils than the Hord (Hd) soil series. The area of higher soil P associated with Blendon soils periodically has lower crop yields due to saturated soil following heavy rains and loss of plant population. The crop removes less phosphorus due to this saturation in some years, which leads to the gradual accumulation of fertilizer P.

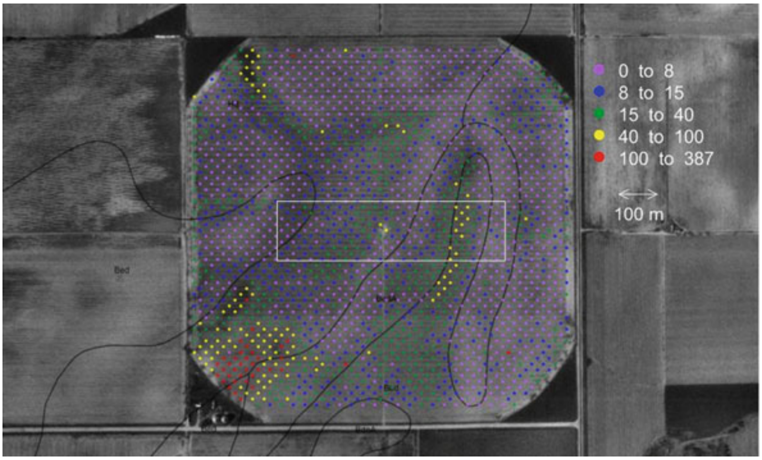

Fig. 1.4 Aerial image and soil series boundaries for a center-pivot irrigated field, Buffalo County, Nebraska, USA. Soil sample locations with Bray-1 P (mg kg^{-1}) concentrations in the upper 20 cm are superimposed

Figure 1.1 illustrates heterogeneity on the national scale; however, for purposes of crop management, variability on the field and sub-field scale are of greatest interest. Agriculturalists must sample thoroughly to accurately determine variability in the soil properties of interest. When designing a sampling procedure for the field, any known factors which may influence patterns of soil properties (e.g., historic manure applications or the former presence of a farmstead) should be considered. Figure 1.5 is a detailed section from the middle of the field illustrated in Fig. 1.4, showing trends in soil P concentration with samples collected every 24 m. Trends over distances of 100 m and greater are consistent with changes in soil series and topography; variability at distances of 50 m or less are more likely related to management.

Figure 1.6 illustrates soil P heterogeneity in both horizontal and vertical dimensions. Created using a transect sampling of a ridge-tilled row in 5 cm increments (horizontally and vertically), this graph illustrates the formation of a band of high soil P concentration. With ridge-till systems, the row location is maintained from year to year, often with repeated application of starter fertilizer at planting. Soil

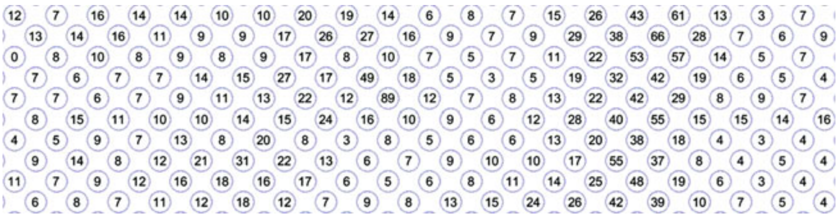

Fig. 1.5 Transect subsection from Fig. 1.4, illustrating variability in soil Bray-1 P (mg/kg) concentration every 24 m

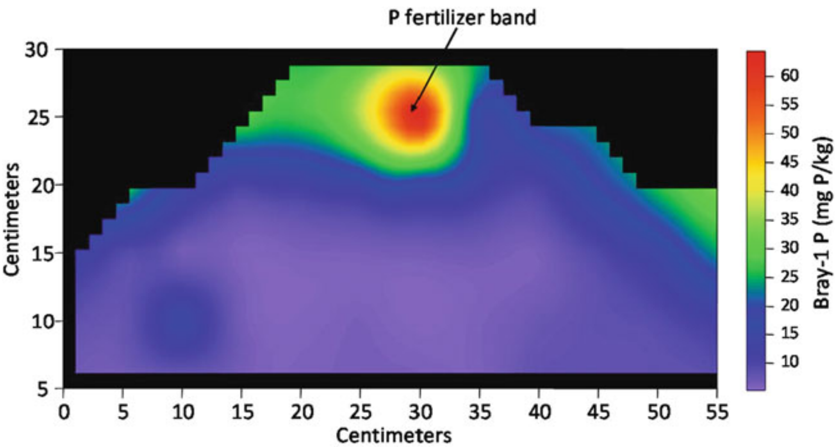

Fig. 1.6 Cross-section across a ridge-tilled row, of Bray-1 P concentration (Clay County, Nebraska, USA)

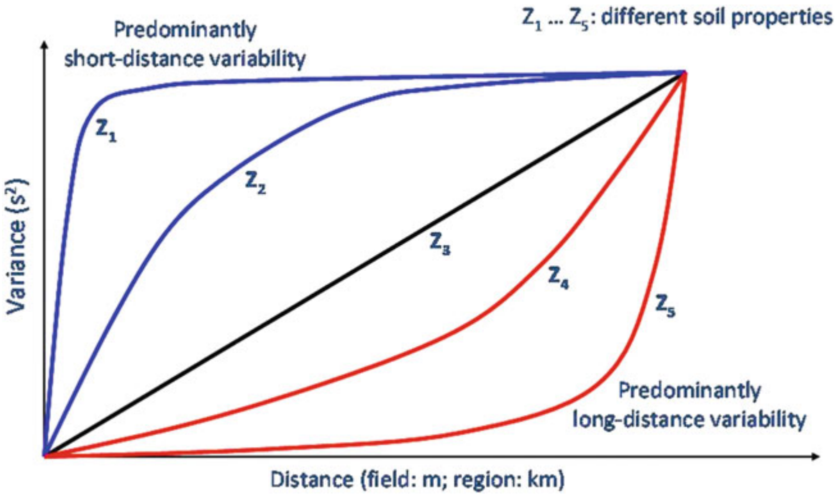

Fig. 1.7 Different potential relationships between sample distance and variance

P concentration varies significantly in both horizontal and vertical dimensions, but in a predictable pattern, given the history of ridge tillage and starter fertilizer use. Knowing this, the agriculturalist can derive a sampling technique which accurately represents the availability of soil P to the crop.

The spatial scale of variability for a given soil property of interest can differ with the property (Fig. 1.7). Some properties, such as soil nitrate, are highly variable over short distances (mm to m). Other properties, such as soil carbon, vary primarily over distances of m to km. Table 1.1 lists ranges of semivariogram models (measures of soil spatial structure) and coefficients of variation for several influential soil attributes (Mulla and McBratney 2000).

Soil properties can vary over time as well as space. Also, some properties are highly dynamic, changing rapidly with time, while other properties are relatively static, varying little from year to year. In assessing spatial variability, temporal variability can sometimes prove to be an important factor. Dynamic properties may change at different temporal scales as well. For example, at shallow depths, soil temperature follows one pattern diurnally and a different pattern seasonally. As depth increases, these patterns are dampened until at some depth temperature is almost constant. Other examples of highly dynamic properties are: soil moisture, microbial activity, water soluble salts, nutrient concentration in soil solution, and soil redox potential. Examples of relative static properties include: soil depth, texture, color, cation exchange capacity, and bulk density.

2 Methods of Assessment

To properly account for existing soil heterogeneity, agriculturalists must assess and interpret measures of mechanical, physical, chemical, biological and other phenomena related to various processes occurring within the root zone. Traditionally this

Table 1.1 Typical Variability of Soil Properties (Mulla and McBratney 2000)

Property	Range for semivariogram models [m]	Spatial dependency	Coefficient of variation [%]	Magnitude of variability
Saturated hydraulic conductivity	1–34	Short range	48–325	High
Percent sand	5–40	Short range	3–37	Low to moderate
Saturated water content	14–76	Short to moderate range	4–20	Low to moderate
Soil pH	20–260	Short to long range	2–15	Low
Crop yield	70–700	Moderate to long range	8–29	Low to moderate
Soil Nitrate-N	40–275	Moderate to long range	28–58	Moderate to high
Soil available potassium	75–428	Moderate to long range	39–157	High
Soil available phosphorous	68–260	Moderate to long range	39–157	High
Organic matter content	112–250	Long range	21–41	Moderate to high

has been accomplished through soil sampling (extracting a fixed amount of soil from a predefined depth) for off-site laboratory evaluation (Peck and Soltanpour 1990). Equipment and methodology used to conduct laboratory soil analyses continue to evolve, but a proper soil sampling scheme is equally important (Crepin and Johnson 1993, Tan 2005, de Gruijter et al. 2006).

To observe spatial heterogeneity in soils, samples from multiple locations within a landscape must be obtained. A model-based principle of sampling is the most promising when it comes to addressing spatial and temporal variability (de Gruijter et al. 2006). Geostatistical methods are used to analyse variability and to predict soil attributes in non-sampled locations using (Wollenhaupt et al. 1997). The major drawback of these conventional strategies is that a relatively coarse sampling density is often deemed most economical. This might not suffice to reveal true spatial variability in soils (McBratney et al. 2005).

To overcome the low spatial resolution of economically feasible sampling, both remote and proximal sensing technologies have been used. Remote sensing relies on acquiring imagery-type data using optical and radiometric sensors installed on an aerial platform or a satellite. Proximal sensing systems are placed near the surface or in contact with soil being tested. When proximal soil sensors are used while traveling across the landscape (on-the-go), geo-referenced data can be used as it is with yield maps to create high-density maps of sensor measurements.

The usefulness of remote sensing data in characterizing soil heterogeneity (Frazier et al. 1997, Leon et al. 2003) depends on spatial, spectral, radiometric and temporal resolution. Spatial resolution (pixel size) depends on the instrumentation and altitude of the measurement platform. Spectral and radiometric resolution also depends on the type of instrument and may be related to imagery that is panchromatic (having light reflectance integrated over the entire visual part of spectrum), multispectral (typically blue, green, red and near-infrared), or hyperspectral (typically more than 200 narrow spectral bands). Panchromatic and multispectral data suffice to visualize the overall spatial variability of soil reflectance. Hyperspectral data has been used to create various models used to predict individual soil parameters of interest (Christy 2008). Temporal resolution of remote sensing data relies on service availability. Images obtained on a clear day with minimal vegetation coverage have been viewed as the most suitable for soil heterogeneity analysis. When agriculturalists attempt to use remote sensing imagery to study soil variability, dense crop residue resulting from no-till crop production is a source of noise.

On-the-go proximal soil sensing systems can be deployed in direct contact with soil while mounted to a vehicle (Hummel et al. 1996, Sudduth et al. 1997, Adamchuk et al. 2004, Shibusawa 2006). The design concepts are many and varied, but most on-the-go soil sensors involve one of the following measurement methods: (I) electrical and electromagnetic sensors that measure electrical resistivity/conductivity or capacitance affected by the composition of the soil tested; (II) optical and radiometric sensors that use electromagnetic waves to detect the level of energy absorbed/reflected by soil particles; (III) mechanical sensors that measure forces resulting from a tool engaged with the soil; (IV) acoustic sensors that quantify the sound produced by a tool interacting with the soil; (V) pneumatic sensors that assess the resistance to the air injected into the soil, and (VI) electrochemical sensors that use ion-selective membranes producing a voltage output in response to the activity of selected ions (e.g., hydrogen, potassium, nitrate, etc.).

Ideally, a soil sensor would respond to the variability of a single soil attribute and would be highly correlated to a particular conventional analytical measurement. Unfortunately, in reality, every sensor developed responds to more than one soil property. Separating their effects is challenging; the process depends on many region-specific factors. Figure 1.8 provides a classification summary of the main types of on-the-go soil sensors with corresponding agronomic soil properties affecting the signal. In many instances, an acceptable correlation between the sensor output and a particular agronomic soil property was found for a specific soil type, or was achieved when the variation of interfering properties was negligible.

Remote and proximal sensing data provide low-cost, high-density information on spatial variability in soils. The resulting maps can be integrated along with digital field elevation maps to delineate field areas with significantly different crop production environments, and to prescribe locations for targeted soil sampling. Delineation of relatively homogeneous areas within fields using sensor measurements allows the producer to establish soil-based management zones (Fridgen et al. 2004, Simbahan and Dobermann 2006). Targeted soil sampling can be used to investigate whether soil properties of interest (e.g., soil nutrient content) relate significantly to field topography and/or sensor measurements. If such relationships are found, sensor measurements can be used to produce high-resolution maps of indirect predictions of different agronomic soil properties. For example, maps of apparent soil electrical conductivity (Allred et al. 2008) frequently reveal boundaries of soil series,

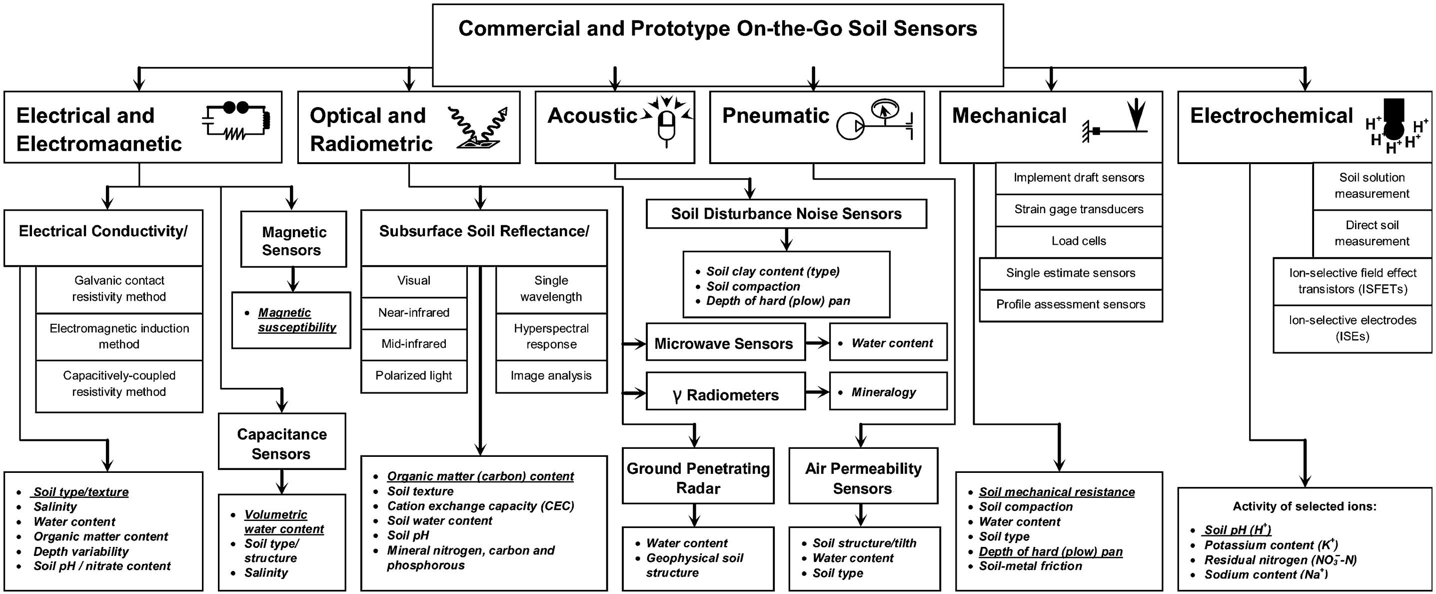

Fig. 1.8 Family of on-the-go soil sensing systems

including soil-forming anomalies such as eroded hillsides or landscape depressions. Because of the differences in yield potential – and therefore, nutrient uptake – it's logical to assume that certain nutrients may vary according to the same patterns (Corwin and Lesch 2003, Heiniger et al. 2003).

When looking at the family of remote and proximal soil sensing systems, it is important to remember that crops themselves are the most effective sensors indicating the quality of a local environment. The spatial distribution of the overall crop performance that in many instances can be explained by soil heterogeneity can be revealed by remote sensing imagery taken during vegetation stages, proximal sensing of crop canopy reflectance, and, ultimately, yield maps. Current precision agriculture research is focused on the integration of various sources of soil- and crop-based sensing technologies to discover and understand spatial variability of soil attributes limiting yield potential. Variable rate application of agricultural inputs according to local needs (economically optimized while considering spatially variable crop production potential) can be the means to increase profitability while preventing unnecessary environmental pressure in a given cropping system.

3 Spatially Differentiated Crop Management

Providing differentiated crop management according to soil variability is a matter of knowing what is manageable and what is not. As noted previously, spatial variability arises from different sources that generally fall into two broad categories: natural and management-induced. The natural sources of variability are primarily those associated with the soil formation processes. However, once we start managing land, we induce additional changes in the crop-growing environment. These changes can affect the soil, soil water, air, and soil temperature. The interactions among these factors, along with changes in weather, also cause variability sometimes attributed to soil heterogeneity.

Variability in soil properties can be categorized as either static or dynamic. The appropriateness of addressing these variations changes, depending on the probability of achieving a positive economic return and the justification for using the required time. Therefore, the list of economically manageable factors becomes operation-specific, dependent upon the resources available and the benefit-to-risk ratio. When producers begin to think about spatially differentiated crop management, they must first determine the types and levels of soil variability they have. In other words, they must ask which soil properties vary and how much? Secondly, producers must determine the size of a manageable area (under one acre or hectare of land versus large portions of a landscape). Regardless of the area of differentiated management, producers must develop a qualitative selection method to define the factors to be addressed. After the qualitative assessment, producers should carry out a quantitative evaluation that measures the degree of variability with respect to the available resources (money and time). It is also advisable to determine what is causing the variability and whether or not one can make a profitable change. In other words, will the increased income from site-specific management be significantly greater than the costs involved?

Differentiated field management requires a significant commitment of both time and money, including the cost of gathering and interpreting information as well as any add-on costs affiliated with site-specific management technology. Producers should consider seven steps: (I) data collection; (II) data management and storage; (III) data processing; (IV) data analysis; (V) data interpretation; (VI) synthesis of information; and (VII) decisions and changes in management.

All the changes in crop management fit into a decision framework made up of three categories: strategic, tactical and operational decisions. Generally, strategic decisions are those that will have effects lasting for 10 years or more. The economic impact is experienced over the long-term and, therefore, the payoff is distributed over many years. These decisions can affect not only current but future environmental considerations related to land and input management. The main question is whether the variability is great enough to warrant a change in management. Tactical decisions are those that have an impact during the coming 5 years. They may involve equipment as well as cropping systems, and may include data management. For instance, producers can delegate information processing to a professional service provider to give themselves needed time for farm-related work (marketing, equipment repair, record keeping, etc.). Operational decisions affect management during the upcoming year only. These primarily include: agronomic input needs, input costs and purchases, equipment maintenance, management of hired labor, etc.

Implementing spatially differentiated crop management assumes that additional information helps producers to make decisions that increase farming efficiency and/or reduce negative environmental impact. Bear in mind that 'data' and 'information' are not the same. The decision framework discussed above should illustrate that differentiated field management frequently requires additional time and monetary investments. As producers approach making changes in their management process, they must determine which factors are most important. According to Covey (1998) one must take care of the 'big rocks' before one worries about the 'pebbles'. In terms of managing and making operational versus tactical versus strategic decisions, the major factors to be addressed depend on the producer's situation. For example, rain-fed production as compared to irrigated management. In a rain-fed environment, the big management factors include: drainage (surface and internal), soil erosion (resulting from mechanical soil and crop residue management), pH, soil nutrients and compaction. Under irrigated conditions, the major factors include: water management (both land preparation and irrigation water distribution) and residue management (which affects both surface and internal soil water flow). The other important factors in irrigated agriculture include compaction, soil nutrients, pH, and salinity.

When approaching management changes, producers must perform qualitative assessments of their operations. They should undertake this mental journey before making any purchases of software or equipment. Simply think about a field or an area, gathering and summarizing all the information available. Use available soils maps, imagery downloadable from the Internet free of charge, and/or create

Table 1.2 Qualitative assessment example

Problem	Yield variability	Complexity of addressing the problem	Expected yield increase [%]	Expected payback (year)
Low spot (topography)	High	Hard (level the field)	10	4
Soil pH	Low	Easy (variable rate liming)	5	7
Sandy patches	High	Medium (variable rate seeding and fertilization)	20	1

hand-drawn maps based on personal experience. Next, draw a map of the changes anticipated once management is altered. As shown in Table 1.2, such information can be summarized using a template to see what problems to address first. Figure 1.9 shows potential factors that can cause inconsistent crop-growing conditions according to their influence on yield variability and complexity of remedy. Clearly the factors that fall in the lower right corner of this grid should be dealt with first.

Also, producers must keep in mind that yield maps are the ultimate illustrators of potential limitations associated with soil heterogeneity. Figure 1.10 shows the process one might follow in deciding whether to invest in site-specific crop management, based on analysis of yield maps. If yield variability across the field cannot

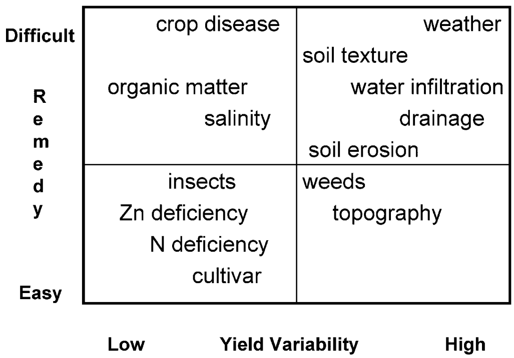

Fig. 1.9 Decision grid with factors that may affect soil heterogeneity in a given growing environment

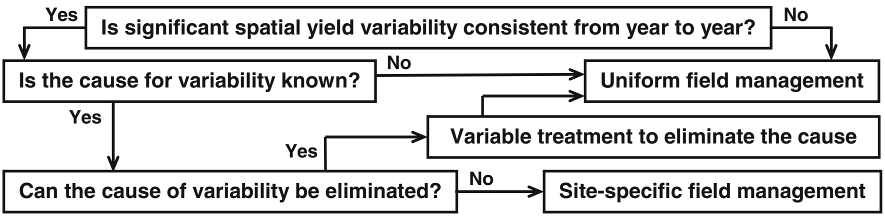

Fig. 1.10 Yield-based decision-making tree

be explained by any spatially inconsistent soil property, uniform management may be appropriate. Site-specific management becomes a promising strategy if yield patterns are consistent from year to year and can be correlated to a layer (or layers) of spatial data (e.g. nutrient supply, field topology, past management, etc.).

4 Summary

Soil heterogeneity is caused both by natural and management-induced processes, and can be described in terms of static and dynamic variables. The manageability of these variables is defined primarily using the rules of production economics. Producers must understand the sources of soil heterogeneity and be able to make qualitative, and, if appropriate, quantitative assessment of spatial variability in soils. If the potential benefits exceed the necessary cost and time needed to address soil heterogeneity, differentiated treatment of an agricultural field according to local conditions may be appropriate and can potentially improve economic and environmental outcomes of crop production. A variety of sensor-based technologies have been transitioning from research into production agriculture that may improve our understanding of soil heterogeneity and provide the technical means to optimize the crop growing cycle.

References

Adamchuk VI, Hummel JW, Morgan MT, Upadhyaya SK (2004) On-the-go soil sensors for precision agriculture. Comput Electron Agric 44:71–91

Allred BJ, Ehsani MR, Daniels JJ (2008) General considerations for geophysical methods applied to agriculture. In: Allred BJ et al (eds) Handbook of agricultural geophysics. CRC Press, Boca Raton, pp 3–16

Christy CD (2008) Real-time measurement of soil attributes using on-the-go near infrared reflectance spectroscopy. Comput Electron Agric 61:10–19

Corwin DL, Lesch SM (2003) Application of soil electrical conductivity to precision agriculture: theory, principles, and guidelines. Agron J 95:455–471

Covey SR (1998) The seven habits of highly effective people. Free Press, New York

Crepin J, Johnson RL (1993) Soil sampling for environmental assessment. In: Carter MR (ed) Soil sampling and methods of analysis. Lewis Publishers, Boca Raton, pp 5–18

de Gruijter J, Brus D, Bierkens M, Knotters M (2006) Sampling for natural resource monitoring. Springer, The Netherlands

Frazier BE, Walters CS, Perry EM (1997) Role of remote sensing in site-specific management. In: Pierce FT, Sadler EJ (eds) The state of site-specific management for agriculture. ASA-CSSA-SSSA, Madison, pp 149–160

Fridgen JJ, Kitchen NR, Sudduth KA et al (2004) Management zone analyst (MZA): software for subfield management zone delineation. Agron J 96:100–108

Heiniger RW, McBride RG, Clay DE (2003) Using soil electrical conductivity to improve nutrient management. Agron J 95:508–519

Hummel JW, Gaultney LD, Sudduth KA (1996) Soil property sensing for site-specific crop management. Comput Electron Agric 14:121–136

Jenny H (1941) Factors of soil formation: a system of quantitative pedology. McGraw-Hill, New York

Leon CT, Shaw DR, Cox MS et al (2003) Utility of remote sensing in predicting crop and soil characteristics. Prec Agric 4:359–384
McBratney A, Whelan B, Ancev T, Bouma J (2005) Future directions of precision agriculture. Prec Agric 6:7–23
McBratney AB, Mendonca Santos ML, Minasny B (2003) On digital soil mapping. Geoderma 117:3–52
Mulla DJ, McBratney AB (2000) Soil spatial variability. In: Sumner ME (ed) Handbook of soil science. CRC Press, Boca Raton, pp A321-A352
Peck TR, Soltanpour PN (1990) The principles of soil testing. In: Westerman RL (ed) Soil testing and plant analysis, 3rd edn. SSSA, Madison, pp 1–10
Pierce FJ, Nowak P (1999) Aspects of precision agriculture. Adv Agron 67:1–85
Robert PC (1993) Characterization of soil conditions at the field level for soil specific management. Geoderma 60:57–72
Shibusawa S (2006) Soil sensors for precision agriculture. In: Srinivasan A (ed) Handbook of precision agriculture, principles and applications. Food Products Press, New York, pp 57–90
Simbahan GC, Dobermann A (2006) An algorithm for spatially constrained classification of categorical and continuous soil properties. Geoderma 136:504–523
Sonka ST, Bauer ME, Cherry ET et al (1997) Precision agriculture in the 21st century. Geospatial and information technologies in crop management. National Academy Press, Washington
Sudduth KA, Hummel JW, Birrell SJ (1997) Sensors for site-specific management. In: Pierce FT, Sadler EJ (eds) The state of site-specific management for agriculture. ASA-CSSA-SSSA, Madison, pp 183–210
Tan KH (2005) Soil sampling, preparation, and analysis, 2nd edn. CRC Press, Boca Raton
Webster R (2000) Is soil variation random? Geoderma 97:149–163
Wollenhaupt NC, Mulla DJ, Gotway Crawford CA (1997) Soil sampling and interpolation techniques for mapping spatial variability of soil properties. In: Pierce FT, Sadler EJ (eds) The state of site-specific management for agriculture. ASA-CSSA-SSSA, Madison, pp 19–53

Chapter 2
Spatial and Temporal Dynamics of Weed Populations

Roland Gerhards

Abstract Spatial and temporal variations in weed seedlings distributions often occur in arable fields and can be assessed and mapped using modern sensor- and information technologies. Both management and site-characteristics can result in the heterogeneity of weed populations. When site-specific weed management decisions were taken based on distribution maps a high potential for herbicide savings was calculated. It was found that for many weed species distribution remained stable over time when site-specific herbicides applications were realized based on economic weed thresholds.

1 Introduction

Weed seedling distributions have been found spatially and temporally heterogeneous within agricultural fields. They often occur in aggregated patches of varying size or in stripes along the direction of cultivation (Marshall 1988, Gerhards and Christensen 2003, Christensen and Heisel 1998). The spatial distribution of weeds has often been ignored in weed management because the techniques to measure the spatial variation of weeds have so far not been implemented. With a large within-field variation in weed occurrence, patch spraying, based on the need for weed control reduces costs as well as herbicidal loading to the environment and the risk of herbicide residues in the food chain (Dammer et al. 2003, Timmermann et al. 2003, Gerhards and Oebel 2006). In many studies, weed species were grouped into grass weeds, annual broadleaves and perennial weeds. Perennials such as *Convolvulus arvensis* and *Cirsium arvense* were found to be highly aggregated in small annual grains, maize and sugar beets with less than 20% of the field being infested. Grass weeds covered on average 30–40% of the fields at infestation levels higher than the economic thresholds and annual broadleaves between 20 and 90% (Timmermann et al. 2003, Gerhards and Oebel 2006).

R. Gerhards (✉)
Department of Weed Sciences (360b), University of Hohenheim, Stuttgart D-70599, Germany
e-mail: gerhards@uni-hohenheim.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_2,

2 Weed Mapping

Weed seedling distribution in the field was assessed using discrete weed mapping or continuous-area sampling (Rew and Cousens 2001). In most studies, discrete weed mapping was applied in a regular sampling grid that was established in the field. The grid size varied from a few meters up to approximately 50 m and was dependent on the width of the spray boom used for site-specific herbicide application. Density and/or coverage of emerged weed seedlings were counted and measured prior to and after post-emergence herbicide application in a sampling frame placed at all grid intersection points.

A major step towards a practical solution for site-specific weed management was the development of precise and powerful sampling techniques to automatically and continuously determine in-field variation of weed seedling populations. Airborne remote sensing was applied to identify *Avena fatua* L. and *Avena sterilis* ssp. *ludoviciana* (Durieu) Nyman populations in wheat but could not detect densities of less than 19 plants m^{-2} (Lamb and Brown 2001). A finer resolution of the sensor, however, is required to detect low density weed seedling populations. Therefore, optoelectronic sensors and digital cameras were mounted on the tractor to detect weeds in the near range. Felton and McCloy (1992), Vrindts and de Baerdemaeker (1997) and Biller (1998) used optoelectronic sensors to measure the reflectance in the green, red and near-infrared light wave bands. Green leaves were characterised by a high reflectance in the green and near-infrared and a low reflectance in the red spectrum compared with the reflectance curve of bare soil.

Different methods to continuously record in-field variation of weed distributions were to surround and record the borders of aggregated patches of weed species such as *Avena fatua* using a data logger connected to a differential global positioning system (DGPS) (Colliver et al. 1996) or to map weed patches during harvest operations (Barroso et al. 2005).

However, the most promising approach for weed detection is a continuous ground-based detection method based on image analysis (Weis et al. 2008). With this method, weeds and crops were segmented from digital images in real-time using a bi-spectral camera system connected to DGPS. Weed species as well as crops were identified and counted based on automatic classification of shape features (Fig. 2.1).

Different mapping programs have been applied to characterize spatial distribution of weeds and soil parameters within fields. Maps differed based on the interpolation method that was applied and the sample spacing. Johnson et al. (1995) used geostatistical methods to quantify spatial dependence of weed seedling populations. Kriging methods were then applied to estimate and map weed density at unsampled positions in the field. Gerhards et al. (1997) found that a triangulation interpolation method was more accurate than ordinary kriging to characterize weed seedling populations with a directional pattern. This method overcomes the problem of discontinuities between adjacent sampling points that result from grid sampling. A plane is fitted through three sampling points that surround the point being estimated. The equation of the plane can be expressed as:

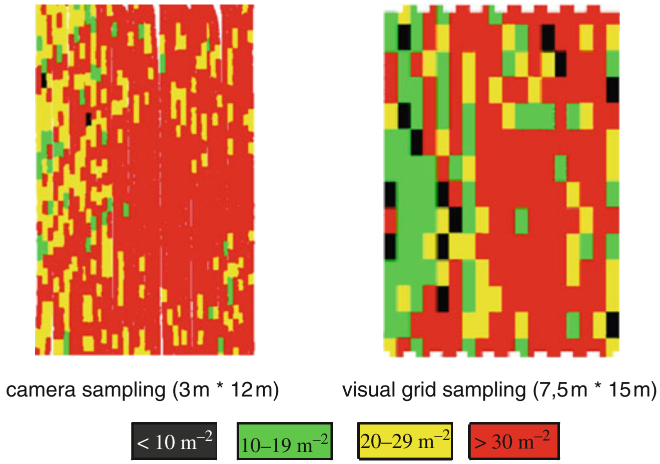

Fig. 2.1 Distribution maps using camera sampling and visual grid sampling for broad-leaved weed species on a 2.4 ha maize field, Dikopshof Research Station, in 2004 (modified after Gerhards and Oebel 2006)

$$Z = a\,x + b\,y + c \tag{1}$$

where Z is the observed seedling density, x and y are the coordinates in east-west and north-south directions and a, b, and c are parameters that can be calculated by solving the following system of equations:

$$\begin{aligned} Z_1 &= a\,x_1 + b\,y_1 + c \\ Z_2 &= a\,x_2 + b\,y_2 + c \\ Z_3 &= a\,x_3 + b\,{}_3 + c \end{aligned} \tag{2}$$

Starting with the density count at the first x, y intersection, weed density is calculated for each pixel between the sampling points. Different from ordinary kriging, equal weight was given to all sampling points with this interpolation method (Isaaks and Srivastava 1989). Interpolated weed maps were reclassified based on weed infestation levels (Gerhards et al. 1997). Density classes were equal for all species in this study to facilitate the analysis of overlay maps. A weed treatment map was created to provide a decision rule for the patch sprayer (Fig. 2.2).

3 Temporal and Spatial Dynamics of Weed Populations

The dynamics of weed populations are influenced by the biological characteristics of weed species, farming practices such as tillage, crop rotation, time of seeding, harvesting competitiveness of the crop and direct weed control methods as well as soil

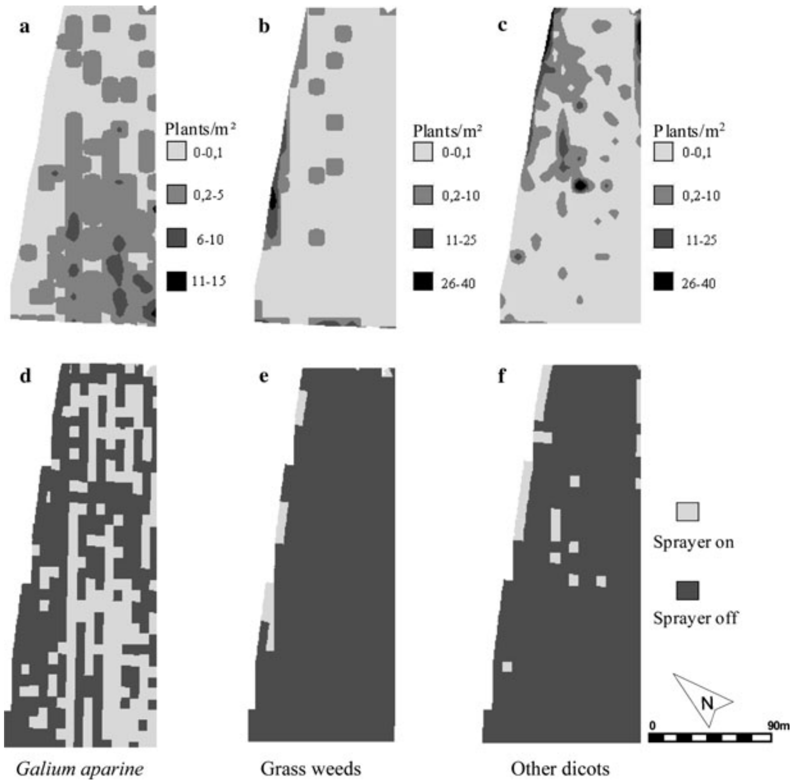

Fig. 2.2 Distribution of different weed species (**a**–**c**) in a 3 ha spring barley field 2003 and application maps as a decision rule for the patch sprayer (**d**–**f**). Maps were created according to economic weed thresholds for all three weed species classes (Gerhards et al. 1997)

parameters (Mortensen et al. 1998, Nordmeyer and Niemann 1992, Timmermann et al. 2002). The major weed species have developed specific adaption- and survival strategies to persist in cropping systems (Radosevich et al. 1997). Those strategies include the production of a high number of seeds over a long period of time and seed dormancy (e.g. *Chenopodium album*). In addition, successful weed species have the capacity to survive under variable environments based on high phenotypic and genetic plasticity to invade new sites (e.g. *Abutilon theophrasti*). Many weeds are able to strongly compete for space, light, water and nutrients with the crops by high growth rates and efficiency in using water and nutrients. Several weeds produce mature seeds in a much shorter time than crops so that the seeds are spread long before a dense crop stand has been established (e.g. *Galinsoga parviflora*). Other weed species, such as *Cirsium arvense* and *Agropyron repens* have the ability to persist and spread via seeds and vegetative reproduction tissues. Those perennial weeds can emerge much faster than annual plants. These are only few reasons for spatial and temporal dynamics of weed populations.

Nordmeyer and Niemann (1992) found that blackgrass (*Alopecurus myosuroides*) populations mostly occurred at locations in the field where the clay content was relatively high. Timmermann et al. (2002) reported that the crop rotation had a long-term effect on weed density and weed species composition. In fields that had been planted with 50% maize in the rotation more than 20 years ago, the density of *C. album* was still much higher than in fields with a high percentage of winter annual grains in the rotation. The crop rotation had also a very strong effect on the organic matter content. Fields that had been planted with potatoes were lower in the organic matter content than fields where mostly grains were planted. The difference in organic matter content again had a strong influence on the weed species composition. *Galium aparine* predominantly occurred in fields with high organic matter contents (Timmermann et al. 2002).

Krohmann et al. (2002) studied the dynamics of weed seedling distribution over 5 years in a rotation of maize, sugar beet, winter wheat and winter barley and in continuous maize. They found that weed distribution maps obtained in maize and sugar beet were suitable for site-specific weed control in winter wheat and winter barley (Fig. 2.3).

Ritter and Gerhards (2008) reported that populations of *Alopecurus myosuroides* did not significantly change in density, location and size when site-specific weed

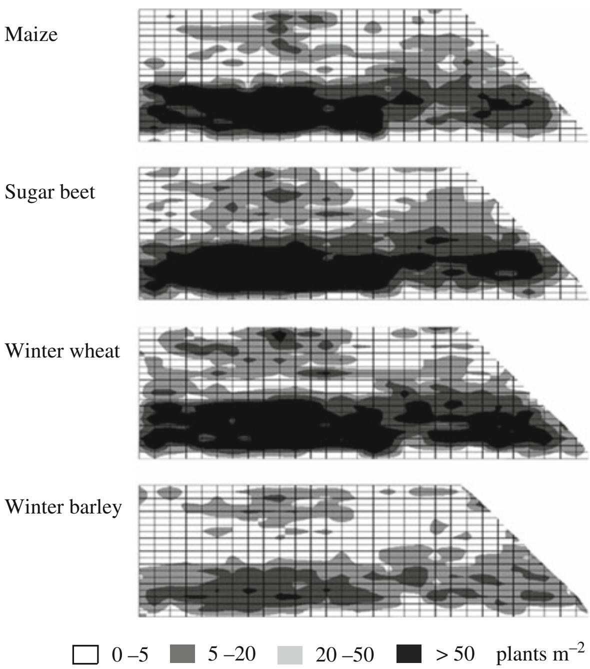

Fig. 2.3 Distribution of *Viola arvensis* in maize, sugar beet, winter wheat and winter barley in 5 ha arable field at Dikopshof Research Station near Bonn, Germany (modified after Krohmann et al. 2002)

control methods were applied over a period of 8 years in a rotation of winter annual cereals, maize and sugar beet. In all of three field studied, weed seedling distribution was heterogeneous. Density was higher in maize and sugar beet than in winter cereals. High density patches with densities higher than 25 plants m^{-2} consistently recur over the years at the same areas in the fields. Weed density reduction due to herbicides and other weed control methods was satisfying in each year indicating that site-specific weed control methods are sustainable for long-term weed suppression. Herbicide savings against *A. myosuroides* ranged from 50% in sugar beet to 75% in winter barley.

Ritter and Gerhards (2008) also studied weed population dynamics of *Galium aparine* and *A. myosuroides* under the influence of site-specific weed management. It was found that most of the tested population parameters were weed density dependent. It was presumed, that individual weeds without competition evolve better and produce more seeds but this study showed opposed results. With increasing weed density weed biomass and fecundity increased in this study (Figs. 2.4 and 2.5). All findings support that weed density has to be considered in weed management strategies.

An understanding of fundamental weed population biology would improve our ability to develop site-specific management decisions. Weed populations models have been applied to quantify the effects of site-specific weed management practices (Paice et al. 1997). However, the mechanism of weed patch stability is rather untapped. A few results are reported that efficacy of weed control methods was lower in weed patches that at low density locations (Mortensen et al. 1998). Krohmann et al. (2002) found that the persistence of weed populations was also attributed to weed seedlings that emerged after weed control methods had been

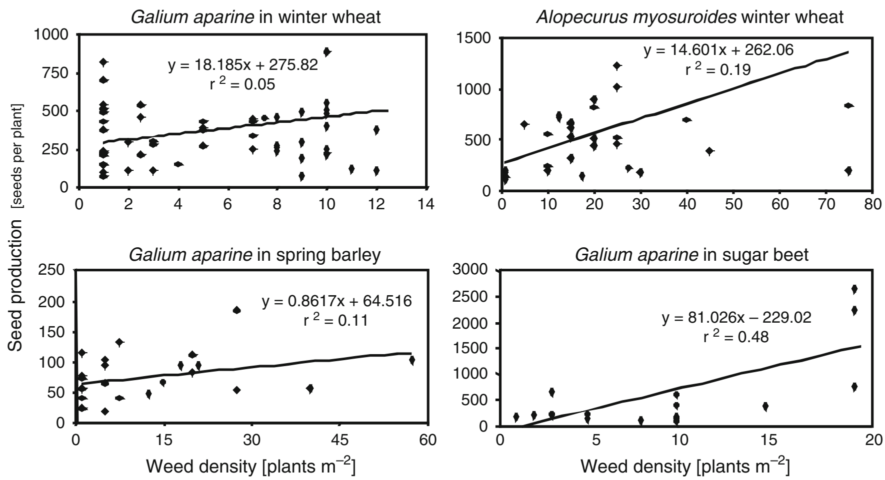

Fig. 2.4 Weed density and seed production of *Galium aparine* and *Alopecurus myosuroides* in various crops (Ritter and Gerhards 2008)

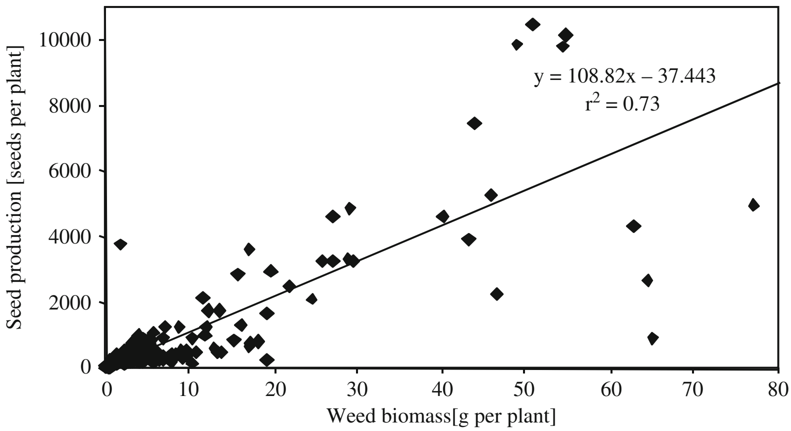

Fig. 2.5 Correlation of weed biomass and seed production of *Galium aparine* and *Alopecurus myosuroides* over all crops (Ritter and Gerhards 2008)

applied. Those individuals were able to produce viable seeds in maize and sugar beet but not in winter wheat and winter barley. The authors assume that competition of the crop was higher in winter annual grains and therefore late emerging weed seedlings were suppressed.

Few studies have attempted to quantify spatial stability of weed patches in agricultural fields. If weed patches were consistent in density and location over years, maps from 1 year could be used to direct sampling plans and to regulate weed control methods in subsequent years. Wilson and Brain (1991) found that the pattern of blackgrass (*A. myosuroides* Huds.) patches persisted during a 10 year study. Persistence of patches was attributed to the poor ability of blackgrass to colonize new locations when effective herbicides were applied. The pattern of patches was most stable in fields planted to cereals. Pester et al. (1995) observed significant stability for velvetleaf populations using Pearson, Spearman rank, and chi-square correlation analysis to quantify year by year relationships between weed density at individual X,Y-coordinates of the sampling grid in four fields. Walter (1996) also used the chi-square correlation method and found that field violet (*V. arvensis* Murr.), common lambsquarters (*C. album* L.) and prostrate knotweed (*Polygonum aviculare* L.) distributions were stable in cereal grain fields over 3 years.

Gerhards et al. (1996) studied the spatial stability of velvetleaf (*A. theophrasti* Medik.), hemp dogbane (*Apocynum cannabinum* L.), common sunflower (*Helianthus annuus* L.), yellow foxtail (*Setaria glauca* L.) and green foxtail (*Setaria viridis* L.) over 4 years (1992–1995) in two fields in eastern Nebraska. The first field was planted to soybean in 1992 and corn in 1993, 1994 and 1995. The second field was planted to corn in 1992 and 1994 and soybean in 1993 and 1995. Weed density was sampled prior to post-emergence herbicide application at approximately 800 locations per year in each field on a regular 7 m grid. The same locations were sampled every year. Weed density at locations between the sample sites was determined by linear triangulation interpolation. Weed seedling distribution was significantly aggregated with large areas being weed free in both fields. Common sunflower, velvetleaf, and hemp dogbane patches were very persistent in the east-west and north-south directions and in location and area over the 4 years in the first field. Foxtail distribution and density continuously increased in each of the 4 years in the first field and decreased in the second field. A Geographic Information System was used to overlay maps from each year for a species. This showed that 36% of the sampled area was free of common sunflower, 62.5% was free of hemp dogbane and 11.5% was free of velvetleaf in the first field, but only 1% was free of velvetleaf in the second field. The persistence of broadleaf weed patches observed in this study suggests that weed seedling distributions mapped in 1 year are good predictors of future seedling distributions.

Heijting et al. (2007) found strong spatial correlations for *Echinochloa crus-galli, C. album, C. polyspermum* and *Solanum nigrum* in 3 years continuous maize cultivation. They attributed spatial and temporal stability of weed populations to their high recruitment capacity.

4 Conclusions

Knowledge of spatial and temporal variability of weed populations offers large potential for precise control methods using less herbicides resulting in less herbicide residues in the environment and food chain. Site-specific weed control methods can be realized when automatic sensor technologies for weed detection and patch spraying technologies are combined with precise decision algorithms.

In addition to this practical benefit, weed mapping helps to understand weed-crop interactions and population dynamics of weed species. It allows quantifying yield effects of different weed infestations in the fields and modelling the spatial and temporal variability of weed populations under different crop management systems.

References

Barroso J, Ruiz D, Fernandez-Quintanilla C, Leguizamon ES, Hernaz P, Ribeiro A, Dias B, Maxwell BD, Rew LJ (2005) Comparison of different sampling methodologies for site-specific management of *Avena sterilis*. Weed Res 45:165–174

Biller RH (1998) Pflanzenunterscheidung und gezielter Einsatz von Herbiziden. Forschungs-Report 1, 34

Christensen S, Heisel T (1998) Patch spraying using historical, manual and real-time monitoring of weeds in cereals in cereals. Z PflKrankh PflSchutz XVI(special issue):257–263

Colliver CT, Maxwell BD, Tyler DA et al (1996) Georeferencing wild oat infestations in small grains: accuracy and efficiency of three survey techniques. Proceedings 1996 of the 3rd International Conference on Precision Agriculture, Minneapolis, pp 453–463

Dammer KH, Böttger H, Ehlert D (2003) Sensor-controlled variable rate application of herbicides and fungicides. Prec Agric 4:129–134

Felton WL, McCloy KR (1992) Spot spraying. Agric Eng 11:9–12

Gerhards R, Christensen S (2003) Real-time weed detection, decision making and patch spraying in maize, sugar beet winter wheat and winter barley. Weed Res 43:1–8

Gerhards R, Oebel H (2006) Practical experiences with a system for site-specific weed control in arable crops using real-time image analysis and GPS-controlled patch spraying. Weed Res 46:185–193

Gerhards R, Pester DY, Mortensen DA (1996) Characterizing spatial stability of weed populations using interpolated maps. Weed Sci 45:108–119

Gerhards R, Sökefeld M, Schulze-Lohne K et al (1997) Site-specific weed control in winter wheat. J Agron Crop Sci 178:219–225

Heijting S, Van Der Werf W, Stein A, Kropff MJ (2007) Are weed patches stable in locations? Application of an explicitly two-dimensional methodology. Weed Res 47:381–395

Isaaks EH, Srivastava RM (1989) Point estimation and ordinary kriging. In: Isaaks EH, Srivastava RM (eds) Applied geostatistics. Oxford University Press, New York

Johnson GA, Mortensen DA, Martin AR (1995) A simulation of herbicide use based on weed spatial distribution. Weed Res 35:197–205

Krohmann P, Timmermann C, Gerhards R, Kühbauch W (2002) Ursachen für die Persistenz von Unkrautpopulationen. J Plant Dis Prot XVIII(special issue):261–268

Lamb DW, Brown RB (2001) Remote sensing and mapping of weeds in crops. J Agric Eng Res 78:117–125

Marshall EJP (1988) Field-scale estimates of grass populations in arable land. Weed Res 28: 191–198

Mortensen DA, Dieleman JA, Johnson GA (1998) Weed spatial variation and weed management. In: Hatfield JL, Buhler DD, Stewart BA (eds) Integrated weed and soil management. Ann Arbor Press, Chelsea, p 293

Nordmeyer H, Niemann P (1992) Möglichkeiten der gezielten Teilflächenbehandlung mit Herbiziden auf Grundlage von Unkrautverteilung und Bodenvariabilität. Z PflKrankh PflSchutz XIII (special issue):539–547

Paice MER, Day W, Rew LJ, Howard A (1997) A simulation model for evaluating the concept of patch spraying. Weed Res 43:373–388

Pester DY, Mortensen DA, Gotway CA (1995) Statistical methods to quantify spatial stability of weed populations. North Central Weed Science Society 50:52

Radosevich S, Holt J, Ghersa C (1997) Weed ecology – implication for weed management. 2nd edn. John Wiley & Sons, New York, 589p

Rew LJ, Cousens RD (2001) Spatial distribution of weeds in arable crops: a current sampling and analytical methods appropriate. Weed Res 41:1–18

Ritter C, Gerhards R (2008) Population dynamics of *Galium aparine* L. and *A. myosuroides* (Huds.) under the influence of site-specific weed management. J Plant Dis Prot XXI (special issue):209–214

Timmermann C, Gerhards R, Kühbauch W (2002) Ursachen für Ertragsunterschiede in Ackerschlägen. J Agron Crop Sci 187:1–9

Timmermann C, Gerhards R, Kühbauch W (2003) The economic impact of the site specific weed control. Prec Agric 4:249–260

Vrindts E, de Baerdemaeker J (1997) Optical discrimination of crop, weed and soil for on-line weed detection. In: Stafford J (ed) Precision agriculture 1997, Proceedings of the 1st European conference on precision agriculture. vol 2: Technology, IT and Management. BIOS Scientific Publishers, Warwick, pp 537–544

Walter W (1996) Temporal and spatial stability of weeds. In: Brown H (ed) Proceedings of the 2nd international weed congress, Flakkebjerg, pp 125–130

Weis M, Ritter C, Gutjahr C et al (2008) Precision farming for weed management: techniques. Ges Pflanzen 60:171–181

Wilson BJ, Brain P (1991) Long-term stability of distribution of *Alopecurus myosuroides* Huds. within cereal fields. Weed Res 31:367–373

Chapter 3
Spatial and Temporal Dynamics of Plant Pathogens

Forrest W. Nutter Jr., Neil van Rij, Sharon K. Eggenberger, and Noha Holah

Abstract Plant disease risk varies not only temporally, but also spatially. Adding the spatial component to disease risk detection and disease risk assessment will help farmers, researchers, and policy decision makers make informed, science-based decisions. By integrating GPS, GIS, and remote sensing technologies (especially satellite remote sensing platforms), new, quantitative information concerning disease risk can now be obtained. Moreover, ground-based methods and models previously developed and used to detect and quantify disease gradients and healthy green leaf area (HGLA) gradients can now be coupled with aerial and satellite imagery datasets. Previously, remote sensing technologies have been used successfully to detect, quantify, and map disease stress. However, the inability to discriminate accurately among the causes of biotic and abiotic crop stress agents has greatly limited the adoption of remote sensing-based technologies to improve disease risk assessment and disease management. This chapter describes how GPS, GIS, and remote sensing technologies can be integrated and used to extract pathogen-specific temporal and spatial 'signatures' that have tremendous potential to accurately identify the cause(s) of biotic and abiotic stress in crops. Moreover, we describe a new paradigm in which remote sensing can be used to quantify, evaluate, and compare specific disease management strategies, and tactics (or entire integrated disease management programs) for their abilities to optimize and maintain crop health (i.e., healthy green leaf area).

1 Introduction

The temporal and spatial dynamics of plant pathogens can be quantified by visually assessing disease intensity (Nutter 2001, Nutter and Esker 2006, Nutter et al. 2006). However, the accuracy and precision of visual disease assessments performed by

F.W. Nutter Jr. (✉)
Department of Plant Pathology, Iowa State University, Ames, IA 50011, USA
e-mail: fwn@iastate.edu

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_3,

different raters continues to be called into question (Guan and Nutter 2003, Nutter et al. 2006, Pethybridge et al. 2008, Steddom et al. 2005). The integration of remote sensing, global positioning systems (GPS), and geographic information systems (GIS) technologies provides new opportunities to obtain, process, and analyze geospatially referenced data (Esker et al. 2006, 2007, Pethybridge et al. 2009). Thus, data for pathogen and host populations, biotic and abiotic risk factors, and yield and yield components can be mapped, overlaid, and displayed at multiple spatial scales (plant, plot, field, farm, county, production region, etc.) to elucidate associations and cause and effect (i.e., stimulus-response) relationships among data layers (Esker et al. 2006, Gleason et al. 1994, Hijmans et al. 2000, Huang et al. 2008, Leckie et al. 2005, Nutter et al. 2002, Nutter et al. 2010, Pethybridge et al. 2009).

Remote sensing can be defined as the acquisition of data from an object using a sensor that is not in direct contact with the object of interest (Nutter 1990). A GIS is a computer (hardware and software) system that captures, stores, manages, queries, analyzes, and displays geographically-referenced (or geospatially-referenced) data (Wang 2006). Data is often geospatially-referenced using a GPS that provides users with accurate positioning, navigation, and timing services (Burrough 1986, Chang et al. 2007).

There is a need to develop metrics for evaluating and monitoring Integrated Pest Management (IPM) performance (Hamerchlag and Kaplan 2007). Remote sensing, when coupled with GPS and GIS technologies, has the potential to assess crop health (rather than disease intensity) over time and space, with greater accuracy and precision (Nutter 1990, 2001, Nutter et al. 2009). Therefore, the integration of remote sensing, GPS, and GIS technologies represents a new paradigm in that disease management strategies and tactics could, in the future, be evaluated and deployed based upon the capability of a disease management program to produce and maintain (protect) healthy green leaf area (Lathrop and Pennypacker 1980, Nutter 1989, 1999, 2001).

2 Testing Conceptual Stimulus-Response Relationships Using GPS, GIS, and Remote Sensing

One of the primary advantages in coupling GPS, GIS, and remote sensing technologies with geospatially-referenced data is that GIS maps can be produced for each variable. Maps can then be rectified and overlaid upon each other to visually assess which variables are likely to have associations with response variables (Burrough 1986, Chong et al. 2001, Gleason et al. 1994, Nutter et al. 2002, Pethybridge et al. 2007a). The predictive value of selected variables can then be used to evaluate stimulus-response relationships. For example, a new, large-scale pathogen dissemination mechanism was found to play a critical role in the prevalence of Moko disease of banana (caused by *Ralstonia solanacearum*) in the Amazon River Basin (Coelho-Netto and Nutter 2005, Nutter et al. 2010). When a GIS map showing the locations of subsistence farms subject to periodic river flooding was overlaid with another map showing locations of subsistence farms where Moko disease was present, the two maps were found to be nearly identical. Using Chi square analysis, subsistence farms that were periodically flooded had a significantly higher risk for Moko disease ($X^2 = 40.55$, $P < 0.0001$) compared to subsistence farms not exposed to periodic flooding (35 times higher risk). Moreover, *k*-function analysis revealed that Moko-infected subsistence farms were negatively impacting the health status of other subsistence farms with banana, up to a distance of several hundred kilometers.

In a recent study, Nutter et al. (2002) obtained geospatially-referenced data layers to map remotely-sensed data obtained from three different platforms: a hand-held CropScan multispectral radiometer (CropScan, Inc., Rochester, MN), an aerial platform using color and infrared film, and a satellite platform using Landsat 7 imagery (Fig. 3.1). The remote-sensing data layers were overlaid with GIS maps for a 1.2 ha soybean field located in Ames, Iowa, that showed soybean yield and soybean cyst nematode population density. Relationships for stimulus-response models were evaluated using linear regression in order to quantify the predictive power of the three remote sensing platforms (i.e., the stimulus variables) to predict soybean cyst nematode (SCN) populations and soybean yield (the response variables). The satellite and ground based remote sensing platforms explained more of the variation in SCN population density ($R^2 = 58\%$ and 48%, respectively), compared to the aerial platform, which explained only 33% of the variation in nematode density (Fig. 3.2, Nutter et al. 2002).

The ground-based and aerial remote sensing platforms had excellent relationships with soybean yield, with ground-based platform data explaining 90% of the variation in soybean yield ($R^2 = 90\%$), and aerial platform data explaining 84% of

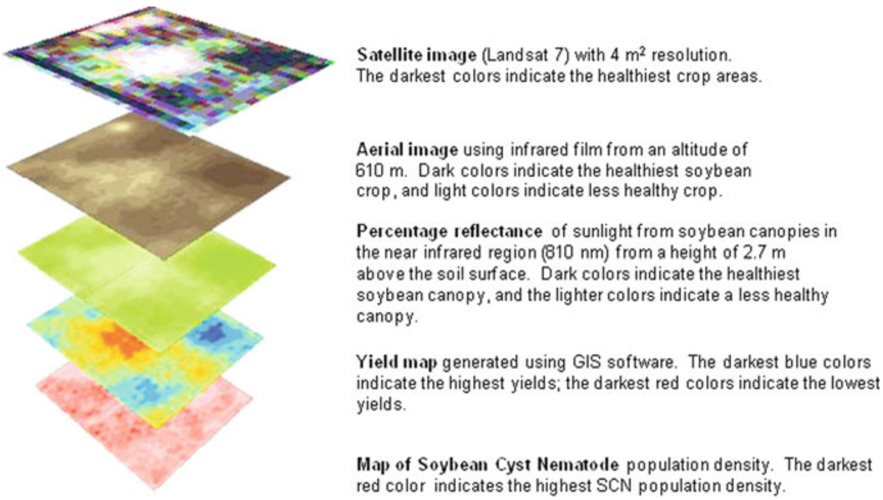

Fig. 3.1 Overlay of GIS maps for three remote sensing platforms (satellite, aerial, and ground-based), along with maps for yield and soybean cyst nematode population density for a 1.2-ha soybean field located at Woodruff Farm, Ames, IA

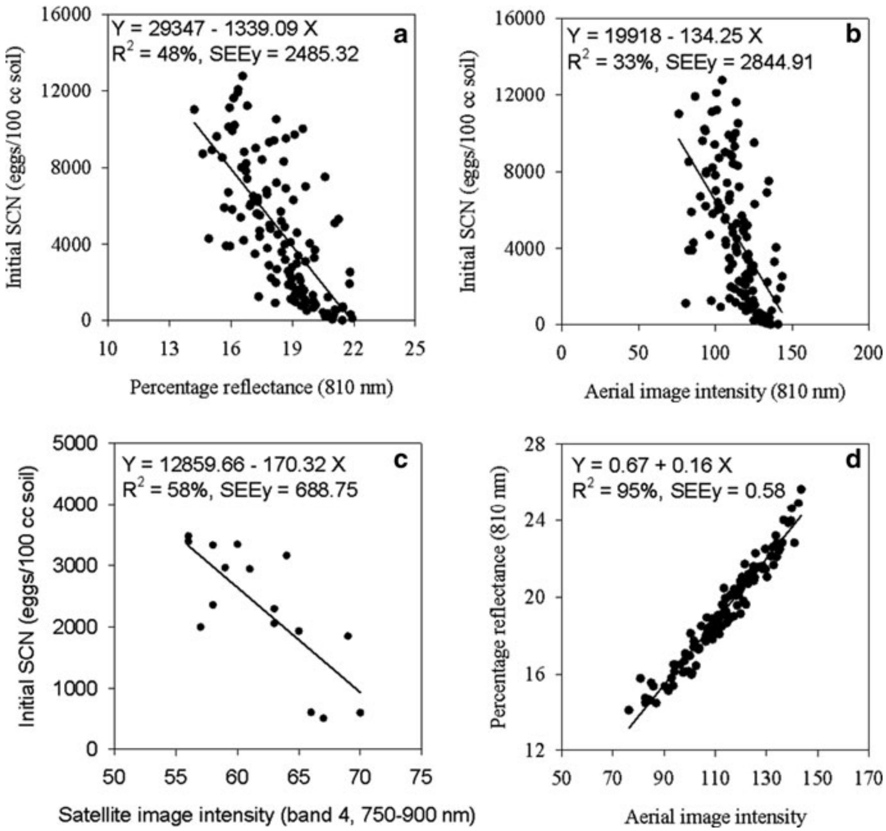

Fig. 3.2 Quantitative relationships between (**a**) ground-based, (**b**) aerial, and (**c**) satellite (Landsat 7) remote sensing data (near-infrared wavelength band) in relation to the population density of soybean cyst nematode for a soybean field located in Ames, Iowa. In (**d**), NIR data obtained from the aerial platform had a strong linear relationship with NIR data obtained using a ground-based multispectral radiometer (CropScan, Inc., Rochester, MN)

the variation in yield (Fig. 3.3). The fact that these two remote sensing platforms accounted for approximately half of the variation in SCN population density, but 84–90% of the variation in soybean yield, indicates that not all of the variation in crop stress, as measured by NIR reflectance values, was due to SCN population density. Thus, these remote sensing platforms were likely detecting other biotic or abiotic stresses affecting the health of the soybean canopy. One such abiotic stress, which was present in this particular field, is iron chlorosis deficiency, which, like SCN, causes plant stunting and chlorosis (Hartman et al. 1999). This points out an important consideration for using only the NIR band when collecting remote sensing data. Although this band has a strong relationship with healthy green leaf area (HGLA), it quantifies the effects of all stresses in the field that affect HGLA. This problem can be overcome, however, by taking advantage of high resolution sensors

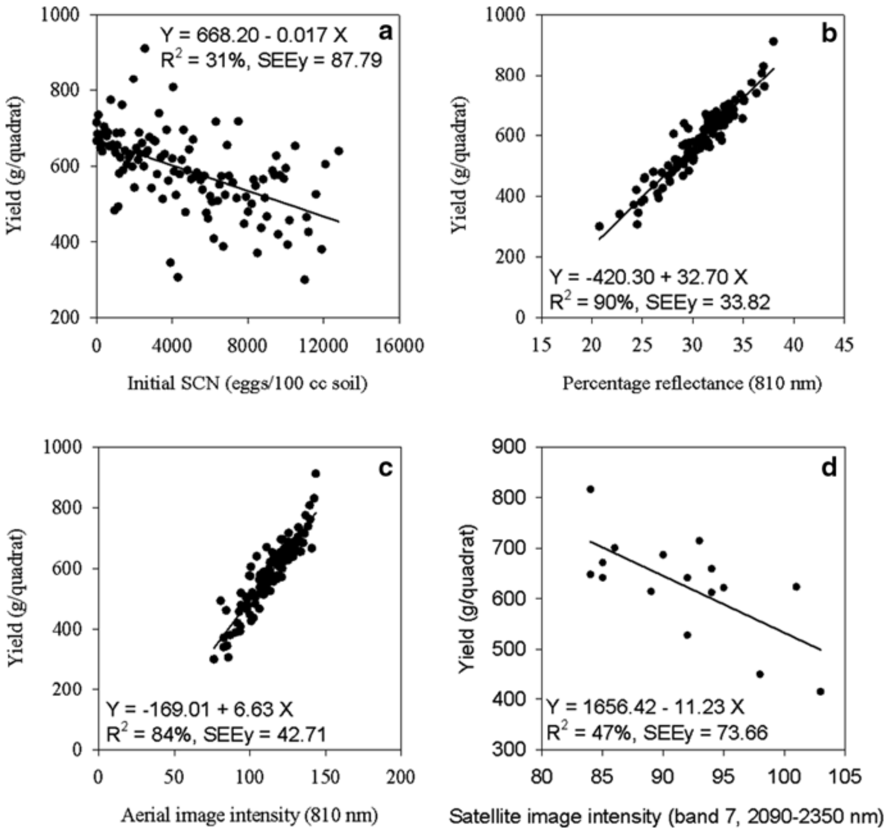

Fig. 3.3 a–d Quantitative relationships of (**a**) SCN population density (eggs 100^{-1} ccm soil), (**b**) ground-based measurement of percentage of sunlight reflectance (810 nm), (**c**) aerial image intensity (810 nm), and (**d**) Landsat 7 satellite imagery with soybean yield, for a soybean field located in Ames, Iowa

that will allow researchers to extract pathogen-specific temporal and spatial signatures, i.e. the unique temporal and spatial patterns when specific pathogens remove or reduce HGLA over time and space within the crop canopy. It is well known that iron chlorosis deficiency has a different temporal signature (due to chlorosis and stunting) that occurs earlier in the growing season compared to symptoms caused by SCN, and a spatial signature that is related to soil type and soil pH. Iron chlorosis causes patches which vary little in extent from season to season, but which do vary in symptom severity as affected by edaphic factors such as rainfall and soil moisture. The effects of SCN on HGLA are seen in irregular to oval patches that tend to enlarge from season to season, due to nematode dispersal by farm machinery.

The high resolution (<1 m^2) of today's satellite images, and those in the future, will account for more of the variation in yield than was possible with the resolution from earlier satellites, such as Landsat 7. In the SCN study, the Landsat 7 satellite platform explained 47% of the variation in soybean yield, but this satellite platform had only 4 m^2 resolution, compared to 1 and 2 m^2 resolution for the aerial and ground-based platforms, respectively. In subsequent studies using IKONOS and QuickBird satellite platforms with < 1 m^2 resolution, we have been able to obtain R^2 values that are comparable or even higher than those obtained with ground-based and aerial platforms.

3 The 'Unique Spectral Signature' Paradigm

Scientists have long hypothesized that for every new sensor developed (multispectral, hyperspectral, etc.) and every new platform (hand-held, aerial, satellite, etc.), specific biotic or abiotic stresses must elicit unique spectral signatures or spectral indices or ratios that can be used to discriminate among specific biotic and abiotic stress agents. Although this approach has been tried for many decades (without much success), and researchers continue to search for the silver bullet of pathogen-specific spectral signatures (Apan et al. 2004, Girma et al. 2005, Malthus and Madeira 1993, Sullivan and Holbrook 2007, Zhao et al. 2005), this paradigm has met with less than satisfactory results. Most such investigations have used types of correlation analyses to look for unique pathogen-specific spectral signatures, and incorporated the most promising spectral indices/ratios with discriminant analyses (Girma et al. 2005).

4 Use of Satellite Imagery to Detect and Quantify Healthy Green Leaf Area Gradients (1-*y*) Versus Disease Gradients (*y*)

Disease gradients are the result of two biological processes: pathogen dissemination and pathogen infection (Fig. 3.4). The process of dissemination can be broken down into three sub-processes: (I) removal/escape of dispersal units from a source of inoculum, (II) transport (dispersal) of dispersal units from a source of inoculum to distance (x), and (III) the deposition of dispersal units onto a susceptible host. A dispersal unit is defined as any device for the spread and/or the survival of a pathogen that can be visually recognized and counted (Zadoks and Schein 1979). Dispersal units may be pathogen (spores, cells, sclerotia, etc.) and/or potential inoculum carriers (insect vectors, pollen, infected/infested seed, cultivation, planting equipment, infested soil, pots, etc.).

Once dispersal units are removed from a point line or an area source of inoculum (Fig. 3.4), a dispersal gradient will result in which relatively more pathogen dispersal units will be found close to an inoculum source and progressively fewer dispersal units will occur as distance from the inoculum source increases. Larger dispersal units (spores, etc.) will have steeper dispersal gradients relative to smaller dispersal units due to their higher terminal velocities (Ward et al. 1999, Zadoks and Schein 1979). Dispersal gradients of fungal and bacterial pathogens can be quantified by placing five or more spore or live plant traps with respect to distance from a local source of inoculum (Parker et al. 1995).

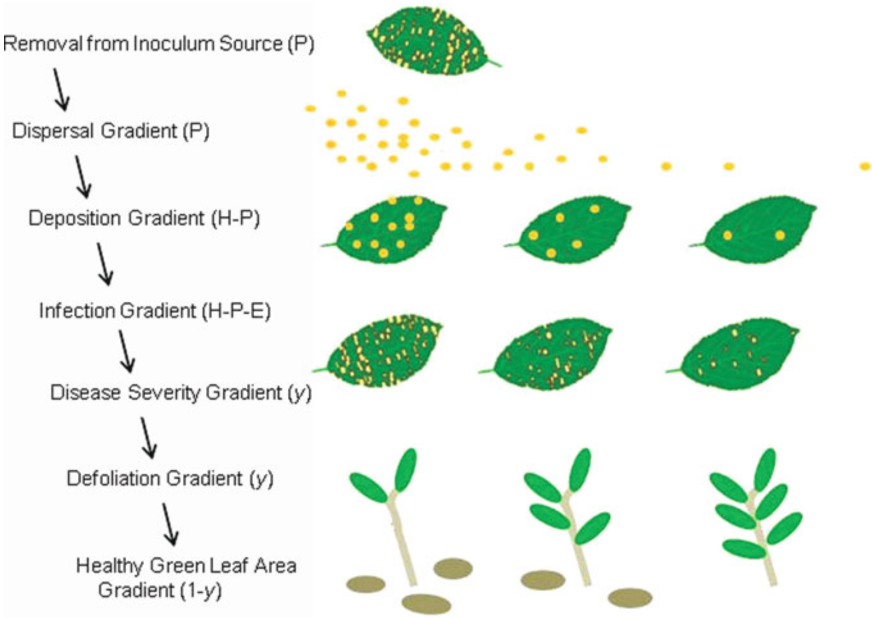

Fig. 3.4 Processes (dissemination, infection, and pathogenesis) and sub-processes leading to disease severity, defoliation, and healthy green leaf area (HGLA) gradients. Sub-processes of dissemination involving the pathogen (P), the host (H), and/or the environment (E) are shown in *parentheses*. The symbol *y* represents a measure of disease intensity (e.g., severity or defoliation, expressed as a proportion), the quantity 1-*y* represents the proportion of the crop that is healthy

The third sub-process of dissemination is deposition, defined as the landing of dispersal units (P) onto a susceptible host (H) by one of two deposition sub-processes: sedimentation or impaction (Zadoks and Schein 1979) (Fig. 3.4). Deposition should, in theory, closely mirror the dispersal gradient. Deposition gradients can be quantified using passive spore traps (such as glass slides coated with silicon grease or petri dishes containing selective or semi-selective media), or, as in the case of insect vectors, using yellow sticky or vacuum traps (Esker et al. 2004).

Once the process of dissemination has been completed, the host and pathogen (HP) are now in direct contact, and dispersal units may then become infection units, if and when environmental conditions are favorable for infection to occur (Fig. 3.4). Once the environment (E) is favorable, the deposition gradient will give rise to an infection gradient. One incubation period later, a primary disease gradient (i.e., disease symptoms such as lesions, leaf spots, pustules, etc.) will be present. The resulting disease gradient can be detected and quantified by visually assessing disease severity (e.g. % severity, lesions/leaf), or by assessing disease incidence (number of diseased sampling units/number of sampling units assessed) with respect to distance from a source of inoculum (Esker et al. 2007; Nutter 1989, 2001; Nutter et al. 2006). Thus, disease gradients result from the preceding infection, deposition, and dispersal gradients.

Epidemiologically, the presence of a disease gradient (change in disease intensity with respect to distance) is important because this indicates the presence of a local source of inoculum (Nutter et al. 1989, Zadoks and Schein 1979). Disease gradients often result in defoliation gradients (Fig. 3.4), as well as gradients of healthy green leaf area, with HGLA being lowest close to an inoculum source and HGLA increasing with respect to distance from an inoculum source (Nutter 1989, Parker et al. 1995). Plant pathologists have long been interested in detecting and quantifying disease gradients, but the concept of HGLA gradients (1-*y*) has received little attention.

With regards to remote sensing, the distinction between disease and HGLA gradients is critical, as there is often a misconception that remote sensing can be used to detect and quantify disease stress (*y*), when in fact, most remote sensing instruments are actually detecting and quantifying not disease intensity (*y*), but the effects of disease intensity (*y*) on healthy HGLA, i.e. 1-*y* (Nutter 1990). We believe that the NIR band is detecting HGLA, and not disease, because there are always very strong (positive), linear relationships between percentage reflectance (or image intensity) in the near infrared band with both yield and green leaf area index (Chong et al. 2001, Guan and Nutter 2002a, Guan and Nutter 2002b, Lathrop and Pennypacker 1980, Nutter 1989, Nutter et al. 2010). Vegetation indices that include a near infrared band (e.g., NDVI, GDVI, etc.) are actually measuring 1-*y*, not disease (*y*) (Guan and Nutter 2002a, Nutter 1989, 2006, Pethybridge 2007b, Pethybridge et al. 2008). Thus, researchers who state that they are detecting and/or quantifying disease severity would be more correct to state that they are attempting to detect and quantify the effects of disease (or disease stress) on HGLA.

5 Pathogen-Specific Temporal and Spatial Signatures – A New Paradigm

As shown in Fig. 3.1, plant pathogens can create HGLA gradients by differentially removing healthy green leaf area with respect to distance from a source of inoculum (Nutter 1989). Based upon this concept, we have advanced a new paradigm that quantifies the removal of HGLA within a plant canopy over time and space as a means to extract unique, pathogen-specific, spatiotemporal signatures. Some plant pathogens are *r*-strategists and produce tremendous numbers of wind-dispersed spores, resulting in large dispersal, deposition, infection, disease, and HGLA gradients. Smaller dispersal units, such as rust spores, will result in shallower HGLA gradients compared to HGLA gradients caused by larger-spored pathogens (thereby resulting in unique HGLA gradients). Fungal pathogens that are *k*-strategists produce fewer dispersal units per infection and will have a slower rate of focal expansion than *r*-strategists. Pathogens that rely on splash dispersal may result in very steep disease and HGLA gradients that expand at relatively slow rates compared to expansion rates associated with wind-dispersed pathogens. The rate of gradient expansion adds another potential 'signature' that can be used to discriminate among biotic and abiotic causes of crop stress. The speed with which disease and HGLA gradients change from focal epidemics to general epidemics, as well as differences in the general shapes of disease foci, contribute to potential pathogen-specific temporal signatures that, collectively, could be used to discriminate among the many biotic and abiotic stress agents that affect crop health.

6 Detecting and Quantifying Healthy Green Leaf Area (1-y) Gradients

As plant pathogens spread over time and space within a crop canopy, HGLA is removed; it is our hypothesis that the resulting temporal and spatial patterns are unique to specific plant pathogens. The temporal and spatial spread of Asian soybean rust (ASR) was quantified for an infected soybean field located in Cedara, South Africa. Satellite imagery (IKONOS) with 1 m^2 per pixel resolution was obtained for 6 and 11 April in 2006 (Fig. 3.5). Image intensities in the near-infrared band (recorded as grayscale values ranging from 0 to 255) were extracted and geospatially-referenced using IMAGINE (ERDAS, Inc., Atlanta, GA) and ArcGIS software (ESRI, Redlands, CA). Maps of image intensities in the NIR were created and analyzed (Fig. 3.5a). Darker areas of the NIR image represent low image intensities, which correspond with areas within the soybean canopy with low HGLA (due to higher levels of disease severity). Lighter areas of the image represent areas of the soybean field where HGLA is higher (due to lower disease severity).

The circled area in the northwest part of the soybean field was not treated with fungicide at any time during the growing season, whereas the rest of the field received a single application of fungicide early in the growing season (Fig. 3.5a). The non-treated area developed a severe epidemic of ASR, which then served as a small area source of soybean rust inoculum. This area source produced tremendous numbers of dispersal units (spores) that resulted in large dispersal, deposition, and infection gradients. As the fungicide application lost effectiveness over time, a large disease gradient (nearly 300 m) was created, due to higher spore deposition close to the area source. As a result, more new infections occurred close to the area source of inoculum, and progressively fewer infections occurred as distances from the area source increased (as illustrated conceptually in Fig. 3.4).

Consequently, the disease gradient produced a HGLA gradient. This HGLA gradient was detected in NIR-band images obtained from the IKONOS satellite, and a false-color map was produced by kriging (Coelho-Netto and Nutter 2005, Ellsbury et al. 2001, Nutter et al. 2002, Wang 2006) to depict areas of low image intensity (low HGLA) relative to areas of higher image intensity (high HGLA) (Fig. 3.5b). In this false-color map, the darkest reds indicate the lowest image intensities (low HGLA) and the darkest greens indicate the highest image intensity values (highest HGLA). This false-color map clearly shows both the area source of inoculum (as the dark red area) and the resulting HGLA gradient (as the progression from dark red to dark green). Disease severity was visually assessed on the ground in twelve 1 m^2 diameter quadrats established within the soybean field. These 12 quadrats

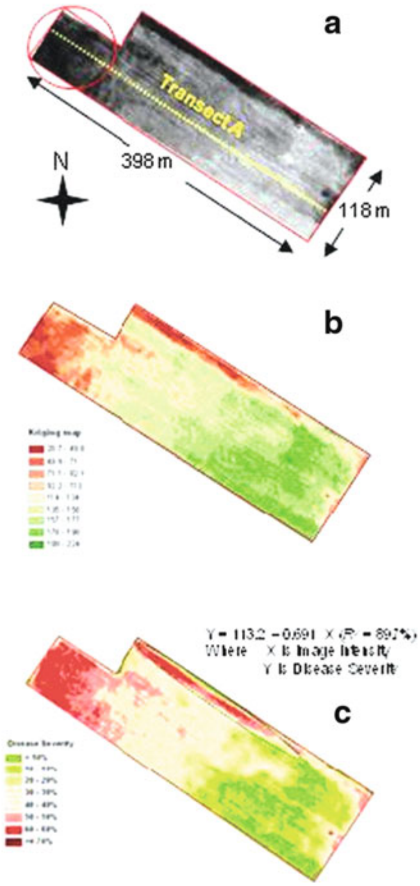

Fig. 3.5 IKONOS satellite imagery (resolution 1 m^2 per pixel) obtained on 6 April, 2006, of a soybean field in Cedara, South Africa, infected with Asian soybean rust. Image intensities in the near-infrared band (**a**) depict the presence of a healthy green leaf area gradient (HGLA); *dark areas* represent low NIR image intensity and less HGLA due to high disease severity, and *light areas* represent areas with higher image intensities (more HGLA and lower disease severity). A false-color map produced by kriging (**b**) depicts the presence of a HGLA gradient with a progression from *dark red* (low HGLA) to *dark green* (high HGLA). The false-color map in **c** depicts the soybean rust disease gradient, with *dark red* values indicating high disease severity and *dark green* values showing low disease severity

were geospatially-referenced using GPS, and the corresponding NIR-band image intensities were extracted. Image intensity (x) was regressed against the corresponding (GPS-referenced) disease severity assessments (y), resulting in the following equation:

$$y = 113.2 - 0.691x \quad (1)$$

where y = predicted disease severity (%), and x = image intensity, with image intensity explaining 89.7% of the variation in disease severity. Using this equation, image intensity pixel values were converted into pixel values for disease severity and then mapped, generating the soybean rust disease gradient map shown in Fig. 3.5c.

A potential pathogen-specific spatial signature might be developed by quantifying the change in disease intensity (Y) with respect to distance from a source of inoculum. Four disease gradient models have been proposed to quantify disease gradients: Gregory's power law (ln x − ln y), Kiowsawa and Shiyomi's model (linear x − ln y), Fry's model (linear x − logit y), and Berger and Luke's model (ln x − logit y), where x is linear or transformed distance and y is ln or logit disease intensity (usually severity or incidence data) (Alderman et al. 1989, Nutter 1989). However, these models have not been used to quantify the HGLA gradient (Nutter 1989, Pethybridge et al. 2007b).

The above models all utilize measures of disease intensity (y), but applying these models to image intensity data has tremendous potential to detect and quantify HGLA gradients. We applied the above disease gradient models using image intensity data (1-y) with 1-m^2 resolution extracted from IKONOS satellite images obtained on 6 and 11 April, 2006, for the soybean field infected with Asian soybean rust located in Cedara, South Africa (see Fig. 3.5 for GIS image intensity and disease severity gradient maps). Image intensities were extracted from a 3 pixel wide transect (equivalent to 3 m wide), beginning from the northwest edge of the field (where the area source of Asian soybean rust is shown circled in red), and continuing 398 m to the opposite edge of the field (along the transect shown in yellow), as shown in Fig. 3.3a. Of the four gradient models, the Kiyosawa and Shiyomi model (linear x − ln y) best explained the relationship between distance from the area source (x) and image intensity (y), with R^2 values of 78.9% and 93.8% for 6 April and 11 April, respectively. The slopes for these two models indicate that soybean rust reduced HGLA along a gradient where HGLA increases with respect to distance from the area source. On 6 April, HGLA increased by 0.004 units of image intensity for each 1 m increase in distance from the source; on 11 April, HGLA increased by 0.003 units m^{-1}. It is important to emphasize that these slopes provide quantitative spatial signatures (HGLA gradient signatures) for Asian soybean rust, and that the flattening of the HGLA gradients over time also provides a spatiotemporal signature, i.e., the time required for the HGLA gradient to become undetectable because the disease foci have coalesced over time and space. The change in HGLA gradient slope from 6 April to 11 April represents a flattening of the HGLA gradient by 0.0002 units m^{-1} day^{-1}.

7 Lessons Learned from the Past: Quantifying Disease and HGLA Gradients

Hand-held multispectral radiometers were first used in the 1980s to detect and quantify disease and HGLA gradients (Nutter 1990) and to quantify injury from herbicide drift (Adcock et al. 1990). In one such study, a CropScan multispectral radiometer was used to quantify the primary gradient arising from a within-field source of inoculum that was deliberately introduced (Nutter 1989). Peanut leaves with sporulating lesions caused by late leafspot of peanut (*Cercosporidium personatum*) were sandwiched between 0.1 cm wire mesh screens and placed within a peanut row. A travelling overhead sprinkler was used to irrigate the peanut field and provide conditions favorable for the establishment of a primary infection gradient (which arose from the primary dispersal and deposition gradients, as described in Fig. 3.4). Three weeks later, the resulting disease and HGLA gradients were quantified. To determine if four different raters could detect the exact position where the inoculum source was placed within the peanut row, each of the four was asked to record the percentage of sunlight reflected by the peanut canopy in the near-infrared wavelength band (800 nm) using a CropScan hand-held multispectral radiometer. Each rater recorded % reflectance at 1.8 m intervals beginning at one edge of the field and continuing until the opposite side of the field was reached. Each measurement covered a 0.6-m-diameter area of peanut canopy.

Without knowing the position of the initial source of inoculum (the wire mesh with the inoculum source had been removed), all four raters were able to pinpoint the exact location where the inoculum source had been placed within the peanut row (Fig. 3.6). The length of the HGLA gradient, as indicated by the reduction in % reflectance in the near-infrared band (800 nm), was approximately 8 m (measured between outer edges of the focus). It is important to mention again that higher % reflectance values at 800 nm indicate more healthy green leaf area

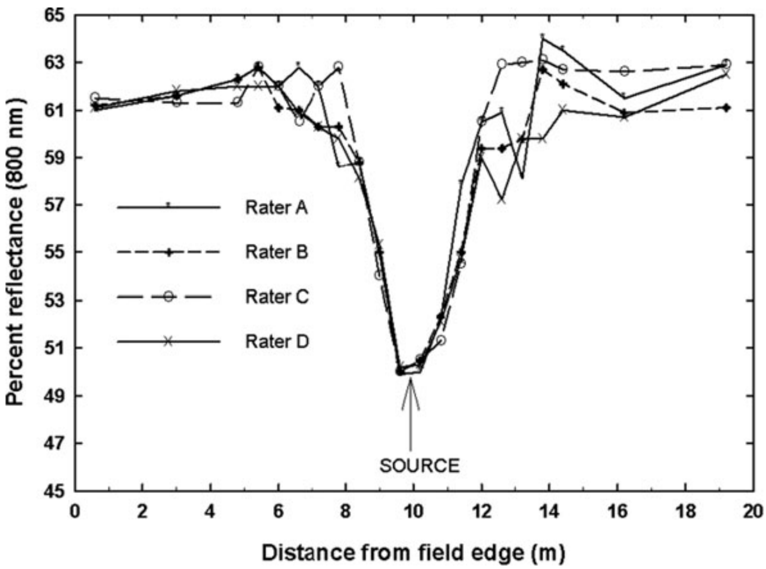

Fig. 3.6 Detection of a source of inoculum (leaves infected with *Cercosporidium personatum*, the causal agent of late leaf spot of peanut) deliberately introduced into a peanut field in Plains, Georgia, by recording the percentage of sunlight reflected by the canopy in the near infrared band (800 nm) using a CropScan multispectral radiometer (Nutter 1989)

(HGLA). Therefore, the multispectral radiometer (using the NIR band) was not detecting disease severity, but was detecting the removal of HGLA, which is the effect of plant disease. However, there was a very good relationship between percentage reflectance at 800 nm and percent defoliation of leaflets ($R^2 = 95\%$), showing that disease gradients can result in defoliation gradients (y), which then create HGLA gradients that can be quantified using remote sensing (Nutter 1989, Nutter and Littrell 1990).

8 Quantifying Additional Temporal and Spatial Signatures for Asian Soybean Rust

In the study in Cedara, South Africa, soybean rust disease foci were detected and the rate of focal expansion was quantified. IKONOS satellite images for 6 April and 11 April, 2006 were rectified. A 20 × 20 pixel grid (1 pixel = 1.0 m^2) was overlaid on an image of the disease focus (Fig. 3.7a). Transects corresponding to the short and long axes of the focus were identified, and image intensities (pixel values and locations) were extracted along the transects. Changes in image intensity (1- y) with respect to distance (pixel location) were plotted and inspected (Fig. 3.7b, c). The lowest NIR pixel intensities represent areas within the disease focus where HGLA is lowest, and are located at the x-coordinate for the epicenter of the short axis (Fig. 3.7b) and the epicenter for the y-coordinate along the long axis (Fig. 3.7c). The outer (healthier) edges of each focus along both the short and the long axes can be determined by finding the pixel coordinates where pixel image intensities were at their highest (representing where HGLA was highest). For example, the width of the short axis for the soybean rust focus in Fig. 3.7b was 13 m wide, and the length of the long axis of the focus was 17 m (Fig. 3.7c). The size of the focus (m^2) can be estimated using the equation for the area of an ellipse.

This process was repeated for the NIR image acquired on 11 April using a 40 × 60 m grid (Fig. 3.7d). The larger grid size was used for the 16 April satellite image because this focus had greatly expanded in just 5 days. Again, GPS coordinates were used to find the epicenter of this focus by extracting image intensities along the short and long axes of the focus and identifying pixel locations where NIR image intensities were lowest (Fig. 3.7e, f). On 11 April, the distance between the outer edges of the focus for the short axis measured 22 m and the long axis was 46 m. The area of the rust focus expanded from 173.6 m^2on 6 April to 794.8 m^2 by 11 April. The rate of focal expansion can be calculated by subtracting the size of the focus on 6 April (173.6 m^2), from the size of the rust focus on 11 April (794.8 m^2), and dividing by the change in time (5 days). Therefore, over the 5-day period, the rate of focal expansion for this focus was 120.2 m^2 day^{-1}, a rate of focal expansion that is surely unique to ASR relative to the rates of focal expansion by other soybean pathogens.

It is important to note that the size, shape, and rate of focal expansion should be extremely useful as 'pathogen-specific' signatures that are unique to ASR, as no other plant pathogen of soybeans would possess such rapid temporal and spatial

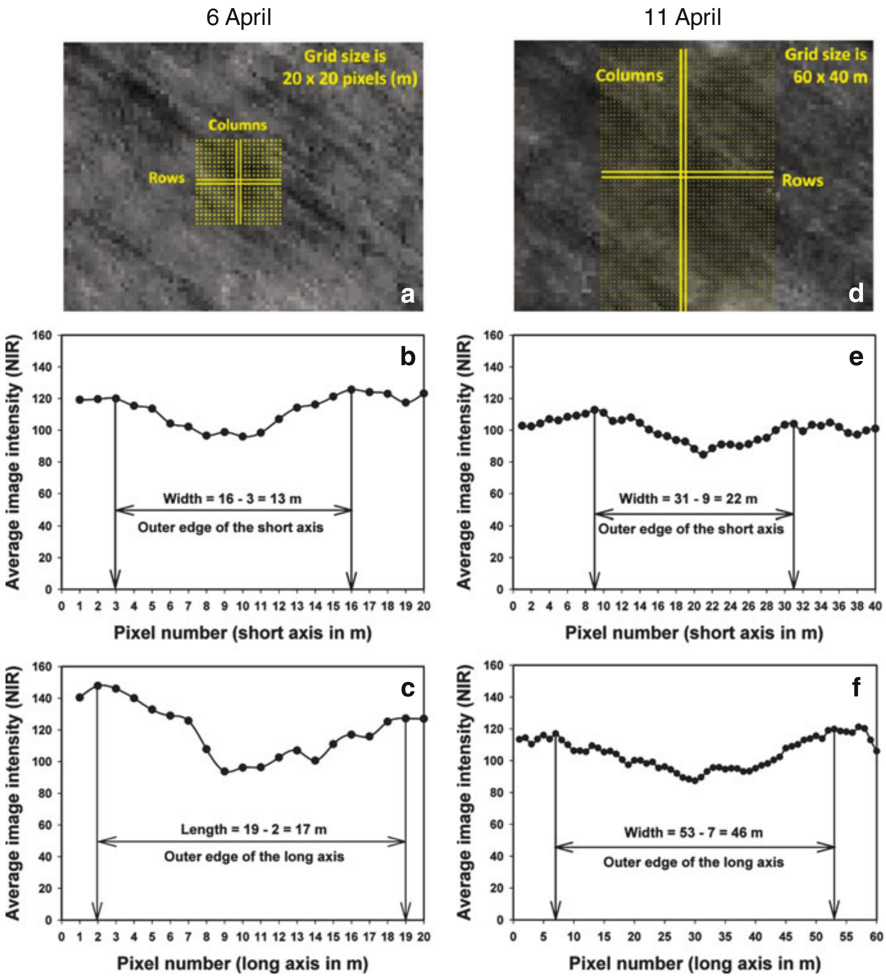

Fig. 3.7 a–f Quantifying the shape, size, and rate of focal expansion of a disease focus of Asian soybean rust. Image intensities in the near-infrared band were extracted from IKONOS satellite images (1 m^2 resolution) obtained on 6 April and 11 April 2006 from a soybean field infected by Asian soybean rust in Cedara, South Africa

signatures. The creation of a library of the temporal and spatial 'signatures' with which different plant pathogens remove HGLA has tremendous potential for future applications to identify the causes of biotic and abiotic stress agents using satellite, GPS, and GIS technologies. The use of pathogen-specific temporal and spatial signatures, when coupled with discriminant analyses (Girma et al. 2005), could serve in much the same way that DNA fingerprints are used to detect and identify plant pathogens.

In a similar study, Oudemans et al. (2008) also used NIR satellite imagery (QuickBird Satellite, Space Imaging, Thornton, CO) to detect and quantify injury from fairy rings (caused by the fungus *Psilocybe agrariella*) in cranberry bogs located in New Jersey. The change in the number of fairy rings detected each year over a 10-year period and the change in area affected by fairy rings was determined by integrating GPS, GIS, and remote sensing technologies. While the authors stated that they used NIR imagery to detect and quantify the injury caused by fairy rings in cranberry, the NIR wavelength band was actually depicting the removal of healthy green leaf area by this disease. The size, shape, and rate of focal expansion of ‘rings’ provide pathogen-specific temporal and spatial signatures that are unique to the fairy ring pathosystem.

9 Comparison of Pathogen-Specific Temporal and Spatial Signatures to Differentiate Two Fungal Pathogens of Soybean

The ability to detect and quantify the shapes, sizes, and rates of focal expansion using high resolution satellite imagery (when coupled with GPS and GIS technologies), has tremendous potential not only to detect disease stress in crops, but to identify the causal organisms involved. Using the transect method to determine the size, shape, and epicenters of disease foci, satellite imagery of disease foci caused by Asian soybean rust were analyzed and compared to satellite imagery of disease foci caused by Cercospora leaf blight (Fig. 3.8 a–d).

Cercospora leaf blight (CLB) is a disease of soybean in which initial inoculum comes largely from infected seed and/or infested crop debris from previous crops (Hartman et al. 1999). Infected/infested seed will result in a random spatial pattern of Cercospora leaf blight disease foci early in the season (spatial signature), because the temporal and spatial expansion of CLB disease foci is due to the dissemination of fungal spores (dispersal units) primarily via splash dispersal.

Disease foci of CLB are circular in shape, and the kriged map of a single focus clearly delineates the gradual, circular expansion of this pathogen over a 60-day

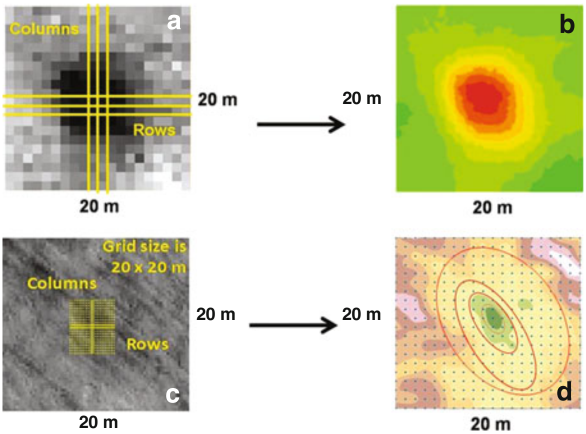

Fig. 3.8 a–d Comparison of temporal and spatial ‘signatures’ for disease foci of (**a** and **b**) Cercospora leaf blight, and (**c** and **d**), Asian soybean rust. The shapes of Cercospora leaf blight foci were circular, whereas the shapes of Asian soybean rust foci were elliptical. The rate of focal expansion for Cercospora leaf blight was 6.9 m^2 day^{-1}, whereas the rate of focal expansion of Asian soybean rust was 120.2 m^2 day^{-1}

period due to splash dispersal of *Cercospora kikuchii* spores (Fig. 3.8a, b). Focal expansion in this pathosystem is often circular in nature, compared to the elliptical shapes of disease foci produced by wind-disseminated spores. In contrast, disease foci caused by ASR were elliptical in shape, with much larger foci and much faster rates of focal expansion than are observed with CLB (Fig. 3.8c, d). This research provides two additional criteria, pathogen-specific spatial signatures (foci shapes) and spatiotemporal signatures (rate of focal expansion in m^2 day^{-1}), that can be used to discriminate among biotic pathogens causing crop injury (i.e., removal of HGLA over time and space).

Cumulatively, there are a number of unique temporal and spatial signatures that could be used in logistic regression or Classification Regression Tree (CRT) models (Esker et al. 2006), as well as a number of types of discriminate analyses that could be employed to identify the causes of disease stress (Apan et al. 2004, Girma et al. 2005, Malthus and Madeira 1993, Schut et al. 2006, Zhao et al. 2005). Examples of pathogen-specific temporal and spatial signatures that could be used to discriminate ASR from CLB of soybean are shown in Table 3.1.

Table 3.1 Summary of temporal and spatial 'signatures' that can be used to discriminate Asian soybean rust from Cercospora leaf blight of soybean, using GPS, GIS, and remote sensing (satellite imagery)

Discrimination criteria	Asian soybean rust	Cercospora leaf blight
Origin of inoculum	Outside the crop	Within the crop
Seasonality	Anytime, but usually after anthesis	Any time after crop emergence
Disease gradients present within field	Likely[a]	Not likely
Disease foci present	Yes	Yes
Shape of foci	Elliptical	Circular
Size of disease foci	794.8 m^2	360 m^2
Rate of focal expansion	120.2 m^2 day^{-1}	6.9 m^2 day^{-1}
Time from focal → general epidemic	Fast	Moderate
Temporal rate of infection	2.9–8.3 days	Unknown, but much longer
Doubling time (temporal)	Fast	Moderately slow

[a]If a local source of rust inoculum is present

10 Comparison of NDVI with the NIR Band to Quantify HGLA

A large volume of research has been conducted to try to find unique spectral signatures (indices, ratios) that can discriminate among the many causes of biotic and abiotic crop stress. Among the most widely used indices is the Normalized Difference Vegetation Index (NDVI), which has been used in many plant pathosystems to detect, quantify, and map crop stress. However, this index has not resulted in any real success in terms of accurately discriminating among the causes of crop stress. Originally, NDVI was used to provide a measure of the percentage of the ground that was covered by vegetation, and was not intended to provide a measure of HGLA. Several researchers have found that the near infrared band alone can more accurately estimate HGLA over time, space, and different vegetation types, than NDVI (Guan and Nutter 2002a, b, Moreira 2004, Nutter 1989, Nutter and Littrell 1990, Pethybridge et al. 2007b, 2008). For example, in a study conducted in Quincy, FL, Nutter et al. (2009) compared the resolution of NDVI and the NIR wavelength band (IKONOS satellite imagery) to determine which method of representation (image intensities, false-color, and kriging) could most accurately determine the GPS coordinates of the epicenters of soybean rust disease foci where the pathogen was deliberately introduced into field plots. Kriged maps using the NIR wavelength band had slightly better accuracy than NDVI kriged maps in determining the GPS coordinates where rust was deliberately introduced into soybean field plots (Fig. 3.9). Moreover, the NIR band explained more of the variation in crop yields, compared to NDVI and most other indices (Guan and Nutter 2002a, Moreira 2004, Pethybridge et al. 2007b).

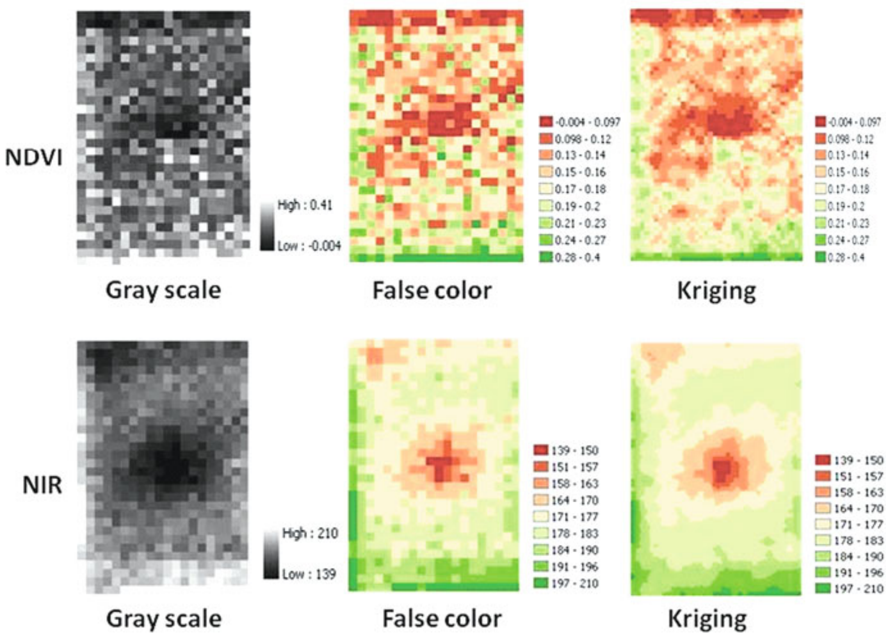

Fig. 3.9 Comparison of using the Normalized Difference Vegetation Index (NDVI) versus the near-infrared wavelength band to detect and locate the GPS epicenters of disease foci caused by Asian soybean rust. Using kriging, the NIR band had slightly better accuracy (1.8 ± 1.3 m) in detecting the actual GPS coordinates (epicenters) where Asian soybean rust was deliberately introduced by researchers, compared to NDVI (2.3 ± 1.2 m)

11 Implications for Plant Pathogen Forensics

The ability to accurately detect and geospatially-reference the exact GPS locations of the epicenters of disease foci has important implications with regards to pathogen forensics (Fletcher et al. 2006, Nutter 2005), given the potential threats associated with the deliberate introduction of plant pathogens (Nutter and Madden 2008). After the GPS coordinates of the epicenters of primary disease foci have been determined (using integrated remote sensing, GPS, and GIS technologies), this information can be passed immediately to law enforcement personnel on the ground to direct forensic teams where to best search for physical evidence (such as the presence of chemical surfactants (Tween 20), culture media residue or gelatin used as sticking agents for spore deposition, spray bottles, syringes, and other pathogen delivery tools). Thus, law enforcement personnel can direct their resources to intensely survey smaller areas for evidence, as opposed to expending additional time and money to search much larger areas in affected fields (tens to thousands of hectares). The GPS locations of primary foci could also be used to direct ground personnel where to collect pathogen isolates (both within and among disease foci) to detect the presence of population genetic anomalies that might suggest that the new pathogen threat was the result of a deliberate attack (biocrime) (Nutter and Madden 2008). In a recent study, Nutter et al. (2009) used the transect method described in Section 8 (Figs. 3.6 and 3.7) to predict the precise GPS coordinates where Asian soybean rust was deliberately introduced into nine soybean plots by researchers. Using this technology, they were able to predict the actual epicenters accurately, to within 1.8 ± 1.3 m.

12 A New Paradigm for Crop Health Management

In the present paradigm, the efficient evaluation and/or application of today's disease management programs requires the acquisition of accurate and precise information concerning the temporal and spatial dynamics of disease intensity assessments (y) over time and space (Ellsbury et al. 2001, Nutter 2007, Nutter et al. 2010, Steinlage et al. 2002). A new, emerging paradigm focuses on assessing both disease intensity (y) and how effectively disease management practices maintain the health of the crop canopy (1-y). The relationship between diseased and healthy plant tissue is described by the equation $1.0 = y + (1\text{-}y)$, where 1.0 represents the crop canopy as a whole, y is a measure (proportion) of disease intensity, and 1-y is the proportion of the crop (healthy green leaf area) that is available to produce a crop (Nutter 1999, Nutter 2007). In the not too distant future, it is very likely that management strategies and tactics will be evaluated based upon assessments of '1-y' (healthy green leaf area) as opposed to assessments of disease intensity 'y'. Waggoner was one of the first to propose that healthy leaf area duration, which is the integration of healthy green leaf area over the growing season (time), would have a better relationship with crop yield than visual estimates of disease intensity (Waggoner and Berger

1987). Whether HGLA is measured destructively or is estimated using remote sensing technologies, measurements of HGLA have nearly always explained more of the variation in yield (and quality), compared to visual estimates of disease intensity (*y*) (Guan and Nutter 2002a, Nutter 1989, Nutter and Littrell 1990, Nutter et al. 2002, Pethybridge et al. 2008).

An example of the new paradigm in managing crops for maintaining 'crop health', as opposed to assessing the impact of management practices by assessing disease intensity, involves the Cercospora leaf blight of soybean pathosystem. The image intensities (NIR) for 3-pixel wide (3 m) transects were extracted from IKONOS satellite imagery obtained from a soybean field located in Chaco, Argentina. The NIR image intensities were extracted from transects placed over NIR images for each of three 50 × 95 m soybean plots that received different fungicide management programs. Image intensities extracted from transects from one edge of the field to the opposite edge of the field were graphed to look for spatial anomalies that represented changes in HGLA with respect to distance. Most notable is the lack of any HGLA gradients within the three soybean plots on either 7 February or 8 April (Figure 3.8a–c), indicating that pathogen inoculum most likely originated from within-field sources of inoculum or from long distance dispersal of fungal spores (which is highly unlikely for this fungal pathogen, because spore size is quite large) (Hartman et al. 1999). Image intensities in the non-treated control plot, displayed in grayscale (0–255), (Fig. 3.10) ranged from 119 (lowest HGLA) to 139 (highest HGLA). Fluctuation in the image intensity signal from 119 to 139 likely represents areas where the transect passed through the epicenters and outer edges of disease foci (see Fig. 3.7 for determining the epicenters and size of disease foci).

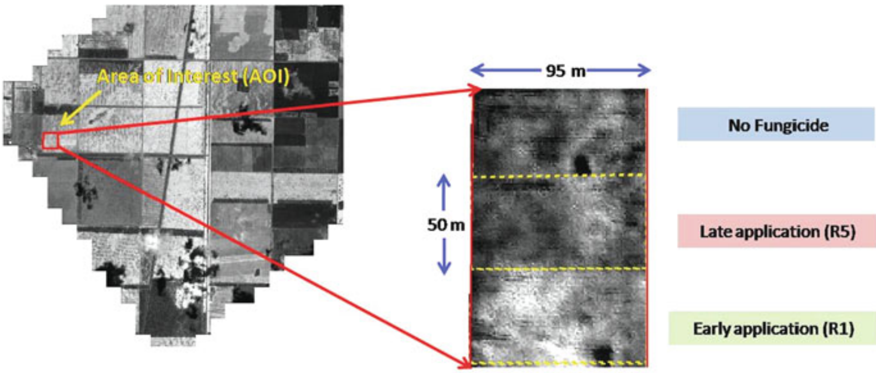

Fig. 3.10 IKONOS NIR satellite image (1 m^2 resolution) of soybean field in Argentina infected with Cercospora leaf blight (caused by the fungus *Cercospora kikuchii*). The area of interest is a soybean field with fungicide applied early in the reproductive growth stage of the crop (R1), late in the reproductive growth stage (R5), or left untreated (no fungicide). The *lighter areas* represent higher image intensities (healthier areas of the soybean canopy) and *darker areas* represent lower image intensities (i.e., less healthy areas due to higher disease severities)

Image intensities from the 8 April IKONOS image were extracted (following the same transect as was used for the 7 February image), graphed, and compared to the image from the earlier date. Image intensities along the 8 April transect ranged from 93 to 115, a reduction in 24–26 image intensity units, indicating an overall decrease in HGLA from 7 February to 8 April. This drop in image intensity represents a ‘crop health’ gap in HGLA that needs to be narrowed through the deployment of integrated disease management practices that are the most cost-effective. Nutter (1999) first introduced the concept of ‘crop health gaps’ caused by biotic and abiotic stresses, but it is only recently that satellite imagery, GPS, and GIS technologies have come together to quantify this gap.

In contrast to the non-treated control soybean plot, late-season fungicide application resulted in a slightly flatter HGLA signal for the image intensity transects graphed for 7 February and 8 April, but the ‘crop health gap’ was only slightly narrowed by this treatment (Fig. 3.11b). Relative to the non-treated control plot and the soybean plot that was treated with fungicide late in the reproductive growth cycle (R5), the soybean plot that received a one-time application of fungicide early in the reproductive growth cycle (R1) had a much narrower ‘crop health gap’, as indicated

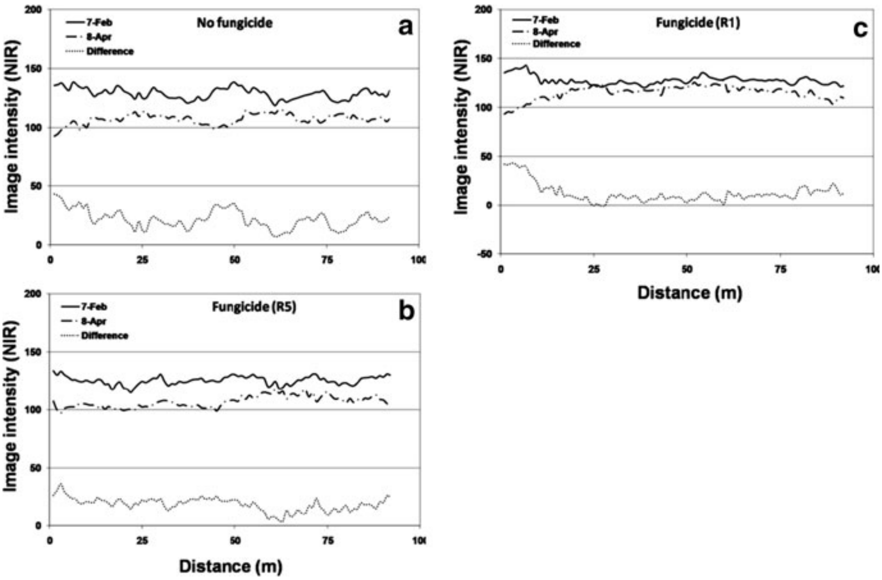

Fig. 3.11 a–c Image intensity transects extracted from three soybean field plots on 7 February (*solid line*), 8 April (*dashed line*), and the difference in image intensities for these two dates (*dotted line*). Treatments applied to soybean plots were: (**a**) not treated with fungicide, (**b**) treated with fungicide late in the reproductive growth stage (R5), and (**c**) treated with fungicide early in the reproductive growth stage (R1). The lowest image intensities indicate the least healthy areas of the soybean canopy (due to higher disease intensities within soybean plots affected by Cercospora leaf blight, caused by *Cercospora kikuchii*)

by a much smaller reduction in image intensities along the 7 February versus 8 April transects (Fig. 3.11c). This indicates that the R1 fungicide application maintained a high level of HGLA from 7 February to 8 April, which should translate into higher yield. In fact, satellite image intensity explained 85% of the variation in soybean yield in this experiment (data not shown).

13 Conclusions

The integration and use of GPS, GIS, and remote sensing technologies has tremendous potential to obtain temporal and spatial information concerning disease risk at multiple spatial scales. Moreover, integrated GPS, GIS, and remote sensing technologies using aerial and satellite platforms have cutting-edge applications to obtain science-based, pathogen-specific temporal and spatial 'signatures' that can be used to correctly identify the cause(s) of crop stress. Exciting opportunities are on the horizon using GPS, GIS, and remote sensing technologies to develop new metrics for evaluating and monitoring IPM performance. In the short to midterm future, visual, ground-based assessments of disease intensity will continue to be employed to quantify the temporal and spatial dynamics of pathogen and disease. Visual-based methods will also be used to evaluate and deploy the most cost-effective and environmentally-friendly disease management programs. However, the future will likely rest on the use of high resolution satellite imagery (when coupled with GPS and GIS technologies) to analyze spatially-referenced data for multiple spatial scales, which can be extracted from a single satellite image. Remotely-sensed data also provides more objective data related to crop health assessments (1-*y*), as opposed to subjective visual-based disease intensity assessments (1-*y*). Finally, imagery provides a permanent record that can be stored and re-analyzed as GPS and GIS technologies advance in the future.

References

Adcock TE, Nutter FW Jr, Banks PA (1990) Measuring herbicide injury to soybeans (*Glycine max*) using a radiometer. Weed Sci 38:625–627

Alderman SC, Nutter FW Jr, Labrinos JL (1989) Spatial and temporal analysis of spread of late leaf spot of peanut. Phytopathology 79:837–844

Apan A, Held A, Phinn S et al (2004) Detecting sugarcane 'orange rust' disease using EO-1 Hyperion hyperspectral imagery. Int J Remote Sens 25:489–498

Burrough PA (1986) Principles of geographical information systems for land resources assessment. Oxford University Press, Clarendon, Oxford

Chang J, Hansen MC, Pittman K et al (2007) Corn and soybean mapping in the United States using MODIS time-series data sets. Agron J 99:1654–1664

Chong CS, Basart JP, Nutter FW Jr et al (2001) Use of remote sensing to determine plant health and productivity. In: Strojnik M, Andersen BF (eds) Infrared spaceborne remote sensing IX, SPIE-The International Society for Optical Engineering, San Diego

Coelho-Netto RA, Nutter FW Jr (2005) Use of GPS and GIS technologies to map the prevalence of Moko disease of banana in the Amazonas region of Brazil. In: Proceedings of the 3rd International Bacterial Wilt Symposium. St Paul

Ellsbury MM, Clay SA, Fleischer SJ et al (2001) Use of GIS/GPS systems in IPM: Progress and reality. In: Kennedy GC, Sutton TB (eds) Emerging technologies for integrated pest management. APS Press, St Paul

Esker PD, Gibb KS, Dixon PM, Nutter FW Jr (2007) An application of space-time analysis to improve the epidemiological understanding of the papaya-papaya yellow crinkle pathosystem. Plant Health Progress doi:10.1094/ PHP-2007-0726-02-RS. http://www.plantmanagementnetwork.org/pub/php/symposium/melhus/esker/

Esker PD, Harri J, Dixon PM, Nutter FW Jr (2006) Comparison of models for forecasting of Stewart's disease of corn in Iowa. Plant Dis 90:1353–1357

Esker PD, Obrycki J, Nutter FW Jr (2004) Trap height and orientation of yellow sticky traps affect capture of *Chaetocnema pulicaria* (Coleoptera:Chrysomelidae). J Econ Entomol 97:145–149

Fletcher J, Bender C, Budowle B (2006) Plant pathogen forensics: capabilities, needs, and recommendations. Microbiol Mol Biol Rev 70:450–471

Girma K, Mosali J, Raun WR (2005) Identification of optical spectral signatures for detecting cheat and ryegrass in winter wheat. Crop Sci 45:477–485

Gleason ML, Taylor SE, Loughin TM, Koehler KJ (1994) Development and validation of an empirical model to estimate the duration of dew periods. Plant Dis 78:1011–1016

Guan J, Nutter FW Jr (2001) Factors affecting the quality and quantity of sunlight reflected from alfalfa canopies. Plant Dis 85:865–874

Guan J, Nutter FW Jr (2002a) Relationships between defoliation, leaf area index, canopy reflectance, and forage yield in the alfalfa-leaf spot pathosystem. Comput Electron Agric 37:97–112

Guan J, Nutter FW Jr (2002b) Relationships between percentage defoliation, dry weight, percentage reflectance, leaf-to-stem ratio, and green leaf area index in the alfalfa leaf spot pathosystem. Crop Sci 42:1264–1273

Guan J, Nutter FW Jr (2003) Quantifying the intra-rater repeatability and inter-rater reliability of visual disease and remote sensing assessment methods in the alfalfa foliar disease pathosystem. Can J Plant Pathol 25:143–149

Hamerchlag K, Kaplan J (2007) How USDA could deliver greater environmental benefits from farm bill conservation programs. The National Resources Defense Council, Inc. (NRDC), Washington

Hartman GL, Sinclair JB, Rupe JC (eds) (1999) Compendium of soybean diseases. APS Press, St Paul

Hijmans RJ, Forbes GA, Walker TS (2000) Estimating the global severity of potato late blight with GIS-linked disease forecast models. Plant Pathol 49:697–705

Huang Y, Lan Y, Westbrook JK, Hoffman WC (2008) Remote sensing and GIS applications for precision area-wide pest management: Implications for homeland security. In: Sui DZ (ed) Geospatial technologies and homeland security, Springer, Netherlands

Lathrop LD, Pennypacker SP (1980) Spectral classification of tomato disease severity levels. Photogramm Eng Remote Sens 46:1433–1438

Leckie DG, Cloney E, Jay C et al (2005) Automated mapping of stream features with high-resolution multispectral imagery: an example of the capabilities. Photogramm Eng Remote Sens 71:145–155

Malthus TJ, Madeira AC (1993) High resolution spectroradiometry: spectral reflectance of field bean leaves infected by *Botrytis fabae.* Remote Sens Environ 45:107–116

Moreira AJD (2004) Use of remote sensing, geographic information systems, and spatial statistics to assess spatio-temporal population dynamics of *Heterodera* glycines and soybean yield quantity and quality. PhD Dissertation, Iowa State University, Ames

Nutter FW Jr (1989) Detection and measurement of plant disease gradients in peanut with a multispectral radiometer. Phytopathology 79:958–963

Nutter FW Jr (1990) Remote sensing and image analysis for crop loss assessment. In: ABC (eds) Crop loss assessment in rice. International Rice Research Institute, Manila
Nutter FW Jr (1999) Understanding the interrelationships between botanical, human, and veterinary epidemiology: The Y's and R's of it all. Ecosyst Health 5:131–140
Nutter FW Jr (2001) Disease assessment. In: Malloy OC, Murray TD (eds) Encyclopedia of plant pathology. John Wiley and Sons, Inc, New York
Nutter FW Jr (2004) Developing forensic protocols for the post-introduction attribution of threatening plant pathogens. Phytopathology 94:S77
Nutter FW Jr (2007) The role of plant disease epidemiology in developing successful integrated disease management programs. In: Ciancio A, Mukerji KG (eds) General concepts in integrated pest and disease management. Springer, The Netherlands
Nutter FW Jr, Byamukama EZ, Coelho-Netto RA, Eggenberger SK, Gleason ML, Holah N, Robertson AE, and Van Rij N (2010) Integrating GPS, GIS, and remote sensing technologies with disease management principles to improve plant health. In: Clay SA (ed) GIS applications in agriculture volume 2 invasive species. Taylor & Francis Group LLC, Boca Raton
Nutter FW Jr, Esker PD (2006) The role of psychophysics in phytopathology: the Weber-Fechner law revisited. Eur J Plant Pathol 114:199–213
Nutter FW Jr, Esker PD, Coelho Netto RA (2006) Disease assessment concepts and the advancement made in improving the accuracy and precision of plant disease data. Eur J Plant Pathol 115:99–103
Nutter FW Jr, Guan J (2001) Disease losses. In: Maloy OC, Murray TD (eds) Encyclopedia of plant pathology. Wiley, Inc, New York
Nutter FW Jr, Holah N, Eggenberger SK, Byamukama E, Wright DL, Marois J (2009) Integrating GPS, GIS and remote sensing technologies for improved crop biosecurity. In: Proceedings of the 10th International Epidemiology Workshop, 7–12 June, Cornell University, Geneva
Nutter FW Jr, Littrell RH, Brenneman TB (1990) Utilization of a multispectral radiometer to evaluate fungicide efficacy to control late leaf spot in peanut. Phytopathology 80: 102–108
Nutter FW Jr, Madden LV (2008) Plant pathogens as biological weapons against agriculture. In: Lutwick LI, Lutwick SM (eds) Beyond anthrax: the weaponization of infectious disease. Springer Science + Business Media LLC, New York
Nutter FW Jr, Rubsam RR, Taylor SE et al (2002) Geospatially-referenced disease and weather data to improve site-specific forecasts for Stewart's disease of corn in the US corn belt. Comput Electron Agric 37:7–14
Nutter FW Jr, Schultz PM, Hill JH (1998) Quantification of within-field spread of soybean mosaic virus in soybean using strain-specific monoclonal antibodies. Phytopathology 88:895–901
Nutter FW Jr, Tylka GL, Guan J, Moreira et al (2002) Use of remote sensing to detect plant stress caused by soybean cyst nematode. J Nematol 34:222–231
Oudemans PV, Polashock JJ, Vinyard BT (2008) Fairy ring disease of cranberry: assessment of crop losses and impact on cultivar genotype. Plant Dis 92:616–622
Parker SK, Gleason ML, Nutter FW Jr (1995) Influence of rain events on spatial distribution of Septoria leaf spot of tomato. Plant Dis 79:148–152
Pethybridge SJ, Esker P, Dixon P, Hay F, Groom T, Wilson C, Nutter FW Jr (2007a) Quantifying loss caused by ray blight disease in Tasmanian pyrethrum fields. Plant Dis 91:1116–1121
Pethybridge SJ, Gent DH, Esker PD, Turechek WW, Hay FS, Nutter FW Jr (2009) Sitespecific risk factors for ray blight in Tasmanian pyrethrum fields. Plant Dis 93:229–237
Pethybridge SJ, Hay F, Esker PD et al (2007b) Use of a multispectral radiometer for noninvasive assessments of foliar disease caused by ray light in pyrethrum. Plant Dis 91:1397–1406
Pethybridge SJ, Hay FS, Esker PD et al (2008) Visual and radiometric assessments for yield losses caused by ray blight in pyrethrum. Crop Sci 48:343–352
Schut AGT, van der Heijden GWAM, Hoving I, Stienezen MWJ, van Evert FK, Meuleman J (2006) Imaging spectroscopy for on-farm measurement of grassland yield and quality. Agron J 98:1318–1325

Steddom K, Bredehoeft MW, Khan M et al (2005) Comparison of visual and multispectral radiometric disease evaluations of Cercospora leaf spot of sugar beet. Plant Dis 89:153–158

Steinlage TA, Hill JH, Nutter FW Jr (2002) Temporal and spatial spread of soybean mosaic virus (SMV) in soybeans transformed with the coat protein gene of SMV. Phytopathology 92: 478–486

Sullivan DG, Holbrook CC (2007) Using ground-based reflectance measurements as selection criteria for drought- and aflatoxin-resistant peanut genotypes. Crop Sci 47:1040–1050

Waggoner PE, Berger RD (1987) Defoliation, disease, and growth. Phytopathology 77:393–398

Wang F (2006) Quantitative methods and applications in GIS. Taylor & Francis, New York

Ward JMJ, Stromberg EL, Nowell DC et al (1999) Gray leaf spot: a disease of global importance in maize production. Plant Dis 83:884–895

Zadoks JC, Schein RD (1979) Epidemiology and plant disease management. Oxford University Press, New York

Zhao D, Raja Reddy K, Vijaya Gopal Kakani et al (2005) Selection of optimum reflectance ratios for estimating leaf nitrogen and chlorophyll concentrations of fieldgrown cotton. Agron J 97:89–98

Chapter 4
Spatial and Temporal Dynamics of Arthropods in Arable Fields

Maarten van Helden

Abstract Pest distribution in an arable field is rarely homogeneous. As for diseases and weeds many different abiotic and biotic factors can induce non-homogeneous or even aggregated distributions. Moreover animal pests are able to respond actively themselves to external factors such as small differences in local habitat quality through their behaviour. The combined effects of variations in plant physiological stage and local climate, arthropod behaviour and population dynamics, and (tri-)-trophic interactions often result in aggregated spatial distributions of the pest, which can evolve over time due to pest-plant interactions. The large number of potential interactions makes it almost impossible to foresee spatial distributions at the field scale. In situ studies on spatial distribution of the pest can be used to reveal (stable) distribution patterns. Then it can be tempted to correlate these to intra-field variation in (plant, climate, etc.) characteristics. Stable (and/or predictable) patterns will certainly not occur for all pests. Some examples are cited, mainly occurring in perennial crops and/or for highly mobile pests. Knowledge of such sustainable patterns can then be used to optimise field monitoring and/or management. However, practical implementation of such knowledge in pest management seems still very limited because of technical (equipment) reasons and impacts on working methods

1 Introduction

In this chapter we will focus on the spatial distribution of arthropod pests in a crop over time at the intra-field scale. The focus of this book being precision agriculture we will not consider the population dynamics alone (without spatio-temporal effects), such simple dynamics being described in many studies.

M. van Helden (✉)
UMR Santé Végétale, University of Bordeaux, Gradignan cedex 33175, France
e-mail: m-vanhelden@enitab.fr

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_4,

On the field scale many different phenomena can be observed resulting in non homogeneous distribution of arthropods. Larger ‘landscape’ scale phenomena are being studied today (Thies et al. 2003, Schmidt et al. 2005, van Helden et al. 2006, Tscharntke et al. 2007, Reeve et al. 2008) but these are beyond the scope of this book.

I will mainly concentrate on phytophagous pest insects, but occasionally data on the distribution of other phytophagous arthropods (mites) or of natural enemies (insect parasitoids and predators, other arthropods as spiders, etc.) will be mentioned either as an illustration or because these can be an explanatory factor for the pests’ distribution. The agronomical definition of a field is a ‘continuous and uniform production area, where cultural practices are applied homogeneously’. As is clear from this definition, farmers tend to handle the field as a single management unit. This man-made ‘functional’ definition of a field is clearly not respected by biotic factors such as pests, diseases and weeds. Spatial distributions of pests in a field are rarely homogeneous (Dalthorp et al. 2000). Many different reasons can explain a non-homogeneous distribution of pests, from pure and simple stochastic effects of ‘passive’ colonization of wind-borne pests, to abiotic border effects (temperature, humidity, wind) acting on the survival rate of the insect. In spite of this non-homogeneous distribution the farmer will still use the field scale for pest management decisions (monitoring, intervention thresholds) and interventions (pesticide applications) whereas this is clearly not always justified. Pesticide treatments, applied to the whole field whereas attacks are only local, represent a substantial waste of pesticide, and an additional hazard for environment and health (Bongiovanni and Lowenberg-Deboer 2004).

If we would understand the underlying mechanisms of such spatial heterogeneity and/or if we could determine them in a reliable way, we then could in theory adapt the management of the crop to either create a more homogeneous situation, or to limit the management to those areas where an intervention is needed. This could in theory reduce pesticide use in a very significant way (see also Chapters 19, 22, and 23).

2 Field, Field Borders and Core Area

Defining a field as a ‘continuous and uniform production area, where cultural practices are applied homogeneously’ is a contradiction in terms since a field (habitat patch for the pest) is not ‘continuous’ but inevitably has a ‘border’ and a central part (core) (Fagan et al. 1999). In the ‘border’ of the field many biotic and abiotic parameters will show a gradient from the exterior of the field up to a certain distance into the field. The range of this gradient and thus the width of the border area depend on the system studied. For example some edge effects such as uneven light exposure due to the presence of a hedge will not go beyond the length of its shadow, but other effects, such as wind speed effects (Chojnacka-Ozga and Ozga 1998, Chen and Ruberson 2008) or the predation by syrphid flies ((highly mobile natural enemies) foraging for nectar and pollen outside the crop and entering in the field seeking egg laying sites near aphid colonies), can have a much bigger range (Cowgill et al. 1993a, Arrignon et al. 2007). It is only beyond this (variable) 'border area' that conditions for a certain factor can be considered as really homogeneous in the central part of the field. This central homogeneous area will be referred to as 'core area' throughout this chapter. Straightforward metric definitions of 'border' and 'core area' are inappropriate and need to be defined for each case or each system studied.

In the core area of the field the climatic growing conditions for the plants should ideally be homogeneous. However, differences in soil quality (such as nutrient and water availability) often occur, thus changing plant growth.

In perennial crops, or in fields where the same annual crop is grown in successive years such as maize (*Zea mays;* Weisz et al. 1996, Kiss et al. 2005), the effect of such small local abiotic differences tends to accumulate over years (Bramley 2005), amplifying the differences in plants growth, resulting in clearly non-homogeneous crops, in which pest insects will indeed encounter large habitat quality differences (Decante and van Helden 2008). Therefore non-homogeneous distributions of pests are more often observed in such (non-homogeneous) perennial crops.

If the pest population can hibernate inside the field such small initial differences in population levels will re-enforce themselves over time, especially for pests that are of limited mobility (scale insects, nematodes). In such cases of 'perennial' field (crop) and pest combinations, interactions can potentially accumulate over time and evolve to comparable (perennial) spatial distributions over years, even if overall population levels can vary according to annual conditions. Arthropods, being often quite mobile, can be strongly influenced 'passively' by border effects during the dispersal to, from, or inside the field. However, they are also potentially capable of responding 'actively' to non-homogeneous conditions in the field (Couty et al. 2006).

In this chapter we will differentiate the two main phases of population dynamics as distinguished by epidemiologist: the 'primary infection' (colonisation of the crop by the migrating insect from outside the field) and the secondary spread (due to dispersal and/or reproduction of the arthropod inside the field). Since many arthropods will leave the crop again at the end of season (for example to hibernate elsewhere: complementation) the 'emigration phase' will also be illustrated.

The primary/secondary infestation process is often a 'yearly' process especially in annual crops (where many of the pests will be 'removed' with the harvest, or (in both annual and perennial crops) for pests hibernating outside the field).

For perennial crops, or for annual crops repeated several times on the same field, pest insects that are capable of completing their whole cycle inside the field will not show a 'colonisation' phase every year. As far as I am aware very few species of arthropod pests have a diurnal (daily) 'immigration/emigration' behaviour such as some mammals and birds (roe deer, sparrows). The only exceptions are social insects when they have their colonies outside the field (wasps, bees). This seems no viable strategy for most (non-social) arthropod pests.

3 Primary Colonization of the Field

Let's consider the (hypothetical) case of a homogeneous rectangular field containing a single crop, totally free of pest insects, and surrounded by bare soil. This habitat patch is potentially a very interesting resource for a pest, much bigger and with a higher resource concentration than in a natural situation, and therefore we will probably observe the installation of the first 'immigrants' quite rapidly. The way this immigration takes place depends on the pests' behaviour. Most pests will arrive 'through the air' and we will focus mainly on aerial migration in this chapter. Colonisation can also happen through animals migrating over the ground (especially larger mammals) or farmer operations using 'contaminated inputs' (soil transfer during tillage, contaminated seed etc.).

3.1 Passive Migration

Many (smaller) pest arthropods will actually not be able to locate and move towards the crop for the simple reason that their active migratory capacity is limited by their flight speed (Ellington 1991). During migration these 'air-borne' pests will therefore behave as 'aerial plankton' transported passively by the wind. Wind speed is correlated to elevation and active directed movement is only possible close to the ground in what is often referred to as the 'flight boundary layer' (FBL; Gatehouse 1997). For an insect present above this FBL no orientation is possible, it will simply be 'gone with the wind'. For such wind borne pests showing purely passive migration the colonisation in the core area of the field will therefore be purely random process (Fievet et al. 2007).

However border effects will occur. In the edge of our hypothetical field, where the wind will encounter the field vegetation the (horizontal) air flow will be affected by the border of the field. Aerial plankton moving horizontally into the crop will thus be 'sieved out' by the crop, acting here as mechanical barrier (Fig. 4.1). Such effects are for instance particularly visible for 'ballooning' small spiders that will clearly accumulate at such borders because the silk threads that carry them get tangled up in the vegetation (Thomas et al. 2007).

Moreover the wind speed will also be reduced by this mechanical resistance of the crop (Fishpool et al. 1988, Pasek 1988, Chojnacka-Ozga and Ozga 1998) and such an air speed reduction will increase passive deposit of aerial plankton. When wind speed is sufficiently reduced, below the maximum flight speed of the pest, it can even start 'active' orientated dispersal inside the field.

When field borders are not 'bare soil' but have a vertical structure (such as hedgerows or lines of trees), wind speed changes due to mechanical effects of this ruggedness of the area will not only change air flow speed but can cause turbulence, resulting in more or less deposit of aerial plankton in certain areas (Yudin et al. 1991, De Guimaraes et al. 1997). These phenomena have been studied extensively in agriculture on related 'passive drift' systems such as spore and seed dispersal or pesticide drift (Lazzaro et al. 2008). The width of the 'border area' of such

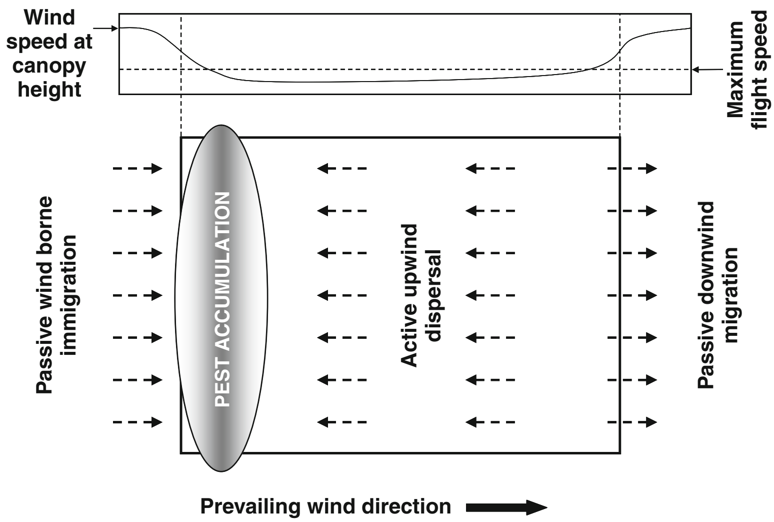

Fig. 4.1 Insect accumulation of an 'air-borne' pest due to wind speed reduction below its maximum flight speed inside the crop. The highest population density is observed at the upwind border due to a combination of sieving out of passive leeward immigrants and upwind active dispersal inside the crop, where wind speed under the canopy drops below flight-speed

phenomena can be quite important, up to several times the height of the structure (Chojnacka-Ozga and Ozga 1998).

In a few cases the passively migrating insect can slightly influence its landing moment (and thus to a lesser extend the landing site). While the migrant can actively 'maintain height' during long range dispersal by wing flapping movements, it can also fold its wings, thus reducing its air resistance resulting in a 'crash landing' without precise selection of the landing area. Such phenomena have been described for aphids and colonisation could even be influenced by changing crop or soil characteristics (Stapleton and Summers 2002), apparently interfering with the visual observation of the pest.

3.2 Active Migration

Larger insects, capable of flying at speeds above wind speed (inside the FBL, often closer to the ground) can, at some stage during the migration, orient themselves actively to the resource, using some 'long distance' indication such as odour or vision (Visser and Nielsen 1977, Szentesi et al. 2002, Fernandez and Hilker 2007, Carde 2008, Carde and Willis 2008, Spencer et al. 2009). In the absence of such stimuli many insects will attempt to move both upwind and slightly perpendicular (Visser and Nielsen 1977, Colvin et al. 1998) probably to 'cover' the largest possible area during host plant localisation. When the insect does perceive host plant stimuli it will show directed upwind movement towards the field. Since odour 'cones' are wind dispersed upwind movement will normally result in localisation and immigration of the crop from the 'downwind (lee) side', this will result in an initial colonisation of this lee side border. However these phenomena are not easy to observe because of changing wind directions and because of continuing dispersal inside the crop (see below).

4 Dispersal of Immigrants Inside the Field

Once the arthropod has invaded the field it can start dispersing actively. Wind speed inside the crop is often below flight speed so the arthropod is free to move around inside the FBL, in search of appropriate habitat characteristics. In a natural situation but even in our 'unnatural' field (high density monoculture) such dispersal is a natural risk factor for mortality (for instance by spider-predation), and will have energetic costs, so the pests should optimise its foraging behaviour.

Here the evolution of the eco-ethology of the pest will determine its behaviour and preference for specific habitat types or environmental conditions.

If the field is perfectly homogeneous (our hypothetical case) and if the arthropod has no preferential direction of migration, the pest-plant interaction should not result in any preferential distribution. However the migration of insects inside the field is often still preferentially upwind (Fishpool et al. 1988, Colvin et al. 1998, Decante and van Helden 2008, Hsu et al. 2009). The combination of downwind passive immigration and upwind active dispersal inside the field can cause pest accumulation in the upwind field border (Fig. 4.1; Fishpool et al. 1988, Colvin et al. 1998).

In contrast to our hypothetical case many different factors will vary inside a field resulting in non-homogeneous habitat quality and this can influence pest distribution. Soil characteristics, fertilizer levels, water availability and many other factors can vary. The pest individual is potentially able to respond to these factors, again in relation to its mobility. Leafhoppers such as *Empoasca vitis* in Europe or *Erythroneura* sp. in North America (Martinson et al. 1994, Decante and van Helden 2008) are highly mobile insects that clearly show a preferential distribution in the fields, preferring higher plant vigour (Fig. 4.2, correlated to nitrogen levels and water availability; Bentz and Townsend 2003, Daane and Williams 2003, Decante et al. 2009).

Even the pest itself sometimes has an advantage in showing an aggregated distribution. The classic example is that of bark beetles, unable to attack a pine tree individually, using an aggregation pheromone (combined with kairomones from the attacked plant) to accumulate on certain trees and overcome its defence due to a 'group attack' (Wermelinger 2004), resulting in a much aggregated distribution of these immigrants. The fact that the same compound, above a certain concentration will become a dispersal pheromone avoids intra-specific competition on the individual plants, the late arrivals focussing on nearby, less attacked trees (Sun et al. 2006).

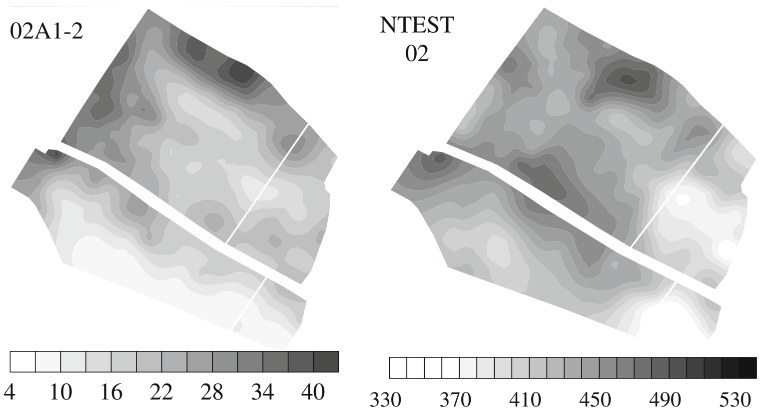

Fig. 4.2 (**a**) Adult spatial distribution of *Empoasca vitis* as observed on *yellow sticky traps* (legend = number of adults trapped during a 1 week interval) compared with (**b**) Plant vigour (as measures by chlorophyll content through an N-tester) in a 25 ha vineyard (data from Decante et al. 2009). Insect distribution has a high significant correlation with plant vigour, especially in the core area, but edge effects occur especially in the north-west border

5 Population Build-Up and Dispersal Inside the Field

As most pests will show a population increase once they are in the field the initial distribution of the new-born individuals (less mobile non-winged larval stages) should be linked to the reproduction (egg lying) site of the females. Since egg laying sites are abundant inside the field, dispersion of the egg-laying female is not necessary – it can still occur as part of the reproductive strategy – and this will potentially lead to a population increase in these areas. The population levels can lead to direct (population density) crowding effects that, in certain arthropods, will induce dispersal activities (Mackay and Lamb 1996).

Moreover, since we are considering phytophagous pests these will generally increase to population levels damaging the plant, this will decrease plant growth or alter its physiology, thus changing – often reducing- its quality as a resource for the pest. According to the pest species this will induce dispersal of individuals to other higher quality areas, generally present close by in the field.

In the case of ‘low’ to ‘moderately’ mobile pests such as aphids and mites, not able to disperse actively over long distances to find their host, this population build-up will result in a gradual spread of the pest from the initial infestation spot into a larger infestation patch. If the effect of the pest on the plant does reduce the plants’ growth, these infestation foci can be observed in the field. Because of the reduction in resources in such a patch this is not always the area with most pest individuals. The highest infestation levels are often found on the edge of the infestation patch, where new, not yet damaged, plants are being colonized (Logan 1997). Population levels can build up to high numbers on these so far healthy plants before they start to suffer from the pest attack. In this case it is the pest that will induce 'non-homogeneous' conditions inside the field. Population levels observed at one moment in the field will often not be linked directly to the severity of the observable symptoms because there often is this lag between population and damage (Decante and van Helden 2008).

6 Border Effects on Dispersal and Emigration

Just like the arthropods immigrating to the field, the arthropods dispersing inside the crop can be influenced by the border. For a pest insect dispersing inside the high quality habitat of the field leaving the habitat patch can be considered as a major risk. Therefore individuals might perceive the border as a natural barrier. The insect might be moving preferentially into a certain direction (upwind) inside the field until it is confronted with the field edge. It might be reluctant to leave the field, especially if the transition from habitat to non habitat is very abrupt. When a whole population of pest insects is migrating in a certain direction and 'hampered' by this border effect, population density can build up close to the border as observed for populations of *E. vitis* (Decante and van Helden 2008) and *Bemisia tabaci* (Gatehouse 1997, Colvin et al. 1998). The higher wind speed observed at field borders can re-enforce this phenomena, if the insects are unable to keep flying upwind beyond the border of the field as observed for *B. tabaci* in cassava fields (Colvin et al. 1998).

7 Effects of the Plant Physiology

The (physiological) state of the plant can influence the acceptance of the plant by the pest insect, or its reproduction rate. Nitrogen availability and water stress are considered as the major factors that will influence insect population dynamics and distribution. Uneven nitrogen fertilisation of the field will in most cases favour insect development in those areas where nitrogen is more abundant (thus having a higher nutritional value). Especially piercing-sucking homopterous insects such as aphids are known to respond strongly to this parameter (Kyto et al. 1996, Bentz and Townsend 2003, Bongiovanni and Lowenberg-Deboer 2004, Hogendorp et al. 2006, Chen and Ruberson 2008), even though this correlation is not always positive (Zehnder and Hunter 2009).

Host plant quality will vary over the growing season since phenology of the plant (from budding to seed ripening and leaf shedding) will change. If, for whatever reason, the phenology of the plant varies in the field, this can influence the pests' distribution or reproduction rate. Border effects and slope/exposure effects will often induce differences in phenology, and plants in this area might therefore be more or less attractive or acceptable than the core area (Fagan et al. 1999).

8 Effects of Natural Enemies

So far we have only considered the interaction of the pest (second trophic level) with abiotic factors and the first trophic level (plant). For the natural enemies (NE: the third trophic level) of the pests the field itself is not an exploitable resource when the pest (or any other possible food source) is not present in the crop. In most cases the NE will not overwinter in the crop and when it migrates into the crop 'accidentally' it will leave (or die in) the field when no resources are present. Orientation of the migrating NE to stimuli (odour, vision) from the pest or the attacked crop – or a combination of them – from outside the field is possible, but have rarely been shown to play a role at this spatial scale (Williams et al. 2007).

8.1 Immigration

The fate of the NE entering the crop is depending on its ecology. Some very mobile NEs being able to 'explore' a crop patch over large distances from the border to locate their prey (syrphid flies, dragonflies), others being more 'clumsy' fliers (lacewings) or too small to be able to compensate wind speed (many microscopic parasitic wasps). A strong 'border effect' of NEs can be expected, especially during the period when the natural enemy has not located its prey and reproduced inside the crop.

Even with the prey present the habitat quality of the crop patch might not be sufficient to provide all resources for the NE survival. Complementation of the NE diet with pollen and nectar (increasing mobility, fecundity and longevity) is often necessary for the adult NE (Cowgill et al. 1993), whereas only the larvae will attack the prey. In such cases a 'sustainable' colonization of the field is not even possible and floral resources will need to be available in the vital space of the NE (Cowgill et al. 1993, van Helden and Decante 2001, van Helden et al. 2003, 2006). Many studies and projects aim at creating flower strips at the field border containing food resources for natural enemies such as pollen and nectar and thus increase its potential impact on the pest. However, offering good resources in strips bordering the crop might also reduce the motivation to enter the more hostile environment inside the field or – even worse – attract the few NE present in the field towards the flower strip outside of the field. Few results illustrate the migrations between surrounding vegetation and the crop or the real impact (predation rate, range of action) of natural enemies coming from such border strips in the field itself (Lovei et al. 1993, Robinson et al. 2008). It seems clear that additional resources (such as flowers) should better be located throughout the field to be most efficient to increase natural enemies. In perennial systems (orchards, vineyards) and even some annual crops the undergrowth can play such a role (White et al. 1995), even though unwanted effects can occur (Irvin et al. 2006).

8.2 Functional and Numerical Response

Inside the crop, when directional movement is possible, functional response through tri-trophic communication occurs. At this finer scale the NE can be attracted by kairomones from its host or synomones emitted by the attacked plant, guiding it towards the pest infestation focus. Literature on the role of semiochemicals is numerous and many examples do exist, but cannot be mentioned here. See Dicke (1995) for a review on this fascinating part of chemical ecology.

Once a NE has located its host inside the crop it can start predation and reproducing (numerical response). If the NE has a real impact (being able to reduce the pest population level while increasing its own population) at this local level, the pest population is condemned to local extinction. This will result in high local NE populations with insufficient resources that will spread out in search for new populations. Dispersing pest individuals (sometimes these are even migrating as a response to the presence of NE (Fievet et al. 2008)) might have started new populations elsewhere in the field, which will be discovered with a certain lag, thus creating strong local variations (Sabelis et al. 1999, Ellner et al. 2001). The phytophagous mites/predatory mite system in greenhouses as studied by Sabelis (2005) is a beautiful example with a global equilibrium (efficient biological control) in spite of such very strong local fluctuations.

9 Overall Effects

As illustrated in the preceding paragraphs many different phenomena can influence the pest distribution inside the field. It is not possible to predict any form of pest distribution without sufficient knowledge of the pest biology and eco-ethology and the crop/pest combination. It seems impossible to understand all factors influencing spatial distribution in order to predict the final outcome. Therefore, in situ observations are needed to describe population dynamics and spatial distribution (Decante and van Helden 2008, Decante et al. 2009). From such descriptive work a more general conceptual model can then be developed for each case and this can be tested by more precise observations (multiple sites or several years) (Colvin et al. 1998, Decante and van Helden 2006, Fievet et al. 2007, Fishpool et al. 1988, Decante and van Helden 2008, Decante et al. 2009). This allows identifying the main factors (Fig. 4.2), and – if these seem to be able to explain the patterns observed – this might lead to changes in management practices (Daane and Williams 2003).

10 Practical Implications for Precision Farming

When aiming at precision farming for pest control at the intra-field scale, we want to characterise the pest distribution in order to be able to adapt management locally. As explained in the introduction to this chapter this concept is clearly not yet habitual for the farmer/manager.

As a first step we will have to be able to predict or observe the (unequal) pest distribution at this scale. This requires time and money intensive multi-site observations inside the field (Alexander et al. 2005, Decante and van Helden 2008, Fievet et al. 2007). It seems quite unlikely that this can be done in a 'real time' approach since the time needed for the observation is probably long, and economic considerations will limit this option. Moreover, since pest damage often occurs with some time lag after the attack, observation of damage or symptoms often is not appropriate to localise the 'target' for spraying.

However, in the case of more predictable distributions, sustaining from one year to another, or when general understanding of the factors influencing pest distribution is precise enough to predict where the highest population levels will occur, monitoring can focus on such historical 'high-risk' areas to be able to decide on the need for intervention (Decante and van Helden 2008). In the case of the green leafhopper leaf scorching is located in the same area of the field each year. This allows starting observations in these 'sensitive' areas, to be able to decide on the need to spray (or not spray).

If the intervention threshold is not exceeded in such 'more sensitive' areas, then monitoring can end, but if it is surpassed, observations should also include less sensitive areas. Then the farmer has to decide if he has to spray the whole field or just the most attacked area. The application of such decision rules often remains hypothetical since spraying equipment is not designed to spray only some parts of a field. In most cases the smallest decisional level is the field or the 'size of the spraying tank', generally larger than just the field size. Monitoring techniques and spraying equipment will have to be re-designed if aiming at the economically viable implementation of precision pest management (Krell et al. 2003, Bongiovanni and Lowenberg-Deboer 2004, Patzold et al. 2008).

References

Alexander CJ, Holland JM, Winder L et al (2005) Performance of sampling strategies in the presence of known spatial patterns. Ann Appl Biol 146:361–370

Arrignon F, Deconchat M, Sarthou JP et al (2007) Modelling the overwintering strategy of a beneficial insect in a heterogeneous landscape using a multi-agent system. Ecol Modell 205:423–436

Bentz JA, Townsend AM (2003) Nitrogen fertilization and use of container-grown maple selections as hosts by the potato leafhopper. J Am Soc Hort Sci 128:821–826

Bongiovanni R, Lowenberg-Deboer J (2004) Precision agriculture and sustainability. Prec Agric 5:359–387

Bramley RGV (2005) Understanding variability in winegrape production systems – 2. Within vineyard variation in quality over several vintages. Aust J Grape Wine Res 11:33–42

Carde RT (2008) Insect migration: do migrant moths knows where they are heading? Curr Biol 18:472–474

Carde RT, Willis MA (2008) Navigational strategies used by insects to find distant, wind-borne sources of odor. J Chem Ecol 34:854–866

Chen YG, Ruberson JR (2008) Impact of variable nitrogen fertilisation on arthropods in cotton in Georgia, USA. Agric Ecosyst Environ 126:281–288

Chojnacka-Ozga L, Ozga W (1998) The air flow direction and speed in the forest edge area. Sylwan 142:65–72
Colvin J, Fishpool LDC, Fargette D et al (1998) *Bemisia tabaci* (Hemiptera: Aleyrodidae) trap catches in a cassava field in Cote d'Ivoire in relation to environmental factors and the distribution of African cassava mosaic disease. Bull Entomol Res 88:369–378
Couty A, van Emden H, Perry JN et al (2006) The roles of olfaction and vision in host-plant finding by the diamondback moth, *Plutella xylostella*. Physiol Entomol 31:134–145
Cowgill SE, Wratten SD, Sotherton NW (1993a) The effect of weeds on the numbers of hoverfly (Diptera, Syrphidae) adults and the distribution and composition of their eggs in winter wheat. Ann Appl Biol 123:499–515
Cowgill SE, Wratten SD, Sotherton NW (1993b) The selective use of floral resources by the hoverfly *Episyrphus balteatus* (Diptera, Syrphidae) on farmland. Ann Appl Biol 122: 223–231
Daane KM, Williams LE (2003) Manipulating vineyard irrigation amounts to reduce insect pest damage. Ecol Appl 13:1650–1666
Dalthorp D, Nyrop J, Villani MG (2000) Foundations of spatial ecology: the reification of patches through quantitative description of patterns and pattern repetition. Entomol Exp Appl 96: 119–127
De Guimaraes AM, Pavan MA, Kurozawa C (1997) Effect of corn windbreaks on the incidence of tospovirus on tomato crop. Fitopatol Brasil 22:142–147
Decante D, van Helden M (2006) Population ecology of *Empoasca vitis* (Gothe) and *Scaphoideus titanus* (Ball) in Bordeaux vineyards: influence of migration and landscape. Crop Prot 25: 696–704
Decante D, van Helden M (2008) Spatial and temporal distribution of *Empoasca vitis* within a vineyard. Agric For Entomol 10:111–118
Decante D, van Leeuwen C, van Helden M (2009) Influence of plot characteristics and surrounding vegetation on the intra-plot spatial distribution of *Empoasca vitis*. Agric For Entomol 11: 377–387
Dicke M (1995) Why do plants 'talk'? Chemoecology 5/6:159–165
Ellington CP (1991) Limitations on animal flight performance. J Exp Biol 160:71–91
Ellner SP, McCauley E, Kendall BE et al (2001) Habitat structure and population persistence in an experimental community. Nature 412:538–543
Fagan WE, Cantrell RS, Cosner C (1999) How habitat edges change species interactions. Am Nat 153:165–182
Fernandez P, Hilker M (2007) Host plant location by Chrysomelidae. Basic Appl Ecol 8:97–116
Fievet V, Dedryver CA, Plantegenest M et al (2007) Aphid colony turn-over influences the spatial distribution of the grain aphid *Sitobion avenae* over the wheat growing season. Agric For Entomol 9:125–134
Fievet V, Lhomme P, Outreman Y (2008) Predation risk cues associated with killed conspecifics affect the behavior and reproduction of prey animals. Oikos 117:1380–1385
Fishpool LDC, van Helden M, van Halder I et al (1988) Controle des populations de *Bemisia tabaci* sur manioc: comptages en champ et capures par pièges. Proceedings of the International Seminar on African cassava mosaic disease and its control, Yamassoukro, Ivory Coast, CTA, Wageningen, pp 59–70
Gatehouse AG (1997) Behavior and ecological genetics of wind-borne migration by insects. Annu Rev Entomol 42:475–502
Hogendorp BK, Cloyd RA, Swiader JM (2006) Effect of nitrogen fertility on reproduction and development of citrus mealybug, *Planococcus citri* Risso (Homoptera: Pseudococcidae), feeding on two colors of coleus, *Solenostemon scutellarioides* L. Codd. Environ Entomol 35:201–211
Hsu CL, Agnello AM, Reissig WH (2009) Edge effects in the directionally biased distribution of *Choristoneura rosaceana* (Lepidoptera: Tortricidae) in apple orchards. Environ Entomol 38:433–441

Irvin NA, Scarratt SL, Wratten SD et al (2006) The effects of floral understoreys on parasitism of leafrollers (Lepidoptera: Tortricidae) on apples in New Zealand. Agric For Entomol 8:25–34

Kiss J, Komaromi J, Bayar K et al (2005) Western corn rootworm (*Diabrotica virgifera virgifera* LeConte) and the crop rotation systems in Europe. In: Vidal S, Kuhlmann U, Edwards CR (eds) Western corn rootworm: ecology and management. CABI Publishing, Wallingford, pp 189–220

Krell RK, Pedigo LP, Babcock BA (2003) Comparison of estimated costs and benefits of site-specific versus uniform management for the bean leaf beetle in soybean. Prec Agric 4:401–411

Kyto M, Niemela P, Larsson S (1996) Insects on trees: population and individual response to fertilization. Oikos 75:148–159

Lazzaro L, Otto S, Zanin G (2008) Role of hedgerows in intercepting spray drift: evaluation and modelling of the effects. Agric Ecosyst Environ 123:317–327

Logan DP (1997) Distribution of eggs and larvae of Childers canegrub, *Antitrogus parvulus* Britton (Coleoptera: Scarabaeidae), in relation to patches of canegrub-damaged sugarcane. Proceedings of the 3rd Brisbane workshop on soil invertebrates, Brisbane, pp 52–55

Lovei GL, Hickman JM, McDougall D, Wratten SD (1993) Field penetration of beneficial insects from habitat islands – hoverfly dispersal from flowering crop strips. Proceedings of the 46th New Zealand plant protection conference, Christchurch, pp 325–328

Mackay PA, Lamb RJ (1996) Dispersal of five aphids (Homoptera: Aphididae) in relation to their impact on *Hordeum vulgare*. Environ Entomol 25:1032–1044

Martinson TE, Dennehy TJ, Hoffman CJ (1994) Phenology, within-vineyard distribution, and seasonal movement of Eastern grape leafhopper (Homoptera, Cicadellidae) in New-York vineyards. Environ Entomol 23:236–243

Pasek JE (1988) Influence of wind and windbreaks on local dispersal of insects. Agric Ecosyst Environ 22:539–554

Patzold S, Mertens FM, Bornemann L et al (2008) Soil heterogeneity at the field scale: a challenge for precision crop protection. Prec Agric 9:367–390

Reeve JD, Cronin JT, Haynes KJ (2008) Diffusion models for animals in complex landscapes: incorporating heterogeneity among substrates, individuals and edge behaviours. J Anim Ecol 77:898–904

Robinson KA, Jonsson M, Wratten SD et al (2008) Implications of floral resources for predation by an omnivorous lacewing. Basic Appl Ecol 9:172–181

Sabelis MW, Janssen A, Diekmann O et al (2005) Global persistence despite local extinction in acarine predator-prey systems: lessons from experimental and mathematical exercises. Adv Ecol Res 37:183–220

Sabelis M, Janssen A, Pallini A et al (1999) Behavioral responses of predatory and herbivorous arthropods to induced plant volatiles: from evolutionary ecology to agricultural applications. In: Agrawal A, Tuzun S, Bent E (eds) Induced plant defenses against pathogens and herbivores. American Phytopathological Society, St. Paul, pp 269–296

Schmidt MH, Roschewitz I, Thies C, Tscharntke T (2005) Differential effects of landscape and management on diversity and density of ground-dwelling farmland spiders. J Appl Ecol 42:281–287

Spencer JL, Hibbard BE, Moeser J, Onstad DW (2009) Behaviour and ecology of the western corn rootworm (*Diabrotica virgifera virgifera* LeConte). Agric For Entomol 11:9–27

Stapleton JJ, Summers CG (2002) Reflective mulches for management of aphids and aphid-borne virus diseases in late-season cantaloupe (*Cucumis melo* L. var. *cantalupensis*). Crop Prot 21:891–898

Sun X, Yang Q, Sweeney JD, Gao C (2006) A review: chemical ecology of *Ips typographus* (Coleoptera, Scolytidae). J Forestry Res (Harbin) 17:65–70

Szentesi A, Weber DC, Jermy T (2002) Role of visual stimuli in host and mate location of the Colorado potato beetle. Entomol Exp Appl 105:141–152

Thies C, Steffan-Dewenter I, Tscharntke T (2003) Effects of landscape context on herbivory and parasitism at different spatial scales. Oikos 101:18–25

Thomas CFG, Brain P, Jepson PC (2007) Aerial activity of linyphiid spiders: modelling dispersal distances from meteorology and behaviour. J Appl Ecol 44:1263–1263

Tscharntke T, Bommarco R, Clough Y et al (2007) Conservation biological control and enemy diversity on a landscape scale. Biol Control 43:294–309

van Helden M, Decante D (2001) The possibilities for conservation biocontrol as a management strategy against *Empoasca vitis*. Bulletin OILB/SROP 24:291–297

van Helden M, Decante D, Papura D (2003) Possibilities for conservation biological control against grape pests in the Bordeaux region. Bulletin OILB/SROP 26:191–196

van Helden M, Fargeas E, Fronzes M et al (2006) The influence of local and landscape characteristics on insect pest population levels in viticulture. Bulletin OILB/SROP 29:145–148

Visser JH, Nielsen JK (1977) Specificity in olfactory orientation of Colorado beetle, *Leptinotarsa decemlineata*. Entomol Exp Appl 21:14–22

Weisz R, Smilowitz Z, Fleischer S (1996) Evaluating risk of Colorado potato beetle (Coleoptera: Chrysomelidae) infestation as a function of migratory distance. J Econ Entomol 89:435–441

Wermelinger B (2004) Ecology and management of the spruce bark beetle *Ips typographus* – a review of recent research. Forest Ecol Manag 202:67–82

White AJ, Wratten SD, Berry NA, Weigmann U (1995) Habitat manipulation to enhance biological control of *Brassica* pests by hover flies (Diptera, Syrphidae). J Econ Entomol 88:1171–1176

Williams IH, Frearson DJT, Barari H, McCartney A (2007) First field evidence that parasitoids use upwind anemotaxis for host-habitat location. Entomol Exp Appl 123:299–307

Yudin LS, Tabashnik BE, Mitchell WC, Cho JJ (1991) Effects of mechanical barriers on distribution of thrips (Thysanoptera, Thripidae) in lettuce. J Econ Entomol 84:136–139

Zehnder CB, Hunter MD (2009) More is not necessarily better: the impact of limiting and excessive nutrients on herbivore population growth rates. Ecol Entomol 34:535–543

Part II
Sensing and Sensor Technologies in Crop Protection

Chapter 5
The Use of Laboratory Spectroscopy and Optical Remote Sensing for Estimating Soil Properties

Joachim Hill, Thomas Udelhoven, Michael Vohland, and Antoine Stevens

Abstract The success of precision agriculture requires accurate methods for monitoring the state and health of crops. An additional key issue is the availability of accurate and efficient techniques for in-situ determination of soil properties. Reflectance spectroscopy, a technique which can be applied in the laboratory, in the field and from remote observation systems has attracted the attention of scientists in a variety of disciplines. In soil science, this technology as it relates to precision farming is rapidly developing and has triggered new research initiatives. Although a number of studies are available where soil properties have been derived from reflectance spectra the approach involves substantial scaling problems when transferring methods from laboratory spectroscopy to optical sensor systems onboard satellites and aircrafts. The analysis of reflectance images also requires dealing with data having limited signal-to-noise level, being distorted by atmospheric effects and largely affected by bidirectional effects in reflectance distribution. Starting with a short review of the state-of-the-art we present the potential use of reflectance spectroscopy for retrieving useful soil parameters based on several case studies. These studies serve to illustrate the existing limitations for retrieving soil properties over large heterogeneous areas.

1 Introduction

The success of precision agriculture not only depends on accurate methods for monitoring the state and health of crops buts also relies on accurate and efficient techniques for in-situ determination of soil properties. Soil parameters are neither static nor homogenous in space and time, however analytical costs are often a limiting factor when attempting to address spatial soil variability especially in large-scale

J. Hill (✉)
Remote Sensing Department, Faculty of Geography/Geosciences, Trier University, Trier D-54286, Germany
e-mail: hillj@uni-trier.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_5,

applications (Plant 2001, Viscarra-Rossel and McBratney 1998). Some applications, such as precision farming, even require the diagnosis of short or medium term changes in the nutrient content of soils. The traditional way to explore in field soil variation is grid-sampling, which is time consuming, labor intensive and lacks spatial exhaustiveness. Schnug et al. (1998) identified the development of actual physico-chemical soil maps as one of the major bottlenecks for continuous soil monitoring at the farm level. When a new technology saves time and results in greater profitability and reduced environmental risk, it will be rapidly adopted by farmers (Schepers and Francis 1998). Thus, the demand on new techniques for soil monitoring is to find a compromise between analytical speed and precision (Shepherd and Walsh 2002).

The first scientists who systematically investigated the relationship between soil spectral information and soil properties were Condit (1970) and then Stoner and Baumgardner (1981). Their soil spectral library quickly became a classical tool for soil scientists and was further used as a fundamental reference source for future studies. Over the past few years, it has been shown that soil spectra across the Visible (VIS, 0.4–0.7 μm), Near Infrared (NIR, 0.7–1.1 μm) and Short-Wave Infrared (SWIR, 1.1–2.5 μm) spectral regions are characterized by significant spectral features that enable quantitative analysis of several soil properties (e.g. Ben-Dor et al. 1999, 2008, Nanni and Demattê 2006, Schnug et al. 1998, Shepherd and Walsh 2002, Viscarra-Rossel et al. 2006). Pure soil minerals and soil organic matter exhibit distinct spectral fingerprints caused by electronic transitions in the VIS and by overtones and the combination modes of functional groups in the NIR and SWIR, which derive from their respective C-H, N-H and O-H fundamental vibrations bonds in the MIR (2.5–25 μm) region (Salisbury 1993). In general, these overtones and combination modes have reflectance peaks that are less clear than those at the fundamental frequencies. A linkage between the two spectral domains can be established using 2D- correlation analysis (Barton and Himmelsbach 1993). Respective models are useful to interpret broad spectral features in the NIR selected by some multivariate statistical calibration model by means of the related primarily absorption features in the middle infrared. A wide range of soil constituents can be identified from the VIS, NIR and SWIR spectral regions under laboratory conditions if advanced analytical techniques such as artificial neural networks and partial least-squares regression analysis are used (e.g. Ben-Dor and Banin 1995a, b, Udelhoven et al. 2003, Viscarra-Rossel 2007).

It was also suggested that methods which are successful for analyzing spectra recorded in the laboratory or in the field, including traditional quantitative approaches that successfully work for laboratory spectrometry of minerals (Clark and Roush 1984), also may be applicable for analyzing the spatially continuous reflectance data provided by multi- or hyperspectral imaging systems. For the emerging discipline of precision agriculture, optical remote sensing and imaging spectrometry in particular were expected to provide soil parameters before and after the growing season, and thus provide farmers with a spatially explicit quantitative overview of the soil properties and phenomena in question. In this way, farmers may be able to control resources such as irrigation, nutrients and cultivation, as well as obtain better yields per hectare and gain substantial savings through optimized fertilizer, herbicide and pesticide application.

2 Background

Bi-directional soil reflectance in the wavelength range between 0.4 and 2.5 μm is a cumulative property, which derives from the inherent spectral behaviour of the heterogeneous combination of minerals, water, organic matter and other chromophores (Udelhoven et al. 2003). A chromophore – a part of a molecule that causes it to be colored – is a parameter or substance (physical or chemical) that significantly affects the shape and nature of a soil spectrum. A single soil sample usually features a range of chromophores, which may vary with the environmental conditions and soil forming processes.

Soil chromophores can be divided into chemical and physical categories (Ben-Dor et al. 1999). Chemical chromophores are those materials that absorb incident radiation in discrete energy levels (Fig. 5.1). Usually the absorption process appears on a reflectance spectrum as a feature whose position is attributed to specific chemical groups in various structural configurations, overtone, combination modes, and electronic processes. All features in the VIS- NIR- SWIR spectral regions have a physical basis. In soils, three major optically active chemical chromophores can be roughly categorized as follows: (I) minerals, mainly clay, iron oxide, primary minerals feldspar, salt, and hard to dissolve substances such as carbonates, phosphates; (II) fresh and decomposing organic matter; and (III) water in solid, liquid, and gas phases (Fig. 5.1). Minerals, for example, exhibit distinct spectral fingerprints caused by electronic transitions in the VIS and NIR (0.4–1.1 μm) and by overtones and combination modes of OH-, SO-, and CO-groups in the SWIR (1.1–2.5 μm) (Hunt and Salisbury 1970). Often the spectral signals related to a given chromophore overlap with the signals of other chromophores and thereby render the assessment of a specific chromophore difficult.

Physical chromophores are properties that affect the overall spectral region and a particular waveband position, or in other words, do not relate to the chemical functional group. Examples of these are particle size variation and refraction indexes of a material that changes from one illumination condition to another. A comprehensive review of chemical and physical chromophores in soil and elaborating more generally on minerals, some of which are important in the soil environment is given in Irons et al. (1989), Ben-Dor et al. (1999), Clark (1999) and McBratney et al. (2006).

Soil color is one of the most useful attributes for characterization and identification of soil types that can also be derived from most operational multi- and hyperspectral sensor systems (Torrent and Barron 1993). Its relevance is mainly attributed to the fact that soil color can be correlated to important soil properties (Mulders 1987). Traditionally, soil color is measured using the Munsell soil color chart (Munsell Colour Company 1975), which is a useful system for categorizing soil color, but does not lend itself to statistical analysis (Viscarra-Rossel et al. 2006). Therefore, Melville and Atkinson (1985) recommended the use of the CIE-LAB

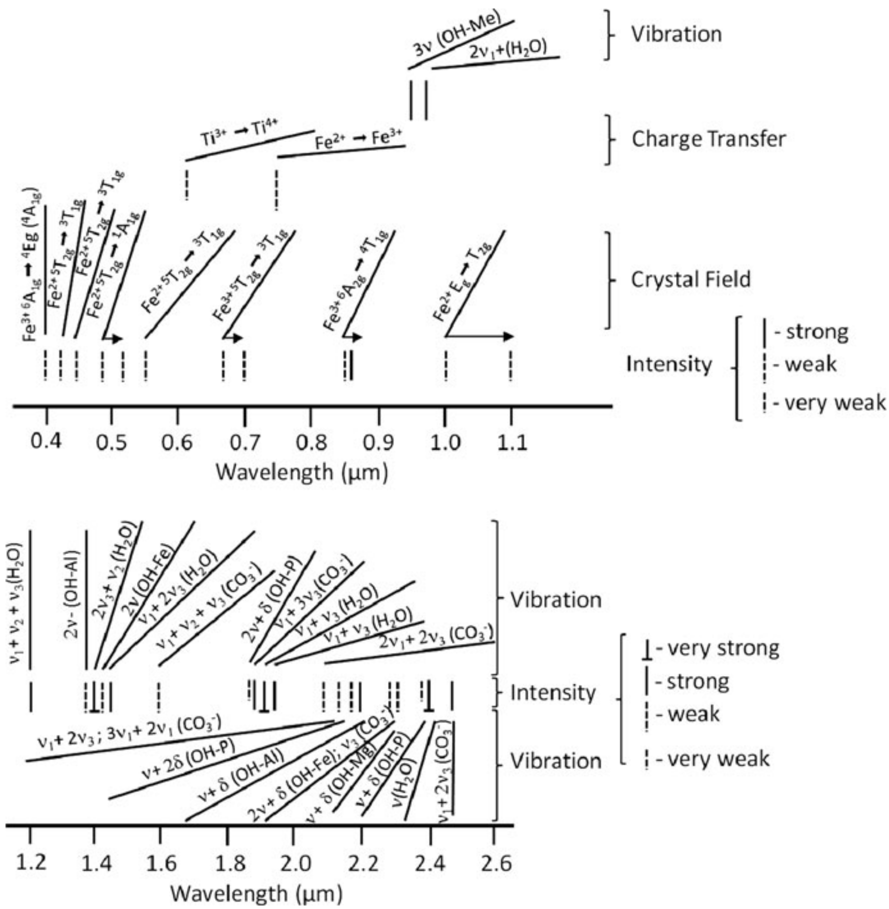

Fig. 5.1 Active groups and mechanisms of chemical soil chromophores. For each possible group, the wavelength range and absorption feature intensity are given (Ben-Dor et al. 1999, modified)

color system instead, and more recently, Jarmer et al. (2009) successfully applied the CIE (Commission Internationale de l'Eclairage) color system from 1931 to assess soil organic carbon concentrations from Landsat TM data on a regional scale level. In the CIE system, color is calculated from reflectance values. In addition the possibility of using statistical analysis of the calculated color values provides another substantial advantage. Satellite data are often characterized by redundant information leading to high correlation among spectral data recorded in various spectral bands, especially those data in the visible domain. Transforming reflectance into the CIE color values leads to a substantial de-correlation of spectral data which is an important advantage for statistical data analysis. Additionally, this transformation additionally allows comparison of soil color derived from different sensors and sensor independent use of developed prediction models.

Major drawbacks for scaling from point (laboratory) to imaging systems are the large size of the pixels that results in a significant mixed pixel problem and the wide spectral band response function and incomplete capture of specific spectral features of the chromophore. While the latter can be efficiently compensated for by using high spectral resolution imaging systems, surface roughness effects cause substantial bidirectional effects which are not straightforwardly controlled. Additional problems arise from the necessity to correct atmospheric distortions in the reflectance signal (Ben-Dor et al. 2009).

3 Retrieval Methods

The general concept for retrieving soil properties requires that a spectrum is processed to provide quantitative information about its chromophores. This can be an index, an equation or a model that is extracted from the spectral information, usually combined with the traditional chemical information. This is usually done by selecting a group of samples, followed by traditional chemical analysis and spectral measurements. Manipulations are done between the two data sets in order to derive a parameter or set of parameters that can describe the property solely from the reflectance readings. Theoretical or empirical models are allowed, whereas validation of each model is essential using external samples (Ben-Dor et al. 2008). This technology is termed Visible and Near-Infrared Spectroscopy (VNIRS) and was adopted from a strategy developed about 40 years ago in food science. In this approach, the reflectance measured from powder or aggregates, across the VIS-NIR- SWIR region, is modeled against constituents determined by wet chemistry methods. After this theoretical chemical model is validated, it can be applied to unknown samples (e.g. Awiti et al. 2008).

In soil science the VNIRS concept has provided promising results for rapid determination of several soil properties. Optically active soil components comprise organic matter (Dalal and Henry 1986, Krishnan et al. 1980, Wilcox et al. 1994, iron oxide minerals, Kosmas et al. 1984, clay and sand content, Al-Abbas et al. 1972, Selige et al. 2006, Waiser et al. 2007), specific surface, hygroscopic moisture, metal and carbonate content (Ben-Dor and Banin 1995a, b). These soil attributes play a decisive role in assessing topsoil characteristics e.g. soil aggregation, aggregate stability and resistance to water and wind erosion (Selige et al. 2006). Recently, He et al. (2007) demonstrated that macronutrients could be predicted via VNIRS for precision farming purposes, although not all are optically active substances. This phenomenon deserves special attention and will be discussed in more detail in one of the next sections. A comprehensive literature review summarizing the VNIRS optical concept and its achievements in soil science can be found in Malley et al. (2004). Another recent review was provided by Nanni and Demattê (2006), who elaborate on the current utilization of this technique for soils, whereas Viscarra-Rossel et al. (2006) provided a detailed list where all soil constituents successfully predictable by VNIRS are presented.

In fact, laboratory VNIRS is accepted as a fast and non-destructive approach (Chang et al. 2001, Shepherd and Walsh 2002), and more recently a number of advanced methods have been suggested to transform reflectance spectra into quantitative estimates of soil constituents. These include multivariate adaptive regression splines (Shepherd and Walsh 2002), radial basis function networks (Fidêncio et al. 2002), and artificial neural networks (Daniel et al. 2003). An important requirement for advanced statistical methods is the ability to handle large sets of collinear predictor variables and to deal with noisy patterns.

3.1 Artificial Neural Networks

The application of artificial feed-forward neural networks (ANNs) is one of the standard methods in spectroscopic applications (Udelhoven and Schütt 2000). A three-layer ANN represents a universal approximator able to fit any continuous function, linear or non-linear, between independent and dependent variables to a pre-defined arbitrary degree of accuracy. A major drawback of ANNs is that they appear to be black boxes due to their high degree of flexibility and the variety of learning parameters and network architectures. ANNs require a learning function to adjust all the weights and biases of a given neural network. There exists a variety of different training algorithms for feed-forward ANNs, including gradient descent methods, conjugate gradient methods, the Levenberg-Marquardt algorithm, to mention only a few. A detailed mathematical description can be found, for example, in Bishop (2005).

Udelhoven and Schütt (2000) tested several variants of feed-forward ANNs for chemical characterization of sediments based on reflectance measurements in a laboratory approach. Ten chemical properties including inorganic carbon, Fe, S, Al, Si, Ca, K, and Mg from 214 samples from various drilling locations all over the central part of the Iberian Peninsula were simultaneously estimated using one ANN model. They concluded that the combined methodology of diffuse reflectance spectroscopy evaluated with a trained and representative neural network can be applied as a rapid and cost-effective screening method to characterize solid samples provided that a representative set of analytical data for the network training is available. A similar conclusion has been drawn by Kemper and Sommer (2002) who used an ANN to predict heavy metals in soils contaminated by mining residuals using reflectance spectroscopy.

3.2 Partial Least Squares Modeling (PLSR, PLSR Combined with a Genetic Algorithm)

Partial least squares regression (PLSR) is an extension of the multiple linear regression and principal component regression models. PLSR projects the data into a low-dimensional space (i.e. a set of orthogonal variables, called latent variables).

It maximizes the covariance between the spectral matrix (X) and chemical concentration matrix (Y) by accomplishing eigendecomposition of both matrices (Otto 1998, Wold et al. 2001). The objective is to model X in such a way that the information in Y can be predicted as precisely as possible. The first latent variable, which is extracted from the matrix X, explains a maximum of the variance of matrix Y. The second latent variable describes a maximum of the residual variance, which has not been described by the first latent variable, and so on. The optimum number d of latent variables to be used in the analysis is determined by comparing the root mean square errors of cross-validation ($RMSE_{cv}$) of the predictions with different values of d. Alternatively, a validation data set can be used to determine an appropriate number of latent variables.

In the following, one example for using PLSR to estimate soil clay content from spectroradiometric measurements is briefly documented. In total 64 soil samples with prevailing loamy sand texture were collected in a floodplain in Central Europe. An ASD FieldSpec II Pro FR instrument (Analytical Spectral Devices, Boulder, USA) was used for the spectral readings of these samples after air drying and grinding. Measured reflectance data were resampled to 10 nm resolution over the 0.4–2.5 μm wavelength range (211 spectral predictor variables). In the PLS approach an optimum number of seven latent variables was found. For this model, the influence of the original spectral variables is reflected by the PLS regression coefficients. The coefficient profile (Fig. 5.2b) exhibits several peaks throughout the complete wavelength range, and thus does not represent the intrinsic spectral features of clay minerals e.g. illite with two strong absorption bands at 2.2 and 2.34 μm. The PLS model provides estimates with an r^2_{cv} value of 0.68 (Fig. 5.2a). $RMSE_{cv}$ amounts to 43.3 g kg^{-1} (relative $RMSE_{cv} = 0.33$), and the RPD (ratio of standard deviation of measured samples to $RMSE_{cv}$) is 1.77. According to the guideline of Malley et al. (2004) these results may be categorized as moderately useful for screening purposes, such as distinguishing low, medium and high values.

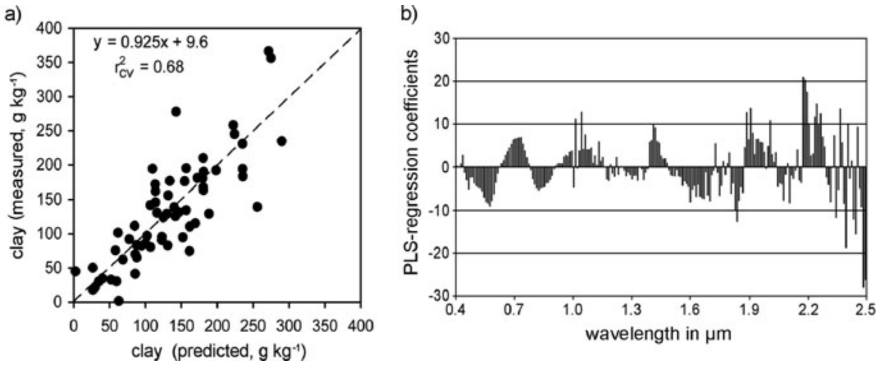

Fig. 5.2 Partial least squares regression (PLSR) for calibrating soil clay contents: Predicted vs. measured values (**a**) and PLS regression coefficients (**b**)

An important factor that contributes to the performance and robustness of a statistical prediction model is its parsimony. The parsimony of PLSR is to use a limited number of latent variables for the prediction of a dependent variable. Nevertheless, the number and prediction quality of the relevant latent variables strongly depends on the spectral information that is used to calculate these factors. Therefore improved prediction by PLSR may be achieved by applying some form of variable selection to optimize the quality of the latent variables.

With a large number of features it is not feasible to test all possible subsets for an optimal calibration model. Several techniques can be employed to identify a near optimal solution, among which genetic algorithms allows an efficient search in high-dimensional and complex response surfaces. The overall goal is to identify the most informative variables that allow an improved predicitive capacity of the calibration model, or at least a simplified model with less variables and without loosing prediction accuracy (Leardi and González 1998, Yoshido et al. 2001).

The genetic algorithm used in our example mainly follows the principles described by Leardi and González (1998). Each chromosome of the initial population is composed of 211 genes (corresponding to the 211 original spectral predictors), each gene being formed by a single bit or binary coding, where each spectral variable can be switched on or off. Chromosomes with an above-average fitness (fitness criterion: cross-validated variance explained by the PLS-regression) are selected as parents. Offsprings are obtained by reproduction (cross-over method) and mutation, and the responses of the new chromosomes are evaluated with the decision to be included in the population or to be discarded. At the end of each run each with 200 evaluations, the selected variables of the fittest chromosome are identified. Selection frequencies at the end of all runs (100 runs per cycle, and then ten repetitions of the complete cycle), decide on the most predictive variables that are accepted for the final PLS calibration (Fig. 5.3).

In this case, only 29 of the 211 original variables are selected. Based on now 6 latent variables, the PLS regression model provides estimates with an r^2_{cv} value

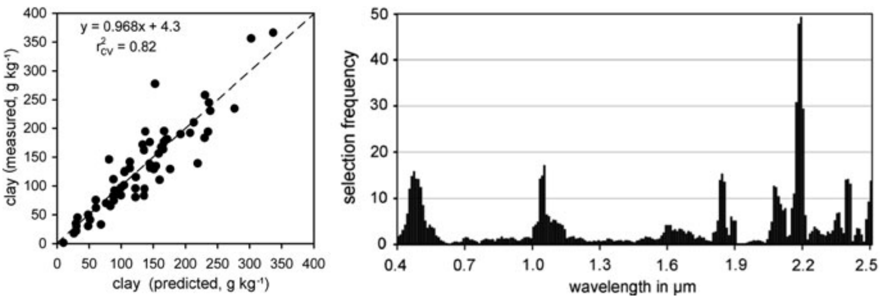

Fig. 5.3 Partial least squares regression with genetic algorithm (GA-PLSR): Predicted versus measured values; based on the averaged frequency of selection per 100 runs (10 repetitions), 29 spectral variables are selected by GA

of 0.82 (Fig. 5.3), and a $RMSE_{cv}$ of 32.0 g kg^{-1} (relative $RMSE_{cv} = 0.24$). In comparison to PLS without feature selection the RPD value of 2.40 proves a considerable improvement of GA-PLS up to useful levels for quantification purposes (Malley et al. 2004).

3.3 Support Vector Machine Regression

Support vector machine regression (SVM-R) represents a different model class compared with PLSR techniques since it is based on statistical learning theory (Vapnik 1995). SVM-R has recently be successfully applied for the retrieval of soil organic carbon in Luxembourg based on airborne AHS imaging data (Stevens et al. 2010). The most valuable properties of SVMs are their ability to handle large input spaces efficiently, to deal with noisy patterns and multimodal class distributions, and their restriction to only a subset of training data in order to fit a non-linear function. The SVM-R methodology is described in detail in Schölkopf and Smola (2002). In principle an input vector X is mapped from the input domain into a higher dimensional feature space via a kernel function, where data are spread out in a way that facilitates the finding of an interpolation function (Vapnik 1995). This function is identified by fitting a tube with radius ε to the training data using boundary samples, the so-called support vectors (SV). The optimization problem is solved using Quadratic Programming (QP) techniques (Schølkopf and Smola 2002). This requires fixing a free regularization parameter C beforehand that confines the influence of critical training patterns. As kernel the Gaussian radial basis function (RBF) is often selected due to computational convenience. The RBF kernel requires only selecting one free parameter (σ) beforehand that controls the smoothness properties of the interpolating function.

3.4 Penalized-Spline Signal Regression (PSR)

Penalized-spline Signal Regression (PSR) is a novel technique that has been developed by Marx and Eilers (1999, 2002); PSR is – like PLSR – able to solve a multivariate calibration problem in which the predictors are highly correlated and their number exceeds the number of observations. The main difference between the PLSR and the PSR is that in the former the order of the predictor variables i.e. wavelengths in spectrometry, does not influence the model, whereas PSR forces the coefficient of the regression to vary smoothly across the wavelengths. This is attained by projecting the coefficients onto a set of smooth functions (B-splines). There are several PSR parameters that must be fixed beforehand, including the degree of B-splines and the number of intervals between knots, the point where B-splines join. Stevens et al. (2010) found PSR to be superior to PLSR in the estimation of soil organic carbon from airborne hyperspectral AHS-160 data in an area in Luxembourg.

4 Applications

One soil parameter that is of special relevance in precision farming applications is soil organic carbon (SOC), since it plays an important role with respect to chemical and physical processes in the soil environment (Ben-Dor et al. 1999). Together with clay content and composition, it has a major effect on major soil properties such as the stability of soil aggregates and water retention (Stevens et al. 2010). Furthermore, soil organic carbon strongly influences soil fertility, plant nutrient supply, microbial activity and soil physical properties (Wilcox et al. 1994). The following examples focus on the assessment of organic carbon at different scales.

4.1 Scale Dependencies in the Assessment of Chemical Soil Constituents

Soil monitoring using VNIRS has been applied on different scales, ranging from laboratory measurements, field approaches to airborne and satellite hyperspectral imaging devices. At a field scale VNIRS has been used to estimate chemical soil constituents with portable spectrometers (Kooistra et al. 2003, Odlare et al. 2005, Udelhoven et al. 2003). At the regional scale soil properties were assessable by multispectral satellite systems (Hill and Schütt 2000, Jarmer et al. 2009), airborne imaging spectrometry (Ben-Dor et al. 2002, Stevens et al. 2010, 2006), and recently also from the hyperspectral satellite platform HYPERION (Gomez et al. 2008).

Udelhoven et al. (2003) evaluated soil chemical properties from different locations in the Trier region (Rhineland-Palatinate, Germany) under field and laboratory conditions using a portable spectrometer and PLSR. Generally, laboratory spectrometry using air dried and sieved samples performed better than field spectrometry. This was probably due to strong interferences of soil surface properties such as moisture content, roughness and crusting. In a plot experiment they investigated the accuracy in the retrieval of chemical soil parameters such as Ca, Mg, Fe, Mn, K and SOC. In Fig. 5.4 a spline interpolation is shown for organic and inorganic carbon for both measured and estimated contents from the data set. The prediction accuracy of the SOC-model with the best performance corresponded to a mean square error for cross-validation ($RMSE_{CV}$) of 0.14, and to a coefficient of determination (r^2_{cv}) of 0.6, respectively. Although statistically significant, Fig. 5.4 illustrates that at this level of accuracy measured spatial concentration pattern in the plot are not sustained. In contrast, PLS estimations of inorganic carbon were more accurate ($r^2_{cv}=$ 0.93), resulting in a much better representation of the inorganic carbon values in the plot. This demonstrates that a statistically significant relation between dependent and spectral variables does not guarantee that the spatial patterns in concentration can be well reproduced. This is due to the fact that the spatial interpolation also fits the prediction errors of the target variable.

Airborne imaging spectrometry has an even greater potential to overcome the restrictions of ground based or laboratory spectroscopy as spatial interpolation is circumvented and upscaling over large areas is possible. These systems provide high

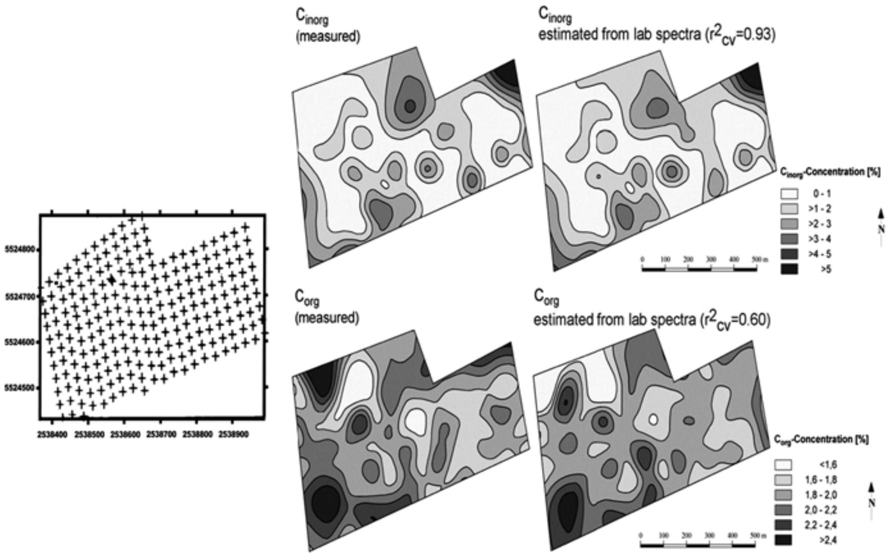

Fig. 5.4 Spline interpolation of measured and estimated (cross-validation) inorganic carbon and organic carbon contents at field scale (plot 'Dietrichskreuz', Helenenberg, Rhineland-Palatinate, SW Germany; Udelhoven et al. 2003)

spatial and spectral resolution along with flexible temporal resolution which is ideally suited for soil monitoring in the context of precision agricultural applications. Major constraints include atmospheric absorptions interfering with the spectral measure, spatial variation in surface properties and a lower signal-to-noise ratio, which might result in an incompatibility between field and airborne spectroscopic measurements (Ben-Dor et al. 2008, Chappell et al. 2005, Stevens et al. 2010). Hill and Schütt (2000) could demonstrate that meaningful spatial patterns of soil organic matter which exhibited a positive correlation to crop productivity could be derived from multispectral satellite systems. Gomez et al. (2008) estimated SOC from reflectance data from vertisols in Australia using HYPERION data and a portable field spectrometer and partial least squares regression (PLSR).

Ben-Dor et al. (2002) could explain 83.3% of the variability of SOC using DAIS-7915 airborne data (400–2,500 nm) of clay soils in Israel. Uno et al. (2005) and Stevens et al. (2006) found between 74 and 85% common variability of SOC and spectrometry data from the CASI airborne hyperspectral sensor (400–950 nm). Selige et al. (2006) achieved slightly better results ($r^2 = 0.9$) with the HyMap sensor (420–2,480 nm). Less satisfactory prediction models of SOC were obtained by Bajwa and Tian (2005) with the RDACS/H-3 sensor (471–828 nm; $r^2 = 0.66$) and De Tar et al. (2008) with the AVNIR sensor (429–1,010 nm; $r^2 = 0.48$).

Whereas the majority of these studies addressed comparably small areas or homogeneous soil types, Stevens et al. (2010) analyzed hyperspectral images acquired with the AHS-160 sensor to predict variation in SOC content in Luxembourg (Fig. 5.5), a country which is covered by different soil types and

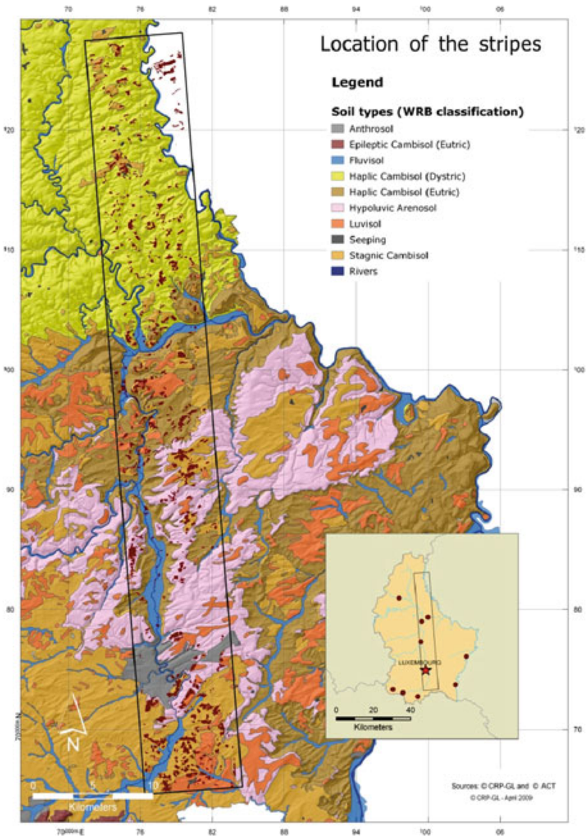

Fig. 5.5 Locations of bare soils within five parallel flight stripes using the AHS-160 sensor in Luxembourg

a large variation in SOC contents. Reflectance data were related to surface SOC contents of bare croplands ($n = 325$) by means of 3 different multivariate calibration techniques: PLSR, PSR and least square support vector machine (SVM-R). Their performance was tested under different combinations of global and local calibrations stratified according to agro-geological zone. Figure 5.6 illustrates the results for the global calibration and for four separate sub-models obtained for the different agro-geological zones and for each statistical model using an internal validation data set. The measure of accuracy is related to the root mean squared error of prediction (RMSEP).

Nevertheless, a substantial spread in observed versus predicted SOC values above 30 g C kg^{-1} indicates a higher degree of variability in the reflectance data. This is not solely attributed to the organic carbon content, but to other soil chromophores such as soil moisture and ferrous oxides that differ between the agro-geological regions. These chromophores disturb the global correlation with SOC.

Figure 5.6, right, shows the results obtained for the local calibrations over each agro-geological subset separately. This strategy allowed considerable improvement in the accuracy of the models. In addition the problem of non-linearity of PLSR and

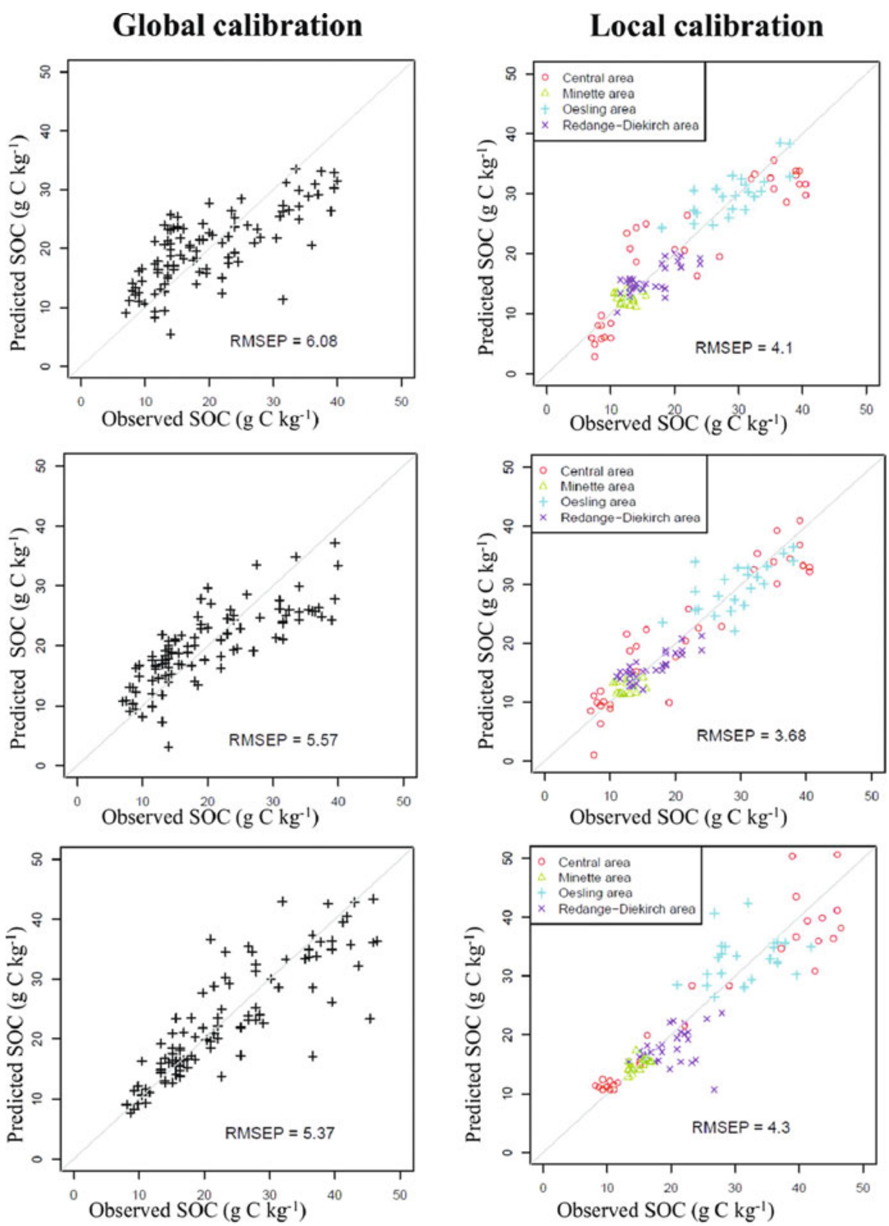

Fig. 5.6 Plots of measured versus predicted SOC as obtained by PLSR (*top*), PSR (*middle*) and SVR (*bottom*) using AHS-160 data validation data set

PSR models at high SOC content no longer occurs when applying local calibrations for each of the agro-geological regions. Other attributes used to stratify the data set e.g. soil type and image number also led to an improvement when compared to the global models (Stevens et al. 2010). For the stratified samples PSR demonstrated the best ability to predict SOC content in the stratified samples. These findings are in line with the conclusions of Marx and Eilers (2002) who showed that PSR offers greater stability in predictions under changing experimental conditions compared to PLSR.

4.2 Estimation of Optically Featureless Soil Components

A number of studies suggest that it is possible to estimate even optically non-active chemical soil properties with featureless spectra. This is possible in that these elements are bonded to active soil components such as Fe oxides, organic matter and clay and these bonds provide a major predictive mechanism (Kemper and Sommer 2002, Kooistra et al. 2003, Vohland et al. 2009, Wu et al. 2007). In statistics this phenomenon is known as spurious correlation. Martínes-Carreras et al. (2010) predicted different chemical properties of suspended sediments from the small catchment of the Wollefsbach, (4.4 km^2), a sub-catchment of the Attert River catchment located in the NW of Luxembourg, from spectroradiometer data through PLSR. Apart from major suspended particle components such as organic carbon, calcium and iron oxides they were able to predict trace minerals, such as Li, Sc, Cr, Ni and Cs and even rare earth elements like La, Ce, Pr, Nd, Sm, Eu and Dy. This is due to indirect correlation with spectra caused by optically active background variables, in particular iron oxides, organic matter and clay and clearly reflects the mineralogical nature of the investigated catchments. Spurious correlation can be detected by statistical techniques. Wu et al. (2007) used Principal Component Analysis (PCA) with varimax rotation to clarify the relationships between different chemical tracers. The conception is that highly correlated variables might be estimated from reflectance data if at least one of these properties is optically active.

Another approach is to analyze patterns in the correlation spectra for each soil constituent of interest. The value of the correlation coefficient at a single wavelength describes the univariate importance of a wavelength for the prediction of the given constituent. Another possibility is to analyze factor loadings or regression coefficients in PLSR or related statistical calibration models (Malley and Williams 1997, Vohland et al. 2009). An example is given in Fig. 5.7 which shows the correlation spectra (correlograms) for the sediment properties from the study of Udelhoven and Schütt (2000). The two correlograms are grouped according to the correlation structure of the considered chemical compounds. The first class consists of Fe, K, Al and Si while the second of C, LOI, Ca and calcite. Within both groups the correlation structure is to some extent redundant, however only Fe, C (in carbonates) and calcite have direct optical features. The prediction of the remaining properties is based on spurious correlation. It can be assumed that these patterns cannot be attributed to only one dominant chemical characteristic in these groups, but to the

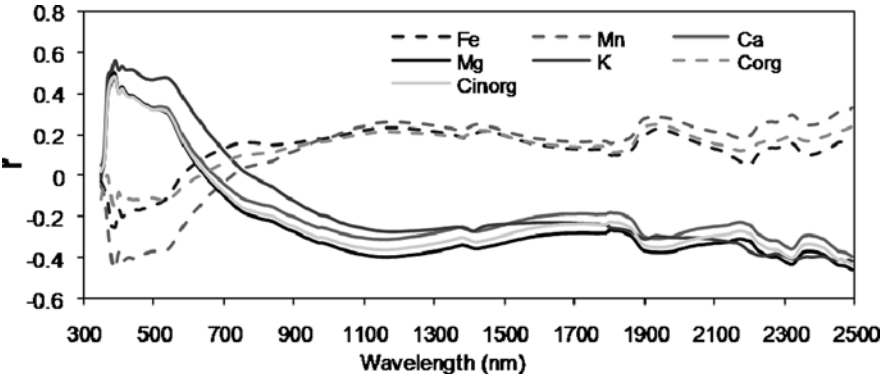

Fig. 5.7 Correlograms of selected soil properties in a plot experiment (Udelhoven and Schütt 2000)

collective occurrence of several optically active minerals in the samples from a specific petrography. The explanatory optically active components in the first groups are iron oxides and clay minerals.

This example demonstrates that spurious correlation of chemical soil constituents with the soil reflectance pattern is often caused by the soil's geological and mineralogical nature. By no means can statistical regression models based on spurious correlation be transferred to other regions beyond the study area with different underlying geology or to soil parameters that are highly variable in space and time. This excludes VNIRS as a diagnosis tool of short or medium term changes of the soil's nutrient status e.g. potassium or phosphorus.

5 Conclusions

Arable soils are important resources which should be preserved for present and future human needs by sustainable agriculture. The monitoring of environmental processes on large-scales requires up-to-date maps of physico-chemical soil properties. Soil reflectance is determined by soil chromophores that are basically determined by soil chemical composition and to soil albedo that is related to soil physical characteristics. Consequently, soil mapping in the context of precision agriculture applications may largely benefit from imaging and non-imaging diffuse reflectance spectrometry, which has the potential to overcome the current problems of high costs, labor and time. Soil mapping should aim to represent the temporal and spatial variability of soil properties at different scales using in-situ and laboratory methodologies. There are still some restrictions that hinder the transfer of visible and infrared spectroscopic methods from the laboratory to the field scale. Two of the most disturbing factors for in-situ spectral measurements are soil roughness and moisture content that must be taken into account to enable models to work accurately under a variety of conditions.

The spectral prediction mechanism may be a direct one that is based on diagnostic spectral fingerprints of the studied parameter, or indirect when variables of interest are without spectral features but correlated with spectrally active soil components. Airborne imaging spectrometry has the advantage that spatial interpolation is circumvented and upscaling over large areas is possible. The spectral range of current and forthcoming airborne (e.g. HyMap, APEX, ARES, AISA, HySpex) and satellite imaging spectrometers (HYPERION, EnMAP) is excellent for detecting electronic transitions in minerals e.g., iron oxides, Fe^{2+} bearing minerals, and vibrational absorptions due to lighter elements e.g. OH, SO_4, CO_3, CH, etc.. Therefore, the spatial distribution of OH-bearing minerals, carbonates, sulfates and organics can be mapped on bare soil surfaces. A substantial restriction in regional soil monitoring is that the related statistical models to retrieve soil parameters from spectroscopic data are applicable only to geological homogeneous areas or 'soilscapes'. Otherwise a stratification of the soil samples according to geological conditions and the calibration of respective sub-models are suggested due to the correlation of the strata with important chromophores like soil moisture or ferrous oxide content.

Despite many encouraging results, the exploitation of chemical soil property maps derived from imaging spectrometry data should still be considered with some caution. In particular, a post-validation over fields not covered by the existing calibration/validation sets would be necessary to assess the actual accuracy of the statistical models. This is important particularly in cases of the prediction of featureless soil properties. Another critical issue is the representativeness of statistical models in case of varying surface and illumination conditions.

Beyond the increasing number of airborne systems, spaceborne hyperspectral imagers provide a viable coverage for large-scale studies of bare soils for future operational applications. HYPERION, a hyperspectral imaging instrument on the EO-1 platform is currently the only operational spaceborne hyperspectral sensor. The sensor measures the radiance with 242 continuous spectral bands, ranging from 356 to 2,577 nm with approximately 10 nm of spectral resolution and 30 m of spatial resolution. HYPERION collects image data for an area of about 7.7. km in the across-track direction and 42 km in the along-track direction.

In 2014 the German Hyperspectral Environmental Mapping and Analysis Program (EnMAP) satellite will be launched. This sensor is expected to provide a higher signal-to-noise ratio than that of HYPERION. However it will not solve the problem of the rather limited spatial resolution of 30 m. Thus, the recorded reflectance is often the mixed result of several surface components. This makes it necessary, especially in heterogeneous landscapes, to apply spectral unmixing techniques to isolate the reflectance signals of soils from disturbing influences especially from green vegetation and crop residues.

Acknowledgements Soil data presented in Section 3.2 were collected and analyzed in a joint project of the University of Applied Sciences of Osnabrück (Department of Agricultural Sciences and Landscape Architecture, Prof. Dr. H.-C. Fründ) and the University of Trier (Remote Sensing Department). This is gratefully acknowledged by the authors.

References

Al-Abbas AH, Swain PH, Baumgardner MF (1972) Relating organic matter and clay content to the multispectral radiance of soils. Soil Sci 6:477–485

Awiti AO, Walsh MG, Shepherd KD, Kinyamario J (2008) Soil condition classification using infrared spectroscopy: a proposition for assessment of soil condition along a tropical forest-cropland chronosequence. Geoderma 143:73–84

Bajwa SG, Tian LF (2005) Soil fertility characterization in agricultural fields using hyperspectral remote sensing. Trans Am Soc Agr Eng 48:2399–2406

Barton FE, Himmelsbach DS (1993) Two-dimensional vibrational spectroscopy II: correlation of the absorptions of lignins in the mid- and near-infrared. Appl Spectr 47:1920–1925

Ben-Dor E, Banin A (1995a) Near infrared analysis (NIRA) as a simultaneously method to evaluate spectral featureless constituents in soils. Soil Sci 59:259–269

Ben-Dor E, Banin A (1995b) Quantitative analysis of convolved TM spectra of soils in the visible, near infrared and short-wave infrared spectral regions (0.4–2.5 μm). Int J Rem Sens 18: 3509–3528

Ben-Dor E, Chabrillat S, Demattê JAM et al (2009) Using imaging spectroscopy to study soil properties. Rem Sens Environ 113 (suppl 1):S38–S55

Ben-Dor E, Irons JA, Epema A (1999). Soil spectroscopy. In: Rencz A (ed) Manual of remote sensing. Wiley, NewYork, pp 111–188

Ben-Dor E, Patkin K, Banin A, Karnieli A (2002) Mapping of several soil properties using DAIS-7915 hyperspectral scanner data – a case study over clayey soils in Israel. Int J Remote Sens 23:1043–1062

Ben-Dor E, Taylor RG, Hill J et al (2008) Imaging spectrometry for soil. In: Sparks DL (ed) Advances in agronomy. Elsevier/Academic Press, Amsterdam, pp 321–392

Bishop CM (2005) Neural networks for pattern recognition. Oxford University Press, Oxford

Bowers S, Hanks RJ (1965) Reflectance of radiant energy from soils. Soil Sci 100:130–138

Chang CW, Laird DA, Mausbach MJ, Hurburgh CR (2001) Near-infrared reflectance spectroscopy – principle components regression analyses of soil properties. Soil Sci Soc Am J 65: 480–490

Chappell A, Zobeck TM, Brunner G (2005) Using on-nadir spectral reflectance to detect soil surface changes induced by simulated rainfall and wind tunnel abrasion. Earth Sur Process Landforms 30:489–511

Clark RN (1999) Spectroscopy of rocks and minerals, and principles of spectroscopy. In: Rencz AN (ed) Remote sensing for the earth sciences. Wiley, New York, pp 3–58

Clark RN, Roush TL (1984) Reflectance spectroscopy: quantitative analysis techniques for remote sensing applications. J Geophys Res 89:6329–6340

Company MC (1975) Munsell soil color charts. Macbeth Division of Kollmorgen, New Windsor

Condit HR (1970) The spectral reflectance of American soils. Photogram Eng Remote Sens 36:955–966

Dalal RC, Henry RJ (1986) Simultaneous determination of moisture, organic carbon and total nitrogen by near infrared reflectance spectroscopy. Soil Sci Soc Am J 50:120–123

Daniel K, Tripathi N, Honda K (2003) Artificial neural network analysis of laboratory and in situ spectra for the estimation of macronutrients in soils of Lop Buri (Thailand). Aus J Soil Res 41:47–59

De Tar WR, Chesson JH, Penner JV, Ojala JC (2008) Detection of soil properties with airborne hyperspectral measurements of bare fields. Trans Am Soc Agric Biol Eng 51:463–470

Fidêncio P, Poppi R, De Andrade J (2002) Determination of organic matter in soils using radial basis function networks and near infrared spectroscopy. Anal Chim Acta 45:125–134

Gomez C, Rossel RAV, McBratney AB (2008) Soil organic carbon prediction by hyperspectral remote sensing and field vis-NIR spectroscopy: An Australian case study. Geoderma 146: 403–411

He Y, Huang M, Garcia A et al (2007) Prediction of soil macronutrients content using near-infrared spectroscopy. Comp Electron Agric 58:144–153

Hill J, Schütt B (2000) Mapping complex patterns of erosion and stability in dry Mediterranean ecosystems. Remote Sens Environ 74:557–569

Hunt GR, Salisbury JW (1970) Visible and near-infrared spectra of minerals and rocks: I. Silicate minerals. Mod Geol 1:283–300

Irons JR, Weismiller RA, Petersen GW (1989) Soil reflectance. In: Asrar G (ed) Theory and application of optical remote sensing. Wiley, New York, pp 66–106

Jarmer T, Hill J, Lavée H, Sarah P (2009) Mapping topsoil organic carbon in non-agricultural semi-arid and arid ecosystems of Israel. Photogram Eng Remote Sens 76:85–94

Kemper T, Sommer S (2002) Estimate of heavy metal contamination in soils after a mining accident using reflectance spectroscopy. Environ Sci Technol 36:2742–2747

Kooistra L, Wanders J, Epema GF et al (2003) The potential of field spectroscopy for the assessment of sediment properties in river floodplains. Anal Chim Acta 484:189–200

Kosmas CS, Curi N, Bryant RB, Franzmeier DP (1984) Free iron oxide determination in Mediterranean soils using diffuse reflectance spectroscopy. Soil Sci Soc Am J 48:401–405

Krishnan P, Alexander DJ, Butler B, Hummel JW (1980) Reflectance technique for predicting soil organic matter. Soil Sci Soc Am J 44:1282–1285

Leardi R, González AL (1998). Genetic algorithms applied to feature selection in PLS regression: how and when to use them. Chemom Intel Lab Sys 41:195–207

Malley DF, Williams PC (1997) Use of near-infrared reflectance spectroscopy in prediction of heavy metals in freshwater sediment by their association with organic matter. Environ Sci Technol 31:3461–3467

Malley DP, Martin D, Ben-Dor E (2004) Application in analysis of soils. In: Craig R, Windham R, Workman R (eds) Near infrared spectroscopy in agriculture. Soil Science Society of America Inc. Publishers, Madison, pp 729–784

Martínes-Carreras N, Krein A, Udelhoven T et al (2010) A rapid spectral reflectance-based fingerprinting approach for documenting suspended sediment sources during storm runoff events. J Soil Sediment 10:400–413

Marx BD, Eilers PHC (1999). Generalized linear regression on sampled signals and curves: a P-spline approach. Technometrics 41:1–13

Marx BD, Eilers PHC (2002) Multivariate calibration stability: a comparison of methods. J Chemomet 16:129–140

McBratney AB, Minasny B, Viscara-Rossel R (2006) Spectral soil analysis and inference system: a powerful combination for solving soil data crisis. Geoderma 136:272–278

Melville MD, Atkinson G (1985) Soil color: its measurement and its designation in models of uniform color space. J Soil Sci 36:495–512

Mulders MA (1987) Remote sensing in soil science. Elsevier, Amsterdam

Nanni MR, Demattê JAM (2006) Spectral reflectance methodology in comparison to traditional soil analysis. Soil Sci Soc Am J 70:393–407

Odlare M, Svensson K, Pell M (2005) Near infrared reflectance spectroscopy for assessment of spatial soil variation in an agricultural field. Geoderma 126:193–202

Otto O (1998) Statistics and computer application in analytical chemistry. Wiley, Weinheim

Plant RE (2001) Site-specific management. The application of information technology to crop production. Comp Electron Agric 30:9–29

Salisbury JW (1993) Mid-infrared spectroscopy: laboratory data. In: Pieters CM, Englert PAJ (eds) Remote geochemical analysis: elemental and mineralogical composition. Cambridge University Press, Cambridge, pp 79–98

Schepers JS, Francis DD (1998) Precision agriculture –What's in our future. Comm Soil Sci Plant Anal 29:1463–1469

Schnug E, Panten K, Haneklaus S (1998) Sampling and nutrient recommendations – The future. Comm Soil Sci Plant Anal 29:1455–1462

Schölkopf B, Smola A (2002) Learning with Kernels. MIT Press, Massachusetts Institute of Technology, Cambridge

Selige T, Böhner J, Schmidhalter U (2006) High resolution topsoil mapping using hyperspectral image and field data in multivariate regression modeling procedures. Geoderma 136: 235–244

Shepherd KD, Walsh MG (2002) Development of reflectance spectra libraries for characterization of soil properties. Soil Sci Soc Am J 66:988–998

Stevens A, Udelhoven T, Denis A et al (2010) Measuring soil organic carbon in croplands at regional scale using imaging spectroscopy. Geoderma in press, doi:10.1016/j.geoderma.2009.11.032

Stevens A, van Wesemael B, Vandenschrick G et al (2006) Detection of carbon stock change in agricultural soils using spectroscopic techniques. Soil Sci Soc Am J 70:844–850

Stoner ER, Baumgardner MF (1981) Characteristic variations in reflectance of surface soils. Soil Sci Soc Am J 45:1161–1165

Torrent J, Barron V (1993) Laboratory measurement of soil color: theory and practice. In: Bigham JM, Ciolkosz EJ (eds) Soil colour. Soil Science Society of America, Madison, pp 21–33

Udelhoven T, Emmerling C, Jarmer T (2003) Quantitative analysis of soil chemical properties with diffuse reflectance spectrometry and partial least-square regression: a feasibility study. Plant Soil 251:319-329

Udelhoven T, Schütt B (2000) Capability of feed-forward neural networks for a chemical evaluation of sediments with diffuse reflectance spectroscopy. Chemomet Intel Lab Sys 51:9–22

Uno Y, Prasher SO, Patel RM et al (2005) Development of field-scale soil organic matter content estimation models in Eastern Canada using airborne hyperspectral imagery. Can Biosys Eng 47:9–14

Vapnik VN (1995) The nature of statistical learning theory. Springer, New York

Viscarra-Rossel RA (2007) ParleS: Software for chemometric analysis of spectroscopy data. Chemomet Iintel Lab Sys 90:72–83

Viscarra-Rossel RA, McBratney AB (1998) Soil chemical analytical accuracy and costs. Implications from precision agriculture. Aus J Exp Agric 7:765–775

Viscarra-Rossel RA, Walvoort DJJ, McBratney et al (2006) Visible, near infrared, mid infrared or combined diffuse reflectance spectroscopy for simultaneous assessment of various soil properties. Geoderma, 131:59–75

Vohland M, Bossung C, Fründ HC (2009) A spectroscopic approach to quantify trace heavy metal contents in contaminated floodplain soils via spectrally active soil components. J Plant Nutr Soil Sci 172:201–209

Waiser TH, Morgan CLS, Brown DJ, Hallmark CT (2007) In situ characterization of soil clay content with visible near-infrared diffuse reflectance spectroscopy. Soil Sci Soc Am J 71: 389–396

Wilcox CH, Frazier BE, Ball ST (1994) Relationship between soil organic carbon and Landsat TM data in Eastern Washington. Photogram Eng Remote Sens 6:777–781

Wold S, Sjöström M, Eriksson L (2001) PLS-regression: a basic tool of chemometrics. Chemomet Intel Lab Sys 58:109–130

Wu Y, Chen J, Gong P et al (2007) A mechanism study of reflectance spectroscopy for investigating heavy metals in soil. Soil Sci Soc Am J 71:918–926

Yoshido H, Leardi R, Funatsu K, Varmuza K (2001) Feature selection by genetic algorithms for mass spectral classifiers. Anal Chim Acta 446:485–494

Chapter 6
Sensing of Photosynthetic Activity of Crops

Uwe Rascher, Alexander Damm, Sebastian van der Linden, Akpona Okujeni, Roland Pieruschka, Anke Schickling, and Patrick Hostert

Abstract The light use efficiency of photosynthesis dynamically adapts to environmental factors and is one major factor determining crop yield. Optical remote sensing techniques have the potential to detect physiological and biochemical changes in plant ecosystems, and non-invasive detection of changes in photosynthetic energy conversion may be of great potential for managing agricultural production in a future bio-based economy. Here we give an overview on the principles of optical remote sensing in crop systems with a special emphasis on investigating hyperspectral reflectance data and the sun-induced fluorescence signal. Especially sun-induced fluorescence as a parameter, which becomes important in remote sensing research may have great potential quantifying the physiological status of the photosynthetic apparatus. Both remote sensing principles were applied during the CEFLES2 campaign in Southern France, where the structural and functional status of several crops was measured on the ground and using state-of-the-art optical remote sensing techniques. Sun-induced fluorescence measurements over a variety of crops showed that additional information can be retrieved also over dense canopies, where classical remote sensing signals often saturate. With a view to the future, we discuss how hyperspectral reflectance and sun-induced fluorescence can quantitatively be related to photosynthetic efficiency and help to measure and manage productivity of natural and agricultural ecosystems.

1 Background on Optical Spectroscopy of Plant Canopies

Solar radiation that interacts with plant tissues or plant canopies is either reflected, absorbed or transmitted (Fig. 6.1, left). The spectral characteristics of the three components at leaf or canopy scale are a function of (I) leaf level absorption and scattering, (II) the optical properties of other canopy components and the canopy

U. Rascher (✉)
Institute of Chemistry and Dynamics of the Geosphere, ICG-3: Phytosphere, Forschungszentrum Jülich, Jülich D-52425, Germany
e-mail: u.rascher@fz-juelich.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_6,

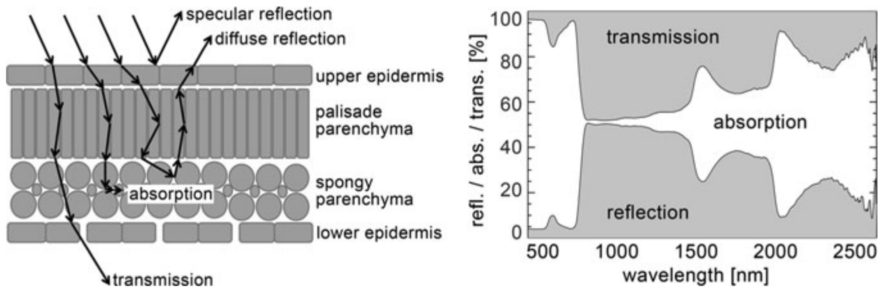

Fig. 6.1 *Left*: Conceptual scheme of light absorption, transmission and reflection in plant tissues. *Right*: Spectral characteristics of absorption, reflection, and transmission illustrated at a winter wheat leaf (*Tritium aestivum* L.)

architecture itself, and (III) external effects (illumination, observation geometry) (Goel 1988, 1989, Chen et al. 2000). Optical spectroscopy mainly focuses on the reflected part of radiation as a measure to derive information about the biochemical and structural properties of plants at leaf and canopy level (Fourty and Baret 1998, Liang 2004), whereas the optical properties of leaf tissues significantly determine the canopy optical parameters (Asner 1998, Otterman et al. 1995). For instance, the low intensity reflectance of plant leaves in the visible (400–700 nm) part of the light spectrum results from strong absorbance by the photosynthetic foliar pigments, while the high reflectance in the near infrared (700–1,100 nm) is due to low absorption of light by the internal leaf mesophyll tissues, and the reflectance intensity in the shortwave infrared (1,100–2,500 nm) is strongly affected by the amount of water in plant tissues (Curran 1989) (Fig. 6.1, right).

During the phenological cycle, in response to an adaption of plants to environmental conditions, or between different species, leaf biochemical components vary and cause variations in the interaction of solar radiation with leaf tissues (Gausman and Allen 1973, Grant 1987). This, in turn, results in changing optical properties of leaf tissues. Figure 6.2 exemplarily shows the variation of reflected radiation in response to varying chlorophyll and water content.

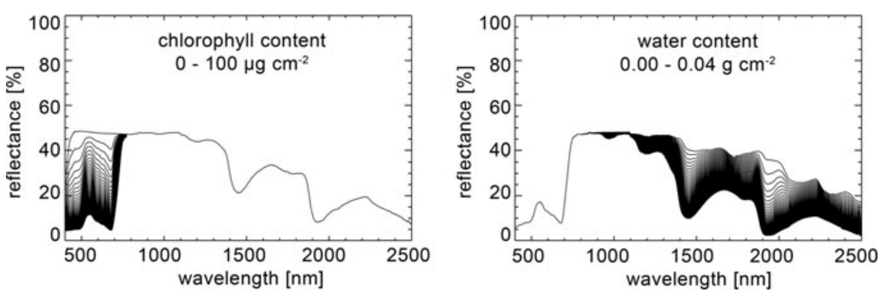

Fig. 6.2 Leaf reflection in response to the varying leaf biochemical components chlorophyll (*left*) and water content (*right*). Simulations were performed using the leaf reflectance model PROSPECT (Jaquemoud and Baret 1990)

2 Remote Sensing of Photosynthesis

Sensing the state of photosynthetic activity, however, is much more complex and the sole information about pigment content is insufficient to predict the current photosynthetic rate. In fact, plant photosynthesis is a dynamically regulated process that quickly adapts to environmental conditions and is affected by the ecological plasticity of each species (Turner et al. 2003b, Rascher and Nedbal 2006). Consequently, photosynthetic rates may greatly vary between different species with similar pigment composition and, additionally, both photosynthesis and pigment composition is dynamically adjusted in diurnal and seasonal cycles (Schurr et al. 2006). Most of the time, natural canopy photosynthesis is not operating at its maximum potential rate and may be largely reduced under prevailing environmental conditions. For example, Bergh et al. (1998) estimated that the CO_2 uptake by a frost stressed boreal forest over a growing season reached only 44% from its potential rate or, Rascher et al. (2004) observed a 30% decrease in photosynthesis as response of drought stress in a tropical ecosystem. These reductions of photosynthetic rates cannot be tracked by the pigment content and the pigment composition itself.

The remote observation of photosynthetic rates can principally be grouped into two approaches: methods that indirectly relate photosynthesis to environmental stresses and approaches that estimate photosynthesis directly from remote sensing data. Recent research effort has focused on estimating the physiological status of photosynthesis directly from remotely sensed data because remote sensing provides the only practical approach to characterize photosynthesis and productivity of vast crop and natural ecosystems. The efficiency of photosynthesis is controlled on various levels involving biophysical and biochemical mechanisms (see Schulze and Caldwell 1995 for a summary on the ecophysiology of photosynthesis). Light absorbed by chlorophyll can be used to (I) drive photosynthesis, and (II) excess energy can be dissipated by a variety of non-photochemical processes usually as heat or, (III) it can be reemitted as fluorescence at longer wavelengths. These three processes compete with each other and an increase in the efficiency of one will result in the decrease of yield in the other two. The major component of the Non-Photochemical Quenching (NPQ) is related to a transthylakoid pH gradient, which activates enzymes altering the epoxidation state of xanthophyll molecules associated with the light harvesting complex and this affects the energy dissipation as heat (Demmig-Adams and Adams 1996, Müller et al. 2001, Baker 2008).

In the following two state-of-the-art remote sensing approaches (based on hyperspectral reflectance data and on the emitted sun-induced fluorescence signal) are described for the potential to directly measure the functional status of photosynthesis.

2.1 Photochemical Reflectance Index (PRI)

The Photochemical Reflectance Index (PRI) is related to NPQ and was developed to serve as an estimate of photosynthetic light use efficiency. This normalized difference reflectance index uses two wavebands (Eq. 1): 531 nm, which is correlated with the xanthophyll pigment composition during the NPQ energy dissipation, and 570 nm, which serves as a reference waveband (Gamon et al. 1992).

$$PRI = \frac{R_{531} - R_{570}}{R_{531} + R_{570}} \tag{1}$$

PRI has been used in a variety of case studies and positively correlates with photosynthetic efficiency. It has been successfully used to detect changes in photosynthetic efficiency at the leaf level (see Rascher et al. 2007, for an overview of the literature).

However, PRI values vary greatly between species with the same photosynthetic capacity (Guo and Trotter 2004). Additionally, the PRI is greatly affected by the geometry of the sun, the leaf, and the detector (Barton and North 2001). As natural canopies are an assembly of differently oriented leaves that additionally change their orientation during development of the plant and as a response to environmental conditions, canopy measurements of PRI often were greatly affected by seasonal changes in canopy structure (Filella et al. 2004). Thus, challenges remain to transfer the very promising results from the laboratory to the canopy and field scale. One of the first successful demonstrations of field measurements was performed in a Siberian forest (Nichol et al. 2002). Since then several groups have further evaluated the potential of PRI and are currently identifying procedures to scale and use the PRI on natural canopies (Hall et al. 2008).

2.2 Fluorescence

Light energy that is absorbed in photosynthetic pigments is partly re-emitted as fluorescence light with well defined wavelength characteristics. Chlorophyll fluorescence is emitted in two broad, overlapping bands with peaks at 685 nm and around 740 nm (Fig. 6.3a; Lichtenthaler and Rinderle 1988). However, the total amount of the emitted fluorescence signal is small in comparison the reflected light (Fig. 6.3b). The intensity of the emitted fluorescence signal is reversely correlated to the energy used for photosynthesis and thus can serve as an indicator for photosynthetic light conversion (see Baker 2008 for a recent review). Fluorescence approaches for analysis of photosynthesis have been developed over the past couple of decades. The most commonly used technique is the Pulse Amplitude Modulation (PAM) fluorometry, which uses the saturating light pulse method (Schreiber and Bilger 1993, Schreiber et al. 1995, Genty et al. 1989, Maxwell and Johnson 2000). PAM data can be analyzed to determine the efficiency with which absorbed photons are being used for photosynthesis, the rates of electron transport, and the degree of non-photochemical protection. This approach requires measurements very close to the leaf as a saturating light pulse has to be applied and is therefore not practical for measurements of plant canopies. However, processes within canopy with millions of leaves – each in its unique environment and all contributing to the overall performance of the canopy – provide many challenges and cannot be derived from

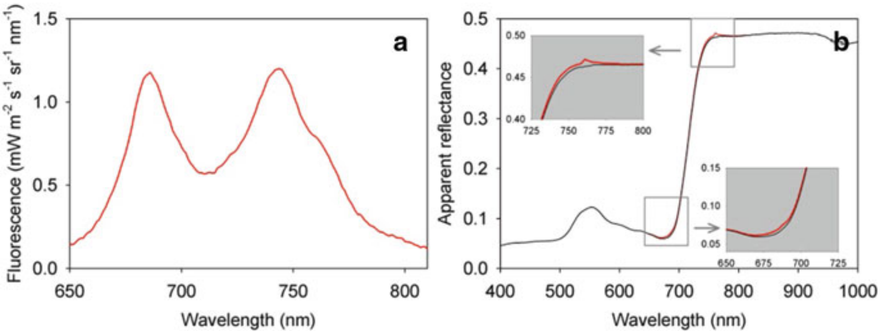

Fig. 6.3 (**a**) Fluorescence and reflectance spectra of a sugar beet leaf. (**a**) Fluorescence emission spectrum in the region between 650 and 820 nm. (**b**) Reflectance with and without fluorescence, i.e. real and apparent reflectance. Measurements were performed on a sugar beet leaf under solar illumination with an ASD FieldSpec Pro coupled with the FluoWAT leaf clip (Alonso et al. 2007), which enables the extraction of the fluorescence spectrum by selectively filtering the incoming light. For details see Meroni et al. (2009)

single leaf measurements. Therefore, techniques and instruments for measurements on canopy scale are required and several approaches are currently being developed for application from a distance for the remote quantification of plant canopies and fields (Osmond et al. 2004, Rascher et al. 2009).

One way of remote quantification of photosynthesis by fluorescence relies on making it possible to measure and analyze fluorescence transients at a distance from the target leaf. A newly developed Laser Induced Fluorescence Transient (LIFT) instrument makes use of a telescope to collect light from target leaves and a low power laser to manipulate the light regime of the target. Constraints on the power of lasers for use in open environments make it impossible to use the same protocols that have been used with PAM fluorometers. New approaches make use of the laser to make much smaller but highly replicated modification of the light regime to analyze the efficiency of photosynthesis (Kolber et al. 2005). The LIFT instrument is required to make measurements that are at the noise limit and computer assisted fitting of the data to a theoretical model are substituted for brute force and simple analysis used in PAM fluorometery (Ananyev et al. 2005, Kolber et al. 1998). The LIFT approach was successfully used to monitor spatial and temporal dynamics of the photosynthetic properties of leaves in the inaccessible outer canopy of trees (Osmond et al. 2004, Rascher and Pieruschka 2008). However, it is limited to measurements at a distance of 5–50 m from the canopy.

2.3 Retrieval of Remotely Measured Sun-Induced Chlorophyll Fluorescence

Fluorescence measurement of large ecosystems relies on passive measurements of solar induced fluorescence (F_S). The approach uses Fraunhofer lines with reduced incoming solar radiation reaching the Earth surface in three main absorption bands in the red and near infrared spectral domain: the Hα line at 656.3 nm is due to the hydrogen absorption by the solar atmosphere whereas two bands at 687 nm (O_2-B) and 760 nm (O_2-A) are due to the molecular oxygen absorption by the terrestrial atmosphere. Fluorescence originated from the canopy occurs in these otherwise 'black' absorption bands and, therefore, can be selectively quantified. Especially the O_2-A and O_2-B bands overlap with the chlorophyll fluorescence emission spectrum and are wide enough to allow quantifying fluorescence from air- and space-borne platforms. The Fraunhofer Line Discrimination method (FLD) has been proposed for this purpose (Plascyk and Gabriel 1975) and was used with success in different works (Carter et al. 1990, Moya et al. 2004, Meroni et al. 2009).

Retrieval of sun-induced fluorescence takes advantage of the great difference in incoming radiation in a small spectral window around the atmospheric oxygen absorption lines. Incoming and outgoing radiance is measured on the shoulders outside of the absorption lines and inside the absorption lines. Fluorescence is a spectrally comparably broad signal which is added to the reflected signal and by comparing values inside and outside of the oxygen absorption feature sun-induced fluorescence can be quantified (Fig. 6.4).

Approaches to quantify F_s can be divided in two major categories: radiance- and reflectance-based approaches. Radiance-based approaches exploit the narrow absorption feature of a Fraunhofer line and so make use of high spectral resolution data (from few nanometres up to 0.03 nm Full Width at Half Maximum (FWHM)). The main methods proposed in the literature require 2–3 spectral channels near the investigated absorption line, while other three methods require a set of contiguous channels covering the whole spectral range of interest. Reflectance-based approaches on the contrary compute optical indices related to F_s but cannot provide direct F_s estimates, neither in physical nor in auxiliary units. In fact, these

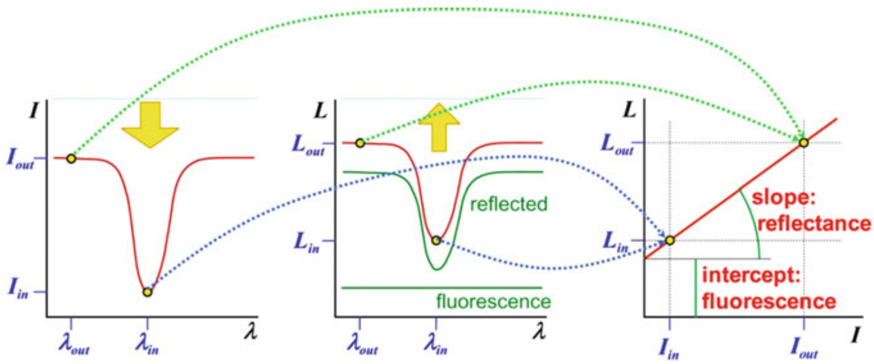

Fig. 6.4 Principle of retrieval of sun-induced fluorescence in the atmospheric absorption lines, where I is incoming radiance and L is reflected, i.e. outgoing radiance, the subscripts 'in' and 'out' refer to radiance inside and outside of the atmospheric absorption lines (courtesy Jose Moreno, University of Valencia)

methods exploit the effect of F_s on the apparent reflectance spectrum in the red-edge region (from 650 to 800 nm) and several indices have been proposed for this purpose (Meroni et al. 2009).

Taking the advantages and disadvantages of the different approaches into account and considering several sensitivity studies, the method proposed by Maier et al. (2003) may be a good compromise between low complexity and stability among a wide range of applications. According to the common measurement procedure of field spectroscopy, this method needs the hyperspectral reflectance measurement of a white (non-fluorescing) reflectance standard (e.g. a calibrated Spectralon^{TM} panel) that is mounted on the same height as the vegetation or alternatively if applied on the larger scale non-fluorescent surfaces, such as fields of bare soil that are large enough to be not-influences by diffuse fluorescence from adjacent fields. Radiance measurements from the non-reflecting surface are compared with radiance measurements of the fluorescing canopy. Fluorescence can then be calculated according to Eq. (2)

$$F_s = \frac{I_{in} - \dfrac{L_{in}}{L_{out}} \cdot I_{out}}{1 - \dfrac{L_{in}}{L_{out}}} \tag{2}$$

with I being the incoming radiance, L is the radiance of vegetation, and the subscripts 'in' and 'out' indicate the wavelengths within and outside of the absorption line, respectively (see also Fig. 6.4).

The magnitude of fluorescence emission is primarily driven by the amount of absorbed light in the photosynthetic 'machinery' and secondly depends on the physiological properties of the photosynthesis. If one is interested in the physiological status, the fluorescence signal (F_s) has to normalize by incoming or absorbed light. This can be achieved by rationing the number of photons emitted (F_s) and the number of photons absorbed by the plants (APAR). The resulting signal is termed fluorescence quantum yield (Fs_{yield}). Changes in Fs_{yield} are independent of the light level and thus reflect the functional status of photosynthesis.

3 Case Studies

3.1 CEFLES-2 Campaign

Field data were acquired as part of the European Space Agency (ESA) supported CEFLES-2 campaign in April, June and September 2007 (http://www.esa.int/esaLP/SEMQACHYX3F_index_0.html). The campaign was performed in the Les Landes area, Southwest France. The main site is located in a plain of the Garonne valley and dominated by intensive agriculture (Fig. 6.5). CEFLES-2 was designed to provide extensive and spatially resolved validation of photosynthesis estimates based on remote sensing fluorescence measurements obtained by using

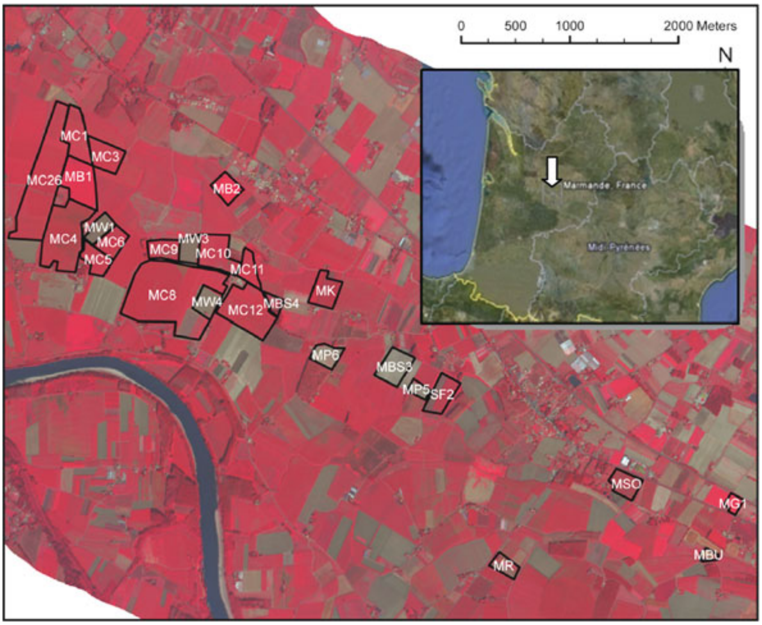

Fig. 6.5 Aerial view of the main study site Les Landes in Southern France. The RGB false color image was derived from the Airborne Hyperspectral Scanner (AHS) airborne sensor (R: 855 nm, G: 652 nm, B: 539 nm) on September 15, 2007, around 11:44 local time, close to Marmande. The image dataset was acquired in a flight height of 2,840 m above ground with a spatial resolution of 6 m. Several corn fields (MC) and selected sunflower (SF), potato (MP), grass (MG, MBU), Kiwi (MK) and Rapeseed (MR) field that were intensively characterized for their structure and photosynthetic function are marked

airborne instrumentation. Remotely sensed fluorescence parameter were validated by extensive ground measurements of structural parameters (leaf area index (LAI)), canopy height or fractional cover (f_{cover}), biochemical characterizations (chlorophyll, water and dry matter content), physiological parameters (PAM fluorometry, gas exchange) and standard field spectroscopy. These more traditional measurements were complemented with novel set-ups aimed to quantify fluorescence at the canopy level. Winter wheat and maize were chosen as species of major interest in April and September, respectively. Additionally, investigations were expanded to rapeseed, grassland, pine, maize, potato, sunflower, bean, kiwi, grapevine and oak forest. A detailed overview of the campaign is published in Rascher et al. (2009).

3.2 Characterization of Spatial and Species Dependent Variability of Photosynthesis Using Fluorescence Estimates

Some basic information about the spatial and species dependent variability of canopy fluorescence was investigated covering 36 individual fields in 8 different crop types, including bare soil. Main focus of this analysis was to investigate the variability of sun-induced fluorescence within the same field, of the same crop, and in different canopies (Fig. 6.5). A comparison of the well established Normalized Difference Vegetation Index (NDVI) and F_s was performed to investigate the plausibility of the derived F_s values. The NDVI typically shows the 'greenness' i.e. the index is a measure for green biomass or canopy chlorophyll content (Goetz and Prince 1999). As fluorescence is also a function of canopy chlorophyll content, we expect that low F_s values correspond to low NDVI values and high F_s values go along with high NDVI values respectively. Important is the dependency of F_s to photosynthesis and F_s covers complementary information about photosynthetic activity. Hence, we also expect a non linear relationship between both parameters.

A first relative evaluation of the data showed that the F_s signal exponentially increases with increasing NDVI (Fig. 6.6). A clear difference in the inter- and intra-field variation was obvious for both parameters. This result is mirroring the heterogeneity of cultivation, nutrient availability, or simple species composition within one field being much lower compared to different fields. Principally, the

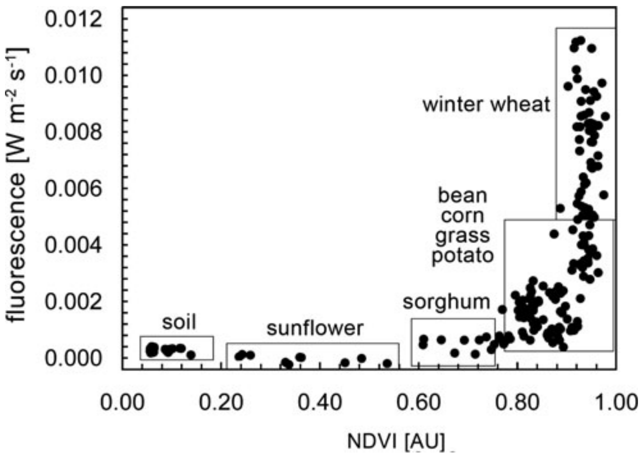

Fig. 6.6 Comparison between the NDVI and sun-induced fluorescence (F_s). Measurements were taken over a wide range of agricultural crops and surface classes. During the three campaigns in April, June, and September 2007, 8 different crops and bare soil were characterized. To cover the spatial heterogeneity of each field, four representative places were selected and three measurements per place were performed. Measurements were taken top-of-canopy using a FieldSpec Pro high resolution spectroradiometer (Analytical Spectral Devices, Boulder,USA), which measures reflected radiation within the spectral domain of 350–2,500 nm with a spectral resolution (FWHM) of 3.0 nm (350–1,050 nm) and a field-of-view (FOV) of 25°. A calibrated Spectralon^{TM} panel (25 × 25 cm) served as white reference to estimate incident irradiance. The fluorescence signal was quantified using the FLD method according to Maier et al. (2003) in the O_2-A band. At each place in the field, the instrument's fibre optic was mounted on a tripod, approximately 1 m above the canopy. Three different spots with a circular area of 0.5 m diameter each were recorded moving the fibre optic manually over the canopy

results seem to describe the status of vegetation: the vital and dense winter wheat fields reach the highest F_s values, slightly senescent corn field medium F_s values and dry stressed grassland and senescent sunflowers have lowest F_s values (Fig. 6.6). Moreover, the sensitivity of both parameters differs especially at the boundaries of the parameter range. On the one hand, the classical vegetation index saturated in dense canopies (e.g. when LAI is higher than 4) at a NDVI value of 0.9, where F_s still provided a differentiation of values (e.g. Fig. 6.6, for winter wheat). On the other hand, NDVI showed a significant variability for non vegetated surface classes (e.g. bare soil or water). F_s values of non-vegetated surfaces, such as bare soil and burned grass were close to zero, or greatly senescent sunflower field also showed F_s slightly below zero (Fig. 6.6).

The relationship between F_s and NDVI indicates that both parameters are driven by canopy chlorophyll content, but also that the fluorescence signal is complementary driven by other parameters and may support the theory that F_s is sensitive to photosynthetic activity. The results clearly show that the observed canopy F_s signal is affected by various structural effects, e.g. canopy structure, fractional cover, or canopy height. A comparison of F_s values from canopies with different structural characteristics and the linkage of derived F_s values to photosynthesis necessitate a proper normalization for the mentioned structural effects.

4 Conclusions

Quantum yield of photosynthetic energy conversion can be related to photosynthetic light use efficiency (LUE), which represents photosynthetic processes, by the amount of fixed carbon per unit of absorbed solar radiation (Genty et al. 1989). Estimation of plant productivity is often based on the linear relationship between net primary productivity (NPP) and the fraction of absorbed PAR (f_{APAR}), with LUE as the slope of this relationship (Monteith 1972, 1977). However, LUE is often estimated from physiological models or look-up tables, and LUE can vary greatly among different vegetation types (Gower et al. 1999, Ruimy et al. 1995, Weis and Berry 1987). Monitoring of LUE by measurement of sun-induced fluorescence could greatly improve these models.

Crop productivity varies within fields and between fields due to various environmental factors, diseases, and management practices. Photosynthetic efficiency may be a promising parameter to detect limitations or down-regulation of photosynthesis regardless of its cause on thus may serve as an early indicator for reduced productivity. Air- and space-borne fluorescence or hyperspectral sensors may provide spatio-temporal information for better response and managing of crops.

Different studies have shown that fluorescence is somehow related to photosynthesis or LUE, respectively (Damm et al. 2009, van der Tol et al. 2009, Meroni et al. 2008). However, the existence of non-photochemical quenching mechanisms may influence the relationship of F_s and LUE within a diurnal course and between different species. Understanding the relation of sun-induced fluorescence and photosynthetic efficiency in structurally complex and diverse canopies and ecosystems is extremely complex and challenging but it may provide a very useful tool to quantify productivity of natural and agricultural ecosystems.

Acknowledgements This work has been made possible by the funding support of the ESA-projects (1) Technical Assistance for Airborne/Ground Measurements in support of Sentinel-2 mission during CEFLES2 Campaign (ESRIN/Contract No. 20801/07/I-LG) (2) Technical Assistance for Airborne/Ground Measurements in support of FLEX mission proposal during CEFLES2 Campaign (ESRIN/Contract No. 20802/07/I-LG) (3) FLEX Performance analysis and requirements consolidation study (ESTEC/Contract No. 21264/07/NL/FF). Additional financial and intellectual support was provided by the SFB/TR 32 'Patterns in Soil-Vegetation-Atmosphere Systems: Monitoring, Modelling, and Data Assimilation' – project D2, funded by the Deutsche Forschungsgemeinschaft (DFG).

References

Alonso L, Gómez-Chova L, Vila-Francés J et al (2007) Sensitivity analysis of the FLD method for the measurement of chlorophyll fluorescence using a field spectroradiometer. Proceedings of the 3rd International Workshop on Remote Sensing of Vegetation Fluorescence, Florence, Italy, 7–9 Feb 2007

Ananyev G, Kolber ZS, Klimov D et al (2005) Remote sensing of heterogeneity in photosynthetic efficiency, electron transport and dissipation of excess light in *Populus deltoides* stands under ambient and elevated CO_2 concentrations, and in a tropical forest canopy, using a new laser-induced fluorescence transient device. Global Change Biol 11:1195–1206

Asner GP (1998) Biophysical and biochemical sources of variability in canopy reflectance. Rem Sens Environ 64:234–253

Baker NR (2008) Chlorophyll fluorescence: a probe of photosynthesis in vivo. Ann Rev Plant Biol 59:89–113

Barton CVM, North PRJ (2001) Remote sensing of canopy light use efficiency using the photochemical reflectance index; model and sensitivity analysis. Rem Sens Environ 78: 264–273

Bergh J, McMurtrie RE, Linder S (1998) Climatic factors controlling the productivity of Norway spruce: a model-based analysis. Forest Ecol Manage 110:127–139

Carter GA, Theisen AF, Mitchell RJ (1990) Chlorophyll fluorescence measured using the Fraunhofer line-depth principle and relationship to photosynthetic rate in the field. Plant Cell Environ 13:79–83

Chen JM, Li X, Nilson T et al (2000) Recent advances in geometrical optical modelling and its applications. Rem Sens Rev 18:227–262

Curran PJ (1989) Remote-sensing of foliar chemistry. Rem Sens Environ 30:271–278

Damm A, Elbers J, Erler E et al (2009) Remote sensing of sun induced fluorescence to improve modelling of diurnal courses of gross primary production (GPP). Global Change Biol DOI: 10.1111/j.1365-2486.2009.01908.x

Demmig-Adams B, Adams WW (1996) The role of xanthophyll cycle carotenoids in the protection of photosynthesis. Trends Plant Sci 1:21–26

Filella I, Peñuelas J, Llorens L et al (2004) Reflectance assessment of seasonal and annual changes in biomass and CO_2 uptake of a Mediterranean shrubland submitted to experimental warming and drought. Rem Sens Environ 90:308–318

Fourty T, Baret F (1998) On spectral estimates of fresh leaf biochemistry. Int J Rem Sens 19: 1283–1297

Gamon JA, Peñuelas J, Field CB (1992) A narrow-waveband spectral index that tracks diurnal changes in photosynthetic efficiency. Rem Sens Environm 41:35–44

Gausman HW, Allen WA (1973) Optical parameters of leaves of 30 plant species. Plant Physiol 52:57–62

Genty B, Briantais JM, Baker NR (1989) The relationship between the quantum yield of photosynthetic electron transport and quenching of chlorophyll fluorescence. Biochim Biophys Acta 990:87–92

Goel NS (1988) Models of vegetation canopy reflectance and their use in estimation of biophysical parameters from reflectance data. Rem Sens Rev 4:1–122

Goel NS (1989) Inversion of canopy reflectance models for estimation of biophysical parameters from reflectance data. In: Asrar G (ed) Theory and applications of optical remote sensing. Wiley, New York, pp 205–251

Goetz SJ, Prince SD (1999) Modelling terrestrial carbon exchange and storage: evidence and implications of functional convergence in light-use efficiency. Adv Ecol Res 28:57–92

Gower ST, Kucharik CJ, Norman JM (1999) Direct and indirect estimation of leaf area index, f(APAR), and net primary production of terrestrial ecosystems. Rem Sens Environ 70:29–51

Grant L (1987) Diffuse and specular characteristics of leaf reflectance. Rem Sens Environ 22: 309–322

Guo JM, Trotter CM (2004) Estimating photosynthetic light-use efficiency using the photochemical reflectance index: variations among species. Funct Plant Biol 31:255–265

Hall FG, Hilker T, Coops NC et al (2008) Multi-angle remote sensing of forest light use efficiency by observing PRI variation with canopy shadow fraction. Rem Sens Environm 112: 3201–3211

Jacquemoud S, Baret F (1990) PROSPECT – a Model of leaf optical-properties spectra. Rem Sens Environ 34:75–91

Kolber Z, Klimov D, Ananyev G et al (2005) Measuring photosynthetic parameters at a distance: laser induced fluorescence transient (LIFT) method for remote measurements of PSII in terrestrial vegetation. Photosyn Res 84:121–129

Kolber ZS, Prasil O, Falkowski PG (1998) Measurements of variable chlorophyll fluorescence using fast repetition rate techniques: defining methodology and experimental protocols. Biochim Biophys Acta 1367:88–106

Liang SL (2004) Quantitative remote sensing of land surfaces. Wiley, Hoboken

Lichtenthaler HK, Rinderle U (1988) The role of chlorophyll fluorescence in the detection of stress conditions in plants. Crit Rev Anal Chem 19:S29–S85

Maier SW, Günther KP, Stellmes M (2003) Sun-induced fluorescence: a new tool for precision farming. In: McDonald M, Schepers J, Tartly L et al (eds) Digital imaging and spectral techniques: applications to precision agriculture and crop physiology, vol 66. ASA Special Publication, Madison, pp 209–222

Maxwell K, Johnson GN (2000) Chlorophyll fluorescence – a practical guide. J Exp Bot 51: 659–668

Meroni M, Picchi V, Rossini M et al (2008) Leaf level early assessment of ozone injuries by passive fluorescence and photochemical reflectance index. Int J Rem Sens 29:5409–5422

Meroni M, Rossini M, Guanter L et al (2009) Remote sensing of solar induced chlorophyll fluorescence: review of methods and applications. Rem Sens Environ 113:2037–2051

Monteith JL (1972) Solar radiation and productivity in tropical ecosystems. J Appl Ecol 9:747–766

Monteith JL (1977) Climate and efficiency of crop production in Britain. Phil Trans Royal Soc London B Biol Sci 281:277–294

Moya I, Camenen L, Evain S et al (2004) A new instrument for passive remote sensing. – 1. Measurements of sunlight-induced chlorophyll fluorescence. Rem Sens Environ 91:186–197

Müller P, Li XP, Niyogi KK (2001) Non-photochemical quenching. A response to excess light energy. Plant Physiol 125:1558–1566

Nichol CJ, Lloyd J, Shibistova O et al (2002) Remote sensing of photosynthetic-light-use efficiency of a Siberian boreal forest. Tellus B 54B:677–687

Osmond CB, Ananyev G, Berry J et al (2004) Changing the way we think about global change research: scaling up in experimental ecosystem science. Global Change Biol 10:393–407

Otterman J, Brakke T, Smith J (1995) Effects of leaf-transmittance versus leaf-reflectance on bidirectional scattering from canopy soil surface – an analytical study. Rem Sens Environ 54:49–60

Plascyk JA, Gabriel FC (1975) The Fraunhofer line discriminator MKII – an airborne instrument for precise and standardized ecological luminescence measurements. IEEE Trans Instrum Measure 24:306–313

Rascher U, Bobich EG, Lin GH et al (2004) Functional diversity of photosynthesis during drought in a model tropical rainforest – the contributions of leaf area, photosynthetic electron transport and stomatal conductance to reduction in net ecosystem carbon exchange. Plant Cell Environ 27:1239–1256

Rascher U, Agati G, Alonso L et al (2009) CEFLES2: the remote sensing component to quantify photosynthetic efficiency from the leaf to the region by measuring sun-induced fluorescence in the oxygen absorption bands. Biogeosciences 6:1181–1198

Rascher U, Nedbal L (2006) Dynamics of plant photosynthesis under fluctuating natural conditions. Curr Opin Plant Biol 9:671–678

Rascher U, Nichol CL, Small C et al (2007) Monitoring spatio-temporal dynamics of photosynthesis with a portable hyperspectral imaging system. Photogram Eng Rem Sens 73:45–56

Rascher U, Pieruschka R (2008) Spatio-temporal variations of photosynthesis: the potential of optical remote sensing to better understand and scale light use efficiency and stresses of plant ecosystems. Prec Agric 9:355–366

Ruimy A, Saugier B, Dedieu G (1995) Methodology for the estimation of terrestrial net primary production from remotely sensed data. J Geophys Res 99:5263–5283

Schreiber U, Bilger W (1993) Progress in chlorophyll fluorescence research: major developments during the past years in retrospect. Proc Bot 53:151–173

Schreiber U, Bilger W, Neubauer C (1995) Chlorophyll fluorescence as a nonintrusive indicator for rapid assessment of in vivo photosynthesis. In: Schulze ED, Caldwell MM (eds) Ecophysiology of photosynthesis. Springer, Berlin, Heidelberg, pp 49–70

Schulze ED, Caldwell MM (1995) Ecological studies. In: Schulze ED, Caldwell MM (eds) Ecophysiology of photosynthesis. Springer, Berlin, Heidelberg, p 100

Schurr U, Walter A, Rascher U (2006) Functional dynamics of plant growth and photosynthesis – from steady-state to dynamics – from homogeneity to heterogeneity. Plant Cell Environ 29:340–352

Turner DP, Urbanski S, Bremer D et al (2003) A cross-biome comparison of daily light use efficiency for gross primary production. Global Change Biol 9:383–395

Van der Tol C, Verhoef W, Rosema A (2009) A model for chlorophyll fluorescence and photosynthesis at leaf scale. Agric Forest Meteorol 149:96–105

Weis E, Berry JA (1987) Quantum efficiency of photosystem II in relation to `energy-´dependent quenching of chlorophyll fluorescence. Biochim Biophys Acta 894:198–208

Chapter 7
Remote Sensing for Precision Crop Protection – A Matter of Scale

Kerstin Voss, Jonas Franke, Thorsten Mewes, Gunter Menz, and Walter Kühbauch

Abstract Management strategies for precision crop protection necessitate spatially and temporally explicit knowledge about crop growth heterogeneity within fields. Remote sensing techniques are appropriate tools for the derivation of relevant crop parameters. However, even for a first discrimination between stressed and productive crop stands, several aspects related to phenomenon and sensor characteristics need to be considered. The question of which prerequisites a sensor must fulfil at specific scales for an effective identification of within-field heterogeneities arises. Besides scale-related issues of the observed phenomenon, the scale of remote sensing data needs to be differentiated into the sensor-defining dimensions: *spatial, temporal and spectral*. This chapter examines each dimension in detail. For the spatial dimension, different landscape metrics were calculated and a threshold of the minimal spatial resolution of remote sensing data for crop stress detection could thus be defined. The temporal scale of remote observations is rather phenomenon-dependent, as various factors such as the crop stress type produce different temporal dynamics, which determine the sensor-technical prerequisites. With respect to the spectral scale, its characteristics strongly depend on the given spatial and temporal dimensions. Different spectral wavebands need to be considered at different spatial scales (e.g., near-range sensing *vs.* remote sensing) as well as temporal variances (e.g., different phonological stages). The chapter demonstrates the importance of scale-related issues for precision crop protection and highlights that various perspectives have to be taken into account by using remote sensing.

1 Introduction

Precision crop protection requires spatially explicit information on the within-field heterogeneity of crop growth conditions at particular times. Remote Sensing offers the possibility to identify these heterogeneities with comparatively small

---

K. Voss (✉)
Remote Sensing Research Group, Department of Geography, University of Bonn, Bonn D-53115, Germany
e-mail: k.voss@geographie.uni-bonn.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_7,

expenditure. However, using remote sensing as a tool to provide decision support for precision crop management necessitates focusing on aspects of the spatial, temporal and spectral scale of the data and the scale of the observed phenomena.

The aim of this chapter is to discuss the influence of scale of remote sensing data on precision crop protection. In general, scale can be defined in a number of ways. '*The term 'scale' has a variety of meanings and has been used in different contexts in various disciplines, such as spatial, temporal or spatiotemporal scales'*(Cao and Lam 1997). The definition of scale must consider scale as a quantity, giving the physical dimensions of observed phenomena, and should at least imply measurements or measurement units (O'Neill and King 1998, Turechek 2006). Dungan et al. (2002) related the term 'scale' to the three categories: (I) the scale of the phenomenon; (II) the scale of the experimental or sampling units; and (III) the scale of the analysis that is used to describe a phenomenon. Scale primarily refers to extent and grain, whereby both parameters can refer to space and/or time (Turner et al. 1989, Musick and Grover 1991, Quattrochi and Pelletier 1991, O'Neill et al. 1996, O'Neill and King 1998, Gustatfson 1998, Blaschke and Petch 1999). Depending on which of the three categories should be addressed, 'extent' and grain can have different meanings. In the context of Remote Sensing, extent describes the spatial expansion of an observed area, duration of measurements or the spectral range, whereas grain is defined by the spatial resolution, sample frequency or spectral resolution of the data. To address the influence of scale of remote sensing applications on precision crop protection, the three dimensions of spatial, temporal and spectral scale are considered, as well as the scale of the observed phenomena.

2 The Spatial Dimension of Remote Sensing

Many precision crop protection-related studies address issues concerning the spatial scale of either crop stress factors, sensors that are used to detect a plant's stress symptoms or application techniques, to assess the potential of a site-specific crop management. The hypothesis is that due to the decrease of the spatial resolution of remote sensing data, the information content of the images will be reduced. In the context of implementing remote sensing data in precision crop protection, the question arises whether the spatial resolution of the image has any influence on the recognition of site-specific plant stress. Also, which spatial resolution is necessary for identifying site-specific stress?

The objective of this subsection is the formulation of a threshold value of spatial resolution, from which site-specific plant stress can no longer be assessed correctly. For the formulation of the threshold, a new technique is proposed to quantify spatial pattern changes of an agricultural test site, depending on changing resolution. In the vegetation period 2001/2002, winter wheat was cultivated on an agricultural test site of the University of Bonn. The surface of the test site was 5.22 ha, which was divided into 12 plots with a size of 44.85 $\times$ 45 m (Fig. 7.1). For the determination of healthy and diseased patches, 4 different agrochemical treatments were applied. In 9 of the 12 plots, plant stress arose, caused by a lack of nitrogen, an infestation

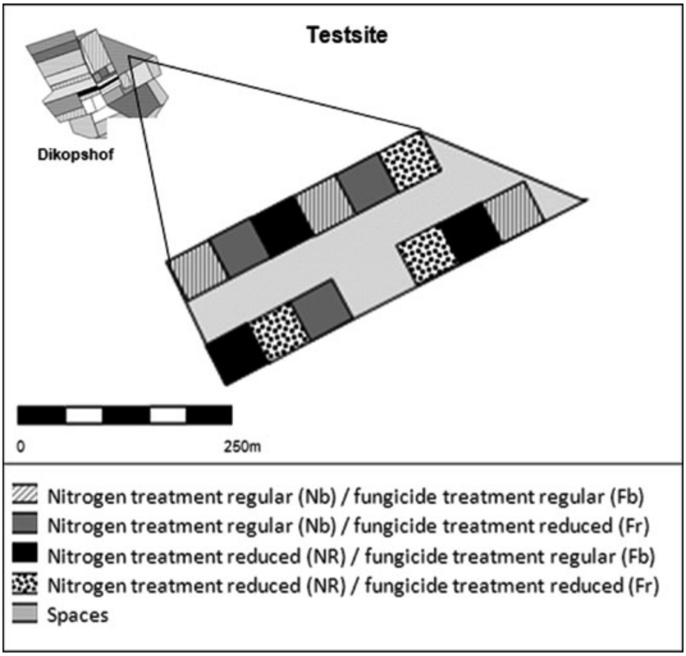

Fig. 7.1 Description of the Dikopshof test-site in 2001/2002

with fungal decay, or the combination of nitrogen deficiency and fungal decay (Voß 2004).

The assessment of the influence of spatial resolution is based on a QuickBird-2 satellite image. To identify the minimum resolution that is necessary to estimate site-specific plant stress, QuickBird images were systematically degraded in spatial resolution from originally 0.7 to 30 m. After the implementation of a maximum likelihood classification for these datasets, different landscape metrics were calculated to quantify the influence of spatial resolution on the assessment of site-specific plant stress. Landscape metrics offer the possibility to compare changes of the landscape structure with changes of the spatial resolution. They are defined as quantitative indices to describe structures and patterns of a landscape (O'Neill et al. 1988). The development of the landscape metrics is based on information theory (Shannon and Weaver 1964) and the theory of fractal geometry (Goodchild and Marks 1987, Xia and Clarke 1997). Landscape metrics can be computed for three levels: patch, class and landscape. The changing values of the landscape metrics reflect the change of spatial resolution.

The calculation of the landscape metrics was accomplished with the public domain Fragstats program (Version 3.3; McGarigal and Marks 1994). For all classification results, seven landscape metrics at the class and landscape level were calculated. The criteria for selecting the landscape metrics was based on the information content of the metrics with regard to the spatial structure and their sensitivity

Table 7.1 Overview of calculated landscape metrics to analyze raster images using FRAGSTATS 3.3

Metrics	Range of values	Level
Percentage of Landscape (PLAND)	0 < PLAND ≤ 100	Class
Number of Patches (NP)	NP ≥ 1	Class & landscape
Total Edge (TE)	TE ≥ 0	Class & landscape
Area-Weighted Mean-Shape-Index (AWMSI)	1<=AWMSI<=2	Class & landscape
Patch Richness (PR)	PR ≥ 1	Landscape
Mean Nearest-Neighbor Distance (MNN)	MNN > 0	Class & landscape
Contagion (CONTAG)	0 < CONTAG ≤ 100	Landscape

in relation to resolution-dependent changes. Table 7.1 gives an overview of the calculated landscape metrics.

The first metric, *PLAND,* represents the different surface portions of the patches of different land cover classes. The specification of this index is measured in percent. The index *Number of patches (NP)* represents the extent of subdivision of the patch type and represents the patch number of a specific land cover class or the entire landscape. Also, the number of the existing edges influences the structure of the landscape. The metric *Total edge (TE)* computes the total edge length both for all patches of each land cover class and for all patches of the entire landscape. The indication of the edge length is counted in meters. The *Area Weighted Mean Shape Index (AWMSI)* describes the shape complexity of the patches. The shape complexity of smaller patches is affected by pixel size rather than by real characteristics. Therefore, this index performs better for larger patches than for trivial patches consisting of 1–3 pixels. *Patch richness (PR)* is a simple measure of landscape composition and diversity. The basis of the calculation is the number of land cover classes in the entire landscape. On the basis of the distance metric *Mean Nearest Neighbour Distance (MNN),* specifications about the configuration of landscape features can be derived. This index calculates the middle distance of neighbouring patches belonging to the same land cover class. The *Contagion index (CONTAG*') measures the degree of clumping of all landscape patches and is based on two probabilities: (I) The probability that a randomly chosen cell belongs to patch type i, and (II) the probability that – given a specific cell is of patch type i – one of its neighbouring cells belongs to patch type j. The product of these probabilities equals the probability that 2 randomly chosen adjacent cells belong to patch type i and j (McGarigal and Marks 1994). The *Contagion index* measures both patch type spreading as well as patch type dispersion. The values are indicated in percent, approaching 0 when the patch types are maximally disaggregated, and approaching 100 when all patch types are maximally aggregated, i.e., when the landscape consists of a single patch type only.

Since landscape metrics offer the possibility to describe the spatial pattern of a landscape, the changes of these metrics in relation to changing pixel size were analysed. The analysis results of the landscape level are displayed in Fig. 7.2 for the spatial resolutions 0.7, 2.8, 4, 15, 20 and 30 m. The PR values show no changes

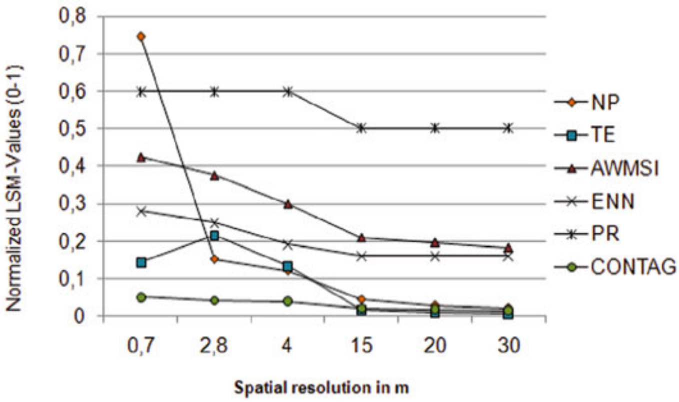

Fig. 7.2 Variation of selected landscape metrics by changing spatial resolution form 0.7 to 30 m (all calculations were performed on the landscape level and the results were normalized)

between the resolutions of 0.7 and 4 m, as all land cover classes are identified up to a spatial resolution of 4 m. Similar to the PR value, the other five calculated metrics decrease with the reduction of the spatial resolution as well but are more sensible at primary reduction stages. Between a resolution of 0.7 and 2.8 m, NP values decrease from 0.75 to 0.15. That means that the number of identified patches of the test site is reduced from 750 to 150 patches. These results indicate a loss of information about structural characteristics of the test site, as the aggregation of the pixels led to an incorrect representation of the pixels with plant stress. The AWMSI values also decrease with resolution changes from 0.7 to 15 m. This decrease of information about the shape complexity occurs especially between a spatial resolution of 2.8 and 15 m. In this range, the shape complexity of the individual patches is more and more characterized by the pixel size than by the real characteristics. The decrease of the Indices CONTAG and MNN is smaller than the decrease of AWMSI. This indicates that the spatial distribution of several land cover classes is seized over a larger range of different spatial resolution than the shape complexity.

The change of the values permits a conclusion about the change of the information content of the images in comparison to the spatial structure of the test site. A significant loss of information about the structure of the test site is identified, indicated by the decrease of values for the spatial resolution classes of 0.7–15 m.

The analysis of the landscape metrics at class level between 1 and 15 m allows a specification of this statement (Fig. 7.3). The PLAND values show that the surface portions of the analysed land cover classes are relatively constant up to a spatial resolution of 5 m. At a spatial resolution of 6 m, all diseased land cover classes exhibit variations of the surface portions. This indicates that the surface portions of the three land cover classes are not identified correctly with resolutions beyond 5 m. The analysis of the metrics NP and TE shows a reduction of values between a spatial resolution of 1 and 5 m. Due to the aggregation of the pixels, it is not possible to differentiate all patches, and particularly small patches are no longer

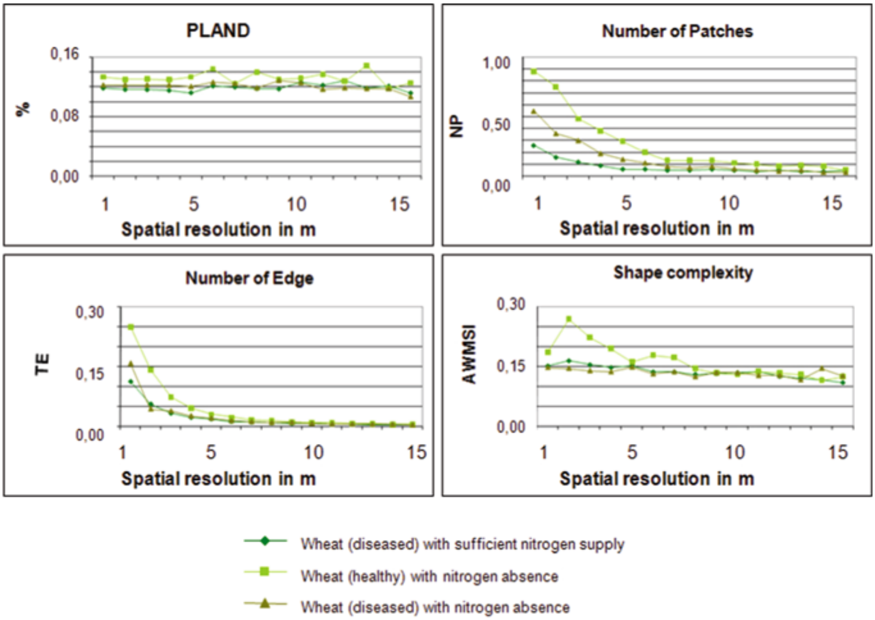

Fig. 7.3 Variation of the landscape metrics (LSM) by changing spatial resolution (class level) – LSM-Values are normalized between 0 and 1

recognizable. This explains the decrease of the TE values as well, because the edge length correlates with the number of patches.

The separation of different land cover classes on the basis of their shape complexity is possible up to a spatial resolution of 5 m. A further decrease of the spatial resolution leads in similar AWMSI values for all three land cover classes.

Both the correctness and detailedness of the information content on the structure of the agricultural test site decline with decreasing spatial resolution.

The results indicate that in general terms, the structure of the test site cannot be identified any longer correctly at resolution levels of 5–6 m and beyond (Fig. 7.3). The analysis of the landscape metrics suggests a mean threshold value of 6 m spatial resolution. Consequently, the identification of site-specific plant stress with remote sensing techniques requires very high spatial resolutions. Thus, the requirement of a spatial resolution of 10 m – claimed by Wiltshire et al. (2000) – is assessed as not sufficient for the identification of site-specific plant stress.

At present, these very high spatial resolutions are provided only by airborne sensors or very few satellite systems (e.g., Ikonos or QuickBird-2). The disadvantages of these satellite systems are the very small Instantaneous Field of View (IFOV) and a low temporal and spectral resolution. However, the recently launched satellite sensor RapidEye does not exhibit these disadvantages. With a spatial resolution of 5 m, the IFOV contains an extent of 77 × 1,500 km by a daily repetition rate. For the identification of site-specific plant damage, this satellite will therefore play an important role.

3 The Temporal Dimension of Remote Sensing

In contrast to the multitude of studies addressing the spatial dimension, only a few studies highlight the temporal dimension of precision crop protection, even though crop stresses are generally dynamic phenomena in spatial as well as temporal aspects. Therefore, the importance of the temporal scale of crop growth phenomena and sensor systems as well as temporal adjustment of within-field operations should come into focus (McBratney et al. 2005, Franke and Menz 2008). Management actions are not only adjustable in space, but also to the date on which they are most effective. Time-specific crop management thus may improve efficiency and even reduce the number of agrochemical applications (Moran et al. 1997, Franke et al. 2009). Similar to site-specific crop protection, which requires sensor systems that detect crop stress symptoms with an appropriate spatial resolution, time-specific crop protection has requirements on temporal resolution or repetition rate of sensor data. In general, two different sensing-based crop stress detection approaches exist: satellite-/air-borne sensors and near-range sensors. Moran et al. (1997) and West et al. (2003) provided detailed overviews of sensor-based crop stress detection. Concerning the suitability of sensor systems for precision crop protection in general, however, many limitations exist, depending on the temporal scale of each system. These limitations as well as further constraints with respect to temporal aspects of crop stress control are here addressed. Temporal scale aspects are distinguished in three categories: (I) the inherent phenomenon scale (PS_t) that describes the temporal scale on which a crop stress phenomenon operates, (II) the sensor observation scale (OS_t) that is defined by the potential sample frequency of a sensor system and the duration for data pre-processing, and (III) the management scale (MS_t), which is affected by the duration of information extraction from sensor data and the time efficiency of agrochemical applications. In the following section, each aspect will be separately addressed for plant diseases as an example of a crop stress factor.

3.1 The Temporal Scales of Crop Stress Phenomena

Various crop stress phenomena basically operate on different spatiotemporal scales depending on their physiological characteristics and environmental conditions. On the one hand, there are comparatively spatiotemporally stable stress factors such as soil characteristics and, on the other hand, highly dynamic crop stress phenomena such as plant diseases. With respect to the temporal phenomenon scale (PS_t) , each stress factor therefore requires a different temporal resolution of stress monitoring and adjusted time-specific crop protection. A higher level of complexity results if several crop stress phenomena with different PS_t coincide, which further affects aspects of temporal scaling of monitoring or management actions. Only detailed analyses of the temporal characteristics of each stress factor can provide relevant information for a time-specific crop protection. To exemplify the PS_t of crop stresses, their driving factors and the resulting requirements on precision crop

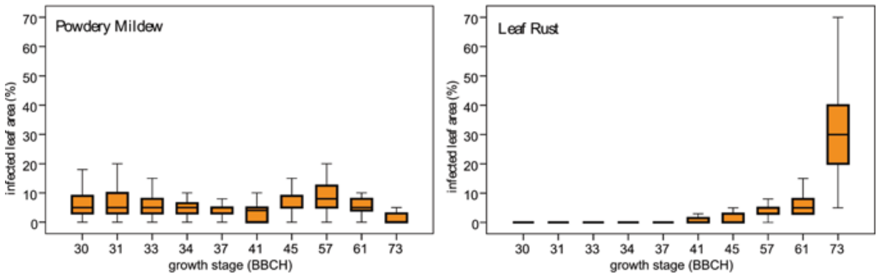

Fig. 7.4 Disease progress curves (boxplots with median, quartiles and extrema) of powdery mildew and leaf rust in wheat as observed at 28 sample points in a test plot where no fungicides were applied in 2005 (modified from Franke et al. 2009)

management, plant diseases as temporal dynamic phenomena are described in the following section.

There are various approaches to quantify and describe the temporal dynamics of plant diseases such as the disease progress curve, the area under the disease progress curve or the linear, monomolecular, exponential, logistic, and Gompertz population model. Each of them can serve as an interpretive tool to analyze temporal occurrence of plant diseases (Nutter 1997). For instance, Fig. 7.4 shows disease progress curves used to analyze the temporal dynamics of leaf rust and powdery mildew in wheat (Franke et al. 2009). This case demonstrates that the onset of stress factors may temporally defer, but fungal diseases may also coincide at higher growth stages with additionally different severities. In addition, a differing disease trend is obvious with an approximately exponential trend of leaf rust and rather high temporal dynamics/different PS_t of powdery mildew. Depending on the pathogen species, driving factors such as soil characteristics, micro-topography, plant density, host resistance, host growth stage, amount of existing spores, microclimatic conditions etc. affect the spatial and temporal development of plant diseases (Nelson and Campbell 1993, Tubajika et al. 2004). Hence, such complex and multi-factorial bio-physiological systems such as fungal crop diseases necessitate adjusted time-specific detection methods and stress control strategies. Savary and Cooke (2006) as well as Madden (2006) stated that plant disease epidemiology leads to specific disease control recommendations and conceptual innovations in the management of plant diseases. Regarding all spatiotemporal facets of stress factors and their determining factors, a time-specific crop management strategy seems to hold a high potential for precision crop protection.

3.2 *The Temporal Sensor Observation Scale*

Previous studies demonstrated the potential and limitations of disease mapping with satellite-/airborne remote sensing data (e.g., Apan et al. 2004, Shaw and Kelley 2005, Franke and Menz 2007) and with near-range sensors (e.g., Bravo et al. 2003, Moshou et al. 2006). The still cost-intensive use of sensor data for disease mapping is only reasonable if the phenomenon to be observed is detected at appropriate times and with a temporal resolution that is required to reproduce its trend adequately. An efficient agrochemical application can only be assured if there is an early detection of stress incidence. Hence, the time of sensor-based stress identification is a crucial and restrictive factor.

Besides the sensor repetition rate, the temporal resolution of remote sensing sensors is additionally affected by cloud cover (Jackson et al. 1986, Moran et al. 1997). All time-related parameters have to be taken into consideration, to avoid temporal over- or under-sampling of the phenomenon. Whereas temporal over-sampling via sensor data impairs the cost-benefit ratio due to additional data acquisition and processing costs, temporal under-sampling may result in a reproduction of a pseudo-phenomenon, i.e. aliasing (Fig. 7.5). Aliasing is a common problem in signal processing that often occurs in audio and video signals (Flaten and Parendo 2001). Temporal aliasing may occur when the sample frequency (f_s) or OS_t – for instance, due to low temporal resolution of the sensor – does not match the frequency of the phenomenon (f_p), i.e. the PS_t. Hence, considering a disease progress curve, as exemplarily shown in Fig. 7.5, sensor-based stress monitoring could miss infection peaks and disease trends could be inaccurately reproduced, since OS_t is not suitable. To avoid temporal aliasing or inappropriate sampling dates, knowledge about the PS_t is essential. In temporal respects, the suitability of a certain sensor system for precision crop protection thus primarily depends on the temporal scale of the monitored phenomenon.

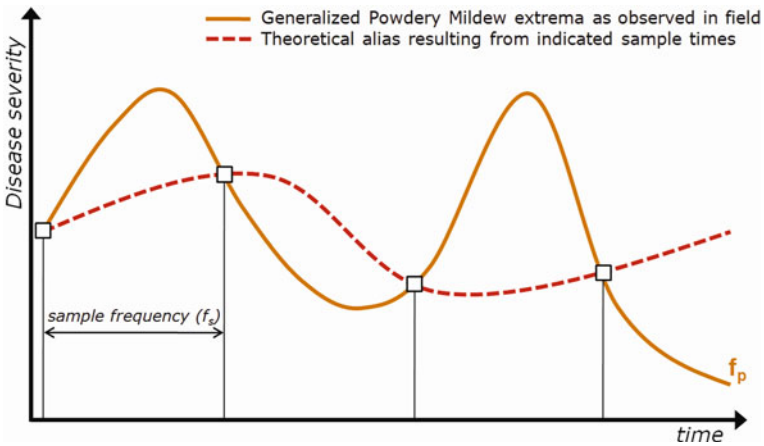

Fig. 7.5 Example for temporal aliasing. Generalized temporal frequency of powdery mildew severity (f_p) derived from in-field observed extremes in 2005 (*solid line*), and an alias (*dashed line*) that would result from exemplarily shown sample dates (*boxes*). The temporal sample frequency f_s (or temporal observation scale) would not be suitable in this case to reproduce the phenomenon correctly

Maximum temporal frequency of coverage – affected by repetition rate of the sensor and constraints such as cloud cover, time of the day and data availability (e.g., conflicts with other users) – as well as timeliness are the major limitations for a utilization of optical sensor data for farm management (Jackson et al. 1986, Moran et al. 1997). Timeliness implies the time between data acquisition and data delivery to the farmer (duration of data pre-processing). Moran et al. (1997) gave an overview of repetition rates of satellite sensors and discussed the delivery times for the data and stated that, at that time, satellite sensors were inappropriate for intensive agricultural management due to low temporal resolution and long periods between data acquisition and delivery. Unfortunately, these limitations have not yet been overcome in the meantime. However, with recently launched satellite sensors such as RapidEye or future missions as EnMap with improved repetition rates, as well as with near-range sensors, limitations for the use of sensor data due to temporal aspects can be overcome.

3.3 The Temporal Management Scale

Agrochemical applications are generally limited to defined crop growth stages and additionally require certain weather conditions (West et al. 2003),which implies that the MS_t is temporally constrained. In addition, crop protection applications are most effective when applied early after stress incidence. For instance, the control of polycyclic pathogens with fungicides depresses lesion expansion and reduces sporulation. The disease cycle is slowed down since the latent period between infection and sporulation is increased by preventing the pathogens from generating fresh inoculums (Lucas 1998, West et al. 2003). Since crop disease progress depends on environmental conditions, however, this slowdown of the disease cycle can also be used to bridge periods with favourable environmental conditions for pathogens, which would impede disease progress. The knowledge about temporal characteristics of crop stresses is important for a determination of their impact on plants and may allow for a stress-specific application. This is particularly the case when different stress factors coincide and the total stress effect on the crop exhibit an assimilated impact. In these cases, a site-, time- or stress-specific crop management is challenging and decision support systems might be helpful. The number of agrochemical applications per season could be reduced and their effectiveness improved by an optimal timing of disease control.

The MS_t is also affected by the duration of sensor data processing. Besides the temporal aspects of data acquisition, pre-processing and delivery to the user, which were discussed above, there are further limitations due to the duration of the actual data processing, i.e., the information extraction about crop stress occurrence. Even though several analysis techniques exist, such as temporal mixture analysis (e.g., Asner 2004) or time series analysis (e.g., Hill 2004), the duration for processing is particularly extended with multi-temporal data, because these require inter-calibration procedures due to different image characteristics for a temporal comparability (Moran et al. 1997).

In conclusion, the temporal dimension of precision crop protection is a multifactorial subject, affected by multifold factors such as the crop stress type and their different temporal dynamics (onset, trend and coincidence), crop growth characteristics, trend of environmental conditions, type of sensor which is used to monitor stress impact (repetition rate, duration of data pre-processing and delivery), data processing time as well as weather conditions and applicable growth stages for agrochemical applications. Hence, to find appropriate times for sensor-based crop stress detection and optimal stress control dates, decision support systems are fundamental, considering every single temporal aspect affecting crop stress. For example, Dammer et al. (2008) presented a decision support system, which provides information on crop stress probabilities, application time and application rates.

From the sensor side of view, near-range sensors, particularly imaging sensors, allow for a sensing of crop stress symptoms in greater temporal and spatial detail and thus have basically a higher potential for use in precision crop protection than remote sensing. However, monitoring of complex biochemical systems such as crop stresses, particularly crop diseases, is limited by spatiotemporal scale issues of sensor systems. Assessments of the temporal dimension of crop stresses demonstrated that required temporal resolution of stress detection systems OS_t and the temporal scale of crop protection management MS_t are primarily dominated by individual characteristics of stress phenomena PS_t, i.e., the PS_t dictates the requirements on technical systems used to detect (OS_t) and to control (MS_t) them.

4 The Spectral Dimension of Remote Sensing

Besides spatial and temporal preconditions, a third factor needs to be considered for precision crop protection: the spectral dimension. Nowadays, several near-range-, airborne- and satellite-based remote sensing systems with different temporal, spatial and also spectral resolution are available for data acquisition. To prove their potential for precision crop protection, or rather to build up an optimal sensor system, all three interrelated dimensional prerequisites need to be known before focusing on specific phenomena. Since the early 1970s, the use of spectral reflectance of different vegetation types has been studied at leaf scale. Researchers demonstrated that the concentration of several organic compounds can be estimated by the use of reflectance measurements, because plant elements like starch, lignin or pigments determine specific absorption features within the electromagnetic spectrum (Curran 1989). Those absorption features can only be detected by sensor systems that cover phenomenon-specific wavelengths with an adequate spectral resolution. Recent hyperspectral spectrometers usually gather reflectance data in the range between 400 and 2,500 nm in many contiguous bands. They are suitable for the detection and quantification of plant-related spectral features (Curran 1989, Carter and Estep 1994, Yoder and Pettigrew-Crosby 1995, Blackburn 1998). However, the identification of relevant bands and thus a reduction of redundant information of adjacent bands without loss of significance are essential for a rather phenomenon-focused use of hyperspectral data. This may speed up the data supply and accuracy for precision agriculture.

A study by Yoder and Pettigrew-Crosby (1995) focused on prediction-possibilities of chlorophyll and nitrogen concentrations of bigleaf maple trees at leaf scale. Relevant bands for the estimation were thereby found. At the canopy scale, different bands needed to be used and the prediction was less successful due to measurement noise and environmental variations in atmospheric conditions and canopy structure. At canopy scale, Blackburn (1998) identified relevant wavebands for pigment estimations, i.e., 664.3 nm for chlorophyll a, 658.4 nm for chlorophyll b and 452 nm for carotenoids, using first and second derivative pseudoabsorbance. Different wavelengths were optimal at leaf scale. The study showed high potential for estimations of chlorophyll concentration at leaf and canopy scale using near range reflectance measurements. Asner and Martin (2008) verified that multiple leaf chemicals can be estimated from canopy reflectance spectroscopy if different LAIs and viewing geometries are considered. Nonetheless, there is still a gap in prediction accuracy between near-range and airborne- or satellite-based remote sensing data. It is necessary to know which wavelengths are the most suitable for detecting a specific spectral crop stress phenomenon, at specific spatial scales and specific times.

4.1 Near-Range Spectroscopy for Crop Stress Detection

Moran et al. (1997) stated a promising vision for the use of hyperspectral sensors for determination of the cause of plant stress for making application management decisions. Until now, an operational implementation of these data could not yet be realized in practice, but several works have shown possibilities and limitations (Carter and Estep 1994, West et al. 2003, Jain et al. 2007). Reflectance data have been widely used as a tool for the detection of nitrogen deficiencies (e.g., the Yara N-Sensor, Agri Con GmbH, Ostrau, Germany) and optimal spectral wavebands of near-range hyperspectral data have been identified (Jain et al. 2007). In contrast, less attention has been paid to the detection of diseases, but it is known that diseases can affect the optical properties of crops.

Lorenzen and Jensen (1989) studied the spectral changes of barley leaves at leaf scale after an inoculation with mildew. Six days after inoculation, a spectral discrimination between control plants and infected plants was possible using a Licor spectroradiometer. Their study showed that spectral differences first occur in the visible region of the electromagnetic spectrum. The NIR region, however, is clearly more affected by changes in leaf or canopy structure (Lorenzen and Jensen 1989). Bravo et al. (2003) investigated the potential of early disease detection of foliar diseases in wheat at canopy scale using spectral reflectance. Optical data of healthy and yellow rust-infected plots were obtained with a near-range spectrograph. Five wavebands could be identified for optimal discrimination after first physiological changes of the plant occurred. Mewes et al. (2008) focused a study on band selection techniques for the detection of powdery mildew and leaf rust on wheat using a spectrometer in a greenhouse experiment. A semi-automated derivative analysis technique was applied on all recorded spectra to localize general positions of reflectance minima and maxima. Finally 13 wavebands were identified for significant disease detection via decision tree analysis also at early disease stages. The used band selection technique has shown that only a few bands within the VIS/NIR spectrum were needed for spectral separability between healthy and infected crops.

West et al. (2003) stated that the use of hyperspectral data leads to a very large amount of data handling, which is impractical for practical farming systems. The identification of phenomenon-specific wavebands or combinations of wavebands and thus a data reduction will therefore be necessary.

4.2 Airborne Hyperspectral Imaging for Crop Stress Detection

Compared to near-range measurements, only a few studies have been focused on the potential use of hyperspectral airborne and satellite-borne data for precision crop protection. Fungal diseases often appear in patches, resulting in field heterogeneities. For the localization of those patches, sensor-based techniques are of increasing importance (Franke and Menz 2007). Remote sensing data has the benefit of mapping vegetation over a large spatial area and the use of multispectral data has been proven for site-specific identification of fungal infections (Shaw and Kelley 2005, Jacobi and Kühbauch 2005, Franke and Menz 2007). Hyperspectral data may enhance the detection with phenomenon-specific sensor technology and analysis.

Apan et al. (2004) proved the use of EO-1 Hyperion hyperspectral data for the discrimination of fungal infected sugarcane crops. Different hyperspectral indices were tested all related to stress influenced plant parameters, i.e., pigments, leaf structure, water content. Highest separability could be obtained by the use of band combinations of wavebands within the green range of the electromagnetic spectrum combined with bands of the NIR and SIWR (Apan et al. 2003, 2004). Franke et al. (2008) proved the potential of airborne hyperspectral imagery for early disease detection. Figure 7.6 shows the result of a Mixture Tuned Matched Filtering (MTMF) conducted on 126 spectral bands between 450 and 2480 nm of the Hyperspectral Mapper sensor (HyMap, HyVista, Sydney, Australia). A map of the test site with differently treated plots giving the fractions of fungal-infected wheat, non-infected wheat and soil was derived, which might be useful information for precision crop protection. A regression analysis of fraction estimates of infected wheat and in-field-observed powdery mildew severities showed promising results ($r^2 = 0.67$).

In 2008, another field campaign was carried out at the University of Bonn. The study focused on the derivation of different disease severities using hyperspectral data. A field with 4 ha in size was divided into 12 subplots with 40×60 m each, with different disease severities. Multitemporal measurements at randomly distributed sample points were taken with a near-range spectrometer. In addition, hyperspectral image data was acquired by the Airborne Imaging Spectrometer for Applications (AISA, Specim, Oulu, Finland). For the derivation of severity estimations, optimal

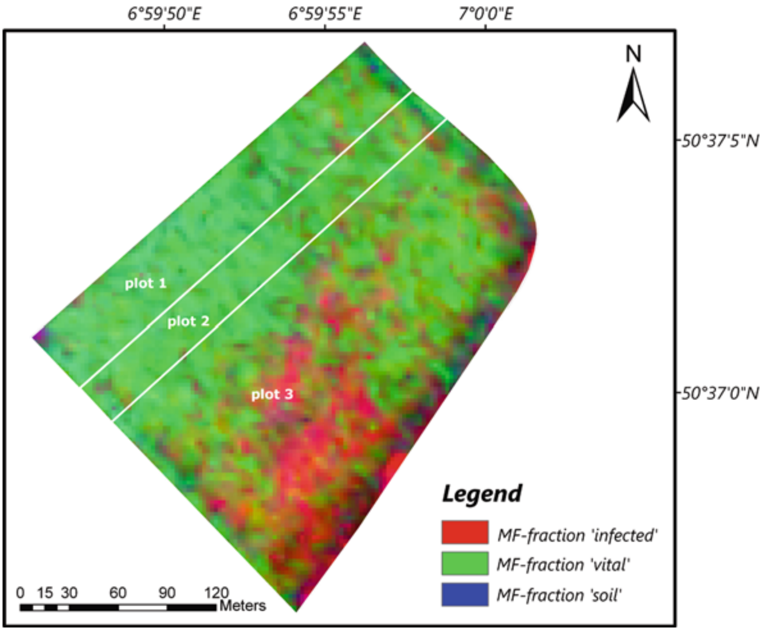

Fig. 7.6 False-color composite of an experimental field showing fractions of the spectral endmembers 'infected wheat' (R), 'healthy wheat' (G) and 'soil' (B) as estimated by the MTMF (Franke et al. 2008)

wavebands and waveband combinations are identified. Temporary changes in waveband compositions will be observed, as well as the difference between near-range and airborne hyperspectral data to bridge the gap between both scales. Figure 7.7 shows the experimental setup on the left and a false-colour-composite with hyperspectral data on the right. The composite shows high potential of the data with high spectral resolution. Different variants within the 4 ha field can even be visually identified. Further analyses point out which bands are relevant to discriminate stressed and vital wheat areas at specific phonological stages. In addition, the spectral resolution of the data will be resampled to get an idea about the optimal bandwidth for crop stress detection.

The ongoing research focuses on band selection methods to reduce data redundancy which should result in a minimum number of spectral bands relevant for precision crop protection. To use scale-related terminology, a reduction of the extent, i.e. the spectral range, will be analyzed. First results show that not only bands in the visible spectrum but also wavelengths in the SWIR are suitable for a discrimination of stressed wheat areas (Mewes et al. 2009). A combination of bands in the visible with bands in the NIR and SWIR enhances the classification results in this study. However, not all bands of hyperspectral data are needed for this purpose. In addition, the grain of the spectral dimension, i.e., spectral resolution, has to be considered, whereby the optimal spectral sample frequency should be defined.

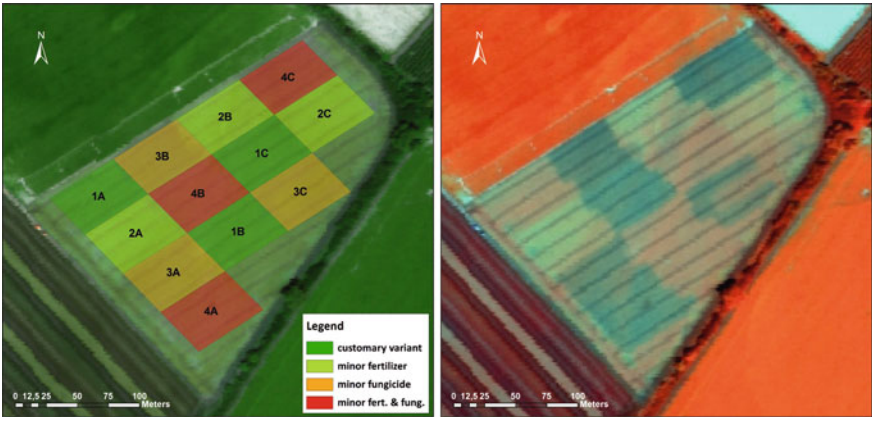

Fig. 7.7 Map of a winter wheat field with subplots differently treated with agrochemicals (vector data over true-colour RGB from AISA data) (*left*), false-colour AISA image taken on 01/07/2008 (R: 490 nm, G: 552 nm, B: 810 nm) (*right*). *Dark lines* represent the tractor lanes

5 Conclusion

Precision crop protection has specific requirements on *spatial, temporal and spectral* characteristics of sensor data used to derive relevant information on crop status. Studies that focus on the effect of these characteristics on the detection accuracy of crop growth heterogeneities are fundamental to implement remote sensing techniques in precision crop protection. The objective of the present chapter was therefore to highlight relevant analyses with respect to these dimensions of sensing data. The analysis of the influence of spatial scale of remote sensing data on precision crop protection suggests a threshold value of 6 m spatial resolution. As a result, the identification of site-specific plant stress with remote sensing techniques requires extremely high spatial resolutions. At present, these high spatial resolutions are only provided by airborne sensors or very few satellite systems. The disadvantages of these satellite systems are the very small Instantaneous Field of View (IFOV) and a low temporal and spectral resolution. However, the RapidEye satellite sensors with spatial resolutions up to 6.5 m that were launched in 2008 do not exhibit this spatial disadvantage so that restriction for the use of remote sensing data concerning spatial resolution can be resolved.

The temporal scale of precision crop protection exhibits a dimension with high complexity. It is affected by various factors such as the crop stress type and their different temporal dynamics, crop growth characteristics, trend of environmental conditions, type of sensor for stress monitoring, data processing time, weather conditions and specific times for agrochemical applications. Due to this complexity, the use of sensor-based techniques such as remote sensing in precision crop protection is rather challenging. The results of this chapter demonstrated that required temporal resolution of stress detection systems OS_t and the temporal scale of crop protection management MS_t is primarily dominated by individual characteristics of stress phenomena PS_t. Hence, the phenomenon of interest dictates the requirements on temporal scale-related characteristics of remote sensing techniques and stress control mechanisms.

Concluding the considerations about the spectral dimension of sensor data for precision crop protection, it can be stated that hyperspectral data, either near-range or remote sensing, have a high potential for detection of crop stress symptoms. There are obvious interdependencies between the spatial and the spectral resolution; i.e., for near-range and airborne/satellite-borne data different wavebands are relevant. The interdependencies between temporal and spectral resolution, or which wavebands are relevant at specific phenological stages, have to be considered as well. However, further work is needed to explore the spectral scale in detail, i.e., spectral extent and spectral grain of the data.

To control spatiotemporally dynamic systems such as crop stress in precision crop protection, decision support systems are necessary that integrate all relevant driving factors. Either for an experimental design or for the implementation of certain techniques in precision crop protection, the importance of scale-related issues always has to be taken into consideration.

References

Apan A, Held A, Phinn S, Markley J (2003) Formulation and assessment of narrow-band vegetation indices from EO-1 Hyperion imagery for discriminating sugarcane disease. Proceedings of the Spatial Sciences Conference, Canberra, 2003

Apan A, Held A, Phinn S, Markley J (2004) Detecting sugarcane 'orange rust' disease using EO–1 Hyperion hyperspectral imagery. Int J Rem Sens 25:489–498

Asner GP (2004) Biophysical remote sensing signatures of arid and semiarid ecosystems. In: Ustin SL (ed) Remote sensing for natural resource management and environmental monitoring. ASPRS, Wiley, New York, pp 53–109

Asner GPA, Martin RE (2008) Spectral and chemical analysis of tropical forests: scaling from leaf to canopy levels. Rem Sens Environ 112:3958–3970

Blackburn GA (1998) Quantifying chlorophylls and carotenoids at leaf and canopy scales: An evaluation of some hyperspectral approaches. Rem Sens Environ 66:273–285

Blaschke T, Petch J (1999) Landscape structure and scale: comparative studies on some landscape indices in Germany and the UK. In: Maudsley MJ, Marshall EJP (eds) Heterogeneity in landscape ecology. IALE, Bristol, pp 75–84

Bravo C, Moshou D, West JS et al (2003) Early disease detection in wheat fields using spectral reflectance. Biosyst Eng 84:137–145

Cao C, Lam NS (1997) Understanding the scale and resolution effect in remote sensing and GIS. In: Quattrochi DA, Goodchild MF (eds) Scale in remote sensing and GIS. CRC Lewis, Boca Raton, pp 57–72

Carter GA, Estep L (1994) Ratios of leaf reflectances in narrow wavebands as indicators of plant stress. Int J Rem Sens 15:697–703

Curran PJ (1989) Remote sensing of foliar chemistry. Rem Sens Environ 30:271–278

Dammer KH, Thöle H, Volk T, Hau B (2008) Variable-rate fungicide spraying in real time by combining a plant cover sensor and a decision support system. Prec Agric, Online first. Published online Nov 2008

Flaten JA, Parendo KA (2001) Pendulum waves: a lesson in aliasing. Am J Phys 69:778–782
Franke J, Gebhardt S, Menz G, Helfrich HP (2009) Geo-statistical analysis of the spatiotemporal dynamics of powdery mildew and leaf rust in wheat. Phytopathology 99:974–984
Franke J, Menz G (2007) Multi-temporal wheat disease detection by multi-spectral; remote sensing;. Prec Agric 8:161–172
Franke J, Menz G (2008) Spatiotemporal dynamics of stress factors in crops analysed by multisensoral remote sensing and geo-statistics. Vdm-Verlag, Saarbrücken, p 142
Franke J, Mewes T, Menz G (2008) Airborne hyperspectral imaging for the detection of powdery mildew in wheat. Proceedings of the SPIE Optics & Photonics, San Diego, 2008
Goodchild MF, Mark DM (1987) The fractal nature of geographic phenomena. Ann Assoc Am Geogr 77:265–278
Gustafson EJ (1998) Quantifying landscape spatial pattern: what is the state of the art? Ecosystems 1:143–156
Hill MJ (2004) Grazing agriculture: managed pasture, grassland, and rangeland. In: Ustin SL (ed) Remote sensing for natural resource management and environmental monitoring. ASPRS, Wiley, New York, pp 449–530
Jackson RD, Pinter PJ, Reginato RJ, Idso SB (1986) Detection and evaluation of plant stresses for crop management decisions. IEEE Trans Geosci Rem Sens 24:99–106
Jacobi J, Kühbauch W (2005) Site-specific identification of fungal infection and nitrogen deficiency in wheat crop using remote sensing. Proceedings of the 5th European Conference on Precision Agriculture, Stafford, 2005
Jain N, Shibendu SR, Singh JP, Panigraphy S (2007) Use of hyperspectral data to assess the effect of different nitrogen applications on a potato crop. Prec Agric 8:225–239
Lorenzen B, Jensen A (1989) Changes in leaf spectral properties induced in barley by cereal powdery mildew. Rem Sens Environ 27:201–209
Lucas JA (1998) Plant pathology and plant pathogens. Blackwell Publishing, Oxford
Madden LV (2006) Botanical epidemiology: some key advances and its continuing role in disease management. Eur J Plant Pathol 115:3–23
McBratney A, Whelan B, Ancev T, Bouma J (2005) Future direction of precision agriculture. Prec Agric 6:7–23
McGarigal K, Marks B (1994) FRAGSTATS – Spatial pattern analysis program for quantifying landscape structure. Forest Science Department, Oregon State University, Corvallis
Mewes T, Franke J, Menz G (2008) Multitemporal spectroscopy for crop stress detection using band selection methods. Proceedings of the SPIE – Optics & Photonics, San Diego, 2008
Mewes T, Franke J, Menz G (2009) Data reduction of hyperspectral remote sensing data for crop stress detection. Proceedings of the IGARSS, Cape Town, 2009
Moran MS, Inoue Y, Barnes EM (1997) Opportunities and limitations for image-based remote sensing in precision crop management. Rem Sens Environ 61:319–346
Moshou D, Bravo C, Wahlen S et al (2006) Plant stress type identification based on optical sensing and self-organising neural networks. Prec Agric 7:149–164
Musick HB, Grover HD (1991) Image textural measures as indices of landscape pattern. In: Turner MG, Gardner RH (eds) Quantitative methods in landscape ecology. The analysis and interpretation of landscape heterogeneity. Springer, New York, pp 77–103
Nelson SC, Campbell CL (1993) Comparative spatial analysis of foliar epidemics on winter clover caused by viruses, fungi and a bacterium. Phytopathology 83:288–301
Nutter FW Jr (1997) Quantifying the temporal dynamics of plant virus epidemics: a review. Crop Prot 16:603–618
O'Neill RV, Hundsaker CT, Timmins SP et al (1996) Scale problems in reporting landscape pattern at regional scale. Landscape Ecol 11:169–180
O'Neill RV, King AW (1998) To St. Michael; or, why are there so many books on scale? In: Peterson DL, Parker VT (eds) Ecological scale: theory and applications. Columbia University Press, New York, pp 1–5
O'Neill RV, Krummel J, Gardner R et al (1988) Indices of landscape pattern. Landscape Ecol 2:153–162

Quattrochi DA, Pelletier RE (1991) Remote sensing for analysis of landscapes. An introduction. In: Turner MG, Gardner RH (eds) Quantitative methods in landscape ecology. The analysis and interpretation of landscape heterogeneity. Springer, New York, pp 51–76

Savary S, Cooke BM (2006) Foreword. Eur J Plant Pathol 115:1–2

Shannon C, Weaver W (1964) The mathematical theory of communication. University of Illinois Press, Urbana

Shaw D, Kelley F (2005) Evaluating remote sensing for determining and classifying soybean anomalies. Prec Agric 6:421–429

Tubajika KM, Civerolo EL, Ciomperlik MA et al (2004) Analysis of the spatial patterns of Pierce's disease incidence in the lower San Joaquin Valley in California. Phytopathology 94:1136–1144

Turner MG, O'Neill RV, Gardner RH, Milne BT (1989) Effects of changing spatial scale on the analysis of landscape pattern. Landscape Ecol 3:153–162

Voß K (2004) Remote sensing and landscape metrics to identify and to assess site-specific damage in cultivation systems of Central Europe. Erdkunde 58:283–289

West JS, Bravo C, Oberti R et al (2003) The potential of optical canopy measurement for targeted control of field crop diseases. Ann Rev Phytopathol 41:593–614

Wiltshire J, Clark WS, Riding A et al (2002) Spectral reflectance as a basis for in-field sensing of crop canopies for precision husbandry of winter wheat. HGCA Project Report No. 288

Yoder BJ, Pettigrew-Crosby RE (1995) Predicting nitrogen and chlorophyll content and concentrations from reflectance spectra (400–2,500 nm) at leaf and canopy scales. Rem Sens Environm 53:199–211

Xia ZG, Clarke KC (1997) Approaches of scaling geo-spatial data. In: Quattrochi DA, Goodchild MF (eds) Scale in remote sensing and GIS. CRC Lewis, Boca Raton, pp 309–360

Chapter 8
Detection and Identification of Weeds

Martin Weis and Markus Sökefeld

Abstract This chapter reviews the approaches for the automation of weed detection. Site-specific plant protection needs to address the varying weed infestation, but the automation is only partially solved and research is still ongoing. The properties for plant species distinction as well as approaches that use them are presented. The focus is on image based methods, of which an example is given.

1 Introduction

The detection of weeds is the prerequisite for successful site-specific weed management. For a uniform treatment the average weed infestation level, weed species composition and growth stages of weeds and crop have to be known. Herbicides or mechanical weed control methods are applied uniformly across the total field, if the economic weed threshold is exceeded. The spatial and temporal variation of weed populations needs to be assessed, if the treatment should vary within a field. It is also needed to select and adapt the herbicide mixture. Commonly, the number of weeds per square meter and/or the weed coverage for each species are measured. This data can be used to estimate the expected yield loss and to decide for each part of the field which weed control method is warranted.

Different methods have been proposed to assess the weed infestation within a field. The most common approach is the weed scouting by human experts. This approach can be done by the experienced farmer or a consultant. An expert can take the history of the weed infestation over the years into account and focus on the most prominent weed species, which are relevant for the yield loss. Different sampling schemes for the within-field estimation were used. Weed infestation can be measured by regular or irregular sampling. Positions of the sampling points can

M. Weis (✉)
Department of Weed Science, Institute for Phytomedicine, University of Hohenheim, Stuttgart D-70599, Germany
e-mail: martin.weis@uni-hohenheim.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_8,

be determined using a local coordinate system and regular distances between the sampling points, or their coordinates can directly be measured with GPS (Global Positioning System) technology. Most studies used a sampling scheme which was constrained by the time and manpower available. The effect of different grid sizes and interpolation techniques have been discussed by Backes et al. (2005), Hamouz et al. (2006), and Heijting et al. (2007). Many weed patches remained undetected, if the grid size exceeded a distance of 15–30 m between the sampling points. An economic evaluation of the manual sampling versus an automatic approach was done by Oebel and Gerhards (2005), estimated costs are about 60€/ha for the manual sampling at regular spaced grid points (8×8 m). The use of a mobile GIS (geographic information system) to map the infestation reduced the costs to 26€/ha.

Since the manual weed sampling is too expensive for practice-oriented management, automatic methods to assess the infestation have been developed (Brown and Noble 2005). Automatic weed sampling provides a way to increase the amount data gathered in the field (smaller sampling intervals) at lower overall costs of 6–11€/ha (Oebel and Gerhards 2005). Sensor technology has already been used to apply herbicides site-specifically, resulting in 30–70% reduction of herbicide use. Depending on the application technology the sensor design has to be adapted; if small robots are used to manage weeds, the driving speed may be lower than with a boom-sprayer.

2 Properties to Distinguish Plant Species

To distinguish plant species from each other, certain characteristic properties have to be identified, which can be measured automatically. Experts identify species by their shape and plant morphology. The location of a plant is a useful property to distinguish species, on the large scale there are several habitats, on the small scale there are locations within a field with a higher probability of occurrence, e.g. at the borders of a field, on certain soil types or between the rows in row cropping systems. In the following sections useful properties for distinguishing plant species are evaluated.

2.1 Spectral Properties

Intact green plants transform the incoming light by their chlorophyll pigments, which absorb mostly red as well as violet and blue light. Only a fraction of the green and most of the near infrared light is reflected. The spectral reflectance of plants has a minimum in the visible wavelengths of about 650 nm and increases towards the invisible near infrared above 700 nm. The steep part of the curve is called the 'red edge' (Fig. 8.1; Guyot et al. 1992). Plant characteristics – chlorophyll content, leaf area index LAI, biomass and water status, age, plant health levels (Shafri et al. 2006) – can be derived from the position of the red edge (REP), usually

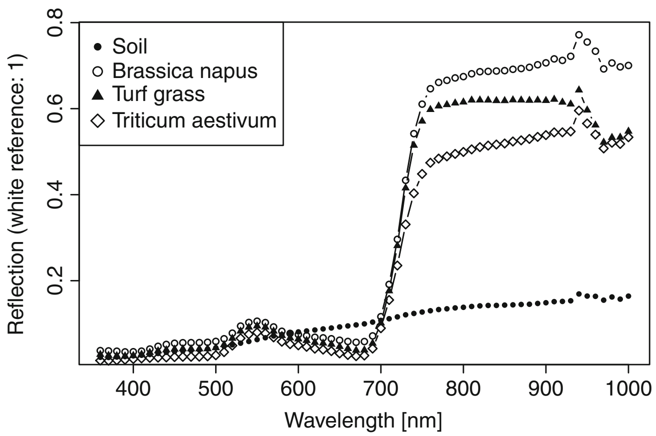

Fig. 8.1 Reflectance curves for soil (*filled dots*) and different plant species with the typical steep incline (*red edge*) between 680 and 750 nm wavelength

determined by the position of the turning point (point of maximum slope). The spectral curves of different plants have a similar nonlinear shape, but the soil curve in Fig. 8.1 is linear. The local extremes of the plant curves are within the green band (550 nm, maximum), the red band (660 nm, minimum) and near infrared (750 nm, maximum).

Several spectral indices have been proposed that make use of the different reflectance in the green (G), infrared (IR) and red (R) part of the spectrum. Ratios or subtraction of the values at the extremes lead to the highest differences for plants and soil and are therefore useful for the discrimination of plants against their background. From Fig. 8.1 we can conclude, that the highest difference exists in the near infrared and red spectrum (see also image example in Fig. 8.4). One important index is the normalised difference vegetation index NDVI (Eq. 1), the values are normalised to the interval $[-1, 1]$, with values near one meaning a high amount of chlorophyll. This index correlates well with the biomass and LAI and has been used in remote sensing applications (Godwin and Miller 2003, López-Granados et al. 2006, Reyniers et al. 2006) and for near-range sensors to measure plant biomass production, crop vitality and to forecast crop yield. A few commercial products for weed control with optoelectronic equipment exist that use this spectral information: DetectSpray® (evaluated by Biller 1998) and WeedSeeker® (used by Sui et al. 2008).

Depending on the availability of the measured wavelengths several indices have been used and compared to identify living plant material against the background (Woebbecke et al. 1995, Meyer and Neto 2008). The soil adjusted vegetation index (SAVI, Eq. 1) introduces a variable *L* into the formula of the NDVI. *L* can be used to adjust for the soil component; values near 0 are used for high vegetation cover. Variations of these indices exist; Haboudane et al. (2004) compared several indices for an estimation of the leaf area index. Langner et al. (2006) developed an index called DIRT (difference index with red threshold) to improve the contrast between plants and background in mulched areas (DIRT = sign(β - R) NDVI, with β = 0.12).

$$\begin{aligned} &NDVI = (IR - R)/(IR + R) \\ &SAVI = [(IR - R)/(IR + R + L)](1 + L); L[0, 1] \\ &EGI = 2G - R - B \\ &NDI = (G - R)/(G + R) \end{aligned} \tag{1}$$

Transforming RGB colour space images into the HSI (hue, saturation, intensity) colour space leaves the brightness in the intensity channel and colour information in the hue and saturation channels, which then can be used to identify green parts. For standard RGB images the excess green index EGI has proven to be useful for the enhancement of green plant material in many studies (Rasmussen et al. 2007, Burgos-Artizzu et al. 2008). An example for the EGI is shown in Fig. 8.2. Equation (1) contains the formulae for the most important indices.

The spectral reflectance is influenced not only by the plant characteristics, but also depends on the illumination conditions. Atmospheric changes lead on the one hand to different spectral characteristics of the illumination, on the other hand the amplitudes can vary much; direct sun and cloudy conditions differ by factors of 1,000 or more in the amount of light. Therefore some approaches use controlled conditions with artificial lighting and exclude the natural illumination. Artificial lighting equipment has the advantage to make the measurement independent of the external illumination conditions.

Piron et al. (2008) evaluated 22 wavelength bands for weed and crop (carrots) discrimination, and found an optimum with three wavelengths at 450, 550 and 750 nm, reaching a classification accuracy of about 65% for carrots and 80% for weeds. They used artificial lighting to reduce the variability of the natural light conditions in the field. Paap et al. (2008) used a line sensor and LED illumination (635, 670 and 785 nm) to distinguish plants from background. Several approaches explored the spectrometric properties to distinguish different species. Zwiggelaar (1998) found the spectral properties alone not to be able to discriminate all weed species. In more specific cases the spectral information was successfully used to discriminate weed and crop. Borregaard et al. (2000) used a line scanning spectrometer with artificial

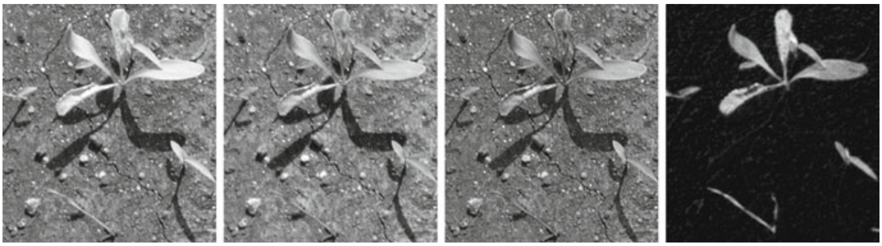

Fig. 8.2 *Green*, *red* and *blue* components of a standard RGB camera combined to EGI image (from *left* to *right*), enhancing the plants (*bright*) against the background (*dark*). *Gray* values were stretched for better contrast in print

light and were successful in discrimination of plant and soil as well as crops (sugar beet and potatoes) and three weed species. They used stepwise linear discriminant analysis to select six wavelengths (694, 970, 856, 686, 726 and 897 nm), of which they found the first three to be able to discriminate the five species with an accuracy of 60% and crop and weeds with an accuracy of 90%. Girma et al. (2005) selected five bands between 515 and 865 nm and ratios of them (515/675, 555/675, 805/815, and 755) to distinguish two weed species and winter wheat under controlled conditions (greenhouse). Two trials led to classification accuracies of 64 and 90%. Wang et al. (2001) also selected five wavelengths (496, 546, 614, 676, and 752 nm) and reached 62–86% classification accuracy for the discrimination of nine grouped weed species, soil and wheat. Okamoto et al. (2007) use a spectrometric line sensor with 420 channels of 10 nm to distinguish sugar beet and four weed species with a success rate of about 75–89%, if the data were transformed by a wavelet decomposition and classified using selected wavelet coefficients.

2.1.1 Remote Sensing

Lamb and Brown (2001) reviewed the use of remote sensing (RS) imaging for weed detection. They conclude, that the use of remote sensing is limited in general due to the low spatial resolution, which does not permit the analysis of weeds on a sub-field scale.

A high infestation level of weeds within patches is accompanied by locally increased biomass production. Early in the season the effect can be used to locate the patches, if the weeds germinate earlier than the crop. Backes and Jacobi (2006) explored remote sensing techniques to detect patches of dicotyledonous weeds in sugar beet using the NDVI.

Thorp and Tian (2004) identified the problem, that the spectral measurements are mixed signals of soil and plant material. The proposed analysis methods for weed detection have to be improved and further developed to reliably detect different weed species, not only local changes in biomass density. Another problem remains the availability of up-to-date imaging material, since RS sensors need clear sky conditions (without clouds) and their update cycles might be of too large intervals. Later in the season patches can be identified using RS: López-Granados et al. (2006) used hyperspectral RS to map grass weed infestations in wheat late in the season. Their accuracies for the grass weed patch detection were about 90%.

2.1.2 Fluorescence

Chlorophyll fluorescence of the plant photosystem is an indicator for the effectiveness of the photosynthesis. The fluorescence intensity shows a typical temporal change after saturation of the photosynthesis system with light, called the Kautsky effect. Kautsky functions indicate healthiness of the plants but can also be used to distinguish different species due to the different leaf structure and leaf angle of grasses and dicotyledons. The fluorescence effect can be used to distinguish living plants from other objects and may lead to methods for species discrimination in the future. A problem for online weed identification is the time of measurement, since the effect can be explored best when the measurements are taken over a certain period of time (seconds to minutes). Current research tries to explore shorter measurements, which may lead to suitable sensing equipment for online species discrimination in the future. Keränen et al. (2003) reduced the measurement time by reducing the pre-measurement dark adaption period to practicable times under field conditions. They were able to distinguish six species using a neural network classifier.

2.2 Location and Temporal Properties

The location of plant species can be used to identify them. Most weeds occur in patches within a field (Heijting et al. 2007) and their location was found to be stable over years. This effect is due to persistent seed banks in the soil and variable germination conditions. The germination rate is higher in areas with a high seed density. Perennial weeds have additional vegetative reproduction organs such as rhizomes, tubers and roots, from which the plants regenerate (e.g. *Convolvulus arvensis, Cyperus esculentus, Cirsium arvense, Agropyron repens*). Therefore, patches of perennial weeds were found to be most aggregated and stable. Historical maps can be used to predict the occurrence of weeds (Dille et al. 2002, Mortensen 2002). This information is especially useful for preemergence herbicide applications.

The position of weeds can also be helpful on a smaller scale, the plant level. In row crops weeds can be detected between the rows, since no crop plant is expected to grow there. Sensors detecting green plants between the rows have successfully been used for this purpose (Åstrand and Baerveldt 2004). Slaughter et al. (2008) described the robust weed detection as a primary obstacle for robotic weed control technology and review the approaches for weed detection as well as actuator technology.

Several image processing approaches for row detection have been proposed, most of them using standard RGB images. Bossu et al. (2009) determined crop rows for intra-row weed detection and Jones et al. (2007) developed a system to create artificial images to test weed detection algorithms in crop rows. Bakker et al. (2008) used a Hough transformation to detect linear structures in images to find the rows. Åstrand and Baerveldt (2004) modelled Gaussian location probability functions for the crop plants in the row and locate the weed plants at locations with low probability values, either between the rows or within the row at locations between crop plants. Burgos-Artizzu et al. (2008) used large row spacing (barley) and the column sums of the intensities to determine crop rows. They determined crop rows and used additional (expert) knowledge about the scenes to determine optimal parameters for the image processing and feature extraction process.

2.2.1 Morphological Properties

The morphology of the plants is important for the determination of the species by a human expert. Dicotyledons and monocotyledons have a different morphology, e.g. the number of cotyledons and the structure, compactness and diameter of the leaves, which contribute to the overall appearance.

The third dimension can provide information about the orientation of the leaves and the height above ground and leaf structure. The three-dimensional (3D) structure of the plants is a feature, which has not yet been investigated often. Reasons are that the acquisition of suitable 3D data is computationally intensive or requires special 3D measuring equipment, which became available in the recent years. Chapron et al. (1999) and Andersen et al. (2005) proposed a stereo vision method, extracting height information from two aligned images. The height information can be used to detect overlapping of leaves and can be helpful to separate leaves above others from the ones below.

2.2.2 Overlapping

Occlusion and overlapping is one of main problems for all image processing approaches. The plants in the images, especially the long-leaved ones like cereals and grass weeds, tend to overlap. Overlapped leaves are segmented as one object, since they lead to connected regions, of which parts belong to different plants. It is difficult to detect and separate these leaves from each other, since therefore context information is necessary to assemble occluded leaf shape and assign these to plants. The mentioned 3D approaches provide segment information directly, and a few 2D image processing techniques have been used to overcome this situation (Søgaard and Heisel 2002, Manh et al. 2001, Neto et al. 2006a). These approaches are based on heuristics about the occluded parts. Piron et al. (2009) combine stereoscopic multispectral images with height information from a coded structered light technique, which uses a projected known pattern to derive the distance to the camera.

2.2.3 Texture

More general approaches distinguish plant species based on the texture, which is different for overlapped broad leaved and narrow leaved plants in cluttered conditions. Ishak et al. (2009) present a texture analysis for images of two weed species (a broadleaved and a grass weed) in late growth stage. Weeds in grassland require different approaches, because the plants cannot be separated to single plants from the background (soil), because the overall coverage is very high and the plants overlap. But the most important weeds in grassland have leaves with a different morphology (bigger, broader and more homogeneous surface). These properties can be quantified by textural analysis of 2D images. Gebhardt and Kühbauch (2007b) segmented the image according to a homogeneity criterion and use a textural and colour features to find *Rumex obtusifolius*, *Taraxacum officinale* and *Plantago major* in a grassland plant community with an accuracy of over 70%. Van Evert et al. (2009) used a partial 2D Fourier transformation to determine homogeneous regions, which were identified to be the broadleaved weed leaves of *R. obtusifolius*. From 3D sensor data Šeatović (2008) segmented broad leaves and classified them as weeds in grassland. Klose et al. (2008) developed a robot with weed detection capabilities in maize using a sensor fusion approach: A vertical laser triangulation sensor measuring the thickness of the maize plant stem is combined with a horizontally mounted camera viewing the maize row from above to find weeds within the row.

Morphological properties can also be explored with 2D shape features, which is the focus of the following image processing part.

3 Image Processing for Automatic Weed Species Identification

In the following the general image processing steps will be outlined. Fig. 8.3 shows the workflow of the basic steps image creation, segmentation, feature extraction and classification.

Imaging sensors like cameras or line sensors deliver 2D images of agricultural fields. These images are the input for the following image processing procedures. Depending on the type of imaging sensor the resulting images may have to be preprocessed to normalise the values or reduce noise. Noise can be reduced in the original images before segmentation into foreground and background objects takes place. Typical pre-processing steps of the original images include filtering with a low pass filter to minimise the effect of Gaussian noise or the use of median filters to suppress pixels with outlier values (zero or maximum values).

3.1 Segmentation

A segmentation of the image into regions with homogeneous properties is the next step, which results in a separation of the image according to the measured properties. One or more intermediate images can be created that enhance the contrast between object and background. In this step homogeneous regions with different gray or colour values are created. This image can be computed using one of the colour indices mentioned before, if colour images are the input, or texture features, if the image should be segmented according to the texture (e.g. grassland images). Fig. 8.4 gives an example for an IR and R difference image (IR-R), the resulting image enhances the plants (bright) and the background objects have been suppressed (dark). The enhanced image is then separated into foreground and background objects, resulting in a binary image (black/white).

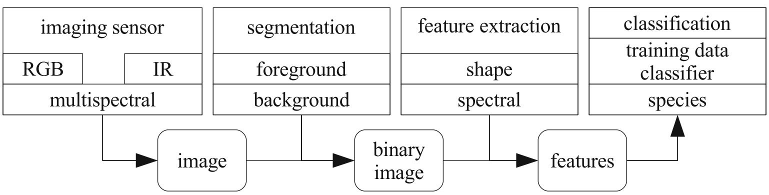

Fig. 8.3 General image processing steps leading from the image to a classification

Fig. 8.4 Example for the difference (*right*) of an infrared (*left*) and *red* (*middle*) image. Plants are bright due to the spectral difference in the red and infrared, background objects like dead material (mulch, stones) disappear in the difference image. Gray values were stretched to increase the contrast for the print version

A threshold can be used to label the enhanced regions (e.g. white), which are above the threshold and the background (e.g. black). More advanced methods use spatial homogeneity criteria to improve the segmentation (Gorretta et al. 2005). If the foreground regions have been identified, connected foreground regions can be assembled to objects. Noise may have lead to small regions in the thresholding step and can now be filtered using either a size criterion or morphological image processing (Soille 2003). Figure 8.5 shows the result of a segmentation using a threshold and pre-processing steps to reduce noise. Mathematical morphology provides erosion and dilation operators as basic filters for regions. Erosion of region leads to a shrinking, the borders of the region are cut. If an object has a hole (inner borders), this hole will grow bigger. The dilation operation does the opposite: the region grows around the border and small holes can be closed this way. Both operators can be combined to the so called opening (erosion, then dilation) and closing (dilation, then opening) operators. Since both operators are nonlinear the results of the opening and closing are different: opening tends to separate an object at small connections and prune small elongated spikes, closing can combine regions with little distance into one, e.g. leaves which have been separated by the thresholding. It may also happen that small regions disappear in the opening step, which are then gone in the dilation step of an opening. Figure 8.5 (right) shows the result of a morphological closing, leading to connected regions for the dicotyledonous leaves near the centre of the image and the elongated leaves in the top left.

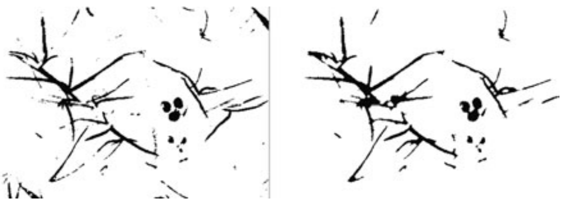

Fig. 8.5 Binarisation and preprocessing of the difference image in Fig. 8.4. *Left*: the result of the thresholding, *right*: the result after applying morphological operators (closing with circle of 5 pixel diameter) and area size selection (regions with more than 30 pixel), as well as discarding regions which are cut by the image border. Foreground objects are black, the background is white

Morphological operators were used by Hemming and Rath (2001) to extract broad leaves from scenes with overlaps. Pérez et al. (2000) used morphological operators to separate the germination leaves of dicotyledonous weeds and analyse the shape of each leaf.

The resulting blobs are the objects of interest for the following feature extraction. Shape, texture or colour features (the latter derived from the input image) describe the properties of each foreground object in the image. These features are used for a classification of each object in the image.

3.2 Shape-Based Weed Discrimination

Several researchers used shape features to discriminate weed and crop (Gerhards and Christensen 2003, Åstrand and Baerveldt 2004, Berge et al. 2008). The shape features were derived for each connected foreground region. Image processing techniques provide a set of commonly used shape features. To describe the shape of a region one of the simplest feature is the size, expressed either in number of pixels or scaled by the ground resolution. There may be objects of different size, but with similar overall shape characteristics (geometrically congruent). Therefore shape descriptors have been developed which are invariant to the size of the region. Two other properties are often not relevant for the shape description: the position and the orientation of a region within the image. Certain shape descriptors are normalised and invariant to translation, rotation and size. Some well known invariant features are derived from statistical moments of the pixel distribution (Hu features; Hu 1962). This type of features is called region-based, since they are derived from the spatial distribution of the region pixels.

Other features are computed from the outline of a region, given by the border pixels that have neighbouring background pixels. Since the border of an object is a closed contour, a periodic representation can be derived (either using a chain code or polar coordinates; see Jähne 2001 for details). Fourier analysis can be used to analyse the periodic representation (Neto et al. 2006b). The resulting parameters are phases and amplitudes of periodic functions, which can easily be normalised to translation, rotation and size invariant parameters, since this information is located only in the first two of them. The lower order parameters contain the overall shape of the object and the higher order parameters contain information about the small scale curvature changes of the contour (notches and small convexities). A curvature description can be derived from the contour, if it is computed for different scales (by smoothing), then this is called a CSS (curvature scale space) representation (Mokhtarian et al. 1996). Zhang and Lu (2004) review shape description techniques and distinguish between region-based and contour- based ones.

We found also skeleton features helpful for the discrimination of plant species (Weis and Gerhards 2007). The skeleton is the central line (also called core) of a region, and can be derived from a distance transform of the region or by morphological operators (Soille 2003). A distance transform assigns a distance value to each region pixel: the shortest distance to the contour. Local maxima form a line which

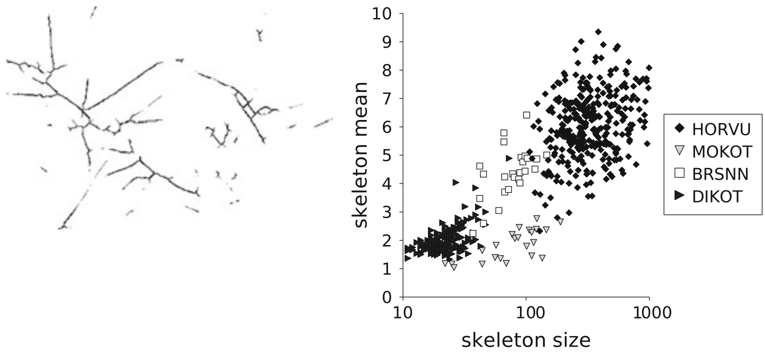

Fig. 8.6 *Left*: skeleton of image in Fig. 8.5. *Right*: two skeleton features (size and mean distance to leaf border) for *Hordeum vulgare* (HORVU), monocotyledons (MOKOT), *Brassica napus* (BRSSN) and dicotyledonous weeds (DIKOT) in the feature space

is located in the middle of the object and with maximum distance to the borders. Statistical measures (mean, maximum, variance, number of pixels) of these maxima yield a thickness description of the shape, which is especially useful to discriminate broad and narrow leaved species, since the core of a broad leaf has a bigger distance to the border than elongated, thin leaves. Figure 8.6 shows the distribution of four different classes in the feature space of two skeleton features. These features are well suited to discriminate these classes, since the classes have a clustered occurrence in the feature space.

There exist also 'high level' shape descriptions, that involve models for the shape description and try to fit the model to the shape. Søgaard and Heisel (2002) and Manh et al. (2001) used active shape models respectively deformable templates for the species discrimination. Templates of various shapes are generated and parametrised (these parameters are the features) and the deformations necessary to match the templates to the shape lead to a similarity measure. The more a model has to be deformed to fit the shape, the higher is the dissimilarity. One problem with these models is the comparably high complexity of the description, leading to a high dimensional search space of the parameters and therefore a high computational load. On the other hand these models can deal with partial occlusion.

3.3 Classification

All numeric features can be combined to feature vectors. The according feature space has as many dimensions as there are features and is usually high dimensional. A high dimensionality of the feature space opposed to the relatively low number of training samples exposes the problem that the samples are 'vanishing' in the space and can decrease the performance of a classifier, this is known as the 'curse of dimensionality'. Features without discriminative abilities to the problem introduce noise into the classification process. Therefore a feature selection process should be performed before classification, aiming at the reduction of the number of features to the most relevant ones. Combinations of features can lead to new features with higher discriminative abilities. An example for the combination of features are the spectral indices (see Eq. 1), combining the amplitude values of different wavelengths to a new value. A popular feature selection algorithm is discriminant analysis (Cho et al. 2002, Borregaard et al. 2000, Gebhardt and Kühbauch 2007a, Neto et al. 2006b).

The classification is the last step of the analysis. Classification algorithms can be grouped into unsupervised classifiers, also known as clustering, and supervised classifiers. Unsupervised classifiers use the feature vectors without additional information and create groups of similar objects according to a distance measure of the vectors in the feature space. These groups are called clusters and may refer to classes of the problem. A supervised classifier has to be trained with prototype information, which are selected feature vectors of known class. Classifiers compare the features of the unknown objects to the trained ones and assign a class. The number of classification algorithms is large, ranging from simple algorithms like kNN (k-nearest-neighbour), that uses the training data directly, to complex functions and function systems like neural networks, tree classifiers or support vector machines, which generate a classifier model from the training set and use that for the classification. Cho et al. (2002) successfully trained neural networks, Pérez et al. (2000) used Bayes rules and a nearest neighbour classifier with shape features. Burks et al. (2005) used neural networks to classify texture features.

A shape based approach was tested by Oebel (2006) under field conditions, the classification accuracies were suitable for the creation of application maps. Table 8.1 shows the detailed results for *Zea mays* and *Hordeum vulgare* crops using discriminant analysis.

Table 8.1 Confusion matrices (predicted and true class in percent) for *Zea mays* (corn, ZEAMX, left) and *Hordeum vulgare* (spring barley, HORVS, right), taken from Oebel (2006)

pred\true	ZEAMX	DICOT	MOCOT	CHEAL	pred\true	HORVS	DICOT	MOCOT	GALAP
ZEAMX	100	0	0	0	HORVS	97	4	4	4
DICOT	0	98	1	1	DICOT	0	87	9	5
MOCOT	0	6	90	4	MOCOT	0	4	93	0
CHEAL	0	11	0	89	GALAP	0	0	0	100

DICOT: dicotyledonous weeds, MOCOT: monocotyledonous weeds, CHEAL: *Chenopodium album*, GALAP: *Galium aparine*. The test sets were independent from the training data with more than 500 samples each

An example for a classification with shape features (region-based, Fourier and skeleton features) is shown in Fig. 8.7. The image was composed of samples from several IR-R difference images. A small training set was created containing prototypes of the species. Nine different species have been classified using a radial basis function network classifier. The objects in the image were labelled according to the classification result.

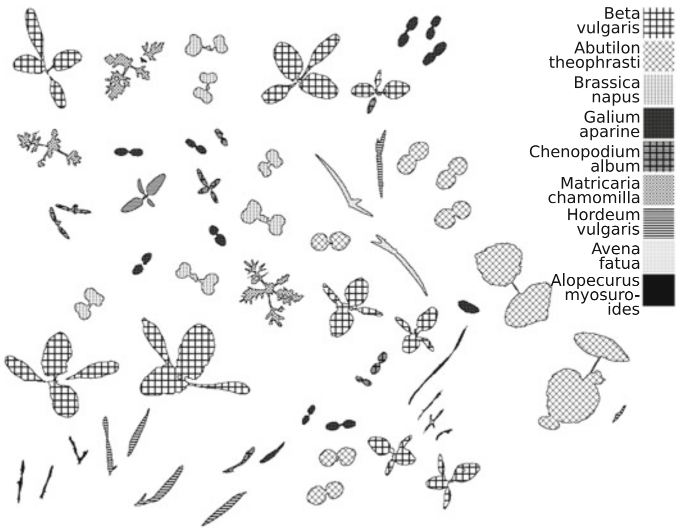

Fig. 8.7 Labelled image, each region is labelled with the classification result (the species)

The shape based approach has its limitations due to the number of plant species and the shape variability within different growth stages of each species. A class scheme was developed (Weis and Gerhards 2007) for these variations and used to create training data for various weed and crop species.

4 Conclusions

The automation of weed detection in the field is a very challenging topic, which is a current research topic of several working groups. The complexity of this task originates in the variability of the plant species in the field. Several plant properties have been presented, which can be used to distinguish species. Approaches and results, achieved with available sensor technology, were reviewed. Some sensors were already used successfully for weed detection and discrimination under controlled conditions and also in field experiments, but yet there is no general best practice to achieve this, especially under changing conditions within the field. The combination of different techniques might lead to robust solutions in the future. Sensor fusion and integrative analysis of multiple sensor data could improve the weed detection rate and also influence other precision-farming technologies. Commercial products like special sensors and analysis equipment for this task are to be developed. If such systems are available, the weed infestation can be assessed for site-specific management and population dynamics research. These will add valuable data for precision farming applications and decision support systems.

References

Andersen HJ, Reng L, Kirk K (2005) Geometric plant properties by relaxed stereo vision using simulated annealing. Comput Electron Agric 49:219–232

Åstrand B, Baerveldt AJ (2004) Plant recognition and localization using context information. In: Proceedings of the Mechatronics and Robotics 2004 (MechRob2004), Sascha Eysoldt Verlag, Aachen, pp 1191–1196

Backes M, Jacobi J (2006) Classification of weed patches in Quickbird images: verification by ground truth data. EARSeL eProceedings 5:173–179

Backes M, Schumacher D, Plümer L (2005) The sampling problem in weed control. Are currently applied sampling strategies adequate for site-specific weed control. In: Stafford J (ed) Precision agriculture 2005. Wageningen Academic Publishers, Wageningen, pp 155–161

Bakker T, Wouters H, van Asselt K et al (2008) A vision based row detection system for sugar beet. Comput Electron Agric 60:87–95

Berge T, Aastveit A, Fykse H (2008) Evaluation of an algorithm for automatic detection of broad-leaved weeds in spring cereals. Prec Agric 9:391–405

Biller RH (1998) Reduced input of herbicides by use of optoelectronic sensors. J Agric Eng Res 71:357–362

Borregaard T, Nielsen H, Nørgaard L, Have H (2000) Crop-weed discrimination by line imaging spectroscopy. J Agric Eng Res 75:389–400

Bossu J, Gée C, Jones G, Truchetet F (2009) Wavelet transform to discriminate between crop and weed in perspective agronomic images. Comput Electron Agric 65:133–143

Brown R, Noble S (2005) Site-specific weed management: sensing requirements – what do we need to see? Weed Sci 53:252–258

Burgos-Artizzu XP, Ribeiro A, Tellaeche A et al (2009) Improving weed pressure assessment using digital images from an experience-based reasoning approach. Comput Electron Agric 65: 176–185, doi:10.1016/j.compag.2008.09.001

Burks T, Shearer S, Heath J, Donohue K (2005) Evaluation of neural-network classifiers for weed species discrimination. Biosyst Eng 91:293–304

Chapron M, Requena-Esteso M, Boissard P, Assemat L (1999) A method for recognizing vegetal species from multispectral images. In: Stafford J (ed) Precision agriculture 1999. Sheffield Academic Press, Sheffield, pp 239–248

Cho SI, Lee DS, Jeong JY (2002) Weed-plant discrimination by machine vision and artificial neural network. Biosyst Eng 83:275–280

Dille JA, Mortensen DA, Young LJ (2002) Predicting weed species occurrence based on site properties and previous year's weed presence. Prec Agric 3:193–207

van Evert F, Polder G, van der Heijden G et al (2009) Real-time vision-based detection of *Rumex obtusifolius* in grassland. Weed Res 49:164–174

Gebhardt S, Kühbauch W (2007a) A new algorithm for automatic *Rumex obtusifolius* detection in digital images using colour and texture features and the influence of image resolution. Prec Agric 8:1–13

Gebhardt S, Kühbauch W (2007b) Continous mapping of *Rumex obtusifolius* during different grassland growths based on automatic image classification and GIS-based post processing. In: Stafford J (ed) Precision agriculture '07, 6th European Conference on Precision Agriculture (ECPA), Wageningen Academic Publishers, Wageningen, pp 499–506

Gerhards R, Christensen S (2003) Real-time weed detection, decision making and patch spraying in maize, sugar beet, winter wheat and winter barley. Weed Res 43:385–392

Girma K, Mosali J, Raun WR et al (2005) Identification of optical spectral signatures for detecting cheat and ryegrass in winter wheat. Crop Sci 45:477–485

Godwin R, Miller P (2003) A review of the technologies for mapping within-field variability. Biosyst Eng 84:393–407

Gorretta N, Fiorio C, Rabatel G, Marchant J (2005) Cabbage/weed discrimination with a region/contour based segmentation approach for multispectral images. In: Bellon Maurel V, Carbonneau A, Regnard JL et al (eds) Information and technology for sustainable fruit and vegetable production. Production, Proceedings of FRUTIC'05, AgroM ENSA Montpellier; Cemagref Montpellier; CIRAD; INRA, Cemagref, Montpellier France, pp 371–380, 7th Fruit nut and vegetable production engineering symposium, 12–16 Sep 2005

Guyot G, Baret F, Jacquemoud S (1992) Imaging spectroscopy for vegetation studies. In: Toselli F, Bodechtel J (eds) Spectroscopy: fundamentals and prospective applications. Kluwer Academic Publishers, Dordrecht, pp 145–165

Haboudane D, Miller JR, Pattey E et al (2004) Hyperspectral vegetation indices and novel algorithms for predicting green lai of crop canopies: modeling and validation in the context of precision agriculture. Rem Sens Environ 90:337–352

Hamouz P, Novakova K, Soukup J, Tyser L (2006) Evaluation of sampling and interpolation methods used for weed mapping. J Plant Dis Prot XX (special issue):205–215

Heijting S, van der Werf W, Stein A, Kropff MJ (2007) Are weed patches stable in location? Application of an explicitly two-dimensional methodology. Weed Res 47:381–395

Hemming J, Rath T (2001) Computer-vision-based weed identification under field conditions using controlled lighting. J Agric Eng Res 78:233–243

Hu MK (1962) Visual pattern recognition by moment invariants. IRE Trans Inf Theory 8:179–187

Ishak AJ, Hussain A, Mustafa MM (2009) Weed image classification using gabor wavelet and gradient field distribution. Comput Electron Agric 66:53–61

Jähne B (2001) Digital image processing, 5th edn. Springer, Berlin

Jones G, Gée C, Truchetet F (2007) Simulation of perspective agronomic images for weed detection. In: Stafford J (ed) Precision agriculture '07, 6th European Conference on Precision Agriculture (ECPA), Wageningen Academic Publishers, Wageningen, pp 507–515

Keränen M, Aro EM, Tyystjärvi E, Nevalainen O (2003) Automatic plant identification with chlorophyll fluorescence fingerprinting. Prec Agric 4:53–67

Klose R, Thiel M, Ruckelshausen A, Marquering J (2008) Weedy – a sensor fusion based autonomous field robot for selective weed control. In: VDI (ed) Land technik 2008. VDI Verlag, Stuttgart, pp 167–172

Lamb D, Brown R (2001) Remote-sensing and mapping of weeds in crops. J Agric Eng Res 78:117–125

Langner HR, Böttger H, Schmidt H (2006) A special vegetation index for the weed detection in sensor based precision agriculture. Environ Monit Assessm 117:505–518

López-Granados F, Jurado-Expósito M, Peña-Barragán JM, García-Torres L (2006) Using remote sensing for identification of late-season grass weed patches in wheat. Weed Sci 54:346–353

Manh A, Rabatel G, Assemat L, Aldon M (2001) Weed leaf image segmentation by deformable templates. J Agric Eng Res 80:139–146

Meyer GE, Neto JC (2008) Verification of color vegetation indices for automated crop imaging applications. Comput Electron Agric 63:282–293

Mokhtarian F, Abbasi S, Kittler J (1996) Robust and efficient shape indexing through curvature scale space. In: Pycock D (ed) Proceedings of the British Machine Vision Conference 1996, BMVC, British Machine Vision Association, Edinburgh, pp 53–62

Mortensen DA (2002) Crop/weed outcomes from site-specific and uniform soil-applied herbicide applications. Prec Agric 3:95

Neto JC, Meyer GE, Jones DD (2006a) Individual leaf extractions from young canopy images using Gustafson-Kessel clustering and a genetic algorithm. Comput Electron Agric 51:66–85

Neto JC, Meyer GE, Jones DD, Samal AK (2006b) Plant species identification using elliptic fourier leaf shape analysis. Comput Electron Agric 50:121–134

Oebel H (2006) Teilschlagspezifische Unkrautbekämpfung durch raumbezogene Bildverarbeitung im Offline- und (Online-) Verfahren (TURBO). PhD thesis, Universität Hohenheim, Fakultät Agrarwissenschaften

Oebel H, Gerhards R (2005) Site-specific weed control using digital image analysis and georeferenced application maps – first on-farm experiences. In: Stafford JV (ed) 5th ECPA, Uppsala, Wageningen Academic Publishers, Wageningen, pp 131–138

Okamoto H, Murata T, Kataoka T, Hata SI (2007) Plant classification for weed detection using hyperspectral imaging with wavelet analysis. Weed Biol Manag 7:31–37

Paap A, Askraba S, Alameh K, Rowe J (2008) Photonic-based spectral reflectance sensor for ground-based plant detection and weed discrimination. Opt Express 16:1051–1055

Pérez A, López F, Benlloch J, Christensen S (2000) Colour and shape analysis techniques for weed detection in cereal fields. Comput Electron Agric 25:197–212

Piron A, Leemans V, Kleynen O et al (2008) Selection of the most efficient wavelength bands for discriminating weeds from crop. Comput Electron Agric 62:141–148

Piron A, Leemans V, Lebeau F, Destain M (2009) Improving in-row weed detection in multispectral stereoscopic images. Comput Electron Agric 69:73–79, doi: 10.1016/j.compag.2009.07.001

Rasmussen J, Nørremark M, Bibby B (2007) Assessment of leaf cover and crop soil cover in weed harrowing research using digital images. Weed Res 47:299–310

Reyniers M, Vrindts E, De Baerdemaeker J (2006) Comparison of an aerial-based system and an on the ground continuous measuring device to predict yield of winter wheat. Eur J Agron 24:87–94

Shafri HZM, Salleh MAM, Ghiyamat A (2006) Hyperspectral remote sensing of vegetation using red edge position techniques. Am J Appl Sci 3:1864–1871

Slaughter DC, Giles DK, Downey D (2008) Autonomous robotic weed control systems: a review. Comput Electron Agric 61:63–78

Søgaard H, Heisel T (2002) Machine vision identification of weed species based on active shape models. In: van Laar HH, Bastiaans L, Baumann DT et al (eds) EWRS 12th EWRS Symposium, European Weed Research Society. Grafisch Service Centrum Van Gils BV, Wageningen, pp 402–403

Soille P (2003) Morphological image analysis, 2nd edn. Springer, Heidelberg

Sui R, Thomasson JA, Hanks J, Wooten J (2008) Ground-based sensing system for weed mapping in cotton. Comput Electron Agric 60:31–38

Thorp K, Tian L (2004) A review on remote sensing of weeds in agriculture. Prec Agric 5:477–508

Šeatović D (2008) A segmentation approach in novel real time 3D plant recognition system. In: Proceedings of the Computer Vision Systems, Lecture Notes in Computer Science, vol 5008. Springer, Berlin/Heidelberg, pp 363–372

Wang N, Zhang N, Dowell FE, Sun Y, Peterson DE (2001) Design of an optical weed sensor using plant spectral characteristics. In: ASAE (ed) Transactions of the ASAE, vol 44. American Society of Agricultural Engineers, St. Joseph, pp 409–419

Weis M, Gerhards R (2007) Feature extraction for the identification of weed species in digital images for the purpose of site-specific weed control. In: Stafford J (ed) Precision agriculture '07, 6th European Conference on Precision Agriculture (ECPA). Wageningen Academic Publishers, Wageningen, pp 537–545

Woebbecke D, Meyer G, von Bargen K, Mortensen D (1995) Color indices for weed identification under various soil, residue and lighting conditions. American Society of Agricultural Engineers, St. Joseph, pp 259–269

Zhang D, Lu G (2004) Review of shape representation and description techniques. Pattern Recognit 37:1–19

Zwiggelaar R (1998) A review of spectral properties of plants and their potential use for crop/weed discrimination. Crop Prot 17:189–206

Chapter 9
Detection of Fungal Diseases Optically and Pathogen Inoculum by Air Sampling

Jonathan S. West, Cedric Bravo, Roberto Oberti, Dimitrios Moshou, Herman Ramon, and H. Alastair McCartney

Abstract Practical solutions to measure temporal and spatial differences in the epidemics of specific fungal plant diseases are described here. For diseases that develop from widespread airborne inoculum, timing of disease control methods are key. Air sampling, integrated with appropriate diagnostic methods can be used to identify and quantify the presence of pathogen inoculum in order to guide spray decisions. Where diseases are already established but with spatially variable severity (disease foci), spatially selective spraying of crops is possible using different optical disease detection methods and knowledge of pathogen biology to estimate an area of latent (invisible but developing) infection around disease foci. Spatially-selective spraying mediated by optical sensors may also be beneficial when there are crop patches that have low yield potential due to other factors such as poor emergence, moisture or nutrient stress, or soil compaction. Precision agriculture methods to improve the efficiency of fungicide applications in terms of timing and selective spatial application can optimise the use of fungicides in integrated crop production systems to provide the lowest environmental impact per unit of produce while maintaining a high protection efficacy.

1 Introduction

The importance of understanding temporal and spatial differences in the development of plant disease epidemics is discussed in other chapters (see Chapter 3). Here, we investigate practical solutions to account for these differences and improve disease control by using precision-agriculture. Such spatial and temporal differences in plant disease epidemics occur due to variation in factors that drive disease epidemics, such as weather and arrival or survival of inoculum. As a result, farmers need to react to seasonal and site-specific differences in disease epidemics. Methods already exist to improve disease control by pinpointing the timing of airborne inoculum or by mapping the spatial location of infected plants, which often act as

J.S. West (✉)
Plant Pathology and Microbiology Department, Rothamsted Research, Harpenden AL5 2JQ, UK
e-mail: jon.west@bbsrc.ac.uk

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_9,

foci for the development of further disease and which make accurate assessment of disease levels and therefore spray decisions difficult. Both approaches can deliver economic and environmental benefits and are becoming increasingly feasible due to advances in diagnostics and biosensors, global positioning system (GPS), and variable rate spray technology.

2 The Opportunity for Optical Detection of Disease

Variability in environmental conditions (microclimate) needed for infection, patchiness of inoculum or variation in crop growth (where the coincidence of inoculum and a susceptible crop growth stage is important for disease development) can lead to spatially variable diseases in crops (Waggoner and Aylor 2000). In many polycyclic diseases (diseases caused by many successive cycles of sporulation and re-infection), the dispersal of spores around the original foci, intensifies the development of visible patches of disease (McCartney et al. 2006, Zadoks and van den Bosch 1994). If these foci of infection can be detected and treated, particularly at early stages, it may be possible to curtail disease development without needing to spray entire fields. Optical methods, using satellite, aircraft, model aircraft or tractor-mounted sensors, enable such foci of diseases to be detected and mapped. Disease maps can then be used to direct spray equipment to deliver fungicides to prevent further disease development around the disease foci. Recent developments in computer processing speed and in agricultural machinery that can spatially adjust spray applications (Audsley and Beaulah 1996, Secher 1997), along with GPS allow the prospect of Precision Pest Management (PPM) (West et al. 2003). PPM aims to target chemicals where and when needed and at an appropriate dose. Recent increases in grain prices have encouraged spray applications to be applied to whole fields. Crop protection practices generally have a relatively low carbon footprint compared to field operations such as ploughing and nitrogen application which represents a carbon cost in production and due to subsequent emission of N_2O – a powerful greenhouse gas (Berry et al. 2009). However, the use of sprays to remove early foci of certain diseases, such as rusts, would avoid the farmer needing to 'chase the disease' through the rest of the growing season and will reduce the total amount of spray applied, which could reduce residue levels in food and water. Applications of the methods to greenhouse crops have great potential since the indoor microclimate and high crop canopy density typically results in very favourable conditions for disease epidemics. In this situation, early detection of disease foci would have a great impact on the amount of pesticide used.

3 Effects of Diseases on Plants

Disease can cause changes in leaf colour and shape, transpiration rate, crop canopy morphology and density. This section explains how these changes affect the optical properties of the canopy and allow the prospect of diseases to be detected optically

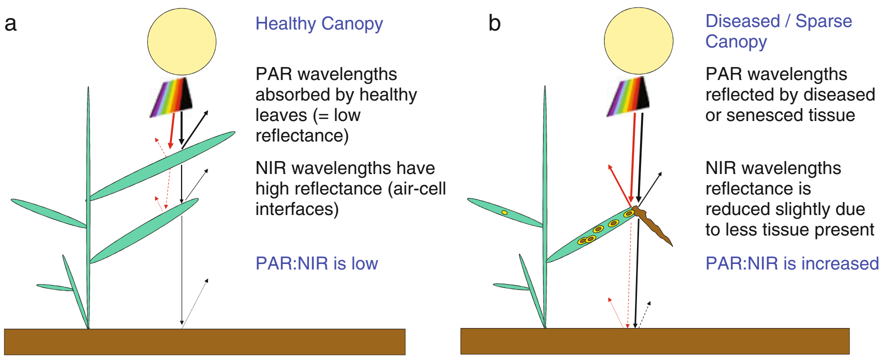

Fig. 9.1 Summary of spectral reflectance from a healthy (**a**) and diseased (**b**) plant canopy

(Fig. 9.1). Changes in the quality of light emerging from a crop canopy may be measured by spectroscopy or by imaging methods, which are explained below. Spectroscopy measures the 'average' intensity of light at narrow selected wavebands within the field of view of the light sensor (which may be deliberately or accidentally biased towards the light arriving from the centre of the field of view). An entire spectrum of light can be measured and the light intensity in one or a few wavebands may then be used for diagnostic purposes. Imaging methods on the contrary, record the light intensity at one, a few or hundreds of wavebands for each individual pixel forming a focussed image. Therefore, imaging methods take up much more processing resources than spectrophotometric methods and require more sophisticated optical sensors but provide more information. This can be important, as some disease symptoms can only be distinguished from other stresses, such as nutrient deficiency, when imaging with high spatial-resolution is used.

Light diffusely reflected from a crop canopy is influenced not only by the quality of the illuminating light but also by numerous reflections, transmissions, and absorptions, within the tissues of the crop, which gives the canopy a specific spectral signature. The spectral reflectance is the ratio of the intensity of reflected light to the illuminated light for each wavelength. Standard optoelectronic sensors allow the investigation of visible (VIS = 400−700 nm), near-infrared (NIR = 700−1,200 nm) and shortwave infrared (SWIR = 1,200−2,400 nm) spectral bands. A healthy canopy typically exhibits low reflectance at VIS wavelengths, due to strong absorption by photoactive pigments (Fig. 9.1). These photoactive pigments (e.g. chlorophylls, anthocyanins, and carotenoids) collectively absorb blue, yellow, and red bands but reflect green light (ca 550 nm), so healthy plants appear green. Healthy canopies also exhibit high reflectance in the NIR due to the absence of absorbers and due to multiple scattering at the air-cell interfaces in the leaf internal tissue, and low reflectance in most parts of the SWIR due to absorption by water, proteins, and other carbon constituents (Ceccato et al. 2001, Wooley 1971, Fig. 9.1a). The substantial change from low reflectance in the VIS range, to high reflectance in the NIR, is known as the red edge, and occurs at wavelengths around 730 nm. Leaves also emit radiation in the thermal infrared band (TIR $\approx$ (8,000 − 14,000 nm)) according to their temperature.

In diseased plants, by contrast, disfunction or destruction of the photochemical pigments lead to the appearance of necrotic or chlorotic lesions on leaves, which, along with the possible presence of pathogen spores on the leaf surface, lead to an increased reflectance in the VIS range, especially in the chlorophyll absorption bands (Fig. 9.1b). In particular, reflectance changes at wavelengths around 670 nm, causes the red edge to shift to shorter wavelengths. In addition, biomass reduction linked to tissue senescence, reduced growth, and defoliation decreases the canopy reflectance in the NIR band (Fig. 9.1b).

Subtle changes in leaf water content can be detected in the SWIR range (1,400–1,600 and 1,900–2,100 nm), while changes in the transpiration rate can be detected in the TIR (8,000–14,000 nm), both of which can be caused by root and stem base diseases in addition to foliar pathogens (Berliner et al. 1984, Mottram et al. 1983, Pinter et al. 1979). For example, Lili et al. (1991) suggested that the diseases, eyespot (due to *Oculimacula yallundae*) and cereal cyst nematode (due to *Heterodera avenae*), in winter wheat, could be detected and mapped using aerial instant thermal imagery.

In addition to changes in light reflected directly from crop canopies, the photochemical efficiency of a plant, i.e., its health status, can be indicated by measurement of chlorophyll fluorescence (450–550 nm; 690–740 nm). Not all absorbed light is used in photosynthesis, some is dissipated as fluorescence and re-emitted at VIS-NIR wavelengths (peak emission at 690 nm) and as radiative heat in the TIR region. Increases in chlorophyll fluorescence intensity can indicate early stages of disease or other stresses as plants react by decreasing photosynthesis, thus increasing fluorescence and heat emissions (Scholes 1992, Wright et al. 1995). Spots of high fluorescence emission occurring on leaves are often small e.g. spots of high emission < 1 mm in diameter were caused by tobacco mosaic virus on tobacco (Daley 1995), by bean rust on beans (Peterson and Aylor 1995) and initially (2–5 days after inoculation) by brown rust of wheat (Fig. 9.2; Bodria et al. 2002). Spots of high fluorescence may be adjacent to positions of low fluorescence emission, as found in the case of wheat brown rust several days after inoculation (Fig. 9.2; Bodria et al. 2002). The low emission spots were found to be locations of small chlorotic spots where pustules of spores (still beneath the epidermis) were developing and these were surrounded by a halo of high fluorescence emission. Therefore, detection of stresses by fluorescence emission lends itself to imaging methods rather than spectroscopy (discussed later) since with spectroscopy, the overall light intensity of the field of view, measured at a specific wavelength, may appear ‘normal’ when it in fact includes spots of high and low fluorescence emission. Although, in general, changes in fluorescence emission do not provide a precise and unambiguous indication of the cause of specific stress factors, fluorescence does enable anticipation of disorders, such as disease in plants, since the photosynthetic process is affected before tissue modifications occur.

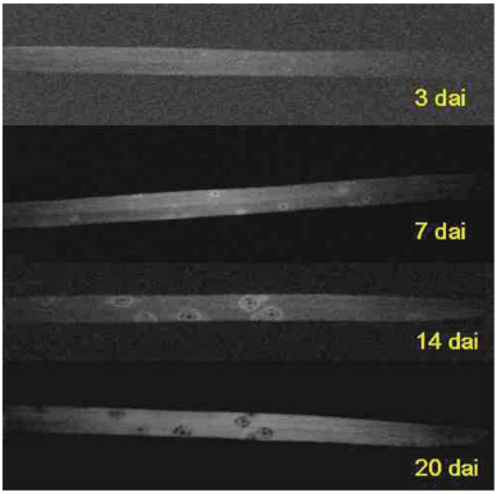

Fig. 9.2 Changes over time in fluorescence emissions from a wheat leaf inoculated with brown rust recorded by fluorescence imaging. A spectrographic method would not differentiate the dark and bright areas from the normal healthy leaf-reflectance at early stages of disease development

4 Fusion of Optical Factors to Diagnose Diseases from Other Stresses

The previous section discusses how different diseases may affect the optical properties of plant canopies in different ways. Hence different wavebands may be indicative of different diseases (Bryson et al. 1998, Dudka et al. 1998, Lorenzen and Jensen 1989, Nutter et al. 1993, Nutter and Littrell 1996, Polischuk et al. 1997, Sasaki et al. 1998). Practical systems tend not to measure high-resolution spectra over wide spectral ranges, as this causes large amounts of data handling while discriminating information are often concentrated at relatively few wavebands. For each crop-disease system, canopy reflectance data collected by spectroscopy or by imaging methods may be processed to simplify and automate disease detection. This can be based on simple formulae, algorithms or done by neural networks e.g. Moshou et al. (2004) and Bravo et al. (2003) used image analysis algorithms to discriminate between background and wheat canopy (based on reflectance at 675 and 750 nm) and then by classification of combinations of spectral wavebands to discriminate between healthy leaf tissue and disease lesions (West et al. 2003). This algorithm was used under a wide range of field conditions and the output correlated well with manual disease severity assessments (Fig. 9.3; Bravo et al. 2003, Moshou et al. 2004). Further improvement resulted from multi-sensor fusion of spectral and fluorescence features (Moshou et al. 2005), where a spectrograph provided a combination of reflectance intensities at selected wavebands. These data, in turn, were combined or ‘fused’ with lesion indices resulting from fluorescence imaging of the same plants.

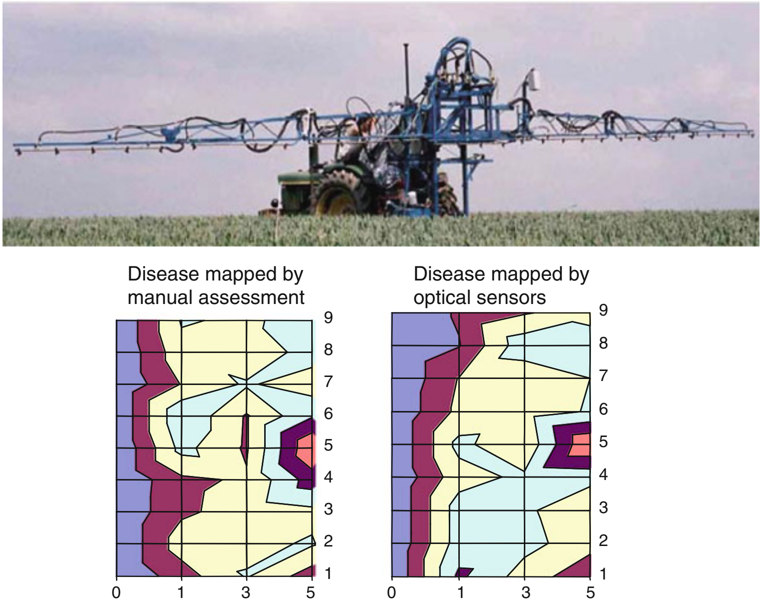

Fig. 9.3 Maps of the severity of stripe rust on wheat in early June, produced by manual assessment (*bottom left*) of disease severity on ten tillers located 1 m apart or by optical sensors (*bottom right*) mounted on a tractor boom (*top*). The disease focus was mapped half-way up the right-hand side of the plot and had been established in late-winter by hand planting a pot of inoculated wheat

Therefore for practical reasons it is best to identify wavebands or combinations of wavebands that can discriminate between diseased and healthy plants. The light intensity measured in different wavebands, either by imaging or by spectrophotometric methods, may be processed to produce a ratio between two different wavebands, which is associated with a particular spatial reference point, allowing a map of the ratio to be produced. For example, the ratio between reflectance at 700 nm and at 550 nm, which is highly correlated with total leaf chlorophyll content (Carter and Knapp 2001, Gitelson and Merzlyak 1996), could be used to produce a chlorophyll content map of the field. However, Carter (1993) and Carter and Knapp (2001) found that the same canopy optical signature was found in nitrogen-deficient plants due to reduced chlorophyll content. A possible solution arose since the nutrient deficient plants were found to have a relatively uniform pattern of high reflectance symptoms compared to localized, discrete lesions caused by many diseases (Bausch and Diker 2001, Bausch and Duke 1996, Wiesler et al. 2002, Yoder and Pettigrewcrosby 1995). Therefore imaging methods with associated sophisticated processing methods, such as those described by Moshou et al. (2006) and Bravo et al. (2002), can be used to distinguish disease symptoms from nutrient stresses and classify images to estimate a percentage area affected by the principal disease or diseases.

5 Measurement Techniques

Different methods are available for each type of measurement described above: spectrophotometry, spectral line imaging (or spectrographic imaging), and multispectral imaging can be used for canopy reflectance measurements; fluorescence kinetics, spectrometry, and imaging can be used to measure canopy fluorescence; and thermoradiometry and thermography can be used for thermal sensing.

5.1 Reflectance

Disease detection based on canopy reflectance requires measurements in one or more wavebands to be made simultaneously. Spectrophotometers are the simplest equipment to use for this purpose as they measure the spectrum of light reflected from the whole (mostly circular) field of view of the instrument, but do not provide any spatial information on canopy reflectance data. The reflectance spectra can be measured in narrow (0.5–5 nm) or broad (20–100 nm) wavebands. A large field of view reduces the sensitivity of spectrophotometers as diseased areas may represent only a small part of the reflection combined with reflection from healthy leaves and soil.

Spectral line or spectrographic imaging can be used to provide spatial resolution by measuring individual spectra along a target line in the canopy. Light reflected from the target line is split by a spectrograph into individual wavelengths that are focused onto a camera sensor to create an image with a spectral and a spatial axis. The spatial resolution along the line depends on the optics used, but can be as small as 0.5 mm (Jørgensen 2002). The system used by Bravo et al. (2003) to detect wheat diseases had a spatial resolution of 0.65 mm, a target line length of 0.5 m and a spectral resolution of 7 nm over a range of 450–900 nm.

Spatial resolution can be increased by using array-sensors. Multispectral cameras can be used to capture images in different spectral bands to give both spatial and spectral information, but unfortunately, the spectral resolution is generally low with a low number of possible working spectral bands. However, these can be chosen among the most discriminating wavelengths, and the images can be processed to provide information about the measured area to identify crop features and remove background information from the signal; e.g. pixels representing reflectance from plants or soil in an image can be separated using two wavebands (NIR and red or green and red) or even a single NIR waveband because of the high reflectivity of plant tissue compared to soil at this waveband (Andersen et al. 2000, Marchant et al. 1998). If a relatively small number of wavebands can be used to identify the presence of disease symptoms robustly, detection equipment could be made cheaper by using simple digital cameras equipped with suitable optical filters.

5.2 Fluorescence

Disease detection by fluorescence requires the sensed crop area to be exposed to an excitation pulse of light and equipment to detect the resulting fluorescence. The excitation sources are typically lasers or UV lamps. Images of fluorescence can be recorded by digital cameras either fitted with a single bandwidth filter (usually at 690 nm) or by multispectral cameras if many fluorescence wavebands are used for diagnosis. Due to their low intensity, fluorescence signals can be masked by background ambient light, and pulsed sources coupled with synchronized gated detectors or, alternatively, less complex differential systems can be used, by subtracting an image acquired with an exciting source on, from a background image acquired without the excitation. The latter method was used at night to detect brown rust infections in a wheat canopy under field conditions (Bodria et al. 2002). Pulsed gated systems have been used in daylight to obtain multispectral fluorescence images of leaves over several tens of metres, by integrating the fluorescence signal over numerous (≈100) excitation exposures (Johansson et al. 1996, Saito et al. 1997). A prototype system to measure chlorophyll fluorescence in the field, based on multispectral imaging, comprised a xenon arc lamp, fitted with a 420 nm low-pass filter, as an excitation source, an opaque shield to reduce background illumination. Images were acquired with the excitation off and on and the data processed to form a 'fluorescence map' (the difference between the two images). Research is progressing to develop faster measurement systems for use on moving platforms such as tractors and aircraft (Cecchi et al. 1994, Corp et al. 1997, Ludeker et al. 1996, Flexas et al. 2000, Morales et al. 1999). However, practical field-based fluorescence detection is currently limited due to the complexity of equipment required for operation in daylight, the energy demand for the excitation source when used on a reasonably wide measurement area, and the costly equipment necessary for the high resolution needed to detect relatively small differences in fluorescence. Remote-sensed kinetic fluorescence techniques offer potential for future use in the field as these methods are not affected by variations in ambient light.

5.3 Thermal Radiation

Infrared thermometers or thermoradiometers can be used remotely to measure thermal radiation, allowing the temperature of a surface to be estimated in the field of view of the instrument. The field use for disease detection is very limited as they do not provide any spatial information. Thermal imaging however, has great potential although equipment is still expensive, and this is reviewed in Chapter 11.

6 Practical Considerations for Disease Mapping

Spectral reflectance is affected by the quality and quantity of the illuminating light in addition to the reflection characteristics of the target leaves. Therefore it is best practice to normalize reflectance spectra to account for variations in illumination, so practical reflectance measurement systems usually monitor the spectral content of incident illumination (Price 1994, Borel and Gerstl 1994).

Furthermore, reflectance spectra are also affected by the angle between the direction of illumination (usually the direction from the sun) and the viewing direction of the sensor. For a large angle, i.e. when the sensor is orientated towards the light (forward scattering), the measured spectra will include a significant proportion of light transmitted through leaves as well as reflected from them, which will complicate the interpretation of the image. As a result, vehicle mounted optical sensors need to be mounted to minimize the influence of solar elevation on the measured signal. Alternatively, interpretation algorithms may be used to account for solar angle and proportions of direct to diffuse radiation (e.g. BRDF correction). In addition, the viewing angle of any vehicle-mounted optical sensors must be chosen (a) to reduce the impact of reflections from background soil (which are transmitted through leaves to augment reflections directly from the canopy), and (b) to avoid too shallow an angle, which will view predominantly the top leaves of the canopy – these leaves usually have little or no disease symptoms visible in actively growing crops as they will have only recently unfolded and relatively long incubation periods mean that disease symptoms will not yet have developed.

In addition to practical tractor-mounted optical sensors, other platforms such as satellite, aircraft or model aircraft may be used. These alternative platforms also have their own technical problems and interpretation difficulties. Satellite systems tend to have pixel sizes representing 10–1,000 m^2 compared to less than 0.5 mm^2 for tractor mounted systems (Blakeman et al. 2000, Bravo et al. 2002). As a result, it is difficult for satellite systems to allow identification of the cause of patches of plant stress, or to detect very small (early) patches of disease, but they can prompt a visual inspection and so serve a useful purpose in scouting for diseases and other stresses. Satellite-based optical sensing has proven very effective in identifying foci of pasture infected with wheat streak mosaic virus (Rush et al. 2008). Satellite systems can be expensive but are likely to reduce in price over coming years (see Chapter 24 for further examples). Nevertheless, imaging from satellites also has problems due to revisit frequency and cloud cover at key times of the year in some locations. Cloud cover may also be a problem for aircraft systems and to model aircraft-mounted sensors but the latter has added flexibility (in locations where it is allowed). Improved spatial resolutions (down to < 0.1 m) are possible from aircraft compared to satellite platforms (Blakeman et al. 2000) but costs are also increased since data acquisition equipment needs to be faster than that for terrestrial vehicle-mounted systems. An alternative approach is to use more than one sensor technology and to integrate measurements in order to obtain a more sensitive and discriminating system than could be obtained using a single sensor.

Currently, limitations in computer processing power mean that spectral data, from remote sensors or from tractor-mounted sensors, cannot be collected and used in real time to direct spray equipment. For real-time sensing and spray operation, sensors, algorithms and spray application systems would need fast response times (Giles et al. 2002), which has only been achieved for control of targets that are easy to identify, e.g. weeds – often growing against contrasting backgrounds (Miller and Stafford 1993, Ramon et al. 2002, Slaughter et al. 1999). For identification of patchy diseases, it is likely that manned vehicles operating at currently acceptable speeds would need to pre-map the site (other operations may be done while the optical data are collected) before returning for spray application with equipment directed using GPS or a local reference system.

7 Limitations to Precision Disease Control

Control of many arable crop diseases may not be improved by disease mapping. Control of diseases that occur uniformly over the field (e.g. Septoria leaf blotch of wheat), that appear and spread quickly (i.e. with a high epidemic rate), or that manifest themselves too late for control measures to help (e.g. root and stem-base diseases), may still be best controlled by sprays to protect certain growth stages of the crop or when inoculum-based (discussed later) or weather-based decision support systems suggest that there is a high risk of disease (West et al. 2003). There would be an advantage to mapping the locations of soilborne diseases that produce relatively static foci, such as the potato cyst nematode (*Globodera rostochiensis* and *G. pallida*), so that future treatment programmes could be targeted. Optical sensing and mapping may be better suited to improving disease control in protected crop systems, where conditions may be manipulated to improve disease detection (e.g. detecting fluorescence at night) and where sensors may be moved above the crop on a system of cables to scout for diseases and other stresses. See Chapter 25 for examples of precision disease control in bed-grown crops.

In practical arable crop systems, since many latent infections will not be detectable, patches of disease will often be underestimated by disease mapping and since many fungicides are curative, not eradicative, for polycyclic diseases, applications to patches of disease and a surrounding area of the crop at risk of receiving propagules from the existing patch may still need a repeated follow-up application to a larger zone at a later date as latent infections mature to sporulate (West et al. 2003). The estimation of the zone of latent infection and area at risk of receiving enough inoculum to cause economic damage requires an understanding of the temporal and spatial dynamics of disease foci development for each disease. Prediction of disease patch expansion is complex [for reviews see Zadoks and van den Bosch 1994, McCartney et al. 2006, Waggoner and Aylor 2000], but simple empiric estimations of areas at risk of developing disease around a detected patch of disease could be built into the maps used to control spray equipment.

Despite improvements in technology that now enable precision disease management to be realised, there is likely to be a case for adopting precision disease control only in a limited number of systems, where there is a demand for reduced spray applications but a relatively high value crop to justify the outlay for equipment. Currently, many arable crops are at relatively high values and as a result, farmers are more likely to spray entire fields to 'protect their investment'. Although weather-based disease forecast models and crop-growth stage-based decision support systems exist to aid farmers to spray entire fields, an approach that has been neglected to improve the precision of the timing of spray applications is that of inoculum-based disease forecasting, which is described in the next section.

8 Precision Pest Management by Air Sampling

Precise detection of inoculum can assist disease control in systems where disease development is usually widespread but where the timing of epidemics may vary. Air dispersal is one of the main ways for many plant pathogens to reach new locations with some fungal spores able to travel great distances and remain viable to cause disease (Brown and Hovmøller 2002, McCartney et al. 2006). Spores released from sources either a long distance from the crop or from multiple sites throughout a region result in well dispersed airborne inoculum, which, if infection conditions are suitable, lead to a relatively uniform distributions of disease. However, seasonal differences in weather patterns, which influence the production of spores, affect the timing of onset of epidemics and therefore the optimal time for control strategies to be deployed. Although there is potential for weather-based models to predict spore release, this has not been developed for some pathogens or may be inaccurate due to wide diversity of responses to environmental cues in pathogen populations or a wide diversity of microclimates in certain systems. Inoculum detection has been used as a component of disease warning schemes to guide disease control measures in some systems (West et al. 2008), and is of particular value if the disease incubation period is long.

Interest in the use of air sampling in precision disease detection has increased recently because DNA-based diagnostic methods such as quantitative PCR (qPCR) have been demonstrated to be applicable to samples collected on many different types of traditional air samplers (Rogers et al. 2009, West et al. 2008; Fig. 9.4). Some newly developed air samplers (miniature cyclone, MicroTitre Immuno Spore Trap, and the Ionic spore trap) have been, designed specifically for analysis using non-visual methods such as immunological and molecular diagnostics (West et al. 2009, Anonymous 2009). The fusion of air sampling and analysis of appropriate genetic markers is now enabling genetic traits within populations to be monitored in an unbiased way. This can provide information on whether resistance to certain fungicides may be widespread within a particular species of pathogen, whether the pathogen strains present are likely to produce food-spoilage mycotoxins, and even which cultivars may be at risk of infection by the predominant pathogen races. This level of information was not available previously by analysis of air samples by microscopy or even by immunology.

The optimal location of air samplers depends on how widespread the host crop is and how common the pathogen is, since air samples, particularly if collected at ground level, are heavily weighted in favour of spores produced nearby. Further work is required to investigate the spatial variability of spore production and the resulting air spora at different scales and at different sampling heights above or distances away from crops in order to guide disease control decisions regionally. A key

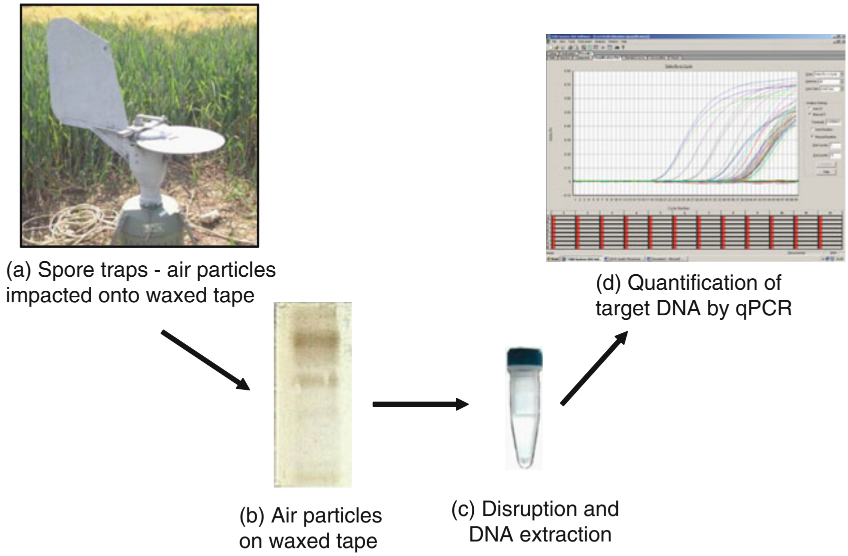

Fig. 9.4 Example of processes currently used to detect airborne inoculum of fungal plant pathogens. Burkard 7 day spore trap (**a**), daily air sample on waxed tape (**b**) processing for DNA extraction from all spores, pollens and other particles on the tape (**c**) quantification of the number of target spores present by quantifying the pathogen's DNA by qPCR. Various genetic traits of the pathogen population can be monitored if suitable genetic markers are available

factor to enhance this approach further is to develop methods, such as biosensors, that can detect pathogens rapidly and on site.

9 Discussion

For optical disease detection systems to be useful, it is essential to understand whether detected foci are still compact and can be treated discretely, or whether spore dispersal conditions will mean that the entire field needs to be sprayed. New modelling approaches (Aylor and Ferrandino 2008) are allowing predictions of the spread of inoculum and disease patch expansion. Optical techniques can now be used for disease detection and reflectance measurement offers the most cost effective method for field-based systems with spatial resolutions superior to that available from aircraft- or satellite-systems. This can allow discrimination between diseases and other stress factors but further improvements are required to overcome practical problems such as vibration, variations in illumination, sun/sensor orientation, background soil reflection, mechanical stress, and dust. Promising, sophisticated methods, such as fluorescence measurement may be more feasible in protected crop systems. In arable systems, a barrier to the uptake of this technology is that there are relatively few patchy diseases that are likely to be detected in time for spatially variable spray application to be effective.

Inoculum-based disease forecasting could be viewed as an additional form of precision pest management and offers great potential for future information-driven disease control systems as biosensors able to detect inoculum become available for use on-site or as lab-based methods become cheaper, quicker and able to detect and quantify inoculum of a wide spectrum of pathogens.

Acknowledgements We thank the EC Quality of Life Programme-Framework V, which funded the OPTIDIS project. Rothamsted Research receives funding from the BBSRC (UK).

References

Andersen HJ, Onyango CM, Marchant JA (2000) Design and operation of an imaging sensor for detecting vegetation. Int J Imag Syst Tech 11:144–151

Anonymous (2009) The ionic spore trap. http://ionicsporetrap.com/main/inside.php?page=about. Accessed May 2009

Audsley E, Beaulah SA (1996) Combining weed maps to produce a treatment map for patch spraying. In: Aspects of applied biology, modeling in applied biology: spatial aspects, vol 46. Association of Applied Biologists, Wellesbourne, pp 111–118

Aylor DE, Ferrandino FJ (2008) Prospects for precision agriculture to manage aerially dispersed pathogens in a patchy landscape. Proceedings of the 9th international congress of plant pathology, healthy and safe food for everybody, August 24–29, 2008, Torino. Plant Pathol 90 (Suppl 2):59

Bausch WC, Diker K (2001) Innovative remote sensing techniques to increase nitrogen use efficiency of corn. Commun Soil Sci Plant Anal 32:1371–1390

Bausch WC, Duke HR (1996) Remote sensing of plant nitrogen status in corn. Trans Am Soc Agric Eng 39:1869–1875

Berliner P, Oosterhuis DM, Green GC (1984) Evaluation of the infrared thermometer as a crop stress detector. Agric For Meteorol 31:219–230

Berry PM, Kindred DR, Paveley ND (2008) Quantifying the effects of fungicides and disease resistance on greenhouse gas emissions associated with wheat production. Plant Pathol 57:1000–1008

Blakeman RH, Bryson RJ, Dampney P (2000) Assessing crop condition in real time using high resolution satellite imagery. In: Aspects of applied biology, Remote sensing in agriculture, vol 60. Association of Applied Biologists, Wellesbourne, pp 163–171

Bodria L, Fiala M, Oberti R, Naldi E (2002) Chlorophyll fluorescence sensing for early detection of crop's diseases symptoms. Proceedings of the American Society of Agricultural Engineering – CIGR World Congress, Chicago

Borel CC, Gerstl SAW (1994) Are leaf chemistry signatures preserved at the canopy level? Proceedings of International Geoscience and Remote Sensing Symposium, Pasadena

Bravo C, Moshou D, West J et al (2002) In field disease and nutrient stress detection by imaging spectrography at canopy level. Proceedings of AgEng 2002, Budapest

Bravo C, Moshou D, West JS et al (2003) Early disease detection in wheat fields using spectral reflectance. Biosyst Eng 84:137–145

Brown JKM, Hovmøller MS (2002) Epidemiology – aerial dispersal of pathogens on the global and continental scales and its impact on plant disease. Science 297:537–541

Bryson RJ, Clark WS, Madeira AC et al (1998) Explaining the variation in yield response to disease control through estimates of radiation interception by crop canopies – an opportunity for remote sensing. International Congress of Plant Pathology (ICPP98), Edinburgh, 9–16 Aug. Abstract. 2.8.6S

Carter GA (1993) Responses of leaf spectral reflectance to plant stress. Am J Bot 80:239–243

Carter GA, Knapp AK (2001) Leaf optical properties in higher plants: linking spectral characteristics to stress and chlorophyll concentration. Am J Bot 88:677–684

Cecchi G, Mazzinghi P, Pantani L et al (1994) Remote-sensing of chlorophyll-a fluorescence of vegetation canopies .1. Near- and far-field measurement techniques. Rem Sens Environ 47: 18–28

Ceccato P, Flasse S, Tarantola S et al (2001) Detecting vegetation leaf water content using reflectance in the optical domain. Rem Sens Environ 77:22–33

Corp LA, McMurtrey JE, Chappelle EW et al (1997) UV band fluorescence (in vivo) and its implications for the remote assessment of nitrogen supply in vegetation. Rem Sens Environ 61:110–117

Daley PF (1995) Chlorophyll fluorescence analysis and imaging in plant stress and disease. Can J Plant Pathol 17:167–173

Dudka M, Langton SJ, Schuler RT et al (1998) Use of digital imagery to evaluate disease incidence and yield loss caused by Sclerotinia stem rot of soybeans. Proceedings of International Precision Agriculture Conference, St. Paul

Flexas J, Briantais JM, Cerovic Z et al (2000) Steady-state and maximum chlorophyll fluorescence responses to water stress in grapevine leaves: a new remote sensing system. Rem Sens Environ 73:283–297

Giles DK, Slaughter DC, Upadhyaya SK (2002) Biological target sensing and sprayer control. In: Aspects of applied biology, international advances in pesticide application, vol 66. Association of Applied Biologist, Wellesbourne, pp 129–138

Gitelson AA, Merzlyak MN (1996) Signature analysis of leaf reflectance spectra: algorithm development for remote sensing of chlorophyll. J Plant Physiol 148:494–500

Johansson J, Andersson M, Edner H et al (1996) Remote fluorescence measurements of vegetation spectrally resolved by multicolour fluorescence imaging. J Plant Physiol 148: 632–637

Jørgensen RN (2002) Study on Line Imaging Spectroscopy as a Tool for Nitrogen Diagnostics in Precision Farming. Risø, Denmark: Risø Natl. Lab. http://www.risoe.dk/rispubl/PRD/ris-r-1327.htm. 322 pp.

Lili Z, Duchesne J, Nicolas H, Rivoal R (1991) Détection infrarouge thermique des maladies du blé d'hiver. Bull OEPP/EPPO Bull 21:659–672

Lorenzen B, Jensen A (1989) Changes in spectral properties induced in barley by cereal powdery mildew. Rem Sens Environ 27:201–209

Ludeker W, Dahn HG, Gunther KP (1996) Detection of fungal infection of plants by laser-induced fluorescence: an attempt to use remote sensing. J Plant Physiol 148:579–585

Marchant JA, Tillett RD, Brivot R (1998) Real-time segmentation of plants and weeds. Real-Time Imag 4:243–253

McCartney HA, Fitt BDL, West JS (2006) Dispersal of foliar fungal plant pathogens: mechanisms, gradients and spatial patterns. In: Cooke BM, Jones DG, Kaye B (eds) The epidemiology of plant diseases. Springer, Dordrecht, pp 159–192

Miller PCH, Stafford JV (1993) Spatially selective application of herbicide to cereal crops. Comput Electron Agric 9:217–229

Morales F, Belkhodja R, Goulas Y et al (1999) Remote and near-contact chlorophyll fluorescence during photosynthetic induction in iron-deficient sugar beet leaves. Rem Sens Environ 69: 170–178

Moshou D, Bravo C, Oberti R et al (2005) Plant disease detection based on data fusion of hyper-spectral and multi-spectral fluorescence imaging using Kohonen maps. Real-Time Imaging 11:75–83

Moshou D, Bravo C, West JS et al (2004) Automatic detection of yellow rust in wheat using reflectance measurements and neural networks. Comput Electron Agric 44:173–188

Moshou D, Bravo C, Wahlen S et al (2006) Simultaneous identification of plant stresses and diseases in arable crops using proximal optical sensing and self-organising maps. Prec Agric 7:149–164

Mottram R, DeJager JM, Duckworth JR (1983) Evaluation of a water stress index for maize using an infra-red thermometer. Crop Prod 12:26–28

Nutter FW, Gleason ML, Jenco JH, Christians NC (1993) Assessing the accuracy, intra-rater repeatability, and interrater reliability of disease assessment systems. Phytopathology 83: 806–812

Nutter FW, Littrell RH (1996) Relationships between defoliation, canopy reflectance and pod yield in the peanut-late leafspot pathosystem. Crop Prot 15:135–142

Peterson RB, Aylor DE (1995) Chlorophyll fluorescence induction in leaves of *Phaseolus vulgaris* infected with bean rust (*Uromyces appendiculatus*). Plant Physiol 108:163–171

Pinter PJ, Stanghellini ME, Reginato RJ et al (1979) Remote detection of biological stresses in plants with infrared thermometry. Science 205:585–587

Polischuk VP, Shadchina TM, Kompanetz TI et al (1997) Changes in reflectance spectrum characteristic of *Nicotiana debneyi* plant under the influence of viral infection. Arch Phytopathol Plant Prot 31:115–119

Price JC (1994) How unique are spectral signatures? Rem Sens Environ 49:181–186

Ramon H, Anthonis J, Vrindts E et al (2002) Development of a weed activated spraying machine for targeted application of herbicides. In: Aspects of applied biology, international advances in pesticide application. Association of Applied Biologists, Wellesbourne, pp 147–162

Rogers SL, Atkins SD, West JS (2009) Detection and quantification of airborne inoculum of *Sclerotinia sclerotiorum* using quantitative PCR. Plant Pathol 58:324–331

Rush CM, Workneh F, Price J et al (2008) Application of remote sensing technologies for study of wheat streak mosaic virus. Proceedings of 9th international congress of plant pathology, healthy and safe food for everybody, Torino, 24–29 Aug, 2008. Plant Pathol 90 (Suppl 2):60

Saito Y, Hatake K, Nomura E et al (1997) Range-resolved image detection of laser-induced fluorescence of natural trees for vegetation distribution monitoring. Jpn J Appl Phys 36: 7024–7027

Sasaki Y, Okamoto T, Imou K, Torii T (1998) Automatic diagnosis of plant disease – spectral reflectance of healthy and diseased leaves. Presented at AgEng Conference, Oslo

Scholes JD (1992) Photosynthesis: cellular and tissue aspects in diseased leaves. In: Ayres PG (ed) Pests and pathogens: plant responses to foliar attack. Bios Scientific Publishers, Oxford, pp 85–106

Secher BJM (1997) Site-specific control of disease in winter wheat. In: Aspects of applied biology, optimising pesticide applications, vol 48. Association of Applied Biologists, Wellesbourne, pp 57–64

Slaughter DC, Giles DK, Tauzer C (1999) Precision offset spray system for road-way shoulder weed control. J Transport Eng 125:364–371

Waggoner PE, Aylor DE (2000) Epidemiology: a science of patterns. Annu Rev Phytopathol 38:71–94

West JS, Atkins SD, Emberlin J, Fitt BDL (2008) PCR to predict risk of airborne disease. Trends Microbiol 16:380–387

West JS, Atkins SD, Fitt BDL (2009) Detection of airborne plant pathogens; halting epidemics before they start. Outlooks Pest Manag 20:11–14

West JS, Bravo C, Oberti R et al (2003) The potential of optical canopy measurement for targeted control of field crop diseases. Annu Rev Phytopathol 41:593–614

Wiesler F, Bauer M, Kamh M et al (2002) The crop as indicator for sidedress nitrogen demand in sugar beet production – limitations and perspectives. J Plant Nutr Soil Sci 165:93–99

Wooley JT (1971) Reflectance and transmittance of light by leaves. Plant Physiol 47:656–662

Wright DP, Baldwin BC, Shepard MC, Scholes JD (1995) Source-sink relationship in wheat leaves infected with powdery mildew. 1. Alterations in carbohydrate metabolism. Physiol Mol Plant Pathol 47:237–253

Yoder BJ, Pettigrewcrosby RE (1995) Predicting nitrogen and chlorophyll content and concentrations from reflectance spectra (400–2,500 nm) at leaf and canopy scales. Rem Sens Environ 53:199–211

Zadoks JC, Vandenbosch F (1994) On the spread of plant-disease – a theory on foci. Annu Rev Phytopathol 32:503–521

Chapter 10
Remote Sensing for the Detection of Soil-Borne Plant Parasitic Nematodes and Fungal Pathogens

Christian Hillnhütter, Astrid Schweizer, Volker Kühnhold, and Richard A. Sikora

Abstract This chapter reviews past developments and the present state-of-the-art remote sensing for the detection of soil-borne nematodes and plant pathogens. Nematodes and soil-borne pathogens are considered ideal targets for the application of precision agriculture with non-contact sensing methodologies. The clustered occurrence and low level of mobility of nematodes and pathogens in the soil and the induction of symptoms in the leaves make them perfect targets for remote sensing detection. Data obtained with infrared thermography and hyperspectral reflectance for the remote sensing of plant parasitic nematodes and root rotting fungi in sugar beet as well as delineation of complex-disease interactions is also presented. The management of these two pest groups usually relies on full field pesticide treatments, even when only a small section of the field is infested. This underscores the need for remote sensing of disease clusters and the resulting application of site-specific management.

1 Introduction

Remote sensing (RS) for the detection of damage caused by plant parasitic nematodes and/or soil-borne pathogens for optimization of integrated pest management is a 'best-fit technology'. There are a number of biological and technical factors that favor the use of RS for these two pest groups: (I) damage caused by root infections is visible in the foliage at different times in the growing season; (II) nematode and disease infestations are clustered in the field; (III) movement out of a cluster is slow due to low nematode and pathogen mobility; (IV) introduction of new infection loci into a field are rare; (V) precision detection used in one season can be applicable for future crops and (VI) chemical and biological control technologies are available that

C. Hillnhütter (✉)
Institute of Crop Science and Resource Conservation (INRES) – Phytomedicine, Bonn D-53115, Germany
e-mail: chillnhu@uni-bonn.de; christian.hillnhuetter@gmx.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_10,

allow site-specific treatment. These control methodologies include: granular pesticides for targeted treatment, single and combined fungicide and nematicide seed treatments, biopesticide soil and seed treatments as well as resistant and tolerant varieties. The use of this knowledge to develop site-specific plant health management can significantly reduce yield losses due to these two pest groups and can lead to a high cost/benefit return for the grower.

Plant parasitic nematodes have been estimated to cause crop losses of up to 20% or approximately 100 billion US$ annually worldwide on crops such as cotton, soybean, cereals, tuber crops, legumes as well as fruits and vegetables (Cai et al. 1997, Luc et al. 2005). Crop losses due to fungal and bacterial pathogens, many of them soil-borne, also are reported to inflect annual losses of 7–15% in major field crops such as wheat, rice, potato, maize and soybean (Oerke 2005).

A major limiting factor in the use of precision crop protection technology has been the complex soil-ecosystem itself and the difficulty involved in prediction of nematode or disease occurrence. The analysis of soil samples to determine whether or not nematode densities exceed the action threshold is expensive and in some cases for technical reasons not feasible. In Germany the cost for analysis of a soil sample for the sugar beet cyst nematode *Heterodera schachtii* ranges from 24 to 61€, whereas in Iowa (USA) analysis of a soil sample for the soybean cyst nematode *H. glycines* can cost 15–60 US$ (Tylka 2006). The cost of analysis of soil samples to estimated pathogen thresholds by ELISA or PCR can range from 25 to 100€.

The number of samples and follow-up laboratory examinations needed on a per hectare basis to give a reasonable estimate of potential damage when the nematode or pathogen has a cluster distribution is large and costly. Therefore, in many instances threshold estimation is limited to one extraction from a single composite soil sample that produces an average infestation level over the entire field. Considering the total cost of sampling and lab analysis, the true dimension of crop loss and the cost of conventional full scale field application of a pesticide – the use of RS that leads to site-specific variable rate application would be more efficient, economical and environmentally friendly.

The use of newly developed and/or refined components of current precision agricultural technology such as RS and soil electric conductivity (EC_a) coupled with geo-information systems (GIS) allows instant detection and generation of digital maps that clearly represent the heterogeneous distribution of soil-borne nematodes and pathogens. Based on the information obtained with these measurements, either from previous crops in a rotation or prior to planting, precision crop protection decisions can be made and proper site-specific plant protection applied.

The use of high resolution RS equipment for the detection of insect and foliar pathogens in traditional field crops and agro forestry and has been reviewed elsewhere (Nutter 1990, Nilsson 1995, Stafford 2000, Zhang et al. 2002, Pinter et al. 2003, Lu et al. 2004). Our knowledge regarding the use of RS for detection and management of soil-borne plant parasitic nematodes and pathogens, however, is still poorly developed.

This chapter will: (I) review the state of the art of RS based on measurement of leaf and canopy reflectance for detection of nematode and pathogen damage; (II) present recent findings on RS for nematode and crown-rot in sugar beet; (III) give data on the discrimination of complex nematode-pathogen interactions; and (IV) discuss the need for future research in RS.

2 Review of Research on Remote Sensing of Plant Parasitic Nematodes and Soil-Borne Pathogens

Steddom et al. (2005) stated that RS is the practice of gathering information on an object without touching it and that most such technologies measure different parts of electromagnetic radiation such as heat or light. Plants depend on radiant energy for conversion of solar energy into organic substances. The leaf can absorb light in the visible part (VIS) of the electromagnetic spectrum (400–700 nm), where the spectrum of reflectance is quiet low, with a peak at about 550 nm in the green region. In the near infrared (NIR) short-wave region (700–1,400 nm) reflectance increases up to 50%, whereas in the long-wave (1,400–2,500 nm) reflectance decreases due to water absorbance. Leaves not only absorb and reflect light but light also is transmitted through the leaf. The far infrared (FIR) which starts at a wavelength of 5,000 nm is important in thermometry.

Disturbance or destruction of normal root functioning induced by soil-borne nematodes or pathogens causes decreases in the content of water, chlorophyll, carotinoids and anthocyanin levels in the leaves which simultaneously leads to shifts in reflectance of the electromagnetic spectrum or changes in leaf temperature. The use of reflectance in the NIR and FIR spectrum, therefore, can be effectively used to detect disease symptoms even before they are visible.

The first aerial images of damage caused by a soil-borne plant disease were made in the year 1927 when Taubenhaus et al. (1929) took pictures from an US Army airplane at an altitude of 75–150 m to detect symptom development of cotton root rot caused by *Phymatotrichum omnivorum*. Black and white panchromatic film sensitive to all wavelengths of VIS light and a light yellow filter were used for estimation of damage and yield loss. Once the use of aerial photography was established as a technique, false color infrared (IR) film, new cameras, films and filter combinations were developed and available for experimentation. The films were called false color, because healthy green vegetation appears red or pink on the positive photographic transparency. Infrared film is sensitive to light in the green and red regions at wavelengths of 500–700 nm and in the NIR region at 700–950 nm (Tarkington and Seren 1963). The first use of IR imagery for detection of plant parasitic nematodes was conducted in the early 1960s in citrus plantations by Norman and Fritz (1965) to detect the burrowing nematode *Radopholus similis* in citrus trees before visible symptom development. This work resulted in a reduction in sampling and the introduction of site-specific nematicide treatment. Heald et al. (1972) took IR aerial images of Texas cotton fields and were able to detect the reniform nematode *Rotylenchulus reniformis* as well as early symptoms of *P. omnivorum* root rot. Brodrick et al. (1971) examined the use of multispectral sensors that had a combination of four or more spectroradiometers. Each sensor records one scene of a small band which are then all combined to obtain the multispectral image. With this technique avocado trees infected with *Phytophthora cinnamomi* root rot were photographed from an altitude of 1,500 m which resulted in 100% identification of diseased trees verse only 80% with IR film. Gausman et al. (1975) using a spectroradiometer detected differences in cotton leaf reflection levels in nematode infested compared to control plants. Plants with high populations of *R. reniformis* showed lower leaf reflectance compared to the control plants in the wavelengths 500–2,500 nm. Leaves of the nematode parasitized plants were thinner and more compact in the inner cellular layers and therefore caused lower light reflection.

Pinter et al. (1979) conducted the first experiments on the detection of biological stress in plants by IR thermometry. The soil-borne root rotting pathogens *Pythium aphanidermatum* on sugar beet and *P. omnivorum* on cotton caused a measurable increase in leaf temperature of 3–5°C before visible disease symptoms occurred. Toler et al. (1981) and Lee (1989) published two short reviews on aerial IR imagery, economic cost-benefits and future perspectives of remote sensing. They summarized most of the work conducted on soil-borne organisms up to 1980.

Based on earlier work, Gebhardt (1989) demonstrated differences in water availability in agricultural crops by aerial thermometry. Plant parasitic nematodes and many soil-borne pathogens cause reduced water uptake in infested plants. A decrease in water uptake results in decreased leaf transpiration and influences overall plant temperature which is usually lower than the surrounding environment. The decreased transpiration due to biotic stress causes an increase in leaf temperature that is detectable by IR thermometry.

IR thermometry has been sporadically used in nematology. Berg (1980) working in nematode infested sugar beet fields in Germany and in Italy was able to differentiate *H. schachtii* infested symptomless patches from healthy areas. Gebhardt (1984) also showed differences in canopy temperature of potato plants infested with the potato cyst nematode *Globodera rostochiensis*. On winter wheat Nicolas et al. (1991) detected significantly higher canopy temperatures in areas moderately infested with *H. avenae* as compared to low infestations and considered this effect to be caused by increased stomatal resistance.

Using multispectral video imagery Cook et al. (1999) were able to discriminate between damage by the root-knot nematode *Meloidogyne incognita* and root rot due to *P. omnivorum* alone as well as in combination. This was the first attempt to detect a complex-disease interaction with RS.

Heath et al. (2000) conducted experiments to predict the number of *G. pallida* and *G. rostochinensis* parasitizing potato plants using non-destructive hyperspectral measurements. High correlations were found between the numbers of juveniles per gram of potato roots and the Normalized Difference Vegetation Index (NDVI) values calculated from handheld FieldSpec® FR (Analytical Spectral Devices Inc., Boulder, USA) spectroradiometer reflectance data. Hyperspectral sensors offer contiguous band placement over a wide spectral range and are superior to multispectral sensors with fewer spectral bands (Schowengerdt 1997).

The development of narrowband hyperspectral sensors was an important development in RS due to the greater amounts of data obtained. With the combination of

GIS and RS technologies Nutter et al. (2002) was able to map the spatial distribution of soybean cyst nematode, *H. glycines*, in soybean fields. Appropriate calibrations were made for different atmospheric conditions by collecting data at different times in the growing season simultaneously by satellite, aircraft and ground-based multispectral sensors. With the same nematode and crop but increasing nematode densities, Asmus and Ferraz (2002) tried to detect differences in leaf area, leaf color, photosynthetic rate and chlorophyll fluorescence in greenhouse trials. Leaf area, chlorophyll content and photosynthetic rate were reduced by *H. glycines*.

Wheeler and Kaufman (2003), however, obtained negative results in the prediction of *M. incognita* damage in cotton by IR aerial imagery. At that time, multiple flight campaigns and data analysis for variable-rate nematicide application was more expensive than uniform treatment of the entire field. Using multispectral canopy and hyperspectral leaf reflectance data Steddom et al. (2003) were unable to differentiate differences between yellowing of sugar beet leaves due to a lack of nitrogen and the yellowing caused by rhizomania, a soil-borne virus disease.

Lawrence et al. (2004) using aerial and handheld hyperspectral sensors to detect *R. reniformis* in cotton and data analysis with the MATHLAB program in combination with self-organizing maps developed by Kohonen (1998), obtained a prediction accuracy that ranged between 83 and 97%. They suggested the need for research on the effects of different soil types and in scaling leaf level measurements into a commercially viable orbital or suborbital system to validate the robustness of this approach (Lawrence et al. 2007).

Hyperspectral data is highly adaptable to the identification of soil-borne pests and diseases because of the higher amount of data available as a result of the narrower bands and the possible use of hyperspectral vegetation indices. In addition, the identification of the most sensitive bands of hyperspectral data for a specific pest group seems promising. Rupe et al. (2005) for example, isolated four bands out of 300 which were most responsive to *H. glycines* in soybean fields. These bands were found in near range reflectance by the Maximum R^2 procedure. Hillnhütter and Mahlein (2008) noted the importance not only of high spectral resolution, but also that spatial resolution and the temporal factor are important in detection of small areas in a field before yield loss increases.

3 Remote Sensing of Nematodes and Fungal Root Rot in Sugar Beet

The European Union is one of the world's most important sugar producers with a yearly harvest of 19–20 million tons. The vast majority of this sugar is obtained from the sugar beet *Beta vulgaris*. Sugar beet covers 2.1 million hectares and is 1.4% of the agricultural area (European Commission 2006). Sugar beet will become even more important as the need for bioethanol production increases.

The cyst nematode *H. schachtii* is a major constraint to the sugar beet crop in most European countries. The nematode is found in all sugar beet growing regions and losses of up to 50% have been reported. Management of the nematode is very important, but varies from country to country and includes the use of: rotation with non-hosts, resistant and tolerant cultivars, resistant green manure break crops and the use of nematicides (Schlang 1991). *Rhizoctonia solani* crown and root rot is the most important soil-borne disease impacting yield (Kiewnick et al. 2001). Yield losses can range from 5 to 10% in the EU and USA (Büttner et al. 2004). Control is usually attained by planting tolerant cultivars or through the use of fungicides even though the latter are only partially effective. In most cases field symptoms develop in patches due to the clustering nature of the pest and the disease. In some cases both pests occur simultaneously in a field. This makes *H. schachtii* and *R. solani* ideal for RS and site-specific application of pesticides, biopesticides and the site-specific sowing of resistant cultivars to reduce input costs and increase yield.

The sugar beet crop is highly suited for RS analysis because it is a complanate growing plant with a planophile leaf structure. Furthermore, there is a direct relationship between root development and plant vitality (Nowatzki et al. 2009). This makes *B. vulgaris* a good target for research into the use of RS for control of nematodes and fungi. In addition, damage to the root has direct effects on the leaves (Franke 1997). The sugar content of the beet also is negatively affected by root damage or direct damage to the root by both pest groups. The development of complex-diseases when these two pests simultaneously infect the plant also can lead to synergistic interactions and additional root damage and crop loss.

Very few studies have been conducted on the use of RS for the detection of soil-borne pests in sugar beet. *Heterodera schachtii*, studied by Sanwald (1979) using IR aerial images resulted in the lack of significant changes in spectrometric reflectance. Using high spatial resolution digital multispectral video Hope et al. (1999) detected root rot in sugar beet caused by *R. solani*. Their goal was to use reflectance data to determine the most valuable vegetation index for classification of sugar beet root rot. The NDVI developed by Rouse et al. (1974) was considered the best predictor of root rot infestation and is the most commonly used vegetation index. Spatial and temporal distribution as well as the economic impact of *R. solani* on sugar beet using multi- and hyperspectral, airborne and handheld data was successfully used to differentiate infected areas within a field (Laudien et al. 2004). The integration of a multi-temporal knowledge based approach might increase detection of a disease. The use of an internet based spectral library for diseases is also important and was simulated by Laudien et al. (2006).

Investigations in the field, greenhouse and climate chambers were conducted in Germany on the use of IR thermography and leaf reflectance for the detection of *H. schachtii*, *Ditylenchus dipsaci* and *R. solani* in sugar beet. The use of thermal imaging has been shown to be suitable for the detection of foliar plant pathogens elsewhere (Chaerle et al. 2004, Lindenthal et al. 2004, Oerke et al. 2006, Lenthe et al. 2007) and is discussed in Chapter 11. Research using IR thermometry to detect soil-borne organisms is less developed (Pinter et al. 1979). Schmitz (2005) showed significantly higher leaf temperatures in sugar beet varieties susceptible to *H. schachtii* (Table 10.1). The nematode parasitizes the roots of the plants over the entire growing season, producing a cell syncytium responsible for disruption

Table 10.1 Mean leaf temperature of the nematode susceptible sugar beet cultivar Monza inoculated with increasing densities of *Heterodera schachtii* over time (growth period 2003, Schmitz 2005)

Nematode density [eggs and juveniles per 100 ml soil]	Time of assessment			
	June 13th	July 17th	July 29th	August 7th
<500	21.45°C a	24.87°C a	25.30°C n.s	35.63°C n.s
500–1,500	21.86°C ab	25.08°C ab	25.41°C n.s	36.37°C n.s
>1,500	22.28°C b	25.28°C b	25.76°C n.s	36.53°C n.s

Means with different letters in one column are significantly different, Tukeys HSD-Test ($p < 0.05$; $n = 10$), n.s. = not significant

of the xylem tissue and reduction in nutrient and water uptake. Nematode damage results in stunted growth, leaf yellowing and wilting under water stress conditions. Nematode infestation, therefore, is responsible for a significant reduction in leaf transpiration which leads to increased leaf temperature. These symptoms usually appear in elongated patches in the field or in bands caused by soil cultivation later in the growing season.

Significant differences also were detectable between the lowest and highest nematode density in greenhouse tests (Table 10.1) as well as in field experiments (Schmitz et al. 2004a, Schmitz 2005). These results confirmed those obtained by the European Community in Germany and Italy in the early 1980s (Berg 1980). On potato Gebhardt (1984) showed significant canopy temperature differences induced by *G. rostochiensis*. However, Schmitz et al. (2004a) were the first to show these canopy temperature differences in sugar beet induced by *H. schachtii* by aerial images taken with a helicopter from an altitude of 200 m at a correlation of $r = 0.6$ (Fig. 10.1).

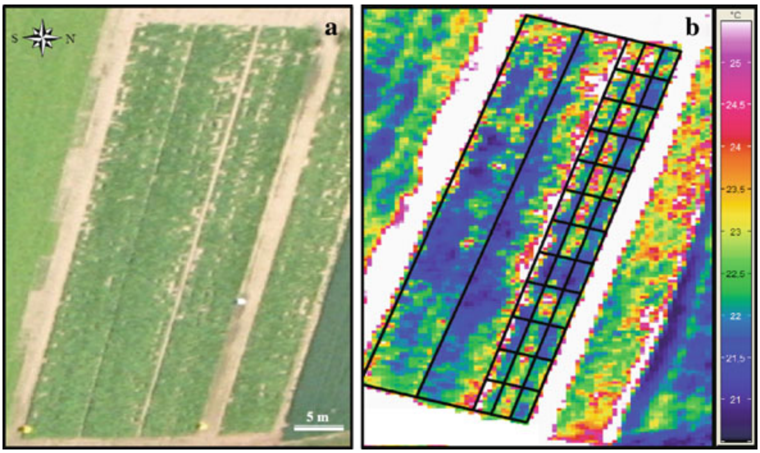

Fig. 10.1 Digital RGB picture (**a**) and digital IR thermography picture (**b**) of a field infested with pre-adjusted *Heterodera schachtii* population densities in the rectangular plots (Schmitz 2005)

Laser-induced chlorophyll fluorescence (LIF) and also pulse amplitude modulated chlorophyll fluorescence (PAM) are two other non-contact methods used to detect biotic and abiotic plant stress (Lichtenthaler and Miehé 1997, Apostol et al. 2003, Asmus and Ferraz 2002, Cervantes-Martínez et al. 2002, Chaerle et al. 2004). LIF and PAM are methods that gather data on photosynthesis and chlorophyll content (Tartachnyk and Rademacher 2003). Schmitz et al. (2006) conducted greenhouse experiments to test LIF and PAM for the detection of damage caused by increasing densities of *H. schachtii* on sugar beet. Plants showed a strong reduction in CO_2 assimilation with increasing nematode densities. Nematode infection led to a degradation of leaf chlorophyll in later stages of infestation and led to an increase in the F_{680}/F_{740} ratio and ground fluorescence (Fo) and a decrease in photochemical efficience (Fv/Fm) (Schmitz et al. 2004b). Discrimination analysis of the combined data from LIF and PAM resulted in a 100% correct classification of control plants and 60–100% classification of nematode infested plants at all sampling dates (Schmitz et al. 2006).

A sugar beet field study using IR picture was conducted in an experimental field with pre-adjusted preplant nematode densities in an attempt to estimate damage in the growing season and this damage to the preplant densities (Schmitz et al. 2003). The field was divided into 4 × 5 m quadrates, whereby each quadrate had a different infestation level of *H. schachtii*. The NDVI was calculated by using the near IR and the red bands of the IR picture with a spatial resolution of 70 cm for each pixel. Their results showed differences in spectral patterns between the infested and healthy sugar beets by supervised classification of the IR picture, but were unable to detect differences caused by the pre-adjusted nematode densities. The preplant densities were probably not sufficiently large enough for this type of separation (Fig. 10.2).

The use of precision agriculture techniques to detect *H. schachtii* damaged sugar beets for site-specific treatment can be complicated by the simultaneous infestation with the stem nematode *D. dipsaci*. This nematode causes high yield losses in

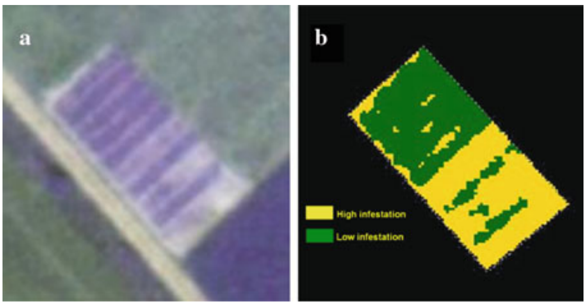

Fig. 10.2 IR airborne image (**a**) of a sugar beet field infested with *Heterodera schachtii* in 1999 (provided by LIZ: Landwirtschaftlicher Informationsdienst Zuckerrübe/Elsdorf), (**b**) Spectral classification into high and low nematode infestations (Schmitz et al. 2003)

central European sugar beet production areas (Kühnhold et al. 2006). Symptoms include malformed and bloated cotyledon petioles and swollen stem tissue. As the season progresses the beet develops cankers and secondary fungal infections (Dunning 1957, Griffin 1974). A correlation between soil clay content and the occurrence of *D. dipsaci* was observed by Seinhorst (1956).

Mapping of spatial nematode distribution by electric conductivity (EC_a) values and variable rate nematicide application for precision plant protection were successfully used in the USA for the root-knot nematode (*M. incognita)* and the ectoparasite *Hoplolaimus columbus* by Muller et al. (2002) and for root-knot and the reniform nematode (*R. reniformis)* on cotton (Wolcott et al. 2004, Davis et al. 2008, Lawrence et al. 2009) see Chapter 24. Estimation of the effects of soil type on the spatial distribution of the stem nematode, *D. dipsaci,* and the cyst nematode *H. schachtii* were investigated for the first time in field trials in Germany (Kühnhold, Kiewnick and Sikora unpublished data) using EM38 (Geonics Limited, Ontario, Canada) measurements. The EM38 measures apparent EC_a of the soil and leads to production of geo-referenced maps of EC_a (Mertens et al. 2008). According to Sudduth (2005) and Friedmann (2005) the main parameters which correlate directly or indirectly with EC_a values are clay and sand content, soil moisture, soil salinity and organic carbon.

In 2005, Kühnhold, Kiewnick and Sikora (data unpublished) used Spatial Analyses by Distance Indices software (SADIE®, Perry 1995) to analyze aggregation and spatial correlation of nematodes with soil properties. The nematode count data and the cluster indices obtained with SADIE® are presented in Fig. 10.3 in a geo-referenced map. The results provided new insights into the spatial distribution

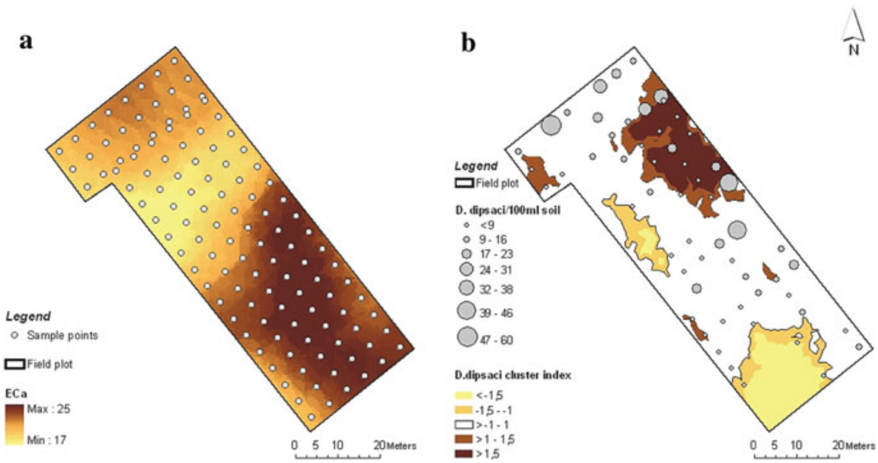

Fig. 10.3 Sample points and apparent electrical conductivity (EC_a) of the sampling area (**a**), spatial distribution of *Ditylenchus dipsaci* counts and the interpolated SADIE cluster analysis (**b**) (Kühnhold, Kiewnick and Sikora, unpublished data)

of *D. dipsaci* and *H. schachtii* in sugar beet. The data demonstrated that site-specific management is an appropriate tool for *H. schachtii* management. However, no clear correlation was found between EC_a values and the nematode densities of the two species. The differences in EC_a values characterizing soil properties (range 8 mS s^{-1}; Fig. 10.3) is considered to be low (Domsch and Giebel 2004). In contrast, Scholz et al. (2009) established a good correlation between the density of *H. schachtii* and EM38 values in sugar beet fields. This discrepancy may be due to the greater range of EC_a values within the field investigated by Scholz et al. (2009). They detected the highest density of cysts of *H. schachtii* in the sandy soils as identified by EM38 values.

The number of interactions that can occur between nematodes and pathogens in the sugar beet rhizosphere is great and such interactions can distort RS efficacy if only a single pest is targeted. To determine whether or not RS can be applied to complex interactions Hillnhütter et al. (2009) used hyperspectral data acquisition on sugar beet plants grown in the greenhouse inoculated with *H. schachtii* or *R solani* alone and in combination. Similar experiments were conducted with *D. dipsaci* and *R. solani.* Data was recorded with a handheld spectrometer with a foreoptic contact probe and a leafclip holder (ASD FieldSpec® Pro, Analytical Spectral Devices Inc.). The results showed that disease-complexes can be detected by hyperspectral measurements. The plants treated with *H. schachtii* and *R. solani* exhibited accelerated disease development over the plants inoculated with only one pathogen (Fig. 10.4). In addition, a *Rhizoctonia* crown and root rot rating index was developed to detect correlations between disease etiology and vegetation indices in order to find the most suitable index for pathogen development and disease severity. IR thermal images also were recorded. The results supported the findings obtained with hyperspectral measurements (Fig. 10.5).

Further experiments with an imaging hyperspectral line sensor in combination with a mirror scanner (ImSpector V10, Spectral Imaging Ltd., Oulu, Finland) also were conducted with the nematode-fungal disease complex. ImSpector captures a line image of a target and disperses light from each line image pixel to spectrum. Each spectral image then contains line pixels in the spatial axis and spectral pixels in the spectral axis. With this imaging system, a more detailed analysis of etiopathology was obtained (Hillnhütter et al. 2010).

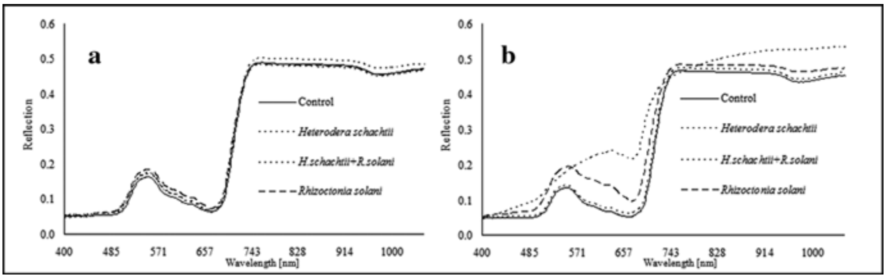

Fig. 10.4 Effect of *Heterodera schachtii*, *Rhizoctonia solani* alone and in combination on spectral reflectance of sugar beet plants, (**a**) 0 dpi, (**b**) 14 dpi (Hillnhütter et al. 2009)

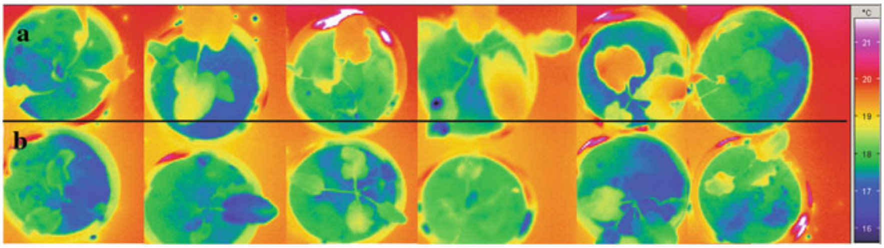

Fig. 10.5 Infrared thermographic images of sugar beet plants inoculated with *Rhizoctonia solani* showing *orange* and *yellow* leaf coloring (**a**) compared with non-inoculated *green* to *blue* control plants (**b**) 9 days after inoculation

4 Outlook

Experience obtained in the past with remote sensing to determine temporal and spatial distribution of nematodes and soil-borne diseases has produced a significant amount of baseline information. The development of new sensor technology will stimulate fundamental and applied research that will significantly improve RS and site-specific treatment methodologies for integration into plant protection programs. The research results presented here for two sugar beet nematodes and fungal crown rot demonstrated that RS and the use of site-specific application of crop protection is feasible in sugar beet production. In addition to economic benefits of this technology, improved environmental protection would be considerable. Nematodes and soil-borne fungal pathogens are good targets for site-specific control, because of clustered forms of aggregation, limited mobility and characteristic aboveground symptoms. Detection and localization of these organisms in clearly delineated patches in a field and the fact that these patches are reasonably stable in long term rotations over many years makes site-specific management to prevent yield losses a long term proposition.

However, improvements in the analysis of hyperspectral data are still required. This will require evaluation of larger amounts of data and the need for expanded computer capacity (Lawrence et al. 2004). The detection of spectral wavebands for specific symptoms caused by soil-borne pathogens and nematodes is also required. Such wavebands could be identified by simple or multiple regressions, principal component analysis or by partial least squares regression analysis. These disease-specific wavebands could be derived from spectra obtained under environmentally controlled conditions and then adapted to field situations. Based on these wavebands, indices could be calculated in order to predict the damage of each organism in the growing season. In addition, disease-specific wavebands also may allow detection of complex-disease interactions.

Collecting and analyzing soil and root samples for quantitative determination of nematode and pathogen action threshold levels is extremely expensive and in many cases still impractical. The costs incurred through sampling and the waste often associated with full scale field application of pesticides could be greatly reduced if multiple biotic stress factors and the clusters could be effectively detected by sensor technology. The future use of new megaspectral sensors coupled for example with PCR or ELISA would also improve site-specific plant protection acceptability (Ophel-Keller et al. 2008). These technological developments could make precision plant protection of soil-borne nematodes and pathogens a reality in the near future.

Acknowledgements The authors acknowledge financial support of the German Research Foundation (DFG). In addition we would like to recognize the strong support offered to us by the late Dr. Josef Schlang, nematologist at the Biologische Bundesanstalt, Institute for Nematology, Elsdorf, Germany who assisted us in many of the initial field trials.

References

Apostol S, Viau AA, Tremblay N et al (2003) Laser-induced fluorescence signatures as a tool for remote monitoring of water and nitrogen stresses in plants. Can J Remote Sens 29: 57–65

Asmus GL Ferraz LCCB (2002) Effect of population densities of *Heterodera glycines* race 3 on leaf area, photosynthesis and yield of soybean. Fitopatol Bras 27:273–278

Berg A (1980) Remote sensing techniques applied to sugar beet diseases in Germany and Italy: introduction to the results of a European project. Int Arch Photogramm 23:457–462

Brodrick HT, Gilbertson B, Kreitzer MH (1971) Advances in aerial photography. SA Citrus J 449:9–13

Büttner G, Pfähler B, Märländer B (2004) Greenhouse and field techniques for testing sugar beet for resistance to *Rhizoctonia* root and crown rot. Plant Breed 123:158–166

Cai D, Kleine M, Kifle S et al (1997) Positional cloning of a gene for nematode resistance in sugar beet. Science 275:832–834

Cervantes-Martínez J, Flores-Hernández R, Rodrígez-Graray B, Santacruz-Ruvalcaba F (2002) Detection of bacterial infection of agave plants by laser-induced fluorescence. Appl Opt 41:2541–2545

Chaerle L, Hagenbeck D, De Bruyne E et al (2004) Thermal and chlorophyll-fluorescence imaging distinguish plant-pathogen interactions at an early stage. Plant Cell Physiol 45: 887–896

Cook CG, Escobar DE, Everitt JH et al (1999) Utilizing airborne video imagery in kenaf management and production. Ind Crop Prod 19:205–210

Davis RF, Ortiz BV, Perry C et al (2008) Considering field physical characteristics in assessing risk and delineating nematode management zones. Proceedings of 5th International Congress of Nematology, Brisbane

Domsch H, Giebel A (2004) Estimation of soil textural features from soil electrical conductivity recorded using the EM38. Prec Agric 5:389–409

Dunning RA (1957) Stem eelworm invasion of seedling sugar beet and development of crown canker. Nematologica 2:362–368

European Commission (2006) The European sugar sector. http://ec.europa.eu/agriculture/capreform/sugar/infopack_en.pdf. Accessed 15th Dec 2009

Franke W (1997) Nutzpflanzenkunde: nutzbare Gewächse der gemäßigten Breiten, Subtropen und Tropen. Thieme, Stuttgart & New York

Friedmann SP (2005) Soil properties influencing apparent electrical conductivity: a review. Comput Electron Agric 46:45–70

Gausman HW, Heald CM, Escobar DE (1975) Effect of *Rotylenchulus reniformis* on reflectance of cotton plant leaves. J Nematol 7:368–374

Gebhardt A (1984) Möglichkeiten zur Früherkennung phytopathologischer Erscheinungen mit Hilfe der Thermographie – Übersicht und erste Ergebnisse. Arch Phytopathol PflSch 20: 437–445

Gebhardt A (1989) Differenzierte Einschätzung des Wasserversorgungszustandes landwirtschaftlicher Kulturen mittels thermographischer Luftaufnahmen. Arch Acker- Pflanzenbau Bodenkd 34:741–748

Griffin GD (1974) Parasitism of nonhost cultivars by *Ditylenchus dipsaci*. J Nematol 7:236–239

Heald CM, Thames WH, Wiegand CL (1972) Detection of *Rotylenchulus reniformis* infestations by aerial infrared photography. J Nematol 4:298–300

Heath WL, Haydock PPJ, Wilcox A, Evans K (2000) The potential use of spectral reflectance from the potato crop for remote sensing of infection by potato cyst nematodes. Asp Appl Biol 60:185–188

Hillnhütter C, Mahlein AK (2008) Early detection and localisation of sugar beet diseases: new approaches. Ges Pflanzen 60:143–149

Hillnhütter C, Mahlein AK, Sikora RA, Oerke EC (2010) Hyperspectral imaging of sugar beet symptoms caused by soil-borne organisms. Proceedings of the 10th international conference on precision agriculture, St. Paul, Minnesota

Hillnhütter C, Sikora RA, Oerke EC (2009) Detection of complex soil-borne disease interactions by hyperspectral foliar surface monitoring in sugar beet. Phytopathology 99:53

Hillnhütter C, Mahlein AK, Sikora RA, Oerke EC (2010) Hyperspectral imaging of sugar beet symptoms caused by soil-borne organisms. Proceedings of the Tenth International Conference on Precision Agriculture, St. Paul, Minnesota

Hope A, Coulter L, Stow D, Peterson S, Service D, Telk A, Melin D (1999) Root rot detection in sugar beet using digital multispectral video. Proceedings of AARS, 12th Asian Conference Remote Sensing, Hong Kong

Kiewnick S, Jacobsen BJ, Braun-Kiewnick A et l (2001) Integrated control of *Rhizoctonia* crown and root rot of sugar beet with fungicides and antagonistic bacteria. Plant Dis 85:718–722

Kohonen T (1998) The self-organizing map. Neurocomputing 21:1–6

Kühnhold V, Kiewnick S, Sikora RA (2006) Development of an in vivo bioassay to identify sugar beet resistance to the stem nematode *Ditylenchus dipsaci*. Nematology 8:641–645

Laudien R, Bareth G, Doluschitz R (2004) Comparison of remote sensing based analysis of crop diseases by using high resolution multispectral and hyperspectral data – case study: *Rhizoctonia solani* in sugar beet. Proceedings of 12th International Conference on Geoinformatics, Gävle, pp 670–676

Laudien R, Bürcky K, Doluschitz R, Bareth G (2006) Establishment of a web-based spectral database for the analysis of hyperspectral data from *Rhizoctonia solani*-inoculated sugarbeets. Sugar Ind 131:164–170

Lawrence GW, Doshi RA, King RL et al (2007) Nematode management using remote sensing technology, self-organized maps and variable rate nematicide applications. Proceedings of World Cotton Research Conference. http://wcrc.confex.com/wcrc/2007/techprogram/P1787.htm. Accessed 28 Aug 2009

Lawrence GW, Kelley AT, King RL et al (2004) Remote sensing and precision nematicide applications for *Rotylenchulus reniformis* management in cotton. In: Cook R, Hunt DJ (eds) Nematology monographs and perspectives. Brill, Leiden and Boston.

Lawrence GW, Lawrence KS, van Santen E et al (2009) Use of hyperspectral imagery and soil electron conductivity for site specific reniform nematode (*R. reniformis*) evaluations and management. Proceedings of World Cotton Research Conference, San Antonio, pp 139–143

Lee YJ (1989) Aerial photography for the detection of soil-borne disease. Can J Plant Pathol 11:173–176

Lenthe JH, Oerke EC, Dehne HW (2007) Digital infrared thermography for monitoring canopy health of wheat. Prec Agric 8:15–26

Lichtenthaler HK, Miehé JA (1997) Fluorescence imaging as a tool for plant stress. Trends Plant Sci 2:316–320

Lindenthal M, Steiner U, Dehne HW, Oerke EC (2005) Effect of downy mildew development on transpiration of cucumber leaves visualized by digital infrared thermography. Phytopathology 95:233–240

Lu D, Mausel P, Brondizio E, Moran E (2004) Change detection techniques. Int J Rem Sens 25:2365–2407

Luc M, Sikora RA, Bridge J (2005) Plant parasitic nematodes in subtropical and tropical agriculture. CABI Bioscience, Egham

Mertens FM, Pätzold S, Welp G (2008) Spatial heterogeneity of soil properties and its mapping with apparent electrical conductivity. J Plant Nutr Soil Sci 171:146–154

Muller J, Kahalilian A, Kirkpatrick T et al (2002) Using electrical conductivity to predict nematode distribution in cotton fields. Proceedings of 4th International Congress of Nematology, Tenerife. http://www.ifns.org/cd2002/main.pdf. Accessed 28 Aug 2009

Nicolas H, Rivoal R, Duchesne J, Lili Z (1991) Detection of *Heterodera avenae* infestations on winter wheat by radiothermometry. Rev Nématol 14:285–290

Nilsson HE (1995) Remote sensing and image analysis in plant pathology. Annu Rev Phytopathol 15:489–527

Norman GG, Fritz NL (1965) Infrared photography as an indicator of disease and decline in citrus trees. Proc Florida State Hort Soc 78:59–63

Nowatzki J, Andres R, Kyllo K (2009) Agricultural remote sensing basics. Bulletin AE-1262. NDSU Extension Service. http://hdl.handle.net/10365/5408. Accessed 28 Aug 2009

Nutter FW (1990) Remote sensing and image analysis for crop loss assessment. In: IRRI (ed) Cop Loss Assessment in Rice. Online edition

Nutter FW, Tylka GL, Guan J et al (2002) Use of remote sensing to detect soybean cyst nematode-induced plant stress. J Nematol 34:222–231

Oerke EC (2005) Crop losses to pests. J Agric Sci 144:31–43

Oerke EC, Steiner U, Dehne HW, Lindenthal M (2006) Thermal imaging of cucumber leaves affected by downy mildew and environmental conditions. J Exp Bot 57:2121–2132

Ophel-Keller K, McKay A, Hartley D et al (2008) Development of a routine DNA-based testing service for soil-borne diseases in Australia. Australas Plant Pathol 37:243–253

Perry JN (1995) Spatial analysis by distance indices. J Anim Ecol 64:303-314

Pinter PJ, Hatfield JL, Schepers JS et al (2003) Remote sensing for crop management. Photogramm Eng Rem Sens 69:647–664

Pinter PJ, Stanghellini ME, Reginato RJ et al (1979) Remote detection of biological stresses in plants with infrared thermometry. Science 205:585–586

Rouse JW, Haas RH, Schell JA, Deering DW (1974) Monitoring vegetation systems in the Great Plains with ERTS. Proceedings of 3rd Earth Resources Technology Satellite-1 Symposium, Greenbelt. NASA SP-351:3010-3017

Rupe J, Kirkpatrick T, Bajwa S, Cartwright R (2005) Application of precision agriculture technology to define and manage nematodes and diseases of soybean. Int Plant Nutr Inst http://www.inpofos.org/far/farguide.nsf/926048f0196c9d4285256983005c 64de/8c963348cc505d6f86256e8c005391bc/$FILE/AR-24F%20Rupe%202004%20Annual%20rpt.doc. Accessed 28 Aug 2009

Sanwald E (1979) Die spektralen Reflexionseigenschaften gesunder und durch Zystennematoden geschädigter Zuckerrübenpflanzen und ihre Abbildung auf Infrarotluftaufnahmen. Dissertation University Freiburg, Germany

Schlang J (1991) Anbau resistenter Zwischenfrüchte zur biologischen Bekämpfung des Rübenzystennematoden. Zuckerrübe 40:476–488

Schmitz A (2005) Eignung berührungsloser Messverfahren zur Erkennung des Befalls von Zuckerrüben durch *Heterodera schachtii* (Schmidt) und Möglichkeiten der teilflächenspezifischen Bekämpfung. Dissertation University Bonn, Germany

Schmitz A, Kiewnik S, Schlang J et al (2003) Use of remote sensing to identify the spatial distribution of the sugar beet cyst nematode *Heterodera schachtii*. In: Werner A, Jarfe A (eds) Programme book of the joint conference of ECPA – ECPLF. Wageningen Academic Publishers, Wageningen

Schmitz A, Kiewnick S, Schlang J, Sikora RA (2004a) Use of high resolution digital thermography to detect *Heterodera schachtii* infestation in sugar beets. Comm Appl Biol Sci 69:359–363

Schmitz A, Tartachnyk II, Noga G, Sikora RA (2004b) Einfluss unterschiedlicher Populationsdichten des Rübenzystennematoden *Heterodera schachtii* auf die laserinduzierten Fluoreszenzmuster von Zuckerrüben. Mitt Biol Bundesanst Land- Forstw Berlin-Dahlem 396:566

Schmitz A, Tartachnyk II, Kiewnick S, Sikora RA, Kühbauch W (2006) Detection of *Heterodera schachtii* infestation in sugar beet by means of laser-induced and pulse amplitude modulated chlorophyll fluorescence. Nematology 8:273–286

Scholz C, Pätzold S, Welp G (2009) Spatial variability of soil properties and the occurrence of soil-borne pests in sugar beet. Programme book of the joint conference of JIAC. Wageningen Academic Publishers, Wageningen

Schowengerdt RA (1997) Remote sensing, models and methods for image processing. Elsevier, San Diego

Seinhorst JW (1956) Population studies on steem eelworms (*Ditylenchus dipsaci*). Nematologica 1:159–164

Stafford JV (2000) Implementing precision agriculture in the 21st century. J Agric Eng Res 76:267–275

Steddom K, Heidel G, Jones D, Rush CM (2003) Remote detection of rhizomania in sugar beets. Phytopathology 93:720–726

Steddom K, Jones D, Rush C (2005) A picture is worth than thousand words. http://www.apsnet.org/online/feature/remote. Accessed 8 Sept 2009

Sudduth KA, Kitchen NR, Wiebold WJ et al (2005) Relating apparent electrical conductivity to soil properties across the north-central USA. Comput Electron Agric 46:263–283

Tarkington RG, Seren AL (1963) Color and false color films for aerial photography. Photogramm Eng 29:88–95

Tartachnyk II, Rademacher I (2003) Estimation of nitrogen deficiency of sugar beet and wheat using parameters of laser induced and pulse amplitude modulated chlorophyll fluorescence. J Appl Bot 77:61–67

Taubenhaus JJ, Ezekiel WN, Neblette CB (1929) Airplane photography in the study of cotton root rot. Phytopathology 19:1025–1029

Toler RW, Smith BD, Harlan JC (1981) Use of aerial color infrared photography to evaluate crop disease. Plant Dis 65:24–31

Tylka D (2006) Two nematode soil sample analysis options. Integrated crop management. http://www.ipm.iastate.edu/ipm. Accessed 28 Aug 2009

Upchurch DR (2003) Remote sensing for crop management. Am Soc Photogramm Eng Rem Sens 69:647–664

Wheeler TA and Kaufman HW (2003) Relationship of aerial broad band reflectance to *Meloidogyne incognita* density in cotton. J Nematol 36:48–57

Wolcott MC, Overstreet C, Padgett B, Burris E (2004) Using soil electrical conductivity to denote potential nematode managements zones. Proceedings of the Beltwide Cotton Conferences, San Antonio, pp 349–353

Zhang Z, Wang M, Wang N (2002) Precision agriculture-a worldwide overview. Comput Electron Agric 36:113–132

Chapter 11
Potential of Digital Thermography for Disease Control

Erich-Christian Oerke and Ulrike Steiner

Abstract Infrared thermography is highly suitable for the detection of disease-induced changes in plant transpiration and water status. Depending on the host-pathogen system diseases can be detected at various stages of development. Pathogens attacking plant roots or colonizing the vascular system affect water uptake and translocation within the plant and cause a decrease in transpiration associated with an increase in leaf temperature. Diseases causing early malfunction of stomatal regulation produce pre-symptomatic modifications in transpiration, some affect cuticular transpiration when visible symptoms appear or only in later stages when tissue is severely damaged. Diseases without or with only minor effects on transpiration cannot be detected thermographically. In some host-pathogen systems a close relationship between disease severity and thermal effect exist which may be used for disease quantification. The low specificity of the signal limits the use of thermography for disease identification, however, this may be compensated by the use of patterns of leaf temperature. IR remote sensing has a large potential in disease forecasting and the definition of management zones because of its high sensitivity to changes in plant water relationships.

1 Introduction

With shrinking resources for arable land and water, the optimization of crop productivity by early detection of biotic (and abiotic) stress factors and the remediation of these perturbations by effective disease control become more and more important. Technical sensors for non-destructive detection, identification, quantification, and monitoring of biotic plant stress(ors), therefore, are highly needed.

E. Oerke (✉)
Institute of Crop Science and Resource Conservation (INRES) – Phytomedicine, University of Bonn, Bonn D-53115, Germany
e-mail: ec-oerke@uni-bonn.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_11,

The visual assessment of plant diseases is often tedious and expensive and is fraught with variations among assessors. Technical sensors for non-destructive remote sensing are more objective and should improve accuracy as well as sensitivity of disease assessment as sensors are not limited to the visible range of the electromagnetic spectrum. Non-destructive, pre-visual detection and quantification of diseases can contribute to facilitate and limit the timely application of appropriate control activities to the specific sites where needed.

Digital infrared thermography permits remote recording of plant surface temperature as affected by disease development on different scales – leaf, shoot, crop canopy, field, and region – without interfering with plants. Imaging thermography is able to produce spatial and temporal patterns of plant temperature. Its – potential – use in plant pathology and crop protection is summarized.

2 Temperature of Plants

The temperature of plants largely depends on temperature of the environment; only a few thermogenic species – members of the Araceae, such as *Philodendron selloum*, *Symplocarpus foetidus* and *Dracunculus vulgaris* and non-aroids such as *Nelumbo nucifera* – are able to actively increase tissue temperature well above air temperature by a mitochondrial respiratory pathway that is distinct from the cytochrome chain (Wagner et al. 2008); volatile compounds are released by the inflorescences in order to attract insects for pollination. In all other plants, the metabolic activity is described to have no effect on leaf temperature (Chaerle and Van der Straeten 2000) and transpiration reduces tissue temperature below air temperature.

Transpiration rate has been shown to be negatively correlated to leaf temperature (Inoue et al. 1990) physically linked to its stomatal resistance (= 1/stomatal conductance). Leaf temperature results from the incoming irradiation, the water status of the plant and the functionality of the epidermal layer (cuticle and stomata) to regulate the transpiration of leaves, as well as from environmental conditions like air temperature, relative humidity (RH) and wind speed (Jones 1992). Unintentional transpiration is prevented mainly by the coverage of leaf surfaces with the cuticle which is an effective barrier against water loss (Schönherr 1982) whereas the water status of the shoot tissue determines the temperature of plants via stomatal transpiration. Leaf temperature increases as transpiration rate decreases. There is a correlation between leaf temperature and water status (Farquhar and Sharkey 1982, Cohen et al. 2005, Jones and Schofield 2008).

Leaf temperature is a highly sensitive indicator of stomatal aperture as latent heat loss is a large component of the overall leaf energy balance that determines leaf temperature (Jones 1992). The transition of liquid water into water vapor requires a high amount of energy because of the high latent heat of vaporization of water – the energy required for the vaporization of 1 mg H_2O is able to cool 600 mg H_2O by 1 Kelvin (K). Transpiration at the cell walls below stomata, therefore, is accompanied by a significant cooling of the plant tissue and the surface. As leaf temperature is directly related to the rate of evapotranspiration from the canopy surface, infrared sensing of the canopy temperature may be used to monitor the transpiration rate of plants (Jones 1999, Jones et al. 2002, Merlot et al. 2002). Digital infrared thermography allows the quantitative analysis of spatial and dynamic physiological information on the plant status at the canopy and leaf level without interfering with plants (Jones 2004). In plant sciences, the method has been applied to study the relationship between stomatal conductivity and leaf temperature, to visualize temperature stress of plants or plant parts, the drying of fruits and for yield estimations as well as for scheduling irrigation.

Control of transpirational water loss through stomata on plant leaves is an important mechanism for maintaining leaf surface temperature. Stomatal transpiration accounts for 94–99.7 % of the total gas exchange of leaves under normal conditions (Körner 1994). The transpiration rate of astomatous cuticles isolated from the adaxial leaf surface of *Prunus laurocerasus* was two to three orders of magnitude lower than that of the abaxial leaf side (Schreiber and Riederer 1996). Furthermore, the cuticular permeance of astomatous and stomatous leaf surfaces has been reported to differ by a factor of 11 in *Hedera helix*, indicating pronounced differences in barrier properties between cuticles (Santrucek et al. 2004).

In addition to the abiotic environment, pathogenic organisms may affect both cuticular and stomatal conductance of plant tissue resulting in significant modifications of leaf temperature (Ayres and Jones 1975, Smith et al. 1986, Wright et al. 2000, Chaerle et al. 2001, Bassanezi et al. 2002). Depending on the site of attack – roots, vascular system, photosynthetic active tissue – water relations of crops are affected directly or indirectly, localized to (some parts of) organs or the whole plant. Perturbations of transpiration may be used as cues for the development of plant diseases affecting stomatal aperture and functionality of cuticle integrity.

3 Principles of Infrared Thermography and Instrumentation

All objects above 0 K emit electromagnetic radiation, especially infrared (IR) radiation allowing the measurement of their surface temperature. IR radiation is part of the electromagnetic spectrum and spans a range – 0.75–1,000 μm – between the visible light and radio waves. It may be divided into several bands of interest to disease detection: NIR (near infrared, IR-A) 0.75–1.4 μm; SWIR (short-wavelength infrared, IR-B) 1.4–3 μm; MWIR (mid-wavelength infrared, IR-C) 3–8 μm (3–5 μm, atmospheric window used by ‘heat-seeking’ missiles); LWIR (long-wavelength infrared, IR-C) 8–15 μm (thermal infrared TIR); FIR (far infrared) 15–1,000 μm (according to International Commission on Illumination).

According to Planck’s Law and Wien’s displacement Law the wavelength at which the maximum amount of energy is emitted increases from hot to colder objects (Fig. 11.1). Sensors for biological samples in their natural environment, therefore, should have a maximum sensitivity in the range from 9.5 to 10 μm. Stephan Boltzmann Law allows calculation of the object’s temperature from its total radiated energy. Atmospheric attenuation of radiation caused by water vapor and

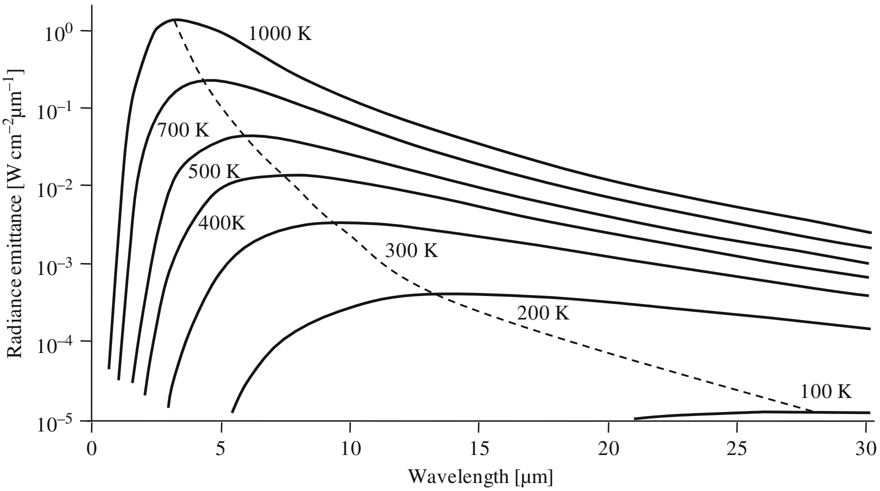

Fig. 11.1 Emission spectra of surfaces with temperatures ranging from 100 K (= −173°C) to 1,000 K (= 727°C). The maximum of surfaces with temperatures from 0 to 40°C ranges from 9 to 10.5 µm

other gases strongly depends on the wavelength; for thermography the mid-wave window (3–5 µm) and the long-wave window (8–14 µm) may be used.

Emissivity is the ability of a material to emit or absorb thermal radiation; it ranges from 0.0 – no emission − to 1.0 – complete emission (of a Black Body). Infrared radiation of real-world objects tends to be less than the actual temperature; the rate between infrared radiation and contact temperature of an object is its emissivity. For plant physiological experiments emissivity of plant tissue is often set to fixed values from 0.95 to 1. However, differing emissivities of various plant tissues and reflections from other surfaces – like the soil – interferes with IR measurements.

Non-contact thermometers (pyrometer, radiothermometer) have been applied in agricultural sciences since the 1980s. Their use is limited as they provided no spatial information and comparative measurements are affected by transient changes in environmental conditions. Originally developed for military use – forward looking infrared (FLIR) imaging technology –, thermographic cameras (thermal imaging = thermography) have a wide area of application ranging from firefighting, assessment of thermal insulation of buildings to industrial applications like online quality control.

Thermographic cameras detect electromagnetic radiation in the range of 3–15 µm and produce images of that radiation. Thermal energy is emitted by all objects based on their temperatures. As the amount of radiation increases with temperature variations in temperature in space and time may be detected. Thermal sensors are specialized focal plane arrays (FPAs) and non-cooled microbolometers. FPAs with low thermal resolution require cryogenic cooling by liquid nitrogen or a miniature Sterling cycle refrigerator.

Table 11.1 Bands of thermal infrared and suitable sensors for thermal imaging

Band	Wavelength [μm]	Sensor(s)
Short-wavelength infrared (SWIR)	1 – 3	InGaAs
Mid-wavelength infrared (MWIR)	3 – 5	InSb, HgCdTe
Long-wavelength infrared (LWIR)	8 – 14	HgCdTe, microbolometer

The imaging system is a scanner – a single detector in combination of rotating mirrors or oscillating refractive elements which scan the field of view (FOV) in horizontal and vertical directions – or a focal plane array – a matrix of detectors to resolve the FOV (Meola and Carlomagno 2004). The detectors are photon detectors requiring cooling by liquid nitrogen or Stirling coolers for rapid scanning, high sensitivity and low noise. Infrared systems may use the mid-wave (MW, 3–5 μm) and the long-wave (LW, 8–12 μm) IR range with mercury cadmium telluride (HgCdTe) photon detectors being used for both ranges (Table 11.1). Sensors may be used on handheld systems, ground-based equipment or may be airborne.

The performance of an infrared camera is expressed in terms of thermal sensitivity, scan speed, image resolution and intensity resolution. Thermal sensitivity – expressed as noise equivalent temperature difference (NETD) – is typically 80–200 mK for uncooled detectors and approaches 10 mK for cooled photon detectors. The rate at which an image is acquired may be higher than 1,600 Hz for new systems. Pixel resolution may reach 15 μm in microscope applications and the number of pixels per image is often 640×512. Modern systems provide 14-bit recording for a broad dynamic range (= intensity resolution). New detector systems may be also used for spectral analysis of radiation resulting in multispectral IR signatures.

In passive thermography the object is measured in its environment without any additional influence; in active thermography, an additional energy source is used and the thermal response of the object to this energy is recorded.

4 Detection of Disease Symptoms

4.1 Use of Radiometers in the Field

Early reports on the use of hand-held IR thermometers for quantifying the effect of root and vascular diseases on field crops have been summarized by Nilsson (1995). He pointed out that the radiometric response of crops to diseases may be divided into two groups: (I) a modification of the plant–water relationship, and (II) the expression of symptoms of senescence. Various diseases caused by bacteria, fungi, oomycetes, and nematodes affect the water supply of crops and result in an increase of canopy temperature, often in the range from 1 to 4 K, however, sometimes exceeding 10 K above air temperature (Pinter et al. 1979, Nicolas et al. 1991, Nilsson 1991). In contrast, stripe rust caused by *P. striiformis* reduced leaf temperature of wheat in early disease stages by 0.2–1.0 K (Smith et al. 1986).

The results obtained for several pathosystems made it difficult to quantify an attack in a reliable way, but led locally to good relationships between remote sensing data and indicators of the severity of the attack (Lili et al. 1991, Duchesne et al. 1992).

4.2 Infrared Imaging

As radiothermometers provide no spatial information, their use is limited because of influences of environmental conditions like sunlight, wind, soil, etc. (West et al. 2003). The development of thermal imaging systems, although more expensive, has increased considerably the potential of IR thermography in plant stress detection. The investigations have focused on the – sometimes pre-symptomatic – detection of diseases caused by viruses, bacteria, oomycetes and fungi infecting leaves. Imaging systems allow, however, the assessment of spatial heterogeneities on various scales, from the leaf level to canopies and landscapes.

4.2.1 Leaf Level

Localized changes in leaf temperature have been used as indicator of several biotic stresses (Chaerle and Van der Straeten 2000, Chaerle et al. 2001, 2006). Hypersensitive reaction of tobacco to tobacco mosaic virus (TMV) infection was preceded by a local, rapidly expanding increase in tissue temperature because of the accumulation of salicylic acid, a pivotal compound in plant resistance to pathogens, also known for its stomatal closing activity (Chaerle et al. 1999). During establishment of hypersensitive response of *Nicotiana sylvestris* to *Erwinia amylovora* 3–4 h after harpin-infiltration, tissue temperature decreased associated to stomatal opening. The marked drop in temperature reached 2 K and preceded necrotic symptoms for several hours (Boccara et al. 2001). Toxins released by pathogens are also described to alter stomatal behavior (Chaerle and Van der Straeten 2001); they may also cause tissue degradation associated to a localized decrease in tissue temperature in early stages of *Cercospora* leaf spot of sugar beet (Chaerle et al. 2004).

The oomycete *Pseudoperonospora cubensis* causing downy mildew of cucumber and fungi of the genus *Phyllosticta* acting on two tree species caused an increase in overall leaf temperature at early stages of infection (Lindenthal et al. 2005, Aldea et al. 2006, Oerke et al. 2006). Leaf spot due to *Phyllosticta* sp. increased temperature of surrounding leaf tissue of *Quercus velutina*, in contrast to a cynipid gall wasp which resulted in a spatially very limited decrease of temperature (Aldea et al. 2006). Transient decreases in temperature of infected leaf areas due to the evaporation of leaf water resulting from damage of plant cuticle or degradation of cells have been also described for downy mildew of cucumber, late stages of TMV infection and apple scab (Chaerle et al. 1999, Lindenthal 2005, Oerke et al. 2005).

In greenhouse experiments *Plasmopara viticola* caused a pre-symptomatic increase in leaf temperature at the site of infection in irrigated grapevine, whereas drought-stressed plants showed a localized drop in temperature 2–3 days before typical symptoms of downy mildew appeared (Stoll et al. 2008b). Spatial and temporal analysis of leaf temperature improved the differentiation between healthy and infected leaves irrespective of their water status (Stoll et al. 2008a).

Single mature rust colonies may reduce temperature by up to 0.7 K compared to the non-diseased surrounding tissue (Lenthe 2005). The cool spots have a clear temperature gradient with the center displaying the lowest temperature. This thermal signal can be detected only when cuticular transpiration is largely uncontrollable because of the cuticle perforation by the urediniospores (Fig. 11.2). Healthy and diseased plants may differ also in the pattern of leaf temperature. Bean rust due to *Uromyces phaseoli* caused a greater heterogeneity in small-scale temperature variability in later stages of the disease (Lenthe 2005). Dense colonies of powdery mildew, in contrast, were associated with a temperature only slightly lower (0.2 K) than healthy tissue. In later stages, powdery mildew tends to slightly increase tissue temperature because of reduced water potential of diseased leaf areas (Fig. 11.3). These results also reflect the subtle way biotroph pathogens maintain the functionality of host tissue they are living from.

The fungus *Venturia inaequalis* causes scab of apple, a hypostomatous plant species. Despite of the limitation of this pathogen to subcuticular colonization of leaf tissue, scab symptoms on one leaf side significantly reduced temperature of both, adaxial and abaxial leaf surface. Scab lesions are associated with a localized increase in intercellular free water which results in a significant increase of stomatal conductivity and a spatially limited cooling effect for the complete leaf profile. This effect stresses the correlation between leaf temperature and water status – water is the primary source of infrared absorption in plant tissue (Kümmerlen et al. 1999).

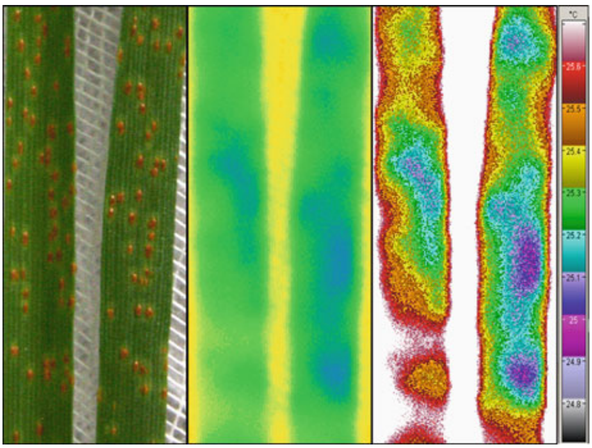

Fig. 11.2 Effect of leaf rust caused by *Puccinia triticina* on leaf temperature of wheat leaves. Reflectance image (*left*), thermographic image with low (*centre*) and maximum contrast displaying areas with similar temperature (*right*)

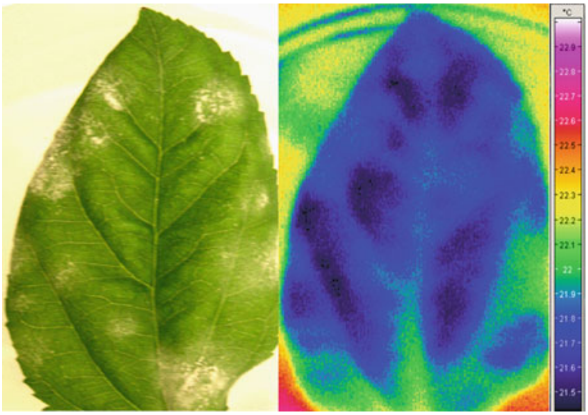

Fig. 11.3 Temperature response of apple leaf to well-established powdery mildew on the adaxial surface

Root diseases due to bacteria, oomycetes, fungi or nematodes may be detected by an increase in shoot temperature as all these pests affect water uptake and transport, ultimately reducing transpiration of shoots (Jones 2004, Schmitz et al. 2004). Mechanical wounding and tissue loss to chewing arthropods feeding on crops may result in a short temperature increase, followed by a localized decrease due to water loss from damaged cells, that progressively disappears again upon wound healing (Chaerle et al. 2002, Aldea et al. 2006).

The leaf area assessed thermographically for disease may be larger than that with visible symptoms. The leaf area affected by fungal colonization and its effect on host plant physiology – transpiration – often exceed the size of the visible damage. For other diseases like rusts thermographic anomalies linked to the impairment of cuticle function become only detectable after the appearance of symptoms. As powdery mildews seem to have only a very limited effect on stomatal transpiration and almost no effect on cuticular transpiration, thermography proved to be rather insensitive for this type of disease (see Table 11.2).

An effect of disease stage on leaf temperature – decrease for colonized, but living tissue, temperature rise (above the level of non-diseased tissue) for necrotic tissue – has been reported for various host-pathogen interactions (Chaerle et al. 2004, Lindenthal et al. 2005, Oerke et al. 2005).

Measurements of absolute temperatures are inappropriate for disease assessment, especially under varying environmental conditions. The use of the temperature difference between air temperature and leaf tissue (= transpirational cooling) and the assessment of spatial heterogeneity of temperature within leaves are more suitable. Similar, the maximum temperature difference (= range, MTD) of a leaf may be used as a sensitive parameter for an early detection (Lindenthal et al. 2005). MTD of leaves is more sensitive to pathogen-induced alterations than the mean, minimum or maximum of leaf temperature because this parameter assesses spatially restricted rare modifications in early disease stages. As it is less dependent on environmental conditions and does not significantly exceeds 1 K in healthy leaves, MTD may be used as a threshold level for disease detection (Lindenthal et al. 2005, Oerke et al. 2006).

Table 11.2 Effects of diseases on canopy/leaf temperature studied by infrared thermography

Crop	Disease	Response: Intensity	Response: Effect	Level	Source(s)
Apple	Powdery mildew	+		L	See above
	Scab	+++	▼[1]	L, F	Oerke et al. (2005)
Barley	Leaf stripe	+++	▲	F	Nilsson (1991)
	Net blotch	+		F	Nilsson (1991)
	Nematodes	+		F	Nilsson (1991)
	Powdery mildew	++/+++	▲	F	Nilsson (1991)
Cotton	Root rot	+++	▲	F, L	Pinter et al. (1979)
Cucumber	Downy mildew	+++	▼,▲	L, F	Lindenthal et al. (2005)
	Powdery mildew	+		L	See above
Grapevine	Downy mildew	+++	▼,▲	L	Stoll et al. (2008a, b)
Oats	Crown rust	+		F	Nilsson (1991)
	Oat red leaf (BYDV)	+		F	Nilsson (1991)
Oak	Phyllosticta leaf spot	++	▲	F	Aldea et al. (2006)
Oilseed	Clubroot	+		F	Nilsson (1991)
Rape	Stalk rot	+++	▲	F	Nilsson (1991)
	Verticillium wilt	+++	▲	F	Nilsson (1991)
Potato	Early blight	+		F	Nilsson (1991)
	Late blight	+		F	Nilsson (1991)
	Virus disease	+		F	Nilsson (1991)
Sugar beet	Beet yellows	+/++	▲	F	Nilsson (1991)
	Black root	+++	▲	F, L	Pinter et al. (1979)
	Cercospora leaf spot	+++	▼,▲	F, L	Chaerle et al. (2004), Stenzel et al. (2007)
	Cyst nematodes	++	▲	F	Schmitz et al. (2004)
	Powdery mildew	+/++	▲	L, F	Nilsson (1991)
	Rust	+++		L	Stenzel et al. (2007)
Rose	Rust	++	▲	F	Nilsson (1991)
Tobacco	Bacterial leaf spot	++	▼	L	Boccara et al. (2001)
	Tobacco mosaic	+++	▲,▼	L	Chaerle et al. (1999)
Wheat	*Fusarium* ear blight	+++	▲	L, F	See above
	Leaf stripe	++	▲	F	Nilsson (1991)
	Leaf rust	+	▼,▲	L, F	Lenthe (2005), Nilsson (1991)
	Powdery mildew	++/+++	▲	L, F	Nilsson (1991)
	Septoria leaf blotch	+/++	▲	F	Nilsson (1991, 2004)
	Nematodes	++	▲	F	Nicolas et al. (1991)
	Stripe rust	++	▼,▲	L, F	Smith et al. (1986)
	Take-all	+++	▲	F	Nilsson (1991)

+, + + and + + + = weak, moderate and strong effects on temperature; [1] ▼, ▲ = decrease or increase of temperature compared to non-infected; L, F; experiments under laboratory or field conditions

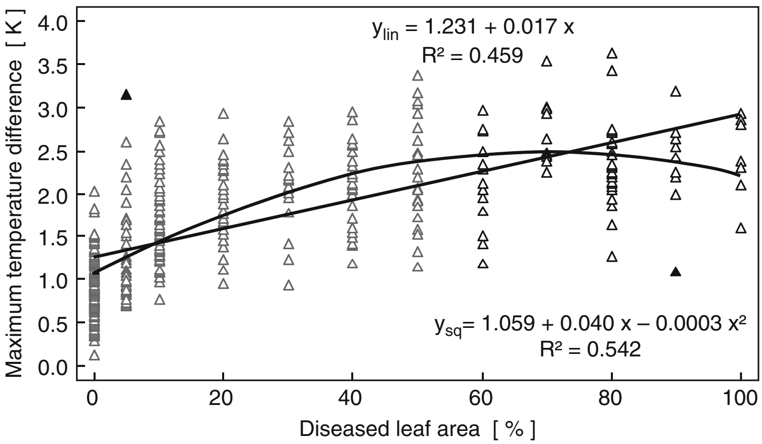

Fig. 11.4 Regression between diseased leaf area of apple scab and maximum temperature difference of apple leaves

Oerke et al. (2006) showed a correlation between disease severity (= percentage of leaf area affected) and MTD with a maximum at about 60–70% both for downy mildew of cucumber and apple scab (Fig. 11.4). MTD of leaves not only increased with the size of scab lesions but also with their number per leaf indicating that the probability of large lesions increases with their frequency. The increase of MTD with colony size may be explained by the high thermal conductivity of water. Small lesions have a very limited effect on transpiration/increase of leaf water content and the cooling effect dissipates very soon because of high lateral thermal flow which restricts the effect on tissue temperature in magnitude and size. With large lesions, the cooling effect is greater and even the largest lesions displayed a temperature gradient from the margin to the center of colonies.

Spatial patterns of temperature abnormalities due to pathogen development may be used for the differentiation of stress factors affecting the plant.

4.2.2 Canopy Level

The detection of primary disease spots in the field is one prerequisite for an efficient disease control. Hatfield (1990) postulated that patterns of reflectance or (thermal) radiation may be used for the identification of disease-induced changes that have within-field heterogeneity. In field experiments, the severity of *Septoria tritici* infection was associated with a decrease of the normalized difference vegetation index (NDVI) and an increase of the canopy surface temperature (<1 K) relative to reference plots (Nicolas 2004). Sensors for the optical range, however, proved to give better results for decision making of fungicide timing.

The complexity and heterogeneity of crop canopies due to varying plant densities, different leaf layers, leaf orientation, etc., restrict the informative value of temperature measurements as well as spatial resolution does. Early detection of primary disease foci on lower leaf levels is impeded by the upper leaf layers, high relative humidity (RH) at lower levels reducing overall transpiration, and the preponderance of healthy tissue often resulting in mixed pixels for diseased tissue. Significant thermal effects, therefore, can be obtained from crops only at later stages of disease development.

Under specific conditions, however, these obstacles play a minor role. In inoculation experiments – for resistance screening of crop varieties, tests on fungicide efficacy, etc. – disease intensity has to be assessed later in the growth period for a large number of plots. In this mono-factorial experiments disease severity may be quantified by areal thermography (Fig. 11.5). Earlier, Eyal and coworkers (1989) successfully used a hand-held thermometer for the differentiation of varieties' response to *Septoria* leaf blotch of wheat. Also diseases affecting only plant parts at the top of the canopy may be localized and quantified by thermographic imaging (Fig. 11.6). Thermograms were used to localize *Fusarium* infected ears in wheat and may be also used for the quantification of *Fusarium* head blight severity in screening plot experiments.

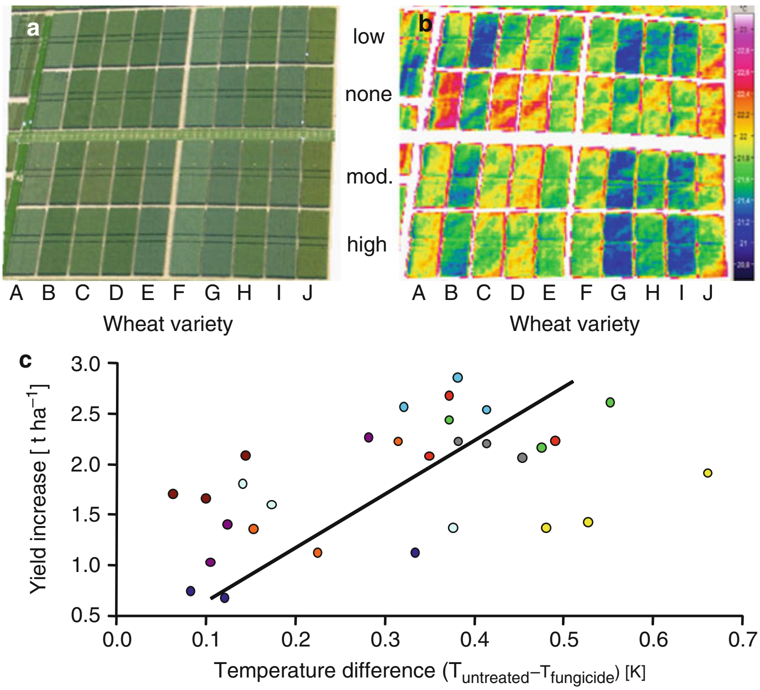

Fig. 11.5 Assessment of plant vitality of 10 wheat varieties depending on the frequency of fungicide applications (none, low, moderate, high). Reflectance image (**a**), thermographic image (**b**) taken at growth stage 75 from a helicopter; relationship between temperature difference between untreated and fungicide-treated plots and yield increase due to fungicide activity (**c**, different colors depict different varieties) (Lenthe 2005)

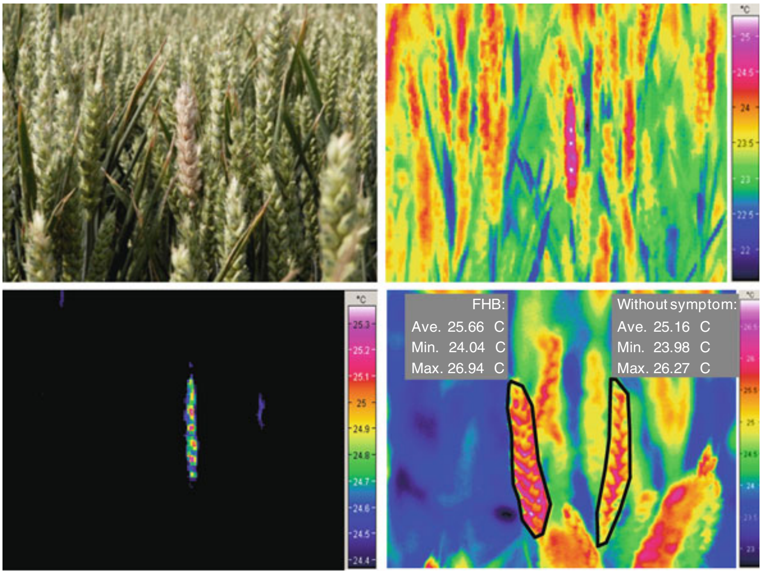

Fig. 11.6 Detection of *Fusarium* head scab infected ears in wheat (GS 77–79). Reflectance image (**a**); thermographic image of the same area with broad (**b**) and narrow temperature range (**c**); effect of infection on absolute temperatures of ears, MTD 2.90 K (infected) and 2.29 K (healthy) (**d**)

Schmitz et al. (2004) were able to differentiate between sugar beet varieties susceptible and resistant to the nematode *Heterodera schachtii* by using aerial thermography. Only the susceptible variety exhibited a significant correlation between canopy temperature and the density of nematodes in the soil.

5 Canopy Temperature and Management Zones

On the field level digital thermography has been evaluated for its potential in the definition of management zones (Lenthe 2005, Stenzel et al. 2007). Canopy temperature is the result of the temperature of the crop – the evaporation increases with crop biomass – and the environment, notably air and soil. Dense canopies with high biomass have lower temperatures than sparse crops when the soil is rather dry (Fig. 11.7). In contrast, when the soil is wet and cool and a reasonable proportion of soil is included in the thermogram, dense crops result in higher temperatures than poor plant stands. The differences in biomass depended on soil type and quality and were rather stable over time.

Even with relative homogenous soil conditions the microclimate within crop canopies may be heterogeneous. Comparing canopy temperature before and after rainfall, a promising degree of spatial similarity between leaf wetness and wheat temperature was detected by Lenthe et al. (2007). It may be possible in the near future to monitor spatial heterogeneity in crop temperature and leaf wetness

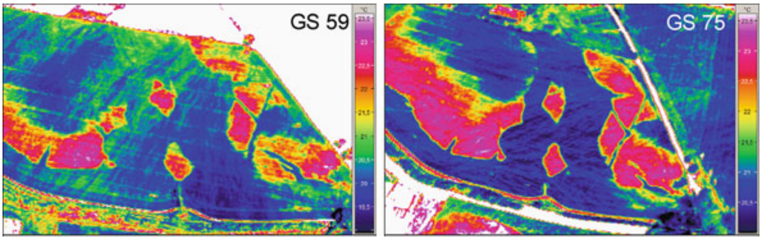

Fig. 11.7 Assessment of plant vitality and crop density of wheat before flowering (GS 59) and at soft dough (GS 75) by thermography from a helicopter (Lenthe 2005). Thermographic patterns display a high level of similarity

(duration), factors related to the incidence and spread of diseases in fields, by using thermograhic imaging.

6 Conclusions and Perspectives

Digital infrared thermography is suitable for the detection and quantification of diseases directly affecting plant transpiration by their activity on stomatal functionality and the integrity of the cuticle. Modifications in the plant's water status may be detected several days before the appearance of visible symptoms. The method, however, is less sensitive to ectoparasitic diseases like powdery mildews and diseases rupturing the leaf cuticle only in late stages of development (like rusts). It largely lacks diagnostic potential because of the uniformity of the stomatal response of plant tissue to various pathogens (and abiotic stressors) and its modulation/variation during various stages of the disease. Environmental factors, especially air temperature, irradiation, relative humidity and wind speed, affect leaf temperature complicating the interpretation of results, notably for images taken under field conditions. Abiotic stressors like water deficit resulting in stomatal closure may interfere with effects of diseases and arthropod pests affecting leaf temperature and compromise the detection and quantification of the primary stress factor. The large diversity of factors affecting stomatal aperture highlights the challenge of identifying and differentiating the cause.

Additional information is required for the identification of the cause. Temporal and spatial dynamics of (canopy) temperature may give additional information – areal thermographs taken at noon and in the evening were used to differentiate permanent wilting of sugar beet due to nematode attack from transient wilting due to circadian water shortage, stresses on leaf level tend to have a more heterogeneous response pattern than root level stresses (Chaerle et al. 2009) – nevertheless, non-specificity of temperature is limiting its application in disease detection and quantification.

Thermal imagery has potential for use in early disease detection which is very important for efficient and environmental friendly disease control since late detection of plant diseases may result in ineffective control reducing the quantity and quality of crop yield. In inoculation experiments when the pathogen is known, IR sensor systems may be used also for the quantification of diseases. Moreover, the technology can be used for the definition of management zones and the monitoring of environmental factors – temperature, leaf wetness – at the canopy level. It has also the potential to assess the quality of spray coverage within a canopy, hence optimizing pesticide application efficiency (Stoll et al. 2008b).

References

Aldea M, Hamilton JG, Resti et al (2006) Comparison of photosynthetic damage from arthropod herbivory and pathogen infection in understory hardwood saplings. Oecologia 149: 221–232

Ayres PG, Jones P (1975) Increased transpiration and the accumulation of root absorbed 86Rb in barley leaves infected by *Rhynchosporium secalis* (leaf blotch). Physiol Plant Pathol 7: 49–58

Bassanezi RB, Amorim L, Bergamin FA et al (2002) Gas exchange and emission of chlorophyll fluorescence during the monocycle of rust, angular leaf spot and anthracnose on bean leaves as a function of their trophic characteristics. J Phytopathol 150:37–47

Boccara M, Boue C, Garmier M et al (2001) Infra-red thermography revealed a role for mitochondria in presymptomatic cooling during harpin-induced hypersensitive response. Plant J 28:663–670

Chaerle L, De Boever F, Van der Straeten D (2002) Infrared detection of early biotic stress in plants. Thermology Int 12:100–106

Chaerle L, De Boever F, van Montagu M et al (2001) Thermographic visualization of cell death in tobacco and Arabidopsis. Plant Cell Environ 24:15–25

Chaerle L, Hagenbeek D, De Bruyne E et al (2004) Thermal and chlorophyll-fluorescence imaging distinguish plant-pathogen interactions at an early stage. Plant Cell Physiol 45:887–896

Chaerle L, Lenk S, Leinonen I et al (2009) Multi-sensor imaging of plant stresses: towards the development of a stress-catalogue for stress diagnosis. Biotechol J. Published online: Jun 25 2009. doi:10.1002/biot.200800242

Chaerle L, Pineda M, Romero-Aranda R et al (2006) Robotized thermal and chlorophyll fluorescence imaging of pepper mild mottle virus infection in *Nicotiana benthamiana*. Plant Cell Physiol 47:1323–1336

Chaerle L, Van Caeneghem W, Messens E et al (1999) Presymptomatic visualization of plant-virus interactions by thermography. Nature Biotechnol 17:813–816

Chaerle L, Van der Straeten D (2000) Imaging techniques and the early detection of plant stress. Trends Plant Sci 5:495–501

Chaerle L, Van der Straeten D (2001) Seeing is believing: imaging techniques to monitor plant health. Biochim Biophys Acta 1519:153–166

Cohen Y, Alchanatis V, Meron M et al (2005) Estimation of leaf water potential by thermal imagery and spatial analysis. J Exp Bot 56:1843–1852

Duchesne J, Lili Z, Nicolas H et al (1992) Elaboration of a pathological stress index from thermal infrared measurements. AAB Symposium, Rennes, 8–10 Sept, pp 49–50

Eyal Z, Wise GS, Blum A (1989) Canopy temperature as a correlative measure for assessing host response to *Septoria tritici* blotch of wheat. Plant Dis 73:468–471

Farquhar GD, Sharkey TD (1982) Stomata conductance and photosynthesis. Annu Rev Plant Physiol 33:317–345

Hatfield JL (1990) Remote detection of crop stress: Application to plant pathology. Phytopathology 80:37–39

Inoue Y, Kimball BA, Jackson RD et al (1990) Remote estimation of leaf transpiration rate and stomatal resistance based on infrared thermometry. Agric For Meteorol 51:21–33

Jones HG (1992) Plant and microclimate, 2nd edn. Cambridge University Press, Cambridge

Jones HG (1999) Use of infrared thermography for estimation of stomatal conductance in irrigation scheduling. Agric For Meteorol 95:135–149

Jones HG (2004) Application of thermal imaging and infrared sensing in plant physiology and ecophysiology. Adv Bot Res 41:107–163

Jones HG, Schofield P (2008) Thermal and other remote sensing of plant stress. Gen Appl Plant Physiol 34(1–2), 19–32

Jones HG, Stoll M, Santoa T et al (2002) Use of infrared thermography for monitoring stomatal closure in the field: application to grapevine. J Exp Bot 53:2249–2260

Körner C (1994) Scaling from species to vegetation: the usefulness of functional groups. In: Schulze ED, Mooney HA (eds) Biodiversity and ecosystem function. Springer, Berlin, pp 119–140

Kümmerlen B, Dauwe S, Schmundt D, Schurr U (1999) Thermography to measure water relations of plant leaves. In: Jähne B (ed) Handbook of computer vision and applications, vol 3. Academic Press, London, pp 636–637

Lenthe JH (2005) Erfassung befallsrelevanter Klimafaktoren in Weizenbeständen mit Hilfe digitaler Infrarot-Thermografie. PhD thesis, University of Bonn, Bonn

Lenthe JH, Oerke EC, Dehne HW (2007) Digital infrared thermography for monitoring canopy health of wheat. Prec Agric 8:15–26

Lili Z, Duchesne J, Nicolas H et al (1991) Détection infrarouge thermique des maladies du blé d'hiver. Bull OEPP 21:659–672

Lindenthal M (2005) Visualisierung der Krankheitsentwicklung von Falschem Mehltau an Gurken durch *Pseudoperonospora cubensis* mittels Thermografie. PhD thesis, University of Bonn, Bonn

Lindenthal M, Steiner U, Dehne HW et al (2005) Effect of downy mildew development on transpiration of cucumber leaves visualized by digital infrared thermography. Phytopathology 95:233–240

Meola C, Carlomagno GM (2004) Recent advances in the use of infrared thermography. Meas Sci Technol 15:R27–R58

Merlot S, Mustilli AC, Genty B et al (2002) Use of infrared thermal imaging to isolate *Arabidopsis* mutants defective in stomatal regulation. Plant J 30:601–609

Nicolas H (2004) Using remote sensing to determine of the date of a fungicide application on winter wheat. Crop Prot 23:853–863

Nicolas H, Rivoal R, Duchesne J et al (1991) Detection of *Heterodera avenae* infestations on winter wheat by radiothermometry. Revue Nematol 14:285–290

Nilsson HE (1991) Hand-held radiometry and IR-thermography of plant diseases in field plots experiments. Int J Remote Sens 12:545–557

Nilsson HE (1995) Remote sensing and image analysis in plant pathology. Annu Rev Phytopathol 33:489–527

Oerke E-C, Lindenthal M, Fröhling P et al (2005) Digital infrared thermography for the assessment of leaf pathogens. In: Stafford JV (ed) Precision agriculture '05. Proceedings of 5th European Conference on Precision Agriculture. Wageningen Academic Publishers, Wageningen, pp 91–98

Oerke EC, Steiner U, Dehne HW, Lindenthal M (2006) Thermal imaging of cucumber leaves affected by downy mildew and environmental conditions. J Exp Bot 57:2121–2132

Pinter PJ, Stanghellini ME, Reginato RJ et al (1979) Remote detection of biological stress in plants with thermography. Science 205:585–587

Santrucek J, Simanova E, Karbulkova J et al (2004) A new technique for measurement of water permeability of stomatous cuticular membranes isolated from *Hedera helix* leaves. J Exp Bot 55:1411–1422

Schmitz A, Kiewnick S, Schlang J et al (2004) Use of high resolution digital thermography to detect *Heterodera schachtii* infestation in sugar beets. Comm Appl Biol Sci 69:359–363

Schönherr J (1982) Resistance of plant surfaces to water loss: transport properties of cutin, suberin and associated lipids. In: Lange OL, Nobel PS, Osmond CB, Ziegler H (eds) Encyclopedia of plant physiology, vol 2B. Springer, Berlin, pp 153–179

Schreiber L, Riederer M (1996) Ecophysiology of cuticular transpiration: comparative investigation of cuticular water permeability of plant species from different habitats. Oecologia 107:426–432

Smith RCG, Heritage AD, Stapper M et al (1986). Effect of stripe rust (*Puccinia striiformis* West.) and irrigation on the yield and foliage temperature of wheat. Field Crops Res 14:39–51

Stenzel I, Steiner U, Dehne HW, Oerke EC (2007) Occurrence of fungal leaf pathogens in sugar beet fields monitored with digital infrared thermography. In: Stafford JV (ed) Precision agriculture ’07. Papers presented at the 6th European Conference on Precision Agriculture. Wageningen Academic Publishers, pp 529–535

Stoll M, Schultz HR, Baecker G et al (2008b) Early pathogen detection under different water status and the assessment of spray application in vineyards through the use of thermal imagery. Prec Agric 9:407–417

Stoll M, Schultz HR, Berkelmann-Loehnertz B (2008a) Exploring the sensitivity of thermal imaging for *Plasmopara viticola* pathogen detection under different water status. Funct Plant Biol 35:281–288

Wagner AM, Krab K, Wagner MJ, Moore AL (2008) Regulation of thermogenesis in flowering Araceae: The role of the alternative oxidase. Biochim Biophys Acta 1777:993–1000

West JS, Bravo C, Oberti R et al (2003) The potential of optical canopy measurement for targeted control of field crop diseases. Annu Rev Phytopathol 41:593–614

Wright KN, Duncan GH, Pradel KS et al (2000). Analysis of the N gene hypersensitive response induced by a fluorescently tagged tobacco mosaic virus. Plant Physiol 123:1375–1385

Chapter 12
Geographical Approaches for Integrated Pest Management of Arthropods in Forestry and Row Crops

Jeffrey L. Willers and John J. Riggins

Abstract With the proper technology and access to geographical information, it is more important to spend time developing an excellent classification scheme of a remotely sensed attribute of crop and forest vigor than to spend that time collecting multiple samples of insect counts. The ability to define zones from remote sensing images of crop or forest systems provides a vastly improved capacity to assess the sample variability of insect counts. Perspectives on defining zones from remote sensing information, including an examination of some relationships between these zones and insect sample counts, are discussed.

1 Introduction

Mankind's interest in controlling insects that attack crop and forest resources has existed since antiquity (Shaw and Willers 2006). Applications of Geographic Information Systems (GIS) and remote sensing (RS) capabilities are among the latest frontiers of this old conflict. Riley (1989) provided an excellent review of many earlier works involving RS. Similarly, Liebhold et al. (1993) provided an early review of the role of geo-statistical methods and GIS applications in entomology. They stated that the lack of adequate analytical and data management tools have been a major impediment to researching spatial processes in insect ecology. They concluded that habitat susceptibility to insect pest outbreaks can be investigated with GIS to better study relationships between biological and physiographic features of the landscape and identified the importance of scale in understanding ecological systems. Parameters and processes important at one scale are often not important or predictive at another scale. In addition, they made the point that insect populations often have spatially heterogeneous densities, which affects sampling procedures, assessment of predator-prey relationships, and pest management. As a consequence, the spatial location of collected samples is an important consideration.

J.L. Willers (✉)
USDA-ARS Genetics and Precision Agriculture Unit, Mississippi State, MS 39762, USA
e-mail: jeffrey.willers@ars.usda.gov

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_12,

Jackson and Huete (1991) provided an early review of important remote sensing concepts. They discussed two general classes of vegetation indices: ratios and linear combinations. Their paper addressed the effects of sensor type, soil background, viewing angle of the sensor, solar angles, atmospheric effects, and canopy architecture on a vegetation index. Entomologists not familiar with RS might consider beginning their exploration on the subject with this paper.

The concept of an ecological basis for insect pest management has a long history, as early addressed by Stern et al. (1959). Smith and McSorley (2000) stated that the key to pest management could be the relationship between insect behavior and their host plants. The example of Kerr et al. (2001) showed the value of RS for insect habitat categorization over a large landscape. The articles by Moran et al. (1997) and Pinter et al. (2003) are other excellent reviews.

Building on these early investigations, recent applications of various sensors installed on near or far RS platforms are leading to innovative efforts for insect pest control. This trend is possible because RS information is geo-referenced to coordinates on the earth at ground spatial distances (GSD) of 4.0 m or smaller. This capability offers an advantage that previous generations of entomologists did not have – specifically, data representing a complete census of one or more attributes of the crop or forest. However, estimates of insect abundance utilizing exclusively RS are still difficult to obtain and require concomitant collection of samples on the ground. As a consequence, the value of RS is the capability of dividing a traditional field or forest tract into smaller pieces, which can be categorically grouped into similar ecological units to control sampling error due to environmental variability. Insecticides can then be applied as needed to only the high risk units within the larger field or forest tract.

Precision agriculture is a new arena where advancements depend on the cooperation of diverse disciplines (Seelan et al. 2003), including entomologists, geographers, mathematicians, computer scientists, hardware or software engineers, and many others. Principal technologies involved include Global Positioning Systems (GPS), GIS, variable-rate controllers and yield monitors.

Forestry and row crop systems have inherent similarities but different goals and problems. Pest damage is often economically important in annual crops at or before the time the best RS technologies can begin to resolve pest effects on plant physiology (Willers et al. 2005), while the longer time horizon in forestry makes the predictive benefits of RS more useful.

The objective of this chapter is to briefly review several concepts of RS processing and then link that information with insect sampling in forests and row crops to promote site-specific Integrated Pest Management (IPM).

2 Forestry Applications

The rugged and inaccessible nature of forest systems promoted early adoption of RS and other geoinformatic applications. Also, due to the relatively long rotation age in agro-forestry, IPM practices in forested settings often tend towards prediction and protection rather than damage reduction or avoidance through direct control measures.

Early foresters typically relied on topography and their vision to detect forest pest activity at a distance. With the advent of the modern airplane, aerial sketch mapping became commonplace, allowing extremely large areas of forest to be covered yearly, or as often as needed, while personnel recorded approximate locations of pest activity on paper maps. This form of scouting progressed to include GIS and is now known as digital aerial sketch mapping. Both types of mapping are valuable tools for collecting cost effective, real time data regarding ongoing pest activity. However, detection of forest health problems often lags at least a year behind the initiation of insect activity. The damage to tree health is often irreversible by the time the human eye can detect when tree crowns begin to fade. Passive reflectance sensors are valuable for forest health assessments since their high spectral resolution provides early detection of changes in pest activity and/or forest health.

Advances in RS, at times, have caused problems of their own. For example, data storage and processing of geomatic information necessitated using more advanced computing resources and analysis algorithms. Since an image contains several layers of information about each square meter in the image (Jähne 1997), the number of bytes of data in one scan of a landscape of interest is tremendous. Also, with increased spatial resolutions, problems associated with variability of reflectance data arise. The possibility of multiple pixels capturing attributes about the crown of an individual tree leads to several questions. Are leaves on all branches the same? If not, how do we account for this variation and explain its causes? Solutions to these and other processing conundrums are still in the future. Nonetheless, these bottlenecks are not an excuse for avoiding the exploration of other RS frontiers for IPM.

2.1 Remote Detection of Vegetation Vigor

Reflectance imagery has been used to detect plant stress for years and is well established in the literature (Kasischke et al. 2004). Both multispectral and hyperspectral sensors show promise in early detection of forest health decline before symptoms are detectable by the human eye (Cibula and Carter 1992, Carter 1993, Carter and Miller 1994, Sampson et al. 2003, Pontius et al. 2005b). Early detection of damage in some forests has been successful using a narrow waveband centered near 700 nm (Hoque et al. 1992, Sampson et al. 2003, Campbell et al. 2004, Pontius et al. 2005a, b, White et al. 2007).

Hyperspectral sensors with greater spectral resolutions continue to be introduced. However, more bands greatly complicate analyses and can lead to problems with autocorrelation and poor signal to sample size ratios. Careful consideration must be given to determine if gains in detection outweigh the added complexity of data analyses with hyperspectral sensor systems.

Remote detection of weakened trees before insect outbreaks occur allows land managers to shift from a reactionary mentality to one of prevention. Proactive management utilizing silvicultural practices can avoid many forest pest problems.

RS of forest insect pest activity has significant potential to increase efficiency when choosing areas for pest control actions.

2.2 Importance of Spatial Variation of Biophysical Variables in Integrated Forest Pest Management (IFPM)

Forest pests are difficult to detect, sample, and treat due to the sheer size and height of the trees (Lu 2006). Most importantly, the long rotation age of forest commodities can sometimes make it impossible to calculate standard IPM variables like EIL (Economic Injury Level) and AT (Action Threshold) because it is difficult to reliably predict the value of the commodity several decades or more into the future, or economically impractical due to the invested cost of treatment over such a long period of time. Therefore, IFPM strategies rely on prediction or prevention rather than direct control measures. Prevention and prediction strategies often utilize a synergy of relatively sparse ground sampling and dense remotely sensed data to make predictions regarding the hazard of future pest outbreaks.

Preventative IFPM strategies often involve silvicultural treatments, such as commercial thinning or prescribed burning to reduce stand density and increase productivity. Collecting data to estimate these conditions using traditional ground-based methods is time consuming, laborious, expensive, and does not provide a continuous estimate across the landscape, like one produced by RS. Often, the remotely sensed variables are stand parameters that describe an important aspect of stand ecology, such as diameter at breast height (DBH), basal area, or aboveground forest biomass. Once these ecologically important variables are estimated through RS, decisions regarding preventative management activities are made and implemented.

Aboveground forest biomass is an estimate of the sum of the aboveground mass (biomass) of all the individual trees in a given area (Parresol 1999). Biomass is perhaps the single most powerful descriptor of structural information about forest stands. Once the biomass is reliably estimated, most other forest parameters (DBH, stand density, age, height, leaf area index, etc.) can be estimated. Therefore, aboveground forest biomass is emerging as an extremely important biophysical variable for use in modeling and predicting forest disturbances, such as insect outbreaks and fire. Monitoring biomass change over time is an integral tool for managing forest health. Measurement of forest parameters by RS allows development of geographical risk models or change maps to prioritize preemptive control measures or identify patterns.

However, often little thought is given to the effects of errors introduced by arbitrarily assigning sampling schemes, analyses, and predictive algorithms to a study area without taking into account the spatial variation in the landscape. (The similar problem exists in row-crop IPM.) In forestry (and row crops), environmental factors such as topography and soil can drastically affect the ecology of the hosts and pests as those factors vary across the study site. Traditional randomized completed block designs, or other randomized methodologies, will mask valuable spatial patterns because they lump spatial variation into random error.

2.3 Specific IFPM Examples: Red Oak Borer and Southern Pine Beetle

Red oak borer (*Enaphalodes rufulus*) and the southern pine beetle (*Dendroctonus frontalis*) are two destructive forest insect pests that gravitate towards densely-stocked, overmature trees. In fact, the outbreaks of many forest pests are linked to the relative density of trees on a given site. Therefore, mechanically thinning dense stands is practiced to reduce the hazard associated with future insect outbreaks.

Sampling for red oak borer, southern pine beetle, or other forest pests is often undertaken through random or arbitrary establishment of many sampling locations, without consideration of the biophysical variables that ecologically effect the distribution of the pest. Traditionally, it was thought that many samples were needed to overcome the unaccounted-for spatial variation in the environment. But, image classification or segmentations provide frameworks that allow researchers to greatly reduce the number of field samples; particularly, if the RS information describes the spatial variation of relevant biophysical variables. Image classification or segmentation divides the data into structurally homogeneous units, decreasing variability of subsequent biomass estimates. These predictions are theoretically more precise because the analytical models take spatial variation of the environment into account, rather than treating it as random error and 'sweeping it under the table'.

Segmentation techniques can yield more precise forest biomass estimates than other methodologies. Riggins et al. (2009) utilized object-based segmentation algorithms to take into account structural heterogeneity at multiple levels within the forest canopy before computing a total aboveground forest biomass model. Similar spatial aggregation techniques that allow the researcher to segment, classify, or otherwise divide the study site into biophysically meaningful zones decrease random error in statistical models and potentially reduce the number of field samples needed to adequately describe the variability present in the system.

The use of object-based image segments derived from remotely sensed imagery is a powerful method for forest attribute prediction. Object level processing divides the data into homogeneous units based on the values of neighboring pixels, minimizing many sources of error during modeling steps. The resultant image segments represent optimized functional units for use during the development and application of forest parameter modeling or forest sampling methodologies.

Figure 12.1 represents total aboveground forest biomass predictions reported by Riggins et al. (2009) for a 1,400 m × 1,400 m study area in Ozark National Forest in northwest Arkansas. Panel A shows the results of an object-based segmentation procedure (Riggins et al. 2009), while panel B shows the results of the same model applied on a per pixel basis. While many areas within these two images exhibit similar trends in aboveground forest biomass distribution, the two techniques provide vastly different results. The difference between each method is best seen by comparing the None and High categories between the two panels. If these two different methods were not attempted and compared, the fact that the object-based methodology yielded more accurate results than a pixel based methodology ($R^2 = 0.72$ vs. 0.54, respectively) would not have been identified (Riggins, personal observation).

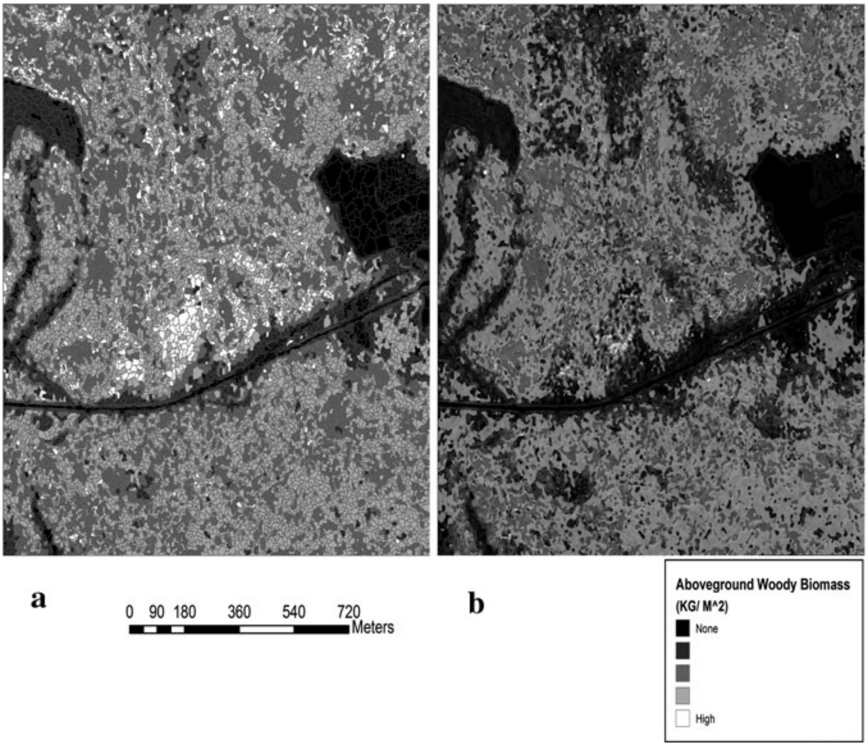

Fig. 12.1 Comparison of object-based (**a**) and pixel-based (**b**) representations of biomass

It is important to consider these techniques not only during the analysis or modeling phases of a project, but perhaps more importantly during the design phase of an experiment. Upfront utilization of segmentation techniques to account for the spatial distribution of aboveground forest biomass allows researchers to biophysically attenuate and optimize a sampling scheme to minimize the number of field samples needed to adequately describe the variability in the system.

3 Row Crop Applications

The major difference between forest and row crop RS applications for site-specific IPM is the time horizon. The ability to estimate the extent of different density distributions of insect populations among crop zones derived from RS fundamentally addresses the short time window problem in row crop IPM (Willers et al. 2005). In general, this is accomplished by (I) utilization of imagery to define appropriate crop zones to support insect scouting (sampling), (II) integration of all information (e.g., experience, field data and image information) to generate a 'map' of areas at risk for economic loss from insect pests, and then (III) uploading the georeferenced map file to instruct a Differential Global Positioning System (DGPS), variable-rate ground sprayer to apply pesticides at spatially variable rates. The first goal is emphasized in this section by demonstrating several concepts. Additional details for the second and third goals are found in Campenella (2000), Dupont et al. (2000), McCarter et al. (2007), McKinion et al. (2009) and Willers et al. (2005, 2009a, b).

Other important considerations for geographical IPM are to recognize that attributes of biological populations (i.e., the insects and the crop) are juxtaposed with (I) the concepts and properties of various statistical distributions (D'Agostino and Stephens 1986), (II) the sampling concept of a statistical population (Thompson 1992) versus a parametric population, and (III) principles involving the various ways to classify multispectral (or hyperspectral) images of farm landscapes (Jensen 2007, Pouncey et al. 1999, Richards and Jia 1999).

3.1 Image Classification

The first RS analysis step for site-specific IPM is to complete an unsupervised classification (Jensen 2005, Pouncey et al. 1999) of the image pixels for the current state of the annual crop, using 20–25 classes. Such a large number of classes enable field consultants to recognize the correspondence between small scale changes in crop vigor seen on the ground with those shown on the map. This correspondence assists them in choosing the locations to sample for insects. After collecting the insect counts, an iterative, supervised classification (Jensen 2005, Pouncey et al. 1999) step regroups (rebins) the initial unsupervised classes into a smaller set of ordinal categories that describe the relationship between crop zones and insect abundance. These ordinal categories are then used to derive the prescription map for the variable-rate controller on the field spraying equipment. Ordinal categories are defined with only the pixels that fall inside the field boundary polygon. It is important to exclude pixel values that do not belong exclusively to the crop of interest in both the unsupervised or supervised classification steps because pixel values not belonging to the crop skew results.

3.2 A General Approach for Linking Remote Sensing Information and Insect Sampling in Row Crops

The importance of the choice for the size of the sample unit on observing sample counts with a value of zero is discussed in Willers et al. (1999, 2005). The relationship among pest density, sample unit size and dispersion within a geographical zone is discussed in Willers et al. (2006). These papers provide further insight when used in conjunction with the following two concepts.

Each concept is illustrated with data obtained from Veris® cart soil electroconductivity (EC_a) measurements (Corwin and Lesch 2003). These EC_a values (mS m^{-1}) were collected from a USDA-ARS research cotton field on the North Farm Complex of Mississippi State University. The Veris® sensor data was chosen to illustrate these concepts because soil properties are typically more static than RS readings involving flora or fauna and because the areal extents of the shallow readings are nested within the deep readings for each EC_a swath element area (i.e. points in the GIS). This nesting trait is similar to the collection of insect counts from a smaller sized sample unit nested in a collection of adjoining pixels belonging to a particular habitat zone (Willers et al. 2005) (or within a feature object, similar to Panel A in Fig. 12.1). Figure 12.2 presents a 25 class, equal interval classification map, using a gray-scale color ramp, where the lighter colors represent higher EC_a values for the Deep profile. The geographical coordinates of these values are provided in the Universal Transverse Mercator (UTM) grid system (Bugayevskiy and Snyder 1995), Zone 16, in the WGS84 datum.

For Concept 1, the Shallow and Deep attributes are examined through simulation experiments to show how estimates of correlation vary if two attributes are sampled from identical geographic locations with different sample sizes. For Concept 2, a second sampling experiment assumes one attribute is measured by RS (i.e. the Deep

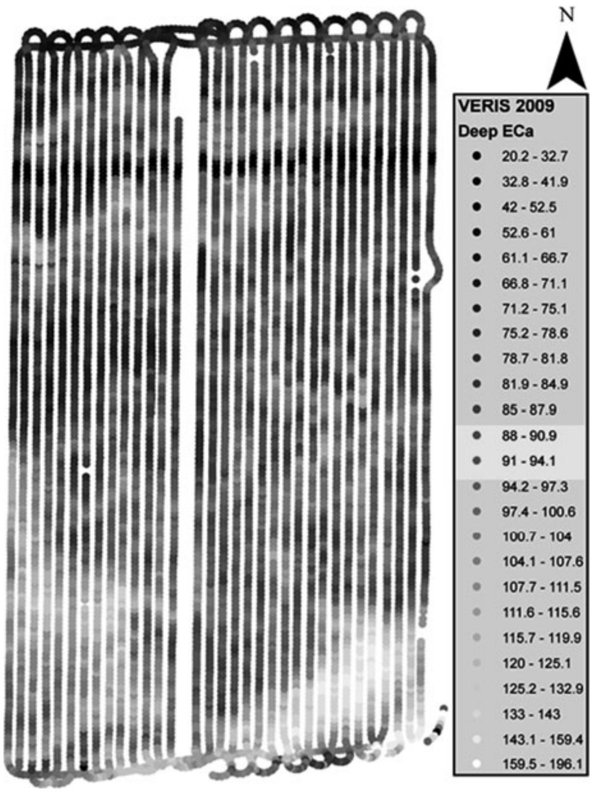

Fig. 12.2 Map of Deep EC_a values (mS m^{-1}) used for classification

attribute) and assumes that the second attribute (i.e. the Shallow) is measured by field sampling and has a small sample size.

Concept 1 – Within practical limits, increasingly larger field sample sizes of one attribute, sampled at the same location as a RS attribute, will not improve the estimate of the correlation between them.

The Pearson correlation between the Shallow and Deep EC_a values is 0.765 ($P < 0.0001$). This value is used later to represent the parametric population value for the correlation between these two attributes within the boundary of this field ($N = 5{,}786$). This estimate is considered to represent the population correlation for this field because the GSD between successive Veris® readings is only a few meters (Fig. 12.2).

This concept assumes the two attributes are being sampled from a homogenous population, such as a crop of the same cultivar, planting date, and growth rate within a single field. However, examination of Fig. 12.2 indicates that some spatial structure exists (a convenient way to address effects of spatial structure, without using geostatistics, is to employ an ordinal classification scheme for the Deep attribute, as shown in Concept 2).

Using SAS® data step programming (SAS® Institute, Cary, NC), a simple random sampling model (Thompson 1992), under the conditions of sampling with replacement, was created using these Veris® readings. The size of the sampling unit (see Willers et al. 2005) was fixed to correspond to the areal size of a single Shallow reading. This sampling model simulated 1,000 runs each for sample sizes of 7, 14, 21, 28 and 35. The sample size was stopped at 35 because obtaining sample sizes larger than 35 on large production farms is not practical due to the cost of sampling and availability of labor.

Table 12.1 presents the minimum, maximum, mean, and median statistics for Pearson correlation between the Shallow and Deep attribute, for 1,000 runs of each sample size. Examination of this table indicates that repeated sampling of this population of Veris® readings at different sample sizes results in a range of correlation estimates that vary widely. With the larger sample size of 35, the range is between about 0.1 and 0.9, indicating that pure sampling error can still mislead investigators a large percent of the time if only a single 'sampling experiment' is conducted. Improving estimates of the parametric population correlation value would result only for extremely large sample sizes – which in commercial fields is not economically possible.

Table 12.1 Summary statistics for the correlation estimates between shallow and deep readings of different sample sizes

Sample size	Runs	Minimum correlation	Maximum correlation	Mean	Standard deviation	Median
7	1,000	−0.896	0.996	0.561	0.356	0.671
14	1,000	−0.460	0.964	0.610	0.231	0.659
21	1,000	−0.100	0.949	0.626	0.178	0.661
28	1,000	−0.038	0.916	0.639	0.150	0.666
35	1,000	0.107	0.900	0.639	0.131	0.659

The results of this sampling experiment show the traditional view of using larger sample sizes to improve the accuracy of estimates of insect or crop attributes is unnecessary if RS information is available. It also shows the problem of trying to estimate the simple correlation between a field sample attribute and a RS attribute.

Concept 2 – Appropriate classification of a densely sampled attribute measurable by RS eliminates the requirement for large field sample sizes of a second geo-referenced attribute.

The issue addressed by this concept is rather simple but leads to a useful result: If crop phenology is densely sampled by RS and geographically classified (zoned) into ordinal categories, then the means of geographically sparse, simple random samples of insect counts obtained from each zone are mutually exclusive.

Here, the Shallow EC_a readings mimic an attribute not measurable by RS. This attribute will be used to derive sparse sample sizes as would arise with sampling insect counts in the field at geographic coordinates within zones established from a RS attribute. The Deep EC_a readings serve as the surrogate for the intensely sampled RS attribute. Consequently, the Shallow attribute, by simulation, was sparsely sampled at geographic coordinates within zones established from the Deep attribute. The use of these two Veris® attributes provide a certain level of control since the values for Shallow and Deep attributes are essentially known at each simulated sample location.

The first step of this exercise was to establish 25 equal interval unsupervised classification classes (de Smith et al. 2007) of the Deep readings similar to the legend of Fig. 12.2. Using these unsupervised class limits, an initial supervised classification of the Deep EC_a values was completed to create 5 zones.

These five ordinal, supervised, classification zones were utilized for 1,000 runs of simple random samples of Shallow readings in each zone with sample sizes = 7 (Concept 1 demonstrated little advantage with larger sample sizes). The results are shown as comparative histograms in Fig. 12.3. For these 5 zones, the distributions of sample means do not overlap for Classes 1 and 5, but do for the middle 3 classes. At first look, this result seems to contradict Concept 2 because 5 mutually exclusive distributions of sample means were not obtained.

This result suggests that RS may have nothing to offer the entomologist since the distinctiveness of the distribution Shallow EC_a means across the Deep EC_a zones is not clear cut, even with the effort of 5,000 independent samples. This conclusion is not valid since it fails to recognize the art of establishing supervised classes in RS. In entomological applications of RS, whenever sample means of the sparsely sampled attribute span one or more adjoining ordinal supervised classes, the first choice of action is to pool two or more supervised classes. Therefore, the Deep attribute was rebinned into 3 new ordinal classes by another iterative supervised classification process whose criteria were based upon the rate of areal change as new class limits were inspected in the GIS.

The SAS® simulation exercise was repeated with these three Deep EC_a zones. The results (Fig. 12.4) now show an appropriate classification of a remotely sensed attribute that eliminated the need for large sample sizes of the sparsely sampled attribute. The means of seven random samples from each of these three zones

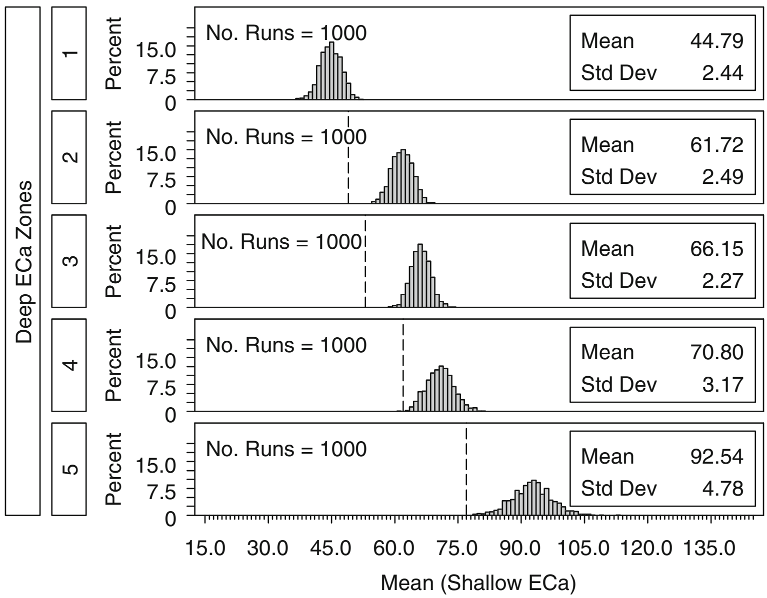

Fig. 12.3 Means of 1,000 runs of 7 samples (using simple random sampling with replacement) for Shallow EC_a readings (mS m^{-1}) from 5 categorical zones derived from Deep EC_a readings (mS m^{-1}). *Dashed lines* correspond to Shallow EC_a values of 50, 70, 75 and 82 mS m^{-1} respectively

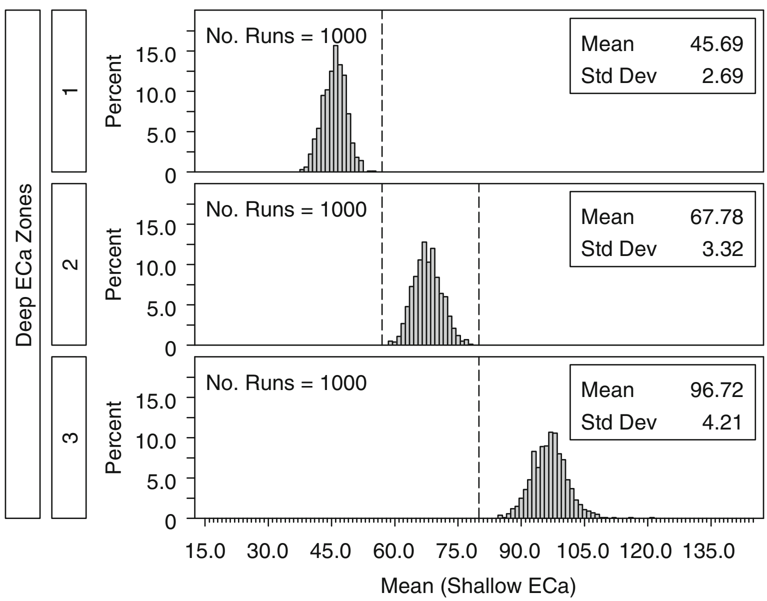

Fig. 12.4 Means of 1,000 runs of 7 samples (using simple random sampling with replacement) for Shallow EC_a readings (mS m^{-1}) from 3 categorical zones derived from the Deep EC_a readings (mS m^{-1}). *Dashed lines* correspond to Shallow EC_a values of 57 and 80 mS m^{-1} respectively

sufficiently describe the ‘state of nature’ in each zone. Any one of these 1,000 sets of 7 samples per zone could be utilized to determine the management actions in that particular zone. This implies, in light of the results from Concept 1 (Table 12.1), that any additional information obtainable from additional samples of the sparsely sampled attribute is already represented by the information content of the classification scheme of the RS attribute. Therefore, it is important to spend more time developing the appropriate classification scheme of the RS information as opposed to spending that time in collecting more field samples.

3.3 Application of Concepts in Cotton

Figure 12.5 shows a map product for a cotton field located in Bolivar County, Mississippi, USA. This map was built by combining a vegetation index from June 2004 multispectral imagery with a digital surface elevation model (DSM) produced from a 3 June 2003 *Li*ght *D*etection *a*nd *R*anging (LiDAR) acquisition for the same

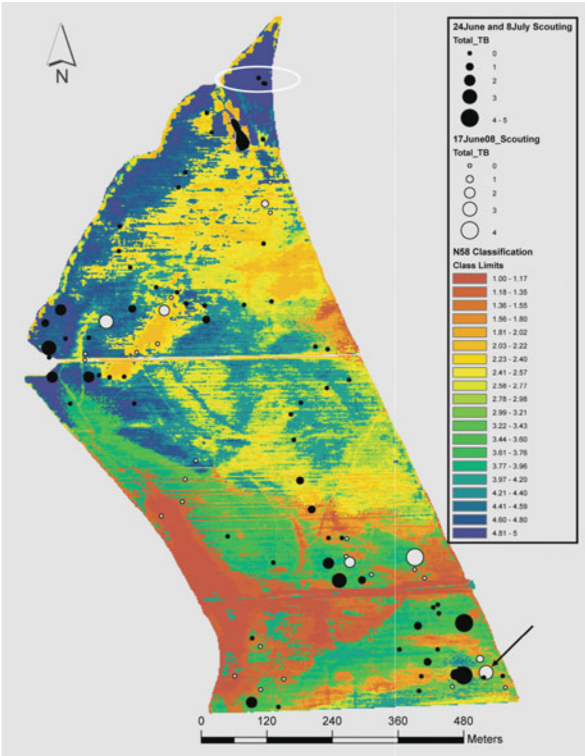

Fig. 12.5 Revised categorical, pseudo-likelihood classification map of cotton during June 2004 (after Strahler 1980 and Willers et al. 2009b). The figure has a spatial resolution of 2 m × 2 m per pixel. Graduated symbols show pre- and post-insecticide application counts of Tarnished Plant Bugs at various sample sites during June 2008

fields. Fusion of these two raster layers to produce this illustrative scouting map follows after Strahler (1980) and Willers et al. (2009b).

To illustrate several points in this section, Fig. 12.5 is used with a June 2008 data set for the cotton insect pest, the Tarnished Plant Bug (*Lygus lineolaris* (Palisot de Beauvois)). The fused map and the georeferenced insect counts are used in this section to establish a hypothetical task that examines whether this map product (Fig. 12.5) provides a useful description for the geographical distribution of the sample insect counts from another year. This hypothetical task is of practical interest because current research on the site-specific management of this pest is examining the seasonal stability of cotton vigor zones among production seasons in relationship to the geographic distribution of Tarnished Plant Bug (TPB) abundance over years.

Overlaid on the figure are graduated symbols to show how the 2008 counts of TPBs vary among georeferenced sampling sites just prior to a blanket spray application (17 June 2008) and at sample sites for 2 weeks following the application (24 June and 7 July 2008). Using these counts and figure, another goal of this section is to demonstrate the applicability of Concepts 1 and 2 to obtain answers for the hypothetical task.

The Pearson correlations between the count values of TPB and the zonal maximum of the pixel values contained within a 7 m circular buffer centered at the coordinates of the sample site, pre- ($r_c = -0.11$; $P = 0.56$) and post-spray ($r_c = -0.06$; $P = 0.65$) are non-significant. These results do not indicate that there is nothing useful to be found. Instead, they indicate that correlation techniques (i.e. ordinary least squares methods) are not useful for questions involving insect sample counts and RS information. The low correlations between these TPB counts and zonal maximum of pixel values within circular buffers at the corresponding sites arose not only because of the differences between years, but also because of causes as shown in Section 3.2, Concept 1. A different analysis approach is necessary.

Concept 2 demonstrated there should exist a RS classification scheme such that the means of a sparsely sampled attribute (i.e. insect counts) obtained from different zones are mutually exclusive. This idea is now employed as the first step toward a different analysis approach that examines relationships across years for stability of cotton vigor zones and TPB counts. To revise the classification shown in Fig. 12.5, GIS processing created two new variables in the attribute table of the insect sample counts. The first new variable, named SAMPL_ID, was coded as ‘1’ for pre-spray sample sites and as ‘2’ for post-spray sample sites. The second new variable, named SPLIT, was coded ‘1’ for pixel values < 4.1 and coded ‘2’ for pixel values ≥ 4.1. The zonal maximum function (de Smith et al. 2007, Willers et al. 2009a) was applied to a 7 m circular buffer at each sample site to extract this information from the mapping layer. The selection of the value, 4.1, is based upon experience and a detailed understanding of the revised process that produced Fig. 12.5 (Willers et al. 2009b).

Inspection of Fig. 12.5 generally indicates that pixel values ≥ 4.1 form a zone consisting of blue-green to blue hued pixels. In Table 12.2, sample sites associated with this zone (Categorical Label = 4) involve collections of pixels whose values

Table 12.2 Distribution of count frequencies for tarnished plant bugs per sample during 17 June 2008 (\ tally), pre-spray, and 24 June and 7 July 2008 (x tally), post-spray, for the four habitat zones from 2004 presented in Fig. 12.5

Zone[a]	Categorical label for habitat zones	Tarnished plant bug count per sample (No. of samples per count value by zone[b]) 0	1	2	3	4	5
Lowest elevation, lowest vigor	1	\\					
High elevation, Low vigor	2	\ xxx	\ xx	\ x	\		
Low elevation, high vigor	3	\\\\\\\\\\ xxxxxxxxxxxxx x	xxx	\ xx	x	\ x	
Highest elevation, highest vigor	4	\\\\\\\\ xxxxxxxxxxxx xxxxxxxxxxxx xxxxxxxxx	\ xxx	xxx	\ x		x

[a]Zones relate to the position of image pixels with respect to a centroid comprised of the global mean ATAN NDVI on the ordinate axis and the global mean elevation on the abscissa for the entire field in Fig. 12.5

[b]Frequency of counts in each sample from a zone is based on 33 sweeps per sample (see Willers et al. 2005). '\' represents counts pre-spray, 'x' represents counts post-spray

are greater than the global mean for the vegetation index and elevation. This zone, while producing numerous sites of '0' counts and several sites with counts between '1 and 3', is the only zone having a site with a count ≥ 5 (one tally). While the range between a count of '0' and '5' is small, inspection of Fig. 12.5 shows that non-zero counts seem to cluster primarily in the green and blue zones and that the highest counts (> 3) are only found in hues associated with a class limit > 3.21. Thus, the geographical distribution pattern of the counts, determined by visual inspection, indicates the TPBs reside in this cotton field with at least two population density distributions – one within the zone comprised of classes somewhat larger than the class value of 4.1 (increasingly deeper blue hues (see legend, Fig. 12.5)) and a second within the remaining zones comprised of class values < 4.1 (the green, yellow, orange and red hues). Thus, the class limit value of 4.1 functionally recodes Fig. 12.5 into two zones (similar to steps illustrated in Concept 2) to correspond to these two population density distributions of TPBs. A preliminary interpretation is that there is some evidence that the dispersion of TPBs follows a pattern of stability in crop vigor over production seasons.

However, the TPB sample counts in these two recoded zones have evidence of many '0' counts (Table 12.2). To complete a further analysis in the presence of these '0' counts, a count model regression method (Long 1997, Willers et al. 2009a) was employed. With a count model, the dependent variable takes on only nonnegative integer (count) values and it is assumed that the conditional mean $E(y_i|\mathbf{x}_i)$ of the dependent variable, y_{i}, is a function of a vector of covariates, $\mathbf{x}_{\mathrm{i}}$. A first step in such a test is to determine if there is evidence of over-dispersion among the collection of TPB counts (Long 1997). The answer determines which type of count model to apply (Long 1997, SAS Institute 2008): Poisson regression, Negative binomial regression, Zero-Inflated Poisson (ZIP) regression, or Zero-Inflated Negative binomial regression. A direct way to test for over-dispersion is to first fit a Negative binomial regression model to the counts of Table 12.2, using SAMP_ID and SPLIT as the co-variates. From this model, a parameter named α is estimated, which, if significant, is evidence for over-dispersion. For these data, it was found that $\alpha = 2.65$, which is significant ($P = 0.013$).

Since these data exhibit over-dispersion, the decision was then made to fit the ZIP regression model. The ZIP model assumes there are two processes at work which give rise to the data. One process is describable by a Poisson distribution and the other process accounts for the excess zeros (Long 1997, SAS Institute 2008). The estimates of the ZIP parameters and other statistics are presented in Table 12.3. The following interpretation is offered. Since the inflated covariate, Inf_Split, is marginally significant ($P = 0.06$), there are too many zero counts within the blue hued zone compared to the other zones, using a threshold of 4.1.

A further look at the data finds that three of these zero-valued counts, associated with pixels > 4.1 are enclosed within the ellipse at the top of Fig. 12.5. The cotton planted in this field during 2008 was comprised of several different sets of planting date by cultivar combinations. Thus, many of the zero counts arise in the youngest cotton (about 600 m south of the northern most tip) or in another area of

Table 12.3 Parameter estimates for the Zero-Inflated Poisson Regression model

Parameter	DF	Estimate	SE	t Value	Approx Pr > |t|
Intercept	1	1.07	0.74	1.43	0.15
SAMPL_ID	1	−0.22	0.39	−0.58	0.56
SPLIT	1	−0.15	0.42	−0.36	0.72
Inf_Intrcept	1	–0.05	1.19	–0.04	0.97
Inf_Sampl_id	1	–0.56	0.64	–0.87	0.38
Inf_Split	1	1.18	0.62	1.90	0.06

cotton planted late with a nectariless cultivar (about 480–680 m north of the southern edge). The regions of the field having the highest counts (>2) are where the cotton was planted first (oldest) and did not have the nectariless trait. Thus, while the years 2004 and 2008 had similar planting dates, they did not have similar spatial assignments of cultivars. Therefore, the conclusion of the analysis at this point is to stop. The occurrence of these three zero counts indicates that the planting and cultivar combination could be another influencing effect.

A final point to consider is the effects of geographic mis-registration. A potential example is the sample location referenced by the black arrow at the southeast edge of the field. This location had a pre-spray count of '3' within the low vigor, high elevation class (Categorical Label = 2 in Table 12.3). Experience suggests that observing a '3' count in this class prior to first bloom is unusual. There are two likely explanations for finding this value in this zone and both are related to mis-registration effects: one possible cause is GPS error while the second possible cause is the year difference between the two data layers. The coordinates of the 2008 sample sites were obtained by a low cost GPS unit having a positional accuracy of 3–5 m, 95 % of the time. To the east and south of the posted coordinate location reside pixels belonging to the Label 3 category. While this '3' count could be the result of a coding error due to mis-registration by the GPS, the more likely cause is a weather effect captured by the 2004 imagery. Thus, while several areas of these fields indicate stability in vigor across years, there are some other areas of the field where vigor is not stable among years. Therefore, in the practice of site-specific IPM and analyses of geo-referenced data, always keep in mind the geo-positional and temporal accuracy of the map product and the accuracy of the sample coordinates obtained by hand-held GPS units.

The simulation exercises developed for Concepts 1 and 2 demonstrated that the analyses of RS data and another field attribute (such as insect counts) sampled with small sample sizes requires concomitant processing steps of data in both the numerical and geographical coordinate systems. These practical realities were demonstrated here by a hypothetical, but near, real-world field example.

These examples show how analysis choices influence the ability of entomologists to discover principles for geographical IPM. Specifically, while of historical significance, ordinary least square approaches should be avoided because (I) attributes of RS data layers are typically not normally distributed, (II) geographical zones of the classification map frequently need to be recoded into ordinal categories, (III) insect counts are integers and often include zero values, and (IV) correlations based on sample counts involving small sample sizes are often low and vary widely between sampling experiments. In situations involving geo-referenced attributes such as insect counts, count model regression methods (Long 1997, Willers et al. 2009a), binary (or multinomial) logistic regression models (Long 1997, Hosmer and Lemeshow 2000), or data mining approaches (Riggins et al. 2009) are better alternatives. On the other hand, if both the dependent and explanatory variables are densely sampled by RS, linear mixed models with covariates (Gotway et al. 1997, Milliken and Johnson 2002, Littell et al. 2006, Willers et al. 2008) provide alternative analysis methods.

4 Conclusion

An entomologist must never abandon a search for useful classifications of RS attributes simply because results at first do not conform to initial expectations or tradition. The search for better ways to process RS information and discern the relationship of RS information to sparsely sampled attributes such as insect counts is an on-going process.

On-site field sampling efforts often take place before, concurrently, or just after RS data acquisition. Field sampling efforts can be optimized if RS collection occurs first; however, weather and other factors often disrupt RS acquisition schedules. Nevertheless, today's RS techniques provide entomologists the capacity to make more informed decisions and interpretations about information derived from their on-site field sampling locations. We anticipate many geographical methods for IPM are still undiscovered. The nascent status of the current knowledge about geographical IPM is obvious when considering the diversity in sensors (active, passive or thermal), bit-depth, and the spectral, spatial and temporal resolution of numerous sensor systems, along with the diversity of processing techniques currently available. Thus, despite the apparent sophistication of current hardware, software and RS technologies, entomologists must consider that large amounts of knowledge about geographical approaches, methods and tools regarding IPM are undiscovered. For these reasons, our progress is rather slow at present. Similar to the centuries of exploration necessary to discover the Northwest and Northeast passages (Stefansson 1947) from Europe to the Orient, once a body of knowledge is mature and matched by appropriate changes in technology, additional discoveries happen rather quickly. Therefore, the opportunity for discovery by today's entomologists working with RS is just as vast and unknown as it was for those exploring our world in the centuries past. Similarly, the science of designing and analyzing experiments to evaluate precision agricultural practices for insects in row crops and forests is currently in transition and requires the development of new concepts and techniques. We look forward to the advancements and development of geographical solutions for insect control created by motivated investigators.

Acknowledgements Appreciation is expressed to Mr. Ronald E. Britton for assistance and discussion on the preparation of the manuscript. Thanks are also expressed to Mr. Kenneth Hood, Perthshire Farms, Gunnison, MS, and Paul Good and Dale Weaver, Longview Farms, Macon, MS. The efforts of the editors and anonymous reviewers are also acknowledged. Approved for publication as Journal Article No. BC-11735 of the Mississippi Agricultural and Forestry Experiment Station, Mississippi State University.

References

Bugayevskiy LM, Snyder JP (1995) Map projections. A reference manual. Taylor and Francis, Philadelphia

Campbell PKE, Rock BN, Martin ME et al (2004) Detection of initial damage in Norway spruce canopies using hyperspectral airborne data. Int J Remote Sens 25:5557–5584

Campenella R (2000) Testing components toward a remote-sensing-based decision support system for cotton production. Photogramm Eng Remote Sens 66:1219–1227

Carter GA (1993) Responses of leaf spectral reflectance to plant stress. Am J Bot 80:239–243

Carter GA, Miller RL (1994) Early detection of plant stress by digital imaging within narrow stress-sensitive wavebands. Remote Sens Environ 50:295–302

Cibula WG, Carter GA (1992) Identification of a far-red reflectance response to ectomycorrhizae in slash pine. Int J Remote Sens 13:925–932

Corwin DL, Lesch SM (2003) Application of soil electrical conductivity to precision agriculture: theory, principles, and guidelines. Agron J 95:455–471

D'Agostino RB, Stephens MA (1986) Goodness-of-fit techniques. Marcel Dekker, New York

de Smith MJ, Goodchild MF, Longley PA (2007) Geospatial analysis. A comprehensive guide to principles, techniques and software tools. Matador, Leicester

Dupont JK, Campanella R, Seal MR et al (2000) Spatially variable insecticide applications through remote sensing. In Duggar P, Richter D (eds) Proceedings of the Beltwide Cotton Conferences, vol 2. National Cotton Council, Memphis

Gotway CA, Bullock DG, Pierce FJ et al (1997) Experimental design issues and statistical evaluation techniques for site-specific management. In Pierce FJ, Sadler EJ (eds) The state of site-specific management for agriculture. American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America, Madison

Hoque E, Hutzler PJS, Hiendl H (1992) Reflectance, colour, and histological features as parameters for the early assessment of forest damages. Can J Remote Sens 18:104–110

Hosmer DW, Lemeshow S (2000) Applied logistic regression. Wiley-Interscience, Wiley, New York

Jackson RD, Huete AR (1991) Interpreting vegetation indices. Prev Vet Med 11:185–200

Jähne B (1997) Image processing for scientific applications. CRC Press, Boca Raton

Jensen JR (2005) Introductory digital image processing: a remote sensing perspective, 3rd edn. Prentice-Hall, Upper Saddle River

Jensen JR (2007) Remote sensing of the environment: an earth resource perspective, 2nd edn. Prentice-Hall, Upper Saddle River

Kasischke ES, Goetz S, Hansen MC et al (2004) Temperate and boreal forests in remote sensing for natural resource management and environmental monitoring. In Ustin SL (ed) Manual of remote sensing, 3rd edn. Wiley, Hoboken

Kerr JT, Southwood TRE, Cihlar J (2001) Remotely sensed habitat diversity predicts butterfly species richness and community similarity in Canada. Proc Natl Acad Sci 98:11365–11370

Liebhold AM, Rossi RE, Kemp WP (1993) Geostatistics and geographic information systems in insect ecology. Annu Rev Entomol 38:303–327

Littell RC, Milliken GA, Stroup WW et al (2006) SAS® system for mixed models, 2nd edn. SAS Institute Inc., Cary

Long JS (1997) Regression models for categorical and limited dependent variables. Sage Publications, Thousand Oaks

Lu D (2006) The potential and challenge of remote sensing-based biomass estimation. Int J Remote Sens 27:1297–1328

McCarter KS, Burris E, Milliken GA et al (2007) Specifications of a prototype software system for developing variable-rate treatment prescriptions for use in precision agriculture. In: Boyer JE (ed) Proceedings of the 19th annual Kansas State University conference on applied statistics in agriculture, Manhattan, Kansas, 27 April–1 May 1 2007

McKinion JM, Jenkins JN, Willers JL, Zusmanis A (2009) Spatially variable insecticide applications for early season control of cotton insect pests. Comput Electron Agric 67:71–79

Milliken GA, Johnson DE (2002) Analysis of messy data. Analysis of covariance, vol. 3. Chapman & Hall/CRC Press, New York

Moran MS, Inoue Y, Barnes EM (1997) Opportunities and limitations for image-based remote sensing in precision crop management. Remote Sens Environ 61:319–346

Parresol BR (1999) Assessing tree and stand biomass: a review with examples and critical comparisons. For Sci 45:573–593

Pinter PJ, Hatfield JL, Scheppers JS, Barnes EM, Moran MS, Daughtry CST (2003) Remote sensing for crop management. Photogramm Eng Remote Sens 69:647–664

Pontius J, Hallett R, Martin M (2005a) Assessing hemlock decline using visible and near-infrared spectroscopy: indices comparison and algorithm development. Appl Spectrosc 59:836–843

Pontius J, Hallett R, Martin M (2005b) Using AVIRIS to assess hemlock abundance and early decline in the Catskills, New York. Remote Sens Environ 97:163–173

Pouncey R, Swanson K, Hart K (eds) (1999) ERDAS field guide, 5th edn. ERDAS, Atlanta

Richards JA, Jia X (1999) Remote sensing digital image analysis. An introduction, 3rd edn. Springer, Berlin

Riggins JJ, Tullis JA, Stephen FM (2009) Per-segment aboveground forest biomass estimation using LIDAR-derived height percentile statistics. GIScience Remote Sens 46:232–248

Riley JR (1989) Remote sensing in entomology. Ann Rev Entomol 34:247–271

Sampson PH, Zarco-Tejada PJ, Mohammed GH, Miller JR, Noland TL (2003) Hyperspectral remote sensing of forest condition: estimating chlorophyll content in tolerant hardwoods. For Sci 49:381–391

SAS Institute Inc (2008) SAS/ETS® 9.2 User's guide. Chapter 10. The COUNTREG Procedure. SAS Institute Inc, Cary

Seelan SK, Laguette S, Sasady GM, Seielstad GA (2003) Remote sensing applications for precision agriculture: a learning community approach. Remote Sens Environ 88:157–169

Shaw DR, Willers JL (2006) Improving pest management with remote sensing. Outlooks Pest Manag 17:197–201

Smith HA, McSorley R (2000) Intercropping and pest management: a review of major concepts. Am Entomol 46:154–161

Stefansson V (1947) Great adventures and explorations. The Dial Press, New York

Stern VM, Smith RF, van den Bosch R, Hagen KS (1959) The integrated control concept. Hilgardia 9:81–101

Strahler A (1980) The use of prior probabilities in maximum likelihood classification of remotely sensed data. Remote Sens Environ 10:135–163

Thompson SK (1992) Sampling. Wiley-Interscience, New York

White JC, Coops NC, Hilker T et al (2007) Detecting mountain pine beetle red attack damage with EO-1 HYPERION moisture indices. Int J Remote Sens 28:2111–2121

Willers JL, Jenkins JN, Ladner WL et al (2005) Site-specific approaches to cotton insect control. Sampling and remote sensing analysis techniques. Prec Agric 6:431–452

Willers JL, Jenkins JN, McKinion JM et al (2009a) Methods of analysis for georeferenced sample counts of tarnished plant bugs in cotton. Prec Agric 10:189–212

Willers JL, McKinion JM, Jenkins JN (2006) Remote sensing, sampling and simulation applications in analyses of insect dispersion and abundance in cotton. In Aguirre-Bravo C, Pellicane PJ, Burns DP, Draggan S (eds) Monitoring science and technology symposium: unifying knowledge for sustainability in the western hemisphere. USDA Forest Service Proceedings RMRS-P-42CD. US Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fort Collins. http://www.fs.fed.us/rm/pubs/rmrs_p042.html. Accessed 9 Dec 2009

Willers JL, Milliken GA, Jenkins JN et al (2008) Defining the experimental unit for the design and analysis of site-specific experiments in commercial cotton fields. Agric Syst 96:237–249

Willers JL, Seal MR, Luttrell RG (1999) Remote sensing, line-intercept sampling for tarnished plant bugs (Heteroptera: Miridae) in Mid-South cotton. J Cotton Sci 3:160–170

Willers JL, Wu J, Jenkins JN (2009b) Categorical likelihood method for combining NDVI and elevation information for cotton precision agricultural applications. Proceedings of the 5th International Workshop on the Analysis of Multi-temporal Remote Sensing Images, Groton, 28–30 July 2009

Part III
Modelling and Decision Support Systems

Chapter 13
Spatial Data Handling and Management

Georg Bareth and Reiner Doluschitz

Abstract Spatial data management and handling is very important in precision crop protection. Such data is collected by remote and proximal sensing. Additionally, soil, elevation, topographical, weather, management data is needed. Here, external data providers play an important role. Nowadays, farmers have to handle huge amount of data which is used for spatial decision support. Besides the farmer's domain, we identified in this contribution, four important domains to develop spatial data management concepts: (I) spatial data service domain, (II) precision farming service domain, (III) spatial modeling and analysis domain, and (IV) communication and server domain. Considering communication and data flow between the domains, the design for a potential data management architecture for precision crop management is introduced.

1 Background

Spatial data handling and management is of key importance in precision agriculture (PA) and therefore in precision crop protection (PCP) which is considered a part of precision crop management (PCM). Such management activities have a spatial nature (compare Chapters 1–4) and technologies which provide tools to capture, manage, analyze, provide, and visualize such data have to be applied (Pokrajac et al. 2002). In Chapters 1–12, spatial sensor and sensing technologies are described in detail and are the important technologies to collect spatial data for plant vitality, pest monitoring and identification etc. However, for the management and handling of spatial data, Geographic Information System (GIS) technologies are the most important of the technologies in PA and are described by Srinivasan (2006) as 'geospatial information and communication technologies', which enabled the implementation

G. Bareth (✉)
Department of Geography, University of Cologne, Köln D-50923, Germany
e-mail: g.bareth@uni-koeln.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_13,

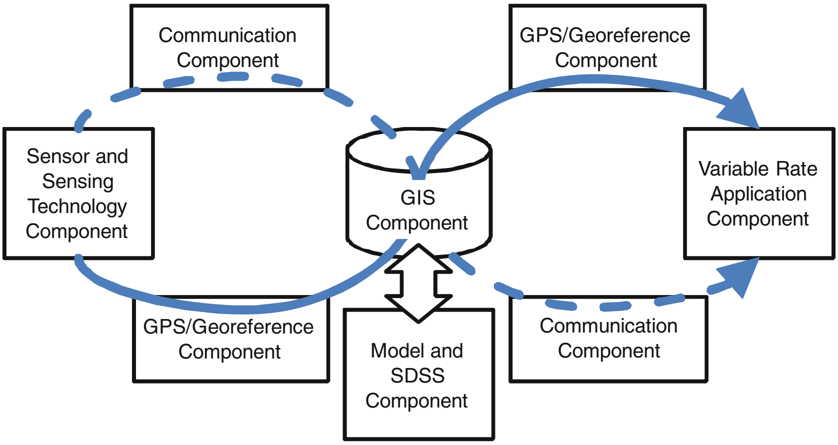

Fig. 13.1 Components of implementation of precision agriculture (modified from Srinivasan 2006)

of PA techniques in the 1990s. Consequently, GIS is of central importance for precision crop management (Fig. 13.1).

As mentioned above, the GIS component is centered in Fig. 13.1. Remote sensing (satellite, aerial imagery) and proximal sensing data (soil, crop parameter) are collected and must be georeferenced. For this purpose, Global Positioning Systems (GPS) are used. Via the communication component, these spatial data flow into the GIS component for further analysis for which additional geodata from official sources (e.g. digital elevation model, topographic data) might be integrated in the system (Rösch et al. 2007). Spatial analyses (e.g. hyperspectral vegetation indices) or simulation results from e.g. plant growth or matter flux models serve as the knowledge base for the variable rate application component in the field. The interaction between this component and the GIS, the spatial data handling and management component is again implemented by the communication component (e.g. wireless data exchange).

Precision agriculture and precision crop management are well investigated research areas as documented in chapters of this book, by the journal Precision Agriculture (e.g. Nash et al. 2009a), several textbooks, and annual conference series on this topic. Additionally, many commercial applications and products are already implemented (e.g. John Deere's GreenStar®; Yara N-Sensor®) or are available as services and software packages on the market (e.g. Agri Con Precision Farming Company). Even products for automated remote sensing data and GIS analyses are commercially available (e.g. Infoterra's Overland® software). Consequently it is not surprising that software solutions for spatial data management of precision farming purposes are on the market, too. All up-to-date plot record software systems for applications for farm management purposes include GIS components and features to document and analyze PA and PCM data. They also provide interfaces to acquire data from remote mobile data collection devices, which are widely available in agricultural crop production.

Since 2005, the European Union (EU) asks for spatial information in terms of GIS data when farmers apply for subsidies (EU regulation 335/2004). This regulation boosted the implementation of GIS documented land use and land cover system for agriculture in Europe and the establishment of spatial data in terms of field border features. This high demand for spatial data solutions led not only to the incorporation of spatial data handling tools in farm software packages, but also supported the development of open source products for spatial data handling and management for agricultural purposes (Kielhorn et al. 2007, Watermeier 2006).

In this chapter on spatial data handling and management for PCP, the focus is not on giving a review on precision agriculture methodologies or available products. Relevant contributions are available in the literature by Srinivasan (2006), Rösch et al. (2007) and many more; and are even available for farmers from relevant agencies (KTBL 2007, 2004, Noack 2007). The objective of this contribution is to focus on the demand of farmers for spatial data, for which software, standards, and services are available, and finally to introduce a design of how spatial data handling and management could be organized on the farm level within the next few years. For latter considerations, the farmer will be centered as the spatial mobile agent acting with diverse devices and tasks for spatial services, data, analyses, spatial decision support (SDSS), and communication systems.

2 Software and Data Standards

It is well known and documented which data are necessary for PCM. For example, in the period 1999–2008 the pre agro project (www.preagro.de) focused on data management issues. Nash et al. (2009a) describe data flow concepts for precision agriculture approaches in this project. The data not only comprise spatial data but also farm management data, which are usually organized by a farm management information system (FMIS; Steinberger et al. 2009). Software products are available (e.g. www. agrocom.de). The growing importance of mobile devices for data collection in precision farming in connection with wireless technologies is documented by e.g. Steinberger et al. (2009) and Luis et al. (2009). In Fig. 13.2 the user interface of Agro-Net is shown (Oetzel 2008). The interface clearly shows the complexity of data management. Besides a spatial data viewer that is centered in Agro-Net, in the left menu bar farm data, field administration, planning, etc. are accessible. In this context, Oetzel (2008) describes the importance of combining spatial data services like OGC's Web Map Service (WMS) with farm office products and introduces an interface library based on Microsoft's net technology to combine such services within a farm management system and agroXML applications.

For spatial data storage in general, GIS software products are available e.g. ESRI's product family (www.esri.com) or open source software developments are integrated in farm management software products like Farm Works Software® (www.123farmworks.com). The latter offers complete farm management and

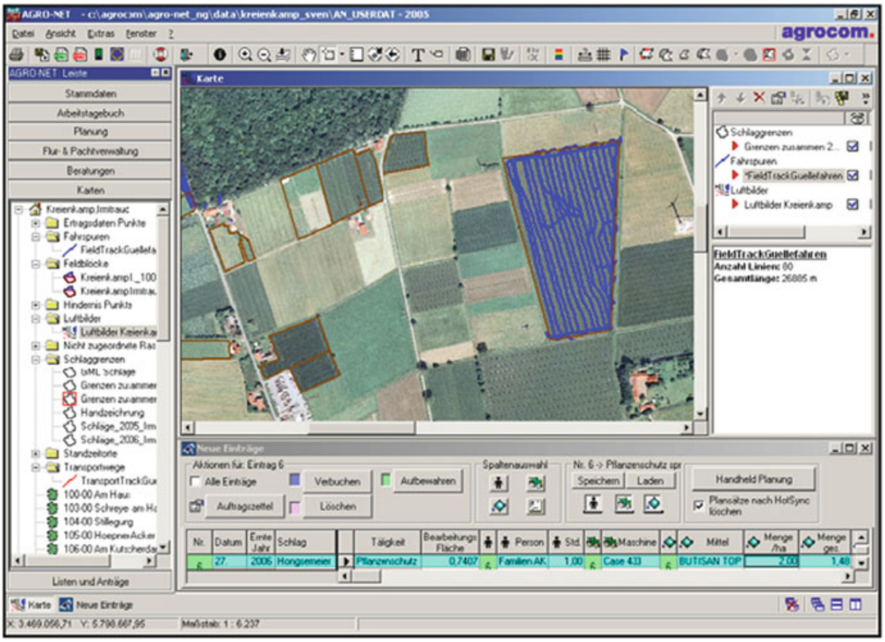

Fig. 13.2 AGRO-NET with process data from Agricultural Process Data Service (APDS) of WP8 of the pre agro project (source Oetzel 2008)

includes accounting, field record keeping, mapping tools, GPS mapping, livestock and herd management, etc. Additionally, mobile applications for portable/mobile guidance, mapping, and data collection are included. Similar products are available from e.g. PROGIS (http://www.progis.com) and many more.

Traditional GIS software resellers like ESRI provide products and services for agricultural application and especially for PA. In the latest ESRI Newsletter 'GIS for Agribusiness' for example, the USDA's 2007 harvested corn acreage map is presented (ESRI 2009). In general, the combination of ESRI's GIS products can be used to implement complex server-client based spatial data management systems for mobile and desktop applications. Developments in the last 5–10 years led to numerous open source GIS software libraries and products (http://www.osgeo.org/). Those also enable setting-up complex server-client based solutions for farm management and PA (Kielhorn et al. 2007, http://openlayers.org/).

In combination with open source or commercial software products, various web services can be used and are important for spatial data access and further analyses in a SDSS context (Bareth 2009, Nash et al. 2009b). Spatial web services are based on standards of the Open Geospatial Consortium (OGC) OpenGIS® standards (www.opengeospatial.org) and represent nowadays the most important spatial data services. For PA and especially PCM, the most relevant standards are Web Map

Service (WMS), Web Feature Service (WFS), Web Coverage Service (WCS), Web Processing Service (WPS), Keyhole Markup Language (KML), Location Service (OpenLS), Sensor Observation Service (SOS), Sensor Model Language (SML), and Catalogue Service (CAT). These standards are described in detail by the OGC (www.opengeospatial.org/standards) and are shortly introduced in the next Section 3 Spatial data and data services.

For spatial data interoperability, OGC's standards and services are the most important. Many GIS and (remote) sensing software products use their own data format, which is not compatible with other software. Before OGC's interoperability activities, this was a severe problem. Quasi standards for spatial data were e.g. ESRI's .shp and .e00 formats. The latter was the file exchange format and was also often used by official agencies to deliver data.

Deficits and barriers for adequate data integration on a horizontal level, in particular in internal areas and vertically along the supply chain, still exist through unavailable or insufficiently developed industry-specific data standards. Standards are otherwise indispensible when it comes to communication between distributed mobile data collection devices, software solutions and data sets, as they are widespread in the area of agriculture (Doluschitz 2007, Kunisch et al. 2009, www.agroxml.de). The standardized data exchange format agroXML has been under development for several years. It is fairly complete for agricultural crop production and still is under development for livestock farming. At the same time, the existing standards, such as ISOagriNet in the field of internal husbandry and/or integrated with agricultural animal husbandry, were created as corresponding interfaces. For external communications with third parties, the agroXML standard will then be used, which is increasingly being established in the industry (Doluschitz and Kunisch 2004, Doluschitz et al. 2005).

Connections of remote mobile data collection devices shall be provided as well as connections of distributed data sources and software tools along supply chains at a vertical direction. The agroXML standard defines the smallest possible information unit which should be considered for data exchange. agroXML orients itself completely at the W3C specification and is therefore open for processing by XML-technologies such as XSLT, XPATH, XLINK, etc.. agroXML is publicly available and is under supervision of a KTBL working group. It allows formal descriptions of agricultural knowledge areas using standardized terms and relationships to apply common understandings. Adjustments to different application fields are done by profiling. Such profiles describe compulsory data inputs, which are required by specific applications.

The elaboration of concepts, structures, and architectures is done by independent third party partners. The benefit for potential users is that redundancies are minimized. Documentation and reporting duties are covered by agroXML and additional information for farm management purposes is provided and communication with partners is optimized. The so far high interest of all kind of members of the agricultural and agribusiness sector indicates a high future adoption rate of the standard.

3 Spatial Data and Data Services

The importance of spatial data increased in the context of PA and PCM. The first question should therefore be what data are really necessary for such applications. Because spatial data very often is the most valuable component in a GIS (Bill 1999), it needs to be considered also in a cost-benefit context (Bachmaier and Gandorfer 2009, Lambert et al. 2006, Tozer 2009). In many publications, the core data for PA and PCM are listed. Hence, we only provide short information on the heterogeneous data sets. According to Rösch et al. (2007) and Srinagar (2006) the following spatial data are required:

• Management data	• Weather data
• Yield maps	• (Remote) Sensing data
• Nutrient maps	• Cadastral maps
• Rating surveys	• Digital Elevation Model (DEM)
• Soil maps	• Topographic maps

Management data are usually generated by the farm itself and, in PA are highly depending on agronomy aspects. Important issues here are the type of management (e.g. weeding), time (e.g. sowing date), amount (e.g. fertilizer application rate), crop rotation, etc. Usually the data are stored for control and documentation, supporting management improvement strategies. For the application of fertilizer and chemicals for crop protection, rating data are required. Ratings include weeds, plant diseases, and plant vitality and are carried out by the farmer or extension specialists. The results answer the questions as to where and how much should be applied. Ratings provide spatial data of within-field variability. Further data collected in the farm domain are yield maps. Nowadays, yield maps are created by combined harvesters in real time during harvest and are available directly after harvest for spatial analysis. Besides amount per unit, water content and ingredients are detected. Combine harvesters can be owned by the farmer himself or are used by machinery co-operations. Proximal and remote sensing applications and their importance for PA and PCM are described in detail in the previous chapters. Such methods are used to derive information for precision crop management. Yield maps are closely connected to nutrition maps. The latter are required to analyze reasons for spatial yield variability and to spatially adjust respective fertilizer applications. Besides plant nutrient contents, available spatial data of soil nutrients are important. These data are usually not collected by the farmer. Extension services can provide such data and usually do this for soil nitrogen content. In this context, soil maps are important and are available from soil surveying companies. Large-scale data provide soil horizons, clay content, soil texture, pH, etc. In Germany for example, such data are available from the official geological and soil survey offices in a scale of 1:5,000 to 1:25,000 (e.g. www.lbeg.niedersachsen.de). The large soil data sets are in some countries combined with cadastral maps like land registers. Such land evaluation maps are used for agricultural taxation purposes. In Germany, the Bodenschätzungsgesetz

'BodenSchätzG (BGBl. I S. 3150, 3176)' (soil evaluation law) was modified in 2008 (www.bundesfinanzministerium.de). Digital elevation models (DEMs) are usually provided by the official surveying and mapping agencies. With GIS software, it is possible to derive relief parameters like inclination, exposition, curvature, slope length, and morphology. This information is of high importance for minimizing soil erosion potentials. Like DEMs, topographical maps and aerial imagery are provided by WMS and are usually delivered by the surveying and mapping bureaus. These data are mostly used for background information in mapping applications.

It is very obvious that the before mentioned data, which is necessary for PA and PCM, are extremely heterogeneous in terms of data formats, spatial and time scales, sources and authors, etc. A conclusion from this fact which is also described in literature is interoperability. The only way to use all these different types of spatial information in the process of PA and PCM is by applying defined data standards, services, and interfaces. Such activities for interoperability are in the focus of the Open Geospatial Consortium which was founded in 1994 (www.opengeospatial.org). In the next paragraphs the OGC standards which are of key importance for PA and PCM are shortly described.

WMS (Web Map Service) is a HTTP-based interface which provides requested spatial data from a single or multiple spatial data server(s) as a map image (OGC 2006). Popular examples are the Landsat Imagery WMS (http://wms.jpl.nasa.gov/wms.cgi), where the server is regularly overloaded or e.g. in Germany, official WMS for topographic, aerial imagery, and surveying data (e.g. http://www.geoserver.nrw.de/home/gbdaten.html).

WFS (Web Feature Service) does not provide, in contrast to WMS, map images. The real map features are accessed which are then represented as vector data and several WFS operations are included (OGC 2005). Hence, it is possible to create, update, or delete map feature instances and to query in a spatial or non-spatial context. For example, the USDA offers WFS for soil data access of soil survey spatial and tabular data (http://sdmdataacess.nrcs.usda.gov/). Another example is the web maps server of the FAO which is hosted by the Environmental Assessment and Management Unit (NRCE) of the FAO (http://dwms.fao.org). At the FAO-NRCE Web Maps Server page, a link to spatial information management for food and agriculture provides general information on the importance of geo-referenced information (http://www.fao.org/spatl/).

WCS (Web Coverage Service) is limited to so-called grid coverage which supports the retrieval of raster data for space-varying phenomena (OGC 2008a). The difference between WCS and WMS is that no static web maps are delivered. It is more comparable to the WFS, but is limited to grid coverage. The Integrated CEOS European Data Server (ICEDS), for example, provides WCS for satellite data retrieval (http://iceds.ge.ucl.ac.uk).

KML (Keyhole Markup Language) is an xml-based spatial data format and was developed for the Keyhole Earth Viewer by Keyhole Inc. Google® acquired the company in 2004 and the technology was used to launch Google® Earth in 2005. With the overwhelming success of Google® Earth and Google® Maps, KML became a very popular data format and nowadays it is readable or importable by most GIS software. Additionally, KML data are easily implemented with open source resources in web pages e.g. OpenLayers (http://openlayers.org/). Google® submitted KML in 2008 to the OGC® to become an OGC® standard (OGC 2008b). According to OGC (2008b), 'the KML Version 2.2 will be an adopted OGC implementation standard'.

WPS (Web Processing Service) defines the standard of web-based geoprocessing such as buffering or polygon overlay (OGC 2007a). Important issue here is that no specific data are required for input or output. And the data are delivered from across the network or are available from a server. This includes data retrieved by WFS or WCS. Several companies, e.g. 52north (http://52north.org), which provide open source services, are pushing this standard to include geo data analysis functionalities in Spatial Data Infrastructure (SDI) development like INSPIRE (http://ies.jrc.ec.europa.eu/SDI) and are very active in the geoprocessing community. The benefit for agricultural applications in the context of PA or PCM is obvious. Spatial questions like what soil parameters are related to low yield could be easily answered online and further investigated.

CAT (Catalogue Service) is also an OGC interface standard. The objective is to provide a service to publish and search metadata collections 'for data services, and related information objects' (OGC 2007c). For finding or providing relevant spatial data, CAT is very important and for example applied by the German SDI initiative (www.gdi-de.org).

SOS (Sensor Observation Service Interface Standard) is a programming interface. Such application programming interfaces (APIs) are used to enable software interaction. 'SOS provides an API for managing deployed sensors and retrieving sensor data and specifically 'observation' data. Whether from in-situ sensors (e.g., water monitoring) or dynamic sensors (e.g., satellite imaging), ...' (http://www.opengeospatial.org/standards/sos). SOS is a result/standard of the OGC Sensor Web Enablement (SWE) activities (OGC 2007b), which already implemented and defined several components needed for a sensor web. These components are Observation & Measurement (*O&M*), Sensor Alert Service (*SAS*), Sensor Model Language (*SensorML*), Sensor Planning Service (*SPS*), Transducer Markup Language (*TML*), and Web Notification Service (*WNS*), which are described in detail by OGC (2007b). Besides the before mentioned spatial service standards like WFS, the OGC standards for Sensor Webs are of key importance for PA and PCP in the future. The interoperability of data acquired by mobile or static soil and plant sensors in combination with spatial data (services), especially WPS, are the basis for spatial analyses, which provide knowledge for SDSS in PA or PCM, and can communicate via agroXML with application devices.

OpenLS (Open Location Services Interface Standard) defines the OGC interfaces for applications in the field of Location Based Services (*LBS*) (OGC 2008c). LBS are especially important for mobile applications and therefore, these concepts are of central importance for the communication with mobile clients within the farm domain. The core services of OpenLS are also defined as GeoMobility Server (*GMS*) and are shown in Fig. 13.3. The location of a mobile client is identified by Positioning Determination Equipment (*PDE*) (Peng and Tsou 2003) and is provided

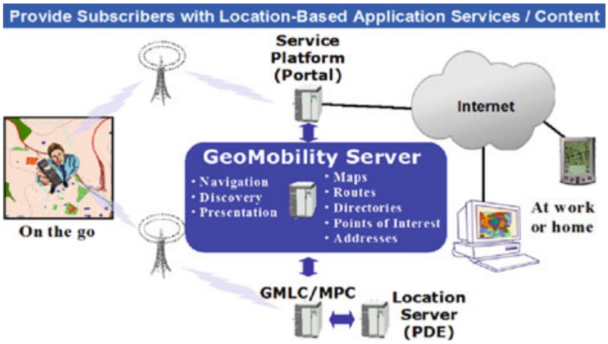

Fig. 13.3 Role of the GeoMobility Server (OGC 2008c)

to the GMS by a location server which communicates with the Gateway Mobile Location Center (*GMLC*)/Mobile Positioning Center (*MPC*). The GMS provides content like maps, routes, addresses etc. Core services of OpenLS are e.g. navigation and tracking. The latter are essential applications in PA and PCP.

Besides the before mentioned OGC spatial service standards like WFS, the standards for Sensor Webs and LBS are of key importance for PA and PCP in the future. The interoperability of data within the farm domain in combination with provided external data are in the focus. Acquired data by mobile or static soil and plant sensors in combination with spatial data (services), especially WPS, are the basis for spatial analyses, which provide knowledge for SDSS in PA or PCP and can communicate via agroXML with application devices. Consequently, such standards and technologies have to be integrated and combined for developing new data management approaches for PA or PCP.

4 Potential Concept of Spatial Data Management

The professional handling and management of all space related data – and in terms of PCP every management task is in a spatial context – is a must for successful PA and PCM. Various approaches have been established and are described in PA textbooks or reviews (e.g. Bramley 2009, Rösch et al. 2007, Srinagar 2006) or are included in latest technologies (e.g. Ambrosio et al. 2009, Bareth 2009, Fountas et al. 2009, Nash et al. 2009b, Oetzel 2008). The objective of this sub-chapter is to summarize and extend the existing ideas of spatial data handling and management for PCM to conclude and suggest an up-to-date architecture that considers the discussions of the Data Management Workshop. This was held in Cologne in October 2009 and focused on latest scientific approaches in interdisciplinary data management projects (Curdt and Bareth 2010).

In Fig. 13.4, the domains involved in farm data management are characterized. The farmer's domain is centred in this figure because all data management

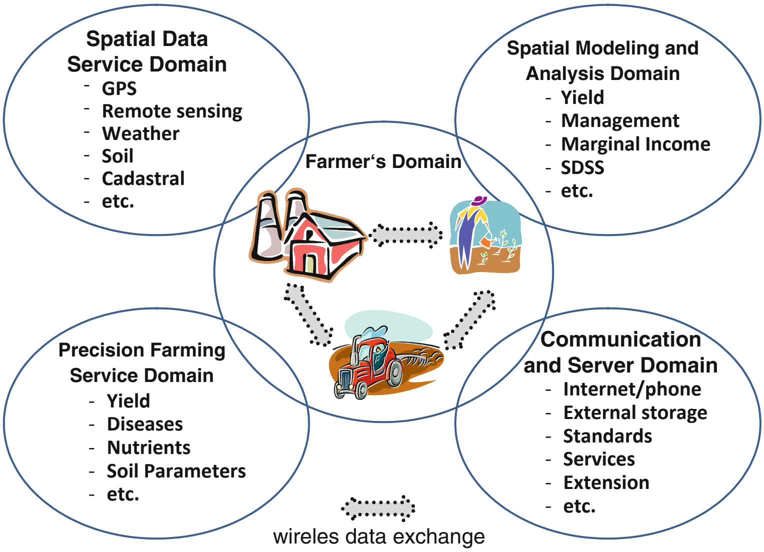

Fig. 13.4 Domains of spatial data management for PA and PCM

efforts should focus on supporting his work flow and decision making (compare Chapters 14 and 15). Within the farmer's domain, communication will be based on wireless technologies (Matese et al. 2009). Sensor networks for example can provide their data e.g. via GSM (e.g. Jiang et al. 2008) or ZigBee radio network (e.g. Bogena et al. 2009, Morais et al. 2008) to a data server within or outside the farmer's domain. But all mobile (e.g. machinery or PDA) and desktop devices within the farmer's domain must be linked with each other in real time for communication and data exchange.

The spatial data service domain comprises spatial data products, which are exclusively not collected within the farmer's domain and are available from extension, official bureaus, or companies. Such data are accessible by farmer's domain via internet and usually OGC standards, services, and interfaces. The latter are part of the communication and server domain. Only standards and services which support interoperability between systems and products should be included. Data storage and backup should not be located within the farmer's domain and are provided by specialized companies. This ensures data access and system performance. The database can be mirrored into the farmer's domain for cases when communication networks are down.

The precision farming domain provides all mentioned technologies for data collection, especially from sensor devices. Many of those data are not collected by the farmer himself and are provided from external management activities. All acquired and collected data will be accessible by the FMIS which provides all necessary inputs for analyzing and modeling approaches. The results are finally disseminated by a SDSS. The interfacing of all data from the farmer's domain and external sources, from sensor webs and sensing devices, and the access via mobile or desktop client interfaces is part of the communication and server domain.

The organized distribution of data, services, and computing capabilities also arrived in agricultural applications as it is outlined by before mentioned literature and summarized in Fig. 13.4. For spatial modeling and computing purposes, grid, parallel, and cloud computing approaches are in development (Birkin et al. 2009, Li 2008, Padberg and Greve 2009, Procari 2009, Stanoevska-Slabeva et al. 2010, Werder and Krüger 2009). In this context, distributed file management and data standards are more and more important (e.g. www.dcache.org). Consequently, a potential design of an architecture for spatial data management for PC and PCM must consider these current developments. Hence, the distributed components and the related data flows for communication processes with selected data standards and servers are summarized and outlined in Fig. 13.5.

The core of the presented concept is that the farmer accesses his data via internet through a webpage. This webpage is his access to his FMIS, which with all data and interfaces is implemented, organized, managed, and maintained by an extension service or a company. For additional backup, the farmer can mirror the content to a hardware component within the farmer's domain. This can be important in cases where the internet is not working properly or is even down. For special desktop or mobile applications, direct access to the file management system or the database should be implemented. Every communication from the farmer's domain must be

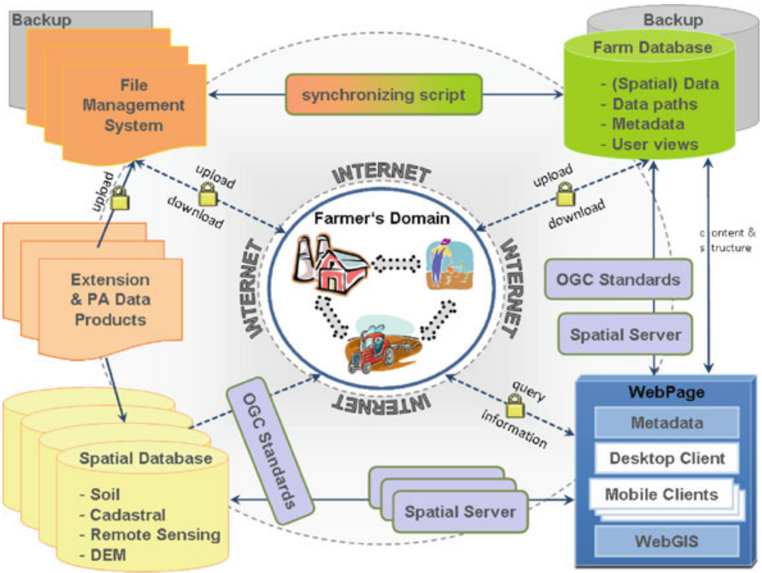

Fig. 13.5 Design of a data management architecture for PA and PCM (modified from Curdt et al. 2009)

protected and secure. The only not password protected link is to the one to the spatial data services, which are available with WMS, WFS, etc. Additionally PA data may be required again from extension or companies and must be available. In the presented structure, such data – equal to similar data from the farmer's domain – is stored in a file management system. The latter is interfaced with the farm database which stores and manages data locations in terms of data paths, metadata, further (spatial) spatial data, content and structure of the webpage. The farm database also manages the user accounts and provides different user views. For example, a mobile client for collecting rating data has online access to all available field data and also data which supports the mapping task, e.g. topography via a WMS. While mapping within the farmer's domain, the data are directly stored in the file management system. This then gives an 'alert' to the farm database that a new data set is uploaded. Afterwards, the mobile client is immediately asked by the farm database to upload metadata for the data set.

An example of an integrated WegGIS user interface which is discussed in Fig. 13.5 is established for the Transregional Collaborative Research Centre 'Patterns in Soil-Vegetation-Atmosphere-Systems: Monitoring, Modelling and Data Assimilation'(www.TR32.de) which is funded by the German Research Foundation (DFG). The WebGIS is implemented by the data management sub-project of the TR32 (www.TR32DB.de). The system provides most of the before mentioned spatial data for the TR32 study region that are needed for PA and PCM (Curdt et al. 2010). In Fig. 13.6, two screenshots of the WebGIS user interface, which is accessible via standard web browsers, are shown. The upper screenshot shows a land use classification map obtained from ASTER multispectral satellite imagery in combination with topographic data of Germany's administrative topographic-cartographic information system (ATKIS). ATKIS provides base topographic data and can be used for map production for a scale of 1:10,000 called the DTK10 (www.adv-online.de). Administrative unit borders like village, township, counties etc. are also included and are important for linking agricultural statistic surveys to map units (Bareth and Yu 2002). In Fig. 13.6, ATKIS is in the background and the land use classification is set online in a transparent display mode. Additional GIS layers are weather stations and sub-watershed boundaries. In the lower screenshot of Fig. 13.6, a larger scale is selected. Activated spatial data layers are the soil information system 1:50,000 (ISBK50) in a transparent viewing mode on top of ATKIS. The black boundary layer represents the land parcel map (ALK) which is used for map scales up to 1:500. The ALK borders do not correspond with field borders because it represents ownership and land parcel units. Therefore one land use can comprise several land parcels or one land parcel can have several land uses.

In Fig. 13.7, two more screenshots of the system in larger scales are shown. In the upper screenshot, again the land parcel map with single building features is drawn. The backround RGB images are digital orthophotos (DOPs) from airborne remote sensing campaigns. The DOPs have a spatial resolution of 30 cm and are used for map products in a scale of 1:5,000 (www.bezreg-koeln.nrw.de). The DOPs are also used to produces a DEM with a 10 m resolution. Nowadays DEMs are produced

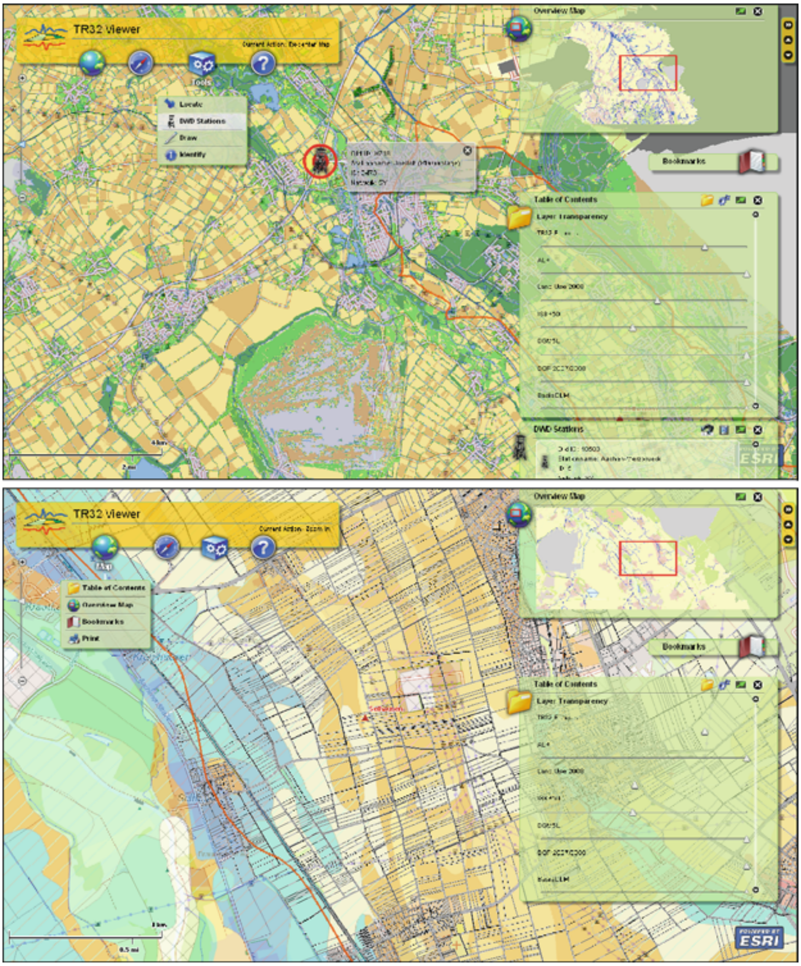

Fig. 13.6 WebGIS interface of the TR32 project: weather stations (German Weather Service), land use classification (ASTER imagery) in transparent mode, and topographic (ATKIS) data in the background (*top*); soil data (ISBK50) in transparent mode, cadastral land parcel map with building features (ALK), ATKIS (*bottom*; http://www.tr32db.de)

by airborne LIDAR campaigns. In North Rhine-Westphalia, Germany, a 1 m and a 10 m DEM are available. In the TR32, an additional airborne LIDAR campaign was carried out in 2008 and the derived digital surface model (DSM) has a 15 cm resolution and is displayed in the lower screenshot of Fig. 13.7. On top of the DSM, the ALK is drawn. Such a service for PA and PCM could easily provide the farmer with actual changes in topography in a cm scale.

Up to now, the TR32 WebGIS provides several basic functionalities with which most users are familiar from other web mapping pages like Google® Maps. In Fig. 13.7 (top) the navigation menu is open and provides users *zoom in*, *zoom out*,

Fig. 13.7 WebGIS interface of the TR32 project: aerial imagery (DOP), cadastral land parcel map with building features (ALK), and ATKIS (*top*); official elevation model from airborne LIDAR campaigns (DEM5L) and ALK (*bottom*) (http://www.tr32db.de)

pan, and *zoom to full map extent* icons. Additionally, the map coordinates of the mouse position can be chosen for display. In Fig. 13.7 (bottom) the help menu is open. Via the help icon, the online help for using the TR32 WebGIS opens. The open tools menu is shown in Fig. 13.6 (top). The location icon allows the direct search for a map location by typing in the map coordinates. In this menu, the user can load the point layer of the DWD weather stations which are available in the project database. A draw tool for the current session enables the users to draw on the map for print purposes. And finally, in the tools menu, spatial database queries with the identify icon are enabled. In the right part of the screenshots, the table of

Fig. 13.8 WebGIS interface of the TR32 project 'Soil-Vegetation-Atmosphere Patterns': Aerial imagery (DOP), ALK, ATKIS, and for within-field variability of plant growth a plant height difference map of sugar beet from May to July 2008 obtained by terrestrial laser scanning (Hoffmeister et al. 2009, http://www.tr32db.de)

content pops up and allows the activation of map layers and e.g. display settings like transparency can be set here, too.

Spatial data which comes from various sensors for supporting PA and PCM could easily be integrated in such a WebGIS. In Fig. 13.8, a spatial data set of terrestrial laser scanning (TLS) campaigns of a sugar beet field in summer 2008 is incorporated. In the TLS campaigns, crop canopy surfaces at different growing stages were captured (Hoffmeister et al. 2009). The results of such campaigns are plant height maps with a spatial resolution of 20 cm. In Fig. 13.8, the difference in plant height between June and July is presented and clearly shows a very high spatial within field variability of plant growth. As soon as data has a georeference, it could be immediately served online.

5 Conclusions and Outlook

Under the pressure to increase yield and marginal income, farmers rely in farming on PA technologies which enable PCM. Furthermore, sustainable issues have nowadays to be considered. Consequently, a central task in PCM is PCP. Hence, the contribution of information technology has to be optimized. In PCM, various spatial data are needed and are collected by remote and proximal sensing. Additionally, many different sources for spatial data are used to provide the needed data. This results in a strong heterogeneity of data formats. Consequently, well accepted data standards and services have to be adopted (e.g. OGC standards, agroXML). Beside the information needs of operators (within and outside of their operation), the challenges encountered by management, resulting from efforts in sustainable resources protection, quality assurance and traceability, as well as the requirements of agricultural and food industry laws with their requests for data and information (e.g. the cross compliance regulation within the EU-CAP), have to be considered. The demand for often spatially distributed data and information must be compared with information availability (both technical feasibility and practical application), through which deficits can be identified.

Given the current potentials, it can be stated that PA technology, from a technological perspective, can deliver almost unlimited amount of data with highest spatial resolution. However, on the other hand, comparably large deficits exist in the fields of data management, analysis, goal-oriented pre-processing, and interpretation of this data. These issues are investigated in the fields of software development, spatial decision-making, and distributed database implementation. The latter is suggested in this contribution for spatial data management in PCM.

Countless studies have demonstrated that, both on the national and international levels, the degree of penetration of agriculture and equally agriculture-related enterprises with hardware infrastructure are high and continue to grow. The question arises if it is economical to organize the complex data management of PA within the farmer's domain. And it is obvious that with more available sensing devices the amount of data in the PA process will exponentially increase. Consequently, new concepts for spatial data management and handling are needed to disburden farmers and to improve decision making. Furthermore, the need for improvement exists with respect to the implementation of spatial data analysis, e-business strategies and, in general, in the field of IT education. It can be clearly stated that research for spatial data management and handling in PCM should be more interdisciplinary and should involve cost-benefit analysis. The factors influencing acceptance, as well as the possibilities and limitations for the integration of IT services within FMIS and SDSS as well as supply chains should be studied.

References

Ambrosio L, Marín C, lglesias L et al(2009) Agricultural and environmental information systems: the integrating role of area samples. Span J Agric Res 7:957–973

Bachmaier M, Gandorfer M (2009) A conceptual framework for judging the precision agriculture hypothesis with regard to site-specific nitrogen application. Prec Agric 10:95–110

Bareth G (2009) GIS- and RS-based spatial decision support: structure of a spatial environmental information system (SEIS). Int J Digital Earth 2:134–154

Bareth G, Yu Z (2002) Benefits of linking agricultural statistics to GIS. Proceedings of Geoinformatics '02, 1–3 June 2002, Nanjing, CD-ROM

Bill R (1999) Grundlagen der Geo-Informationssysteme, Band 1 und 2. Wichmann, Heidelberg

Birkin M, Turner A, Wu B, Townend P, Arshad J, Xu J (2009) MoSeS a grid-enabled spatial decision support system. Soc Sci Comput Rev 27:493–508

Bogena HR, Huisman JA, Meier H et al (2009) Hybrid wireless underground sensor networks: quantification of signal attenuation in soil. Vadose Zone J 8:755–761

Bramley RGV (2009) Lessons from nearly 20 years of Precision Agriculture research, development, and adoption as a guide to its appropriate application. Crop Pasture Sci 60:197–217
Curdt C, Bareth G (2010) Proceedings of the Data Management Workshop, 29–30 Oct 2009, University of Cologne, Germany
Curdt C, Hoffmeister D, Jekel C et al (2010) Implementation of a centralized data management system for the CRC Transregio 32 “Patterns in soil-vegetation-atmosphere-systems”. In: Curdt C, Bareth G (eds) Proceedings of the Data Management Workshop, 29–30 Oct 2009, University of Cologne, Germany
Curdt C, Hoffmeister D, Waldhoff G, Bareth G (2009) Implementierung eines Projektdatenmanagements für das interdisziplinäre Forschungsprojekt TR32 ‚Patterns in soil-vegetation-atmosphere systems: monitoring, modelling, and data assimilation‘. In: Bill R, Korduan P, Theuvsen L, Morgenstern M (eds) Anforderungen an die Agrarinformatik durch Globalisierung und Klimaveränderung, Referate der 29. GIL-Jahrestagung, 9 – 10 März 2009. GI-Edition – Lecture Notes in Informatics 142:37–40
Doluschitz R (2007) Die Rolle der Informationstechnologie in der Landwirtschaft. In: KTBL (ed) agroXML – Informationstechnik für die zukunftsorientierte Landwirtschaft. Beitrag zur KTBL-Tagung am, München, pp 9–32, 17./18. April 2007
Doluschitz R, Kunisch M (2004) agroXML – Ein standardisiertes Datenformat für den Informationsfluss entlang der Produktions- und Lieferkette. Z Agrarinformatik 12:65–67
Doluschitz R, Kunisch M, Jungbluth T, Eider C (2005) agroXML – a standardized data format for information flow in agriculture. Proceedings of EFITA/WCCA 2005, Portugal, pp 26–31, July 2005
ESRI (2009) GIS for Agribusiness. ESRI Newsletter Fall 2009, www.esri.com/agriculture
Fountas S, Kyhn M, Lipczak Jakobsen H et al (2009) A systems analysis of information system requirements for an experimental farm. Prec Agric 10:247–261
Hoffmeister D, Bolten A, Curdt C et al (2009) High resolution crop surface models (CSM) and crop volume models (CVM) on field level by terrestrial laser scanning. Proceedings of the 6th International Symposium on Digital Earth (ISDE6), 9–12 Sept 2009, Beijing, CD-ROM
Jiang JA, Tseng CL, Lu FM et al (2008) A GSM-based remote wireless automatic monitoring system for field information: a case study for ecological monitoring of the oriental fruit fly, *Bactrocera dorsalis* (Hendel). Comput Electron Agric 62:243–259
Kielhorn A, Biermann J, Gervens T et al (2007) Precision farming mit freiem OpenSource. In: Böttinger S, Theuvsen L, Rank S, Morgenstern M (eds) Agrarinformatik im Spannungsfeld zwischen Regionalisierung und globalen Wertschöpfungsketten, Referate der 27. GIL Jahrestagung, 05.-07. März 2007, Stuttgart. GI-Edition – Lecture Notes in Informatics 101:107–110
KTBL (2007) Geodateninfrastruktur und Geodienste für die Landwirtschaft. KTBL-Heft 66, Darmstadt
KTBL (2004) Geographische Informationssysteme in der Landwirtschaft und im ländlichen Raum – Defizite und Entwicklungspotenziale. KTBL-Schrift 428, Darmstadt
Kunisch M, Frisch J, Martini D, Böttinger S (2009) Stand der Entwicklung von agroXML. In: Bill R, Korduan P, Theuvsen L, Morgenstern M (eds) Anforderungen an die Agrarinformatik durch Globalisierung und Klimaveränderung, Referate der 29. GIL-Jahrestagung, 9.-10. März 2009. GI-Edition – Lecture Notes in Informatics 142:93–96
Lambert DM, Lowenberg-DeBoer J, Malzer GL (2006) Economic analysis of spatial-temporal patterns in corn and soybean response to nitrogen and phosphorus. Agron J 98:43–54
Li D (2008) On generalised and specialised spatial information grids: are geo-services ready? Int J Digital Earth 1:315–325
Matese A, Di Gennaro SF, Zaldei A et al (2009) A wireless sensor network for precision viticulture: The NAV system source. Comput Electron Agric 69:51–58
Morais R, Fernandes MA, Matos SG et al (2008) A ZigBee multi-powered wireless acquisition device for remote sensing applications in precision viticulture. Comput Electron Agric 62: 94–106

Nash E, Dreger F, Schwarz J et al (2009a) Development of a model of data-flows for precision agriculture based on a collaborative research project. Comput Electron Agric 66:25–37

Nash E, Korduan P, Bill R (2009b) Applications of open geospatial web services in precision agriculture: a review. Prec Agric 10:546–560

Noack PO (2007) Ertragskartierung im Getreidebau. KTBL-Heft 70, Darmstadt

Oetzel K (2008) Concepts and interfaces with the standardization of office software to integrate process documentation with precision framing. In: Werner A, Dreger F, Schwarz J (eds) Informationsgeleitete Pflanzenproduktion mit Precision Farming als zentrale inhaltliche und technische Voraussetzung für eine nachhaltige Entwicklung der landwirtschaftlichen Landnutzung – *pre agro* II:. http://www.preagro.de/Veroeff/preagro_Abschlussbericht_2008.pdf, pp 379–397

OGC (2005) Web Feature Service implementation specification. Reference number OGC document: OGC 04-094

OGC (2006) OpenGIS® Web Map Server implementation specification. Reference number OGC document: OGC 06-042

OGC (2007a) OpenGIS® Web Processing Service. Reference number OGC Document: OGC 05-007r7

OGC (2007b) Sensor Observation Service. Reference number OGC Document: OGC 06-009r6

OGC (2007c) OpenGIS® Catalogue Services Specification. Reference number OGC Document: OGC 07-006r1

OGC (2008a) Web Coverage Service (WCS) implementation standard. Reference number OGC document: OGC 07-067r5, p 133

OGC (2008b) OGC® KML. Reference number OGC document: OGC 07-147r2

OGC (2008c) OpenGIS® Location Services (OpenLS): Core Services. Reference number OGC document: OGC 07-074

Padberg A, Greve K (2009) Gridification of OGC web services: challenges and potential. GIS Sci14:77–81

Peng ZR, Tsou MH (2003) Internet GIS: distributed geographic information services for the internet and wireless networks. Wiley, Hoboken

Pokrajac D, Fiez T, Oobradovic Z (2002) A data generator for evaluating spatial issues in precision agriculture. Prec Agric 3:259–281

Procari EM (2009) Ubiquitous networks and cloud computing May 10th 2009. CIGAR: connecting people, technology and knowledge for agricultural innovation. http://ictkm.cgiar.org/other_activities/2252_Porcari_Ubiquitous_neworks_and_cloud_computing__2_pdf

Rösch C, Dusseldorp M, Meyer R (2007) Precision agriculture: Landwirtschaft mit Satellit und Sensor. Deutscher Fachverlag, Frankfurt

Ruiz-Garcia L, Lunadei L, Barreiro P, Robla I (2009) A review of wireless sensor technologies and applications in agriculture and food industry: state of the art and current trends. Sensors 9:4728–4750

Srinivasan A (2006) Handbook of precision agriculture: principles and applications. Haworth Press, Binghamton

Stanoevska-Slabeva K, Wozniak T, Ribol S (2010) Grid and cloud computing – a business perspective of technology applications. Springer, Heidelberg

Steinberger G, Rothmund M, Auernhammer H (2009) Mobile farm equipment as a data source in an agricultural service architecture. Comput Electron Agric 65:238–246

Tozer PR (2009) Uncertainty and investment in precision agriculture – is it worth the money? Agric Syst 100:80–87

Watermeier N (2006) Computerized software and mapping technologies for crop management. http://geospatial.osu.edu/resources/cropsoftware.html

Werder S, Krüger A (2009) Parallelizing geospatial tasks in grid computing. GIS Sci 2009(3): 71–76

Chapter 14
Decision Rules for Site-Specific Weed Management

Christoph Gutjahr and Roland Gerhards

Abstract For precision weed management decision rules are needed that take into account spatial and temporal variability of weed populations and weed-crop interactions. The following chapter describes different decision rules for online and offline site-specific weed management. Those decision rules use crop-weed competition models, dose-response functions, weed population models and cost functions to calculate the best intensity of weed control for each field section. It is shown that herbicide input and weed control costs can be significantly reduced when farmers use those models in combination with modern sensor and application technologies.

1 Introduction

The heterogeneous distribution of weeds in agricultural fields allows for site-specific weed management, resulting in significant herbicide savings as well as economic and ecological benefits. The aim of weed management is to keep the density of weed communities on an acceptable level for both the current and forthcoming vegetation periods. The acceptable weed density level depends on several biological, cultivation and economic conditions that have to be considered for creating decision rules for site-specific weed management. To this point, decision support systems give a recommendation for uniform weed control applications across the total field based on the average weed infestation level. Since weed populations have been found to be heterogeneous in their time and location in most arable fields, decision rules need to be developed that take the spatial and temporal variability of weed populations into account. The following chapter gives an overview of already existing decision support systems and describes experiences with decision support systems for patch spraying.

C.Gutjahr (✉)
Department of Weed Sciences (360b), University of Hohenheim, Stuttgart D-70599, Germany
e-mail:cgutjahr@uni-hohenheim.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_14,

2 Decision Rules for Conventional Herbicide Application

In literature, economic thresholds for the control of weeds in small grains vary considerably. The threshold for *Galium aparine* (L.) ranged from 0.1 to 2 plants m^{-2}, while for *Cirsium arvense* (L.) Scop. and *Polygonum convolvulus* (L.) it ranged from 1 to 2 plants m^{-2}. For most broad-leaved weed species, the range is closer to 40–90 plants m^{-2}. Threshold densities of 25–35 plants m^{-2} have been reported for *Alopecurus myosuroides* (Huds.) as compared to 10–20 plants m^{-2} for *Apera spica-venti* (L.) (Niemann 1986). Economic threshold values have not been consequently adjusted to the actual grain price and therefore need to be used as an approximate for making decisions about weed control methods.

Instead of using fixed threshold values, Cousens (1985) applied models to relate yield loss to weed density. Based on early observations of the relative leaf area of the weeds, Kropff and Spitters (1991) developed a simple model to estimate yield loss caused by weed competition. A different approach was to calculate competitive indices for different weed species in order to estimate the expected yield loss due to weed competition (Pallut 1992).

However, none of these decision rules have considered the spatial variation of weed populations within a field. The use of a field-scale means that density estimates in spatially heterogeneous weed populations result in yield loss predictions that are too low in locations where weed density is high and predictions that are too high in parts of the field where weed densities are low or weeds are absent altogether (Lindquist et al. 1998, Brain and Cousens 1990). Spatial variation in weed density must therefore be considered in the development of economic weed thresholds.

3 Offline and Online Site-Specific Weed Management

There are two approaches for site-specific weed management in arable crops. In the offline (or map-based) approach, weed distribution is first measured at georeferenced points. Interpolation methods are applied to create weed distribution maps. A weed threshold is set to determine sections in the map where weed control methods will be applied. Those application maps are then used to direct a patch sprayer or vehicles for mechanical weed control. In many studies, this map-based (offline) approach of site-specific weed management has been applied successfully, resulting in herbicide savings of 20–90% (Timmermann et al. 2003, Gerhards and Oebel 2006, Dicke and Kühbauch 2006).

In order to vary the herbicide dose between 0 and 100% of the recommended dose (Table 14.1), Gerhards and Oebel (2006) used simple weed density thresholds for three classes of weed species. When these thresholds were applied, 6–81% of all herbicides against broad-leaved weed species were saved, while savings ranged from 20 to 79% (Table 14.2) for grass weed herbicides.

The results of these experiments show that site-specific weed management reduced costs for weed control and did not impact the environment as much. However, for a broader acceptance of site-specific weed management in practical

Table 14.1 Applied herbicide doses (100, 85, 70 and untreated 0%) depending on the weed density (plants m^{-2}) for different classes of weed species in spring barley, winter barley, winter wheat, maize, sugar beet and winter rape; the herbicide dose was adjusted to the number of weeds m^{-2}

Weed species	Herbicide dose [% of full]	Weed density [plants m^{-2}] Spring barley	Winter barley	Winter wheat	Maize	Sugar beet	Winter rape
Galium aparine	0	<0.2	<0.2	<0.2	<0.2	<0.2	<0.2
	70	<1	<1	<1	<1	<1	<1
	85	≥1	≥1	≥1	≥1	≥1	≥1
	100	≥1	≥1	≥1	≥1	≥1	≥1
Grass weeds	0	<5	<5	<3	<2	<1	<3
	70	<10	<10	<5	<5	<2	<5
	85	<15	<20	<10	<10	<5	<10
	100	≥15	≥20	≥10	≥10	≥5	≥10
Other weeds	0	<10	<10	<10	<2	<1	<3
	70	<15	<15	<15	<5	<3	<5
	85	<25	<25	<25	<10	<5	<10
	100	≥25	≥25	≥25	≥10	≥5	≥10

Table 14.2 Savings [%] for herbicides using site-specific weed control in 2004 and 2005

Year	Crop (field size)	Savings for herbicides against broad-leaves	Savings for herbicides against grass weeds
2004	Spring barley (17.5 ha)	18	42
2004	Winter rape (11.5 ha)	20	22
2004	Winter barley (8.1 ha)	38	34
2004	Maize (4.6 ha)	6	46
2004	Winter wheat (5.3 ha)	77	69
2004	Sugar beet (5.8 ha)	57	46
2004	Winter barley (8.5 ha)	39	56
2005	Spring barley (8.4 ha)	26	71
2005	Winter rape (6.6 ha)	19	20
2005	Winter wheat (20.0 ha)	58	65
2005	Spring barley (2.4 ha)	40	76
2005	Winter wheat (5.3 ha)	81	79

agriculture, an online system which combines the detection of weed species and herbicide application in one operation would be needed.

Figure 14.1 shows an approach for controlling *C. arvense* patches in sugar beets with an online application. Due to its high competitiveness and the general aim to suppress perennial weeds in arable fields, the application threshold for thistle plants was one plant m^{-2}. The focus of this experiment was to identify and spray all patches of *C. arvense*. The experiment shows the differences between offline and online patch spraying. According to manual sampling, thistle patches covered 5% of the field. With automatic camera-based weed detection (Weis et al. 2008), almost all patches were identified and marked with red points (Fig. 14.1). Images

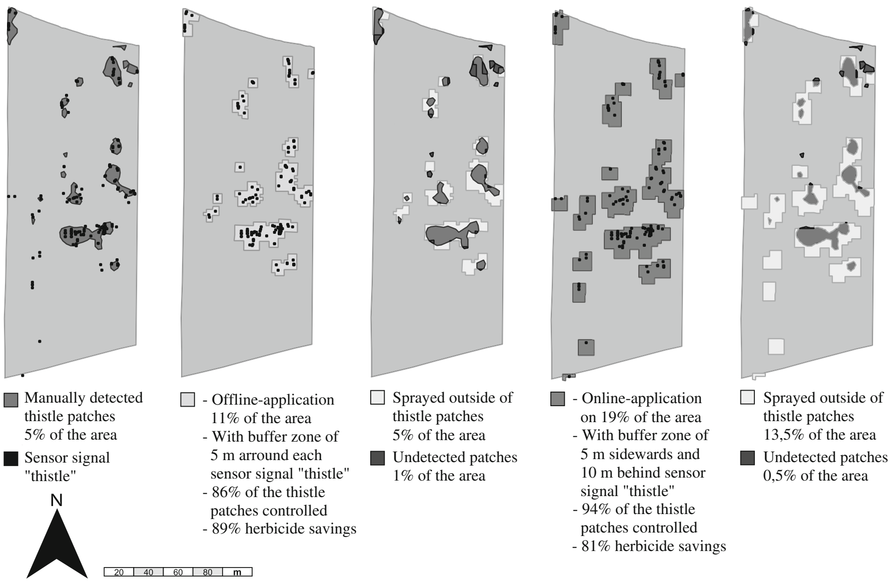

Fig. 14.1 Comparison of manual sampling (map 1) for offline (map 2 and 3) and online patch spraying (map 4 and 5) against *C. arvense* in sugar beets

were taken in a grid of six meters across and three meters along a driving direction. In order to avoid *C. arvense* patches being left unsprayed, a 5 m buffer zone around each thistle was created in the application map. For online application, the buffer zone could only been drawn five meters beside and behind each thistle. However, 94% of all thistle patches were sprayed with online patch spraying; compared to uniform application, 81% of the herbicides were saved. This experiment shows that the success of patch spraying depends on the accuracy and spatial resolution of weed detection. Obviously, the grid size chosen was suitable to recognize *C. arvense* patches within the field. It can be assumed that the higher the sampling resolution, the more exact the patch spraying would be (Wallinga et al. 1998, Hamouz et al. 2006).

4 Decision Support Systems

For more than 20 years, weed scientists have been dealing with decision support systems for weed control (Hoffman et al. 1999). The first steps of these systems were ‘herbicide dose response models’, which aimed at giving advice in herbicide selection as according to their expected efficacy against a given weed infestation (Swinton et al. 2002). The next step was the development of ‘bioeconomic’ models for weed control (Berti et al. 2003). The basis of these models is the optimization of a herbicide application’s net return. Until now, bioeconomic models have contained a voluminous amount of issues with weed management. Crop weed competition, weed seedling emergence, population dynamic aspects, herbicide costs and application costs are often used as input factors. Some of the actual decision support systems combine a herbicide dose response model as well as a bioeconomic model. In the following, some of these models are described.

4.1 Crop Protection Online

The Danish support system Crop Protection Online (CPO) is based on a model which runs in three main model steps (Rydahl 2004). The output of model step one is the level of control needed. It is expressed as a percentage of biomass reduction for each weed species 4–6 weeks after the herbicide application. The required percentage of weed biomass reduction depends on the potential influence of weeds on crops, which is again based on expert knowledge (Rydahl and Thonke 1993). The expert knowledge considers information about the biomass and seed production of the weeds, differences in different crops' ability to compete, crop fitness at the time of spraying, the time of sowing and the expected yield. In model step two, a dose-response model function is used to calculate the herbicide doses needed to achieve the required weed biomass reduction. The dose-response function uses data from Danish field experiments in which the efficacy of over 5,000 combinations of herbicide, crop, season and weed species have been measured. Furthermore, in order to estimate the required herbicide dose, the influence of the weed growth stage and the climatic conditions are considered.

If required, model step three offers the possibility for calculating herbicide mixtures. An Additive Dose Model (ADM) (Streibig et al. 1998) is able to create herbicide mixtures for controlling the actual weed composition.

Since 1987, CPO has often been implemented by scientists, advisors and farmers in Denmark and other European countries. In all experiments, CPO was able to maintain grain yields and keep residual weeds on a low level (>10%). When compared to a common herbicide application, the Treatment Frequency Index (TFI) could be reduced considerably (Rydahl 2004).

4.2 WeedSOFT

WeedSOFT is a bioeconomic decision support system that helps farmers and advisors in Nebraska select an economically and ecologically optimized weed management strategy (Neeser et al. 2004, Hock et al. 2007). It contains two modules that asses the environmental risks of several herbicides depending on the properties of active ingredients and soil conditions. WeedSOFT helps farmers avoid the use of herbicides which may cause groundwater contamination under current conditions. The main component of WeedSOFT is a model which determines yield loss based on inputs provided by the user. The user input contains information on crop species, the crop growth stage, estimated precipitation, the weed density of up to eight weed species and weed growth stages.

A competitive index (CI) is used to transform the densities of the single weed species into a common weed pressure unit in order to determine the percentage yield loss. The CI values have been established through locally conducted field experiments and expert knowledge. Depending on the growth stages of weeds and crops, the CI values can be modified. Through this modification, it is possible to pay attention to a crop's competition advantage, which, for example, is in a later growth stage as compared to weeds which are in an earlier growth stage. The total competitive load (TCL) prior to herbicide treatment can finally be estimated by adding the products of the modified competitive indices (ACIi) and the densities of the present weed species (Di). In WeedSOFT, the percentage yield loss caused by the TCL is estimated by a modified rectangular hyperbolic yield loss function with both linear and nonlinear components. The change between the linear and nonlinear component of the function is defined by the specific crop. The absolute yield loss (t ha^{-1} and ha^{-1}) can then be calculated by multiplying the expected weed-free yield with the estimated percentage yield loss and the attainable crop selling price.

After querying a database containing several weed control treatments and a ranking of different criteria, the most effective herbicide treatment is selected. The database querying considers crop rotation restrictions, soil properties and environmental guidelines. The possible treatments are ranked in an order of economical, biological and environmental factors. The calculation of the economical use of a herbicide treatment also considers the reduced fitness of weeds that survive a herbicide treatment.

WeedSOFT is used by more than 500 advisors and farmers in the USA. The program makes it easier to find an appropriate and cost-effective weed control strategy. It also helps the user understand biological conditions of weed control and shows how different input factors influence, for example, yield loss or the effectiveness of a given herbicide treatment.

4.3 HERB and HADSS

HERB and HADSS (Herbicide Application Decision Support System) are both decision support systems that assist weed managers who are evaluating several weed control strategies in row crops such as corn, cotton, peanut and soybean (Bennett et al. 2003). HERB is a bio-economic decision support system for post-emergence herbicide treatments. It was developed in North Carolina (USA) (Bennett et al. 2003). In HERB, the determination of the total competitive load of the weed before and after herbicide treatment is based on competitive indices of the single weed species. These indices are appointed through expert knowledge. Expected yield loss that is caused by weed infestation is estimated using a simple linear relationship between the competitive load and percentage yield loss at low weed densities – as densities increase, a hyperbolic relationship is assumed. Finally, net return is calculated using expected crop and herbicide prices. In HERB, the determination of herbicide efficacy depends on the growth stages of weeds (three classes) and soil moisture (two levels). As such, six efficacy levels are given for each herbicide and weed species.

HADSS not only includes post-emergence strategies, as it also offers decision support for preplant and pre-emergence application strategies. For pre-emergence treatments, herbicide efficacy depends on the weed species and soil characteristics, such as the content of organic matter and the texture of the soil surface. Organic matter content and soil texture are divided into three categories. As such, there are nine efficacy values for pre-emergence treatments – one for every combination of organic matter content and soil texture. Expected net returns for herbicide treatments are calculated as described above for HERB (Bennett et al. 2003).

4.4 Weed Manager

Weed Manager is a model-based decision support system which assists scientists, advisors and farmers in selecting weed control strategies for winter wheat on two time scales: within a single season and with different crop rotations over several years (Parsons et al. 2009). The 'single season part' of 'Weed Manager' contains models of the growth of wheat and weed species as well as models for estimating the competitive load of the present weed infestation. The competition parameter for each weed species is estimated according to the relative green area indices of crops and weeds. Therefore, the green area index (GAI) of wheat and weeds is measured when the total GAI is 0.75 (Kropff et al. 1995). Weed Manager also contains a model for simulating the emergence characteristics of weed species. The crop is regarded as a single cohort of plants, whereas the germination of weed species can occur in several cohorts. Finally, the growth of the leaf area of crops and weed species between germination and canopy closure can be simulated by using an ecophysiological model (Kropff et al. 1995). As a result, weed-induced yield loss can be predicted. For the estimation of absolute yield loss, the user has to set an expected yield. The effect of herbicides is simulated by the ability of the active ingredient(s) to reduce the GAI of the single weed species. The 'over season part' of the 'Weed Manager' consists of a rotational planning tool that allows users to consider weed control options over several years. This tool is based on the life cycle model developed by Moss (1990). The main component of this population dynamic model is the estimation of changes in the soil seed bank. The soil seed bank is divided into a shallow layer and a deep layer. The model considers the consequences of different crop rotations, cultivation strategies and weed control treatments for weed germination, weed growth, seed fecundity and survival as well as for the changes of the soil seed bank in the two different layers. Implementing costs for herbicides, cultivation strategies and crop prices in both the 'in season part' and 'over season part' of Weed Manager as well as margins of different production strategies can be calculated.

5 Use of Site-Specific Weed Management as a Function of Weed Distribution and Application Techniques

The results of six field experiments conducted by Gutjahr et al. (2009) showed that all three different weed classes (dicots, grass weeds, special weeds) were distributed heterogeneously with a high variation in density (Table 14.3). Similar

Table 14.3 Minimum, maximum and averaged weed densities [plants m^2] of the three weed classes. Areas without weeds for the single weed classes and areas without weeds at all [% of area]

Crop	Dicots [n m^{-2}] average density area without [%]	Grass weeds [n m^{-2}] average density area without [%]	Special weed [n m^{-2}] averaged density area without [%]	Weed-free area [%]
Winter barley	0 – 176 22 10%	0 – 160 10 58%	–	8%
Winter wheat	0 – 49 7.3 30%	0 – 19 1 29%	–	22%
Spring barley	0 – 216 42 59%	–	*Brassica napus* 0 – 108 20 3%	4%
Maize	1 – 150 28.1 0%	0 – 70 15.8 28%	–	0%
Winter wheat	0 – 113 17.8 10%	0 – 95 27.8 10%	*Galium aparine* 0 – 43 7 41%	0%
Maize	0 – 183 27.1 28%	0 – 43 1.3 88%	*Convolvulus arvensis* 79%	9%

observations were made by Cousens et al. (2002), Gerhards and Christensen (2003) and Nordmeyer et al. (2003). They also found that weeds were mostly aggregated in patches. Therefore, site-specific weed management is feasible and may even have economic benefits when herbicide savings compensate for weed mapping and patch spraying costs (Schwarz et al. 1999). Since the distribution of weed species varies within the field, application technologies that allow a variation of active ingredients in real-time are needed (Vondricka 2007). The comparison of the percentage area without any weeds and the percentage area without weeds from a single weed class (Table 14.3) shows that in the case of tank mixture application, individual active ingredients would have been sprayed without indication on 8–79% of the field. Patches of perennial weeds including *C. arvensis* and *C. arvense* covered 20% of the experimental fields. Reduced tillage practices increase the problem of perennials in arable crops (Albrecht and Sprenger 2008). Consequently, effective control units against those weed species are needed. In this case, 80% of the area would not have been sprayed with a herbicide against *C. arvensis* (Table 14.3, maize 2008). Besides significantly saving herbicides, it also avoids crop herbicide stress which is often caused by herbicide mixtures. Kleimann and Vogel (2008) compared the application of different herbicide mixtures in maize. Tank mixtures containing more than two active ingredients often resulted in herbicide stress symptoms and a yield loss of up to 25%.

6 Decision Support System for Patch Spraying

Due to the results described in Chapter 0, a decision support system for online patch-spraying should be able to create suitably optimized economic application decisions for at least two or three separate weed classes. Most decision support systems give a recommendation for uniform weed control applications across the entire field as based on the average weed infestation level. Therefore, their databases have a lot of herbicides available to advise farmers on which herbicide strategy would be the best. During online patch-spraying, the amount of available herbicides is limited to a maximum of four different herbicides. Thus, a decision support system for online patch spraying does not need a tool to choose the correct herbicide. Before herbicide application, the farmer has to select a single herbicide or a mixture of active ingredients to control each weed class. During herbicide application, the decision support system has to adapt the dose of the given herbicide to the density of the weed species of the explicit weed class. Figure 14.2 describes a possible architecture of a decision support system for online patch spraying. The central component of a successful decision support system for patch spraying is the linkage of different models that describe the yield effect of weeds, estimated weed biomass reduction caused by herbicides and the estimated change of the soil seed bank. Using the cost function, it is finally possible to generate an economically optimized herbicide application decision. The firmness of patches with perennials enables one to implicate historical information about weed distribution in the decision making process.

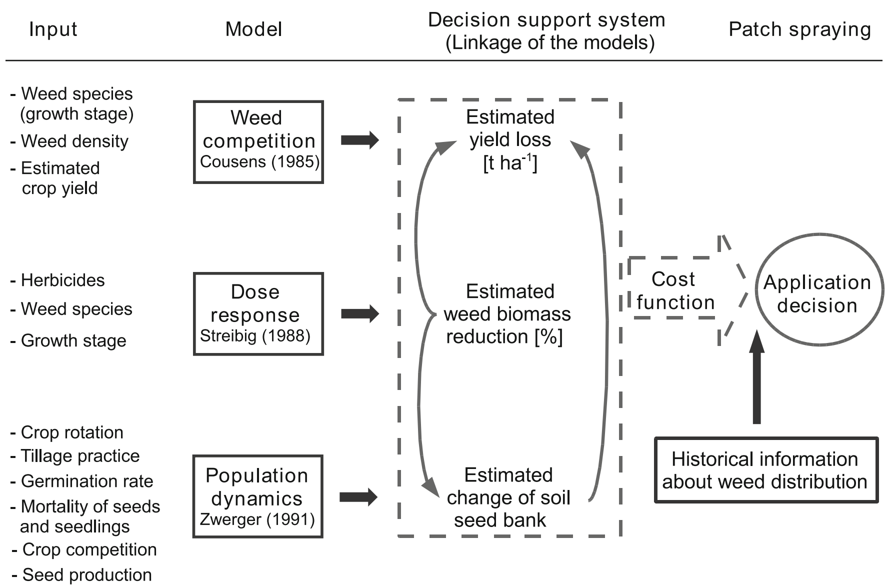

Fig. 14.2 Possible architecture for a decision support system for patch spraying. The main component is the linkage of contained models and finally the economic optimization of the application decision via a cost function

6.1 Decision Algorithm for Patch Spraying

Until now, there have been few decision support systems that enable online patch spraying. Decision Algorithm for Patch Spraying (DAPS) consists of a competition model, a herbicide dose-response model and an algorithm that estimates the economically optimal doses (Christensen et al. 2003). The potential yield loss of uncontrolled weeds is calculated by using the density equivalent model from Berti and Zanin (1994). Therefore, according to their competitiveness, the main weed species are divided into five categories that describe the percentage yield loss per weed plant at low weed densities and the maximum percentage yield loss per weed plant at high densities. Using a hyperbolic relationship between yield loss and weed density, it is possible to convert the density of a given weed species into a density equivalent that describes the expected yield loss. The DAPS user has to predict the crop yield without weeds. Under the assumption that a herbicide treatment reduces weed competition to zero, it is possible to calculate the potential yield gain from weed control.

An important part of DAPS is the link between the herbicide dose model and the yield gain calculations. This link is realised by a 1:1 linear relationship between grain loss and accumulated weed biomass (Fig. 14.3). It is expected that 1 g m^{-2} of accumulated weed dry matter during grain filling causes a 1 g m^{-2} grain yield loss. Under this assumption, the dose response model not only describes the relationship between herbicide dosage and weed biomass reduction, but also the relationship between yield gain and the realised herbicide dose (Use_{rd}).

$$Use[t/ha]_{rd} = Use[t/ha]_{fd}\left(1 - \frac{1}{1 - \exp(-2(\alpha + \beta \log(rd)))}\right) \tag{1}$$

Use_{fd} is the yield gain expected with the full herbicide dose, α is the horizontal displacement of the curve and ß is the slope of the curve. Streibig (1988) showed that α varies between weed species and herbicides, whereas ß only varies between

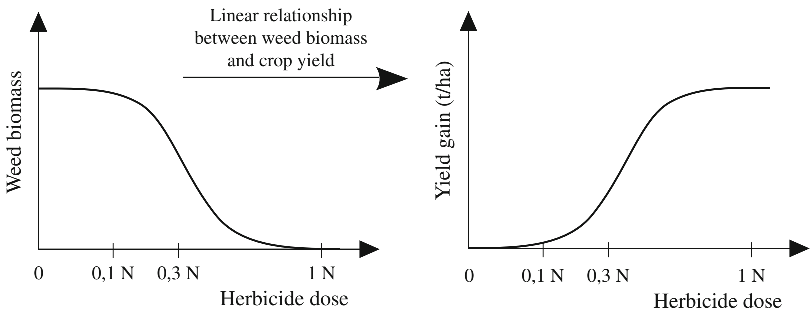

Fig. 14.3 Link between the herbicide dose model and the use of herbicide dose (yield gain) under the assumption of a linear relationship between weed biomass and yield loss (N = recommended dose)

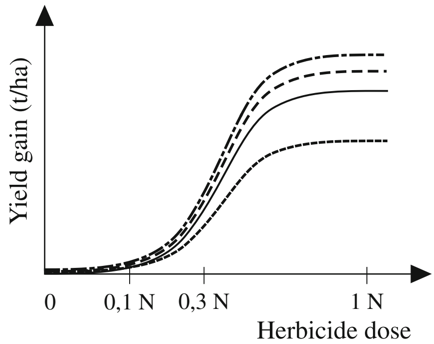

Fig. 14.4 Relationship between use of herbicide application and herbicide dose for three different weed species (*dotted lines*) (Eq. 1). The black line shows the weighted relationship of this weed composition (N = recommended dose)

herbicides. Since an active ingredient of a herbicide is able to control a mixture of several weed species, a dose response curve is needed for a mixed weediness. Therefore, α can be weighted by the relative yield loss of the single weed species – the new α is the sum of these α–values. Due to the fact that α changes the horizontal displacement of the curve, the position of the new weighted curve will be closest to the curve of species that dominates competition with the crop (Fig. 14.4).

The third step of DAPS is the estimation of the economically optimized herbicide dose *profit* (*rd*). Therefore, the anticipated crop price (*cp*) and the costs of herbicide application as a function of the realised dose (*costs(rd)*) are used:

$$Profit_{rd} = Use_{rd} * cp - [\cos ts(rd)] \qquad \text{(Eq. 2)}$$

The economically optimal herbicide dose is calculated by differentiating Eq.(2).

An essential approach in DAPS is the simple weighting of α-parameters by the relative yield impact of the weed species. In combination with an appropriate sensor system for weed recognition and classification (Weis and Gerhards 2007) as well as an improved application technology that allows variable rates and herbicide mixtures in real-time (Vondricka 2007), DAPS enables an economically optimized online site-specific herbicide application. However, there are still a few points of view that are not considered or could be improved.

6.2 HPS-ONLINE

Expert and researched knowledge concerning herbicide application can be divided into two parts: knowledge before herbicide application and knowledge during herbicide application. The decision support system HPS-ONLINE integrates both parts in its decision making. Similar to DAPS, one of the essential approaches is the link between the weed competition model and dose response model as well as the creation of a dose yield gain curve for a mixed weed composition through the weighting of the α-parameter. Since the output of the weed competition model depends on the actual infestation of several weed species, this part can be considered

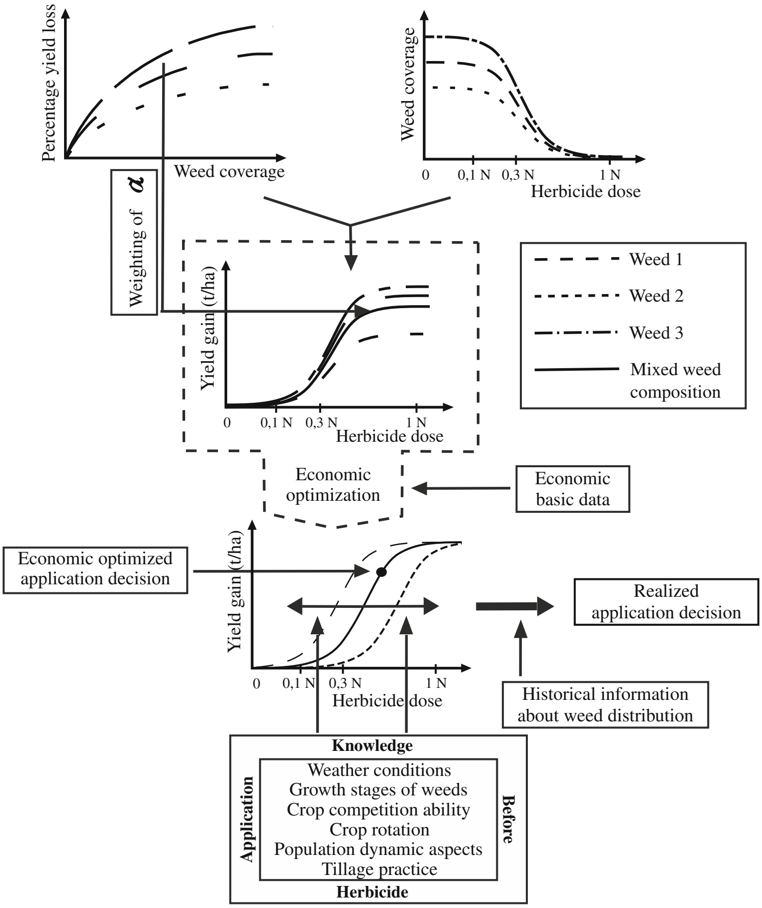

Fig. 14.5 Model of HPS-ONLINE. Linkage of dose response curve and weed competition model. Creating a dose response curve for a mixed weed composition by weighting of α with the relative yield loss caused by the single weed species. Implementation of expert knowledge, 'knowledge before herbicide application' and historical information about weed distribution (control of perennials)

as knowledge during the herbicide application. A further important component of HPS-ONLINE is the implementation of users' expert knowledge and experience on herbicide application. This knowledge can be considered as knowledge before herbicide application (Fig. 14.5).

6.2.1 Knowledge During Herbicide Application

A 1: 1 linear relationship between crop yield loss [g m^{-2}] and accumulated weed biomass [g m^{-2}] during grain filling is used in DAPS to link the weed competition model with the dose response model. Since the main crop yield loss caused by weed competition is induced during grain tillering or before the canopy soil coverage of row crops, HPS-ONLINE uses the weed coverage at the time of weed control for the estimation of weed competition.

A bispectral sensor system (Sökefeld et al. 2007) gives information on the total GAI (Green Area Index) at the time of weed control. In the next step, shape features are calculated for each plant and arranged in the image. Those features are used for automatic plant species classification (Weis and Gerhards 2007). It is now possible to appoint the contingent of the single plant species on the measured GAI. The species are therefore divided up into four classes, while one class consists of the crop. The composition of the other weed classes depends on the competitiveness of weeds as well as the possibility to control them with the same herbicides.

As described in Section 5, a decision support system for online patch spraying should be able to create suitable application decisions that are economically optimized for at least two or three separate weed classes. In combination with a multiple boom sprayer, it is possible to control each weed class separately (Oebel et al. 2004). For this reason, a separate application decision is realized for each weed class in HPS-ONLINE.

For estimating the total competitive load of the weed species' composition within a weed class, a relationship between the single weed species' GAI and the yield loss still has to be determined. It should be possible to translate the GAI of a single weed class into a yield loss percentage. Under the assumption that a full herbicide dose is able to avoid total weed competition, full herbicide dose's usage can be estimated.

The dose response model described by Streibig (1988) gives information on the weed biomass reduction potential of several dosages of a herbicide. Stamps (1998) found a high correlation between weed coverage and weed biomass. Thus, it is possible to describe the output of the dose response model as a percentage of weed coverage reduction instead of a percentage of weed biomass reduction. Under this assumption, the same sigmoid relationship between yield gain and herbicide dosage that is used in DAPS can be used in HPS-ONLINE.

In order to control the mixture of weed species within a weed class, a weighting of α – as is done in DAPS – is necessary (Fig. 14.4). The dose response curve with the weighted α parameter finally shows the relationship between the herbicide dose and the herbicide application. Using a cost function and depending on the product prices, HPS-ONLINE calculates costs for herbicides and the application of the economically optimized application decision.

6.2.2 Knowledge Before Herbicide Application

Compared to the possible architecture of a decision support system for online patch spraying that is shown in Fig. 14.2, DAPS does not offer a possibility for the implementation of population dynamic aspects for weed control. Kropff (1996) declared that an improvement of weed management strategies, including reduced herbicide doses and patch spraying, is only possible when the population dynamics of weeds as well as the interactions between crops and weeds are considered and understood. The aim of site-specific weed management is the sustainable reduction of herbicide doses over multiple years. Thus, for example, it must be guaranteed that high weed control efficacy as well as herbicide savings can be achieved in the following seasons (Ritter and Gerhards 2008). Realising site-specific herbicide application in combination with crop rotations Christensen et al. (2003), Dicke and Kühbauch (2005) and Ritter and Gerhards (2008) found that weed density remained relatively stable and no new weed patches appeared. Dicke and Kühbauch (2005) observed that site-specific herbicide application resulted in an increased density of broad-leaved weeds in continuous maize over a period of 6 years. As such, a well balanced crop rotation seems to be beneficial for the sustainability of patch spraying.

Research indicates that there is a good potential to reduce herbicide doses without the risk of increasing the soil seed bank. Diverse crop rotations, competitive crops, cultivation practice, higher crop seed densities, reduced row spacing and specific fertilizer placement can be regarded as measurements that increase the competitiveness of crops and enable a reduction in herbicide doses (Fernandez et al. 2002, Blackshaw et al. 2006, Beckie et al. 2008, Kristensen et al. 2008). In addition, it can be assumed that weeds that survive a reduced herbicide dose are less competitive than untreated weeds. Thus, they can be completely suppressed by the crop or at least unable to finish their life cycle. Reduced herbicide doses often lead to a decreased amount of produced seeds as well as a decreased fertility of the seeds that are produced (Berti et al. 2003). Thus, an implementation of a specific population dynamic model to estimate the changes in a soil seed bank doesn't seem to be necessary. The HPS-ONLINE user is able to choose the importance of the population dynamic aspects himself. This can be realized through horizontal displacement of the dose response curve (Fig. 14.5). If the user wants reduced tillage to be realised, short or even no crop rotation intervals as well as population dynamic aspects are more important. On the other hand, long crop rotation intervals, narrow row spacing or well developed crops enable farmers to disregard population dynamic aspects.

The impact of weather conditions during and after herbicide application is very important for its efficacy. Depending on the herbicide and its mode of action, different weather conditions are required. If the user finds the application conditions to be optimal, HPS-ONLINE offers the possibility for a general reduction of herbicide doses. Under unfavourable application conditions, the reduction of herbicide doses can be inhibited or limited.

Experiments by Dicke and Kühbauch (2005), Ritter and Gerhards (2008) and Gutjahr et al. (2008) showed that herbicide application reduced grain yield in areas with little or no weed infestation. Thus, the question of whether the effect of herbicides on the crop should be considered in a decision algorithms for site-specific weed control arises. The selectivity of many herbicides is caused by different kinetics of metabolism in the plant. Herbicides could damage the crop when the uptake and translocation within the crop is increased due to less favorable weather conditions for the formation of cuticles (Hock et al. 1995). However, it is very difficult to give a general estimate of the yield effect of the herbicide. It differs significantly between active ingredients, herbicide doses, weather conditions before, during and after application, crops and growth stages (Donald 1998, Kleimann and Vogel 2008). Therefore, HPS-ONLINE offers the possibility to take the yield effect of herbicides into account by horizontally displacing the dose response curve (Fig. 14.5).

References

Albrecht H, Sprenger B (2008) Long-term effects of reduced tillage on the populations of arable weeds. In: Schröder P, Pfadenhauer J, Munch JC (eds) Perspectives for agroecosystems management. Elsevier B.V, Amsterdam, Boston, Heidelbergp, pp 237–256

Beckie JH, Johnson EN, Blackshaw RE, Gan Y (2008) Weed suppression by canola and mustard cultivars. Weed Technol 22:182–185

Bennett AC, Price AJ, Sturgill MC et al (2003) HADSS, Pocket HERB, and WebHADSS: decision aids for field crops. Weed Technol 17:412–420

Berti A, Bravin F and Zanin G (2003) Application of decision-support software for postemergence weed control. Weed Sci 51:618–627

Berti A, Zanin G (1994) Density equivalent: a method for forecasting yield loss caused by mixed weed populations. Weed Res 34:326–333

Blackshaw R, O'Donovan JT, Harker KN et al (2006) Reduced herbicide doses in field crops: a review. Weed Biol Manag 6:10–17

Brain P, Cousens R (1990) The effect of weed distribution on predictions of yield loss. J Appl Ecol 27:735–742

Christensen S (1995) Weed suppression ability of spring barley varieties. Weed Res 35:241–249

Christensen S, Heisel T, Walter AM, Graglia E (2003) A decision algorithm for patch spraying. Weed Res 43:276–284

Cousens R (1985) A simple model relating yield loss to weed density. Ann Appl Bot 107:239–252

Cousens RD, Brown RW, McBratney AB et al (2002) Sampling strategy is important for producing weed maps: a case study using kriging. Weed Sci 50:542–546

Dicke D, Kühbauch W (2005) Einsatz von satellitengestützter Fernerkundung zur Früherkennung von herbizidbedingten Schäden in Mais. 35. GIL Jahrestagung 19:(22.09.2005) 355–359

Dicke D, Kühbauch W (2006) Temporal dynamics of weed populations in arable fields using long-term site-specific weed control. In: Preston C, Watts JH, Crossman ND (eds) Proceedings of 15th Australian Weeds Conference. Gillingham Printers, Adelaide, pp 375–378

Donald DD (1998) Estimating relative crop yield loss resulting from herbicide damage using crop ground cover or rated stunting, with maize and sethoxydim as a case study. Weed Res 38: 425–431

Fernandez ON, Vignolio OR, Requesens EC (2002) Competition between Corn (*Zea mays*) and bermudagrass (*Cynodon dactylon*) in relation to the crop plant arrangement. Agronomie 22:293–305

Gerhards R, Christensen S (2003) Real-time weed detection, decision making and patch spraying in maize, sugar beet, winter wheat and winter barley. Weed Res 43:385–392

Gerhards R, Oebel H (2006) Practical experiences with a system for site-specific weed control in arable crops using real-time image analysis and GPS-controlled patch spraying. Weed Res 46:185–193

Gutjahr C, Weis M, Sökefeld M et al (2008) Erarbeitung von Entscheidungsalgorithmen für die teilflächenspezifische Unkrautbekämpfung. J Plant Dis Prot XXI(special issue):143–148

Hamouz P, Novakova K, Soukup J, Tyser L (2006) Evaluation of sampling and interpolation methods used for weed mapping. J Plant Dis Prot XX(special issue):205–215

Hock B, Fedtke C, Schmidt RR (1995) Herbizide: Entwicklung, Anwendung, Wirkungen, Nebenwirkungen. Thieme, Stuttgart, New York

Hock S, Knezevic S, Johnson W et al (2007) WeedSOFT: effects of corn-row spacing for predicting herbicide efficacy on selected weed species. Weed Technol 21:219–224

Hoffman ML, Buhler DD, Owen MDK (1999) Weed population and crop yield response to recommendations from a weed control decision aid. Agron J 91:386–392

Kleinmann M, Vogel H (2008) Verträglichkeit von Maisherbiziden beachten, AGRAVIS Pflanzenbau-Vertriebsberatung Münster. LOP, Mai, pp 36–39

Kristensen L, Olsen J, Weiner J (2008) Crop density, sowing pattern, and nitrogen fertilization effects on weed suppression and yield in spring wheat. Weed Sci 56:97–102

Kropf MJ, Lotz LAP, Weaver SE et al (1995) A two parameter model for prediction of crop loss by weed competition from early observations of relative leaf area of weeds. Ann Appl Biol 126:329–346

Kropff MJ, Spitters CJT (1991) A simple model of crop loss by weed competition from early observations on leaf area of the weeds. Modeling the effects of weeds on crop production. Weed Res 318:97–105

Kropff MJ, Wallinga J, Lotz LAP (1996) Weed population dynamics. In: Brown H, Cussans GW, Devine MD et al (eds) Proceedings of the 2nd International Weed Control Congress, Copenhagen, pp 3–14

Lindquist JL, Dieleman JA, Mortensen DA et al (1998) Economic importance of managing spatially heterogeneous weed populations. Weed Technol 12:7–13

Moss SR (1990) The seed cycle of *Alopecurus myosuroides* in winter cereals: a quantitative analysis. Proceedings of EWRS Symposium, Helsinki, European Weed Research Society, Wageningen, pp 27–35, 4–6 June 1990

Niemann P (1986) Mehrjährige Anwendung des Schadensschwellenprinzips bei der Unkrautbekämpfung auf einem landwirtschaftlichen Betrieb. EWRS Symposium Economic Weed Control, Wagenigen, pp 385–392

Nordmeyer H, Zuck A, Häusler A (2003) Experiences of site-specific weed control in winter weeds. In: Stafford J, Werner A (eds) Proceedings of the Precision Agriculture 2003. Academic Publishers, Wageningen

Oebel H, Gerhards R, Beckers G et al (2004) Site-specific weed control using digital image analysis and georeferenced application maps – first field experiments. J Plant Dis Prot XIX(special issue):459–465

Pallut B (1992) Zur Verbesserung der Vorhersagegenauigkeit von unkrautbedingten Kornertragsverlusten bei Wintergetreide. Z PflKrankh PflSchutz XIII(Sonderheft):129–137

Parsons DJ, Benjamin LR, Clarke J et al (2009) Weed Manager – A model-based decision support system for weed management in arable crops. Comput Electron Agric 65:155–167

Ritter C, Dicke D, Weis M et al (2008) An on-farm research approach to quantify yield variability and to derive decision rules for site-specific weed management. Prec Agric 9:133–144

Ritter C, Gerhards R (2008) Population dynamics of *Galium aparine* L. and *Alopecurus myosuroides* Huds. under the influence of site-specific weed management. J Plant Dis Prot XXI(special issue):209–214

Rydahl P (2004) A Danish decision support system for integrated management of weeds. Aspects Appl Biol 72:43–52

Rydahl P, Thonke KE (1993) PC-Plant Protection: optimising chemical weed control. Bull OEPP/EPPO Bull 23:589–594

Sökefeld M, Gerhards R, Oebel H, Therburg RD (2007) Image acquisition for weed detection and identification by digital image analysis. In: Stafford JV (ed) Precision agriculture`07. Academic Publishers, Wageningen, pp 523–528

Stamps RH (1998) Correlation between visual ratings with quantitative measurements of weed control during containerized landscape plant production. Proc Fla State Hort Soc 102: 112–113

Streibig JC (1988) Herbicide bioassay. Weed Res 28:479–484

Swinton SM, Renner KA, Kells JJ (2002) On-farm comparison of three postemergence weed management decision aids in Michigan. Weed Technol 16:691–698

Timmermann C, Gerhards R, Kühbauch W (2003) The economic impact of the site specific weed control. Prec Agric 4:249–260

Vondricka J (2007) Study on the process of direct nozzle injection for real-time site-specific pesticide application. Dissertation, University of Bonn, Bonn

Wallinga J, Groeneveld RMW, Lotz LAP (1998) Measures that describe weed spatial patterns at different levels of resolution and their applications for patch spraying of weeds. Weed Res 38:352–359

Weis M, Gerhards R (2007) Feature extraction for the identification of weed species in digital images for the purpose of site-specific weed control. In: Stafford JV (ed) Precision agriculture ’07. Academic Publishers, Wageningen, pp 537–545

Chapter 15
Modelling Plant Diseases for Decision Making in Crop Protection

Vittorio Rossi, Simona Giosuè, and Tito Caffi

Abstract A plant disease model is a simplification of the relationships (between a patho-gen, a host plant, and the environment) that determine whether and how an epi-demic develops over time and space. This chapter describes an approach for de-veloping mechanistic, weather-driven, dynamic models which are suitable to be applied in precision crop protection. Model building consists of four steps: (I) defi-nition of the model purpose; (II) conceptualization; (III) development of the mathe-matical relationships; and (IV) model evaluation. Conceptualization is based on systems analysis; it assumes that the state of the pathosystem can be quantitatively determined and that changes in the system can be described by mathematical equations. A conceptual model describes the system (both conceptually and mathematically), and a set of driving models accounts for changes caused by the external variables. Two main types of conceptual models are described: plant- and pathogen-focused models. Model evaluation is the judgement of the overall adequacy of the model, which includes: verification, validation, uncertainty analysis, sensitivity analysis, and judgement of utility. Finally, the chapter briefly considers how models can be used as tools for decision making at different scales of time and space: from warning services to precision agriculture.

1 Introduction

A model is a simplified representation of reality (De Wit 1993). A plant disease model is then a simplification of the relationships between a pathogen, a host plant, and the environment that cause an epidemic to develop over time and/or space. There are numerous kinds of models and of modelling approaches (Campbell and Madden 1990, De Wolf and Isard 2007, Fry and Fohner 1985, Hardwick 1998, Krause and Massie 1975, Maloy 1993, Shrum 1978, Zadoks 1984). Madden et al. (2007)

V. Rossi (✉)
Istituto di Entomologia e Patologia vegetale, Università Cattolica del Sacro Cuore, I-29100 Piacenza, Italy
e-mail: vittorio.rossi@unicatt.it

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_15,

distinguished models based on their uses; in botanical epidemiology, models are used to describe, understand, predict, and compare epidemics and their components.

Prediction of a disease allows growers to respond in a timely and efficient manner by adjusting crop management practices (Krause and Massie 1975, Maloy 1993, Rabbinge et al. 1989, Zadoks 1979); a prediction of low disease risk may result in reduced pesticide application with positive economic and environmental effects. Most reviews of plant disease prediction models show that far more models have been developed than applied in operational plant disease protection systems (Butt and Jeger 1985, Krause and Massie 1975). A recent work (De Wolfe and Isard 2007) shows that the imbalance between the number of models developed and deployed may be changing, and also indicates that the research effort directed toward evaluation and practical application of disease prediction models is currently much greater than just a few decades ago.

In this chapter, we briefly describe the basic elements we have used for developing several plant disease models (Battilani et al. 1996a, 1997, Rossi and Giosuè 2003, Rossi and Racca 1996, Rossi et al. 1994, 1996, 1997b, 2003, 2007, 2008, Spada et al. 2001) that are extensively used in some Italian warning systems for decision making in crop protection.

Our modelling approach is *fundamental*, where "fundamental" is the alternative to "empirical" (Madden and Ellis 1988). Empirical models describe observed behaviour of the system on the basis of observations alone and explain nothing of the underlying processes; fundamental (also referred to as explanatory, theoretical, or mechanistic) models explain the same behaviour on the basis of what is known about how the system works in relation to the influencing variables (Wainwright and Mulligan 2004). Distinction between empirical and fundamental approaches is often academic because many empirical models have a fundamental basis, and fundamental models usually have many empirical elements (Madden and Ellis 1988). The latter concept is valid for our modelling approach, where the "conceptual model" is mechanistic while the "driving models" are drawn from experimental data. Conceptual and driving models are defined in paragraph 3.

Our modelling approach is *dynamic*. In fact, fundamental models analyse components of the epidemic and their changes over time due to the external variables influencing them (Teng et al. 1980). Dynamic modelling is based on the assumption that the state of the pathosystem in every moment can be quantitatively characterised and that changes in the system can be described with mathematical equations (Rabbinge and de Wit 1989).

Also, our models are *weather-driven*, because the weather variables are the main inputs of the model. When growth and/or development of the host plant play a relevant role in the pathosystem considered, and need to be incorporated into the model, weather-driven models predicting the plant's behaviour are developed and coupled with the disease model (Rossi et al. 1997b).

Finally, our models are *tools for simulation and prediction*, a category of models used for extrapolation beyond measured times and spaces (Anderson 1974, Wainwright and Mulligan 2004). In this context, prediction is the process of estimation in unknown past or current situations, which is different from forecasting, the latter term being reserved for extrapolations at future times. Nevertheless, these prediction models can be used as forecasters by using weather forecasts as input factors, or by linking past or current conditions of the epidemic to the future conditions (Campbell and Madden 1990, de Vallavieille-Pope et al. 2000, Madden and Ellis 1988).

In our modelling approach, there are four main steps: (i) definition of the model purpose, (ii) conceptualization, (iii) development of the mathematical relationships, and (iv) model evaluation (Fig. 15.1). In this work, we will discuss some aspects of these steps in depth while other aspects that have been treated in previous reviews are only mentioned.

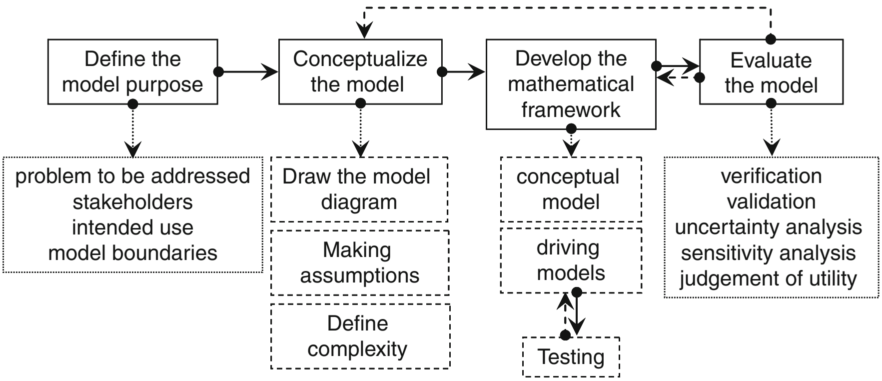

Fig. 15. 1 Flow diagram of the processes leading to the production of mechanistic, weather-driven, dynamic models for plant diseases

2 Defining the Model's Purpose

Defining the purpose of the model implies definition of: (i) the problem to be addressed, (ii) the model's stakeholders (e.g., growers, advisors, policy-makers); (iii) the intended use (e.g., the model should produce information about the disease or the pathogen status, produce warnings, guide the scheduling of fungicide sprays); (iv) the model boundaries. Stakeholders are the main actors in defining the model's purpose; their practical experience makes it possible to delineate the problem. If the problem is not properly identified, then it will not be possible to arrive at a useful solution through modelling (Wainwright and Mulligan 2004).

Model boundaries in time and space must be defined to determine which times and spaces will be modelled and which must be supplied as data. These boundaries also determine the practical constraints under which environmental data must be collected (Pascual et al. 2003).

3 Conceptualizing the Model

The gestation phase of the model building consists in understanding and rationalizing the process to be modelled and the important factors that govern the process. A critical review of the information available in the literature supplies the background knowledge for conceptualizing the system. Pathosystems include pathogens, host plants, weather, human interferences (i.e., cultural practices), and their relationships. Therefore, information must be acquired concerning the pathogen, the plant, the environment influencing the pathogen and host, and the crop growing system.

3.1 Use of Systems Analysis in Model Conceptualization

Systems analysis is a useful tool for conceptualizing the model (Leffelaar 1993). Through the use of systems analysis, the totality of relations within the pathosystem is organized in a relational diagram representing the "system structure" (De Wit 1993). The relational diagram shows the status of the system at a certain moment and its dynamics over time. The building of a model by starting with a relational diagram is based on the assumption that the state of the system at any moment can be quantified and that changes in the state can be described (Rabbinge and de Wit 1989). Main components of the systems analysis approach are: state variables, flows, rate variables, auxiliary variables, driving (external) variables, constants, and parameters.

A *variable* is a value that changes freely in time and space. A *state variable* is one that represents a state of the system (e.g., the number of spores, the amount of infected host tissue). A *rate variable* (or rate) indicates the rate at which a state variable changes. A rate depends on state and driving variables according to rules based on the knowledge of processes in the system. A *constant* is an entity that does not vary within the system; it represents known and unchanging physical, biological, or ecological activities (Pascual et al. 2003). A *parameter* is a value that is constant in a particular case but may vary from case to case, where a case can represent a different model run or a different situation. *Driving variables* are external factors that influence the system but are not influenced by the processes within the system (e.g., the weather variables). *Switches*, which were introduced as additional components in the symbolism of systems analysis by Rossi et al. (2008), account for logical operators with the following syntax: if "condition" then "go to", else "go to".

Model building involves a *conceptual model* that describes the system (both conceptually and mathematically) and a set of *driving models* that account for changes caused by the external variables.

3.2 Types of Conceptual Models

There are two main types of conceptual models: one type focuses on the affected plant and the other focuses on the pathogen. In the *plant-focused models*, the state variables of the system are the stages of host tissue with respect to the disease, as follows: (i) healthy tissue; (ii) tissue carrying latent (not yet visible) lesions; (iii) tissue with visible (but not yet sporulating) lesions; (iv) tissue with visible, spore-bearing lesions (i.e., infectious lesions); and (v) tissue with visible lesions that are no longer sporulating (i.e., removed lesions or removals) (Hau 1985). Transition from one stage to another depends on the rates at which: (i) healthy tissue become infected; (ii) latently infected lesions become visible (i.e., reach the end of incubation period); (iii) visible lesions become sporulating lesions (i.e., reach the end of latency period); and (iv) sporulating lesions become no more sporulating lesions (i.e.) reach the end of infectious period. Quantities can be expressed as densities of individuals in the different states (e.g., number of lesions per leaf) or as percentages or proportions of the plant tissue in the different stages (e.g., percentage of leaf area covered by lesions).

The POWDEP model (Rossi and Giosuè 2003) is a plant-focused model for the epidemics of *Blumeria graminis*, the causal agent of the powdery mildew of wheat (Fig. 15.2). The model calculates the daily progress of disease severity on individual leaves. The model considers four categories of affected leaf tissue: (i) leaf area (LA) with latent infection (LLA), where symptoms of powdery mildew are not yet visible; (ii) LA with powdery lesions that have yet to produce spores (PVLA); (iii) LA with powdery, sporulating lesions (PILA); and (iv) LA with powdery lesions that are older and nonsporulating (PNLA). The amount of LA susceptible to infection (SLA) is the spatial limiting factor for the epidemic growth. Three different rate variables determine changes from one state to the next: INC, LAT, and REM, in order. These rates depend on the length of incubation, latency, and sporulation (or infectious) periods (IP, LP, and SP, respectively), which are all temperature-dependent.

The basic concept of the model is that, on each day, the disease severity (or total LA with powdery mildew, PLA) is the sum of the disease severity of the day before and of the current day. This daily increase results from two compartments: (i) the growth of fungal colonies already present on the leaves, regulated by the colony growth rate (CGR); and (ii) the appearance of new colonies, determined by

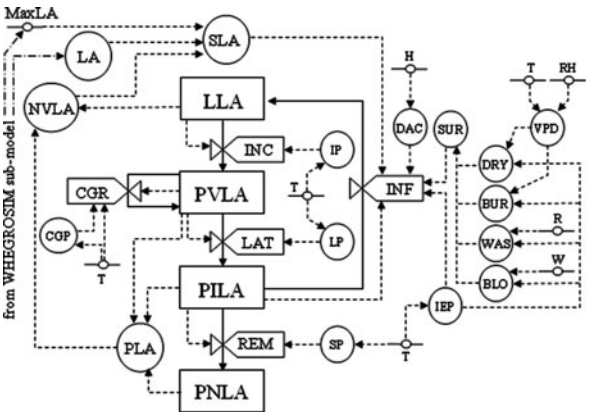

Fig. 15.2 Relational diagram of the model simulating powdery mildew epidemics on wheat (Rossi and Giosuè 2003). The WHEGROSIM sub-model accounts for plant growth and development

the infection rate (INF). INF is a function of the density of airborne conidia (DAC), the time required for the conidia to infect (IEP), and the capability of conidia to survive during IEP (SUR). SUR depends in turn on the possibility that conidia are blown from the leaf surface (BLO) by air currents (W), washed off (WAS) by rain (R), dried out (DRY) by dryness (VPD, vapour pressure deficit), or burst (BUR) by moisture.

In the *pathogen-focused models*, the state variables of the system are the stages of the life cycle of the pathogen. These models partition the epidemic into general biological stages (or components) including dormancy, reproduction, dispersal, and pathogenesis (Campbell and Madden 1990, De Wolf and Isard 2007). Conceptually, these stages can be divided into a seemingly infinite numbers of events, each having a unique relationship with the environment and host (Kranz 2003). Following DeWolf and Isard (2007), the dormancy stage can be further divided into colonization and survival components; dispersal can be divided into release, transport, survival, and deposition; while pathogenesis can be divided into infection, incubation, latency, and senescence components. Although every step in the biological process is potentially important, it is often unnecessary to model all details of the system to produce a useful model. Stages can be considered as occurrences (e.g., the pathogen has infected the plant) or quantities (e.g., number of spores that have caused infection per unit of plant surface). When only the occurrence of stages is considered, the model can be defined as “phenological”.

An example of a pathogen-focused model is that of Rossi et al. (2008), which simulates primary infections of *Plasmopara viticola* on grapevine. The oospores (i.e., the overwintering spores) formed in the affected leaves of the previous season form the seasonal oospore dose, SOD. These oospores enter the morphologically mature stage (MMO) depending on the day of the year (DOY), and then become physiologically mature (PMO) in the following spring depending on the physiological time (hydro-thermal time, HT), which regulates the breaking of dormancy (DOR). HT depends both on temperature (T) and on moisture in the leaf litter (M), which depends in turn on rain (R) and vapour pressure deficit (VPD). When a rainfall wets the leaf litter containing oospores, the oospores in the PMO stage move to the GEO stage (germinated oospores, i.e., oospores that have produced sporangia) according to a germination rate (GER), which also depends on HT; the oospores that have broken dormancy at the time of the rainfall form a cohort that develops in a similar way. Sporangia germinated from oospores can survive for a certain period of time (SUS), which depends on T and relative humidity (RH). Living sporangia release zoospores (REL) as soon as the environmental conditions of T and wetness duration (WD) are favourable. At this stage, zoospores are swimming in the film of water (ZRE) and survive there (SUZ) as long as the water film persists; during this period, any rain that occurs splashes zoospores to grape leaves (ZDI). Based on T and WD, these zoospores can dry out on the leaf surface or infect the host; in the latter case, the zoospores move from the ZDI stage to the infection stage (ZIN). Finally, oil spots appear on leaves (OSL) at the end of a T-dependent incubation period (Fig. 15.3).

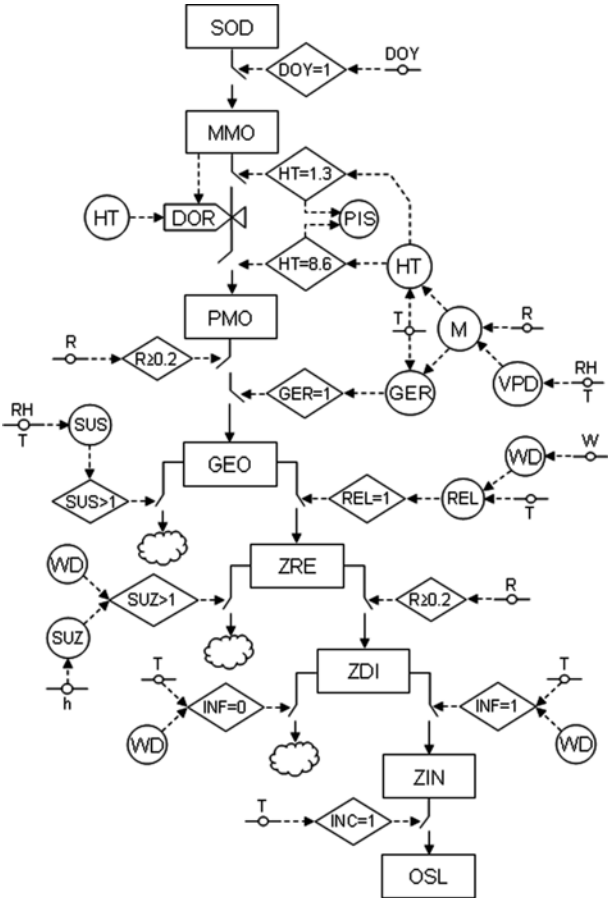

Fig. 15.3 Relational diagram of the model simulating primary infections of grapevine downy mildew (Rossi et al. 2008)

3.3 Complexity Versus *Simplicity*

The dualism between complexity and simplicity is an important concern. Addition of detailed process descriptions, with increased numbers of variables and parameters, may support a theoretical or biological point of view in that it will more completely describe the complex interactions between pathogen, plant, and environment. The added details, however, may not necessarily increase the model's practical capability to predict disease and to guide management. From a practical perspective, models should be parsimonious: a parsimonious model is usually the one with the greatest predictive power and the least process complexity (Wainwright and Mulligan 2004). Although complexity may make the model more accurate, it can also make the model less manageable (Kranz and Hau 1980). Thus, simplicity should be strived for in developing the conceptual model but not at the cost of model performance.

Managing imperfect knowledge. Frequently, the modeller faces the problem of imperfect knowledge and the lack or ambiguity of information regarding aspects of the pathosystem. This deficiency can be solved by collecting additional information or by explicitly accepting (at least temporarily) assumptions about processes; biologically plausible values and empirical probability distributions can be taken from similar pathosystems.

Making assumptions. Whenever assumptions are made, they must be explicitly stated with reference to the conditions under which they are valid and, more importantly, the conditions under which they are invalid (Wainwright and Mulligan 2004). The key to successful modelling is to know which assumptions are likely to be wrong and to ensure that they are not important for the model's stated purpose. Further, one should only use the model for that purpose and should ensure that others do not use the model for purposes that render incorrect assumptions significant or correct assumptions invalid.

4 Developing the Mathematical Model

After an appropriate conceptual model framework (appropriate for answering the problem posed) has been devised, the next stage is to build the model mathematically. Development of the mathematical structure of the model consists of stringing together sets of equations for which an analytical solution will be derived. A possible approach is to build the model graphically by adding compartments and flows, linking them with dependencies, and entering the appropriate equations into the relevant compartments, flows, or variables. When a systems analysis approach is used to conceptualize the model, this process is greatly simplified. Otherwise, PowerSim (Powersim Software AS, Bergen, Norway) and other model-building environments with easy-to-use graphical interfaces and syntax are available.

4.1 Formulation of Conceptual Models

Mathematical principles for the plant-focused models have been described by Madden et al. (2007) when quantities are expressed as densities, and by Vanderplank (1963) when quantities are expressed as proportions. Both models have the same levels of biological detail and biological realism (Madden et al. 2007). For instance, a possible mathematical derivation when the model considers densities gives the following system of equations: $dH(t)/dt = -\beta H(t)I(t)$; $dL(t)/dt = \beta H(t)I(t) - \lambda V(t)$; $dV(t)/dt = \lambda V(t) - \omega I(t)$; $dI(t)/dt = \omega L(t) - \mu I(t)$; $dR(t)/dt = \mu I(t)$; $dY(t)/dy = dL(t)/dt + dV(t)/dt + dR(t)/dt + dI(t)/dt$; $Y(t) = L(t) + V(t) + R(t) + I(t)$ where: Y is the total density (i.e., number per unit area) of individuals that have become infected at time t since the start of the epidemic; dY/dt = rate of change in the density of infected individuals; H, L, V, I, and R are the densities of healthy, latent, visible, sporulating and no more sporulating individuals, respectively; β is the transmission rate; λ is the probability per time unit that a latently infected individual transfers into the visible category; ω is the probability per time unit that a visible non-sporulating individual transfers into the sporulating category; μ is the probability per time unit that a sporulating individual transfers into the no more sporulating category (modified from Madden et al. 2007). A general mathematic framework for the pathogen-focused models has not been developed, because such a framework strongly depends on the life cycle of the specific pathogen. Therefore, it must be created for each model. An example is given by Salinari et al. (2008).

4.2 Formulation of Driving Models

The mathematical structure of the conceptual model links together the state variables of the system through their rates of change. How the system changes over time (i.e., the dynamic component of the model) depends on the rates, which depend in turn from external variables. Driving models express changes of the rate variables quantitatively. Logical operators, numerical thresholds, and different methods of calculus can be used for developing the driving models.

In most cases, definition of these quantitative relationships is based on the data available, in the literature or from specific experiments. Phases in performing experiments to obtain data about relationships between the variables acting in the pathosystem were described by Rossi et al. (1997a), while experimental techniques were widely reviewed (Campbell and Madden 1990, Kranz 1974, Kranz and Rotem 1988, Leonard and Fry 1986, Madden et al. 2007, Zadoks and Schein 1979).

Model fitting is the procedure used to identify the mathematical function that best explains the experimental data. General functions for describing incubation, latent, and infectious periods are available in the literature, as are functions for describing the developmental rates of the pathogen, e.g., spore germination, mycelium growth, spore yield, etc. (Analytis 1980, Friesland and Schröedter 1988, Hau et al. 1985, Hildebrand and Sutton 1984). Parameters of these functions are estimated by regression analysis, as recently described by Madden et al. (2007). Other computationally intensive methods, such as the jackknife and bootstrap methods, can be used to derive estimators for equation parameters (Lehoczky 1990). When a general equation for the data is not known, or when these equations poorly fit the data, the general model of multiple regression can be applied, where all the possible linear combinations of the independent variables are included and selected through any stepwise selection procedure. The process of parameter estimation is often referred as calibration (Pascual et al. 2003). Properly, calibration is the process of adjusting model parameters within physically or biologically defensible ranges until the resulting predictions give the best possible fit to the observed data (Camase 1996).

When the dependent variable is dichotomic (e.g., presence/absence, yes/no) or a grouping variable (e.g., low, intermediate, high), either discriminant analysis (DA) or logistic regression analysis (LRA) can be applied. DA allows the identification of a set of independent variables providing the best distinction of a dependent variable in groups established a priori (see an example in Salinari et al. 2006). LRA determines the probability that an event occurs (for example, ascospore ejection) based on the values of one or more independent variables (see an example in Rossi et al. 2009).

Derivatives are used to calculate rates of change over time. When the mathematical function has been defined, the first derivative of the dependent variable with respect to the independent one can be easily calculated. When rates must by calculated from observed data, it is necessary to assume that there is a straight-line relationship between two successive measurements; accuracy of the calculated rate depends on the validity of the linearity assumption and on the distance between the two measurements (Rossi et al. 1997a).

Integration is used to calculate the area under the function relating two variables or the area under two observed points, and thresholds are used when the biological process considered does not occur when the influencing variable is below a minimum level or above a maximum level. The influencing variables can be qualitative (e.g., presence or absence of rain for spore dispersal) or quantitative (e.g., minimum duration of wet period for causing infection).

4.3 Testing the Driving Models

Each driving model must be tested to determine whether its behaviour reasonably represents the relationship under study (Teng 1981). A number of different goodness-of-fit measures can be used for this purpose (see paragraph 5). When the driving models are based on experiments conducted under environmentally controlled conditions, they must be verified under natural conditions to ensure that additional environmental variables (different from those considered in the controlled conditions) have a relevant impact on performance of the driving model (de Vallavieille-Pope et al. 2002). Testing is very important because errors in the driving models can distort the performance of the whole model, which is difficult to check during model evaluation (see 12.5).

4.4 Introducing Stochasticity

Errors in estimating model parameters are possible sources of uncertainty and are sometimes termed "uncertainty regarding model variables" (Camase 1996). Models accounting for this source of uncertainty include a probability distribution for the estimated parameters and use stochastic procedures to select iteratively the parameter values to be used in each model run (Giosuè et al. 1995, Rossing et al. 1994, Sall 1990). These models are stochastic (Lehoczky 1990), and their output is not a unique value but a set of values whose variance is a measure of model uncertainty.

5 Evaluating the Model

Evaluation is the judging of the overall adequacy of the model. Evaluation includes: (I) verification; (II) validation; (III) uncertainty analysis; (IV) sensitivity analysis; and (V) judgement of utility (Camase 1996, modified).

5.1 Model Verification

Verification is the inspecting of the internal consistency of the model. It includes the analysis of dimensions and units, checks on mass conservation, detection of violation of natural ranges of parameters and variables, etc. (Camase 1996).

5.2 Model Validation

In a broad sense, validation is the establishment of the usefulness and relevance of a model for the defined purpose; for predictive models, a major part of the validation consists of a comparison of model output (the prediction) with a data set of real-world observations (Camase 1996). *Accuracy* is the closeness of a predicted value to its "true" value, while *robustness* is the capacity of the model to perform equally well across the full range of environmental conditions for which it was designed (Pascual et al. 2003).

Rykiel (1996) provided an overview of how validation has been used in modelling, and distinguished: (i) operational or whole-model validation (correspondence of model output with real-world observations); (ii) conceptual validation (evaluation of the underlying theories and assumptions); and (iii) data validation (evaluation of the data used to test the model). He classified thirteen different types of validation procedures that are commonly used, whether explicitly or implicitly. At least two of these validation methods are useful for plant disease models: (i) event validity, i.e., whether the occurrence and pattern of a specific event are reproduced by the model; (ii) predictive validation, i.e., comparison of model output with actual behaviour of the system in question. Irrespective of the validation procedure used, the real data used for validation must be *independent* (i.e., the data must not be used in model building) and *representative* for the situations in which the model is to be used (Battilani et al. 1996b, Caffi et al. 2009, Jesperson and Sutton 1987).

Notwithstanding the developments in the methods for validating models, Teng (1981) correctly stated that "validation will remain much the undefinable phase of modeling" and "issues on subjectivity and objectivity are not likely to be resolved". Therefore, model validation is an iterative process, and the final judgement on model validity comes from a mixture of statistical and intuitive procedures.

Evaluation of event validity. This validation can be performed using Bayesian theory (Yuen and Hughes 2002). For this purpose, model predictions must be divided into positive (P+, the event is predicted) and negative (P−, the event is not predicted); real observations too must be divided in positive (O+, the event occurs) or negative (O−, the event does not occur). Numbers of correct (P+/O+, P−/O−), false positive (P+/O−), and false negative (P−/O+) cases must be organized in a 2×2 contingency table, and correspondent frequencies calculated as: true positive proportion (TPP or model sensitivity), true negative proportion (TNP or model specificity), false positive proportion (FPP), and false negative proportion (FNP). Accuracy of the model is given by the overall accuracy index (correct/total cases) and by the Youden's index (J=TPP-FPP), both of which are equal to 1 in case of perfect model prediction. Furthermore, likelihood ratios of positive (LR(+)) and negative (LR(−)) predictions can be calculated: an accurate model has a large LR(+) value and an LR(−) value close to 0. Posterior probabilities can be calculated that express the probability that the event occurs when predicted (P(P+,O+)), that the event occurs when not predicted (P(P−,O+)), that the event does not occur when not predicted (P(P−,O−)), or that the event does not occur when it has been predicted (P(P+,O−)). Comparison of posterior probabilities with prior ones gives an evaluation of the practical value of the model (see [Madden et al. 2007] for further details).

Evaluation of goodness-of-fit. This validation can be performed by using different goodness-of-fit measures (Snedecor and Cochran 1973), each of which is sensitive to different aspects of model behaviour. The choice of an appropriate measure is therefore vital to a robust model validation. These methods are suitable for comparing quantitative model predictions with observed data for numbers of lesions, disease incidence or severity, numbers of spores, etc. Statistics for evaluation of goodness of fit can be divided into two groups: (i) those measuring correlation between observed and predicted values, and (ii) those considering residues (differences between observed and predicted values).

Regression analysis is a widely used method: model output is regressed against field data, and the properties of the linear model are examined. For each set of results, representing pairs of simulated and field data, the null hypotheses that “a” (intercept of regression line) is equal to 0 and “b” (slope of regression line) is equal to 1 are tested using a t-test. If the t-tests for “a” and “b” are not significant, then both null hypotheses are accepted and the model is considered a statistically accurate predictor of the real data. If the t-test for “a” or “b” is significant, then both null hypotheses are simultaneously tested using the F-test (Teng 1981). When simulated values are very close to the actual ones, this test can lead to misinterpretation (Rossi et al. 1997a) that can be overcome by introducing the concordance correlation coefficient (Lin 1989), as suggested by Madden and Nutter (1995).

The analysis of residues avoids some problems of the regression analysis (Green and Stephenson 1986). The NS model-efficacy is a measure of the mean square error to the observed variance: when the error is zero, NS=1 and the model represents a perfect fit; when the error increases, the NS values become negative. The W index of agreement is the ratio between mean square error and total potential error; W ranges between 0 (total disagreement between model and reality) and 1 (perfect fit). The root mean square error (RMSE) is the square root of the mean square error and represents the average distance of real data from the fitted line. RRMSE (relative root mean square error) is RMSE divided by the average of observed values. MAE (mean absolute error) is very similar to the RMSE but is less sensitive to large prediction errors. The ratio RMSE/MAE is an indicator of the extent to which outliers are affecting the model evaluation. Model efficiency (EF) is a dimensionless coefficient taking into account both the index of disagreement and the variance of the observed values; as its value increases toward 1, the fit of the simulated process increases. The coefficient of residual mass (CRM) is used to measure thetendency of the model to overestimate or underestimate the measuredvalues; a negative CRM indicates a tendency of the model towardoverestimation. Further details are available in Nash and Sutcliffe (1970).

5.3 Evaluation of Model Uncertainty

Uncertainty always exists in model formulation and for model parameters (see paragraphs 3 and 4, respectively) and inputs. Input uncertainty is caused by natural variation (e.g., weather and genetic variation) as well as by imperfection of input data measurement. Although the causes of uncertainties may differ, their effect is the same, namely uncertainty about the model output. Uncertainty analysis is the study of output uncertainty as a function of a careful inventory of the different sources of uncertainty in the model, often expressed as variance.

5.4 Evaluation of Model Sensitivity

Model sensitivity is the dimension of changes in model output due to changes in input variables. Sensitivity analysis is the study of model properties through changes in the input variables and the analysis of its effect on model output (Camase 1996). An important question asked is, for instance, whether some output is affected at all by some input. If a small variation of any input variable results in a greater than proportionate deviation of the model output, the input variable is considered sensitive: it is retained in the model and must be measured as accurately as possible. If significant change in the input variable causes little change in output (i.e., if the input variable is insensitive), either the variable should be removed from the model or its measurement can be simplified. There are several methods for performing sensitivity analysis that have been reviewed by Frey and Patil (2002).

6 From the Model to Practice

In this chapter, we have described a fruitful approach for developing plant disease models and for evaluating their accuracy and robustness. Implementation of such models in practical crop protection is outside the aim of our treatment. This implementation requires additional work, which is only summarised in the following paragraphs.

6.1 Developing a Computerised Version of the Model

Translation of the original model into a computer code is only possible for transparent models. Model transparency is the clarity and completeness with which data, assumptions, and methods used in model development are documented (Pascual et al. 2003). According to the level of transparency, the model is termed “black box” or “white box”. Development of a computer model requires: (i) coding the model in high level computer programming language (e.g., Basic, Fortran, Pascal, C++, or Java); (ii) determining whether the computerized model truly represents the original model and that there are no inherent numerical problems with obtaining the solution; and (iii) verifying that the two (original and computerized) models produce the same output when run with the same input.

6.2 Collecting Input Data

Weather-driven models must be operated using precise measurements of the input variables in representative locations. Therefore, it is necessary to create a network of agro-meteorological stations for collecting weather data at a territorial scale or a net of wireless sensors to collect data at the within-crop scale. Details for environmental monitoring have been discussed by Friesland and Schrödter (1988).

6.3 Designing a Strategy for Decision-Making Based on Model Output

Madden et al. (2007) developed the concept of risk algorithm as “any calculation that uses observations of identified risk factors from the host crop, the pathogen population and the environment to make an assessment of the need for crop protection measures”. Plant disease models produce predictions on the epidemic or on single epidemic components that can be used as risk indicators. Nevertheless, strategies for decision-making based on model output must be designed and their accuracy assessed. Use of Bayesian analysis for this purpose was clearly described by Madden et al. (2007).

6.4 Developing Tools for Supporting Decision-Making

Models can be incorporated in decision support systems (DSSs) that assist tactical and operational decision making in crop protection at the farm, field or intrafield scale. Alternatively, models can be part of disease warning systems (DWSs) at a territorial scale (Rossi et al. 2000).

6.5 Building User Confidence in the Model

Even a perfect model will be not used in practical disease control if the final users lack confidence in the information derived from the model. The probability that potential users will use the model and trust the information derived from the model depends on model reliability and on model performance in comparison to best available practice (Pascual et al. 2003). Therefore, efforts are necessary to foster the model and to demonstrate the advantages of its use in comparison with the alternative, currently used options.

7 Conclusion

Initially, plant disease models were developed as simple rules, graphs, or tables, and later as descriptive tools. Advances in environmental monitoring, automatic data processing, and botanical epidemiology enabled the development of a new class of models, the mechanistic (explanatory) models, which have better accuracy and robustness. These models explain mathematically the relations within a pathsystem by means of linked differential equations, and describe how the system changes over time and space as a consequence of external variables. Thus, the model output varies according to influencing weather conditions.

These models produce predictions of plant disease epidemics and can be used for decision making concerning plant disease management in production fields at different scales of complexity. Scales of time and space may differ according to the application of the model: from warning services, which use models to produce crop protection information at the collective level on a territorial scale, to precision agriculture, which uses models at a within-plot scale. While the use of plant disease models in warning services for crop protection is well established, their use in precision agriculture has yet to be developed.

Precision crop protection is based on the reality that intra-field variation exists for disease and crop conditions (Bjerre et al. 2006). Precision crop protection implies that intra-field variation exists for disease and crop conditions (Bjerre et al. 2006). Spatial variation in disease severity is a prerequisite for site-specific disease management: disease variation must have an appropriate magnitude and occur on spatial and temporal scales that make site-specific management relevant. For this purpose, disease must either be directly observable by automatic monitoring devices or be predictable (Bjerre 1999). Intra-field variation of disease levels is mainly caused by spatial variability of the inoculum dose, of crop conditions (due to variability in soil properties and availability of water and mineral nutrients), and of environmental conditions at the canopy level. Disease models described in this chapter incorporate the above-mentioned sources of variability and can therefore be used as predictors of intra-field disease variation. For instance, these models could be used to draw dynamic maps of the current and future spatial distribution of both visible and latent infections within a field, so that timing, active ingredients, and rates of fungicides could be defined accordingly. The main obstacle that must be overcome before this can be accomplished is the measurement of input variables (concerning both weather and crop) at the within-field level. Wireless sensors are a possible solution. Wireless sensor technologies and standards for wireless communications have been developed in recent years, and the cost of sensors has been continuously declining. Nevertheless, the reliability of wireless systems must be demonstrated for different cropping and disease systems (Wang et al. 2006).

References

Analytis S (1980) Obtaining of sub-models for modeling the entire life cycle of a pathogen. Z PflKrankh PflSchutz 87:371–382

Anderson JR (1974) Simulation: methodology and application in agricultural economics. Rev Marketing Agric Econ 42:3–55

Battilani P, Giosuè S, Racca P, Rossi V (1996a) A decision support system for Cercospora leaf spot management in sugarbeet. Proc IIRB Congress 59:33–44

Battilani P, Racca P, Rossi V et al. (1996b) Validation of ONIMIL, a forecaster for primary infection of downy mildew on onion. Danish Inst Plant Soil Sci, SP Rep 15:9–18

Battilani P, Rossi V, Racca P, Giosuè S (1997) ONIMIL – onion downy mildew, a forecaster for primary infection of downy mildew on onion. EPPO Bull 26:567–576

Bjerre KD (1999) Disease maps and site-specific fungicide application in winter wheat. In Stafford JV (ed) Precision Agriculture '99: Proceedings of the 2nd European Conference on Precision Agriculture. Sheffield Academic, Sheffield

Bjerre KD, Jørgensen LN, Olesen JE (2006) Site-specific management of crop diseases. In: Srinivasan A (ed) Handbook of precision agriculture. principles and applications. CRC Press, Boca Raton

Butt DJ, Jeger MJ (1985) The practical implementation of models in crop disease management. In: Gilligan CA (ed) Advances in plant pathology. Academic Press, New York

Caffi T, Rossi V, Bugiani R et al. (2009) Evaluation of a model predicting primary infections of *Plasmopara viticola* in different grapevine-growing areas of Italy. J Plant Pathol (in press)

Camase (1996) Register of agro-ecosystems models DLO research institute for agrobiology and soil fertility, Wageningen. http://wwwbibwaunl/camase. Accessed 06 May 2009

Campbell CL, Madden LV (1990) Introduction to plant disease epidemiology. Wiley, New York

De Vallavieille-Pope C, Giosuè S, Munk L et al. (2000) Assessment of epidemiological parameters and their use in epidemiological and forecasting models of cereal airborne diseases. Agronomie 20:715–727

de Vallavieille-Pope C, Huber L, Leconte M, Bethenod O (2002) Preinoculation effects of light quantity on infection efficiency of Puccinia striiformis and P triticina on wheat seedlings. Phytopathology 92:1308–1314

De Wit CT (1993) Philosophy and terminology. In: Leffelaar PA (ed) On system analysis and simulation of ecological processes. Kluwer Academic Publishers, Dordrecht

De Wolf ED, Isard SA (2007) Disease cycle approach to plant disease prediction. Annu Rev Phytopathol 45:91–918

Frey HC, Patil S R (2002) Identification and review of sensitivity analysis methods. Risk Anal 22:553–78

Friesland H, Schrödter H (1988) The analysis of weather factors in epidemiology. In: Kranz J, Rotem J (eds) Experimental techniques in plant disease epidemiology, Springer-Verlag, Berlin

Fry WE, Fohner GR (1985) Construction of prediction models I: forecasting disease development. In: Gilligan CA (ed) Advances in plant pathology. Academic Press, New York

Giosuè S, Racca P, Rossi V (1995) Use of stochastic processes in simulating Cercospora leaf spot epidemics on sugarbeet. Phytopathol Mediterr 34:204–206

Green IRA, Stephenson D (1986) Criteria for comparison of single event models. J Hydrol Sci 31:395–411

Hardwick NV (1998) Disease forecasting. In: Jones DG (ed) The epidemiology of plant diseases. Kluwer Academic, Boston

Hau B (1985) Epidemiologische Simulatoren als Instrumente der Systemanalyse mit besonderer Berücksichtigung eines Modells des Gerstenmehltaus. Acta Phytomedica, Parey

Hau B, Eisensmith SP, Kranz J (1985) Construction of temporal models II Simulation of aerial epidemics. In: Gilligan CA (ed) Advances in plant pathology. Academic Press, New York

Hildebrand D, Sutton JC (1984) Relationship of temperature, moisture, and inoculum density to the infection cycle of *Peronospora destructor*. Phytopathology 74:444–1449

Jesperson GD, Sutton JC (1987) Evaluation of a forecaster for downy mildew of onion (*Allium cepa* L). Crop Prot 6:95–103

Kranz J (1974) The role and scope of mathematical analysis and modeling in epidemiology. In: Kranz J (ed) Epidemics of plant diseases. Springer-Verlag, Berlin

Kranz J (2003) Comparative epidemiology of plant diseases. Springer, New York

Kranz J, Hau B (1980) System analysis in epidemiology. Annu Rev Phytopathol 18:67–83

Kranz J, Rotem J (1988) Experimental techniques in plant disease epidemiology. Springer-Verlag, Berlin

Krause RA, Massie L B (1975) Predictive systems: modern approaches to disease control. Annu Rev Phytopathol 13:31–47

Leffelaar PA (1993) Basic elements of dynamic simulation. In: Leffelaar PA (ed) On system analysis and simulation of ecological processes. Kluwer Academic Publishers, Dordrecht

Lehoczky J (1990) Statistical methods. In: Heyvan DP, Sobel MJ (eds) Stochastic models. Elsevier Science Publishers, Amsterdam

Leonard KJ, Fry WE (1986) Plant disease epidemiology: population dynamic and management. Macmillam Publishing Company, New York

Lin LK (1989) A concordance correlation coefficient to evaluate reproducibility. Biometrics 45:255–268

Madden LV, Ellis MA (1988) How to develop plant disease forecasters. In: Kranz J, Rotem J (eds) Experimental techniques in plant disease epidemiology. Springer-Verlag, New York

Madden LW, Nutter FWJ (1995) Modeling crop losses at the field scale. Can J Plant Pathol 17: 124–127

Madden LV, Hughes G, van den Bosch F (2007) The study of plant disease epidemics. APS Press, St Paul

Maloy OC (1993) Plant disease control: principles and practice. Wiley, New York

Nash JE, Sutcliffe JV (1970) River flow forecasting through conceptual models part I –A discussion of principles. J Hydrol 10:282–290

Pascual P, Stiber N, Sunderland E (2003) Draft Guidance on the development, evaluation, and application of regulatory environmental Models. http://wwwepagov/crem/li-brary/CREM%20Guidance%20Draft%2012_03pdf. Accessed 06 May 2009

Rabbinge R, de Wit CT (1989) Systems, models and simulation. In: Rabbinge R , Ward SA, van Laar HH (eds) Simulation and systems management in crop protection. Pudoc, Wageningen

Rabbinge R, Zadoks JC, Bastiaans L (1989) Population models. In: Rabbinge R, Ward SA, van Laar HH (eds) Simulation and system management in crop protection. PDOC, Wageningen

Rossi V, Giosuè S (2003) A dynamic simulation model for powdery mildew epidemics on winter wheat. EPPO Bull 33:389–396

Rossi V, Racca P (1996) Simulation of the infection of strawberry flowers and fruits by *Botrytis cinerea*. Danish Inst Plant Soil Sci, SP Rep 15:73–84

Rossi V, Racca P, Battilani P (1994) A simulation model for Cercospora leaf spot on sugarbeet. Phytopathol Mediterr 33:105–112

Rossi V, Racca P, Pancaldi D, Alberti I (1996) Appearance of *Puccinia recondita* f.sp. *tritici* on winter wheat: a simulation model. EPPO Bull 26:555–566

Rossi V, Racca P, Giosuè S, Battilani P (1997a) Decision support systems in crop protection: from analysis of the pathosystems to the computerized model. Petria 7 (suppl 1):7–26

Rossi V, Racca P, Giosuè S et al. (1997b) A simulation model for the development of brown rust epidemics in winter wheat. Eur J Plant Pathol 103:453–465

Rossi V, Ponti I, Cravedi P (2000) The status of warning services for plant pests in Italy. EPPO Bull 30:19–29

Rossi V, Giosuè S, Pattori E et al. (2003) A model estimating the risk of Fusarium head blight on wheat. EPPO Bull 33:421–425

Rossi V, Giosuè S, Bugiani R (2007) A-scab (Apple-scab), a simulation model for estimating risk of *Venturia inaequalis* primary infections. EPPO Bull 37:300–308

Rossi V, Caffi T, Giosuè S, Bugiani R (2008) A mechanist model simulating primary infections of downy mildew in grapevine. Ecol Model 212:480–491

Rossi V, Salinari F, Pattori E et al. (2009) Predicting the dynamics of asco-spore maturation of *Venturia pirina* based on environmental factors. Phytopathology 99:453–461

Rossing WAH, Daamen RA, Jansen MJW (1994) Uncertainty analysis applied to supervised control of aphids and brown rust in winter wheat Part 2 Relative importance of different components of uncertainty. Agric Syst 44:449–460

Rykiel EJ Jr (1996) Testing ecological models: the meaning of validation. Ecol Model 90:229–244

Sall MA (1980) Uses of stochastic simulation: grape powdery (example). J Plant Dis 87:397–403

Salinari F, Giosuè S, Tubiello FN et al. (2006) Downy mildew (*Plasmopara viticola*) epidemics on grapevine under climate change. Glob Change Biol, 12:1299–1307

Salinari F, Rossi V, Manici LM (2008) A model framework for simulating plant disease epidemics. Ital J Agron 3 (suppl 3):751–752

Shrum RD (1978) Forecasting of epidemics. In: Horsfall JG (ed) Plant Disease. Academic Press, New York

Snedecor GW, Cochran WG (1973) Statistical Methods. The Iowa State University Press, Ames

Spada G, Carli G, Ponti I et al. (2001) Use of a model simulating *Taphrina deformans* infection on peaches for optimal disease control. EPPO Bull 24:319–324

Teng PS (1981) Validation of computer models of plant disease epidemics: a review of philosophy and methodology. Z PflKrankh PflSchutz 88:49–63.

Teng PS, Blackie MJ, Close RC (1980) Simulation of barley leaf rust epidemic: structure and validation of BARSIM-I. Agric Sys 5:85–103

Vanderplank JE (1963) Plant diseases: epidemics and control. Academic Press, London

Wainwright J, Mulligan M (2004) Environmental modeling finding simplicity in complexity. Wiley, Chichester

Wang N, Zhang N, Wang M (2006) Wireless sensors in agriculture and food industry – Recent development and future perspective. Comput Electron Agric 50: 1–14

Yuen JE, Hughes G (2002) Bayesian analysis of plant disease prediction. Plant Pathol 51:407–412

Zadoks JC (1979) Simulation of epidemics: problems and applications. EPPO Bull 9:227–234

Zadoks JC (1984) A quarter century of disease warning, 1958–1983. Plant Dis 68:352–55

Zadoks JC, Schein RD (1979) Epidemiology and plant disease management. Oxford University Press, New York

Chapter 16
Model Validation and Use of Geographic Information Systems in Crop Protection Warning Service

Paolo Racca, Thorsten Zeuner, Jeanette Jung, and Benno Kleinhenz

Abstract Validation is an essential part of the model development process if models are to be accepted and used in decision support systems. Validation ensures that the model meets its intended requirements in terms of the methods employed and the results obtained. The ultimate goal of model validation is to make the model useful in the sense that the model: addresses the targeted problem, provides accurate information about the system being modelled, and makes the model acceptable for practical use. This chapter describes the main validation methods used for models which are validated and currently used in the field by the German Plant Protection Service. Furthermore, the results of a study how to increase the accuracy of simulation models by using Geographic Information Systems (GIS) are presented. The influence of elevation, slope and aspect on temperature and relative humidity were interpolated with GIS methods, whereas precipitation data was obtained from radar measurements; these meteorological data were used as input for the simulation models. The output of these models is presented as spatial risk maps in which areas of maximum risk of a disease are displayed. The use of GIS methods to increase accuracy is expected to increase system adoption by farmers.

1 Validation of Forecasting Models in Crop Protection

There are several definitions of model validation considering generically mathematical simulation of real events (Sargent 1998, Schlesinger 1979) or specific models for plant disease epidemiology (Teng 1985, Kranz and Royle 1978, Reynolds et al. 1981, Welch et al. 1981). The validation process can be summarised as the comparison between the virtual (simulated) and the real (actual) system.

According to Balci and Sargent (1984), model validation of a generic model may be divided into subjective and statistical validation techniques. In other words, the

P. Racca (✉)
Zentralstelle der Länder für EDV gestützte Entscheidungshilfen und Programme im Pflanzenschutz (ZEPP), D-55545 Bad Kreuznach, Germany
e-mail: racca@zepp.info

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_16,

model validation strictly depends on the modelled system, the model output and the availability of field data for the validation.

Simulation models can be differentiated into four types according to the classification of the Central Institution for Decision Support Systems and Programmes in Crop Protection (ZEPP) in Germany (Racca et al. 2009):

- Type 1: Models to predict the first appearance of symptoms of a specific disease or a pest in a field.
- Type 2: Complex simulation models able to predict the epidemiological development, population dynamics (e.g. disease severity, disease incidence) or pest abundance.
- Type 3: Models able to predict a target event such as action thresholds (AT) or periods with high risk for an epidemic development.
- Type 4: Ontogenesis models that simulate crop growth which can be used in combination with disease or pest models.

The validation of these different types of models requires different data sets; (I) the time of first incidence of disease in the field for type 1; (II) surveys of disease development for type 2; (III) type 3 predicts the date of passing the AT; and (IV) type 4 simulates data on crop development. Paradoxically, the simulation model must be constructed to provide an output based on available data for its validation. For each model a subjective and/or a statistical validation is possible.

1.1 Validation of Type 1 Models

Type 1 models forecast the first appearance of a disease or a pest in the crop. Although they are simply constructed they also have great impact on the end user. They are mainly used by advisors to determine the beginning of regional monitoring activities and by farmers to conduct initial checks in their fields. In some cases, e.g. quarantine diseases like blue mold of tobacco or areas with high disease risk, the date of first occurrence is also the date the disease exceeds the AT for the first treatment. The results are generally given on a regional level considering the region as the area surrounding a weather station.

Models currently used by the German Crop Protection Services (CPS) are CERCBET1 used to predict the first appearance of Cercospora leaf spot (due to *Cercospora beticola*) on sugar beet (Roßberg et al. 2000), SIMBLIGHT1 for potato late blight (*Phytophthora infestans*; Kleinhenz et al. 2007), SIMPEROTA1 for blue mold of tobacco (*Peronospora tabacina*; Racca et al. 2007) and, for pests, SIMLEP1-Start to forecast the appearance of the over wintering adults of the Colorado potato beetle (*Leptinotarsa decemlineata*; Jörg et al. 2007).

The output of the CERCBET1 model is disease appearance expressed as percentage of infected fields in a region (Rossi and Battilani 1991). The model was slightly modified and introduced into grower fields in 2000 (Roßberg et al. 2000). The subjective validation of CERCBET1 took place retrospectively with monitoring data of the years 1995–2008 in all German sugar beet growing areas.

Validation was made in using data on:

- First disease occurrence predicted by the model and observed in the field.
- Date when 50% of the fields in one region were infected, which represents the 50th percentiles in the distribution of disease occurrence in several fields in the region, at a time when the probability to detect *Cercospora* infections in the field is very high and the disease has been established in this region.
- Data are grouped into "regions" near a representative meteorological station.
- In order to detect the distribution of infected fields, only regions with data from more than four sugar beet field surveys were considered.

Forecasting with the model was considered (I) correct when the difference between the predicted and the observed date was in the range of ±7 days; or (II) early and late when the difference exceeded this range. In this case the subject of the validation method was to consider a period of ±7 days correct for such kind of model results. The data for the validation were provided from regional surveys conducted in weekly intervals and a 1 week of delay or earlier forecast was acceptable for model validation.

The model was able to predict disease occurrence correctly in approximately 65% of the forecasts, in 32% the date was too early and in 4% the forecasted time of disease occurrence was late. The model had higher levels of accuracy when predicting the time when 50% of fields showed infection. The validation indicated a trend to anticipate the occurrence of disease. This trend can be explained by analyzing the data set used for the validation. Sometimes the sample size used in the surveys is not appropriate for detecting a rare event, like the appearance of first necrotic spots (Roßberg et al. 2000), but then the first spots of *C. beticola* may be confused with spots due to *Alternaria* sp., *Phoma* sp. or bacterial leaf spots.

For an appropriate statistical validation (Balci and Sargent 1984, Rossi et al. 1997) simulation and field data were regarded as two independent random samples in order to compare their distributions. The use of parametric tests like the t- (comparison of means) and F-test (comparison of standard deviation) as well as a non-parametric method like the Kolmogorov-Smirnov test (computing the maximum distance between the cumulative distributions of two samples) is applicable. The null hypothesis of such tests is that simulated and actual data have, within a certain probability level, the same distribution (not significant) or a different distribution (significant). In this case the data were separated by year (Table 16.1).

Statistical analysis of model results revealed significant differences between the distributions indicating a poor correlation between the data in about 50% of the cases. However, when we applied the subjective validation method, and when considering the principal aim of the model to determine the time of initiating disease monitoring in the field the model was acceptable. An early forecast also may be acceptable, since only in 12% of all cases the forecast was more than 3 weeks before the first disease observation.

Table 16.1 Statistical tests on the CERCBET1 Results for the simulation years 1999–2008

		First appearance			50% Infected fields		
Year	N	t-test	F-test	Kol.Smirn. test	t-test	F-test	Kol.Smirn. test
1999	25	n.s.	*	*	n.s.	*	*
2000	16	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
2001	16	n.s.	n.s.	*	n.s.	n.s.	n.s.
2002	27	n.s.	*	*	n.s.	n.s.	*
2003	30	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
2004	22	n.s.	n.s.	*	n.s.	n.s.	*
2005	35	*	*	*	*	*	*
2006	36	*	n.s.	*	*	n.s.	*
2007	28	*	*	*	n.s.	*	*
2008	28	n.s.	n.s.	*	n.s.	n.s.	n.s.

Kol.Smirn.: Kolmogorow-Smirnov test, n.s. not significant, * = significant with $p < 0.05$

1.2 Validation of Type 2 Models

The models of type 2 are examples of classical simulation models. Generally, they are very complex. The ultimate goal is to predict epidemic development, expressed as disease severity and/or disease incidence, or to predict the phenological stages of insects. These models are used in the development phase as a basis for identifying the parameters and variables for the construction of models of type 1 and 3. Examples of these epidemiological models are CERCODEP for Cercospora leaf spot on sugar beet (Rossi et al. 1994), RUSTDEP for leaf rust (*Puccinia triticina*) on winter wheat (Rossi et al. 1997), SIMPHYT2 for potato late blight (Roßberg et al. 2001), and SIMLEP2 to forecast the phenological development of the Colorado potato beetle (Roßberg et al. 1999). Two recent models are used here as examples of the validation methods: PUCREC for leaf rust of winter rye (*Puccinia recondita*) and PUCTRI for leaf rust of winter wheat (*Puccinia triticina*).

The models simulate the epidemic development of rust on the different leaf layers expressed as disease incidence (Räder et al. 2006, 2007, Racca et al. 2008). Models were validated with both subjective and statistical methods using field data collected from 2002 to 2005. In total, 51 data sets for PUCREC and 37 for PUCTRI were available to investigate the predictive ability of the models.

Subjective validation consisted of comparisons of simulated disease incidence with disease incidence data recorded in the field (Fig. 16.1). The simulation was accepted as correct when simulated disease incidence was within the confidence interval of the recorded disease incidence. Overestimation was given when simulated values exceeded the highest level of the confidence interval whereas underestimation occurred when simulated values were below the lowest level of the confidence interval. Both models were validated for each leaf layer, F (flag leaf) to F-3 (Table 16.2). In 71–86% of fields, the progress of disease incidence was simulated correctly. The high proportion of overestimations in winter wheat indicated

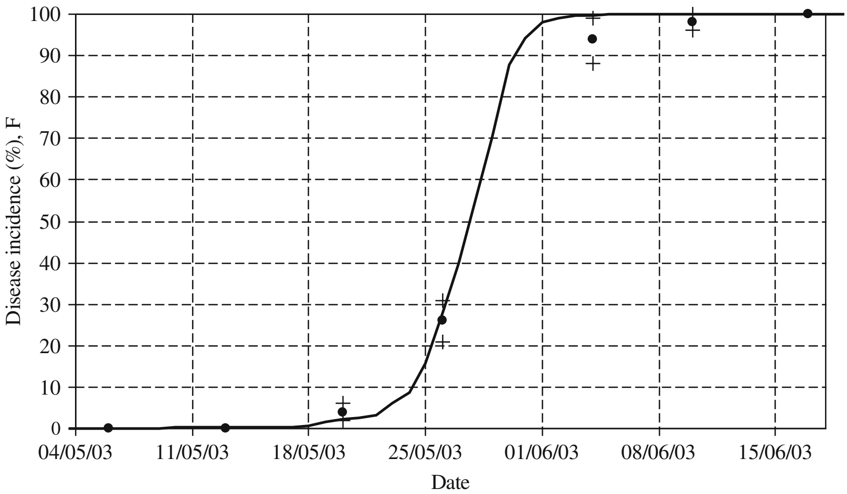

Fig. 16.1 Simulation of leaf rust incidence on the flag leaf (F) of winter rye using PUCREC: — simulation; • field data; + confidence interval of the field data in 2003 (meteorological station Herxheimweiher, Rhineland Palatinate, Germany)

Table 16.2 Validation of PUCREC ($n = 51$) and PUCTRI ($n = 37$). Share (%) of underestimated, correct and overestimated leaf rust epidemics in winter rye and winter wheat, respectively, on different leaf layers (2001–2005)

Leaf layer	PUCREC – Winter rye			PUCTRI – Winter wheat		
	Underestimation	Correct	Overestimation	Underestimation	Correct	Overestimation
F	8	74	18	0	82	18
F-1	2	86	12	0	76	24
F-2	6	84	10	0	71	29
F-3	0	80	20	0	76	24

that epidemics simulated by PUCTRI started earlier and progressed faster than in reality.

Statistical validation was carried out with two parametric tests (regression analysis, test of hypothesis) and one non-parametric test (Kolmogorov-Smirnov). Simulated disease incidence (dependent variable) was linearly correlated with the recorded data (independent variable). Student's t-test demonstrated that a (intercept of the regression line) was equal to 0 and b (slope of regression) was equal to 1 (Table 16.3).

Statistical validation gave very satisfactory results with both parametric and non-parametric methods. The highest values of the non-significant cases of the regression parameters and the Kolmogorov-Smirnov test indicated that the model is considered a statistically accurate simulator of field data.

Table 16.3 Validation of PUCREC ($n = 51$) and PUCTRI ($n = 37$). Regression analysis and Kolmogorov-Smirnov test (2001–2005), share (%) of not significant and significant cases

	PUCREC – Winter rye						PUCTRI – Winter wheat					
	Regression parameters				Kolm.-Smirn.		Regression parameters				Kolm.-Smirn.	
	t-*a*		t-*b*				t-*a*		t-*b*			
Leaf layer	ns	*	ns	*	ns	*	ns	*	ns	*	ns	*
F	93	7	59	41	96	4	95	5	90	10	95	5
F-1	91	9	77	23	98	2	94	6	87	13	94	6
F-2	91	9	68	32	96	4	100	–	100	–	92	8
F-3	88	12	79	21	91	9	100	–	67	33	100	–

t-*a*: hypothesis t-test for regression intercept, t-*b*: hypothesis t-test for regression slope, Kol. Smirn.: Kolmogorov-Smirnov test, ns not significant, * = significant with $p < 0.05$

1.3 Validation of Type 3 Models

Type 3 models are derived from models of type 2. The development of diseases is often simulated to forecast the passing of the action threshold (AT) and is linked to recommendations for pesticide applications. Models of type 3 are sometimes combined with knowledge on the effectiveness of active ingredients. These models often include agronomic parameters such as crop rotation, fertilization, irrigation and cultivar resistance which can influence disease progression. Sometimes type 3 models also include features of type 1 models that are able to predict disease occurrence.

Type 3 models can be used on regional and field-specific levels. Some examples of the most successful type 3 models are: CERCBET3 for Cercospora leaf spot on sugar beet (Racca and Jörg 2007), SIMPHYT3 for potato late blight (Gutsche 1999), PUCREC and PUCTRI for cereal leaf rusts (Racca et al. 2008) and SIMLEP3 for Colorado potato beetle (Jörg et al. 2007).

CERCBET3 simulates the progress of Cercospora leaf spot incidence on sugar beet, expressed as disease incidence (DI) and the passing of an AT which leads to recommendations for fungicide treatments (Racca and Jörg 2007). In Germany, the AT is based on both time and disease incidence and the strategy for decision making is: AT 5% DI until the end of July; 15% DI before August 15; and 45% DI later than August 15 (Jörg et al. 2003).

The data for model validation were collected from 3 years of trials in the major sugar beet growing regions. For a subjective validation the weekly DI assessment was compared with simulated data. The difference between observed and simulated dates when passing the three ATs was classified as follows:

- Early: the model forecast exceeded the threshold more than 7 days earlier than the observed date
- Accurate: the model forecast exceeded the threshold within a period of ± 7 days compared to the observed date
- Late: the model forecast exceeded the threshold more than 7 days later than the observed date.

The results of this subjective validation are summarised in Table 16.4. The same data pool was also used for a statistical validation. For the three ATs the simulated date of threshold passing was linear regressed with the observed date.

Table 16.4 Validation of the type 3 model CERCBET3: Comparison of the observed and the forecasted date of exceeding the three action thresholds

	Mean 2001–2003 ($n = 71$)		
Action threshold	Early	Accurate	Late
5% DI	8.80	89.92	1.28
15% DI	13.23	82.72	4.06
45% DI	10.60	80.04	9.37

The results of the statistical analysis differed from the subjective validation. There was only a strong correlation for AT 5% ($r^2 = 0.72$), whereas the correlations for the other ATs were weak ($r^2 = 0.31$ and 0.19). For all regressions, the intercept and the slope were significant at $p < 0.05$. The concordance correlation coefficient ρ_c (Lin 1989, Madden et al. 2007) was used to avoid problems with misinterpreted results in the regression analysis (failed t-test for a and b). The values of ρ_c range from 1, perfect agreement, to -1, total lack of agreement. Validation of the AT 5% DI showed a high ρ_c (0.82) value indicating strong agreement between simulated data and field observations.

Another example for the validation of a type 3 model is illustrated for the model SIMLEP3 which simulates the development of *L. decemlineata* from the beginning of egg laying to the occurrence of the old larvae at a field-specific scale (Jörg et al. 2007). SIMLEP3 was validated simultaneously in Germany and in several other European countries. For the subjective validation, predicted dates of maximum abundance of egg clusters and young larvae were compared to field observations. The model output was considered accurate when the forecast was within an interval of 1 week compared to the observed date.

In general, SIMLEP3 validation results were very consistent. The first occurrence of young larvae was predicted correctly in most instances. Nevertheless, differences between forecasting and observed date ranging from 18 days too early up to 10 days too late were registered. Positive results were also obtained for the prediction of maximum egg cluster occurrence. In Germany, Poland and Italy the share of correct forecasts given from SIMLEP3 amounted to 92%. In Austria, the share of correct predictions was only 71%. Predictions of the maximum occurrence of young larvae were accurate in 89% of the cases for all countries combined. Optimum results were obtained in Italy and Poland, whereas in Austria and Germany the share of accurate forecasts exceeded 85%. SIMLEP3, therefore, is able to give precise forecast for the most important development stages of *L. decemlineata* needed for effective and sustainable control. The validation also demonstrated the suitability of using the model throughout Europe.

1.4 Validation of Type 4 Models

Ontogenetic models simulate the development of crops over time expressed as BBCH-growth stages (Hack et al. 1982). SIMONTO-models are based on the modelling approaches of CERES-Wheat (Mirschel et al. 1993) and ONTO-models (Wernecke et al. 1996). Ontogenetic progress in SIMONTO is reflected by a developmental rate which is a function of temperature and photoperiod. Parameters for the different models in winter oilseed rape and winter cereals were estimated by employing the Monte-Carlo-method (Falke et al. 2006, 2008, Roßberg et al. 2005).

More than 13,800 observations of BBCH growth stages for winter cereals from 2003 to 2008 were available for a statistical validation of the model validation. In the first step of the validation, the observed BBCH growth stages were regressed linearly with the model and a concordance correlation coefficient was calculated. A high coefficient of determination suggested a good correlation between the data. Both regression parameters, *a* and *b* were significant and the concordance correlation coefficient of 0.93 demonstrated a good agreement between the data.

Unfortunately, BBCH growth stages are not strictly arithmetically dependent. Some stages can appear very early in the season and stay constant for a long period of time. The simple arithmetic difference between two BBCH growth stages may be minimal but the difference in days between the two stages may be considerable. For example, the arithmetic difference between BBCH 21 (beginning of tillering) and 22 (2 tillers detectable) is only 1, but sometimes BBCH 21 is recorded in the fields in autumn and simulated by the model in spring. This means a time difference of 90–150 days.

Therefore, the model should also be validated using a subjective method. A scoring model approach was used for SIMONTO (Morvin 2006, Roßberg et al. 2005) whereby the difference in days between the simulation and the observation was classified with the following subjective weighted error:

- model more than 7 days early or more than 7 days late: weight = 7;
- model early or late by 4–7 days: weight = 3;
- model early or late by 1–3 days: weight = 1;
- no difference between simulation and observation: weight = 0;

The sum of the weights was classified in a weighted error coefficient with values varying from 0 (accurate) to 7 (simulation extremely early or extremely late). Table 16.5 shows that the coefficient ranged from 1.26 to 3.10. Values were classified acceptable when the simulation results were within a period of ± 3 days; values > 3 indicate a larger time difference between simulation and reality. Since most of the coefficients of error were < 3 it was concluded that the model accurately simulates reality within an acceptable time range. In this case, the subjective validation was essential, because the statistical validation could lead to misleading results.

Table 16.5 Validation of SIMONTO. Weighted errors and weighted error coefficient for some BBCH growth stages in winter cereals (seasons 2003–2008)

Growth stage	n	N° of case * weighted error			Sum of weights	Weighted error coefficient
		Weight 7	Weight 3	Weight 1		
BBCH 23	22	28	0	0	28	1.27
BBCH 25	62	70	6	2	78	1.26
BBCH 31	1,368	2,233	957	310	3,500	2.56
BBCH 32	1,490	1,764	846	320	2,930	1.97
BBCH 39	1,070	980	684	188	1,852	1.73
BBCH 61	703	1,512	609	60	2,181	3.10
BBCH 65	732	1,288	636	142	2,066	2.82

2 Use of Geographic Information Systems in Crop Protection

During the last 40 years, a number of weather-based forecasting models have been developed for the control of plant diseases and pest attacks (Kleinhenz and Jörg 2000). Several forecasting models have been established and introduced into practice to support the decisions in the control of diseases in Germany (Kluge and Gutsche 1984, Gutsche 1999, Kleinhenz and Jörg 1999, Kleinhenz and Jörg 2000, Roßberg et al. 2001, Hansen et al. 2002). However, in some agricultural areas, the distance between meteorological stations (MS) exceeds 60 km. Forecast models did not give satisfactory results for fields separated by such large distances to MSs (Zeuner 2007).

With the help of Geographic Information Systems (GIS) a plot-specific classification of temperature and relative humidity (RH) has been developed using complex statistical interpolation methods described by Heller (1996). The method, however, cannot be applied to the parameter precipitation. Especially in the case of frequent spatially and temporally limited rainfall (so-called convective rainfall event, CRE), the interpolation for precipitation does not give plausible results (Zeuner and Kleinhenz 2008). Precipitation data with a high spatial resolution may be obtained from radar measurements.

Using these spatial input parameters for the currently available disease forecast models should lead to accurate forecasting for areas in-between two or more distant MSs. With the use of GIS, daily spatial risk maps for diseases and pests can be created in which the spatial and the temporal process of first appearance and regional development are documented. These risk maps may lead to improved control and a reduction in fungicide use.

In the following study the new method to calculate the input parameters for forecast models with GIS was validated on the first appearance of potato late blight. The models SIMBLIGHT1 and SIMPHYT1 predict the date of first fungicide treatment for late blight control, and are used in practical agriculture (Kleinhenz et al. 2007). Whereas SIMPHYT1 depends on a statistical approach forecast, the result of SIMBLIGHT1 is based on the current infection pressure and is displayed in three classes (Fig. 16.2). The results of the geo-referenced approach are presented in spatial maps and graphs showing the risk of late blight primary infections. The SIMBLIGHT1 calculated risk of late blight infection is presented in three infection classes symbolized by different colours. Later, risk maps will be adapted to an internet application to provide comfortable access to the system for farmers and advisers.

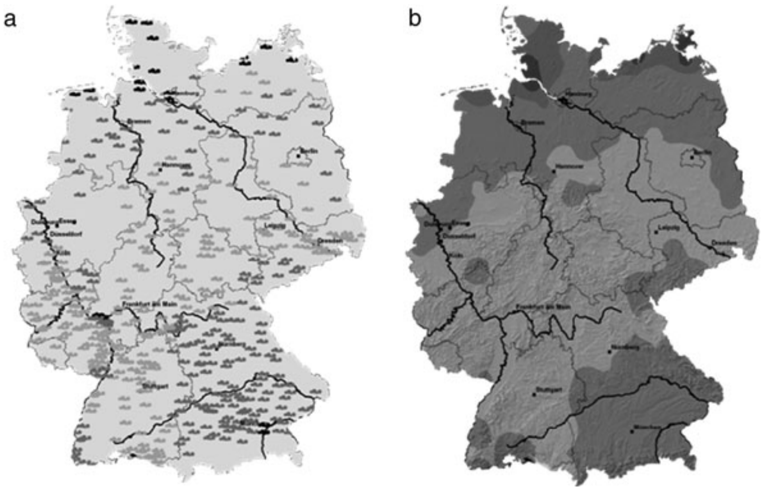

Fig. 16.2 Current and future presentation of SIMBLIGHT1. Currently, forecasting are shown for the sites of the meteorological stations with cloud symbols (**a**). The new presentation is a spatial risk map for late blight (**b**)

2.1 Use of GIS to Prepare Model Input

2.1.1 Workflow

The following steps have to be taken to build spatial risk maps:

- Step 1: data management
- Step 2: interpolation of meteorological data
- Step 3: calculation of the forecasting model using the results of the interpolation
- Step 4: display of the results as a risk map

In step 1 hourly meteorological data which are necessary for the forecast models SIMPHYT1, SIMPHYT3 and SIMBLIGHT1 are imported from a weather database. Then a geographic reference is set to the meteorological data because the weather database is not geo-referenced. Step 2 which is the main and the most difficult step, requires comparison of different types of interpolation methods to identify a method which gives optimum interpolation of the meteorological data. Step 3 uses the interpolated data as input parameters to calculate the forecasting models. In step 4, the results are connected to an internet application in which spatial information is displayed as a risk map of first disease appearance, and then the daily infection risk of late blight.

2.1.2 Data Base

Meteorological Data: The meteorological data are collected by 570 automatic stations operated by the German Meteorological Service (DWD) and CPS. The stations are equipped with sensors for temperature, RH, precipitation and global radiation. All data are tested fot plausibility and stored in a database called AGMEDAWIN (Keil and Kleinhenz 2007).

Geodata: A digital elevation model (DEM) published by Behrens and Scholten (2002) was used to obtain all necessary relief information. The DEM describes the landscape as a three-dimensional grid. It represents the earth's surface through digitally stored x, y, z values, where the x and y values specify the horizontal position and the z-value the vertical height of the grid cell (Bill 1999). Mathematical and statistical methods are used to calculate derivatives, e.g. slope, slope direction, or slope edges. DEM and various derivations provide a basis for the characterization of the meteorological parameters.

Spatial Join: In order to store the results of interpolation, a grid was laid out over Germany. At present, the CPS use about 570 MSs to represent an agricultural area of approx. 200,000 km^2, or an average of one MS per 350 km^2. With the new GIS method, grid cells have a size of 1 km^2 and, after interpolation, are represented by virtual meteorological stations (Liebig and Mummenthey 2002).

Radar Measurements: The DWD records precipitation all over Germany by 16 radar stations. These stations do not measure the amount of precipitation at ground level but the signal reflected from the rain drops in the atmosphere. These measurements at first only allowed calculation of an unspecific "precipitation intensity", a shortcoming. In the system RADOLAN, intensity is now calibrated online with data from a comprehensive network of ombrometers, using complex mathematic algorithms. As a result, the amount of precipitation can be provided in a spatial resolution of 1 km^2 (Bartels 2006). For the sake of readability, these calibrated amounts of precipitation based on radar measured rainfall intensities are called "radar data" below. The validation of precipitation data took place in intensely used agricultural areas, for which the DWD radar grid was spatially joined with the meteorological network. In this way, it was possible to relate each station to a grid cell.

The radar derived precipitation at the station's grid cell and the actually measured data formed the basis for the statistical verification. Because rain events differ throughout the year, two representative months (May and August 2007) were selected to analyse both uniform rainfalls in spring and CREs in summer. This resulted in a validation dataset of 1,488 h for each MS. Depending on the region, the number of MSs ranged from 9 to 29. In addition, the influence of the distance between radar station and MSs was analysed.

Furthermore, a leaf wetness simulation model used by ZEPP was run on data from both methods of precipitation measurement and the results were compared.

2.1.3 Interpolation Methods

Two groups of methods have been tested to identify the best interpolation for meteorological data. *Deterministic interpolation methods,* e.g. inverse distance weighted (IDW) and spline interpolation (SI) based on distance analyses were compared to *geostatistical interpolation methods* like kriging and multiple regression (MR) which uses mathematical and statistical procedures.

MR is an interpolation method that allows simultaneous testing and modelling of multiple independent variables (Javis et al. 2002, Cohen et al. 2003). Parameters that have an influence on temperature and RH, e.g. elevation, slope, aspect, can, therefore, be tested simultaneously. MR uses matrix multiplication and only variables with a defined minimum influence that will be included into the model. The result of MR is a formula ($x = \text{const} + A_1{}^*\text{const}_1 + A_2{}^*\text{const}_2 + A_3{}^*\text{const}_3 + \ldots + A_x{}^*\text{const}$) which allows a calculation of a parameter set for each grid cell from which independent variables are known (Javis et al. 2002, Zeuner 2007, Mense-Stefan 2005).

2.2 Validation of Spatial Input Parameter

2.2.1 Interpolation of Temperature and Relative Humidity

The first calculations with the four interpolation methods showed that deterministic interpolation methods were not suitable. IDW and SI have been rejected because differences in elevation are not accounted for, despite of the fact that the elevation has been identified as a major factor for interpolation of the meteorological parameters needed. Although producing similar results, kriging required more calculation time than MR and slow performance limits the production of daily risk maps in the internet. Multiple regression was, therefore, chosen for interpolation and the results are summarised below.

To validate the results of the interpolation, 13 MSs were ignored in the interpolation process. After interpolation, the deviation between calculated values and measured data of these stations was compared. The study was conducted from January to August in the years 2003–2006. For all stations, MR gave results with highest accuracy (Table 16.6). In all cases, the coefficient of determination (CoD) ranged between 96 and 99% for temperature and 92 and 96% for RH, respectively. For the 13 MSs, the mean deviation for temperature was less than 0.1°C and for RH less than 0.6% as calculated with MR. The absolute maximum and minimum for temperature was less than 4.7°C and for RH less than 32.6%. The data also were tested for significance between calculated and measured data using a t-test. The test indicated that for all stations the differences between the calculated and measured values were random. The MR method gave plausible results, so it was chosen to interpolate the meteorological data to be used as input for the forecasting models.

Table 16.6 Validation of data on temperature and relative humidity; deviation between calculated values and measured data with MR ($n = 92{,}160$ h)

	Temperature [°C]				Relative humidity [%]			
Year	2003	2004	2005	2006	2003	2004	2005	2006
CoD (%)	96	96	99	98	94	96	95	92
Mean dev.	0.0	0.0	0.0	0.1	0.3	0.1	0.1	−0.6
Maximum	4.4	4.1	4.3	4.7	19.6	32.6	21.6	21.2
Minimum	−3.8	−4.5	−4.5	−4.1	−18.9	−21.9	−22.8	−22.8
T-test	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.

n.s. = not significant

2.2.2 Results from Radar Data

The parameters for amount of precipitation, hours with precipitation and leaf wetness showed high correlations between radar values and measured data. The maximum of the hourly deviation of the amount of precipitation was 0.06 mm. In hours with rainfall the deviation was slightly higher (0.36 mm). No correlation could be detected for the distance between radar stations and MSs. For hourly rainfall pattern, a correlation of 91.4% between stations and validation areas was measured. The best correlations were obtained for the leaf wetness model for which values > 99.9% were achieved.

A very good correlation between the data of meteorological and radar stations was found for the amount of precipitation, hours with precipitation and calculated leaf wetness duration. The results clearly show that the use of radar data as an input parameter in disease forecast models is valid. By adding data of temperature and RH with high spatial resolution, an optimal basis for site-specific forecasts has been established. Moreover, this system allows for exact detection of localised convective rainfall events, which at the moment often go undetected in meteorological networks. Significant improvements of the spatial forecasting by plant disease simulation models can be expected from the use of radar data.

2.3 Creating Risk Maps with Spatial Input

Results of the forecast models SIMBLIGHT1 and SIMPHYT1 running on calculated meteorological data were validated against a set of field data collected between 2000 and 2007 in Germany. The prediction was defined as accurate when the date of late blight appearance, given by one of the models was earlier than the date of the first outbreak observed in the field. In Fig. 16.3 (A to D) the results of this study are displayed in box-whisker-plots. The results of the model with interpolated input are denoted with “a −v” and those with measured input with “a −m”.

More than 90% of all calculations over all years have been classified as accurate. Only for 2002, less than 60% of the calculations were accurate due to a high amount

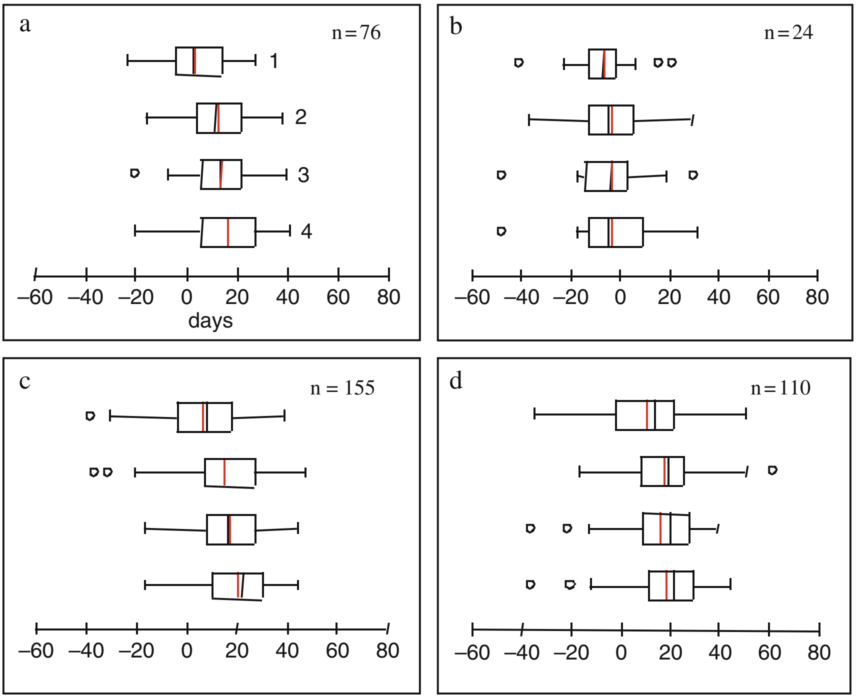

Fig. 16.3 Box-Whisker-Plots of differences between the first appearance of late blight in the field and the model result of SIMBLIGHT1-v-m (1 and 2) and SIMPHYT1-v-m (3 and 4) in Germany in 2001 (**a**), 2002 (**b**), 2003 (**c**) 2004 and 2005 (**d**)

of precipitation during the spring and summer months. The various data sets yielded a similar percentage of accurate results.

In all years, the mean deviation of the model outputs with −v gave better results for the first appearance of late blight detected in the field than the results with −m. For example, in 2001 the mean results of SIMBLIGHT1-v showed a 5–8 days higher accuracy than the calculations based on data measured by a distant MS. In all other years, the results for mean deviation were similar.

The largest differences between the minimum and maximum deviation (range) were demonstrated for SIMBLIGHT1 in 2002. The range of SIMBLIGHT1-m exceeded that of SIMBLIGHT1-v by more than 30 days. In all other years and also with the model SIMPHYT1, the range of results with −v was 5–20 days less than −m. The results showed that calculations based on interpolated data have a higher accuracy for late blight forecast than field data because of their spatial index. Therefore, precise determination of the first fungicide treatment is possible and should result in high efficiency of disease control.

In other forecast models, additional meteorological input data play an important role. It would, therefore, be necessary to analyse whether MR is also able to calculate parameters such as soil temperature, leaf wetness or precipitation with high accuracy. Whereas with soil temperature MR is useful, it is not useful for leaf wetness and precipitation because of regional variation in precipitation especially during summer months. For these parameters, other sources have to be identified, e.g. radar measurements of DWD may be used to classify precipitation.

3 Conclusions

The validation of a simulation model is a critical point in the development of the model itself. Unfortunately, there is no set of specific tests or decision-making algorithms which can determine the best method to validate a model. The procedures for the validation described above can be grouped into two categories: subjective and statistical methods (Table 16.7). In spite of producing numerical outputs, the most common statistical tests not always provide adequate answers. Moreover, the interpretation of the test can be at times misleading.

Subjective methods are more intuitive and provide answers with easy interpretations. In this case, the decision for the method depends on the experience of the person validating the model. It is important to know, for example, what weight should be assigned to the overestimation, but especially to the underestimation of the results of a model. Careful attention must be paid to the quality of data available for validation. They should certainly be adequate in number and represent the different environments involved.

Table 16.7 Some subjective and statistical methods useful for model validation

Model type	Data needed	Subjective methods	Statistical methods
1	Date of disease appearance	Comparison of simulated and observed appearance with subjective early/late criteria	Distribution sample comparison, t- and F-test, Kolmogorov-Smirnov test
2	Disease development data (Incidence or severity)	Comparison of simulated and observed data with confidence interval and/or subjective under-overestimation criteria	Regression analysis, hypothesis test, Kolmogorov-Smirnov test
3	Date of threshold overriding	Comparison of simulated and observed appearance with subjective early/late criteria	Regression analysis, hypothesis test, concordance correlation coefficient
4	Crop development data	Scoring model approach with subjective early/late criteria	Regression analysis, hypothesis test, concordance correlation coefficient

The combination of forecast models for plant diseases and the analyses and interpolation methods based on GIS may allow significant advancement in advice to farmers. GIS methods will help to obtain more detailed calculations and result with higher accuracy and validity than before. Spatial maps will show hot spots of maximum risk which will make the results of forecast models easier to understand and to interpret. This moves decision support systems a step closer to the aim of economical and environmentally friendly crop protection strategies.

The results and methods of this study will lead to the introduction of risk maps in the German crop protection warning service. The internet platform www.isip.de is currently implementing a web GIS application to make use of the new methods. The new components will comply with all relevant standards (OGC, INSPIRE) to ensure interoperability with other geoservices. GIS presentation methods will make DSS results easier to understand and will lead to a higher acceptance of warning systems by farmers.

References

Balci O, Sargent R G (1984) A bibliography on the credibility assessment and validation of simulation and mathematical models. Simuletter 15:15–27

Bartels H (2006) Projekt RADOLAN – Routineverfahren zur Online-Aneichung der Radarniederschlagsdaten mit Hilfe von automatischen. Bodenniederschlagsstationen, Offenbach

Behrens T, Scholten T (2002) DGMK20 + Erstellung der Digitalen Geomorphologischen Karte für das Bundesland Rheinland-Pfalz im Maßstabsbereich 1:25 000 bis 1:50 000. Gießen

Bill R (1999) Grundlagen der Geo-Informationssysteme.- Band 1: hardware, software. Daten Herbert Wichmann Verlag, Heidelberg

Cohen J, Cohen P, West S, Aiken L (2003) Applied multiple regression/correlation analysis for the behavioural sciences, Lawrence Erlbaum ISBN 0805822232

Falke K, Jörg E, Roßberg D (2006) Ursachen für Abweichung zwischen bonitierten und simulierten Entwicklungsverläufen von SIMONTO für Winterraps und Wintergetreide. Mitt Biol Bundesanst Land- Forstwirtsch 400:282

Falke K, Jörg E, Roßberg D (2008) Erhebung von BBCH-Stadien bei Getreide und Winterraps. Mitt. Julius Kühn-Institut 417:413–414

Gutsche V (1999) Das Modell SIMPHYT 3 zur Berechnung des witterungsbedingten Epidemiedruckes der Krautfäule der Kartoffel (*Phytophthora infestans* (Mont.) de Bary). Nachrichtenbl Deut Pflanzenschutzd 51:169–175

Hack H, Bleiholder H, Buhr L et al. (1992) Einheitliche Codierung der phänologischen Entwicklungsstadien mono- und dikotyler Pflanzen – Erweiterte BBCH-Skala. Nachrichtenbl Deut Pflanzenschutzd 44:265–270

Hansen JG, Kleinhenz B, Jörg E, Wander JGN (2002) Results of validation trials of *Phytophthora* DSSs in Europe, 2001. Sixth Workshop of European Network for Development of an Integrated Control Strategy of Potato Late Blight. PPO-Spezial Report 8, 304, 231–242

Heller, S. (1996) Der Einsatz des Geographischen Informationssystems bei der Regionalisierung des Niederschlags im Nationalpark Berchtesgaden. PhD thesis Johannes Gutenberg-Universität Mainz

Jarvis C, Baker R, Morgan D (2002) The impact of interpolated daily temperature data on landscape-wide predictions of invertebrate pest phenology. Agric Ecosyst Environ 94: 169–181

Jörg E, Racca P (2000) CERCBET 1 2 3 – Prognosemodelle zur Simulation von *Cercospora beticola*. Zuckerrübe 49:200–203

Jörg E, Racca P, Mittler S, Petersen J (2003) Spritztermine optimieren. DLG-Mitt 4:42–47
Jörg E, Racca P, Preiß U et al. (2007) Control of Colorado potato beetle with the SIMLEP decision support system. EPPO Bull 37:353–358
Keil B, Kleinhenz B (2007) AGMEDAWIN-a tool for easy and flexible management of meteorological data. Proceedings of EPPO conference on computer aids for plant protection, Bull OEPP 37(2):335–338, Wageningen
Kleinhenz B, Falke K, Kakau J, Roßberg D (2007) SIMBLIGHT1 – A new model to predict first occurrence of potato late blight. EPPO Bulletin 37:339–343
Kleinhenz B, Jörg E (1999) Validation of SIMPHYT I/II – A decision support system for late blight control in Germany. In: Schepers H, Bouma E (eds) Workshop on the European Network for development of an integrated control strategy of potato late blight. Uppsala, Sweden, 1999, PAV-Special Report 5, pp 115–128
Kleinhenz B, Jörg E (2000) Results of validation trials of *Phytophthora* DSS in Europe in 1999. PAV-Special Report 6:180–190
Kluge E, Gutsche V (1984) Untersuchungen zum Einfluß des Braunfäulebefalls der Pflanzkartoffelknollen auf das Erstauftreten der Krautfäule (*Phytophthora infestans* (Mont) de Bary) mittels SIMPHYT I. Arch Phytopathol PflSchutz, Berlin 20:361–369
Kranz J, Royle DJ (1978) Perspectives in mathematical modelling of plant disease epidemics. In Scott R, Bainbridge A (eds) Plant disease epidemiology. Blackwell, Oxford
Liebig W, Mummenthey RD (2002) ArcGIS – ArcView 8.1. Auflage. Halmstad
Lin LIK (1989) A concordance correlation coefficient to evaluate reproducibility. Biometrics 45:255–268
Madden LV, Hughes G, van den Bosch F (2007) The study of plant disease epidemics. APS-Press, St.Paul
Mense-Stefan A (2005) Standortdifferenzierte Abschätzung von Sickerwasserraten in Hessen. Mainzer Geographische Studien 53. Mainz
Mirschel W, Schultz A, Wenkel KO (1993) Vergleich der Winterweizenmodelle AGROSIM-WHEAT und CERES-Wheat. Ber Ges Informatik in der Land-, Forst- und Ernährungswirtschaft 5:29–34
Morvin SM (2006) Validation of simulation based models: a theoretical outlook. Electron J Business Res Meth 4:39–46
Racca P, Jörg E (2007) CERCBET 3 – a forecaster for epidemic development of *Cercospora beticola*. EPPO Bull 37:344–349
Racca P, Kleinhenz B, Jörg E (2007) SIMPEROTA 1/3 – a decision support system for blue mold disease of tobacco. EPPO Bull 37:368–373
Racca P, Kleinhenz B, Jörg E et al. (2009) ZEPP & ISIP from the realisation to the praxis – The decision support systems for the plant protection in Germany. Proceedings of the 4th conference statistical, mathematical and computer methods on plant pathology and forestry – research and application. Aracne, Roma
Racca P, Räder T, Hau B, Jörg E (2008) A decision support system for controlling leaf rust in winter rye and winter wheat. J Plant Pathol 90:169 (Abstract)
Räder T, Racca P, Jörg E, Hau B (2006) PUCREC – ein Entscheidungsmodell zur Bekämpfung von Braunrost in Winterroggen. Mitt Biol Bundesanst Land- Forstwirtsch 400:281–282
Räder T, Racca P, Jörg E, Hau B (2007) PUCREC/PUCTRI – a decision support system for the control of leaf rust of winter wheat and winter rye. EPPO Bull 37:378–382
Reynolds MR, Burkhart HE, Daniels RF (1981) Procedures for statistical validation of stochastic simulation models. For Sci 27:349–364
Roßberg D, Gutsche V, Kleinhenz B (2001) Prognose von Phytophthora infestans mit den SIMPHYT Modellen. Ges Pflanzen 53:37–43
Roßberg D, Jörg E, Kleinhenz B (1999) SIMLEP2 – A model for plot-specific forecast of Colorado Potato Beetle. Nachrichtenbl Deut PflSchutzd 51:81–87
Roßberg D, Jörg E, Falke K (2005) SIMONTO- ein neues Ontogenesemodell für Wintergetreide und Winterraps. Nachrichtenbl Deut PflSchutzd 57:74–80

Roßberg D, Racca P, Jörg E, Kleinhenz B (2000) Erste Erfahrungen mit dem Modell CERCBET 1. Nachrichtenbl Deut PflSchutzd 52:153–159

Rossi V, Battilani P (1991) CERCOPRI: a forecasting model for primary infections of cercospora leaf spot of sugar beet. EPPO-Bull 21:527–531

Rossi V, Racca P, Battilani P (1994) A simulation model for Cercospora leaf spot on sugarbeet. Phytopathol Mediterr 33:105–112

Rossi V, Racca P, Giosué S et al. (1997) A simulation model for the development of brown rust epidemics in winter wheat. Eur J Plant Pathol. 103:453–465

Sargent RG (1998) Verification and validation of simulation models. Proceedings of the winter simulation conference: the premier forum on simulation practice and theory, pp 121–130

Schlesinger S (1979) Terminology for model credibility. Simulation 34:101–105

Teng P S (1985) A comparison of simulation approaches to epidemic modelling. Annu Rev Phytopathol 1985. 23:351–379

Wernecke P, Claus S (1996) Modelle der Ontogenese für die Kulturarten Winterweizen, Wintergerste und Winterraps. In: Mühle H, Claus S (eds) Reaktionsverhalten von agrarischen Ökosystemen homogener Areale. Teubner Verlagsgesellschaft, Stuttgart-Leipzig, pp 105–120

Welch SM, Croft BA, Michels MF (1981) Validation of pest management models. Environ Entomol 10:425–432

Zeuner T, Kleinhenz B (2008) Schlaggenaue Prognosen. DLG-Mitteil 2:68

Zeuner T (2007) Landwirtschaftliche Schaderregerprognose mit Hilfe von geographischen Informationssystemen. Doktorarbeit, Geographisches Institut, Johannes Gutenberg Universität-Mainz, http://ubm.opus.hbz-nrw.de/frontdoor.php?source_opus=1549 (accessed 24 April 2009)

Part IV
Application Technologies for Site-Specific Crop Protection

Chapter 17
Mechanical Weed Control

Victor Rueda-Ayala, Jesper Rasmussen, and Roland Gerhards

Abstract Side effects of herbicides and increasing prevalence of organic farming induce the need of further developments in mechanical weed control. Mechanical weed control is mainly associated with cultivating tillage (e.g. tertiary tillage), but also primary and secondary tillage influence weeds. Cultivating tillage is performed in growing crops with harrows, hoes, brushes and a number of special tools for intra-row weed control. Inter-row cultivations have been used in many decades in row crops and perform in general well. To increase their capacity and accuracy, guidance systems are important to steer the hoes along the rows. The success of inter- and intra-row cultivation is highly influenced by selectivity factors. The control mechanisms of all cultivating tillage methods are burring in soil, uprooting, and tearing plants into pieces. Especially for whole crop and intra-row cultivators, successful weed control is highly influenced by appropriate adjustment of the intensity (aggressiveness) of cultivation according to the variations of soil resistance, crop and weed resistance to cultivation and the competitive interactions between crop and weeds. Site-specific weed management aims to identify the spatial and temporal variability of weeds and manage them correspondingly. New technologies for sensing crops and weeds in real-time and robotics allow a precise operation of mechanical tools, to improve efficacy of control and reduce operation costs. Hence in this chapter, implements for mechanical weeding are described together with their options for site-specific weed control strategies. Harrows and rotary hoes are used for whole crop treatment, but it is essential to find the right timing and intensity to obtain the best selectivity and yield response. Different implements attached to the same vehicle are combined together attempting more selective weed control, like the in-row cultivator, the rotary harrow, and the precision hoe. Lately, there are prototypes intending automatic adjustment of the aggressiveness for the spring-tine harrow and autonomous guidance for hoes, thus getting closer to a real-time site-specific weed management approach.

V. Rueda-Ayala (✉)
Department of Weed Sciences (360b), University of Hohenheim, D-70599 Stuttgart, Germany
e-mail: victor.rueda.ayala@uni-hohenheim.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_17,

1 Introduction

A crucial element in farm management is the control of weeds, mainly due to their negative implications on crop yield and quality. Conventional farming heavily depends on herbicides, whereas organic farming depends on interactions between preventive methods and mechanical weed control. Efficacy of herbicides is high in many important crops and non-chemical alternatives like mechanical weed control are in general not able to compete due to lower efficacy and higher costs. However, continuous use of herbicides with the same mode of action may cause selection of herbicide resistant weed populations. Herbicides may also show negative side effects like contamination of soils and groundwater as well as herbicide residues in the food chain. These side effects and the increasing prevalence of organic farming have induced the need of further developments in mechanical weed control, which constitutes a key element in non-chemical weed management (Upadhyaya and Blackshaw 2007).

Mechanical weed control is mainly associated with cultivating tillage, often referred to as tertiary tillage, but also primary and secondary tillage as well as mowing and cutting have strong impacts on weeds. In organic farming, a 1–2-year period of grass-clover or alfalfa in the crop rotation is more or less required to suppress weeds including perennials such as *Cirsium arvense* (Peigne et al. 2007, Gruber and Claupein 2009). Perennial weed species such as *C. arvense*, *Calystegia sepium* and *Agropyron repens* are difficult to manage in crop rotations dominated by annual crops, and crop rotations dominated by cereals often result in a strong increase of root/rhizome biomass, especially if conservation tillage is practiced (Hacker 1984, Peigné et al. 2007). A combination of repeated stubble tillage in the summer under dry soil conditions using a cultivator or rototiller combined with inversion tillage using the double-layer plough or a deep mouldboard plough may be successful in terms of weed control (Pekrun and Claupein 2004, Gruber and Claupein 2009), but this control tactic can only be used occasionally in an organic cropping system, otherwise soil fertility will decline.

Cultivating tillage is carried out after crop sowing/planting to control weeds and consists of shallow tillage with a variety of equipments often categorized as hoes or harrows. It includes whole crop cultivation, inter-row cultivation and intra-row cultivation. The action mechanisms are through tearing weeds into pieces, uprooting and covering them with soil (Kurstjens and Kropff 2001). The primary aim of cultivating tillage is to control seed propagated weed species in the earliest development stages. Perennial weeds with vegetative propagation are more or less unaffected by cultivating tillage.

Cultivating tillage is carried out both as pre-emergence and post-emergence cultivation. The primary control mechanism in pre-emergence cultivation is complex and little studied but in post-emergence weed harrowing, burying of weed seedlings in soil has been determined as the primary control mechanism (Kurstjens and Perdok 2000, Jensen et al. 2004). Plants should be covered totally to be killed; the required burial depth depends on plant size and growth habit (Baerveldt and Ascard 1999).

Crop and weed populations are often not uniform in the field, which challenge the use and settings of cultivators. Weeds may occur in patches of varying size, densities and growth stages; some areas may have few or even no weeds within a weedy field. Also soil characteristics such as soil texture, soil moisture content and organic matter may vary significantly within a field. Therefore, there is need to vary the intensity (aggressiveness) of mechanical weed control according to the variations in the field. The objectives of site-specific weed management are to identify the variability, and to analyse and manage weeds according to their spatial and temporal variability (Blackshaw et al. 2007). Lately, new technologies for sensing crops and weeds in real-time with image analysis, global positioning systems (GPS), mapping tools in a geographical information system (GIS) and robotics using autonomous vehicles allow a precise operation of mechanical weeding tools. This may increase the efficacy of weed control and reduce operation costs (Gerhards et al. 2002).

The objectives of this chapter are to give an overview of the various implements for mechanical weed control with their benefits and constraints. Secondly, this paper describes options to use existing mechanical weed control in a more precise way taking into account the heterogeneous weed distributions and soil conditions, i.e. under the precision weed management approach. In order to examine the potential of site-specific mechanical weed management, emphasis is given to cultivating tillage, which includes control of seed propagated weeds in early crop growth states.

2 Implements for Mechanical Weed Control

A large variety of implements are used for mechanical control of weeds, from basic hand tools to sophisticated tractor pulled or self-propelled implements (Dierauer and Stöppler-Zimmer 1994, Van der Weide et al. 2008). In general they are classified into two main groups: *cultivating tools* like hoes and harrows; and *cutting tools* like mowers and strimmers. For cultivating tillage only the first group is relevant.

Cultivating tillage may cover the crop row (*intra-row weeding*), strips between crop rows (*inter-row weeding*) or the full surface (*whole crop weeding*) (Vanhala et al. 2004), and it is mainly carried out with harrows, hoes and brushes (Dierauer and Stöppler-Zimmer 1994, Pallutt 2002).

Inter-row and intra-row cultivation require precision in terms of steering. The highest precision is required for intra-row weeders but also inter-row weeders that operate close to the crop rows require precision. In practice, it is possible to leave about 10 cm wide uncultivated strips around the crop row if steering is highly accurate (Gupta et al. 2008). Most inter-row cultivations are carried out in row crops with rows spaced 50–90 cm apart. Inter-row cultivation, however, is also possible in cereals and other crops normally established in narrow-row systems. Row spacing of about 20 cm is considered as a minimum to allow inter-row cultivation.

2.1 *Whole Crop Cultivation*

2.1.1 Harrows and Rotary Hoes

Weed harrowing and rotary hoeing imply whole crop cultivating and risks of crop damage. However, mechanical weeding may also favour crop growth due to soil loosening, reduction of evaporation, soil aeration and induction of mineralization (Steinmann 2002). The challenge is to achieve a high degree of weed control without unacceptable crop damage. Spring tine harrows, also called flexible tine harrows, are the most utilized implements for whole crop cultivation in Europe, but other types of harrows like the chain harrow, are also used. In North America rotary hoes are commonly used pre-emergence or in very early growth stages (Place et al. 2009).

Weed harrowing in cereals can be performed at pre-emergence, at early post-emergence, and during tillering until the crop becomes about 40–50 cm high (Rasmussen and Svenningsen 1995); the latter is called selective harrowing. Early post-emergence harrowing is estimated to involve the highest risks for crop damage. However, if broadleaved (annual) weeds are at cotyledon stage and the crop has reached at least three true leaves stage, weed harrowing can be highly selective due to higher crop resistance to cultivation (Rasmussen et al. 2008). Under such conditions, 80–90% weed control may be achieved (Rasmussen et al. 2008, Van der Weide et al. 2008). In later growth stages, more aggressive cultivation is required which may involve several passes with the harrow, more aggressive setting of the tines or higher speed (Kurstjens and Perdok 2000). Re-growth of weeds or late germinating weeds may require repeated cultivations, especially in row crops with open canopy structure and low competitive ability (Van der Weide et al. 2008).

Harrowing is a common practice to control weeds in organic small-grain cereals (Fig. 17.1a) and seed legumes (Fig. 17.1b). Early crop emergence, high competitive ability, and high tolerance to cultivation make cereals and seed legumes suitable for mechanical weed control (Jensen et al. 2004, Rasmussen et al. 2009). Weeds in maize (*Zea mays* L.), potato (*Solanum tuberosum* L.), and transplanted vegetables may also be controlled by harrowing, and sensitive row crops like onions

Fig. 17.1 Whole crop cultivation in cereals with a 27 m wide spring-tine harrow (**a**), harrowing in faba beans (**b**). Photos Einböck, Agritechnika 2005

(*Allium cepa* L.), sugar beet (*Beta vulgaris* L.), and carrots (*Daucus carota* L.) can be harrowed after the 3–4-true-leaf stage of the crop (Van derVan der Weide et al. 2008).

Weather and soil conditions are important for successful weed harrowing. Relatively dry soil conditions are preferred, but there is little experimental evidence to quantify the importance of dry weather conditions. It is, however, important that mechanical weeding is not constrained by poor soil workability (Van der Weide et al. 2008). Favourable soil conditions are crucial for the shallow tillage operations. Soil structure must be fine and soil texture light; stone free and plane topography are also desired (Dierauer and Stöppler-Zimmer 1994). Harrowing on windy or hilly areas increases the risk of soil erosion. Additionally, harrowing in late autumn or early spring may provoke frost damage to the crop after treatment mainly due to root injury and reduced drought resistance.

The weed control mechanism of harrowing is mainly by soil burying (crop soil cover), but also uprooting plays a role when weeds are small (Kurstjens and Kropff 2001). If cereals and seed legumes are damaged, it is mainly caused by crop soil cover (Rasmussen et al. 2009, Jensen et al. 2004). A high selectivity means that a high degree of weed control is associated with a small percentage of crop soil cover, which is the percentage of the crop that has been covered by soil. The success of harrowing depends on the balance between weed control and crop soil cover, which is reflected in the selectivity (Rasmussen 1991).

Originally, selectivity was defined as the ratio between percentage of weed control and the percentage of crop soil cover immediately after harrowing (Rasmussen 1990). This definition does not consider recovering or re-germination of weeds after treatment and until recently, crop soil cover was visually assessed due to lack of objective assessment methods. Recently, however, it has been possible to make reliable estimations of the crop soil cover based on digital image analysis (Rasmussen et al. 2007), and a new protocol for the estimation of selectivity has been proposed (Rasmussen et al. 2008).

It is important to distinguish between quantitative and qualitative aspects of selectivity, because the more aggressive the cultivation the lower selectivity. This applies for all implements and it is considered a quantitative aspect of selectivity. Therefore, comparisons of different treatments in terms of selectivity have to be done at the same level of weed control, in order to evaluate whether the treatments represent different qualities of selectivity. In general, the construction and use of cultivators are not considered to influence the qualitative aspects of selectivity (Rasmussen 1992, Rasmussen et al. 2008), whereas the difference between crop and weed plants (i.e. large crop plants and small weeds) is crucial.

Adjustment of the aggressiveness of harrows can be achieved by increasing the working depth (e.g. deeper penetration of the tines into the soil), the forward speed and the number of passes (Søgaard 1998, Engelke 2001, Cirujeda et al. 2003, Rasmussen et al. 2008).

With the use of sensor technology and automatic plant species discrimination, crop and weed responses can be estimated and included in the objective determination of selectivity (Weis et al. 2008, Rueda-Ayala and Gerhards 2009). The curve for leaf cover decline of the crop relative to increasing intensity with the cultivator (Fig. 17.2a) allows the calculation of the percentage of crop soil cover, and the

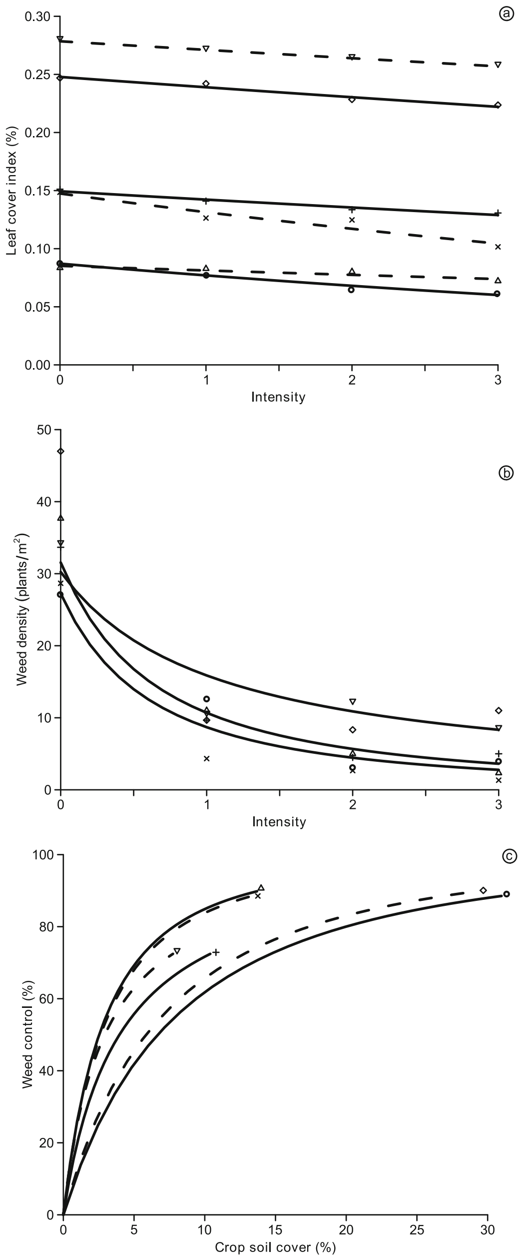

Fig. 17.2 Leaf cover index (Symbols: ○= BBCH 13, △= BBCH 21, += BBCH 24) (**a**); weed density as function of increasing intensity (**b**); selectivity curves response of three timings and two driving directions of harrowing in spring barley (**c**) (Rueda-Ayala and Gerhards 2009). *Solid lines* indicate harrowing across and *dashed lines* along the crop rows. (Symbols **b**, **c**: △= BBCH 13 along, ○= BBCH 13 across, ×= BBCH 21 along, += BBCH 21 across, ∇= BBCH 24 along, ◇= BBCH 24 across)

curve for weed density decline (Fig. 17.2b) allows the calculation of the percentage of weed control. The selectivity (Fig. 17.2c) is calculated as the relationship between crop soil cover and wed control.

After the data acquisition with the sensors, real-time adjustment of the aggressiveness of cultivation (intensity) of the harrow may be possible, according to the site-specific demand for weed control (Søgaard 1998, Weis et al. 2008). To make the adjustments, a predictive model is required to estimate the positive and negative crop yield contributions from harrowing relative to the intensity of cultivation. This model requires site-specific knowledge about (I) the competitive ability of the weeds, (II) selectivity and (III) recovery as outlined in Rasmussen (1991).

Figure 17.3 shows the prototype for automatic adjustment of the harrow. A digital sensor (a) measures the resistance force of the soil to the forward movement of the harrow; the data are transmitted to a control unit (b) that generates an algorithm for the motors (c) to change the tine angle and perform more aggressive treatments according to the soil characteristics. Positioning of the whole system is detected with a real-time kinematic differential global positioning system (RTK-DGPS) (d).

The *rotary hoe* used for pre- and early post-emergence weed control without regard to crop rows, is a non-powered weeder with curved steel spokes radiating as a flat wheel from a hub. The spikes are rotated forward by ground contact (Bowman 1997).

Rotary hoes are mainly used in maize and soybean (*Glycine max*). They are less aggressive than most harrows, but have a high capacity due to high operation speed ranging from 8 to 24 km h^{-1} (Cloutier et al. 2007). The control mechanism is by

Fig. 17.3 Prototype of an automatically controlled flexible tine harrow containing soil sensor (*a*), computing control unit (*b*), motor to change the tine angle (*c*), and RTK-DGPS for positioning (*d*)

pulling weed seedlings after the hoes penetrate and come up of the ground; also movement of the soil towards or away from the crop row generates a burial action. The selectivity of this tool is given when the crop seeds are placed deeper than its working depth – i.e. crop plants are deeper rooted than weed seedlings.

2.2 Inter-Row Cultivation

Inter-row cultivators have been commonly used in row crops like sugar beets and vegetables for many decades. They are manufactured in many different designs, but they are all constructed to kill weeds on their path, which mean that they are operating in a non-selective way between rows. Most inter-row cultivators have sweeps, weed knives or shovels working in a depth of 2–4 cm. The ordinary hoe blades (e.g. *duck foot* or *goosefoot*) are mounted on rigid or vibrating shanks. Usually, three to five shanks constitute a gang that is munted on a toolbar, and each gang cultive an inter-row spacing. However, inter-row cultivation may also be carried out with rolling cultivators and PTO-driven cultivators (Melander 2006).

As for harrowing, success of hoeing depends on dry weather conditions and a workable soil. Unlike harrows, hoes can be used rather in late growth stages and timing is not crucial (Melander et al. 2005). If the hoe is too deeply operated fibrous rooted weeds may grow again when enough moisture is available in the soil.

Instead of cutting blades, horizontal rotating brushes are used for special soil conditions. The weeds are brushed by rotation of hard polypropylene fibres and the control mechanisms are mainly by burial with soil and uprooting of weeds so they stay exposed to desiccation, stripping leafs and breaking stems (Melander 1997). Manual guidance or autonomous guidance system of the brushes between the rows is indispensable. The first inter-row brush was developed in 1985 to be used in cereals with 17 cm row distance (Dierauer and Stöppler-Zimmer 1994). For optimal weed control, the inter-row distance must be at least 17 cm. The main advantage of the brush weeders is that they can effectively be operated on higher soil moisture conditions than for harrows or hoes. The risk of using brushes is that soil structure is destroyed and the soil becomes very sensitive for compaction after rainfall.

Hoes are mainly used in row-crops but may also be used in cereals as a supplement to whole crop cultivation with harrows. For instance in cereals, the effect of weed harrowing is often poor in heavy soils and a combination of inter-row hoeing and whole crop harrowing may improve weed management (Rasmussen and Svenningsen, 1995). Thus, an additional pass with the hoe might be more effective to control problematic weeds such as *Galeopsis tetrahit*, *Galium aparine*, *Matricaria chamomilla* and *Vicia hirsuta* (Dierauer and Stöppler-Zimmer 1994). The crop row distance must not be < 20 cm (Melander 2006). Two passes with the hoe in maize and peas (*Pisum sativum*) may reduce inter-row weed density by 90% and intra-row density by 75% (Dierauer and Stöppler-Zimmer 1994).

An accurate steering of the hoe is required, since its shares undercut everything when being pulled. Therefore precise seeding of the rows eases the guidance of the hoe between the rows (Griepentrog et al. 2006). Manual steering has been the most common guidance method to direct the hoeing implements and reduce crop damage. Some electronic guided hoeing systems based on computer vision technology have been introduced. These systems aim to reduce the concentration needed by the tractor driver (Melander et al. 2005).

2.3 Intra-Row Cultivation

There exist a number of implements for intra-row weeding. Most are low-tech, which means that they are simply pulled along the rows and the success of their performance is highly dependent on crop-weed selectivity factor. Among the most common low-tech implements are finger weeders and torsion weeders, which originate from North America but have been simplified by several companies (Van der Weide et al. 2008).

The c*ycloid hoe* (Fig. 17.4) is a high-tech device for intra-row cultivation. It was developed by the University of Osnabrück, Germany, together with Amazon Werke for weed control in maize (Kielhorn et al. 2000). The machine had a multi-sensor system for plant recognition composed by three sensors: height-profile sensor, area-allocation sensor and soil-plant sensor. A cylindrical rotor works as actuator and contains eight tines placed around a vertical axis. The tines rotate in a circular motion, at a rotational diameter of 0.234 m (Griepentrog et al. 2006). This translation movement of the rotor together with the forward straight-line movement of the implement generates a cycloid. The cyclic movement can be regulated by adjusting the translation and rotation speed. Every single tine can be in- and out-folded by an electromagnetic circuit to avoid crop plants, once the sensors have recognized them. The forward speed of the vehicle is 8.5 km h^{-1}.

The cycloid hoe has been further developed, tested and problems have been reported such as high crop damage and low control efficacy (Griepentrog et al. 2007). Gobor (2007) designed a rotary intra-row hoe in combination with realttime sensors for robotic weeding which is expected to be fast and effective in weed control.

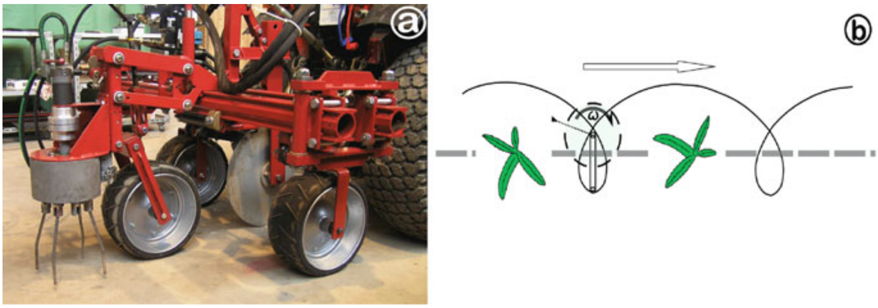

Fig. 17.4 The cycloid hoe (**a**, Griepentrog et al. 2007); forward movement of the cycloid hoe (**b**, after Kielhorn et al. 2000)

Fig. 17.5 Bezzerides-cultivator for in-row and intra-row weed control in maize

Schweizer et al. (1992) carried out an investigation to perform more selective weed control through post-planting cultivating tillage with a so-called Bezzerides *in-row cultivator* (Fig. 17.5), as an attempt to site-specifically manage weeds. The in-row cultivator has tools that move the soil away from the rows and later into rows, thus uprooting and burying in-row weeds. Rotary hoes at the first gang of the implement move soil away from the crop row in the first cultivation and into the row on the second cultivation, covering small weeds. The following gangs are composed by torsion weeders, spinners (rotary harrows), and spring hoe weeders. The torsion weeders and rotary harrows were used during the first pass; the torsion weeders and spring hoes (which replaced the spinners after the first cultivation) were used for the second and third passes.

Brush weeders also exist for intra-row weeding. However, they are designed with vertical brushes that are powered by hydraulic motors. The brushes can be assembled at any desired width and spacing for the crop; the working depth is about 20–30 mm (Melander 1997).

3 Innovative Implements for In-Row Crops

Innovative strategies for weed management in organic farming have been developed with several operating machines in Italy since the year 2000 in carrots, leaf-beet (*Beta vulgaris* var. *cicla*), fresh tomato (*Solanum lycopersicum*), and cabbage (*Brassica oleracea*). Weed control is carried out with a rolling harrow, a precision hoe and flame weeders. All machines were built, tested and patented by the University of Pisa (Peruzzi et al. 2007, Carlesi et al. 2009, Fontanelli et al. 2009, Raffaelli et al. 2009).

The *rolling harrow* (Fig. 17.6a) was used for shallow tillage and showed efficient weed control. It is a modular machine, which means it can be built with different working depths to adapt it to the soil conditions (Raffaelli et al. 2009).

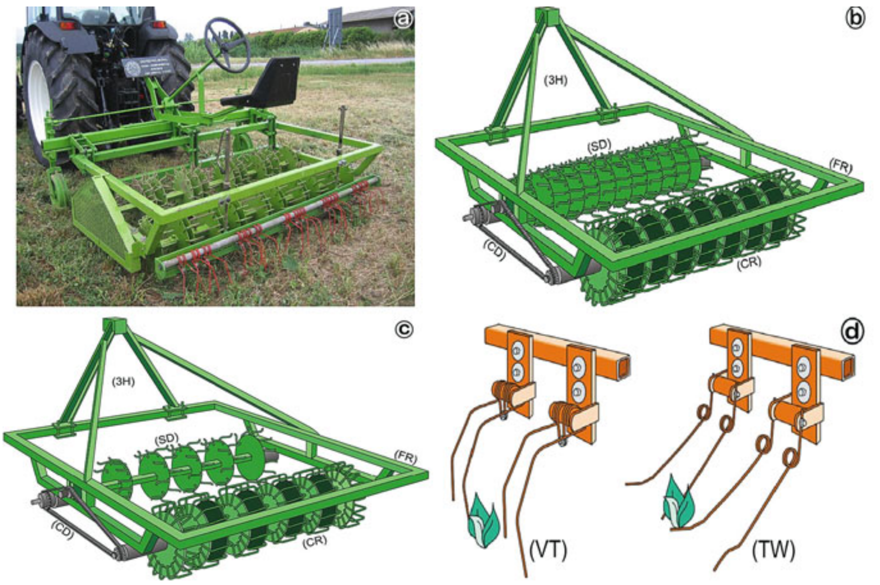

Fig. 17.6 Rolling harrow (**a**) with a scheme of different working widths adaptation for whole crop cultivation (**b**), and inter-row cultivation (**c**). Parts: Three-point hitch (3H); frame (FR); front axle with spike discs (SD); rear axle with cage rolls (CR); chain drive (CD), (**d**) vibrating tines (VT) and torsion weeders (TW). After (Peruzzi et al. 2007), courtesy images by Carlesi et al. 2009, Fontanelli et al. 2009, Raffaelli et al. (2009)

A square frame carries the working tools and has three points for linkage to the tractor (Fig. 17.6b, c). Spike discs of 30–35 cm diameter are placed in the front axle and cage rolls of 27–33 cm diameter placed in the rear axle; these axles are connected one another through a chain drive of an easily adjustable ratio.

The mode of action of the rolling harrow comprises the passage of the spike discs that till the soil at shallow layer of 4 cm; immediately, the gage rolls pass at a high peripheral speed as the rear axle is powered by the front axle, and generate an overdrive tilling and crumbling of the soil at a depth of 1–2 cm.

The discs and rolls may be arranged in a miscellaneous way and also changed with a simple blocking system. When the discs are narrowly distributed along the axle and the whole area is cultivated, a non-selective weed control for seed-bed preparation is obtained; whereas a wider arrangement of the discs allows an efficient selective inter-row weed control at post-emergence weeding. The minimum row distance to operate this machine is 15 cm.

Additionally, couples of elastic tines (Fig. 17.6d) may be attached on the back of the frame (vibrating teeth and torsion weeders) in order to control weeds nearer or even in the crop row (inter-row control).

The *precision hoe* is a 2–3 m wide experimental inter-row weeder which shows promising results in organic horticulture in Italy (Peruzzi et al. 2007, Fontanelli

Fig. 17.7 Scheme of the precision hoe containing an operating seat (OS), steering handle (SH), articulated parallelogram (AP), directional wheel (DW), support wheel, lateral disc (LD), rigid elements with horizontal blade (HB) and elastic tines (ET) (**a**); precision hoeing in cabbage (**b**), in cauliflower (**c**), and in processing tomato (**d**). After (Peruzzi et al. 2007), courtesy images by Carlesi et al. (2009), Fontanelli et al. (2009), Raffaelli et al. (2009)

et al.2009, Raffaelli et al. 2009). This implement is structured on a square draw frame which bears up to 11 working tools (Fig. 17.7a); each tool is placed on articulated parallelogram equipped with a small wheel that allows adjustment of the working width. The working tools consist of rigid elements which have attached a 9 cm wide triangular horizontal blade each, pairs of concave discs and two types of elastic tines: vibrating and torsion (Fig. 17.7d). The steerage is manually performed by a back-seated operator. With this machine it was possible to achieve a more selective weed control on the row in crops like cabbage, cauliflower and tomato (Fig. 17.7b, c, d).

4 Hand Weeding

The highest level of site-specific weed management is achieved through manual weeding with hand hoes, push hoes or simply through pulling weeds by hand. The major constraint is the low capacity (ha hour^{-1}). Nevertheless, hand weeding tools are still used in small-scale horticultural crops especially in organic farming. In crops like carrots and onions they often serve as the last resort control method.

Uprooting of perennial weeds in grassland is still carried out with hand tools such as the spudder (Bond et al. 2007), which is very effective at removing deep rooted weeds.

Bond et al. (2007) describe some hand hoes used in Europe and still produced in a wide range of traditional and improved designs. Hoes with tough blades for cutting large weeds or with plough-shaped blades to move soil and cover small weeds are available. The *draw hoe*, *swan-necked hoe*, *onion hoe*, *draw swan-necked*, *collinear hoe*, *Dutch hoe*, *Swiss oscillating*, *stirrup hoe* are some examples. These tools cut and move the soil while the operator works standing or kneeling on vegetable crops. Their blades may be V-, L- or circle-shaped; they are mounted at right or slight angles to the short or large handles and are pushed, pulled or both to achieve the cutting action.

In developing countries, hand tools are of more readily acceptance and use due to low purchase costs. They are often used in combination with *animal drawn hoeing* or human pushing the *wheeled hoe* between the rows. In this way, manual weeding with hand tools is reduced only to intra-row level, reducing the labour per hour (Benzing 2001).

5 Cutting and Mowing

Cutting involves the mechanical removal of the above-ground portions of weed plants only (Hatcher and Melander 2003), however plant damage by ordinary mechanical weeding on weed suitability for pest and diseases are also considered. This control method is better suitable for crops were the row distance is wide such as potato, maize, beets, and most of vegetables (Pallut 2002); cereals, rapeseed, peas and beans can be included when the row distance is > 16 cm.

Weed control by cutting or mowing may be complicated due to the adaptation mechanisms to continuous defoliation of some weeds, especially perennial ones in grasslands like *Rumex obtusifolius*, *Cirsium arvense* (L.) Scop and *Pteridium aquilinum* (L.) Kuhn. A high frequency of cutting of these weeds is required to achieve high degrees of weed control. Graglia et al. (2006) achieved about 75% weed biomass reduction of *Cirsium arvense* in spring barley, when 6 mowing per growing season were performed in preceding grass/clover leys.

6 Conclusion

Mechanical weed control plays an important role in organic weed management; nevertheless conventional farming may also integrate mechanical weeding into its management plans. Efficacy and selectivity of mechanical weeders can be improved when variations in weed species distribution and soil characteristics are objectively assessed, and taken into account for the regulation of the instruments. Sensors to measure site-specific weed and crop responses to cultivation as well as soil resistance have been developed and combined with steerage and guidance systems. However, only few agronomic results are available showing the potentials of integrating advanced technology into mechanical weed control. So far, little is known about the interactions between soil characteristics in the upper soil layers, weed/crop densities, growth stages, weather conditions and mechanical weed control efficacy. Site-specific weed control may not only increase overall efficacy and selectivity but may also improve crop growth due to positive effects of soil tillage others than weed control. However, intensive studies need to be conducted to quantify positive and negative effects on crops from cultivating tillage to get decision support algorithms for precise mechanical weed control.

References

Baerveldt S, Ascard J (1999) Effect of soil cover on weeds. Biol Agric Horticul 17: 101–111

Benzing A (2001) Agricultura Orgánica: Fundamentos para la Región Andina. Neckar-Verlag, Villingen-Schwenningen

Blackshaw RE, Anderson RL, Lemerle D (2007) Cultural weed management. In: Upadhyaya MK, Blackshaw RE (eds) Non-chemical weed management: principles, concepts and technology. CABI, Oxford, pp 35–47

Bond W, Turner R, Davies G (2007) A review of mechanical weed control. HDRA, Ryton Organic Gardens, Coventry, CV8 3LG, UK.http://www.gardenorganic.org.uk/organicweeds, pp 1–24. Accessed 08 May 2009.

Bowman G (1997) Steel in the field: a farmers guide to weed management tools. Sustainable Agricultural Publications, University of Vermont, Burlington

Carlesi F, Bigongiali D, Antichi D et al (2009) Effect of innovative crop and weed management systems on organic cauliflower in Central Italy. In: Cloutier D (ed) Proceedings of the 8th EWRS Workshop on Physical and Cultural Weed Control, Zaragoza

Cirujeda A, Melander B, Rasmussen K et al (2003) Relationship between speed, soil movement into the cereal row and intra-row weed control efficacy by weed harrowing. Weed Res 48: 285–296

Cloutier DC, Van der Weide RY, Peruzzi A, Leblanc M (2007) Mechanical weed management. In: Upadhyaya MK, Blackshaw RE (eds) Non-chemical weed management: principles, concepts and technology. CABI, Oxfordshire, pp 111–134

Dierauer H U, Stöppler-Zimmer H (1994) Unkrautregulierung ohne Chemie. Ulmer, Stuttgart

Engelke B (2001) Entwicklung eines Steuersystems in der ganzflächig mechanischen Unkrautbekämpfung. Institut für Landwirtschaftliche Verfahrenstechnik. Agrar- und Ernährungswissenschaftlichen Fakultät der Christian-Albrechts-Universität Kiel

Fontanelli M, Raffaelli M, Ginanni et al (2009) Non-chemical weed control on open-field fresh market tomato in the Serchio Valley (Central Italy). In Cloutier D (ed) Proceedings 8th EWRS workshop on physical and cultural weed control, Zaragoza, pp 49–55

Graglia E, Melander B, Jensen RK (2006) Mechanical and cultural strategies to control *Cirsium arvense* in organic arable cropping systems. Weed Res 46:304–312

Gerhards R, Sökefeld M, Nabout A et al (2002) Online weed control using digital image analysis. J Plant Dis Prot IXX (special issue): 421–427

Gobor Z (2007) Development of a novel mechatronic system for mechanical weed control of the intra-row area in row crops based on detection of single palnts and adequate controlling of the hoeing tool in real-time. PhD thesis University of Bonn, Bonn

Griepentrog HW, Noerremark M, Nielsen J (2006) Autonomous intra-row rotor weeding based on GPS. In: CIGR World Congress Agricultural Engineering for a Better World. Bonn, 3–7th September, pp 1–7

Griepentrog H W, Gulhom-Hansen T, Nielsen J (2007) First field results from intra-row rotor weeding. Proceedings of 7th european weed research society workshop on physical and cultural weed control. Salem, Germany

Gruber S, Claupein W (2009) Effect of tillage intensity on weed infestation in organic farming. Soil Tillage Res 105:104–111

Gupta ML, George DL, Norton L (2008) Precision guided mechanical weed control. Proceedings of the 16th Australian Weeds Conference, Brisbane

Hacker E (1984). Untersuchungen zum Einfluß des Lichtes auf den Lebenszyklus der Gemeinen Quecke (*Agropyron repens* (L.) P.B.) vor populationsdynamischem Hintergrund. PhD thesis, University of Stuttgart-Hohenheim, Stuttgart-Hohenheim

Hatcher PE, Melander B (2003) Combining physical, cultural and biological methods: prospects for integrated non-chemical weed management strategies. Weed Res 43:303–322

Jensen RK, Rasmussen J, Melander B (2004) Selectivity of weed harrowing in lupin. Weed Res 44:245–253

Kielhorn A, Dzinaj T, Gelze F et al (2000) Beikrautregulierung in Reihenkulturen – Sensorgesteuerte Querhacke im Mais Zeitschrift für Pflanzenkrankheiten und Pflanzenschutz. Sonderheft XVII:207–215

Kurstjens DAG, Kropff MJ (2001) The impact of uprooting and soil-covering on the effectiveness of weed harrowing. Weed Res 41:211–228

Kurstjens DAG, Perdok UD (2000) The selective soil covering mechanism of weed harrows on sandy soil. Soil Tillage Res 55:193–206

Melander B (2006) Current achievements and future directions of physical weed control in Europe. AFPP 3rd International conference on non-chemical crop protection methods, Lille, 13–15 March. Orgprints. http://orgprints.org/9998. Accessed on 04 January 2009. 49–58

Melander B (1997) Optimization of the adjustment of a vertical axis rotary brush weeder for intra-row weed control in row crops. J Agric Eng Res 68:39–50

Melander B, Rasmussen IA, Bàrberi P (2005) Integrating physical and cultural methods of weed control – examples of European research. Weed Sci 53:369–381

Pallutt B (2002) Maßnahmen zur Unkraut Bekämpfung. In Zwerger P, Ammon HU (ed) Unkraut – Ökologie und Bekämpfung. Eugen Ulmer, Regensburg , pp 105–135

Peigné J, Ball BC, Roger-Estrade J, David C (2007) Is conservation tillage suitable for organic farming? Soil Use Manag 23:129–144

Pekrun C, Claupein W (2004) The effect of stubble tillage and primary tillage on population dynamics of Canada thistle (*Cirsium arvense*) in organic farming. J Plant Dis Prot XIX (special issue):483–490

Peruzzi A, Ginanni M, Fontanelli M et al (2007) Innovative strategies for on-farm weed management in organic carrot. Renew Agric Food Sys 22:246–259

Place GT, Reberg-Horton SC, Burton MG (2009) Effects of preplant and postplant rotary hoe use on weed control, soybean pod position, and soybean yield. Weed Sci 57:290–295

Raffaelli M, Fontanelli M, Frasconi C et al (2009) Physical weed control in protected leaf-beet in Central Italy. In Cloutier D (ed) Proceedings of the 8th EWRS Workshop on Physical and Cultural Weed Control. Zaragoza, pp 69–75

Rasmussen J (1990) Selectivity – an important parameter on establishing the optimum harrowing technique for weed control in growing cereals. In: Proceedings 1990 EWRS Symposium, integrated weed management in cereals, Helsinki, pp 197–204

Rasmussen J (1991) A model for prediction of yield response in weed harrowing. Weed Res 31:401–408

Rasmussen J (1992) Testing harrows for mechanical control of annual weeds in agricultural crops. Weed Res 32:267–274

Rasmussen J, Bibby BM, Schou AP (2008) Investigating the selectivity of weed harrowing with new methods. Weed Res 48:523–532

Rasmussen J, Nielsen HH, Gundersen H (2009) Tolerance and selectivity of cereal species and cultivars to post-emergence weed harrowing. Weed Sci 57:338–345

Rasmussen J, Nørremark M, Bibby BM (2007) Assessment of leaf cover and crop soil cover in weed harrowing research using digital images. Weed Res 47:299–310

Rasmussen J, Svenningsen T (1995). Selective weed harrowing in cereals. Biol Agric Hort 12: 29–46
Rueda-Ayala V, Gerhards R (2009) Selectivity of weed harrowing with sensor technology in cereals in Germany. In: van Henten EJ, Goense D, Lokhorst C (eds) Papers presented at the 7th European Conference on Precision Agriculture'09. Wageningen Academic Publishers, Wageningen, pp 339–348
Schweizer EE, Westra P, Lybecker DW (1992) Controlling weeds in corn (*Zea mays*) rows with an in-row cultivator versus decisions made by a computer model. Weed Sci 42:593–600
Sogaard HT (1998) Automatic control of a finger weeder with respect to the harrowing intensity at varying soil structures. J Agric Eng Res 70:157–163
Steinmann HH (2002) Impact of harrowing on the nitrogen dynamics of plants and soil. Soil Tillage Res 65:53–59
Upadhyaya MK, Blackshaw RE (2007). Non-chemical weed management: Synopsis, integration and the future. In: Upadhyaya MK, Blackshaw RE (eds) Non-chemical weed management: principles, concepts and technology. CABI, Oxford, pp 201–209
Van der Weide RY, Bleeker PO, Machten VTJ et al (2008) Innovation in mechanical weed control in row crops. Weed Res 48:215–224
Vanhala P, Kurstjens DAG, Ascard J et al (2004) Guidelines for physical weed control research: flame weeding, weed harrowing and intra-row cultivation. In: Proceedigns of the 6th EWRS workshop on physical and cultural weed control. Lillehammer. http://orgprints.org/00002445. Accessed 02 January 2008, pp 194–225
Weis M, Gutjahr C, Rueda-Ayala V et al (2008) Precision farming for weed management: techniques. Ges Pflanzen 60:171–18

Chapter 18
Direct Injection Sprayer

Peter Schulze Lammers and Jiri Vondricka

Abstract This chapter describes past and present direct injection systems (DIS). The systems are structured into central (CDIS), boom section (BDIS) and nozzle injection systems (NDIS). A major motivation to develop DIS is to extend the flexibility of applying different pesticides, to advance precision of application, and to enhance the operator comfort and safety. The ultimate goal is to develop a system that works together real-time with detection systems and only treats infested areas. As the injection of pesticides near to the nozzle would be most acceptable technology, further optimisation is required. Based on a response time analysis, a control algorithm is proposed for quicker response of the injection system and new injection valve covering the full range of treatment rates is described. Results of the mixing process are presented as well as the effect of using different supply devices i.e. gear and diaphragm pumps, and air tanks for pesticide injection. In addition, switching of carrier in a DIS to save water and enlarge the capacity of sprayer is discussed along with the aspect of operator safety and tubing system rinsing.

1 Introduction – Direct Injection Systems

Several types of Direct Injection Systems (DIS) have been designed and tested. Amsden (1970) described various methods of direct pesticide injection, including the famous "spray train". Walker and Bansal (1999) defined direct injection as a technique to accomplish variable rate application by spraying the carrier at a predetermined constant flow rate while varying the concentration of the active ingredient on-the-go. Landers (1999) characterised the injection system as a system in which carrier (water) and pesticide are kept in separate containers (Fig. 18.1). When the sprayer is activated, a metered flow of pesticide is injected into the carrier (water) stream at a point situated between the main water tank and the nozzles.

P.S. Lammers (✉)
Institut für Landtechnik, Technology of Crop Farming, D-53115 Bonn, Germany
e-mail: lammers@uni-bonn.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_18,

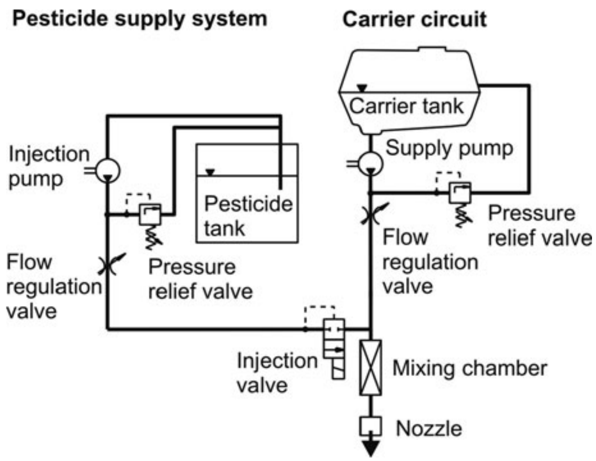

Fig. 18.1 Scheme of a direct injection sprayer

Depending on the injection point, the injection systems are defined as follows:

- Central direct injection system (CDIS)
- Injection in the sprayer boom sections (BDIS)
- Direct nozzle injection system (NDIS)

1.1 Central Direct Injection System (CDIS)

In the CDIS, pesticides are injected into the system downstream from the main water tank and prior to branching of the distribution hoses carrying the solution to different boom sections (Fig. 18.2). The primary disadvantage of the CDIS is the lag time from changes in the flow rate of pesticide into the system to corresponding changes in its concentration at delivery points (Walker and Bansal 1999).

Several systems that have been proposed and launched at agricultural exhibitions which are briefly described on below:

LECHLER SYSTEM (Wichmann 2003) delivers two different pesticides in a range of 0.2–5.0 l ha^{-1}by hydraulically driven piston pumps. This wide range of

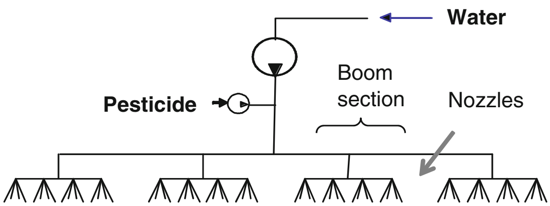

Fig. 18.2 Scheme of a central direct injection system

application rates is provided by different piston sizes and electronically controlled timing. This system is also used to return unused chemicals to their containers and to rinse the tubing system. He solved the problem of dosing discontinuity through development of a two step mixing chamber. In the first step, the pesticide is premixed with small amount of carrier to obtain a continuous flow. In the second step, it is further mixed with the main flow using a static mixer. However, using the same control of dosing can cause problems with mixing and concentration continuity.

DOS-INTRO was a user fitted system using a needle valve for metering the pesticide into the carrier water in front of the boom section valves. The needle valve was motor driven and controlled by a wheel flow meter for adjusting the pesticide flow into a mixing chamber. The pesticide is delivered by a pressure tank supplied by the tractor's air pressure system (Peisl and Estler 1992).

AGROINJECT was the predecessor of the MSR system developed by CIBA GEIGY. The carrier drives hydraulically a dosing pump metering up to four pesticides. By this means the concentration of the pesticides in the carrier is kept constant when the application rate is changing. The MSR system was improved by adjustable orifices of the piston pump able to meter the pesticides in the required range.

SPRAYING SYSTEMS has developed technology for direct injection of pesticides under the Mid-Tech brand. The first system uses a peristaltic pump for dosing and injecting of pesticides, the second system is based on a newly developed piston pump. Both systems are to be combined with a mixing chamber including a static mixer that is 5.08 cm (2″) in diameter.

AMAZONE prepares the injection by mixing the pesticides with water in a container of 10% volume of the carrier tank (Ehlen et al. 2006). This premixing limits the dimensioning of the injection device because adjusting of the pesticide doses is already done by preparing the composition of pesticides diluted with water. As a consequence the injected amount is highly constant. The premixed solution of pesticides is injected into the carrier downstream of the carrier pump in front of the boom section valves. To achieve a homogeneous concentration the system uses a mixing chamber.

Many CDI-Systems have been developed, however no one system is widely used. The main problem of CDIS is caused by the long distance between the injection point and nozzle. It can cause a time delay of more than 20 s, resulting in an application error of more than 100 m on the ground (Koo et al. 1987, Peisl and Estler 1993). Therefore, CDIS is generally not suitable for precision farming.

1.2 Injection in the Sprayer Boom Sections (BDIS)

A boom injection system injects pesticides into the carrier downstream from the branching of the distribution hoses carrying solution to the different boom sections and prior to the branching of boom section hoses carrying solution to different nozzles (Fig. 18.3).

In comparison with CDIS the distance between injection point and nozzle is reduced and the response time also is reduced. The fastest system response times

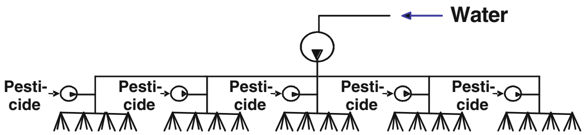

Fig. 18.3 Scheme of pesticide direct injection in sprayer boom sections

measured by Hloben (2007) were less than 4 s, resulting in an application error of less than 20 m on the ground. Such a system is adequate for offline controlled application. Furthermore, BDIS is not as complicated as NDIS (presented in next chapter) and therefore an interesting alternative to direct injection systems.

However, BDI-System is still too slow for real-time controlled application. To reduce the response time the injection point needs to be closer to the nozzle.

1.3 Direct Nozzle Injection System (NDIS)

An alternative to injecting pesticides into the central carrier in the hydraulic system of a field sprayer or in every boom section is to inject the pesticide at each nozzle (Fig. 18.4). Direct nozzle injection has an advantage over boom section injection due to its reduced transport lag time. However, there are problems with the homogeneity of the mixture using direct nozzle injection (Zhu et al. 1998). In boom injection systems, mixing is not a major concern because the pesticide has sufficient time to mix with the carrier before being discharged through the spray nozzles. With direct nozzle injection the time for mixing is significantly reduced (Rockwell and Ayers 1996). An important disadvantage of NDIS is the increase in cost as compared to boom injection due to the equipment required to deliver the pesticide to each nozzle. However, this is the only system setup that will make real-time controlled application practical. For this reason the next chapter deals in more detail with NDIS in order to point out possible means to achieve the required response time.

For comparison of different spraying systems Table 18.1 outlines the mayor characteristics with quality marks. Application flexibility is the weak point of common sprayers as they are only able to spray uniformly over an entire field. This restriction is the motivation behind the development of application systems with more flexibility. Reducing the response time of a direct injection system increases application accuracy and simultaneously reduces time needed for the mixing preparation.

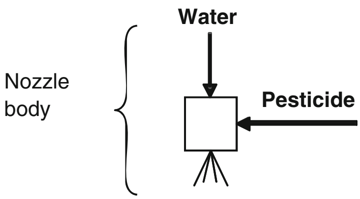

Fig. 18.4 Scheme of a pesticide direct injection in sprayer nozzle

Table 18.1 Comparison of spraying systems application features (CS: common sprayer)

	CS	CDIS	BDIS	NDIS
Application flexibility	--[a]	0	+	++
Response time	++	--	0	++
Mixing quality	++	++	+	0
System costs	++	0	-	--

[a] Impact of factor: ++ very positive; + positive; 0 neutral; - negative; -- very negative.

These counteracting aspects are considered in Table 18.1 as response time and mixture quality. In addition the technical complexity of direct injection systems causes higher costs, which is an important drawback for commercialisation.

2 Direct Nozzle Injection Process

The task of a DIS is to prepare a homogenous mixture of the carrier with the selected pesticide concentration. This is achieved by two independent systems: (1) the injection system, which creates the required concentration of the selected pesticide in the carrier flow, and (2) the mixing chamber, which ensures the mixture homogeneity. The impact of these two stages can be seen in the curve of concentration development after the start of a pulse (Fig. 18.5). The lag time before pesticide appears at the nozzles is caused mainly by the flow delay in the mixing chamber called transport and mixing time (T_{tm}). A small part of the lag time is the time delay (T_{del}) of the injection device. When these two phases have elapsed the concentration increases from zero to full rate, characterised by the concentration increase time (T_c), which depends directly on the design of the injection assembly.

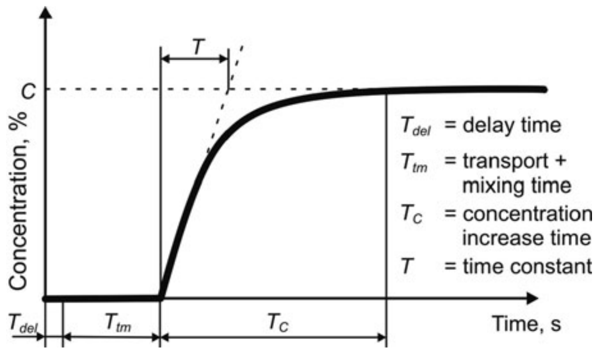

Fig. 18.5 Concentration development in the NDIS after the start of a pulse

2.1 Injection System – Response Characteristic

An injection system is a complex assembly of devices, transporting and adding appropriate quantities of the pesticide from the container directly into the carrier flow. The transport and dosing functions can be provided by two separate devices, a delivery pump and an injection device. They can also be integrated into one dosing pump. Dosing pumps are high precision devices suitable only for systems with a limited number of injection points (e.g. CDIS or BDIS). The NDIS requires injection flow control on every nozzle. The use of dosing pumps on every nozzle is not acceptable in terms of cost. The use of central delivery pump and dosing valves on each nozzle reduces system cost assuming that valve design is not overly complicated.

2.2 DIS Response Time Analysis

The system response time (T_R; Equation 1) consists of the time delay of the injection device (T_{del}), transport and mixing time (T_{tm}), and concentration increase time (T_c).

$$T_R = T_{del} + T_{tm} + T_c \tag{1}$$

The response characteristic of the DIS (concentration *vs.* time) is divided in two parts: (a) injection, and (b) transport and mixing: The injection system injects a metered flow of additive into the carrier. The place where the pesticide meets the carrier is called the injection point (*IP*) (Fig. 18.6). The injected flow should be constant and fast in achieving demanded concentration changes.

The mixing chamber is the area where the carrier and injected fluid are homogenized and transported to the nozzle. The task of the mixing chamber is to create a uniform mixture of all liquids.

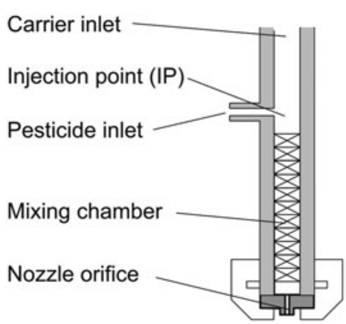

Fig. 18.6 DIS nozzle body cross section

The response delay is called transport and mixing time (T_{tm}). This time delay is caused by transporting and mixing the pesticide flow from the injection point (*IP*) to the nozzle orifice (Fig. 18.5).

The system response time (T_R) is a sum of the injection time (T_{inj}) and the transport and mixing time (T_{tm}) (Equation 2).

$$T_R = T_{inj} + T_{tm} \tag{2}$$

2.2.1 Injection Time

The injection time (T_{inj}) is the response time of injection device and is specified as a sum of the injection device delay and concentration increase time (Equation 3). The time delay (T_{del}) can be characterized as the time after the start of pulse to the first response at the injection point (*IP*).

$$T_{inj} = T_{del} + T_c \tag{3}$$

The time delay (T_{del}) is a constant feature of the injection device (e.g. valve) determined by the device design:

$$T_{del} = const. \tag{4}$$

The concentration increase time (T_c) is the time from the first response of the injection device until reaching the demanded concentration flow. The course of the increase time is an exponential function (Fig. 18.7):

$$Tc = C \cdot (1 - e^{-t/T}) \tag{5}$$

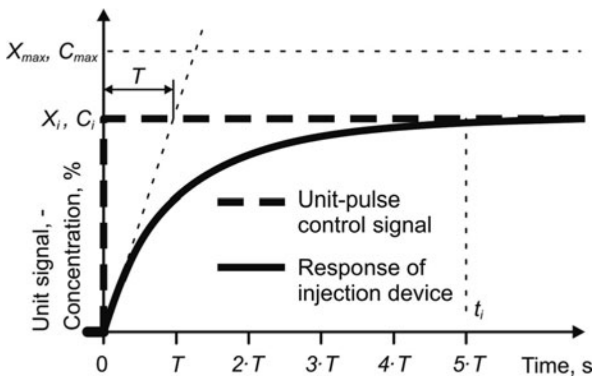

Fig. 18.7 Unit-pulse control signal and first order step response of injection device (Mertz and Jaschek 1993)

where C is the desired concentration [%] and T is a characteristic time constant [s]; as the response on the unit-pulse signal $x(t) = 1(t)$ on the input (Fig. 18.7), commonly used in the automatic control engineering (Merz and Jaschek 1993). This function is characterized by the proportional coefficient C and the time constant T depending on the DIS features. The time constant T is given by the cross points of turn tangent and desired concentration level. This response characteristic, also called "the step response" reaches 98% of concentration final value approximately in time $4 \cdot T$ (Merz and Jaschek 1993).

To reduce the concentration increase time t (Fig. 18.7), the injection process has to be optimised to reach the desired pesticide concentration as fast as possible. Therefore, the unfavourable exponential form of concentration increase shown in Fig. 18.7 has to be optimised by another control process that aims to improve the elasticity of the injection device. (The optimisation of the control process is discussed further in Section 2.2).

2.2.2 Transport and Mixing Time

The transport and mixing time (T_{tm}) is the time delay caused by transport of the injected flow through the mixing chamber up to the nozzle orifice (Fig. 18.6). The transport and mixing time is a dominant part of the response time of CDIS and BDIS. It can be generally calculated from the volume between the injection point and the nozzle orifice, and from the carrier flow rate:

$$T_m = V_m/Q \tag{6}$$

where V_m is the volume [m^3] and Q the carrier flow rate [$m^3\ s^{-1}$]. Consequently, the time delay can be affected by changing the volume of the space between injection point and nozzle orifice when the carrier flow rate is given by the application process. Hence, to reduce the transport and mixing time, the volume between the injection point and nozzle orifice have to be minimized by ensuring desired mixing result.

2.3 Control Process of the Injection System

The easiest way to enhance the reaction of the DIS is through electronic control. The aim is to modify the exponential form of concentration increase into one that enables the target concentration to be reached faster. The finite injection time control algorithm presented in Fig. 18.8 is a system that uses the full potential of a variable control injection device to reach the desired concentration and to stabilise the injected flow afterwards. The injection process occurs in two steps: (I) the injection device starts to inject pesticide at the maximum rate (full control signal), (II) when the required concentration is reached, the signal is reduced and the flow stabilises. If an injection device with sufficient maximum flow is used, the desired concentration can be reached quickly.

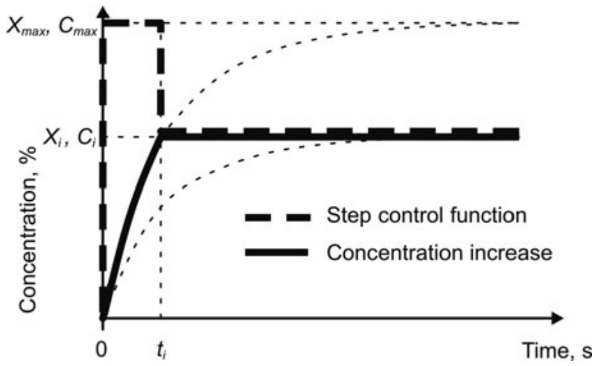

Fig. 18.8 Step control function *x (t)* for finite injection time control and related concentration increase

Applying the finite injection time control process to the valve, the elasticity of the assembly can be described as a linear function by the concentration growth coefficient $c_g[\% \text{ s}^{-1}]$. The higher the coefficient the greater the elasticity of the system and thus the shorter the time of concentration increase. Different injection assemblies were studied to determine the main factors affecting the concentration change speed (Vondricka et al. 2008). As stated above, the speed of the change depends directly on the design of the injection assembly. Three different delivery devices (air pressure tank, diaphragm pump and gear pump) and two different injection pressures (1 and 5 bars) were tested.

Figure 18.9 illustrates the concentration growth coefficient for three delivery devices and two injection pressures. The lowest values of 2–2.3% s^{-1} are generated by the air tank system. The coefficients for the gear and the diaphragm pump are three to four times higher. The relative differences of the growth coefficients between measurements with 1 bar and 5 bar injection pressure for the air

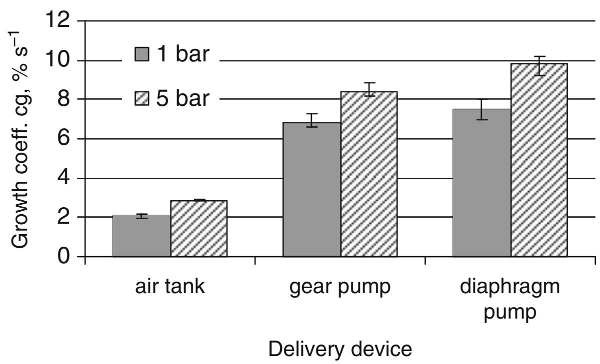

Fig. 18.9 Concentration growth coefficients for different delivery devices and injection pressures (*error bars* represent the scatter between min and max values)

tank, gear pump and diaphragm pump were 0.8, 1.6 and 2.3% s^{-1} respectively. Thus, the injection elasticity increases with more powerful delivery devices, indicating that a powerful pump is more suitable for fast injection systems than an air pressurised tank. However, the main advantage of the air-pressurised tank for the transport of additives is that mechanical elements do not come into contact with the chemicals.

Generally, the higher the available NDIS metered flow the faster the concentration increase. Hence, the injection system has to be designed with a powerful pump and low pressure loss.

2.4 Injection Device

DIS makes high demands on the injection device when used for direct nozzle injection. The device has to be small, reliable, chemical resistant and has to be able to administer a wide range of pesticide doses according to the speed of application. Depending on the dosage and application speed the metered flow rate per nozzle will be in the range from 0.01 to 1.25 ml s^{-1}. To meet these requirements a special injection valve (V 200, German Aerospace Center, Cologne) was developed (Vondricka et al. 2007). This valve (Fig. 18.10) is characterized by high chemical resistance, fast reaction time (< 1 ms) and a wide range of dosing rates. The flows metered by this valve meet the required volumes with both low viscosity and high viscosity liquids.

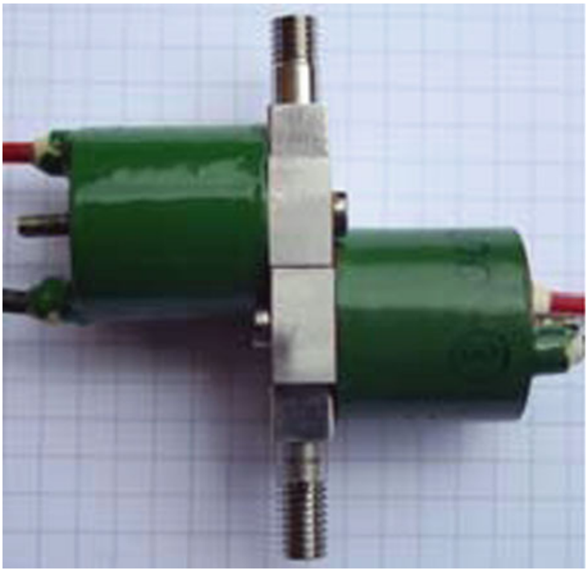

Fig. 18.10 Photograph of the fast reacting injection valve V200 for direct nozzle additive injection

2.5 Homogeneity and Mixing

An effective water-pesticide concentration is needed before the mixture enters the nozzle and before application on to the target area. There are no standards for the homogenisation process in crop sprayers today. The German Federal Biological Research Centre (Julius Kühn Institut) states that "the mixture in the sprayer tank has to have less than a 15% deviation in homogeneity." Though, this only considers the pesticide distribution in the sprayer tank and not in the hoses (Anonymous 2005). For a continuous mixing process, the desired mixture quality is characterized by the coefficient of variation (*CoV*) (Paul et al. 2003):

$$CoV = \sigma/x \tag{7}$$

where σ is the standard deviation of concentration measurements and x is the mean concentration. This function, most often reported in percent, is also often called intensity of mixing or degree of segregation. To define an acceptable coefficient of variation for the direct injection process a typical industrial mixing process could be considered. When applying additives well mixed is defined at 5% *CoV*, whereas in more critical applications, such as addition of colour to an extruded sheet, the product might require 0.5% *CoV* (Paul et al. 2003). The mixing process in the direct injection system for agriculture chemicals should reduce the inhomogeneity in order to achieve effective concentration in the flow cross-section by diluting small clusters of highly concentrated chemicals in the carrier. Søgaard et al. (2006) stated that only 4% of the official label recommendation for glyphosate is effective for highly efficient weed control. Therefore in a direct injection system the 5% *CoV* industry level is sufficient and can be taken as the target for a well mixed homogenous mixture.

The mixing chamber is an additional space between the injection point and nozzle. The time the carrier and pesticide requires to flow through the chamber is called transport and mixing time and depends directly on the volume of this chamber, assuming a constant carrier flow rate (Equation 6). Hence, the volume of this chamber should be small. However, the homogeneity of the mixture has to be ensured under all conditions. Consequently, the mixing process has to be intensified to obtain the best mixture with smaller mixing chamber volume. Static mixers are suitable for mixing under the difficult conditions of NDIS. They are small and highly efficient in continuous mixing processes. Three different static mixers, shown in Table 18.2 have been compared by Computer-Fluid-Dynamics (CFD) software and have been tested experimentally (Vondricka 2008).

Figure 18.11 presents the output mixture homogeneity measured for mixer length 8, 12 and 16 times mixer diameter (L/D). The additive viscosity was 600 mPa s and the concentration set to 0.8, 1.0 and 1.3%. According to the presented results, the extension of the mixer significantly improves the mixture homogeneity, the concentration level and mixing quality.

Table 18.2 Static mixers tested for DIS

Type		Description
KMS		Twisted ribbon or bowtie type, with alternating left- and right-hand twists. Each element has the length of the diameter. (ESSKA, Hamburg, D)
SMX		Several stacked sheets of corrugated metal running at 30° or 45° to the pipe axis. Each element has the length of the diameter and adjacent elements are rotated 90° relative to each other. (Sulzer, Chemtech, Winterthur, CH)
QUADRO		Square-shaped mixer, adjacent elements are rotated 90° relative to each other. One element has 0.75 side size in length. (Sulzer, Chemtech, Winterthur, CH)

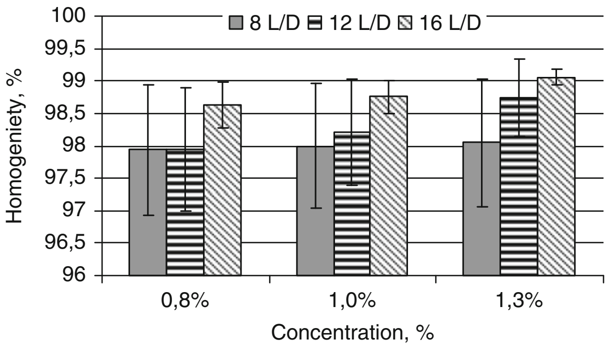

Fig. 18.11 Homogeneity of KMS static mixer for different concentrations, mixer lengths and on additive viscosity: 600 mPa s (error bars represent the scatter between min and max values) (Vondricka 2008)

3 Carrier Saving

To measure the response characteristics of the pesticide direct injection process, a constant carrier flow has been used by Hloben (2007) and Downey et al. (2006). Miller and Watt (1980) studied the effect of carrier switching on spray pattern development. The authors stated that the response time for spray establishment at a distance of 3 cm below the nozzle was 44.7 ms.

The combination of carrier switching and a direct nozzle injection system leads to a potential saving of carrier when switching off over non-infested areas. The efficiency of the crop sprayer increase and therefore the operating cost decrease. The effect of carrier switching on the direct nozzle injection process was studied by Vondricka et al. (2009) using an electro-pneumatic carrier valve. A conventional concentration increase with a constant carrier flow has been recorded as a reference whereby an electro-pneumatic carrier valve was open before the injection

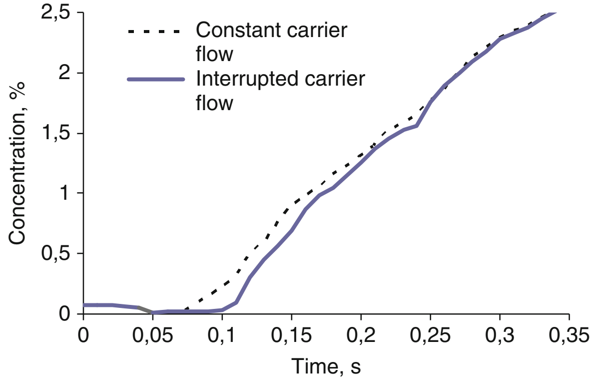

Fig. 18.12 Concentration development at the nozzle orifice after start of control pulse. Comparison of steady carrier flow and electro-pneumatic (EP) valve switched carrier flow

process started. The same injection process with synchronised carrier valve opening where the injection valve and the carrier valve were open at same time, has been measured. The carrier flow was set at 0.02 l s^{-1}. The detected difference in concentration increase was in the early phase only (Fig. 18.12) and the difference in time between the starting points of both processes for the concentration increase was less than 31 ms. The response characteristic showed a faster concentration increase for constant carrier flow in the first 250 ms after the start of the pulse.

The response time of the tested electro-pneumatic valve depended on the operating air pressure. Using an air pressure higher than 4.5 bar (lowest specified pressure) the response of the system was fast and the concentration development was stable in comparison to the injection in a constant carrier flow.

4 DIS Rinsing

Sprayers must be thoroughly cleaned inside and out after use. Pesticide residues left on the outside of the sprayer can cause operator contamination. Residues on the inside of the tank or left-over pesticides trapped inside the sprayer plumbing system can contaminate the operator and possibly lead to crop damage. In some cases, only a small amount of a pesticide remaining in the sprayer can cause significant crop damage (Anonymous 2002a). Crop contamination can even occur several months after a sprayer has been improperly cleaned.

Sprayers can also retain tremendous amounts of pesticide solution. Depending on the size and design of the sprayer, the total tank mix retained in the sprayer ranged from just under 10 l to over 46 l (Anonymous 2002b). The parts that retained the chemical solution are the chemical induction bowl, booms, tank, and the pump and its related piping.

If a premixed solution is used as a carrier in DIS, the whole system has to be cleaned like a conventional sprayer. If clean carrier is used, the premixed solution contaminates only the space between the injection point and the nozzle orifice. This small volume can be easily cleaned by spraying clean carrier. However, there are pesticide supply lines contaminated by high concentrated pesticide on the DIS crop sprayer. Because of relatively large volumes of concentrated chemicals inside the system, the DIS has to be able to reuse the residues within the supply lines at a later time. Thus, all residues have to be sucked back to the pesticide container before rinsing the tubes. Highly concentrated residues inside the tubes can plug the system and even small amounts can cause significant crop damage. Therefore an analysis of rinsing of DIS supply lines is still required to define the requirements on cleaning.

5 Environmental and Operator Protection

One aim of the new DIS development is the reduction of environmental pollution and limiting operator exposure to pesticides. Falber (1993) and Parrymann (1993) reported that refillable containers were successfully used for crop protection products in the US and Canada. Landers (1999) proposed this technology as suitable for the direct injection systems. However, transfer of this technology to Europe has not been overly successful (Falber 1993). The combination of refillable containers and a coupling system makes a positive contribution to on-farm health and safety as follows:

- The container is returned to the supplier for cleaning and refilling, thus danger from on-farm rinsing and removal and the problem of container disposal is eliminated.
- The safety neck in container disables any unauthorised access or farmer exposure.
- The lifetime of the package/coupling system should be up to 25 years and use of bar coding or similar technology provides optimum container traceability.

6 Conclusions

The direct injection systems (DIS) for crop sprayers have been developed to enhance operator safety and comfort and to improve application accuracy and flexibility. DIS is required to improve application techniques in agriculture in the future. The main parts of the DIS are the injection system, which creates the desired concentration of pesticides and the mixing chamber, which homogenises the pesticide-carrier mixture.

The closer the injection point to the nozzle, the faster and more flexible the system. However, higher complexity increases system costs. Central direct injection systems are an alternative to common crop sprayers since these systems enhance operator safety and comfort and decrease environmental side-effects. Systems injecting into the boom section or directly into the nozzle significantly enhance system flexibility and enable site-specific application of pesticides. The real-time controlled application is possible with well-designed direct nozzle injection systems.

References

Amsden RC (1970) The metering and dispersing of granules and liquid concentrates. Br Crop Prot Council Monograph 2:124–129

Anonymous (2002a) Cleaning sprayer after use. Available at: http://nysaes.cornell.edu. Accessed 14 May 2007

Anonymous (2002b) Quantity and location of chemical remnants in crop sprayers. Available at: http://www.hardi-international.com/agronomy/education_material. Accessed 14 May 2007

Anonymous (2005) Richtlinien für Geräteprüfung: Richtlinie für die Rührwerkprüfung (Directive for inspection of crop sprayers: inspection of agitation systems in sprayer tanks). Available at: http://www.bba.de. Accessed 17 January 2007, pp. 2

Downey D, Crowe TG, Giles DK, Slaughter DC (2006) Direct nozzle injection of pesticide concentrate into continuous flow for intermittent spray applications. Trans ASABE 49:865–873

Ehlen V, Marquaring J, Scheufler B (2006) European patent EP 1 749 443 A1.

Felber HU (1993) Closed transfer systems for small volume refillable containers. Proceedings of the ANPO-BCPC – 2nd international symposium on pesticide application techniques, Strasbourg 22–24. September 1993, pp 479–486

Hloben P (2007) Study on the response time of direct injection systems for variable rate application of herbicides. Forschungsbericht Agrartechnik des Arbeitskreises Forschung und Lehre Max-Eyth-Gesellschaft Agrartechnik im VDI (VDI-MEG) No 459, Dissertation, Bonn.

Koo QM, Young SC, Kuhlman DK (1987) Flow characteristics of injected concentrates in spray booms. ASAE Paper No. 87-1602. ASAE, St. Joseph

Landers A (1999) The theory and constituent parts of a direct injection sprayer. Available at: http://www.aben.cornell.edu/extension/pestapp/publications/dir.inj.naac.html. Accessed 27 April 2007

Merz L, Jaschek H (1993) Grundkurs der Regelungstechnik. R Oldenbourg Verlag, München

Miller PCH, Watt BA (1980) The use of a high speed photographic technique to examine the response time characteristics of a solenoid spray valve. J Agric Eng Res 25:217–220

Paul EL, Atiemo-Obeng VA, Kresta SM (2003) Handbook of industrial mixing: science and practice. Wiley, Hoboken

Peisl S, Estler M (1992) Direkteinspeisung von Pflanzenschutzmitteln. Landtechnik 47/3:116–117

Peisl S, Estler M (1993) Direkteinspeisung von Pflanzenschutzmitteln. Landtechnik 48/4: 168–170

Perryman MA (1993) The development and use of a coupling system for small volume refillable containers. Proceedings of the ANPO-BCPC – 2nd international symposium on pesticide application techniques, Strasbourg 22–24. September 1993, pp 487–494

Rockwell AD, Ayers PD (1996) A variable rate, direct nozzle injection field sprayer. Appl Eng Agric 12:531–538

Søgaard HT, Lund I, Graglia E (2006) Real-time application of herbicides in seed lines by computer vision and micro-spray system. ASABE Paper No 061118. ASAE, St. Joseph

Vondricka J (2008) Study on the process of direct nozzle injection for real-time site specific pesticide application. Forschungsbericht Agrartechnik des Arbeitskreises Forschung und Lehre Max-Eyth-Gesellschaft Agrartechnik im VDI (VDI-MEG) N0 465, Dissertation Bonn.

Vondricka J, Hloben P, Schulze Lammers P (2007) Optimization of a direct nozzle injection system for site-specific herbicide Application. ASABE Paper No 71085. ASABE, St. Joseph

Vondricka, J, Schulze Lammers P (2009) Evaluation of carrier control valve for direct nozzle injection system. Biosyst Eng 103: 43–48

Walker JT, Bansal RK (1999) Development and characterization of variable orifice nozzles for spraying agro-chemicals. ASAE Paper No 99-1008. ASAE, St. Joseph

Wichmann WD (2003) German Patent DE 103 53 789 A1

Zhu H; Ozkan HE, Fox RD et al. (1998) Mixture uniformity in supply lines and spray patterns of a laboratory injection sprayer. Appl Eng Agric 14:223–230

Chapter 19
Delivery Optimization for Pesticides

Jürgen Langewald, Helmut Auweter, and Cedric Dieleman

Abstract In the past 15 years spray application technology developed at an incredible pace. In this chapter we describe progress in areas independent of spray equipment that can largely improve the efficacy of pesticide applications and reduce risk to the environment and to human health. The efficacy of foliar application, which is still the predominant pest control method, depends very much on the properties of spray formulations. Not only nozzle types but also formulation adjuvant and solvents can help to optimize droplet size and properties. Encapsulation technologies are described that allow the control of release of active ingredient from a spray formulation after application to the foliage. Pest organisms or diseases often are not evenly distributed across a target crop. Diseased or infested plants can be treated individually, while healthy plants are left untreated through trunk injection. Finally target organisms, particularly insects can be lured to a treated area that is several magnitudes smaller than the area protected, thus reducing the amount of pesticide necessary for effective control.

1 Introduction

The objective of pesticide application is to deliver only those amounts of active ingredients which are necessary to achieve the desired biological effect on the target organisms. Furthermore, economic control must be achieved, and risks to the environment through for instance drift or run-off of plant protection agents must be mitigated (Matthews 1992). Foliar application is still the predominant pesticide application technology, because practical alternatives are often not available. On the basis of data on the global crop protection- and seed treatment market, foliar application can be estimated to cover more than 90% of the crop pesticide treatments (Phillips McDougall 2009, AGROW Report 2006). However, in order for foliar

J. Langewald (✉)
Crop Protection Division, Global Insecticide Research, BASF SE, D-67117 Limburgerhof, Germany
e-mail: juergen.langewald@basf.com

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_19,

sprays to reach the targets, surfaces several magnitudes larger than the target surface need to be treated (Graham–Bryce 1977).

There are several causes why only small portions of the spray liquid might reach the target and contribute to the biological effect. When, for example, the whole area of a crop field is sprayed, many droplets may fall down in-between the foliage (endodrift), especially in the inter-row spaces and may impinge on the soil. Droplets which impact on foliage may also coalesce to such an extent that they cannot be retained, and the surplus liquid may then drip down to lower leaves and thence to the soil. Droplets drifting outside the target area (exodrift) are wasted and might have negative effects on adjacent sensitive ecosystems. Pesticides collected on the target may be washed off later by rain, in some cases even by overhead irrigation. Earlier estimates have suggested that up to 80% of the total pesticides applied to plants may eventually reach the soil (Courshee 1960). Although novel pesticide formulations and current application technologies have improved the grade of application accuracy considerably, there is still potential to further enhance the efficiency of dose transfer to the target.

Generally speaking, the target of foliar pesticide applications is an area occupied by an insect pest, by pathogens or by weeds. Optimizing a dose transfer in terms of percent spray droplets reaching the target organism through improved spray equipment can only be one aspect in optimizing transfer. From a biological point of view, the active ingredients are aiming at molecular targets, at cellular level inside a target organism (Ebert and Downer 2006).

In this chapter we describe examples for ways of improving pesticide applications by adjusting the properties of formulations of the still predominant foliar spray technologies. The range of possibilities is large and multifaceted. On one hand, there are formulation technologies available improving the uptake of active ingredients and their distribution inside the target organism. Such technologies can be more target-specific. Active ingredients can provide greater persistence when protected from sunlight or wash-off through incorporation into the soil or into a bait material, or when they are hidden inside a trap. At the same time, exposure of the environment, of operators or bystanders to the active compounds can be drastically reduced. On the other hand, pesticides can be used much more efficiently when only a fraction of a planted area needs to receive a dose of pesticide. Pesticides can be physically placed with much more precision and closer to the target organism through technologies like seed treatment or target plant injections, or in the case of insect pest control by taking advantage of insect behaviour.

2 Improving the Efficacy of Foliar Sprays of Herbicides, Fungicides, and Insecticides

A successful modern pesticide formulation must provide ample environmental protection and precision delivery of the active ingredient to the target species. Among the existing application methods, foliar sprays are one of the most challenging application technologies available. Many factors – some formulation related – play an important role in determining whether the pesticide application will be successful: (I) location of pests and/or diseases on the crop; (II) water volume and quality; (III) tank-mix partners and adjuvants; (IV) spray equipment (nozzles, spray boom and pattern); (V) weather conditions (sun, rain, wind). All these factors, when properly managed help maximize product coverage on the leaf resulting in enhanced biological performance and reduced off-target effects.

Formulation can be used as a complementary tool to the machinery tools to minimize the impact of the factors mentioned above. Each formulation is composed of a blend of one or more active ingredients and several inert materials. The composition is optimized for stability, biological activity, and application characteristics. Specific additives are developed and incorporated into pesticide formulation to reduce potential drift and to enhance the biological performance through maximizing leaf surface coverage while avoiding run-off and environmental contamination. In addition, additives can reduce the speed of photodegradation of the active ingredients and increase rainfastness for a better persistence of the active ingredient on the leave surface.

2.1 Optimizing Chemical and Physical Properties of Spray Formulations

The major objectives of optimizing the physical-chemical properties of spray formulations are to minimize spray drift, to achieve good spray retention and foliar coverage, and to optimize the uptake of active ingredient(s) into plant tissues. This holds true for post-emergence herbicides, for curative fungicides, and for systemic insecticides. Spray drift, spray retention and deposition are directly related to droplet size. Unfortunately, the optimum size for reduced drift is not the same as for optimal deposition. Large droplets (well above 100 μm in diameter) are desired for reducing spray drift. However, large droplets have a high tendency to bounce off leaves at first contact, reducing product deposition. Small droplets are desired for high adhesion on leave surfaces, for extensive leaf coverage and for good biological performance, but are carried away by the wind more easily. Optimizing physical-chemical properties of spray formulations carefully will circumvent these problems.

First, the process of droplet formation at the spray nozzle outlet has to be considered. The atomization process is primarily controlled by the nozzle type. There are drift-reducing air induction nozzles producing coarse droplets, which are able to reduce spray drift by 99%. However, surface-active additives will also have some effect on droplet formation. Hydrophilic surfactants may decrease droplet size, whereas properly chosen polymers and lipophilic surfactants may increase droplet size.

Large, drift-reducing droplets have a high kinetic energy which either leads to quasi-elastic bouncing off the leaves or to splashing. The challenge is to modify the physical-chemical properties of the large droplets such that they stick to the leaves. Further, the surface tension must be adjusted to the leaf surface properties of a specific crop to allow perfect wetting and spreading. The desired formulation properties are obtained by using additives that lower the surface tension during the very short moment of impact (few milliseconds). The dissipation of excess kinetic energy of large droplets is best achieved by applying combinations of surfactants and oils or solvents, or by applying functional polymers which work through transient viscosity effects caused by polymer entanglement (Bergeron 2003).

Finally, uptake of active ingredients into leaves can be enhanced by lipophilic adjuvants. These "accelerator" molecules increase the permeability of active ingredients into the plant cuticle. Recent investigations have shown that the mechanism of uptake enhancement by accelerator molecules is due to a plasticizing effect of the plant cuticle (Schreiber and Schönherr 2009). Thus recent advances in formulation optimization by means of well-designed adjuvants and polymers can overcome contradictory requirements for spray droplet size distributions, leading to highly targeted and superior performing pesticide formulations.

2.2 Encapsulation and Controlled Release Technologies

Encapsulation is an effective way of combining one or several active substances in a capsule and controlling the release of the contents until they are required. Although there are standard types of encapsulation technologies available, it remains a challenge to develop an encapsulation solution for specific products and/or applications.

Many factors are prohibiting the development of such capsules: active ingredient's physical and chemical properties, application method, or target selectivity. The main drivers for encapsulation technologies are: protection of active ingredient from environmental degradation, extended activity, reduced toxicity, reduced phytotoxicity, and reduced leaching and persistence in the environment.

The controlled release of an active ingredient can be successfully achieved by using different capsule systems, like a polymer shell or polymer matrix (cage) functioning as a reservoir for the active ingredient (Fig. 19.1).

The release of active ingredient into the environment can be characterized as follows:

- Slow or fast release; the capsule releases its content over a defined period of time
- Quick release; the capsule shell breaks upon dilution or contact with a surface

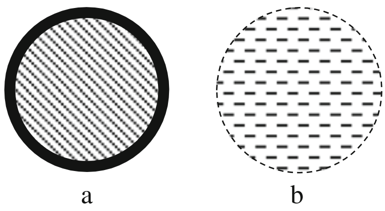

Fig. 19.1 Types of encapsulation for the formulation of active ingredients of pesticides. Core shell encasing active compound (**a**). Polymer matrix or cage with absorbed active compound (**b**)

- Moisture release: the capsule is designed to break down and releases its contents in the presence of water
- Heat-release: the shell releases ingredients only when the environment warms above a certain temperature
- pH release: the capsule breaks up only in a specific acid or alkaline environment
- Release due to degradation of the film (biological or chemically assisted degradation).

The release properties can be controlled through adjustments like the crystallinity of the active ingredient, the polymer cross-linking properties, by using fillers and different solvents or oils. Physical properties like the capsules size, wall thickness can be adjusted. Finally, multiple capsule layers with different properties may be combined. Capsule sizes usually range from 2 to 10 μm; nanocapsules are smaller (200–800 nm).

Through encapsulation, unstable active ingredients can be formulated into stable formulations. In addition, two or more actives can be combined inside a polymer case and even delivered to the plant at different times to provide greater protection against a broad spectrum of pests or diseases.

A number of technologies exist to make capsules, but the main method used is to emulsify the active ingredients in water, either alone or together with oil or an organic solvent which is immiscible in water. A capsule is then made around the droplets of the emulsion by using specific monomers which react and bind together to form a polymer wall. By doing this the active ingredient is contained within an oil droplet surrounded by a polymer shell or cage.

Encapsulation technology is an essential part of the toolbox available to the farmer in order to reduce the environmental impact of pesticides, but also in ensuring that the active ingredient is delivered safely and consistently to the crop or pests that it is targeting.

2.3 Moving Closer to the Target: Plant Injections

Trunk injection is a technology, whose efficacy is gained through applying products closer to the target. Systemic herbicides, fungicides or insecticides and also liquid fertilizers can be applied this way. Regardless of the treatment application, the pesticide is dispersed through the tree's vascular system. For the pesticide to become systemically active, access to the xylem needs to be provided through drilling or cutting a hole into the sap wood of a tree trunk and applying pesticide concentrate into the cavity. Obviously, such application methods require target plants of a certain size.

In Malaysia, a very simple method is used for injecting fertilizer into oil palm (*Elaeis guineensis*) trees. A power drill is used to drill a hole into the palm tree trunk. Then a PVC tube is inserted and liquid fertilizer applied into the tube using a knap sack sprayer. Other types of macro-injections are usually fed from one common product holding container and a system of tubing with injector ends that are attached at intervals around the tree. Some methods of macro-injection require excavation at the trunk-soil interface to expose roots allowing access to this preferred injection site. Macro-injection is defined by the hole diameter being greater than 1.5 cm. Required application volumes can reach several litres.

More sophisticated micro-injection makes use of individual pre-measured dosage capsules, normally spaced at 15 cm intervals around a tree trunk. These capsules are inserted into drilled holes smaller than 1.5 cm diameter and contain less than 10 ml of formulated pesticide.

Pesticides can be injected into trunks under pressure. Low pressure systems are operating with less than 0.5 bar. Chemjet® Injector (Chemjet® Trading Pty Ltd, Bongaree Qld, Australia) works like a syringe the chemical is drawn into the chamber of the injector in 10, 15 or 20 ml quantities. In most cases there is just enough pressure to drain the container. The speed of uptake by the tree depends on soil moisture, temperature, wind speed, time of year, and tree species. High pressure is typical of macro-injected methods. Large volumes of formulation are moved into a tree very quickly (Arborjet VIPER, Arborjet Revolutionary Plant Health Solution, Woburn MA, USA). Some devices are a combination of a power drill and an injection pump (Sidewinder®, Sidewinder Pty Ltd, Noosaville, Australia).

The choice of equipment will depend upon an individual tree species, size, location, and specific problem. With all of the various injection methodologies available today, there are now products available for just about any insect, disease or mineral problem encountered in trees (Shaw and Cortese 2005).

In case of herbicide applications however, also smaller plants like invasive non-native Japanese knotweed (*Fallopia japonica*), giant hogweed (*Heracleum mantegazzianum*), Canada thistle (*Cirsium arvense*) or Himalayan balsam (*Impatiens glandulifera*) can be controlled using herbicidal stem injections. The stem injection system delivers a given dose of concentrate herbicide into the centre of the plant. The weed will also absorb the concentrate into its rhizome at a much faster rate than with foliar spraying, providing faster control than foliar sprays. Hypo-Hatchet® Tree Injector (Forestry Suppliers Inc., Jackson, MS, USA) is a modified hatch with a blade that fuels 1–2 ml of any amine herbicide into a wound of a tree applied through its use. It can be used to control trees with a diameter greater than 15 cm. In the southern US, Hypo-Hatchet is used to remove unwanted hardwood trees like red maple, white oak, hickory and common privet form pine plantations (Kossuth et al. 1980).

For the application of fungicides and insecticides tree injections have to be carried out more carefully, since the aim of the application is to protect the plant. The hole drilled into the trunk usually needs to be sealed carefully with a fungicidal material to prevent infection of the wound by plant pathogens.

Elms can be protected from Dutch elm disease by routine, preventive fungicide injections. This technique is more effective than therapeutic injection. Several different injection methods are currently being used. The most widely used method involves injecting a fungicide diluted in water (20–150 l). For prevention of Dutch elm disease, shallow-pit injection under pressure of fungicide is superior to other methods because it selectively injects the fungicide into the tissue layer attacked by the fungus. In contrast, conventional injections, commonly 10 cm deep, place much of the fluid into non-conducting xylem (Holmes 1982). Annual injections in June protected against infections for the duration of the year, as well as infections during spring of the following year (Rhairl and Ellmore 1984).

Fungicide injections can also be applied for treatment like sudden oak death (*Phytophthora ramorum*) in oaks (*Quercus* spp.) and tanoaks (*Lithocarpus densiflorus*). Two application methods are currently available. Injections use usually about 10–80 ml, to treat a tree. In northern California two applications per year are recommended, one treatment in November or December and a second treatment 6 months later. As for Duch elm disease, preventative treatments, before infection, are more effective than curative treatments. At least 4 weeks are necessary for the applied chemical to take full effect (Garbelotto et al. 2007).

The Asian longhorned beetle *Anoplophora glabripennis* (Motschulsky) is subject of a high-profile USDA eradication program since 2001. This pest is very common in maple, elm and ash trees. It tunnels through tree stems and branches, causing dieback and eventually death. In spring 2008, the US Department of Agriculture's Animal and Plant Health Inspection Service (USDA-APHIS) treated 77,688 trees susceptible to the beetle with insecticide in New York and New Jersey. This pest is potentially one of the most destructive and costly invasive species to enter the United States. Removal and destruction of infested host trees are expensive. Therefore, in addition to cutting and removal of infested trees, the Asian longhorned beetle cooperative eradication program also employs chemical methods such as tree injections. Such treatments are part of an effort to prevent further infestation of this invasive insect and reduce beetle populations (USDA-APHIS 2008).

The emerald ash borer *Agrilus planipennis* (Fairmaire) is a pest in ash trees (*Fraxinus* spp.). It has probably arrived in the United States through commercial trade, in much the same way as the Asian longhorned beetle. This pest has already wiped out millions of trees since its discovery in Michigan in 2002. Infestations have spread to parts of Ohio, Indiana, Illinois, Maryland and Pennsylvania, creating widespread devastation throughout parks and entire neighbourhoods. Similar control methods to those of the Asian longhorned beetle program are effective at preventing new infestations from wood products imported from China. They should be similarly effective against the emerald ash borer. Field tests conducted in China indicate that the chemical treatments including tree injections are suitable for cost-effective control of the beetle in the United States. USDA-APHIS proposed an emergency eradication program in the lower Michigan peninsula (Cappaert et al. 2005).

Another exotic forest pest originating from Japan, the hemlock woolly adelgid *Adelges tsugae* (Annand) was first discovered in western North America in 1924. This pest killed hemlocks from New England to Georgia, in the Appalachians, and in urban areas as well. Adelgid feeding disrupts the normal flow of fluids in trees. Twigs and branches die quickly, and trees can die in as little as 2 years. This insect pest attacks both eastern (Canadian) and Carolina hemlock. Hemlock woolly adelgid is now established from north-eastern Georgia to south-eastern Maine and as far west as eastern Kentucky and Tennessee. Microinjection of insecticide shows promise in reducing hemlock woolly adelgid population densities in affected trees (Doccola et al. 2005).

Approximately 10 years ago, in parts of Europe the leafminer *Cameraria ohridella* Deschka and Dimic (Lepidoptera: Gracillariidae) became established in the horse chestnut trees. Single systemic tree injection treatments with neonicotinic insecticides during May, immediately after blossom, are an effective control tool. The number of mines on the treated plants decreases significantly. Generally, the infestation can be reduced by up to 80% (Ferracini and Alma 2008).

2.4 Turning the Tables: Luring Targets Toward the Site of Application

Unlike plants and plant pathogens, insects can actively move within their environment. In addition, sensory organs allow insects to carry out targeted movements in response to acoustical, visual, or chemical signals. In other terms, insect behaviour can be manipulated using traps or baits, luring the pest organism towards a device that renders it innocuous. Trapping and baiting can reduce the amount of pesticide applied per hectare by several orders of magnitude and reduce environmental and bystander exposure, particularly if the active ingredient is enclosed into a little container. Depending on the specificity of the attractive stimulus provided, traps can be highly species-specific devices, reducing non-target effects to a minimum. Mass trapping has high potential for the suppression or eradication of low-density, isolated pest populations (El-Sayed et al. 2006). In many cases lures or traps might not be efficient enough to control insect pest populations, though they can be used as population monitoring devices, allowing a more efficient use of insecticide.

Acoustic signals, particularly mating calls, are common means of communication between conspecific insects. It was, for instance, demonstrated that female Mediterranean fruit flies were attracted to sites near speakers emitting male fruit fly calling song and synthetic sound more than to sites without sound (Mizrach et al. 2005).

Visual stimuli are more commonly used for insect control. Female tsetse fly (*Glossina* spp.) is a vector of the sleeping disease in cattle and humans. Its host finding is influenced by visual keys like shape, orientation, brightness, contrast movement and colour. Biconical black insecticide coated traps have been developed for tsetse fly control (Colvin and Gibson 1992). But the addition of chemical stimuli like acetone and CO_2, increases the attractiveness of such traps significantly (Vale et al. 1988).

Yellow sticky traps are a popular tool for integrated pest management of greenhouse pests like *Trialeurodes vaporariorum* Westwood (Gillespie and Quiring 1987). They are particularly popular for the control of different species of Tephritidae (fruit flies) in non-commercial small holder orchards. The visual signal, however, is usually not sufficient for fruit fly control and needs to be combined with chemical attractants (Foster and Harris 1997). In addition, yellow sticky traps can be more attractive for beneficials than for the target fruit fly species, causing more harm than benefit (Neuenschwander 1982).

Mediterranean fruit fly (*Ceratitis capitata* Wiedemann) is the most serious Tephritid pest. Many trapping and baiting methods have been developed for its control or monitoring. Mediterranean fruit flies are attracted by visual and chemical stimuli. Yellow reflecting between 500 and 580 nm is highly attractive. International Pheromone McPhail plastic traps combine the colour yellow with the shape of a fruit. In addition, chemical stimuli are needed for trapping programs to become sufficiently effective for fruit fly control. The female fruit fly requires a source of protein for the maturation of her eggs (Gazit et al. 1998).

In the past, most trapping systems made use of fermenting sugars and protein hydrolysates. Recently it was demonstrated that McPhail traps in combination with dry food based synthetic lures based on ammonium acetate, putrescine and trimethylamine, are very efficient (Epsky et al. 1999). While food based lures are attractive to both, female and male fruit flies, baited, male-targeted trapping systems are often preferred because they are more *C. capitata* specific and attract flies over a greater distance. These baits may contain trimedlure or ceralure parapheromone (synthetic compounds, closely related to the natural pheromones) (Jang et al. 2001). A close relative of the Mediterranean fruit fly, the olive fly *Bactrocera oleae* (Gmelin) can be controlled using a very similar system, based on the female sex pheromone (1,7-dioxaspiro[5.5]undecane; Speranza et al. 2004).

More efficient and less expensive than mass trapping are spot sprays with a foliar bait combining a source of protein and sugar with an insecticide attractive for male and female flies. The bait is usually applied in the morning hours as a spot application in the middle of the trees. Many serious infestations of Mediterranean fruit fly were eradicated successfully in the Southern US, using bait spray mixtures applied by ground and/or air (Burns et al. 2001).

Most semiochemical (compounds playing a role in chemical communication) based attract and kill approaches are based on purely chemical stimuli, involving the combination of a semiochemical's lure with an insecticidal effector (Howse et al., 1998). Examples for the application of such baiting strategies are numerous, particularly in the non-crop area for instance in ant control (Silverman and Brightwell 2008) and in the control of cockroaches (Appel and Smith 2002). Outside the non-crop area, semiochemicals are popular in pest control in orchards. In addition to the Mediterranean and the olive fruit fly, "attract and kill" systems based on female sex pheromones have also been developed for codling moth control (*Cydia pomonella* L.; Charmillot et al. 2000).

Malaria control with insecticide treated bed nets can be regarded as "attract and kill" technology, too. In this particular case, the "bait" and the "organism to be protected", a person sleeping under the bed net, are identical. The bed net concept can be considered as a mass trapping strategy and coverage of a high percentage of members of malaria-endemic communities is necessary to provide effective protection from malaria infections (Curtis et al. 2006). Especially long-lasting bed nets in which insecticide is incorporated into the net fibres provide a simple but effective means of preventing malaria (Greenwood et al. 2005).

3 Conclusions

In this book chapter we presented only a small number of examples of how pesticide applications can be optimized to strongly reduce environmental and health risk exposure through means that are independent of spray application technology. Technologies which were not covered here like seed treatments or drip application of fungicides and insecticides are well described elsewhere (Biddle 2009; Lamm et al. 2006). We hope this digression from the main focus of the present book might help to develop a holistic view on pesticide application.

References

AGROW (2006) Seed treatments: trends and opportunities. AGROW Reports, London. 175p

Appel AG, Smith LM (2002) Biology and management of the smokeybrown cockroach. Annu Rev Entomol 47:33–55

Bergeron V (2003) Designing intelligent fluids for controlling spray applications. Comp Rendus Physique 4:211–219

Biddle AJ (ed.) (2009) Seed production and seed treatment in a changing environment. Symposium Proceedings No. 83: BCPC Publications, Alton, Hampshire, 138p

Burns RE, Harris DL, Noreno DS, Eger JE (2001) Efficacy of spinosad bait sprays to control Mediterranean and Caribbean fruit flies (Diptera. Tephritidae) in commercial citrus in Florida. Florida Entomol 84:672–678

Cappaert D, McCullough DG, Poland TM, Siegert NW (2005) Emerald ashborer in North America: a research and regulatory challenge. American Entomol 51:152–165

Charmillot PJ, Hofer D, Pasquier D (2000) Attract and kill: a new method for control of the codling moth *Cydia pomonella*. Entomol Exp Appl 94:211–216

Colvin J, Gibson G (1992). Host-seeking behavior and management of tsetse. Annu Rev Entomol 37:21–40

Courshee RJ (1960) Some aspects of the application of insecticides. Annu Rev Entomol 5:327–352

Curtis CF, Maxwell CA, Magesa SM, Rwegoshora RT, Wilkes TJ (2006) Insecticide-treated bed-nets for malaria mosquito control. J American Mosquito Contr Assoc 22:501–506

Doccola JJ, Ramasamy I, Castillo P, Taylor C, Sifleet S (2005) Efficacy of Arborjet VIPER microinjections in the management of hemlock woolly adelgid (*Adelges tsugae*). J Arboricul 31:203–206

Ebert TA, Downer RA (2006) A different look at experiments on pesticide distribution. Crop Prot 25:299–309

El-Sayed AM, Suckling DM, Wearing CH, Byers JA (2006) Potential of mass trapping for long-term pest management and eradication of invasive species. J Econ Entomol 99:1550–64

Epsky ND, Hendrichs J, Katsoyannos BI, Vásquez LA, Ros JP, Zümreo A, Pereira R, Bakri A, Seewooruthun SI, Heath RR (1999) Field evaluation of female-targeted trapping systems for *Ceratitis capitata* (Diptera: Tephritidae) in seven countries. J Econ Entomol 92:156–164

Ferracini C, Alma A (2008) How to preserve horse chestnut trees from *Cameraria ohridella* in the urban environment. Crop Prot 27:1251–1255

Foster SP, Harris MO (1997) Behavioural manipulation methods for insect pest management. Annu Rev Entomol 42:123–146

Garbelotto M, Schmidt DJ, Harnik TY (2007) Phosphite injections and bark application of phosphite + pentrabark control sudden oak death in coast live oak. Arboricul Urban Forestry 33:8

Gazit Y, Rossler Y, Epsky N, Heatu RR (1998) Trapping females of the Mediterranean fruit fly (Diptera: Tephritidae) in Israel: comparison of lures and trap type. J Econ Entomol 91: 1355–1359

Gillespie DR, Quiring DJM (1987) Yellow sticky traps for detecting and monitoring greenhouse whitefly (Homoptera: Aleyrodidae) adults on greenhouse tomato crops. J Econ Entomol 80:675–79

Graham-Bryce, IJ (1977) Crop protection: a consideration of the effectiveness and disadvantages of current methods and of the scope for improvement. Phil Trans Rl Soc London B 281:163–179

Greenwood BM, Bojang K, Whitty CJ, Targett GA (2005) Malaria. Lancet. 365(9469):1487–1498

Holmes FW 1982. Distribution of dye in elms after trunk or root injection. J Arboricul 8:250–252

Howse P, Stevens I, Jones O (1998) Insect pheromones and their use in pest management. Chapman and Hall, London

Jang E B, Raw AS, Carvalho LA (2001) Field attraction of Mediterranean fruit fly*, Ceratitis capitata* (Wiedemann) to synthetic stereoselective enantiomers of the ceralure B1 isomer. J Chem Ecol 27:235–242

Kossuth SV, Young JF, Voeller JE, Holt HA (1980) Year-round hardwood control using the hypohatchet injector. Southern J Appl Forestry 4:73–76

Lamm FR, Ayars JE, Nakayama FS (2006) Microirrigation for crop production: design, operation and management. Elsevier, Amsterdam, 642p

Matthews GA (1992) Pesticide Application Methods. Longman Scientific and Technical, New York

McDougall P (2009) Industry overview. Pathhead, Midlothian, 28p

Mizrach A, Hetzroni A, Mazor M, et al. (2005) Acoustic trap for female Mediterranean fruit flies. Trans ASAE 48:2017–2022

Neuenschwander, P (1982) Beneficial insects caught by yellow traps used in mass-trapping of the olive fly, *Dacus oleae*. Entomol Exp Appl 32:286–296

Rhairl WE , Ellmore GS (1984) Improved trunk injection for control of Dutch elm disease. J Arboricul 10:273–278

Schreiber L, Schönherr J (2009) Water and solute permeability of plant cuticles. Springer, Berlin Heidelberg

Shaw C, Cortese WJ (2005) Systemic trunk injections: safe, easy, profitable. Landscape Irrig 29:34

Silverman J, Brightwell RJ (2008) The Argentine ant: challenges in managing an invasive unicolonial pest. Annu Rev Entomol 53:231–252

Speranza S, Bellocchi G, Pucci C (2004) IPM trials on attract-and-kill mixtures against the olive fly *Bactrocera oleae* (Diptera Tephritidae). Bull Insectol 57:111–115

USDA-APHIS Plant Protection and Quarantine (2008) Asian Longhorned Beetle – New Pest Response Guidelines (Revised Aug 2008)

Vale GA, Lovemore DF, Flint S, Cockbill GF (1988) Odour-baited targets to control tsetse flies, *Glossina* spp. (Diptera: Glossinidae), in Zimbabwe. Bull Entomol Res 78:31–49

Chapter 20
Autonomous Systems for Plant Protection

Hans W. Griepentrog, Arno Ruckelshausen, Rasmus N. Jørgensen, and Ivar Lund

Abstract Advances in automation are demanded by the market mainly as a response to high labor costs. Robotic outdoor systems are ready to allow not only economically viable operations but also increased efficiency in agriculture, horticulture and forestry. The aim of this chapter is to give examples of autonomous operations related to crop protection probably commercially available in the near future. Scouting and monitoring together with the efficient application of chemicals or mechanical treatments are operations which can be successful automated. Drawbacks are that current systems are lacking robust and safe behaviors. In general the potential of saving e.g. of herbicides are huge when high precision targeting based on individual weed plant detections is used.

1 Introduction

In industrialized countries advances in automation are demanded by the market mainly as a response to high labor costs. Developments in hardware and software systems are ready to be modified and implemented in robotic outdoor systems to allow not only economically viable operations but also increased efficiency in agriculture, horticulture and forestry. Furthermore, negative impacts on the environment will be reduced and a higher quality of products will be achieved by more effective and efficient use of management inputs. Due to minimized exposure time of humans to dust, noise and pesticide the working conditions will improve and reduce health risks.

H.W. Griepentrog (✉)
Department of Agriculture and Ecology, Faculty of Life Sciences, University of Copenhagen, DK-2630 Taastrup, Denmark
e-mail: hwg@life.ku.dk

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_20,

Unmanned, supervised, small machines in semi-public agricultural or horticultural areas will be common in the foreseeable future. The considerable complexity of semi-natural outdoor environments found in agriculture and horticulture and of the mobile robot itself, result in substantial challenges to achieve acceptable performance under unmanned and/or unattended operation.

A mobile robot operating in semi-natural environments like fields, orchards or plantations must cope with a high degree of diversity. The machine must be 'aware' of its close environment to carry out operations efficiently and also to avoid collisions with other objects that could damage the machine and other objects (infrastructure, plants, humans and animals). To meet these performance goals automated perception capabilities are required, and the robot must react promptly and appropriately when unexpected objects are detected or when faults of various severity do occur. A main direction of outdoor robot research is on the development of agent-based architectures suitable for unmanned, possibly unattended, but still supervised systems (Granot 2002).

A number of highly automated machine prototypes exist for outdoor applications mainly at research institutions (Garcia-Alegre et al. 2001, Aastrand and Baerveldt 2002, Pilarski et al. 2002, Zeitzew 2007, Sorensen et al. 2007, van Evert et al. 2007, Griepentrog and Blackmore 2007).

The aim of this chapter is to give examples of autonomous operations related to crop protection which are having these or similar features probably commercially available in the near future. The described machines can be categorized as mobile outdoor robots. Other terms are synonymously used as e.g. autonomous operations, automatic vehicles or unmanned machines.

2 Scouting and Monitoring

2.1 Requirements and State-of-the-Art

Timely and accurate information about the growing crop is a requirement for optimizing crop management. The availability of quantified data is often expensive due to labor intensity of sampling efforts. Scouting robots promise to be less expensive and timelier. An automated system carrying advanced sensors could continuously monitor the crop canopy for later crop status analysis. Due to the task complexity so far no field scouting robot platform is commercially available.

Much effort in mobile robotics has already been focused on Simultaneous Localisation And Mapping (SLAM) of objects, used when a mobile robot collects perceptual information and constructs or updates a local map while navigating.

Advanced actuator-based robots for particular operations have the highest control complexity and expect to have lowest reliability and robustness. This has led to early visions for first applications of robots in agriculture in terms of scouting and monitoring. The concept is already more than 25 years old (Krutz 1984). Georeferenced data from scouting roots can be used for vehicle navigation purposes

(SLAM), but also for optimizing crop management and for decreasing sampling costs for further data logging. Due to progress in Information and Communication Technologies (ICT) the idea of a robotic field scout has recently been implemented in future concepts of agricultural mechanization (Blackmore et al. 2007, Grift et al. 2008).

Especially when Precision Farming principles shall be considered spatial and temporal monitoring is necessary for minimizing negative environmental impacts and increasing economic returns.

The main tasks for a scouting robot are:

- Exploring terrain: Logging and mapping of data of an unknown field as boundary, elevation, topography, soil properties, crop and non-crop plant occurrence, plant density and structure
- Targeted sampling: Monitoring crop growth status and stress at predefined locations during field experiments for breeding purposes (plant phenotyping) as crop characteristics, leaf area index (LAI), crop height, growth stage, biomass, crop nutrient status, weeds, diseases, pests etc.

A field scouting mission focuses on sensing and data logging including some basic data analysis. The mechanical design of a vehicle is mainly defined by its application. For example if the height of crop plants should be measured, the clearance of the robot could be adaptable during the growth stages. In a field scout typically several sensors for robot navigation as well as for monitoring of agro-information from plants, soil and environment are implemented. Moreover, positioning information from GPS or landmarks and further a-priori information such as crop row width can support the navigation and monitoring operation.

First experimental platforms for monitoring use image processing as major sensor information. Examples are the vision-based detection of potato in corn crops using a low-cost robotic platform (Van Evert et al. 2007) or the location of crops and weeds using a camera and GPS for geo-referencing (Bak and Jakobsen 2004). Astand and Baerveldt (2002) as well as Klose et al. (2008) have combined crop/weed detection with the direct control of an implemented weed control actuator. Sensor fusion based on a Camcorder, GPS and laser scanner has been applied to measure growth stages in crop rows (Nagasaka et al. 2004). Iidia et al (2008) have developed a hexapod robot with an implemented gas sensor for detecting CO_2 sources in agricultural fields.

System architecture, sensor and data fusion algorithms as well as data handling are important aspects for the development of a field scout. For the robot navigation real-time information has to be supplied, while for the monitoring information a complete and traceable storage of a large amount of data has the priority. These aspects are relevant for the concept of the system architecture, data handling processes and interpretation of measurement data (Mitchell 2007, Siciliano and Khatib 2008, Noack et al. 2006, Jorgensen et al. 2007b).

2.2 The Scouting Robot 'BoniRob'

In order to be able to support breeding processes the characterization of the crop status at different growth stages is a target parameter. As compared to the state-of-the-art phenotyping of plants based on sampling methods in field trials (Thomas 2006), a crop scout would be a fundamental step towards an automatic data generation for all individual plants (Ruckelshausen 2007, Jorgensen et al. 2007b).

The interdisciplinary project BoniRob (Ruckelshausen et al. 2009) is focusing on the development of an autonomous field scout for plant phenotyping of maize (*Zea mays*) in growth stages based on the Extended BBCH scale as described by Meier and Bleiholder (2007). Plant parameters are the crop density, spacing, height, steam thickness, spectral reflection (VIS/NIR), ground coverage or biomass. The plant characterization concept is based on a multisensory concept for intra-row crop/weed detection in maize fields (Ruckelshausen et al. 1999) with improved sensor technologies (CCD imaging, VIS/NIR spectral imaging, 3D time-of-flight cameras, light curtains and distance sensors). The internal system documentation (control units, sensors, documentation, user interface) is based on Ethernet and thus allows a real-time implementation at high data rates. Sensor data for the navigation are necessarily treated in real-time, some other data are less time critical and are stored for off-line plant phenotyping.

In order to correlate the data of different growth stages to each individual plant a high-resolution RTK-DGPS system is used. The accuracy of such systems is higher as compared to the distance of two maize plants (Fender et al. 2006, Griepentrog et al. 2005), as a consequence each individual plant can be labeled and redetected during measurements at different growth stages.

Due to the combination of partners from agricultural and electronic companies, research institutes and plant breeders the goal of the BoniRob-project is the development of a robust system, which will offer options for other applications and robot swarm concepts. The prototype is shown in Fig. 20.1. The robot allows various movement options, such as turning, changing height or 2- and 4-row movement, a

Fig. 20.1 Autonomous monitoring and scouting robot (BoniRob)

safety concept is included. The navigation is based on methods of the probabilistic robotics (Thrun et al. 2005), taking into account the uncertainties that arise from the application. SLAM uses measured data to ensure correct navigation. As for example positions of maize plants, edges of fields or curvatures of rows can be used for orientation. The real robot as well as the sensor characteristics are implemented in the 3D simulator “Gazebo” to test the robot behavior prior to field tests and to perform hardware-in-the-loop tests.

3 Application of Herbicides

3.1 Requirements and State-of-the-Art

Plant protection is essential for preventing a decline in yields, because of pests, diseases and weeds. Unfortunately the present methods of application of pesticides are always associated with some soil surface losses and spray drift, which may cause pollution of surface- and groundwater, contamination of non-target organisms as well as human hazards.

The most common pesticide application method is the boom sprayer equipped with nozzles each 50 cm. This technology has been optimized during the years and after the introduction of precision farming in the beginning of the 1990s, the sprayer was equipped with computerized variable dose technology for site-specific weed control and several research projects have shown the potential reduction of herbicides by spatially adjusted application to the local need for weed control (Christensen et al. 2003, Gerhards and Oebel 2006).

The aim of the following subchapters is to describe different autonomous technologies used in connection with site-specific application of herbicides and to describe a real-time sensor based system for detection and application of areas containing weed plants only. The objectives are to reduce the herbicide usage as well as the contamination of the surrounding environment.

Several researchers have developed site-specific weed control technologies with different spatial resolution within the field. A review on site-specific weed control technologies is described by Christensen et al. (2009). Research has been conducted in sprayer technology for treatment of weed patches or subfields with clusters of weed plants. Most of the sprayers operate spatially by selective control of small sections of the spray boom. Herbicide dosages are mostly regulated by the pressure in the hydraulic system and standard nozzles. The patch sprayer developed by Gerhards and Oebel (2006) had three separate tanks, with one or more herbicides, three delivery lines and a control system that applies the herbicide and dosage applicable for the three treatment categories. The sprayer had a 21 m boom divided into seven 3.0 m sections that are controlled separately.

Another category of precision sprayers is also reported by Christensen et al. (2009) which is the direct injection sprayers that can apply different herbicides and dosage, e.g. using maps of weed species occurrence to control a series of nozzles, a boom section or the whole boom. Several companies have developed direct injection systems that inject concentrated pesticide solutions into a water stream. Injection pumps have mostly been placed in front of the carrier pump. Consequently, a reaction time of several seconds was required until the pesticide mixture reached the nozzles. Currently, sprayer injection systems that apply concentrated pesticide solutions directly into the nozzles of the sprayer are being investigated.

Lee et al. (1999) developed a real-time robotic weed control system designed for spraying intra-row weeds; the objective of the system is to apply herbicides only to the weed plants without spraying the crop plant or the soil. This precision spraying system has been used in field experiments with an application rate of 37.0 μL liquid spray mixture per spray cell of 0.65 × 1.25 cm. The biological performance of a micro-dosing system was evaluated by Giles et al. (2004). The system was evaluated for the control of weeds growing between tomato plants, using a non-selective herbicide at 0.25, 0.375, and 0.5% concentrations of active ingredient (glyphosate) in the spray solution. Polymer added to the spray solution gave sufficient micro-drift control, thus limiting crop damage.

Sogaard and Lund (2007) describe a prototype micro-dosing system, consisting of a micro boom with a linear array of 20 evenly spaced pieces of tubing covering a 100-mm wide treatment swath at a right angle to the travel direction. The tubes producing the jets were 250 mm long with an inner diameter of 0.5 mm; they were individually controlled by 12 V DC solenoid valves. The volume of the jet emitted from the tubing was 2.5 μL at a pressure of 40 kPa using a 10-ms pulse duration.

The biological efficacy of the application of glyphosate droplets to single seedlings (*Solanum nigrum*) has been studied by Graglia (2004). Doses in the range of 0.125–1.0 μg per plant were tested, and it was found that by applying 0.8 μg or 1.0 μg per plant efficacies of 94% or 95%, respectively, could be achieved.

Drop on demand (DOD) inkjet printers was used to apply very low volume (smaller than 1 μL) of glyphosate to weed plants (Mathiassen et al. 2008).

3.2 The Plant Nursing Robot with Cell Sprayer (HortiBot)

The HortiBot is an autonomous vehicle developed for the use in agriculture (Jørgensen et al. 2007a) (Fig. 20.2). It is equipped with a commercial downward-looking camera from Agrocom Vision, which enables it to navigate using visible rows in the field. In areas with no rows the robot is positioned by use of a real-time kinematic (RTK) global positioning system (GPS). The HortiBot is a lightweight four-wheeled robot and it is based on a modified framework of a commercial available remote-controlled slope mower called “Spider ILD01”.

The use of a vision-based row guidance system and RTK-GPS ensures that the robot covers the whole field very accurate, which means that it is possible to work with implements for precision field application, like e.g. a cell sprayer.

Fig. 20.2 Autonomous application of herbicides (HortiBot with Cell Sprayer)

A cell sprayer is a vision-based spraying system for field crops, which only sprays in areas (cells) in the field where weeds are detected. All other areas without weed plants are not sprayed at all.

Application of cells detected with weeds only will also reduce the contamination of the soil surface. Jensen et al. (2003) has quantified the soil surface loss for broadcast spraying in different arable crops. They measured a soil surface loss of 66% in cereals and up to 99% in sugar beet.

The cell sprayer system is described by Lund et al. (2008). It has a set of video cameras in a vision system which takes images of the soil surface immediately in front of the spraying boom. The images are analyzed for the occurrence of weeds. When one or more weeds are found in the image, the information about their location is saved.

The image is divided into rectangular units (cells) of 30 mm in the driving direction and 107 mm at a right angle to the driving direction. Since the cameras are fixed in relation to the spraying boom, the cells are placed so that the nozzles – with a certain time lapse – pass over the middle of each cell.

The cameras are placed at a height above the soil so that the images include six cell strips in the driving direction and where each strip contains seven cells at right angles to the driving direction. Each image is thus divided in 6 times 7 = 42 cells, which are analyzed individually.

If weeds are detected, then the cell in question is marked for later spraying. On the basis of this information a small spraying map is prepared. This information is used to control an on/off cell sprayer system consisting of separate nozzles for each corresponding cells in the spraying map. It means that cells containing weed plants will be sprayed with the same precision and dosage as if it was applied by conventional uniform application methods.

4 Autonomous Mechanical Weeding

4.1 Requirements and State-of-the-Art

Hoeing of weeds in row crops is one of oldest, highly matured and most common non-chemical weeding operation. According to Laber (1999) its weed control principle can be defined as:

- Operational: Soil engaged treatment (tillage) between crop rows
- Physical: Soil coverage of weeds, weed root/stem cutting and uprooting of weeds (whole plant or partly)
- Physiological: Reduction of photosynthesis and reduction of water transpiration

The first hoes were horse pulled and the ones today are tractor mounted or still tractor pulled. Currently often a second operator is controlling the hoe laterally by hand and based on operator's vision. Tines or rotating discs (rotary hoes) are fixed to a frame and penetrate the upper crust of the soil. The treatment is effective on dry, compact soil and a stable working depth is maintained by ground wheels.

As for most mechanical weeding operations crop plant losses always occur, especially when high weed control efficiencies are aimed at. Crop losses result from soil coverage, crop leaf damage, root damage and disturbance. The standard hoe setting for the untreated crop row strips is 10 cm which gives approximately a maximum of 80% area treatment e.g. in sugar beet. A conflict of aims appears between (I) maximizing treated area to increase weeding efficiency, and (II) minimizing crop losses by keeping a sufficient distance to crop rows. Therefore the adjustment of the hoe unit working width becomes an important factor for achieving an acceptable cultivation result.

Several developments and investigations have been done to automate the lateral control of hoes (Tillett 1991, Home 2003). Today the most promising automation principles are based on GPS (Van Zuydam et al. 1995; Dijksterhuis et al. 1998) and computer vision (Tillett et al. 2002, Sogaard and Olsen 2003, Astrand and Baerveldt 2005). A fusion of both is seen today as the most promising strategy, because advantages and disadvantages of absolute and relative referencing principles compensate each other (Pilarski 2002, Downey et al. 2003).

4.2 The Autonomous Mechanisation System (AMS)

An autonomous tractor was used to operate the inter-row hoe (Fig. 20.3). The 20 kW tractor (Hakotrac 3000) was retrofitted with an RTK-GPS (Trimble MS750) and a controller system for navigation. The tractor navigation controller was designed to follow a predetermined route plan accurately and repeatable e.g. across a field with planned action points for implement control (Blackmore et al. 2004).

Fig. 20.3 Autonomous inter-row hoeing (AMS with inter-row hoe)

A conventional inter-row hoe was used (Baertschi-Fobro, Switzerland) consisting of five units to treat four crop rows. The hoe units including toolbar are light to be operational for a small autonomous tractor.

An electro-hydraulic side-shift system was used to center the hoe units between the rows and parallel to the crop rows with a minimum of lateral deviations (cross track error). Furthermore, the idea was to keep the side-shift somehow independent from the motion behavior of the pulling tractor. The side-shift controller was configured to keep the GPS antenna of the hoe on the same planned route as the automatic tractor was using for its navigation. This setup enables a somehow independency of the implement from the pulling tractor.

The lateral control of the inter-row hoe was based on an RTKGPS (Trimble MS750) and a dual axis tilt sensor (Applied Geomechanics, MD900). The GPS was connected to a local reference station via an FM radio modem (Satel 3ASd). The GPS antenna was mounted at a height of 1.3 m in the middle of the second toolbar and functioned as a closed-loop feedback for keeping the hoe on the planned route.

The weeding cultivation has to be planned prior to the operation. The route way points can be generated from geo-referenced seed positions. The geo-referenced seed positions are determined from the seeding operation of the cultivated crop plants by logging and processing GPS and seeder attitude data (Griepentrog et al. 2005).

Field experiments were conducted to assess the operational performance of the system. The cross track errors were characterized by values of the bias (mean deviation) and the variability (standard deviation). The range of the mean values altered quite low between – 0.016 and 0.011 m. Home (2003) analyzed the cross track errors for different row guidance systems as with a tractor driver, a second operator and a computer vision system. The investigations included no GPS system. The author observed a similar small range of the bias (– 0.017 m and 0.009 m). The range of the standard deviations altered between 0.009 and 0.028 m for the inter-row hoe (ground measurements). Home (2003) published a range for the standard deviation of 0.009–0.022 m for a tractor driver, a second operator and a computer vision system. The best results were obtained by using a computer vision system as a row guidance (0.009 m).

The treated or hoed surface areas were determined based on the analysis of the cross track errors acquired from the field experiments. Small standard deviations of the track errors resulted in wider width of the hoeing units and in high effected field surface areas. The hoe system enables hoeing up to 83% of a field surface area with a speed of 2 km h^{-1} and up to 79% by driving with 4.3 km h^{-1}.

The row guidance method based on a GPS system showed its potential to be used for high accurate crop row guidance e.g. with an inter-row hoe. The mean as well as the standard deviations of the cross track errors were comparable with other row guidance systems as traditional tractor mounted and computer vision systems. Due to its high level of automation the unmanned system is regarded as having high potential in saving labor costs while achieving also high levels of working quality and weed control efficiency.

5 Conclusions

In the near future in industrialized countries outdoor robots allow not only economically viable operations but also increased operational efficiencies. Drawbacks are that current systems are lacking robust and safe behaviors. In general the potential of saving e.g. herbicides is huge when high precision targeting based on individual weed plant detections is used. Furthermore, negative impacts on the environment will be reduced and a higher quality of products will be achieved by more effective and efficient use of management inputs. Due to minimized exposure time of humans to dust, noise and pesticides the working conditions will improve and reduce health risks.

References

Astrand B, Baerveldt AJ (2002) An agricultural mobile robot with vision-based perception for mechanical weed control. Auton Robots 13:21–25

Astrand B, Baerveldt AJ (2005) A vision based row-following system for agricultural field machinery. Mechatronics 15:251–269

Bak T, Jakobsen H. (2004) Agricultural robotic platform with four wheel steering for weed detection. Biosys Eng 87:125–136

Blackmore BS, Griepentrog HW, Fountas S, Gemtos T (2007) A specification for an autonomous crop production mechanization system. Agricultural Engineering International: CIGR Ejournal. Manuscript PM 06 032. vol. IX. April

Blackmore BS, Griepentrog HW, Nielsen H et al (2004) Development of a deterministic autonomous tractor. Proceeding CIGR, Bejing , 11 November 2004

Christensen S, Heisel T, Walter AM, Graglia E (2003) A decision algorithm for patch spraying. Weed Res 43:276–284

Christensen S, Sogaard HT, Kudsk P et al (2009) Site-specific weed control technologies. Weed Res 49:233–241
Dijksterhuis HL, Van Willigenburg LG, Van Zuydam RP (1998) Centimetre-precision guidance of moving implements in the open field: a simulation based on GPS measurements. Comput Electron Agric 20:185–197
Downey D, Giles D, Slaughter DC (2003) Ground based vision identification for weed mapping using DGPS. Proceedings ASAE annual international meeting Las Vegas, Nevada, ASAE, paper no. 03-1005
Fender F, Hanneken M, In der Stroth S et al (2006) Sensor fusion meets GPS – Individual plant detection. Proceedings CIGR EurAgEng/VDI-MEG, pp 279–280
Garcia-Alegre MC, Ribeiro A, Garcia-Perez L et al (2001) Autonomous robot in agricultural tasks. In: Grenier G, Blackmore BS (eds) Proceedings of the 3rd european conference on precision agriculture ECPA, Montpellier, 18 June 2001
Gerhards R, Oebel H (2006) Practical experiences with a system for site specific weed control in arable crops using real-time image analysis and GPS-controlled patch spraying. Weed Res 46:185–193
Giles DK, Downey D, Slaughter DC et al (2004) Herbicide micro-dosing for weed control in field-grown processing tomatoes. Appl Eng Agr 20:735–743
Graglia E (2004) Importance of herbicide concentration, number of droplets and droplet size on growth of *Solanum nigrum* L, using droplet application of glyphosate. Proceedings XIIème Colloque International sur la Biologie des Mauvaises Herbes, Dijon, 31 August–2 September 2004
Granot R (2002) Architecture for human supervised autonomously controlled off-road equipment. In: Proceedings automation technology for off-road equipment (ATOE), Chicago; ASAE, St. Joseph, 26 July 2002, pp 24–32
Griepentrog HW, Blackmore BS (2007) Autonomous crop establishment and control system. In: Proceedings land-technik engineering the future (AgEng 2007) – Engineering solutions for energy and food production, Hanover; VDI-Verlag, Duesseldorf, 9 November 2007, pp 175–181
Griepentrog HW, Norremark M, Nielsen H, Blackmore BS (2005) Seed mapping of sugar beet. Prec Agric 6:157–165
Grift TE, Zhang Q, Kondo N, Ting KC (2008) Review of automation and robotics for the bio-industry. J Biomechatr Eng 1:37–54
Home M. (2003) An investigation into the design of cultivation systems for inter- and intra-row weed control. Unpublished PhD thesis. Cranfield University, National Soil Resources Institute, Engineering Group, Silsoe
Iida M, Donghyeon Kang D (2008) Localization of CO_2 source by a hexapod robot equipped with an anemoscope and a gas sensor. Comput Electron Agric 63:73–80
Jensen PK, Spliid NH (2003) Deposition of pesticides on the soil surface. Pesticides Research, 65. Danish Environmental Protection Agency, 59 pp
Jorgensen RN, Sørensen CG, Pedersen JM et al (2007a) Hortibot – A system design of a robotic tool carrier for high-tech plant nursing. CIGR E-J AE Sci Resand Dev IX:13 pp
Jorgensen RN, Sorensen CG, Sogaard HT et al (2007b) Methodology for a labour extensive and semi-automated field trial design using autoguidance and conventional machinery. In: Stafford JV (ed) Proceedings of the 6th european conference on precision agriculture (ECPA), Skiathos, Greece, Wageningen Press, Wageningen, pp 441–448
Klose R, Ruckelshausen A, Thiel M, Marquering J (2008) Weedy – a sensor fusion based autonomous field robot for selective weed control. Proceedings of the 66th International Conference Agricultural Engineering/AgEng, pp 167–172
Krutz GW (1984) Future use of robots in agriculture. Proceedings of the 1st international conference on robotics and intelligent machines in agriculture, pp 15–29
Laber H (1999) Effizienz mechanischer Unkrautregulationsmaßnahmen im Freilandgemüsebau. Unpublished PhD thesis, University of Hanover, Faculty of Horticulture, Hanover
Lee WS, Slaughter DC, Giles DK (1999) Robotic weed control system for tomatoes. Prec Agric 1:95–113

Lund I, Christensen S, Jensen LA et al (2008) Cellesprøjtning af ukrudt i majs (Cell spraying of weeds in maize) Bekæmpelsesmiddelforskning fra Miljøstyrelsen. Nr. 123, 90 pp

Mathiassen SK, Kudsk P, Lund I (2008) Adjuvants for single droplet application of glyphosate. Proceedings of the 5th international weed science congress, Vancouver

Meier U, Bleiholder H (2007) The BBCH scale – codification and description of phenological growth stages of plants and their international use in agricultural research. Proceedings of the international symposium agricultural field trials – Today and tomorrow, Stuttgart-Hohenheim, 08–10 October 2007, pp 122–125

Mitchell HB (2007) Multi-sensor data fusion. Springer, Berlin/Heidelberg/New York

Nagasaka Y, Zhang Q, Kanetani Y, Umeda N (2004) An autonomous field watching-dog robot for information collection in agricultural fields. Proc ASAE Annual Meeting, Ottawa, August 2004, paper no 043091

Noack PO, Muhr T, Demmel M (2006) GIS and GPS systems enhancing plot parcel creation. In: Proceedings of the Automation Technology for Off-Road Equipment (ATOE), Bonn, 9 September, pp 139–144

Pilarski T, Happold M, Pangels H et al (2002) The demeter system for automated harvesting. Autonomous Robots 13:9–20

Ruckelshausen A (2007) Autonomous robots in agricultural field trials. Proceedings of the international symposium agricultural field trials – Today and tomorrow, Stuttgart-Hohenheim, pp 190–197

Ruckelshausen A, Biber P, Dorna M et al (2009) BoniRob – an autonomous field robot platform for individual plant phenotyping. Proceedings of the european conference on precision agriculture (ECPA), Wageningen

Ruckelshausen A, Dzinaj T, Gelze F et al (1999) Microcontroller-based multisensor system for online crop/weed detection. Proceedins of the Brighton conference, 2, pp 601–606

Siciliano B, Khatib O (2008) Springer handbook of robotics. Springer, Berlin/Heidelberg

Sogaard HT, Lund I (2007) Application accuracy of a machine vision-controlled robotic microdosing system. Biosys Eng 96:315–322

Soerensen CG, Norremark M, Jorgensen RN et al (2007) Hortibot – Feasibility study of a plant nursing robot performing weeding operations – part IV. Proceedings of the ASABE annual international meeting, Minneapolis, 17 June 2007

Sogaard HT, Olsen HJ (2003) Determination of crop rows by image analysis without segmentation. Comput Electron Agric 38:141–158

Thomas E (2006) Feldversuchswesen. Verlag Eugen Ulmer, Stuttgart

Thrun S, Burgard W, Fox D (2005) Probabilistic robotics. MIT Press, Cambridge

Tillett ND (1991) Automatic guidance sensors for agricultural field machines – a review. J Agric Eng Res 50:167–187

Tillett ND, Hague T, Miles SJ (2002) Inter-row vision guidance for mechanical weed control in sugar beet. Comput Electron Agric 33:163–177

van Evert F, van der Heijden G, Lotz L et al (2007) A mobile field robot with vision-based detection of volunteer potato plants in a corn crop. Weed Technol 20:853–861

Van Zuydam RP, Sonneveld C, Naber H (1995) Weed control in sugar beet by precision guided implements. Crop Prot 14:335–340

Zeitzew MA (2007) Autonomous utility mower. Agricultural engineering international - The CIGR Ejournal IX (July)

Chapter 21
Variable Rate Technology for Herbicide Application

Markus Sökefeld

Abstract Variable rate technology (VRT) is used for the application of various agricultural inputs in order to respond adequately to the within-field variability of environmental factors like soil properties, incidence of pests and crop parameters. The areas in plant production in which VRTs are used are highlighted. For the variable rate application of herbicides commercial as well as research solutions are described. The use of VRT for herbicide treatment with regard to pre-emergence and post-emergence applications and the requirements are described. The potential of further herbicides savings due to an additional variation of herbicidal ingredients in consideration of herbicide sensitivity of single weed species and groups of weed species, respectively is shown and evaluated.

1 Introduction

Variable rate technology (VRT) or variable rate application (VRA) are synonyms for a technique to vary the application rate of agricultural inputs in adaptation to heterogeneous features like soil properties or plant density. The range of application covers the whole area of plant production like seeding, fertilization, irrigation and plant protection. Adequate sensors are needed to obtain spatial information about a field, like soil parameters, estimated crop yield, weed density or weed species composition. Collected data are used for the control of the application rate of agricultural machinery like seeders, spreaders or sprayers.

1.1 Seeding

Variable rate seeding is based on the adaptation of the seeding rate to the yield potential. Reduced populations should be established in zones with lower yield potential.

M. Sökefeld (✉)
Department of Weed Science, Institute for Phytomedicine, University of Hohenheim, D-70599 Stuttgart, Germany
e-mail: markus.soekefeld@uni-hohenheim.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_21,

Higher seeding rates are recommended for sites with high-yield potential with high soil-fertility levels and water-holding capacity (Barnhisel et al. 1997). Variability in top soil depth which can be estimated by soil electrical conductivity measurements (Kitchen et al. 1999) is also an actuating variable for the variation in seeding rate (Bitzer et al. 1996). The variation of the seeding rate can be realized by seeders equipped with a microprocessor controlled hydraulic motor which replaces a path-dependent metering mechanism (Maguire et al. 2003).

1.2 Fertilizing

Concerning variable rate technology for fertilizer application, nitrogen fertilization has to be distinguished from the application of phosphate, potassium and lime. Sensor signals of several systems, which provide information about the nitrogen status of the plant or plant biomass, can be used for the variable rate application of nitrogen (Schächtl et al. 2005, Link et al. 2002, Ehlert et al. 2004).

For the variable rate application of the other fertilizers like phosphate, potassium and lime, mainly maps are used which are based on soil test information from grid soil sampling (Wollenhaupt et al. 1994). Predominantly spreaders with additional controller are used for a map-based variable rate fertilizer application as well as for sensor based application.

1.3 Irrigation

Normally center pivot irrigation systems apply a more or less uniform amount of water to a whole field or even several fields with no respect to non-uniform environment like variable soil types, multiple crops or changing topography. Perry et al. (2003) described a control system for variable rate center pivot irrigation which takes changing environmental conditions into account. To divide fields in management zones concerning to their estimated water application rate inputs like aerial images of soil or crops, soil and yield maps and farmer's knowledge of the field was used. The created application maps were realized by a special variable rate irrigation controller which varies the application rate by cycling sprinklers on and off and by varying the travel speed of center pivot irrigation system. Application rates between 0 and 200% were achieved by using this technique.

1.4 Plant Protection

Variable rate technology in plant protection can be divided according to the application of fungicides, growth regulators and herbicides. Dammer and Ehlert (2006) described a technique for variable rate fungicide spraying in cereals. For the control of the sprayer information on the heterogeneity in plant biomass was used.

The concept was based on the idea to apply the same concentration of active fungicidal substance per unit of crop canopy surface area in order to achieve a homogeneous wetting and coverage of the foliar surface. A good indicator for the density of the crop canopy surface is the leaf area index. The crop meter, a real-time sensor for crop biomass density was used for the measurement (Ehlert 2000). Between the sensor signal and the leaf area index, which was measured by an optical handheld sensor, R^2 values from 0.61 to 0.84 were detected. An automatic detection of the fungus or the estimation of the quantity of the disease is not possible.

A similar approach was used for the application of growth regulators in wheat by Volk and Leithold (2006). The sensor signal of the Yara N-sensor®, which analyzes the spectra of the reflected light of the crop surface, was utilized for the calculation of the crop biomass in order to obtain an application rate of the growth regulators proportional to the biomass.

Factors which influence the optimal dose rate of herbicides are diverse. For soil-applied herbicides Williams et al. (2002) mentioned the importance of the amount of active ingredients which are available for the plant. The potential uptake depends on several soil properties which influence the sorption capacity like soil organic matter, soil pH, soil texture, water content and cation exchange capacity. Other authors didn't used soil properties for the adjustment of the optimal herbicide dose rate but they used parameters like weed density or weed species composition. Possible techniques for the automatic inspection of the weed flora within agricultural fields are digital image analysis (Gerhards and Christensen 2002, Weis and Gerhards 2007) remote sensing (Brown et al. 1994) or opto-electronic devices like the commercially available systems WeedSeeker® and DetectSpray®.

2 Technical Solutions for the Control of Application Rate of Sprayers

Since several decades engineers develop techniques for the constant output of sprayers depending on a changing velocity of the sprayer. A regulation of the nozzle flow rate compared to the traveling speed ensures a constant distribution of the spray mixture on the entire plant canopy and thus a uniform wetting of the leaf surface. If a homogeneous plant canopy or weed distribution is assumed this goal is absolutely worthwhile. Many scientific papers showed however that both the weed density and the weed species composition in arable land are usually heterogeneous (Marshall 1998, Gerhards et al. 1997, Christensen and Heisel 1998). The possibility to use sensors for the detection of these heterogeneities resulted in the development of pesticide sprayers with the ability to modify the application rate with regard to the detected weed population. The variation of the application rate has to be achieved without an extreme shift of droplet size spectra or spray distribution pattern. Commercial solutions as well as scientific approaches are known for the selective dose control of sprayers.

2.1 Total Flow Control

From the technical point of view total flow control systems also known as pressure based control systems, are the easiest to realize. In this concept standard sprayers are used to alter the application rate over the entire spraying width (Walker and Bansal 1999). The flow rate of the premixed solution is controlled by adjusting the system pressure. Since the application rate directly depends on the system pressure a good regulation is provided. Changes of the flow rate by means of pressure are subjected to a square root relationship. In order to double the flow rate, the system pressure has to be quadrupled. Flat fan nozzles which are commonly used for the spraying of agro-chemicals have an operating pressure between 2 and 4 bar, thus the possibility to alter the flow rate is limited. Going beyond or below this pressure range is leading to suboptimal droplet size and thus to the risk of drift or an non-uniform wetting of the leaf surface. Depending on the used pressure control valves (e.g. motorized or solenoid) response times are rather long (Stone et al. 1999).

2.2 Pulse Width Modulation Control

Pulse width modulation (PWM) is a common technique for controlling an electrically actuated device by turning the device on and off very quickly (pulsation). The speed at which the device is pulsed is its frequency. The proportion of time during which the device is “on” during each full cycle is the duty cycle, which is expressed as a percentage. To use this technique for sprayers an electrically driven solenoid valve is directly coupled to the inlet of the spray nozzle (Giles et al. 1996). GopalaPillai et al. (1999) stated that duty cycles from 10 to 100% provide a flow rate control in the ratio from 9.5 up to 1 without a significant change in the spray pattern. They observed a constant droplet spectrum for duty cycles between 50 and 100%. A significant change in the droplet spectrum was observed at 10% duty cycle.

2.3 Twin Fluid Nozzles

Twin fluid nozzles use spray liquid and air, both are feed in the nozzle body under pressure to create a spray. Apart from a compressor which is mounted on the sprayer to provide the required air supply, a standard sprayer can be employed with these nozzles. By means of a separate control of spraying pressure and compressed air, nozzle output and droplet size can be adjusted independently from each other (Western et al. 1989). With these commercial available nozzles (e.g. AirJet® by TeeJet, AirTec® by Cleanacres) a flow rate control in the ratio from 2 to 1 is achievable.

2.4 Variable Orifice Nozzles

Another alternative of variable rate application using standard sprayers is to employ nozzles with variable orifices. These nozzles adjust orifice size during a pressure variation automatically (Walker and Bansal 1999). Hereby a constant spray angle and a uniform droplet size is achieved over a wide range of flow rates. A commercial version of this nozzle type is the TurboDrop® VR by agrotop. According to the company's data sheet an extended range of application rates from 100 up to 420 l ha^{-1} at a speed of 7 km h^{-1} and 2–8 bar operating pressure may be realizable. Thus, with this technique doubling the pressure results in doubling the flow rate.

A variant of the variable orifice nozzles is the VariTarget nozzle which was developed by Bui (2005). The concept of the VariTarget design is that the area of the pre-orifice and the spray orifice vary at the same time during operation for various flow rates. This keeps the droplet size optimized over the range of flow rates and maintains a constant spray angle. Using the VariTarget nozzle at an operating pressure from 1 to 3.5 bar a nozzle output of 0.57–3.03 l min^{-1} is obtained; this corresponds to an application rate of 85–455 l ha^{-1} at a speed of 8 km h^{-1} and a distance between the nozzles of 0.5 m.

2.5 Multiple Nozzle Holders

Multiple nozzle holders like the VarioSelect® system by Lechler allow the adaptation to varying spraying conditions on-the-go. Up to four nozzles can be combined at one nozzle holder. Nozzles can be used individually or simultaneously to achieve a range of application rates from 50 up to 600 l ha^{-1}. The control of the individual spray tips is realized by pneumatic control valves directly in front of each nozzle. Thus quick changes in the application rate are feasible.

2.6 Injection Metering Systems

In direct injection systems the active ingredient and the carrier (water) are kept separately. Pesticides are metered into the carrier at the time of application. The rate can be varied, giving the desired concentration at the injection point in accordance with the given operating conditions (see Chapter 19). A major advantage of direct injection systems is the wide range of application rates according to the used metering device and the possibility to change not only the application rate but also the type of pesticide on-the-go.

3 Pre-emergence Herbicide Application

At the time of application of pre-emergence herbicides normally no information about the later weed infestation is available. Thus pre-emergence herbicides are typically used at a uniform rate as broadcast or band applications. In order to use pre-emergence herbicides in a variable rate manner, spatial field information about soil properties or weed maps from previous years (historical weed maps) have to be available.

The amount of soil-applied herbicide needed to control weeds depends on the soil texture and soil organic matter content. Field soil variability can be determined by measuring soil electrical conductivity or using soil survey data. Weber et al. (1987) developed algorithms for herbicide application rates based on soil properties. Humic matter content of the soils was highly correlated ($r = 0.89-0.97$) with herbicide bioactivity. Blumhorst et al. (1990) investigated the efficacy of selected herbicides as influenced by soil properties. They demonstrated that herbicide activity was highly correlated to soil organic matter content, and suggested that herbicide application rates should be determined in accordance with soil properties.

Mohammadzamani et al. (2009) conducted a field trial for site-specific herbicide application using soil parameters. Considering differences in soil organic matter content and soil texture a field was divided into four management zones. Different rates of a pre-emergence herbicide were applied in the zones. Herbicide application could be decreased by up to 13% in comparison to a uniform application rate, retaining successful weed suppression in most management zones.

Due to the stability of soil properties over a long period of time, application maps based on these parameters can be used for variable rate application of herbicides for many years. Weed patches in agricultural fields have been found stable over several years (Wilson and Brain 1991, Wyse-Pester et al. 1995, Jurado-Expósito et al. 2004). Weed seedling emergence, and thus weed density within the weed patches is dependent on parameters like weather conditions, soil properties, planted crop species and crop cover. Walter et al. (1997) suggested that weed maps from previous years could be used for the calculation of herbicide dose maps in the current year.

Koller and Lanini (2005) used weed counts of the previous year to develop maps for pre-emergence herbicide application in the current year. Two types of weed density maps were used for the calculation of the application maps providing zones with three different herbicide rates: one created from seedling counts in the growing crop and another based on mature-weed counts. The authors employed a variable rate sprayer for the application of pre-emergence herbicide in the marked zones. An effective weed control comparable to a uniform one-rate herbicide application was achieved. The seedling map approach resulted in a 47% herbicide reduction compared to a uniform full rate application. A 34% reduction in herbicide use was achieved with the approach based on mature-plant weed maps. They stated that variable-rate spraying based on estimations of weed density in the previous year crop just before harvest gave the best weed control.

4 Post-emergence Herbicide Application

For the site-specific application of post-emergence herbicides information on the weed infestation is needed. Common parameters for the description of weed infestation level and thus the amount of herbicide application are weed density, development stage of the weeds and weed species composition.

Kudsk (1989) stated that the effect of herbicide treatment is dependent on factors like weed species spectrum and development stage of the weeds. Dogan and Hurle (1998) studied the efficacy of reduced herbicide doses subjected to the development stage of weeds, they demonstrated a significantly higher herbicide efficacy at the two-leaf stage than at the four- or six leaf-stage. At the two-leaf stage herbicide reduction up to 63% without loss of efficacy was possible. Dose-response curves describe the effect of herbicide dose on plant growth. The shape of the curve depends on the mode of action of the herbicide, while the performance of the herbicide, which is influenced by weed species and weed growth stage, can be described by a parallel shifting of the dose-response curve (Jensen and Kudsk 1988) The adaptation of the herbicide rate according to the weed density takes into account that the efficacy of foliar-applied herbicides is reduced with an increasing infestation level due to an overlapping weed canopy and reduced spray interception (Dieleman and Mortensen 1998). Christensen (1994) pointed out, that reduced herbicide doses are often not lethal but they lead to a reduction of competitiveness and dry matter production of the weed. Mortensen et al. (1998) stated that the efficacy of herbicide treatments is lower in areas with high weed density than in areas with low weed density. Several studies on variable rate application of post-emergence herbicide have been carried out.

Heisel et al. (1999) conducted two field trials on variable rate herbicide application in winter wheat and winter barley, respectively. Weeds were counted visually at the intersection points of a regular 20 m by 20 m grid. The economically optimal herbicide dose at each sampling point was calculated by a decision support system for patch spraying which took weed density, weed species and expected mean yield for every sampling point into account. The application rate varied between 0 and 100% of the recommended dose. The patch spraying resulted in a 62 and 47% reduction in the two fields. Assuming a weed cover at harvest less than 10% as a sufficient weed control the treatment was successful in the main parts of the field.

Wartenberg and Dammer (2002) used an opto-electronic sensor for weed counts within the tramlines. The speed of the measuring principle of the sensor allowed a real-time weed control. According to the sensor signal the herbicide application rate was reduced by up to 50%. Depending on the cultivated crop herbicide savings up to 30% compared to a 100% application were reached without differences in yield.

Gerhards et al. (2002) performed site-specific herbicide application based on weed grid counts over a four year crop rotation in four fields. Depending on the counted weed numbers they defined infestation levels: weed free (<0.1 seedlings m^{-2}) low (>0.1–1 seedlings m^{-2}), medium (>1–5 seedlings m^{-2}), high (>5–20 seedlings m^{-2}) and very high (>20 seedlings m^{-2}). In areas with a very high weed infestation the full herbicide rate (300 l ha^{-1}) was applied, the rate was stepwise reduced to 200 l ha^{-1} in areas with low weed infestation. Areas with weed level "weed free" remained untreated. Herbicide reductions from 0% in sugar beet up to 98% in maize and winter wheat have been reported.

5 Variable Rate Technique or Variation of Active Ingredients?

In addition to the use of variable rate technology for the application of herbicides the variation of the herbicide ingredients according to weed species composition is a possibility to lower the amount of herbicide applications. Gerhards and colleagues investigated the combination of variable rate application based on weed density with a variation of herbicides based on weed species composition in field trials over several years (Gerhards et al. 1999, Gerhards and Sökefeld 2001, Gerhards and Sökefeld 2003). For the application of post emergence herbicides an experimental sprayer with a 18 m boom divided in 3 sections of 6 m each was used. The regulation of the herbicide rate was carried out by pressure control. During herbicide application, the sprayer was linked to an on-board computer loaded with the treatment maps. First, the application of selective herbicide was realized by up

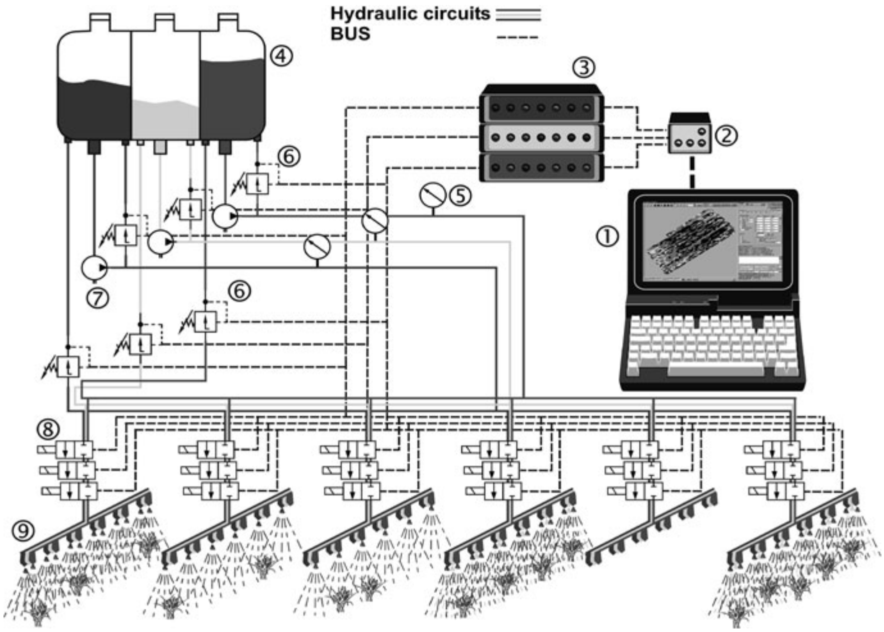

Fig. 21.1 Schematic configuration of the multiple sprayer with: *1* board computer with application map, *2* control unit for spray computer, *3* spray computer, *4* tank, *5* manometer, *6* pressure valve, *7* pump, *8* solenoid valve, *9* boom sections with nozzle (Gerhards and Oebel 2006)

to three field crossings with different herbicides. The three herbicides were active against monocotyledons, dicotyledons and a selective herbicide against thistles or *Galium aparine* for example. Later a multiple field sprayer for herbicide variation on – the-go with three autonomous hydraulic circuits was developed (Fig. 21.1). Each of the three sprayer circuits had a boom width of 21 m divided into 7 sections of 3 m. Each sprayer circuit and each boom section were turned on and off separately via solenoid valves. This sprayer allowed a separate control of each hydraulic circuit according to information from herbicide application maps. The application rate was regulated from 200 to 290 l ha^{-1} over the whole boom width of each sprayer by pressure variation (Gerhards and Oebel 2006).

Figure 21.2 shows application maps for four different groups of weed species according to their sensitivity to post-emergent herbicides (a–d) of a 3 ha sugar beet

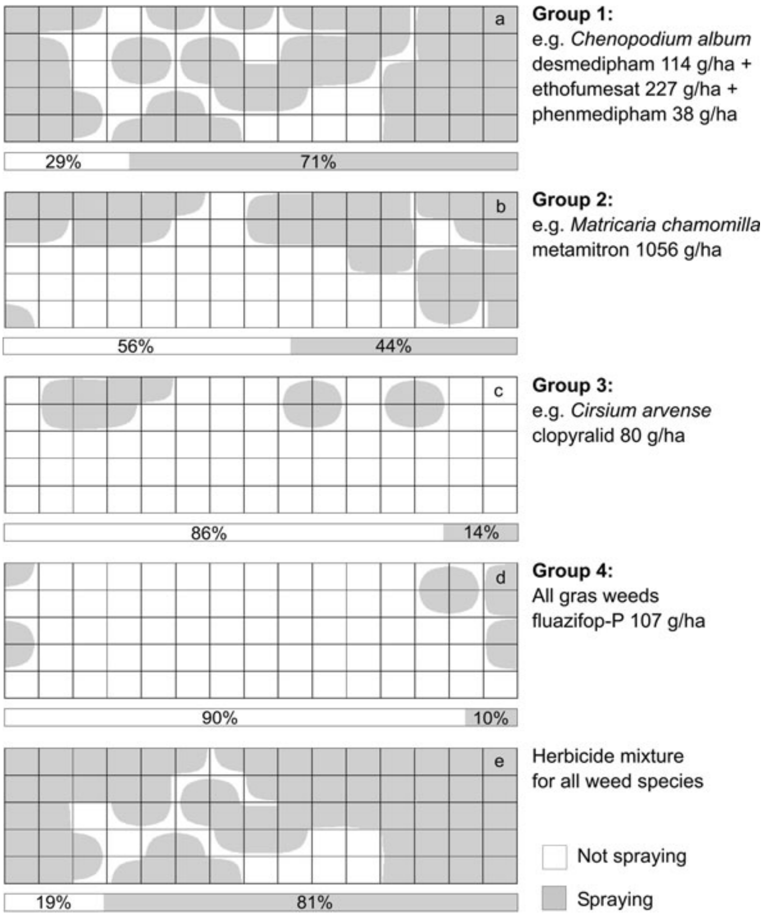

Fig. 21.2 Application maps for a sugar beet field (3.0 ha) subdivided according to herbicide sensitivity of weeds (Gerhards and Sökefeld 2003)

field. The fifth map (e) is an overlay of the maps a-d and represents an application with an herbicide mixture against all weed species within the field. Using map e for site-specific herbicide application only 19% of the field remained unsprayed. By varying the applied herbicides according to the information in the application maps (a to d) herbicide savings on a much higher level was achieved. 71% of the field was sprayed with the combination of desmedipham, ethofumesat and phenmedipham, 44% with metamitron, only 14% with clopyralid and 10% with fluazifop-P. This example shows the huge potential of savings due to herbicide variation and the necessity for the development of sprayers which are able to realize several application maps during one field crossing. Furthermore for a fast and reliable identification of weed seedlings within the field powerful techniques are important. An ideal solution is the combination of weed detection and classification with a spraying device for variable rate and variable herbicidal ingredient application for an online site-specific weed control.

Long-term studies on the implementation of VRA in conjunction with herbicide variation approved, that a higher weed pressure in the subsequent years is not to be suspected. Figure 21.3 shows the changes of the average weed infestation prior to herbicide treatment, split up in monocotyledons and dicotyledons, under the influence of site-specific herbicide application. The weed density of 52 dicotyledons m^{-2} and 11 monocotyledons m^{-2} in the initial year 1997 wasn't exceeded in the following years. In fact the weed density tended to be lower. Certainly, the good efficiency of site-specific herbicide application in this case can be attributed to the crop rotation with its possibility for an intensive weed regulation in maize and sugar beet.

As shown in Table 21.1 in both crops almost the whole field was sprayed with herbicides against dicotyledons. This is due to low competitiveness of sugar beet

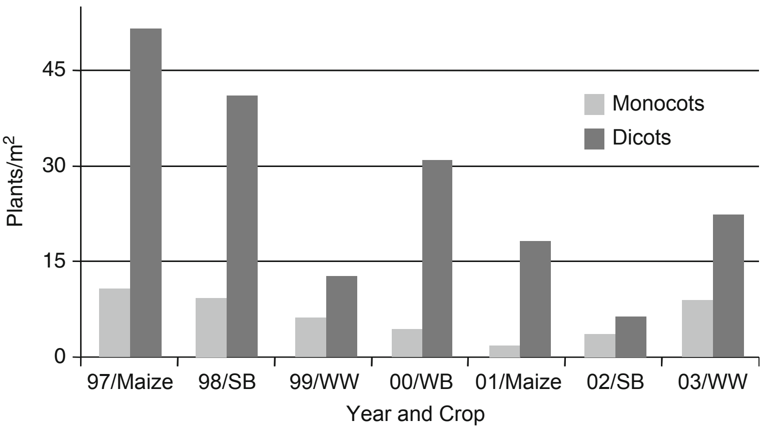

Fig. 21.3 Average weed density in one field over 7 years prior herbicide application under the influence of variable rate application and herbicide variation according to weed species composition (SB sugar beet, WW winter wheat, WB winter barley)

Table 21.1 Herbicide savings over several years in one field using variable rate technology and herbicide variation according to weed species composition

Year	Crop	Monocotyledons (%)	Dicotyledons (%)
1997	Maize	65	13
1998	Sugar beet	75	0
1999	Winter wheat	92	72
2000	Winter barley	92	54
2001	Maize	91	8
2002	Sugar beet	80	0
2003	Winter wheat	49	52

and maize during the juvenile stage. However looking at the cereals the amount of herbicides savings against dicotyledons are much higher. This is attributed to the high competitiveness of cereals which allows the application of economic weed thresholds. Up to 90% savings were achieved in the use of herbicides against monocotyledons. Gras weeds were much more aggregated within the test field. Thus, in sugar beet and maize as well as in cereals large areas of the field remained unsprayed.

The different herbicide saving potential for the two groups of weed species in this field trial is an argument for the application of different selective herbicides in one field according to the present weed species. Combining this with variable rate application depending on developmental stage of the weeds and competitiveness of weeds and crop is promising the highest herbicide savings.

References

Barnhisel RI, Bitzer MJ, Grove JH, Shearer SA (1997) Agronomic benefits of varying corn seed populations: a central Kentucky study. In: Proceedings site-specific management for Agriculture systems. Third International Conference. American Society of Agronomy, Madison, pp 957–966

Bitzer MJ, Barnhisel RI, Grove, JH (1996) Varying corn populations according to depth of top soil. Proceedings of the 1996 information Agriculture Conference, Urbana

Blumhorst MR, Weber JB, Swain LR (1990) Efficacy of selected herbicides as influenced by soil properties. Weed Technol 4:279–283

Brown RB, Steckler J-PGA, Anderson GW (1994) Remote sensing for identification of weeds in no-till corn. Trans ASAE 37:297–302

Bui QD (2005) VariTarget-A new nozzle with variable flow rate and droplet optimization. ASAE paper no 051125. Tampa

Christensen S (1994) Crop weed competition and herbicide performance in cereal varieties and species. Weed Res 34:29–37

Christensen S, Heisel T (1998) Patch spraying using historical, manual and real-time monitoring of weeds in cereals. J Plant Dis Protect XVI (special issue): 257–263

Dammer KH, Ehlert D (2006) Variable-rate fungicide spraying in cereals using plant cover sensor. Prec Agric 7:137–148

Dieleman JA, Mortensen, DA (1998) Influence of weed biology and ecology on development of reduced dose strategies for integrated weed management systems. In: Hatfield JL, Buhler DD, Stewart BA (eds) Integrated weed and soil management. Ann Arbor Press, Inc, Chelsea, pp 333–362

Dogan MN, Hurle K (1998) Einfluss des Entwicklungsstadiums und von Umweltfaktoren auf die Wirksamkeit reduzierter Aufwandmengen von Tribenuron-methyl (Pointer) auf *Chenopodium album L.* Z PflKrankh PflSchutz XVI (Sdh), pp 673–679

Ehlert D (2000) Pflanzenmasseerfassung mit mechanischen Sensoren. In: VDI-MEG-Tagung Landtechnik, 10./11.10.2000, Braunschweig, pp 289–294

Ehlert D, Schmerler J, Völker U (2004) Variable rate nitrogen fertilization of winter wheat based on a crop density sensor. Prec Agric 5:263–273

Gerhards R, Christensen S (2003) Real time weed detection, decision making and patch spraying in maize, sugar beet, winter wheat and winter barley. Weed Res 43:385–392

Gerhards R, Oebel H (2006) Practical experiences with a system for site-specific weed control in arable crops using real-time image analysis and GPS-controlled patch spraying. Weed Res 46:185–193

Gerhards R, Sökefeld M (2003) Precision farming in weed control – system components and economic benefits. In Stafford J, Werner A (eds) Precision agriculture, Wageningen Academic Publishers, Wageningen, pp 229–234

Gerhards R, Sökefeld M (2001) Sensor systems for automatic weed detection. Proceedings of the BCPC Conference – Weeds, pp 827–834

Gerhards R, Sökefeld M, Timmermann C et al (1999) Results of a four year study on site-specific herbicide application. In Stafford JV (ed) Precision agriculture ’99, Vol 2. Sheffield Academic, Sheffield, pp 689–697

Gerhards R, Sökefeld M, Timmermann C et al (2002) Site-specific weed control in maize, sugar beet, winter wheat and winter barley. Prec Agric 3:25–35

Gerhards R, Wyse-Pester DY, Mortensen DA (1997) Characterizing spatial stability of weed populations using interpolated maps. Weed Sci 45:108–119

Giles DK, Henderson GW, Funk K (1996) Digital control of flow rate and spray droplet size from agricultural nozzles for precision chemical application. In: Robert PC et al (eds) Proceedings of the 3rd International Conference on Precision Agriculture, Madison, pp 729–738

GopalaPillai S, Tian L, Zheng J (1999) Evaluation of a flow control system for site-specific herbicide applications. Trans ASAE 42:863–870

Heisel T, Christensen S, Walter AM (1999) Whole-field experiments with site-specific weed management. In: Stafford JV (ed) Precision agriculture ’99, Vol 2. Sheffield Academic, Sheffield, pp 759–768

Jensen PK, Kudsk P (1988) Prediction of herbicide activity. Weed Res 28:473–478

Jurado-Expósito M, López-Granados F, González-Andújar JL, Garcia-Torres L (2004) Spatial and temporal analysis of *Convolvulus arvensis* L. populations over four growing seasons. Eur J Agron 21:287–296

Kitchen NR, Sudduth KA, Drummond ST (1999) Soil electrical conductivity as a crop productivity measure for claypan soils. J Prod Agric 12:607–617

Koller M, Lanini WT (2005) Site-specific herbicide applications based on weed maps provide effective control. Cali Agric 59:182–187

Kudsk P (1989) Experiences with reduced herbicide doses in Denmark and the development of the concept of factor-adjusted doses. Proceedings of the BCPC Conference, Weeds, pp 545–554

Link A, Panitzki M, Reusch S (2002) Hydro N-Sensor: tractor mounted sensing for variable N fertilization. Proceedings of the 6th International Conference on Precision Agriculture, pp 1012–1018

Maguire S, Earl R, Smith DF, Cripsey P, Godwin RJ (2003) Technology for variable rate precision drilling of onions. In: Stafford J, Werner A (eds) Precision agriculture. Wageningen Academic Publishers, Wageningen, pp 373–378

Marshall EJP (1988) Field-scale estimates of grass populations in arable land. Weed Res 28: 191–198

Mohammadzamani D, Minaei S, Alimardani R et al (2009) Variable rate herbicide application using the global positioning system for generating a digital management map. Int J Agric Biol 11:178–182

Mortensen DA, Dieleman JA, Johnson GA (1998) Weed spatial variation and weed management. In: Hatfield JL, Buhler DD, Stewart BA (eds) Integrated weed and soil management. Ann Arbor Press, Inc, Chelsea, pp 293–309

Perry C, Pocknee S, Hansen O (2003) A variable rate pivot irrigation control system. In: Stafford J, Werner A (eds) Precision agriculture. Wageningen Academics Publishers, Wageningen, pp 539–544

Schächtl J, Huber G, Maidl FX, Sticksel E (2005) Laser-induced chlorophyll fluorescence measurements for detecting the nitrogen status of wheat (*Triticum aestivum* L.) canopies. Prec Agric 6:143–156

Stone ML, Giles DK, Dieball KJ (1999) Distributed network system for control of sprayer droplet size at and application rate for precision chemical application. ASAE Paper No 99-3112, St. Joseph

Volk T, Leithold P (2006) Site-specific application of growth regulators in winter wheat with the yara N-sensor and proplant decision support system for growth regulators. Mitt Biol Bundesanst Land- und Forstwirtsch 400, p 68

Walker JT, Bansal RK (1999) Development and characterization of variable orifice nozzles for spraying agro-chemicals. ASAE Paper No 99-1008. St. Joseph

Walter AM, Christensen S, Heisel T (1997) Patch spraying using weed maps from previous years. Proceedings of the 10th EWRS (Eur Weed Res Soc) Symposium 1997, Poznan, p 141

Wartenberg G, Dammer KH (2002) Erfahrungen bei der Verfahrensentwicklung zur teilschlagspezifischen Herbizidanwendung in Echtzeit. Z PflKrankh PflSchutz XVIII (Sdh):443–450

Weber JB, Tucker MR, Isaac RA (1987) Making herbicide rate recommendations based on soil tests. Weed Technol 1:41–45

Weis M, Gerhards R (2007) Feature extraction for the identification of weed species in digital images for the purpose of site-specific weed control. In: JV Stafford (ed) Precision agriculture '07, Proceedings of the 6th european conference on Precision Agriculture, Wageningen Academic Publishers, Wageningen, pp 537–544

Western NM, Hislop EC, Herrington PJ, Jones EI (1989) Comparative drift measurements for BCPC reference hydraulic nozzles and for an Airtec Twin–Fluid nozzle under controlled conditions. Proceedings of the BCPC Conference, Weeds, pp 641–648

Williams MM, Mortensen DA, Waltman WJ, Martin AR (2002) Spatial inference of herbicide bioavailability using a geographic information system. Weed Technol 16:603–611

Wilson BJ., Brain P (1991) Long-term stability of distribution of *Alopecurus myosuroides* Huds. within cereal fields. Weed Res 31:367–373

Wollenhaupt NC, Wolkowski RP, Clayton MK (1994) Mapping soil test phosphorus and potassium for variable-rate fertilizer application. J Prod Agric 7:441–448

Wyse-Pester DY, Mortensen DA, Gotway CA (1995) Statistical methods to quantify spatial stability of weed population. Proc North Cent Weed Control Conf 50:512

Chapter 22
Variable Rate Application of Fungicides

Karl-Heinz Dammer

Abstract Plant diseases often occur in patches within the field. But real-time sensor technology for automatic disease detection which would be a prerequisite for demand related fungicide application is commercially not yet available. In heterogeneous fields growth conditions vary greatly due to soil quality differences. Consequently there exist subareas with varying biomass which affect yield at harvest time. In high biomass and yield subareas the Leaf Area Index (LAI) is greater than in low biomass subareas. In cereals LAI can serve as a parameter to adapt application rate to the growth differences in fields. Sensor controlled variable rate field sprayer technology therefore meets the economic and ecological demands of process optimisation in the production of primary plant goods.

1 Introduction

The uniform application of fungicides over an entire field is common practice in crop protection. However, uniform spatial distribution of fungal pathogens which would warrant a uniform application in a field is an exception and often only occurs at the end of a fungal epidemic (Van der Planck 1963, Jeger 1989). At this stage in plant growth yield loss cannot be prevented and fungicide spraying is basically unwarranted. Especially at the beginning of fungal epidemics plant pathogens often are distributed randomly and diseases may develop in patches (Campbell and Madden 1990, Hughes and Madden 1995). A uniform fungicide application over the entire field at this time is not appropriate. In subareas of the field with no disease a fungicide application would not be necessary.

K.-H. Dammer (✉)
Engineering for Crop Production, Leibniz-Institute for Agricultural Engineering Potsdam-Bornim (ATB), D-14469 Potsdam, Germany
e-mail: kdammer@atb-potsdam.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_22,

Fungicides have to be applied in early stages of disease development in order to prevent negative effects on yield formation of the crop. Therefore the green leaf area has to be protected from pathogen infection with fungicides. Only healthy leaves can effectively produce photosynthetic products the major source of subsequent yield formation.

Beside the heterogeneity in disease occurrence the economics of fungicide use is another aspect that needs consideration. When soil conditions are heterogeneous within a field it is likely that due to differences in water and nutrient availability, crop growth is also heterogeneous. A well established crop produces higher yield than a crop suffering from malnutrition or water stress. This results in largely differing subarea yield. Consequently crop losses prevented by fungicide applications and final marginal income can vary significantly. Marginal income is higher in high yield subareas than in low yield areas. This positive correlation has also been reported by Paveley et al. (1996) and Oerke and Dehne (1997). Fungicide spraying according to disease occurrence will optimize the use of production inputs and would reduce the costs of disease control and energy input. In addition, the impact of biocides on the environment would be reduced.

A prerequisite for fungicide application according to disease occurrence is the determination of the within-field distribution of diseases. An assessment of disease symptoms by visual monitoring is time consuming. When a critical threshold for a disease is exceeded, fungicides have to be sprayed immediately, because if weather conditions are favourable pathogens can quickly spread throughout the crop canopy. Therefore, the collection of data on percentage diseased plants or diseased leaf area is time sensitive. To overcome this problem, research is being conducted to replace visual disease assessment by technical sensors. Sensors may be able to detect diseased plants within the crop in all subareas reliably and in early stages of crop development. These sensors would allow gathering of data on the spatial distribution of fungal pathogens efficiently and quickly and in time to avoid crop loss. To date, however, no real-time sensor technology for automatic disease detection is commercially available that provides data on diseases in the subareas of the field before the pathogens reach critical thresholds. Plant parameters like leaf area index, green biomass or coverage level are commonly used for demand-related fungicide spraying in practice.

This chapter focuses on the variable rate application of fungicides in cereals, because of the world-wide area cultivated and the high potential to reduce fungicide and energy.

2 Off-Line and On-Line Fungicide Application with Variable Rates

The off-line approach is usually based upon disease or crop density maps (Bjerre and Secher 1998). Disease inspection has to include a GPS based recording of the site, the size of disease patches in the field, and disease incidence. Although spatial sampling schemes (Dammer 1999, Fleischer et al. 1999) using the underling mathematical distribution function exist (Campbell and Madden 1990, Hughes and Madden 1995), grid-based disease sampling to compile a reliable map is very laborious. Also the time lag between disease monitoring and spraying is unfavourable. If critical thresholds of disease occurrence are exceeded and weather conditions are favourable, fungal diseases can spread quickly over the entire field. Since time sensitivity is crucial and disease maps are not available in time this technology has not been introduced into practice, but is limited to experimental sites (Secher 1997, Bjerre 1999).

Alternatively, crop density may be used as a parameter for variable rate fungicide application. Maps of crop density can be produced using Geographic Information Systems (GIS). Information can be derived from the following sources:

- Farmers knowledge
- GPS to determine position
- Yield maps
- Vehicle-mounted spectral reflectance or mechanical sensors
- Aerial photography
- Satellite imagery

Crop density maps based on farmers knowledge or yield maps can be drawn in advance. These maps, however, may not represent the actual crop density at the time of spraying. Weather conditions varying from year to year often result in different growth conditions and thus in different within-field patterns of crop density. A more exact map can be obtained by real-time sensors. They can be mounted on tractors, aeroplanes or in satellites. The availability and quality of areal and satellite images, however, largely depends on cloud cover. In addition, long processing times to obtain georeferenced data, especially from imaging sensors, often prevents their use in plant production management processes (Moran 2000). Variable rate fungicide application based on application maps derived from crop density or disease assessment was investigated by Bjerre (1999) and Secher (1997) in experimental fields.

The extent of variable rate fungicide spraying by farmers in the field is unknown, but is still likely to be on a small scale. Lisso et al. (2003) used yield potential maps to generate reference input maps for sowing, nitrogen fertilization and fungicide application.

The on-line approach of variable rate fungicide application has significant advantages over the off-line approach:

- Detection of diseases or plant parameters and variable rate spraying in one operation
- No time lag between data gathering and spraying
- Except for sensor costs no additional costs for data gathering, management, software and computer technology.

3 Leaf Area Index as a Parameter for Variable Rate Application

The on-line technology of applying variable rates of fungicides in cereals described in this chapter uses the Leaf Area Index (LAI) for the characterization of the crop canopy surface to be sprayed. This crop parameter is used for adapting the application volume within the field to crop density in subareas. The LAI quantifies the area of crop surface per area of ground ($m^2\ m^{-2}$). The time necessary for direct destructive measurements (Stroppiana et al. 2006) or the use of hand-held optical instruments (Welles and Norman 1991) exceeds the time available to realize dense sampling over a narrow grid. The costs for hand held instruments like LAI2000 or SunScan (Hiks and Lascano 1995, Wilhelm et al. 2000) are not acceptable for use by most farmers.

Dynamic crop growth models have been used to simulate the LAI (Basso et al. 2003, Guerif et al. 2003). Although the models are used for scientific experiments such complex models for production of georeferenced estimates of LAI for application maps cannot be used by farmers.

A very simple method for estimating the LAI in cereals which can use by farmers is based on a deterministic model (Dammer et al. 2008). Only crop height and the number of tillers per area are used as parameters and works well from stem elongation to flowering. With this method dense sampling within the whole field is not possible.

Real-time sensors also can be used to record the spatial distribution of LAI within the field. Spectral reflectance measurements in the near-infrared and red light zones and the derived vegetation indices are related to LAI values up to 6 (Wiegand et al. 1992). In other words, from stem elongation up to maturation, when multiple leaf layers exist, reflectance measurements for LAI estimation are not suitable, because the measured reflectance comes only from the upper leaf layers. However when maturation of cereals begins and healthy leaves start to senesce, reflectance sensors may again be suitable.

This problem does not exist when using mechanical sensors like the CROP-Meter, a real-time sensor to measure crop biomass density in cereals. It can be used beginning with growth stage GS 35 or stem elongation. While driving through the

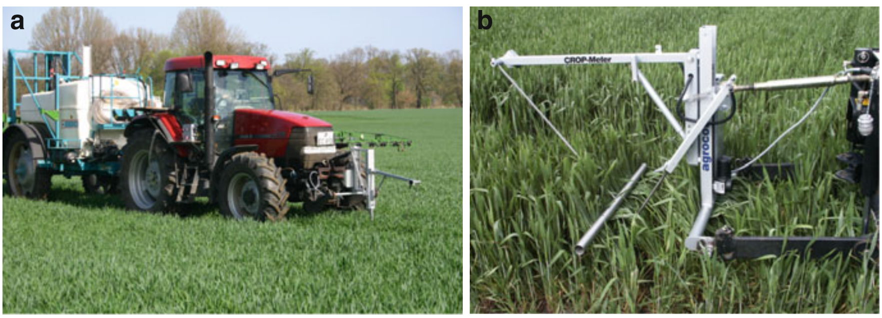

Fig. 22.1 CROP-Meter controlled field sprayer

crop a horizontally pivoted metal rod is deflected by the bending moment of cereal stem resistance (Ehlert and Dammer 2006). The sensor is mounted in front of the tractor (Fig. 22.1). A low deflection angle occurs in areas of the field with low crop density and *vice versa*. The deflection angle of the CROP-Meter is correlated with the LAI measurements of the above mentioned hand held optical instruments (Dammer et al. 2008).

4 Sensor-Controlled Field Sprayer

Burth et al. (1990) reported that fungicide dosage can be reduced when weather conditions at spraying are favourable. The efficiency of disease control by the reduced dosages was similar to the recommended dosage. It is common in practical agriculture to use lower dosages in disease control. Farmers however have to be aware that any guarantee which comes with the fungicide product can be lost. A second reason to use variable rates is the reduction of the off-target deposition of the spray liquid especially in low crop density areas of the field. The third aspect supporting variable rate technology is the positive economic impact. In heterogeneous fields there are within-field yield differences which result in differences in marginal income. This means that in low yield areas costs have to be reduced to make plant production effectively.

The application rate can be varied by variation of tractor speed while spraying or by changing the spray pressure. With conventional flat fan nozzles a variation of about 1:2 can be reached. Air-liquid nozzles allow a variation of about 1:3 of the application amount, whereas multiple nozzles systems can reach a variation of 1:8 without changing the tractor speed. The best technology for variable rate application – not only for fungicides, but also for herbicides – would be the direct-injection technology (Rockwell and Ayers 1996, Hloben et al. 2006). Direct-injection technology is not affected by the lack of information on the heterogeneity of crop density. No spray liquid is left after application compared to common field sprayers.

For an on-line variable rate application of fungicides in cereals the computer of the CROP-Meter is connected to the on-board terminal of the tractor. Using the agricultural bus system (LBS) based on ISO 11783 the field sprayer is controlled by the CROP-Meter. A potentiometer which is connected to the pendulum body generates a voltage between 1 and 4 V which is the input signal to control the flow rate of the field sprayer.

Because of the linear relationship between the deflection angle of the CROP-Meter and LAI, the volume of fungicide application is adapted linearly according to the deflection angle. Figure 22.2 illustrates the distribution of the deflection angle from the CROP-Meter in a winter wheat field on 18 May 2000. The rate of flow is measured from an additional flow meter in the main liquid pipe of the field sprayer. Based on this value the application rate is calculated and mapped in Fig. 22.3.

The areas with high deflection angle match the areas with high application rates. A similar approach, to adapt the dosage according to crop density in order to attain sufficient disease control, was also investigated by Ewaldz (2000).

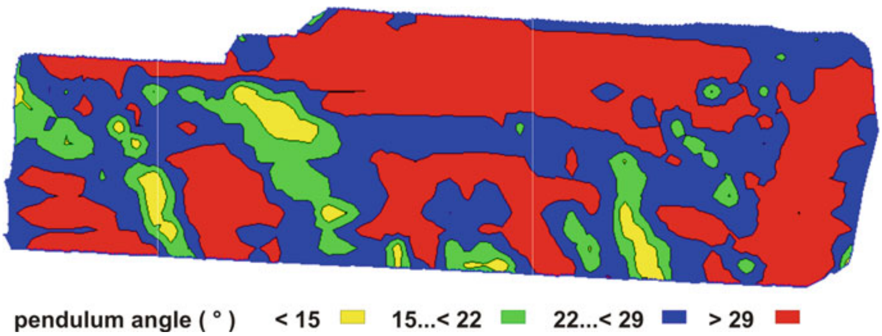

Fig. 22.2 Map of CROP-Meter deflection angle in winter wheat while spraying (Dammer et al. 2008)

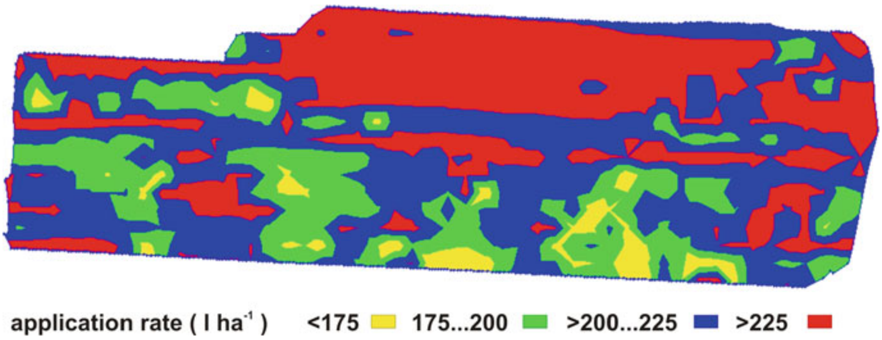

Fig. 22.3 Map of application rate measured by a flow meter of the field sprayer (Dammer et al. 2008)

The field operation is explained briefly below (for details see Dammer et al. 2008):

1. The farmer prepares his standard fungicide dosage in the field sprayer tank.
2. He chooses a typical tramline, which represents the heterogeneity in crop density. A uniform application is carried out along this tramline.
3. The lowest and highest deflection angle is recorded by the on-board terminal.
4. The lowest application rate is assigned to the lowest deflection angle and the highest application rate is assigned to the highest deflection angle at the calibration display.
5. While spraying the application rate is adapted to the deflection angle linearly between the lowest and highest application rate.

The values of the lowest and highest application rate depend on the users past experience with the fungicide product. Whereas minimum and maximum LAI may be used as indicators of the range of application rates, he can estimate these two extremes rapidly with the simple model mentioned above: crop height [m] x number of tillers per [m^2]/100 at the two sites where the lowest and highest deflection angle of the CROP-Meter were measured (Dammer et al. 2008).

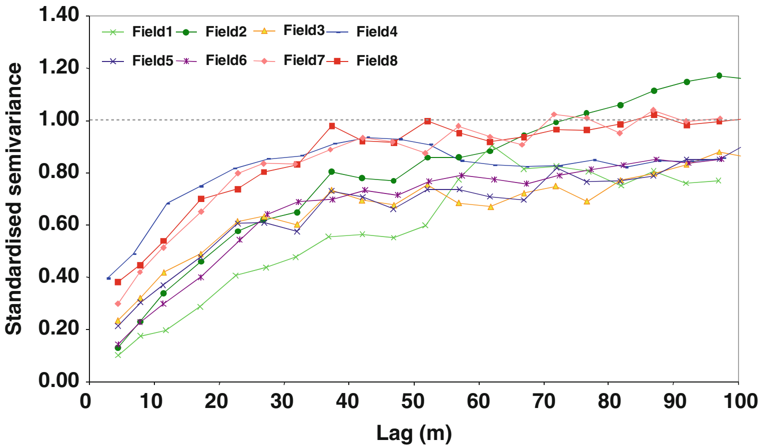

Fig. 22.4 Standardised variogram of the deflection angle from CROP-Meter measurements for eight fields (Dammer and Ehlert 2006)

The reliability of the CROP-Meter readings (operated between the tramlines) representing crop density also outside the tramlines was tested (Dammer and Ehlert 2006). A geostatistical analysis (standardised experimental variogram) of the deflection angle from eight cereal fields showed a spatial dependency from about 25–40 m. This means a change from low to high crop density occurred within a range of 25–40 m (Fig. 22.4).

From the results of these field trials it was demonstrated that crop density outside the tramlines was similar to in between. A section control of the field sprayer was not necessary, because the autocorrelation range was higher than the working width of the spray boom of the CROP-Meter controlled field sprayer.

5 Economic Benefits from Variable Rate Applications

Farmers will accept variable rate fungicide application technology only if the economic benefit is obvious. The most important benefit is savings in fungicides. In eleven field trials conducted with a CROP-Meter controlled field sprayer in commercial cereal fields from 2000 to 2004, savings ranging from 7 to 38% were obtained (Dammer and Ehlert 2006). The level of savings depends on the heterogeneity of crop density and the decision of the farmer concerning the lower and upper limits of application rate. When his strategy is to apply variable rates of fungicides not only at reduced dosages, but to spray more than his standard dosage up to that recommended on the product label in high crop density areas fungicide savings may not be as high.

A reduction in fungicide dosage may not result in yield reduction. The yield effect of variable rate application was investigated in field strip trials in commercial cereal fields. Variable rate application was done in one tramline and a uniform application with the standard fungicide dosage in the neighbouring tramline. With the treatment plot locations next to each other soil influence could be minimized. A combine harvester with a yield monitoring system measured yields along a harvested strip. Depending on the tramline distance and the cutting unit width of the combine harvester, up to two strips per treatment were harvested. From the nearest neighbour pairs of variable rate and uniform application, yield values could be extracted. The local yield values were compared statistically by the "Difference Method" for controlled treatment comparison (Anonymous 1972). The mean of the differences were tested against zero using the t test. All local differences of a field experiment were analyzed graphically using the box-whisker-plots. In Fig. 22.5 the box-whisker-plots of six field trials are summarized. The median and the quartile of the local yield differences between the variable rate and the uniform plot were located around zero, indicating that no yield reduction occurred by a CROP-Meter controlled fungicide application.

In those cases where the strategy is to apply more than the farmers standard dosage in dense cereal canopies Secher (1997) observed a yield increase of 0.3 t ha^{-1} compared with a conventional application. According to Paveley et al. (1996) an explanation could be the positive relation between yield potential of different areas in the field and yield response of a fungicide application. In contrast Bjerre (1999) demonstrated no yield effects in his experiments with variable rate fungicide applications.

Beside fungicide savings there is the effect of saving machine costs. Due to the reduction of the application volume in areas with low crop density more area can

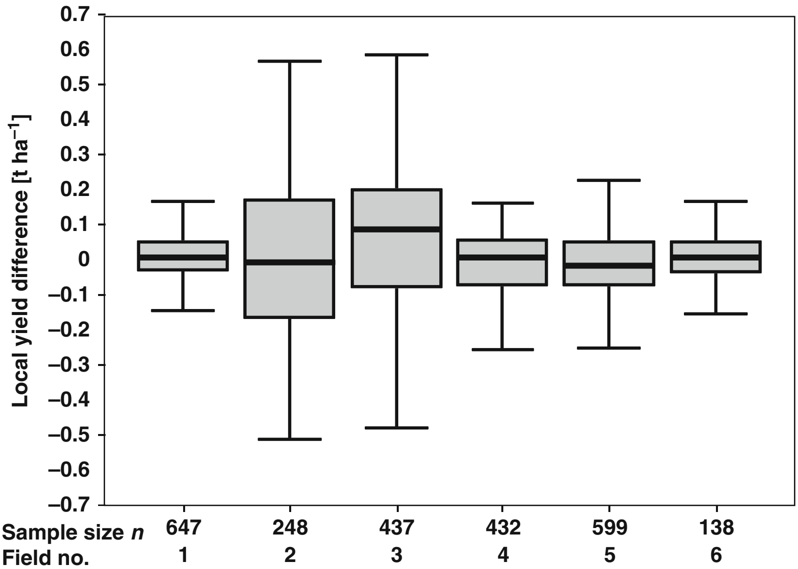

Fig. 22.5 Box-whisker-plots of local yield differences (variable rate – uniform) from six field trials (Dammer and Ehlert 2006)

Table 22.1 Economic evaluation of machine costs of CROP-Meter controlled variable fungicide application in a winter wheat field (Dammer 2005)

Year	Area [ha]	Savings			Increased machine efficiency [ha]	Machine cost savings [€ ha^{-1}]
		Spray liquid [l]	Filling tours [n]	Filling time [h]		
2000	49	1,979	1	0.75	9.37	4.21
2001	27	2,025	1	0.75	9.37	7.64
2002	49	853	1	0.75	9.37	2.10
2003	27	2,241	2	1.50	18.75	7.64
2004 (field 1)	23	1,092	1	0.75	9.37	4.48
2004 (field 2)	26	2,470	2	1.50	18.75	3.96

be sprayed with each tank load. Therefore, there are fewer trips to fill the sprayer tank with water. The filling time also can be reduced. The economic calculations in Table 22.1 are based on CROP-Meter controlled variable rate fungicide spraying in a winter wheat field for the period 2000–2004 in Saxony-Anhalt, Germany (Dammer 2005). The calculation basis was a typical filling time of a 2,000 liter field sprayer of 0.75 h, an output of 12.5 ha per hour and machine costs of 9.50€ per hectare. In 5 years, beside product cost savings of 2.64–12.94€ ha^{-1}, machine cost savings of 2.10–7.64€ ha^{-1} were obtained. Assuming a 1,000 ha farm with 60% cereals in the crop rotation the additional costs of the CROP-Meter and on-board terminal of about 13,000€ will be paid off within 2 years (Dammer 2005).

6 Combining Decision Support Systems with Sensor-Controlled Variable-Rate Fungicide Application

Several crop and environmental parameters can have an influence on the intra-field variability of disease occurrence:

- Soil type
- Topography
- Crop density
- Leaf area index
- Nutritional status of plants
- Water stress.
- Surroundings (hedgerows, forest, etc.).

These parameters can change the microclimate in certain parts of the field. Especially shading by forested areas or hills can lead to longer periods of leaf wetness which can stimulate spore germination and the infection success of pathogens. Shading may result also in lower temperatures in the affected subareas of the field. Fungal pathogens can respond differently to the same microclimatic parameter, and be either inhibited or stimulated. For example a higher crop density due to different seeding rates or higher nitrogen fertilization can lead to higher severity of powdery mildew (*Blumeria graminis*) in spring and winter cereals (Sentelhas et al. 1993, Rozalski et al. 1998) or eyespot disease (*Oculimacula yallundae*) in winter rye (Dammer 1988). Park et al. (1992) and Murray et al. (1994) reported that stripe rust (*Puccinia striiformis* f. sp. *tritici*) occurrence in wheat is correlated with higher temperature. This is the case in field areas with low crop density, because they warm up faster. While Bjerre (1999) observed a negative correlation between leaf blotch (*Septoria tritici*) severity and crop density, Broscious et al. (1985) and Sentelhas et al. (1993) demonstrated that dense canopies were more likely to become diseased in the absence of precipitation.

In the field different fungal pathogens may occur simultaneously or sequentially. The optimum conditions for infection and the length of incubation periods may vary greatly. A further problem is latent infection – the lag phase between successful penetration of the plant and the formation of visible symptoms. The complex relations between disease occurrence, crop development, microclimate and weather parameters for variable rate fungicide spraying cannot be managed effectively by the farmer, but requires special disease forecast models. Simulation models for disease forecast in decision support systems mainly use weather data from meteorological stations (Kleinhenz et al. 1995, Newe et al. 2003). The output is a field-specific decision on crop protection. An intra-field specific forecast for areas in the field with different crop density incorporating parameters on crop and microclimate impacting to the problems mentioned above has not yet been produced.

In heterogeneous crops the amount of crop loss prevented by fungicide applications depends on the site-specific yield potential of the different sub areas of the field. Expert systems like proPlant also incorporate economics as suggestions about the fungicide product to be used (Newe et al. 2003). Economics, especially the different yield potential, mainly due to differences in soil quality within a heterogeneous field, is another reason to identify management zones within the field. As pointed out in Section 2 these zones are the basis in the mapping approach not only in variable rate fungicide spraying but also for other measures of precision plant production. Sowing and fertilization can be done at different rates in these management zones. Within the research project “preagro2” the decision support system proPlant expert.classic was modified for variable rate fungicide application in winter wheat. The developed prototype proPlant expert.precise takes into account different infection probabilities of plant diseases and different marginal factors such as pesticide and nitrogen fertilizer rates. As a result the system generates a spraying map with different application rates of a specific fungicide for up to three management areas separately (Wollny et al. 2007). This map in XML format can be imported to the on-board terminal. Analogous to Section 4 the maximum application rate recalling from the map is assigned to the highest deflection angle from the CROP-Meter for each management zone. The minimum application rate assigned to the lowest deflection angles is decided by the farmer. Between the maximum and the minimum application rate the spraying volume is adapted linearly to the deflection angle of the CROP-Meter (Fig. 22.6).

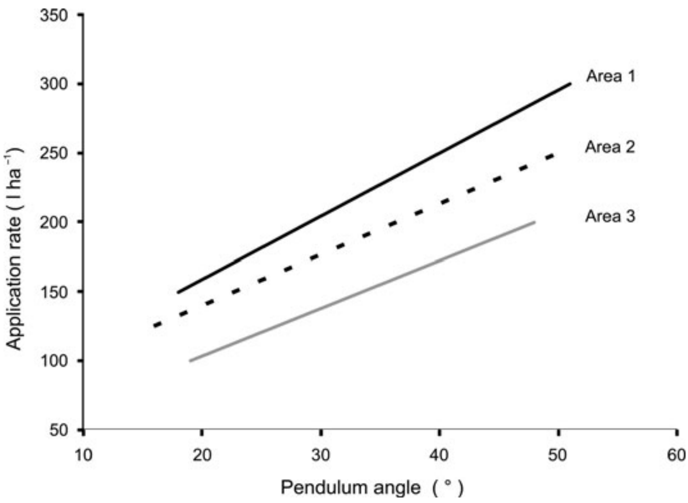

Fig. 22.6 Sprayer control algorithm for three management areas (Dammer et al. 2009)

The application system recognizes the borders of the management areas by GPS. An example of how the system works is shown in Fig. 22.7.

The spray volume is linked to the deviation angle. It cannot exceed the maximum in the respective management zone (200, 250, 300 l ha^{-1}). The proPlant system sets the maximum of the application rate and the CROP-Meter does the fine tuning within the management areas. The CROP-Meter with map overlay system was tested in three winter wheat fields in 2007 (Dammer et al. 2009). The fungicide savings

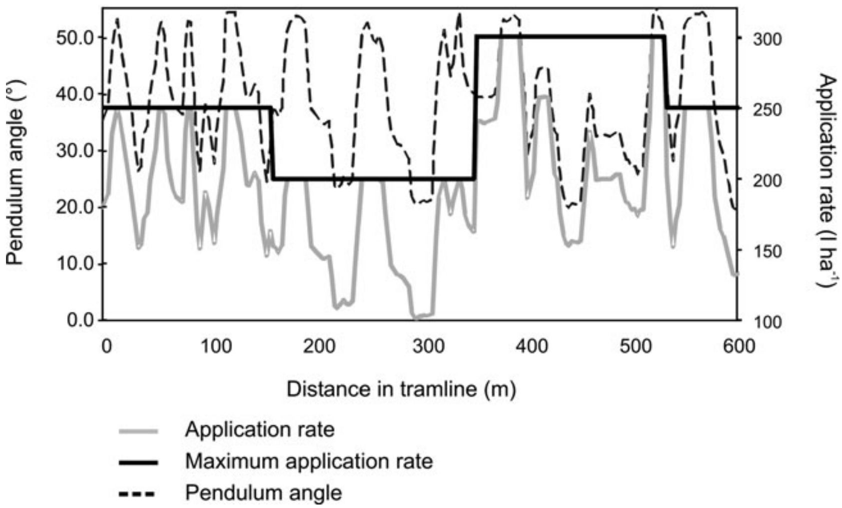

Fig. 22.7 Angle of the CROP-Meter, application rate of the field sprayer and maximum application rate defined by the spraying map along a tramline (Wollny et al. 2007)

increased from the management zone with high yield potential to the zone with low potential. They were higher in the treatment using the CROP-Meter with map overlay than in that with the CROP-Meter only. Savings when compared to a uniform application were 13.9, 21.7 and 32.6%, verse application with CROP-Meter only of 11.9, 11.1 and 20.3%. Similar to Section 5 there were neither yield reductions nor higher disease severities in the plots with variable rate fungicide application.

7 Perspectives

The development of sensors for disease detection would advance progress towards variable rate fungicide application according to disease occurrence. Detection has to be successful in an early stage of disease epidemics and fungal spread. Symptoms on the plant surface are minute and may occur in the crop at random. Moreover, fungal infections may be present even without visible symptoms. Several optical methods for detecting fungal diseases are being developed but are now still used under laboratory conditions where interfering factors can be controlled and image analysis can be applied more easily than under field conditions. In the field environmental factors can change very rapidly. Research has to be conducted to eliminate their influence on detection. Varying levels of illumination under field conditions still prohibits practical implementation of reflectance sensors for disease detection. The reflection behaviour of different wavelengths may vary independently under sunny and shady conditions. Drought or nutrient deficiencies may lead to symptoms similar to diseases. The main problem is distinguishing between plant diseases and other stress symptoms or even among different disease symptoms, which may differ in colour depending on pathogen isolate, disease stage, weather, microclimatic factors and crop variety. Nielson (1995) and West et al. (2003) concluded that remote sensing, which uses optical sensors, is not suitable to detect symptoms of plant diseases.

Farmers generally apply fungicides with broad-spectrum activity for the control of several diseases especially when only one application in cereals is carried out. They attempt to control a spectrum of diseases, including those which may occur a few days after spraying. The differentiation of diseases becomes interesting if two or more fungicide applications are necessary, especially under humid weather conditions. In these cases a demand related spraying of pathogen-specific fungicides would attract more attention by farmers. In order to spray two or more chemicals, spray equipment with fast direct injection systems becomes necessary.

Crop yield reduction caused by plant disease depends on the time of infection. Disease infections at early growth stages reduce crop yields stronger than later infections. At a certain growth stage, protection of plant tissue by fungicides for the production of assimilates is no longer necessary. For cereals Gent (1994) reported that assimilates accumulated in the leaves are transported into the ear starting at grain filling. Chlorophyll in the plant tissue is degraded, senescence begins and plants go into ripeness. Obligate pathogens like fungi causing powdery mildew and rust depend on living cells and can no longer grow. In heterogeneous fields low

Table 22.2 Ontogenetic development of winter wheat in field areas with low (LAI < 4) and high crop density (LAI > 6) (Dammer 2005)

Time	BBCH-growth stage		Description	
28.04.04	32		Node 2 appears	
06.05.04	34		Node 4 appears	
13.05.04	37		Flag leaf just visible	
18.05.04	39		Flag leaf fully enrolled	
25.05.04	41–43		Early/mid boot stage	
28.05.04	45–47		Flag leaf sheath opening	
	Areas with LAI > 6	Areas with LAI < 4	Areas with LAI > 6	Areas with LAI < 4
03.06.04	49	55	First awns visible	Middle of heading
09.06.04	51	61	Beginning of heading	Beginning of flowering
15.06.04	61	69	Beginning of flowering	End of flowering
21.06.04	69	75	End of flowering	Medium milk
29.06.04	73	83	Early milk	Early dough
07.07.04	83	87	Early dough	Hard dough
21.07.04	87	92	Hard dough	Overripe

crop density areas may become senescent earlier than high crop density areas by up to 1 month. Table 22.2 summarizes the growth stage development of winter wheat within a field in Saxony-Anhalt, Germany.

Until the end of May crop development was very similar. Then water became the limiting factor for crop growth and wheat in sandy subareas suffered from drought stress. As of beginning of June, crop development in areas with low LAI was faster. Consequently these plants had to be protected against plant pathogens for a shorter period of time than wheat plants in subareas with higher LAI. In this context research work is necessary to investigate the interaction between pathogens and host when senescence starts.

Because of the difficulties in direct detection of diseases and latent infections the combination of disease forecast models and sensors is important. Beside the horizontal dispersion dynamics of diseases within a field, research should focus on the inclusion of the vertical dispersion dynamics of diseases on plants into disease forecast models. The main factors for the vertical dispersion dynamics are the age of the leaves and their disposition to fungal colonization. The spores are often splash-dispersed by rain drops from older infected leaves onto younger healthy leaves. Lovell et al. (1997) found a negative correlation between crop density and the occurrence of leaf blotch due to *Septoria tritici*. The splash dispersal of the spores from lower infected leaves to the upper leaves was blocked.

Against the background of decreasing energy resources, rising production costs and environmental protection becoming more and more important, the variable rate application of fungicides is one technology of precision farming which helps the farmer to run his business effectively at all levels.

References

Anonymous (1972) Biometrische Versuchsplanung. VEB Deutscher Landwirtschaftsverlag, Berlin

Basso B, De Vita P, Basso F et al (2003) Assessing and modelling spatial variability of yield and grain quality of durum wheat under extreme dry conditions. In: Stafford JV, Werner A (eds), Precision agriculture. Wageningen Academic Publishers, Wageningen, pp 53–59

Bjerre KD (1999) Disease maps and site-specific fungicide application in winter wheat. In: Stafford JV (ed.) Precision agriculture. Sheffield Academic Press, Sheffield, pp 495–504

Bjerre KD, Secher BJM (1998) Field experience with site-specific application of fungicides to winter wheat. In: Brighton crop Protection Conference – Pests and Diseases. British Crop Protection Council, Farnham, pp 987–992

Broscious SC, Frank JA, Frederick JR (1985) Influence of winter wheat management practices on the severity of powdery mildew and Septoria blotch in Pennsylvania. Phytopathology 75: 538–542

Burth U, Hartleb W, Hartmann W, Hamann W (1990) Zur variablen, situationsbezogenen Bemessung der Aufwandmenge bei der Applikation von Pflanzenschutzmitteln. Nachrichtenbl. PflSchutzd. DDR 44:194–196

Campbell CL, Madden LV (1990) Introduction to plant disease epidemiology. Wiley Interscience, New York

Dammer KH (1988) Untersuchungen zur Auslese von Einzelpflanzen im Winterroggen mit Resistenz gegenüber *Pseudocercosporella herpotrichoides* (Fron) Deighton. PhD thesis, Martin-Luther-Universität Halle-Wittenberg

Dammer KH (1999) Analyse und Darstellung der Dispersion von Schaderregern sowie Möglichkeiten der Stichprobenahme bei aggregiertem Auftreten. Eigenverlag, Kropstädt

Dammer KH (2005) Demonstration der Langzeitwirkung bedarfsorientierter Fungizidbehandlung mit dem CROP-Meter. Bornimer Agrartechnische Berichte, Heft 41, Leibniz-Institut für Agrartechnik, Potsdam-Bornim

Dammer KH, Ehlert D (2006). Variable-rate fungicide spraying in cereals using a plant cover sensor. Prec Agric 7:137–148

Dammer KH, Thöle H, Volk T, Hau B (2009) Variable-rate fungicide spraying in real time by combining a plant cover sensor and a decision support system. Prec Agric 10:431–442

Dammer KH, Wollny J, Giebel, A (2008) Estimation of leaf area index in cereal crops for variable rate fungicide spraying. Eur J Agron 28:351–360

Ehlert D, Dammer KH (2006) Widescale testing of the CROP-Meter for site-specific farming. Prec Agric 7:101–115

Ewaldz NAT (2000) Radiometric readings as a tool for predicting optimal fungicide dose in winter wheat. Z PflKrankh PflSchutz 107:594–604

Fleischer SJ, Blom PE, Weisz R (1999) Sampling in precision IPM: when the objective is a map. Phytopathology 89:1112–1118

Gent MPN (1994) Photosynthate reserves during grain filling in winter wheat. Agron J 86: 159–167

Guérif M, Hollecker D, Beaudoin N et al (2003) Site specific calibration of a crop model by assimilation of remote sensing data: a tool diagnosis and recommendation in precision agriculture. In: Stafford JV, Werner A (eds.), Precision agriculture. Wageningen Academic Publishers, Wageningen, pp 253–258

Hiks SK, Lascano RJ (1995) Estimation of leaf-area index for cotton canopies using the LA-COR LAI-2000 plant canopy analyzer. Agron J 87:458–464

Hloben P, Sökefeld M, Schulze Lammers P (2006) Untersuchungen der Verzögerungszeiten von Direkteinspeisungssystemen für die teilflächenspezifische Applikation von Herbiziden. Agrartech Forsch 12:14–18

Hughes G, Madden LV (1995) Some methods allowing for aggregated pattern of disease incidence in the analysis of data from designed experiments. Plant Pathol 44:927–943

Jeger MJ (1989) Spatial components of plant disease epidemics. Prentice Hall, Englewood Cliffs

Kleinhenz B, Jörg E, Kluge E, Rossberg D (1995) PASO – Rechnergestützte Entscheidungshilfen für den Pflanzenschutz. Ges Pflanzen 47:222–230

Lisso H, Trunk K, Jäger S (2003) Drei Beispiele für die Umsetzung. In: Haser G (ed), Zukunftsträchtiger Ackerbau – Systeme der Computer- und GPS-gestützten teilflächenspezifischen Bewirtschaftung praxisnah bewertet. Deutscher Bauernverlag, Berlin

Lovell DJ, Parker SR, Hunter T et al (1997) Influence of crop growth and structure on the risk of epidemics by *Mycosphaerella graminicola* (*Septoria tritici*) in winter wheat. Plant Pathol 46:126–138

Moran MS (2000) New imaging sensor technologies suitable for agricultural management. Asp Appl Biol 60:1–10

Murray GM, Ellison PJ, Watson A, Cullis BR (1994) The relationship between wheat yield and stripe rust as affected by length of epidemic and temperature at the grain development stage of crop growth. Plant Pathol 43:397–405

Newe M, Meier H, Johnen A, Volk T (2003) proPlant expert.com: the online consultation system on crop protection in cereals, rapeseed, potatoes and sugar beet: a concept that meets the requirements of farmers and consultants in both Germany and Europe. EPPO Bull 33:443–449

Nielson HE (1995) Remote sensing and image analysis in plant pathology. Annu Rev Phytopathol 15:489–527

Oerke EC, Dehne HW (1997) Global crop production and the efficacy of crop protection – Current situation and future trends. Eur J Plant Pathol 103:203–215

Park RF, Ash GJ, Rees RG (1992) Effect of temperature on the response of some Australian wheat cultivars to *Puccinia striiformis* f.sp. *tritici*. Mycol Res 96:166–170

Paveley ND, Clark WS, Sylvester-Bradley R et al (1996) Responding to inter- and intra-field variation to optimise foliar disease management in wheat. Brighton Crop Protection Conference, Pests and Diseases, Brighton, pp 1227–1234

Rockwell AD, Ayers PD (1996) A variable rate, direct nozzle injection field sprayer. Appl Engin Agric 12:531–538

Rozalski K, Pudelko J, Skrzypczak G (1998) Disease incidence in winter wheat and spring triticale as influenced by crop protection and nitrogen. Progr Plant Prot 38:551–554

Secher BJM (1997) Site specific control of diseases in winter wheat. Aspects Appl Biol 48:57–65

Sentelhas PC, Pedro MJ, Felicio JC (1993) Effects of different conditions of irrigation and crop density on microclimate and occurrence of spot blotch and powdery mildew. Bragantia 52: 45–52

Stroppiana D, Boschetti M, Confalonieri R et al (2006) Evaluation of LAI-2000 for leaf area index monitoring in paddy rice. Field Crops Res 99:167–170

Van der Plank JE (1963) Plant diseases: epidemics and control. Academic Press, London

Welles JM, Norman JM (1991) Instrument for indirect measurement of canopy architecture. Agron J 83:818–825

West JS, Bravo C, Oberti R et al (2003) The potential of optical canopy measurement for targeted control of field crop diseases. Annu Rev Phytopathol 41:593–614

Wiegand CL, Maas SJ, Aase JK et al (1992) Multisite analyses of spectral-biophysical data for wheat. Rem Sens Environ 42:1–21

Wilhelm WW, Ruwe K, Schlemmer MR (2000) Comparison of three leaf area index meters in a corn canopy. Crop Sci 40:1179–1183

Wollny J, Dammer KH, Hau B et al (2007) Site-specific disease control in wheat by combining the CROP-Meter with the decision support system proPlant. In: Stafford JV (ed) Precision agriculture ’07. Proceedings of the 2nd european conference on precision agriculture, Wageningen Academic Publishers, pp 783–789

Part V
Current Use of Precision Crop Protection in Practice

Chapter 23
Providing Precision Crop and Range Protection in the US Northern Great Plains

George A. Seielstad, David E. Clay, Kevin Dalsted, Rick L. Lawrence, Douglas R. Olsen, and Xiaodong Zhang

Abstract Faculty, students, and staff from eight universities in the U.S. Northern Great Plains formed the Upper Midwest Aerospace Consortium (UMAC) to lead a regional transition to sustainability. One major focus was on agriculture, an important part of the region's economy and social structure. By forming a learning community in concert with farmers and ranchers, UMAC has made information an asset as valuable as land, labor, and capital. One primary source of information combined with traditional sources is remotely sensed imagery. UMAC has created an end-to-end operation, starting with data acquisition by airborne and orbiting sensors customized to acquire data needed to meet producer demands, proceeding to development of value-added products, and finally making them readily accessible on the WWW to non-expert users whom we also train. A specific example of the operation in action illustrates the economic and environmental benefits that result.

1 Introduction

Humanity has arrived at a moment of historic change. The number of people in the world and their collective ability to modify the planet and its living inhabitants have introduced the Anthropocene (Crutzen 2002), a geologic epoch dominated by the single species, *Homo sapiens*. Decisions we make now at the onset of this epoch will have consequences for many generations beyond ours. The historic transition the times demand is one to sustainable practices. Since food is a basic human need, agriculture is and will continue to be a foundation of civilization. It follows, therefore,

G.A. Seielstad (✉)
Bay Area Environmental Research Institute, Missoula, MT 59808, USA
e-mail: g.seielstad@nserc.und.edu

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_23,

that agriculture, too, must change, and that decisions about how to transition it toward sustainability cannot be delayed (Brown 2009).

With that in mind, researchers and educators at eight universities in the northern Great Plains of the United States organized a collaboration called the Upper Midwest Aerospace Consortium (UMAC). The member institutions are the Universities of North Dakota, Montana, Idaho, and Wyoming; South Dakota and Montana State Universities; Sinte Gleska University; and the South Dakota School of Mines and Technology. A driving purpose for the consortium was to assemble both the depth in numbers and breadth in expertise needed for the multi-disciplinary cause of sustainability. A second purpose was to have the capability to customize products and services to specific locations within the wider region. Finally, by forming a distributed organization, UMAC offers access nodes throughout the region so that residents can interact with familiar, local institutions.

Interaction with residents is crucial to the consortium's core mission of sustainability. The challenge is to foster actions that deliver economic benefits now to people who undertake them, while simultaneously delivering benefits to generations not born by sustaining a healthy environment. The method was to create a learning community in which people were encouraged to share their expertise without regard to whether it was acquired through formal education or practical experience (Seelan et al. 2003). A major difference, then, is that agricultural producers are treated as research partners, not as clients. The actual applications that emerge from this inclusive partnership are carried out on farms and ranches in for-profit production. That entails working with agroecosystems, with all their complexity but also with none of the artificiality of controlled experiments. The weakness of the latter is that knowing how components of a system behave when examined individually does not necessarily indicate how the full system will behave when all components are unconstrained. In essence this philosophy accepts crops or livestock as the true biophysical integrator of their environment.

Building a learning community focused on initiating sustainable practices in agriculture was a four-step process. First, UMAC had to create an Environmental Information Bridge. The analogy with a bridge indicates that information flows both ways between producers and researchers. Crucial is to work on challenges or opportunities that producers identify. Knowing the needs of producers leads to a second step, research and development of a kind that is benefits-driven, not purely curiosity-driven. Research relies on use of data, so the consortium's third step was to design, build, and operate data acquisition and data dissemination technologies. Finally, training has to be provided so that consumers of the research and its developments know how to turn them into profitable and environmentally benign actions (Seelan et al. 2007).

The following sections describe how information was incorporated into farm and ranch management strategies, which is to say they describe how precision agriculture was encouraged. A report by the U.S. National Research Council (Sonka 1997) "defines precision agriculture as a management strategy that uses information technologies to bring data from multiple sources to bear on decisions associated with crop production." This became UMAC's working definition.

A significant thrust of UMAC was to synthesize remotely sensed information with that from many other sources to enable wiser decision-making by farmers and ranchers. ZoneMAP (Section 2) automatically characterizes farms' and ranches' heterogeneity. Heterogeneity in evapotranspiration on a farm exemplifies site-specific management of corn yield (Section 3). Methods to assist ranchers to make informed decisions about livestock carrying capacity are described in Section 4. Critical to all UMAC's decisions is Digital Northern Great Plains (Section 5), a system for providing convenient access to the information generated. Since an ultimate goal is to customize products and services to each individual producer's needs, UMAC developed and operates sensors designed specifically to meet the agricultural needs of our region (Section 6). A farm that may be a harbinger of precision crop protection (Section 7) illustrates how all the consortium's activities are brought together. Lessons Learned (Section 8) concludes the chapter.

2 ZoneMAP: Defining Heterogeneity in Crop and Range Lands

Precision agriculture has been made possible by modern technologies on farm implements that permit treatments applied to farms or ranches to be varied. The Global Positioning Satellites (GPS) system allows specification of precise location within a field, and onboard computers can regulate the flow of the treatment being applied. In addition, combines and other harvesting implements can record yields as a function of location. Farming has become, to a large extent, management of variations rather than management of average properties.

The power of the new technologies can only be utilized if a producer knows what the appropriate rate at which an input – of seeds, fertilizer, herbicide, pesticide, irrigated water, or other – should be applied at every location. Zone Mapping Application for Precision Farming (http://zonemap.umac.org) is a web-based decision-support tool developed to meet this need. ZoneMAP can automatically determine the optimal number of management zones and delineate them using satellite imagery and field survey data provided by users. ZoneMAP is linked to a rich archive of satellite imagery called Digital Northern Great Plains (see Section 5).

Remote sensing for precision agriculture is based on the relationships between surface spectral reflectance and various soil properties and crop characteristics (Moran et al. 1997). Satellite observations provide measurements of surface reflectance with ∼15–60 m spatial resolution (e.g. SPOT, Landsat or ASTER) at least a few cloud-free times during a growing season. Objectives of ZoneMAP for using satellite imagery to delineate zones included: (I) streamlining format conversion, reprojection, and gridding of data obtained from a variety of sources, (II) providing straightforward access to satellite images, (III) allowing selection of a specific area of interest within the much larger image, (IV) creating an output map that could be directly ported into farm machinery, and (V) running computing algorithms on a UMAC server to free users from the need to buy expensive, complicated software for which they would need powerful computers.

2.1 ZoneMAP's Classification System

Fuzzy c-means (FCM) (Burrough 1989, Burrough et al. 1992, Fridgen et al. 2004) was the clustering algorithm selected for ZoneMAP. The algorithm determines the degree of similarity between an observed value (say, a surface reflectance point) and a cluster center. The first step was to determine the optimal number of zones into which a field should be divided. To determine this, within-cluster variability for a number n of clusters was compared with that for n–1 clusters. Figure 23.1 illustrates that generally the percentage of total within-cluster variability with respect to the total initial variability decreases as the number of clusters increases. A similar trend was found by Brock et al. (2005). After an initial rapid decrease the total within-cluster variance typically approaches an asymptotic value as the number of clusters increases. The optimal number of zones is therefore the number of clusters that reduces the variance significantly as compared to the initial variability, yet changes little when the number of zones is further increased. Two criteria capture this turning point in a relatively consistent manner: (1) overall reduction of variance >50%; and (2) consecutive reduction of variance <20% or a break at which within-cluster variability begins increasing instead of decreasing.

Such vegetation indices as Normalized Difference Vegetation Index (NDVI) and Green NDVI (GNDVI) have been widely used for developing management zones (Metternicht 2003, Moran et al. 1997). ZoneMAP automatically calculates NDVI and GNDVI on-the-fly. Since a canopy's reflectance changes during a growing season as vegetation goes through stages of emergence, maturity, reproduction, and senescence, zone classifications are improved if more than a single image is used.

A remote sensing image covers a much bigger area than a single farm or ranch field. Instead of processing the entire image, ZoneMAP automatically crops the

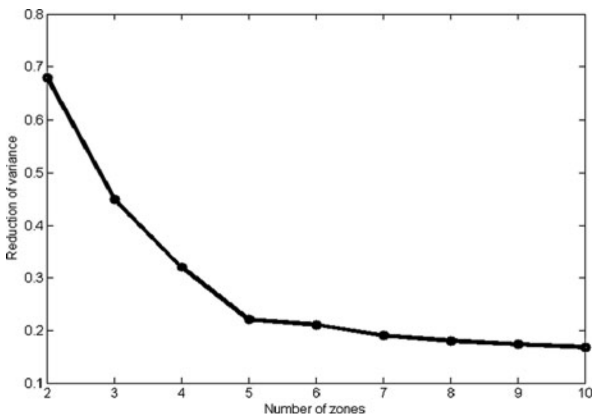

Fig. 23.1 Total within-cluster variability as a percentage of initial variance. For case shown, optimum number of zones is five

image to an area of interest defined by the user. ZoneMAP also automatically reprojects and resamples different images to a common projection plane with an equal ground sampling distance determined by the user.

Properties other than surface reflectance can assist classification into management zones. These include electrical conductivity, soil samples, yield maps, often for multiple years and crops, and other parameters. Usually, though, various data sources come in different formats, projections, and spatial resolutions. ZoneMAP invokes subsetting, reprojecting, and resampling procedures to project them onto the same grid as the one for images.

All users' data are saved in a secure online database so that within-season or multi-year comparisons of management zones can be performed. For each creation of a set of management zones, metadata is generated describing the procedure and datasets used. Users can download their results in three formats, raster image, grid text, and shape file. For each format, one can choose from multiple projections. In addition, users can input application rates for each zone to generate a variable rate application map.

2.2 Sample Map for Production Field

Figure 23.2a shows management zones determined by ZoneMAP from two NDVI images of a 97-ha field in Minnesota, acquired in successive years at the time of

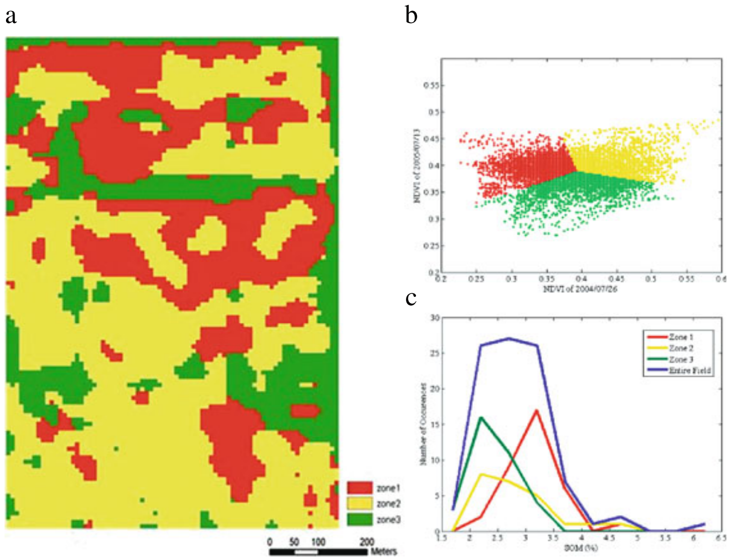

Fig. 23.2 Management zones (**a**) and corresponding scatter plot (**b**) created using reflectance measurements at NIR by Landsat on 26 July 2004 and 13 July 2005. Histograms of SOM within each zone and for the entire field are plotted in (**c**)

maximum canopy cover. The 2004 crop was soybeans and the 2005 crop, wheat. The optimal number of zones was determined to be three. Each zone was clearly defined into distinctive domains defined by NDVI values of 2004/07/26 versus 2005/07/13 (Fig. 23.2b). Histograms of soil organic matter (SOM) within each zone (Fig. 23.2c) show clear separations, with means for each class of 3.15, 2.95, and 2.42. The means of pH values for each zone were 8.42, 8.19, and 8.36, respectively.

These results confirm that remote sensing can be effectively incorporated into delineation of management zones (Zhang et al. 2010a). However, field surveys of soil attributes and nutrient conditions are important and cannot always be replaced by current remote observations. At a minimum, though, a preliminary mapping of subfield zones using remote sensing helps to design a cost-effective survey plan.

3 Mapping Evapotranspiration for Site-Specific Farm Management

Since the global demand for food is projected to double by 2030–2050 (Bruinsma 2003), pressure to increase yields from the Northern Great Plains will mount. The existing delicate balance among crop and livestock production, wildlife, soil sustainability and other goods and services provided by natural resources will be challenged. UMAC is confronting this challenge by integrating spatial technologies fully into production systems. The ability to develop appropriate site-specific algorithms has been limited by the difficulty of quantifying the yield-limiting factors over landscapes and watersheds. Three young technologies, remote sensing, yield monitors, and molecular biology, can provide the information needed to better refine weed, nutrient, and pest management decisions.

Although many factors influence yields, much of the current precision crop protection research has concentrated on evaluating the impact of water and nutrient availability on yields (Clay et al. 2001, Clay et al. 2003). This work has shown that water is scarcer, and therefore yields lower, in summit/shoulder areas. These areas can be defined using a combination of simulation models, remote sensing, and ground-collected data. For example, Mishra et al. (2008) used a Landsat scene acquired on 4 August 2001, ground-based weather station data, and the METRIC (Mapping Evapotranspiration at High Resolution and with Internalized Calibration) model (Allen et al. 2005) to estimate evapotranspiration (ET) over a 65 ha corn (*Zea mays* L.) field in South Dakota. The year 2001 was drier and slightly warmer than average in July and August compared with the 30-year average (1971–2000) of precipitation and temperature for May through August. No precipitation was recorded during the week before the satellite overpass, which suggests soils were not at field capacity when ET was estimated. Soil samples, collected (0–15 and 15–60 cm) periodically during the growing season, were analyzed for gravimetric soil water.

Evapotranspiration values calculated with a spatial resolution of 30 m correlated strongly with corn yield ($r = 0.85^{**}$), and with apparent electrical conductivity, EC_a

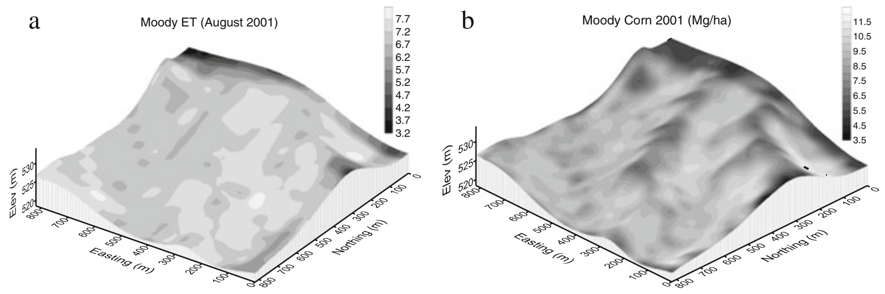

Fig. 23.3 Evapotranspiration based on the METRIC model (**a**). Yield maps draped over the digital elevation map (**b**; Mishra et al. 2008)

(r = 0.71**). In the footslope positions, high ET values were associated with high corn yields, while in the summit/shoulder areas low ET values were associated with low yields. The strong relationship between evapotranspiration and productivity shown in Fig. 23.3 was attributed to landscape processes that influenced plant-available water. Remote sensing-based ET data were most successful in identifying areas where water stress reduced corn yields, while EC_a was most successful in identifying high-yielding management zones.

4 Uses of Satellite Imagery in Range Protection

The arid Northern Great Plains of the United States have a sizable west-to-east precipitation gradient, from approximately 30 cm year^{-1} in the rain shadow of the Rocky Mountains in the west to twice that amount in its extreme east. The region's ranchers must accordingly make critical decisions at the beginning of the cattle-grazing season (Holechek 1988, Sankey et al. 2008). First is the decision about livestock grazing intensity permissible in each pasture based on the best estimates of forage available during the upcoming season. Next is a decision whether certain pastures require differential treatment or can withstand more intensive grazing. These decisions have historically been based on a rancher's sometimes unreliable personal knowledge of the grazing lands. Remotely sensed data provide more reliable information upon which to base grazing decisions, as shown in the following two examples.

4.1 Soil Water Estimation

Remote sensing has been shown to be powerful for estimating forage quantity (see e.g. Maynard et al. 2007a), but most approaches require individual parameterization for each scene. Gathering ground reference data for such parameterization is not practical. An alternative is to focus on water availability, because it is directly correlated to forage amount (Sankey et al. 2008). Rainfall during the season is inherently unpredictable, but it has proved possible to model the amount of water stored in the soil at the beginning of a growing season.

The procedure for modeling soil water was carried out at two ranches, the Decker/Bales Ranch in southeast Montana and the BBar Ranch in south central Montana. To make a practical system that ranchers would use, collection of field data had to be limited to a single day. One hundred samples were collected on the Decker/Bales Ranch and 82 on the BBar Ranch, both with the use of a hand auger. Complementing the field data were Landsat 5 Thematic Mapper images from the previous growing season to represent the potential for evapotranspiration occurring the previous year. Remote sensing successfully quantifies vegetation leaf area (Qi et al. 1994), which is highly correlated with evapotranspiration (Obrist et al. 2003). Other spatial variables important for modeling soil water include topographic slope and aspect, which can be derived from digital elevation models (DEMs), and soil characteristics, which can be derived from soil surveys (Landon 1995). Analysis consisted of least squares regressions with the response variable of water content and the potential predictor variables of spectral, topographic, and soils data.

For both ranches the models predicted soil moisture within 0.04 gravimetric water content, within the predicted margin of error for our sample sizes of 7.6 cm of moist soil (Fig. 23.4). The variables included in the models had both similarities and differences, indicating the method is *ad hoc*. However, it requires only a reasonable level of parameterization. Red and near infrared bands were important as expected, given the established relationship between these two bands and vegetation amount. One might expect that, where vegetation was abundant, evapotranspiration would be correspondingly greater and soil moisture therefore less. Instead, the correlation of the red and near infrared bands to soil water indicated that where biomass was most abundant in one year is where soil water content would be greatest the following spring. Evidently areas were producing more vegetation because there was more water, and this water was either not exhausted or was recharged in the ensuing season.

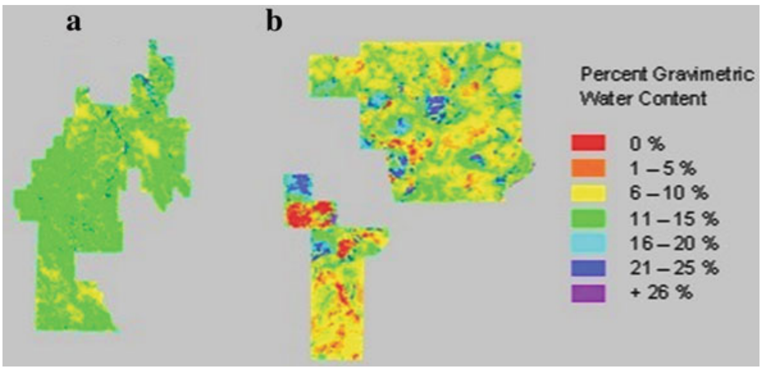

Fig. 23.4 Soil water content on BBar (**a**) and Decker/Bales (**b**) ranches

Slope and percent clay content were also important model variables at the BBar Ranch. Aspect, percent clay content, and the thermal band were important model variables at the Decker/Bales Ranch. The conclusion, though, is that with a minimum level of parameterization on an annual basis, remotely sensed data combined with other spatial data can model soil water within predicted levels of precision. Knowledge of pastures' available soil water can be used to decide upon livestock grazing intensity.

4.2 Rangeland Condition Evaluation

U.S. ranchers can obtain permits allowing their cattle to graze on public lands. Federal government managers, though, are responsible for stewardship of these lands. Remote sensing is almost the only tool for gathering information over large territories with limited personnel (Maynard et al. 2007b, Hunt et al. 2003). Medium resolution satellite imagery provides large fields of view, but at the expense of inadequate spatial detail to quantify factors such as biomass, percent bare soil, species and community types, and soil condition. Consequently, a hybrid method was developed, combining remotely sensed imagery with traditional field-based evaluations.

Remote sensing allowed categorization of rangelands according to their general condition. Then field sampling was conducted in subsets of the various categories. The approach added statistical power to a field-based sampling design. Land managers could either greatly reduce the extent of rangeland they visited on the ground to obtain the same information content, or for the same effort could gather much more information from field sampling.

Stratification was according to ecological site description (ESD) polygons. ESDs are map units of similar soil and climate characteristics. Using them allowed distinction between inherent variability in productivity among differing ecosystems from that caused by management practices. Spectral anomalies in images were not attributed solely to anomalies in rangeland management (Maynard et al. 2007b).

Data were collected from 263 sites on five Montana ranches with respect to two critical measures of rangeland condition, productivity and exposed bare soil. These were then compared to overall measures within each of 24 distinct ESDs to determine whether the site was within or outside the norm for that particular type. Thirteen Landsat ETM+ scenes were acquired to evaluate all 263 sampled sites. Each scene was converted to tasseled cap components, which are standard spectral indices that relate to each pixel's brightness, greenness in terms of vegetation quantity, and wetness in terms of leaf or surface water content. The means and standard deviations were computed for each of these components within each ESD, and the sample sites were evaluated to determine whether they were within or outside the norm for the particular ESD with respect to any of the three components. Only one of the 263 sites was evaluated as not anomalous in the field data but anomalous in the spectral data, and only three sites were evaluated as anomalous in the field data but not in the spectral data (overall accuracy 98.4%).

Remote sensing greatly increases the efficiency of field-based evaluations of rangeland condition. If 75% of an ESD is considered within the norm for its type, it would be grossly inefficient to spend 75% of an evaluator's time in fields that were essentially alike, which is what a random sampling would dictate. If instead only 33% of the field evaluation time were spent on "normal" sites, with no change in the time spent on anomalous sites, then the total effort would be reduced by 42%.

5 Digital Northern Great Plains: A Decision-Support System

Information in both spatial and temporal dimensions is what makes management by precision agriculture possible. Of course, information is valuable only to the extent it is timely, accurate, and can be (I) easily accessed, (II) straightforwardly integrated with multiple sources, (III) analyzed with software and hardware a typical information-seeker possesses, and (IV) used with a minimum of training. These challenges are amplified in the case of precision agriculture by the digital dimensions of satellite scenes and the limited bandwidths available to producers in many rural areas.

A single Landsat scene covers ∼300,000 ha and contains about 500 MB of data. For a 56 k dialup connection to the Internet, still used by some rural residents in the U.S., downloading one scene would take 20 h. A typical farm field of 1,200 ha only occupies 1/250th of a scene. Obviously, if an image can be partitioned, even a slow connection can provide enough bandwidth. A second difficulty associated with sophisticated information technologies and complex scientific datasets can be overcome by providing value-added products that can be easily interpreted. Finally, to be truly useful, the data and products derived from it have to be compatible with other data and products regardless of format.

Digital Northern Great Plains (DNGP, Zhang et al. 2010b) is designed to overcome all these challenges. Its major functions are to subset images, add value to them, and present them in a format compatible with data systems farmers and ranchers already use.

UMAC has collected a rich archive spanning more than 30 years of remote sensing imagery over the northern Great Plains, including the states of North and South Dakota, Minnesota, Montana, Wyoming, and Idaho. Data include high resolution (20–250 m) multispectral images from Landsat MSS, TM and ETM+, ASTER, medium resolution MODIS, surface relief from SRTM, and very high resolution (1–2 m) images from AEROCam (see Section 6.1). To ensure consistency in temporal and spatial comparisons, all images have been atmospherically corrected. The final product is reflectance at the surface. All images are managed through a database system with capability in spatial operation.

Raster and vector data are processed using an Open Source Geospatial Data Abstraction Library (GDAL). Another open source package, MapServer, is the presentation platform. A "thin-client" design ensures the minimum footprint on a client computer; all computing and analyzing are carried out on the server side, with results presented through a web interface accessible via a web browser. The computing power needed by a typical individual can therefore be minimized.

Features that make the Digital Northern Great Plains system (http://dngp.umac.org) attractive include the following:

- Searches can be conducted via spatial coordinates through an intuitive user interface.
- Remote sensing images can be subset either spatially or spectrally.
- Products (e.g., sugar beet yield) are generated on the fly, both simplifying the database design and providing dynamic update capability.
- Images or products can be downloaded in a variety of formats to ensure compatibility with other application software.
- A multitude of identifying vector layers is incorporated into the system.
- "One interface" design ensures a smooth user experience and simplifies the learning curve.

To promote use of the DNGP system by end users UMAC followed the model of Rogers (2003) on adoption and diffusion of innovation. A cadre of early adopters provided feedback that improved the system iteratively. Endorsement of the technology by these early adopters accelerated its widespread adoption.

Two peaks in usage occur annually. The first occurs in March or April, when the growing season begins. The second occurs in late August and early September, the time for harvest. This suggests the system is particularly useful for planning and production.

6 Sensors Customized to Precision Agriculture's Needs

Landsat's value for analysis of vegetation derives from its sun-synchronous orbit and fixed pattern of paths and rows. The result is well-controlled imagery, repeating on a 16-day revisit time, well-suited for scientific investigations over inter-annual and multi-decadal time scales. However, analysis of rapidly changing phenomena on crop and range lands is equally valuable for in-season production management decisions. For critical times or geographic locations prone to frequent cloudy days, typically only a few Landsat scenes can be captured during a growing season, often not when optimal; short northern growing seasons exacerbate this problem. In addition, Landsat's spatial resolution is fine for many agricultural applications, but higher resolution imagery is needed for others.

To meet farmers' and ranchers' requests for higher spatial resolution, more frequent images, and shortened latency, UMAC designed and built two sensors, one operated on an aircraft and the other soon to be operating on the International Space Station.

6.1 Airborne Environmental Research Observational Camera (AEROCam)

AEROCam is flown on one of the University of North Dakota's light aircraft. The sensor consists of a Redlake MS4100 multi-spectral (B, G, R, NIR) area-scan camera. Images can either be RGB (red, green, blue), offering true color, or CIR (near-infrared, red, green), false color. Spatial resolution depends on altitude: 1 m is typical for production agriculture applications, but 0.5 and 2 m are also frequently requested, as is 0.25 m for special purposes. Available products include both individual scenes and mosaics, georeferenced and radiometrically corrected. In addition to superb resolution, AEROCam images can be acquired at the time they are most valuable, not just when a satellite orbit dictates.

The majority of AEROCam requests are from farmers and ranchers directly engaged in production agriculture. Their uses include establishing fine-scale zonal mapping of highly variable soils, assessing effectiveness of variable rate fertility and crop treatments, improving drainage, and identifying areas of soil compaction and salinity. The immediate, in-season decision support made possible with AEROCam often is served by analyzing relative variations within a single scene or mosaic captured at the appropriate time. An example of the degree of detail available in AEROCam images is illustrated in Fig. 23.5. Much of the heterogeneity evident in this image would have been lost in a satellite image with resolution ~30 m.

6.2 International Space Station Agricultural Camera (ISSAC)

AEROCam's successes led to a desire for sensor capabilities in low Earth orbit. A sensor called International Space Station Agricultural Camera, or ISSAC (Hulst et al. 2004), soon to be launched to the International Space Station (ISS) is the result. The sensor will collect two bands, red (630–690 nm) and near-infrared (780–890 nm), such that the Normalized Difference Vegetation Index can be produced. A pointing system allowing off-nadir look angles of up to 30° will enable

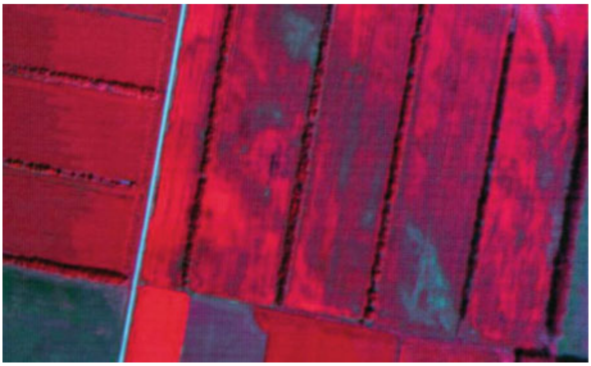

Fig. 23.5 AEROCam image collected in northeast North Dakota, August 2008. The image, a false color composite (G, R, NIR), is approximately 1 km wide with 1 m resolution. Heterogeneity effects are due to management practices (red shading differences on left) and natural variability (*blue*/*red* mottling on right)

images of particular areas to be acquired frequently. ISSAC will be installed on the ISS in 2011 and testing, validating, and verifying its output will occupy much of the 2011 growing season.

ISS's altitude varies between 350 and 420 km; when at a nominal 400 km the size of a scene will be about 57 × 57 km, with a ground spatial resolution comparable to Landsat's. Radiometric calibration will significantly reduce noise and imaging artifacts. Since long-ray paths due to variable sun and look angles will make atmospheric effects more apparent, we will apply correction techniques that will utilize concurrent measurements made by other orbiting NASA sensors of ozone and water vapor. Primary science target area is the UMAC region; secondary science targets could be imaged anywhere under the ISS orbit (inclined 51.6°).

During the growing season, primary targets will have occasional 3–4 week 'blackout' periods when ISS overflights of the northern Great Plains occur either at night or in low-light conditions. Between blackout periods ISSAC imaging opportunities will occur several times per week. A Science Operations Center at the University of North Dakota will convert end user's tasking requests into camera commands; after acquisition, the same operations team will process received telemetry into imagery for distribution via Digital Northern Great Plains (Section 5). The goal is to disseminate corrected, calibrated, geo-located imagery within 24 h of acquisition. For the first time, agricultural producers will have information about crop and range health frequently and in near-realtime throughout the evolution of their fields, from emergence through maturation to senescence.

7 Precision Crop Protection: Its Promise Demonstrated

The Cronin Farms near Gettysburg, South Dakota serves as an example of how the Upper Midwest Aerospace Consortium is bringing about positive changes in agricultural practices. The example verifies the approach of conducting "experiments" in actual producing fields under prevailing conditions.

The first step was to create management zones, the very basis for any differential treatments. The collaborating farmer did this by combining Landsat images, yield maps, and soil surveys into an ArcView Geographic Information System. This took advantage of UMAC's Digital Northern Great Plains data dissemination system and its ZoneMAP product. The resulting zone map for a single 44.5-ha field classified into three zones is shown in Fig. 23.6. By knowing the characteristics of each zone, specific goals for yields of spring wheat could be set. To meet the goals the rate of application of synthetic fertilizer needed in each zone to supplement the nutrients known to be present from soil samples was calculated. The result of this careful management was that actual yields exceeded the goal by 9%.

The enhanced yields, of course, increased income. Using 2008 spring wheat prices, the incremental income from boosting yield in this 44.5 ha field was US$1,870. At the same time, costs were significantly reduced. In the absence of site-specific information, neighboring farms applied as much as 250 kg more urea

Fig. 23.6 Corn field of 44.5-ha classified into three zones on the basis of previous years 'Landsat' images, yield maps, and soil surveys

fertilizer per hectare. By comparison, the Cronin Farms saved US$1,750. The third benefit was environmental: 2,840 kg less fertilizer entered the environment.

One major reason why the fertilizer applications could be less than a standard (i.e., non-precision) prescription was use of no-till practices on Cronin Farms, not just on a single 44.5-ha field but instead on the full 3,620 ha of the farm. A disadvantage of tilling soil is that organic matter contained within it is oxygenated when exposed to air. By not overturning soil, no-till prevents oxygenation and instead increases soil's concentration of organic matter – from 2.1% in 1991 to 3.2% in 2007 on the Cronin Farms. Each increase of 1% in SOM reduces the necessary application of nitrogen by 22–34 kg/ha, of phosphorus by 5–7 kg/ha, and of sulfur by 2–3.5 kg/ha.

Benefits accrue if these practices are followed for several years. Table 23.1 compares yields obtained in 1991, before either precision, variable rate treatments or no-till were being practiced, with those in 2007. The increases are exceptional.

Wise crop-protection strategies offer additional benefits. At the same time one crop is harvested, another is planted atop the residue. Such cover-cropping protects soil against wind and water erosion. It also helps cycle nutrients and retain water. If the rotation of crops includes legumes or other nitrogen-fixing plants, fertilizer requirements can be reduced even more, in one specific case by 90 kg ha^{-1}. At the close of the crop-growing season, one final cover crop is planted. It could be oats, or turnips, radishes, or lentils. This crop and the other residues on the field serve as fodder for cattle that are allowed to graze until the onset of winter. Manure thereby is fed back into the nutrient supply.

Table 23.1 Productivity increases from no-till precision agriculture, Cronin Farms, South Dakota USA

Crop	1991 Yield	2007 Yield
Winter wheat	50 bushels/acre	70 bushels/acre
Spring wheat	40 bushels/acre	60 bushels/acre
Corn	60 bushels/acre	145 bushels/acre
Sunflowers	2,250 kg/ha	2,915 kg/ha

A UMAC-partnering farmer has conducted a crop-protection program that improves soil fertility, prevents its erosion, fixes atmospheric nitrogen, recycles nutrients, retains water and facilitates its infiltration, reduces compaction by minimizing passages of farm machinery over the soil, and does all this while cutting costs and increasing yields or equivalently income – in addition to significantly improving stewardship of the environment (D. Forgey, private communication 2008). Table 23.2 compares how much progress has been made, progress that is strikingly evident in the satellite image (Fig. 23.7), showing fields farmed with precision and no-till for 0, 3, 6, and 13 years.

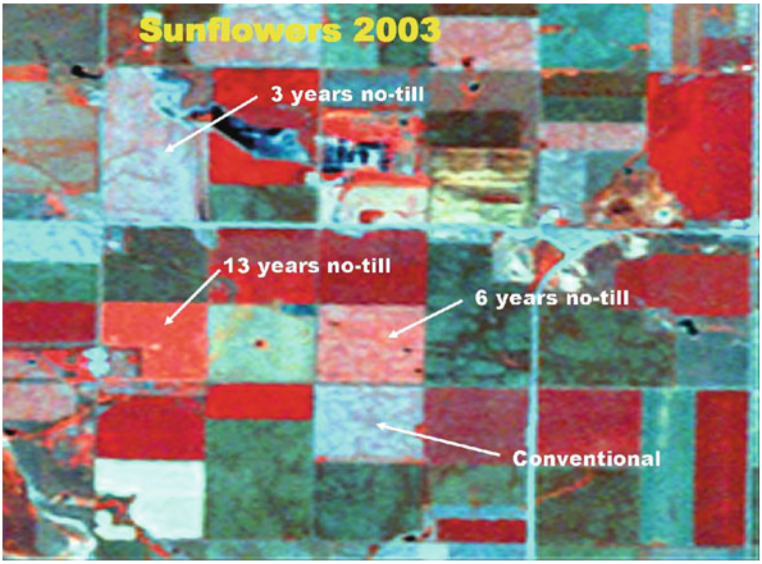

Fig. 23.7 2003 Landsat false-color image identifying sunflower crops grown traditionally and with 3, 6, and 13 years of variable-rate treatments and no soil tillage. The deeper the red, the greater the productivity

Table 23.2 Crop protection progress, Cronin Farms, South Dakota, USA

	1991	2007
Area farmed	2,085 ha	3,620 ha
Number of farmers	4	2
Tractors	3 (525 hp)	1 (255 hp)
Crops raised	6	12

8 Lessons Learned

Producers have made many management decisions in addition to the few we have described. They have been able to delineate acreage damage caused by hail and windstorms, quantify the effectiveness of chemical applications, identify and rectify drainage problems, spot damage caused by drift of applications sprayed on adjacent fields, locate invasive species, detect plant diseases, and many more uses.

From these experiences those in the Upper Midwest Aerospace Consortium have learned several lessons.

- Techniques that work in one region may not be applicable in all others. Agroecosystems are complex and intimately connected to their local environment. In the northern Great Plains they are subjected to short growing seasons, potentially extreme variations in temperature and precipitation, competition between crops for food or for fuel, and limited use of irrigation. Other regions could make similar lists of peculiarities. Nevertheless, the principles of precision crop protection described do have general applicability.
- Imagery from sensors on satellites or aircraft is extremely valuable. But images are not magical solutions that replace all other sources of information. When they are combined with other sources – e.g., electrical conductivity measurements, yield maps, weather data, soil ecology, topography, etc. – their value is greatly amplified.
- Precision crop protection requires a commitment. The rewards come only after a few to several seasons. Knowledge about agroecosystems accumulates over each crop grown each season. Comparisons of geospatial information at various times within a season, between seasons, and between the current season and the average of several give a context upon which to base sound decisions.
- An organization that sets out to empower farmers and ranchers to make informed decisions also must be committed for a long term. With so much income at stake, producers are slow to change practices, and initially new technologies are bewildering to many of them. Unless support has the prospect of continuing, producers are unlikely to begin relying on it.
- UMAC has demonstrated the value of breaking down boundaries: between academia's traditional disciplines, between various academic institutions, and between academia and the public. The world of tomorrow cannot be created by perpetuating the world of yesterday.

Economics, the environment, and depletion of natural resources such as the oil on which industrial agriculture is based, are all converging on a pressing need for change in agriculture. Social pressures also bear heavily. More people are continually added to the planet and among them are many whose improving circumstances allow them to demand richer diets. The consequence is immense pressure to grow more food, even though the best arable lands are already in production. Along with humanity's desire for more food is one for different energy sources. Among the potential new sources are biofuels, the growth of which is a competing use for the same arable land. There is no doubt that agricultural practices will be different in the near future. Precision management is almost certain to be one of the new strategies.

Acknowledgements The work of the Upper Midwest Aerospace Consortium has been partially funded by a series of grants from NASA. The authors are reporting the work of a much larger team, without whose contributions there would have been little to report. The list is too long to name each one, and naming only a few would be unfair to the others. Special note should be made of contributions by exceptional farmers and ranchers whose commitment to tackling some pressing global challenges is a source of hope for everyone wanting a better world for posterity.

References

Allen RG, Tasumi M, Trezza R (2005) METRIC applications manual for Landsat satellite imagery, Version 2.0. Univ Idaho, Kimberly

Brock A, Brouder SM, Blumhoff G, Hofmann BS (2005) Defining yield-based management zones for corn-soybean rotations. Agron J 97:1115–1128

Brown LR (2009) Can food shortages bring down civilization? Sci Am 300:50–57

Bruinsma J (ed) (2003) World agriculture: towards 2015/2030. Earthscan, London

Burrough PA (1989) Fuzzy mathematical methods for soil survey and land evaluation. Eur J Soil Sci 40:477–492

Burrough PA, MacMillan RA, Deurwen WV (1992) Fuzzy classification methods for determining land suitability from soil profile observations and topography. Eur J Soil Sci 43:193–210

Clay DE, Clay SA, Jackson J et al. (2003) Carbon-13 discrimination can be used to evaluate soybean yield variability. Agron J 95:430–435

Clay DE, Clay SA, Liu Z, Reese C (2001) Spatial variability of 13C isotopic discrimination in corn. Comm Soil Sci Plant Anal 32:1813–1827

Crutzen PJ (2002) Geology of mankind. Nature 415:23

Fridgen JJ, Kitchen NR, Sudduth KA et al. (2004) Management zone analyst (MZA): software for subfield management zone delineation. Agron J 96:100–108

Holechek JL (1988) An approach for setting the stocking rate. Rangelands 10:10–14

Hulst NE, Barton JB, Carpenter J et al. (2004) AgCam: scientific imaging for the ISS window observational research facility. Proceedings of 2004 IEEE Aerospace Conference, Big Sky

Hunt ER Jr, Everitt JH, Ritchie JC et al. (2003) Applications and research using remote sensing for rangeland management. Photogram Eng Rem Sens 69:675–693

Landon MA (1995) Soil and terrain attributes for evaluation of leaching in a Montana farm field. MS thesis, Montana St University, Bozeman

Maynard CL, Lawrence RL, Nielsen GA, Decker G (2007a) Modeling vegetation amount using bandwise regression and ecological range units as an alternative to vegetation indices. GIScience Rem Sens 44:68–81

Maynard CL, Lawrence RL, Nielsen GA, Decker G (2007b) Ecological site descriptions and remotely sensed imagery as a tool for rangeland evaluation. Can J Rem Sens 33:109–115

Metternicht G (2003) Vegetation indices derived from high-resolution airborne videography for precision crop management. Int J Rem Sens 24:2855–2877

Mishra U, Clay D, Trooien T, Dalsted K, Malo DD (2008) Using remote sensing based ET maps to assess landscape processes impacting soil properties. J Plant Nutr 31:1188–1202

Moran MS, Inoue Y, Barnes EM (1997) Opportunities and limitations for image-based remote sensing in precision crop management. Rem Sens Environ 61:319–346
Obrist D, Verburg PS, Young MH et al. (2003) Quantifying the effects of phenology on ecosystem evapotranspiration in planted grassland mesocosms using EcoCELL technology. Agric Forest Meteorol 118:173–183
Qi J, Chehbouni A, Huete AR, Kerr YH (1994) A modified soil adjusted vegetation index. Rem Sens Environ 48:119–126
Rogers EM (2003) Diffusion of innovation, 5th edn. Free Press, New York
Sankey JB, Lawrence RL, Wraith JM (2008) Ad hoc modeling of root zone soil water with Landsat imagery and terrain and soils data. Sensors 8:314–326
Seelan SK, Baumgartner D, Casady GM, Nangia V, Seielstad GA (2007) Empowering farmers with remote sensing knowledge: A success story from the US Upper Midwest. Geocarto Int 22:141–157
Seelan SK, Laguette S, Casady GM, Seielstad GA (2003) Remote sensing applications for precision agriculture: a learning community approach. Rem Sens Environ 88:157–169
Sonka ST (1997) Precision agriculture in the 21st century: geospatial and information technologies in crop management. National Research Council Committee, National Academy Press, Washington
Zhang X, Seelan SK, Seielstad G (2010b) Digital Northern Great Plains: a web-based system delivering near real time remote sensing data for precision agriculture, Remote Sens 2(3): 861–873
Zhang X, Shi L, Jia X, Seielstad G, Helgason C (2010a) Zone mapping application for precision-farming: a decision support tool for variable rate application. Prec Agric 11:103–114

Chapter 24
Site-Specific Detection and Management of Nematodes

John D. Mueller, Ahmad Khalilian, W. Scott Monfort, Richard F. Davis, Terrence L. Kirkpatrick, Brenda V. Ortiz, and William G. Henderson

Abstract Nematode distribution varies significantly throughout a field and is highly correlated to soil texture and other edaphic factors. Field-wide application results in nematicides being applied to areas without nematodes and the application of sub-effective levels in areas with high nematode densities. Efforts to use grid maps as a guide to site-specific application have proven to be too expensive to be cost effective. Recently, the availability of GPS–GIS has allowed the use of soil electrical conductivity systems to rapidly and inexpensively develop cost effective soil texture maps. These maps are used to project where nematodes are likely to occur within a field. Variable-rate application systems for granular and fumigant nematicides have been developed and tied via software to soil texture maps providing a mechanism for the effective delivery of nematicides in a site-specific, variable-rate manner in individual fields. Efforts in South Carolina, Georgia, and Arkansas are further developing this system and refining our knowledge of how soil texture and other edaphic factors affect the distribution of cotton nematodes.

1 Introduction to Cotton Nematology

1.1 Species Distribution and Yield Losses

Plant-parasitic nematodes are important pests on cotton in the southern and southeastern United States: each year up to 10% of all US cotton production is lost to nematodes (Blasingame and Patel 2005, Koenning et al. 1999). Nematodes are particularly problematic in the southeastern states (Blasingame and Patel 2005). *Meloidogyne incognita*, the southern root-knot nematode (SRK) and *Rotylenchulus reniformis*, the reniform nematode (RN), are the most common nematodes on cotton in most states (Koenning et al. 2004). SRK occurs from North Carolina to California and has been reported across a wide range of soil types in almost every cotton

J.D. Mueller (✉)
Clemson University – Edisto R.E.C., Blackville, SC 29817, USA
e-mail: jmllr@clemson.edu

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_24,

production area in the world. Distribution and survival of RN is linked to soil types with higher levels of silt and clay than those favored by SRK (Koenning et al. 1996, Robinson et al. 1987). RN is a major pest of cotton in Brazil causing up to 40% yield losses in some years (Farias et al. 2002), and in the southern US from North Carolina to Texas (Koenning et al. 2004). A third major nematode species on cotton is the Columbia lance nematode (CLN), *Hoplolaimus columbus* (Koenning et al. 2004). This nematode occurs primarily in the sandy, coastal plains' soils of Georgia, North Carolina and South Carolina. It is the most common plant-parasitic nematode in South Carolina cotton fields occurring in almost 66% of all fields (Martin et al. 1994). CLN is found most frequently in coarse textured, sandy soils (Lewis and Smith 1976).

1.2 Nematicide Usage

US cotton growers rely heavily on preplant and at-plant applications of nematicides for nematode control due to limited crop rotation and host resistance options (Starr et al. 2007). Although nematode-induced yield losses can easily exceed 15% in a given field, the relatively narrow profit margin for cotton production allows growers to budget only a limited amount for nematode control. The carbamate nematicide aldicarb, applied as Temik 15G®, has filled the role of an inexpensive, generally efficacious nematicide in cotton for over 30 years. Aldicarb is applied to as much as 30% of the total US cotton acreage (Koenning et al. 2004). Aldicarb is applied in-furrow at uniform field-wide rates of 0.50–1.18 kg a.i./ha at an estimated cost of $22.25–$51.90/ha. Unfortunately, these rates of aldicarb may provide only partial nematode control, especially where densities are high. These rates do, however, provide systemic activity against early-season thrips, contributing to the popularity of the product among growers (Thomason 1987). Higher rates of aldicarb to improve efficacy against nematodes cannot be used safely since the potential exists for phytotoxicity. Greater efficacy against nematodes has been demonstrated with in-row treatment with the soil fumigant 1,3-dichloropropene (1,3-D) marketed as Telone II®. This nematicide is more efficacious than aldicarb (Kinloch and Rich 1998, Noe 1990) but due to its higher cost has not been utilized as widely by growers.

1.3 Spatial Distribution of Nematodes

Although nematicides are generally applied field wide at a single rate, the population densities and overall distribution of SRK, RN, and CLN can be highly variable and spatially aggregated in fields (Barker and Olthoff 1976, Monfort et al. 2007, Starr et al. 1993, Wrather et al. 2002, Wyse-Pester et al. 2002). The field-wide uniform rate approach to nematicide application is highly inefficient because some areas in these fields may have nematode population densities below economic or damage threshold levels while other areas may have a severe problem. Therefore, nematicides are either over- or under-utilized in many areas throughout the field. Historically, growers have always utilized field-wide nematode management strategies because of their inability to locate and identify areas of differing nematode densities and then deliver nematicides in a site-specific manner within fields (Evans et al. 2002).

Site-specific application of nematicides offers an opportunity to improve nematode management efficiency. A system that could identify areas within fields with potentially high or low nematode population densities, providing guidance for more efficient, targeted sampling, combined with the technology to deliver a nematicide in a site-specific manner would significantly improve nematode management efficiency, profitability, and environmental stewardship.

1.4 Effects of Soil Texture on Nematode Population Density

In most fields in the southern US, soil types vary significantly. Since soil type and texture are closely correlated with nematode distribution (Monfort et al. 2007, Wyse-Pester et al. 2002), soil texture could be an effective predictor of potentially high or low nematode population densities. In microplots, reproduction of SRK was greater in coarse-textured than in fine-textured soil, and population densities were inversely related to the percentages of silt and clay (Koenning et al. 1996). In the same study RN reproduced best in loamy sand with a silt plus clay content of approximately 28%. Similarly, in South Carolina there was a strong positive correlation between increasing incidence of CLN and increased sand content both at planting and at harvest (Khalilian et al. 2001). An increase of nine percent in clay content of a sandy loam soil resulted in a 57% reduction in nematode population density. In the same study, ring nematodes (*Criconemella* spp.) were found at significant numbers only from plots with the highest levels of sand.

1.5 Early Research on Site-Specific Nematicide Applications

Early studies on site-specific nematicide application were based on establishing mean nematode numbers in grids that were arbitrarily established within fields. A field could be divided into grids of any size from several square meters to several hectares. A soil sample was then taken within each grid and a mean nematode population density value for the grid was developed. Nematicide application decisions could then be made for each grid in the field. Wheeler et al. (1999) in Texas compared variable-rate aldicarb applications to the single rate applications normally applied by growers in eight tests over three years. Baird et al (2001) conducted field trials on site-specific 1,3-D applications based on grid sampling in Georgia cotton fields. While both studies obtained greater economic returns for their site-specific treatment than for uniform rates of either 1,3-D or variable or uniform rates of aldicarb, the costs associated with grid sampling made site-specific applications unfeasible. Wrather et al. (2002) had similar results comparing site-specific applications of aldicarb to uniform aldicarb application rates in a Missouri cotton field. Yields for the two application methods were essentially equivalent, but the site-specific application approach resulted in 46% less aldicarb used in 1997 and 61% less used in 1998 compared to a uniform application rate. Again, the costs associated with grid sampling superseded the savings provided by the variable rate applications; using a 0.10 ha sampling grid cost $220 per ha. In all of these cases, a cost effective system that could be used to construct nematode distribution maps would have made the site-specific approaches much more affordable for growers. Similar constraints to using a site-specific approach to nematicide application have been noted by Evans et al. (2002) in trying to control potato cyst nematode. In a relatively high value crop, potato, yield and quality demands justify high nematicide inputs. The availability of a mechanism to predict where nematode densities are high would be especially valuable in such a system.

2 Site-Specific Nematicide Application Systems

Development of successful variable-rate or site-specific nematicide application systems is dependent upon the development and availability of several key tools including GIS/GPS guided mapping sensors and software and nematicide applicators that can deliver the chemicals with precision according to a prescription. Recently, Clemson University has developed a site-specific application system for nematicides. The Site-specific Nematicide Placement (SNP) system is appropriate for use with either 1,3-D or aldicarb (Mueller et al. 2001, Khalilian et al. 2001, 2003a, b and 2004), and consists of the following components: (I) a soil electrical conductivity meter is used to generate accurate, inexpensive geo-referenced, field-level soil EC_a maps showing zones of similarity in soil texture; (II) the soil EC zones are then used to develop a nematode management map for each field based on targeted sampling for assay and quantification of nematode population densities; (III) geo-referenced nematicide application prescription maps are generated based on ground truthing nematode assays; and (IV) nematicides are applied to the field as appropriate for each management zone using GPS-guided equipment for controlling the nematicide delivery.

2.1 Soil Electrical Conductivity

Predicting nematode distribution by utilizing its strong correlation to soil texture has been common to most precision application projects (Monfort et al. 2007, Wrather et al. 2002). An efficient and economical technique for determining soil texture without the immense cost and time required by grid sampling was needed. Soil EC_a is strongly correlated to soil particle size and texture (Williams and Hoey 1987). Sand exhibits a low electrical conductivity, silts a medium conductivity, and clays a high conductivity. Equipment is now commercially available through Veris Technologies (Lund et al. 1999) for rapid and accurate determination of soil texture within fields. The mapping system consists of a sensor cart on which three pairs of straight-blade disk coulters are mounted. These coulters serve as electrodes from which soil EC_a measurements are made as the sensor cart travels through the field. The Veris unit can map soil EC_a at two depths from 30 to 91 cm, and can be linked to a GPS system to generate a continuous soil texture map of a 40 ha field in less than 3 h.

2.2 Developing Prescription Maps

Before a prescription map for a nematicide application can be constructed, a set of guidelines to determine what nematicide rate goes where is necessary. Research during the past 8 years has shown that soil type and texture significantly affect the distribution of most nematode species and population densities and their damage potential (Khalilian et al. 2001, 2003b, Monfort et al. 2007, Wrather et al. 2002). Therefore, the soil EC_a meter can be used to divide a production field into soil textural zones (Fig. 24.1) used to predict the distribution of nematode species at a fraction of the cost of grid sampling. The nematicide rate that would then be applied within a single zone would be constant and would be determined by the nematode density determined from samples taken from the zone. Geo-referenced nematicide application prescription maps then can be developed using standard GIS software, i.e. Farm Works or SSToolbox.

2.3 Site-Specific Nematicide Delivery System

The third component needed for a functional site-specific nematode management program was a delivery system that allowed precise delivery of the nematicide and the ability to change rates in a relatively short distance. Delivery systems for

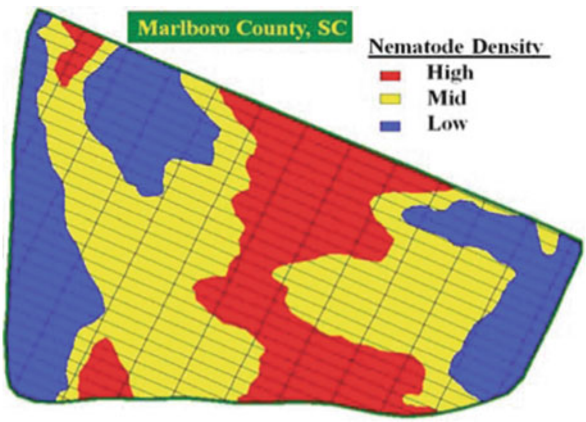

Fig. 24.1 Nematode management zones

both 1,3-D and aldicarb with these capabilities have been developed at Clemson University. These GPS-guided systems allow site-specific application of either granular or liquid nematicides following a prescription map. All of the technologies related to site-specific nematicide applicators are fairly new and still need to be validated by researchers and growers for effectiveness and practicality.

3 Current Research

Researchers in Arkansas, Georgia, Louisiana, Missouri and South Carolina working both independently and cooperatively over the last 10 years have successfully developed cost-effective, variable-rate, site-specific application systems that are now being adapted by their cotton growers. The following is a summary of their progress to date.

3.1 Research in South Carolina

3.1.1 Relationship of Soil EC_a to Soil Texture and Nematode Distribution

The accuracy of the Veris 3100 soil EC_a meter in predicting soil textural characteristics was tested in six production fields in South Carolina that were naturally infested with CLN. Each field was divided into 1,300 plots and the Veris EC meter was used to map each plot for soil EC_a. Soil samples were then collected from each plot and analyzed for soil texture. Comparisons of the soil EC_a maps with the actual soil texture data indicated a very high correlation at several different soil moisture contents. For each level of soil moisture studied, there was a negative correlation between percent sand and soil EC_a and a positive correlation between percent clay and soil EC_a with correlation coefficients >0.91. Soil texture was the major factor affecting soil EC_a. While soil moisture affected EC values to some degree with the overall soil EC_a values higher with increased soil moisture, the relative values remained consistent (Fig. 24.2).

The high correlation of soil EC_a with soil texture in the Southeastern Coastal Plain soils allowed us to predict the distribution of CLN, spiral nematodes (*Helicotylenchus* spp.) and ring (*Criconema* spp.) nematodes in production fields. Each test field was arbitrarily divided into four ranges, and each range was designated as a management zone. Each zone showed distinct distribution patterns for CLN, spiral and ring nematodes. Population densities of CLN both at planting and at harvest decreased as soil EC_a increased, indicating increasing clay content of the soil (Fig. 24.3).

3.1.2 Variable Rate Application Equipment

GPS-based equipment for controlling the application rates of 1,3-D or aldicarb according to a prescription map were developed at Clemson University. These

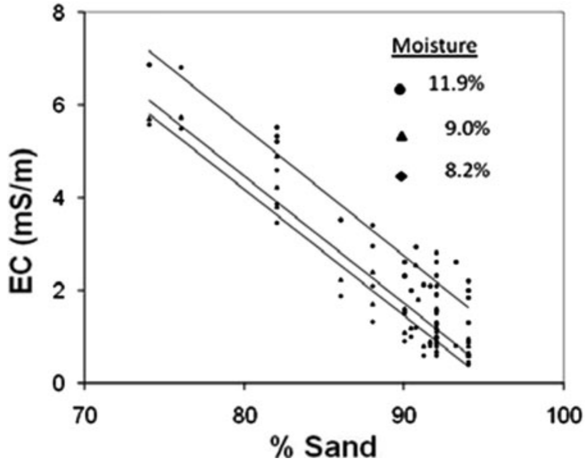

Fig. 24.2 Effects of moisture on soil EC_a

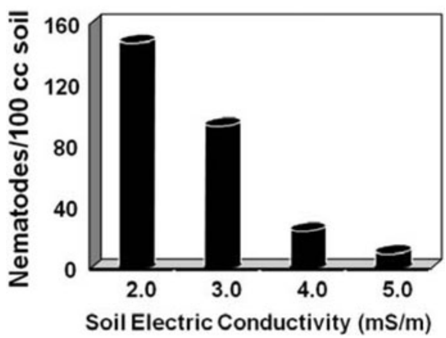

Fig. 24.3 Effects of soil EC_a on Columbia lance nematode *Hoplolaimus columbus*

systems were developed with the capability of being adapted to existing farming equipment. For injecting 1,3-D, three different systems were used:

- A conventional 4-row, 1,3-D injection rig was modified by adding a variable-rate pump and appropriate electronics to control the pump. This system uses a 4-row squeeze-type metering pump, (modified by Chemical Container Corporation, Lakeland, FL) to control the rate of 1,3-D that is injected into the soil. The pump is powered by a 12 V-DC variable-speed electric motor (Rae Corporation, McHenry, IL) with rotational speed ranging from 0 to 50 rpm. An onboard computer with variable rate application software and GPS support provide rate information to the controller system. Prescription application maps, based on nematode population densities in the soil EC management zones, can be loaded on this computer. A Trimble DGPS receiver with "fast rate" option is used to determine the position of the applicator in the field. A Mid-tech rate-controller

(TASC-6500, Midwest Technologies, Inc., Springfield, IL) was used to control the speed of the electric motor.

- A self contained nitrogen gas pressurized 1,3-D injection system (Mid-Tech Legacy-6000) was used to deliver the 1, 3–D. The Legacy 6000, which is a complete system, replaces both the TASC-6500 and the onboard computer. Application rate is controlled by a voltage-regulated butterfly valve.
- A map-based nematicide controller was retrofitted on a grower's existing 1,3-D application equipment. This controller replaces the manual on-off switch for applying 1,3-D, and is attractive to growers because it can communicate with most GIS software (i.e., Farm Site Mate (Farm Works Software LTD)) for precise, map-based application of the fumigant. This affordable system consists of solid-state relays and electronic circuits which can turn the injection pumps on or off based on a prescription map.

A prototype site-specific, variable-rate Temik 15G applicator was developed. This system uses a 12V-DC variable-speed electric motor, to open or close the orifice of the hopper boxes on a Gandy (Gandy Company, Owatonna, MN) granular insecticide-nematicide applicator. The motor can be controlled either by the Legacy-6000 system or using the TASC-6500 and the onboard computer. In our system, one granular applicator hopper was used for every two rows of cotton. These hoppers were equipped with a Lock & Load® system and a positive displacement, gear-type metering device. The hoppers were attached together with a hex-rod so that all were driven by one variable-speed motor.

3.1.3 Field Tests for Application Uniformity

All the applicators were evaluated under field conditions. The 1,3-D and aldicarb systems were calibrated to apply different rates of nematicides. Seven target rates (11.0, 16.6, 22.1, 27.6, 33.2, 38.7 and 44.2 kg a.i. ha^{-1}) were selected for 1,3-D application to test uniformity of application across a range of rates. The test field was divided into 60 $\times$ 3.8-m grids and a nematicide rate was assigned at random to each grid. A geo-referenced nematicide application map was developed using SSToolbox GIS software and transferred to the system's on-board computer. A simple device was developed to collect 1,3-D samples as the chemical was being applied to test uniformity. This device consisted of a 3-way solenoid valve inserted at the discharge end of each chemical hose just before the injectors. In normal solenoid mode, the system performed normally, injecting the 1,3-D 36-cm deep in the crop row. However, by energizing the solenoid, the 1,3-D was directed into a collection cup. Samples were collected for 30-m in each grid and the measured rate of 1,3-D was compared to the target nematicide rate assigned to the same grid. To determine uniformity of application within rows, all four rows were sampled. Each test was repeated four times. A similar procedure was used for the aldicarb application uniformity test. Six different rates (0.34, 0.50, 0.67, 0.84, 1.01 and 1.18 kg a.i. ha^{-1}) were selected for this test and were repeated four times.

All applicators closely followed the prescribed nematicide application-rate maps. For the aldicarb system, the measurement errors ranged from –3 to 4.2% with mean error of 1.1 indicating a high correlation between targeted and measured rates. Results for the 1,3-D were similar: there was a very good correlation between targeted and measured rates with an average overall error of 2.1% with maximum absolute error of 6.7%. These results indicate that it is possible to accurately match nematicide rate with the spatial distribution of nematodes. Our trials also indicated that rates can be changed within 0.33–2.0 m of distance traveled, depending upon the frequency of the GPS output (i.e. either 1, 2, 5 or 10 Hz).

3.1.4 Efficacy of Variable Rate Applications in the Field

Tests were conducted during 2002 and 2003 in the cotton fields described earlier to compare the yield of the crop following site-specific nematicide application based on soil EC management zones with conventional uniform, single-rate application. The soil EC_a maps were used to designate four nematode management zones. In each zone, a minimum of 10 replications of 20-row blocks 15 m long on 0.97 m row centers were established. This large number of replications for each treatment allowed observations to be made on naturally occurring combinations of nematode densities and soil types. Each block was divided into five 4-row plots. Each plot was identified using GPS to allow observations from identical sites during the growing season. The following treatments were assigned randomly in plots of each block: (I) uniform rate aldicarb (1.01 kg a.i. ha^{-1}) applied in-furrow at planting (ifap); (II) variable-rate aldicarb (0.50–1.18 kg a.i. ha^{-1}) applied ifap; (III) uniform rate 1,3-D (33.2 kg a.i. ha^{-1}) injected 36 cm deep 10 days before planting plus 0.50 kg a.i./ha aldicarb ifap; (IV) variable-rate 1,3-D (0.0–44.2 kg a.i. ha^{-1}) injected 36 cm deep 10 days before planting plus 0.50 kg a.i. ha^{-1} aldicarb ifap; and (V) control (no aldicarb or 1,3-D).

Clemson University's current nematode threshold levels for CLN nematodes per 100 cm^3 soil were used for decisions as to the zones that received the site-specific, variable-rate nematicide application (Dickerson et al. 2000). Treatments per zones were: (I) < 51 CLN received 3.4 kg aldicarb ha^{-1}; (II) 51–125 CLN received 5.6 kg aldicarb ha^{-1} or 18.7 L ha^{-1} 1,3-D; (III) 125–200 CLN received 7.8 kg aldicarb ha^{-1} or 28 L ha^{-1} 1,3-D; and (IV) > 200 CLN received 7.8 kg aldicarb ha^{-1} or 37.4 L ha^{-1} 1,3-D. Nematicide application maps were developed and loaded on the onboard computer. The nematicide rate within a single plot was constant and was based on nematode density from the samples taken in the previous year. Cotton (Delta Pine 458 RR) was planted and carried to yield using recommended practices for seeding, fertilization, and insect and weed control. Yield was recorded using cotton yield monitors mounted on a spindle-type picker. A yield map for the test field was developed and the average yield for each plot was determined using geographic information systems.

All of the nematicide treatments increased cotton yield compared to untreated plots (Fig. 24.4). The yield increased with nematicide application compared with

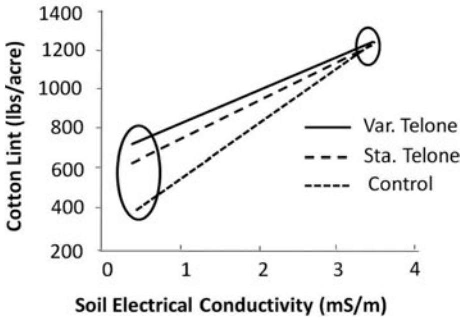

Fig. 24.4 Effects of soil EC_a and nematicide application method on lint yield

Table 24.1 Effects of variable-rate nematicide application on lint yield and chemical use

Treatment	Aldicarb [kg ha^{-1}]	1,3-D [liter ha^{-1}]	Lint yield [kg ha^{-1}]
Uniform rate aldicarb	6.7	0.0	728
Variable rate aldicarb	4.4	0.0	770
Uniform rate 1,3-D	3.4	28.0	743
Variable rate 1,3-D	3.4	5.6	780
Control	0.0	0.0	634

the untreated control in sandy management zones (lower soil EC_a), where nematode population densities were higher, and was significantly higher than where there was higher soil clay content. Variable-rate aldicarb applications improved lint yields by 5% compared to the standard uniform-rate application of 6.7 kg ha^{-1} Temik 15G (Table 24.1). The variable-rate aldicarb approach also resulted in 34% less nematicide applied on a field wide basis than with the single rate application. Similar results were obtained with 1,3-D where the variable-rate application strategy resulted in 5% higher yield and 78% lower nematicide usage than the conventional single rate approach.

3.2 Research in Georgia

Nematode management decisions typically are based on results from soil samples which are collected from an entire field or large sections of a field. If the area represented by a sample has significant nematode aggregation or is non-uniform for factors that influence nematode population levels, crop productivity, or the interaction of the nematodes and the crop, then the assay results may lead to inappropriate or inefficient management decisions. One way to improve the accuracy of information used in making management decisions is to reduce the variability within the area being sampled for factors which affect the variables being measured. Management zones, sub-regions of a field for which a single rate of a specific input is appropriate (Doerge 1999), have been used to study variability in crop yield and variable application of inputs (Aaron et al. 2004, Basnet et al. 2003, Fridgen et al. 2000). A method based on field physical characteristics for delineation of nematode management zones (NMZ) which minimize variability within a zone and maximize the differences among zones was developed in Georgia (Ortiz 2008).

Soil texture, moisture, fertility and terrain may affect nematodes. Monfort et al. (2007) found a strong relationship between cotton yield, SRK levels, and percent sand. Levels of SRK also have been related to changes in soil pH (Melakeberhan et al. 2004) and soil moisture (Wheeler et al. 1991). Evaluation of 26 soil physical and chemical properties (e.g., soil texture, acidity, base saturation, cation-exchange capacity, percent organic matter) found that 50% of the variability in nematode population density was related to high levels of clay, organic matter, low copper concentration, and small changes in percent soil moisture (Noe and Barker 1985). Ortiz (2008) used data from 11 cotton fields infested with SRK to develop and validate the procedures described below for creating NMZ maps.

The delineation of NMZ was based on: (I) the identification of the field physical characteristics correlated with the variability of nematodes, and (II) the evaluation of the best combination of variables and number of zones to represent the variability of nematodes. The relationship between nematode population density and field characteristics was evaluated using canonical correlation analysis (CCA), a procedure which accounts for multicolinearity of variables (Jaynes et al. 2005) and evaluates the correlation between two sets of variables (Johnson and Wichern 2002). The strength of association between SRK population density and edaphic and terrain properties (soil EC_a 0–30 cm deep, soil EC_a 0–90 cm deep, NDVI, elevation, and slope) measured from cotton fields was evaluated by CCA. Elevation data was collected using a real-time kinematic (RTK) GPS at the same time that soil EC_a data was collected using the electrical resistivity method (Corwin and Lesch 2005), and slopes of the terrain were calculated from changes in the elevation. Eigenvalues, the squared canonical correlation from the CCA, were used to assess the proportion of variance in the canonical predictor variable explained by the canonical correlation. Those eigenvalues indicated that in most fields more than 50% of the variability was explained by the canonical correlation between the edaphic terrain variable and nematode counts. The inputs with the greatest influence on the canonical predictor variable (those which had the greatest loading values) were soil EC_a (either 0–30 cm values or 0–90 cm values), elevation, and slope.

The next step after determining which variables optimized the canonical correlation with nematode levels was to determine how to group them and the optimum number of clusters into which they should be divided. Cluster analysis provides a mechanism to identify areas of a field which have similar edaphic and terrain characteristics and to quantify the variability in patterns (Fraisse et al. 2001). A type of cluster analysis using fuzzy c-means can be useful in pattern recognition and in analyzing data with the sort of continuous variability found in nature (Fridgen et al. 2000). Fuzzy c-means classification has been used with data such as soils (Fridgen et al. 2004, McBratney and DeGruijter 1992, Tarr et al. 2003), crop yield (Doberman et al. 2003, Fridgen et al. 2000, Jaynes et al. 2003, Li et al. 2007), and remotely sensed images (Boydell and McBratney 2002, Sullivan et al. 2005), and it is appropriate for use in identifying and optimizing NMZ. The predictor variables previously derived in the CCA were entered into a fuzzy c-means algorithm.

Fuzzy clustering analysis was accomplished using Management Zone Analyst (MZA) software (Fridgen et al. 2004), though other software could be used. MZA separates the data into clusters to maximize the uniformity within a zone. MZA generates multiple scenarios for each data set in which the number of zones is increased incrementally from two to the maximum number chosen by the user. MZA calculates two performance indices, the normalized classification entropy (NCE) and the fuzziness performance index (FPI), which can be used to determine the optimum number of zones which is generally the scenario having the lowest values of FPI and NCE with the least number of clusters (Fridgen et al. 2004). Because several performance measures are being assessed simultaneously, there is some subjectivity in selecting the most appropriate number of zones. A user may choose to reduce the number of zones if one or more zones are deemed too small or discontiguous to be practical. MZA can create maps to visually depict the zones, or the resulting clustering data can be exported for use in other mapping software. An example of a nematode management zone map is shown in Fig. 24.5.

Ortiz (2008) documented that NMZ with the lowest soil EC_a typically had the greatest SRK population levels and zones with the greatest soil EC_a values generally had the fewest nematodes. Because of the strong relationship between soil EC_a and nematode levels, NMZ based only on soil EC_a generally resembled zones which also considered elevation, slope, and NDVI, although including the other variables did improve the relation between the zones and nematode levels. The greater the variation in elevation, slope, and NDVI is in a field, the greater the contribution of those variables is expected to be in creating NMZ.

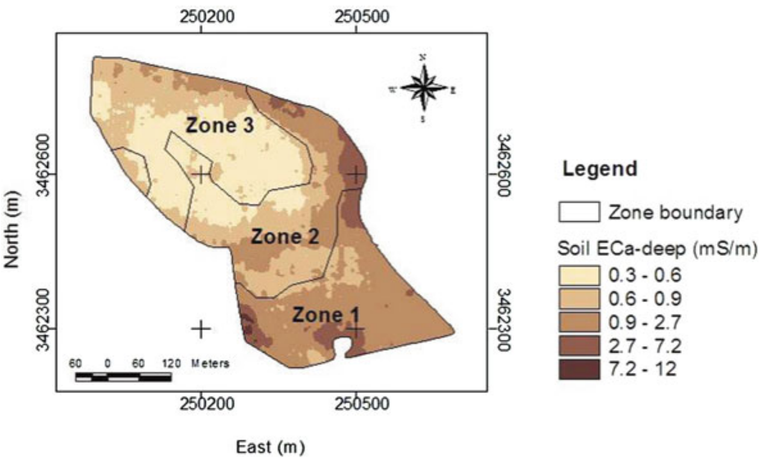

Fig. 24.5 Nematode management zones created based on soil EC_a, elevation, slope, and NDVI

The greatest utility of delineating NMZ based on field edaphic and terrain properties is to provide a guide for directed nematode sampling regardless of prior knowledge of nematode presence or distribution. Because we now know that soil EC_a, elevation, slope, and NDVI are related to levels of SRK, the canonical correlation analysis does not need to be performed for each field, and those variables can be used to create NMZ zones which cluster those factors to minimize variability within a zone while maximizing variability among zones. The resulting zones can then be sampled independently of each other and management decisions for each zone, including site specific nematicide applications, can be made based on those samples. This method of creating zones with homogenous features should be of value in managing any nematode species for which those factors affect its population levels or the damage it causes to the crop.

3.3 Research in Arkansas

In 2001, studies were initiated in a commercial cotton field in Arkansas to more fully understand the relationship between soil texture and SRK population densities and damage potential. As with CLN, our results indicated that SRK population densities were strongly impacted by soil texture, especially changes in percent sand content (Monfort et al. 2007). Nematode population densities increased with increasing sand content across a range from roughly 28–65% sand and declined where soil texture exceeded 65% sand (Fig. 24.6). Although population densities declined at higher sand contents, the damage potential of the nematode continued to increase as sand content increased, likely due to both the influence of texture on nematode survival and reproduction and on the growth of the host crop. Figure 24.6 represents the

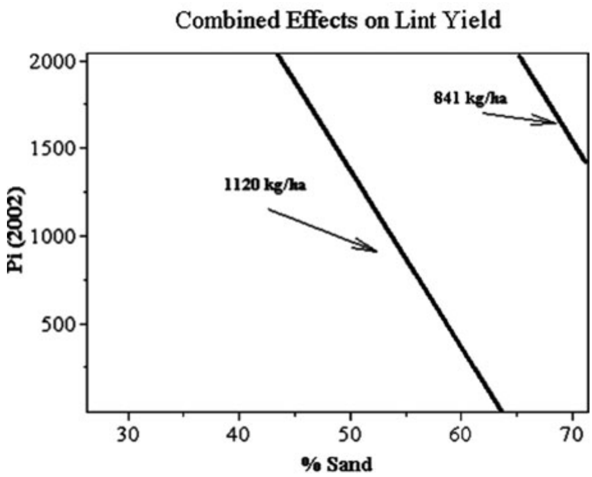

Fig. 24.6 Relationship between *Meloidogyne incognita*, the southern root-knot nematode (Pi), % sand and cotton lint yield

combined effects of both nematode population density and soil sand content on cotton yield where two yield target lines (1120 and 841 kg ha^{-1} lint yield potential) have been constructed.

The relationship between nematode population density (y axis) and percent sand (x axis) are illustrated by these lines. For example, the target yield of 1,120 kg/ha can be maintained at lower soil sand content with considerably higher nematode population densities, whereas at higher percent sand, the plant can maintain the target yield at only a fraction of the population of nematodes. This may be the result of decreased water holding capacity and available fertility at higher sand contents, resulting in greater overall plant stress, but a strong relationship between sand content of the soil and SRK population density was consistently evident over a three year period (Monfort et al. 2007).

3.3.1 On-Farm Experience in Arkansas

A commercial cotton field in northeast Arkansas was chosen as a model to evaluate the potential for site-specific application of 1,3-D for SRK management using precision agriculture technologies at a farm level. An arbitrary composite sample of the field and inspection of roots as well as a history of disappointing yields provided initial indication that the field would be a good model. A soil EC_a map of the field was developed after harvest in 2004 using a Veris 3,100 mobile EC cart as described above, and a soil management zone map was constructed by interpolating the point data using the Kriging interpolation method in SSToolbox (Fig. 24.7). The soil management zone map was then loaded into a handheld computer and used as a guide for taking nematode samples. Each zone sample was a 100 cm^3 subsample of a composite of 20–30 cores collected randomly from the management zone. As expected, the SRK population densities were not uniform across soil management zones (Fig. 24.7). Using the nematode distribution and population densities for

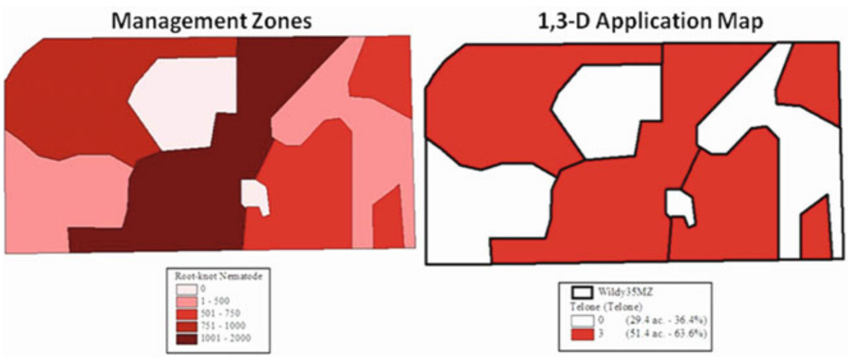

Fig. 24.7 Management zones based upon EC_a and nematode density corresponding 1,3-D application map

each zone, a site-specific nematicide application prescription was devised based on a nematicide action threshold of 500 juveniles per 500 cm^3 of soil (T.L. Kirkptatrick, personal communication). The population densities ranged from 0 to 2,000 juveniles per 500 cm^3 of soil with the nematode being absent or below threshold in an estimated 37% of the field (Fig. 24.7).

Our initial approach in 2005 was to manually turn the nematicide applicator off and on guided by the application prescription map displayed on a hand-held field computer with GPS software to locate zones within the field. When the experiment was repeated in the same field using the same map in 2007, a Legacy 6000 system as described above was installed on the farmer's 1,3-D applicator and delivery of the material was as previously described according to the prescription map.

To measure the efficacy and the potential economic benefits of site-specific application of 1,3-D in the model field, a series of paired comparisons was established in the field in 2005 (10 comparisons) and 2007 (7 comparisons). Each comparison consisted of 6-row field length strips that received the uniform rate of 1,3-D, the site-specific application, or no 1,3-D (control). In 2005, the mean yield for the uniform rate treatments was 127 kg ha^{-1} greater than the control, and the yield for the site-specific application was 104 kg ha^{-1} greater than the control. In 2007, mean yield for the uniform rate was 113 kg ha^{-1} greater than the control while the yield in the site-specific treatments was 143 kg/ha greater than the control. Utilizing the management zones to focus 1,3-D applications in specific areas resulted in a reduction of about 40% in 1,3-D compared to the uniform rate.

4 Discussion

4.1 Summary

Utilization of SEC-GPS and GIS technology allows accurate, efficient and economical development of geo-referenced soil texture maps which, in turn, make site-specific nematicide application systems possible. Application technology and equipment has advanced to the point that cost effective systems that can be used by cotton growers are feasible. SEC maps are capable of predicting where nematodes will occur with a relatively high degree of accuracy, and they also may be useful in predicting where nematodes either will not occur, or where the yield potential of a site is sufficiently high that treatment with a nematicide is not going to be cost effective. Promising results have been obtained across a wide range of soil types and production environments in Arkansas, Georgia, Louisiana and South Carolina. In most instances site-specific application of either aldicarb or 1,3-D resulted in a decrease in the amount of nematicide applied by 30–50% across the field while crop yields were maintained or increased. This reduction in overall nematicide usage is desirable from both economic and environmental perspectives.

4.2 The Future of Site-Specific Nematicide Applications

Utilization of site-specific nematicide application systems likely will continue to grow as researchers and growers gain practical experience with this system. Although we used cotton production systems as our model, this concept is applicable to any agronomic crop that is susceptible to nematode-induced yield losses, and where nematicides are labeled and available. It is likely that the cost associated with the technology and equipment will decrease as the systems become more familiar and are utilized more widely by growers and crop consultants. The potential also exists for interfacing other technologies such as vegetative indices (e.g. NDVI), spectral analysis, SEC-generated soil textural maps, and geo-referenced crop yield maps to create even more efficient and precise maps of problem areas within fields.

Our ultimate goal is to develop a system to identify nematode species and densities in the soil as precisely and rapidly and easily as we now do soil texture. Use of quantitative PCR or a related technology may eventually make this possible. However, for now, the ability of site-specific nematicide application systems to minimize nematode damage while reducing nematicide loading of the environment ensure its utilization as long as soil-applied pesticides are used.

References

Aaron, RS, Shanahan JF, Liebig MA et al (2004) Appropriateness of management zones for characterizing spatial variability of soil properties and irrigated corn yields across years. Agron J 96:195–203

Baird RE, Rich JR, Waters D (2001) Evaluation of variable rate nematicide applications using precision farming methods to manage *Meloidogyne incognita* on cotton. Nematol Medit 29:247–254

Barker KR, Olthof THA (1976) Relationships between nematode population densities and crop responses. Annu Rev Phytopathol 14:327–353

Basnet, B, Kelly R, Jensen T et al (2003) Delineation of management zones using multiple crop yield data. Proceedings of the International Soil Tillage Research Organization Conference, 16th Triennial Conference. The University of Queensland, Brisbane,

Blasingame D, Patel MV (2005) Cotton disease loss estimate committee report. 2005 Procs Beltwide Cotton Conf, National Cotton Council of America, Memphis

Boydell B, McBratney B (2002) Identifying potential within-field management zones from cotton-yield estimates. Prec Agric 3:9–23

Corwin DL, Lesch SM (2005) Apparent soil electrical conductivity measurements in agriculture. Comput Electron Agric 46:11–43

Dickerson OJ, Blake JH, Lewis SA (2000) Nematode guidelines for South Carolina. Clemson Univ Extension Circ 703. Cooperative Extension Service, Clemson University, Clemson. 36pp.

Doberman A, Ping JL, Adamchuk VI et al (2003) Classification of crop yield variability in irrigated production fields. Agron J 95:1105–1120

Doerge TA (1999) Management zone concepts. Site-Specific Management Guidelines. PP Institute. Series, Norcross

Evans K, Webster RM, Halford PD et al (2002) Site-specific management of nematodes – Pitfalls and practicalities. J Nematol 34:194–199

Farias PRS, Sanchez-Vila X, Barbosa JC et al (2002) Using geostatistical analysis to evaluate the presence of *Rotylenchulus reniformis* in cotton crops in Brazil: economic implications. J Nematol 34:232–238

Fraisse, CW, Sudduth KA, Kitchen NR (2001) Calibration of the CERES-maize model for simulating site-specific crop development and yield on claypan soils. Appl Eng Agric 17: 547–556

Fridgen JJ, Fraisse CW, Kitchen NR, Sudduth KA (2000) Delineation and analysis of site-specific management zones. Proceedings of the 2nd international conference geospatial information in agriculture and forestry, CD-ROM. Lake Buena Vista

Fridgen, JJ, Kitchen NR, Sudduth KA et al (2004) Management zone analyst (MZA): software for subfield management zone delineation. Agron J 96:100–108

Jaynes DB, Colvin TS, Kaspar TC (2005) Identifying potential soybean management zones from multi-year yield data. Comput Electron Agric 46:309–327

Jaynes DB, Kaspar TC, Colvin TS, James DE (2003) Cluster analysis of spatiotemporal corn yield patterns in an Iowa field. Agron J 95:574–586

Johnson RA, Wichern DW (2002) Applied multivariate analysis (5th edn). Prentice Hall, Upper Saddle River

Khalilian A, Mueller JD, Han YJ, Wolak FJ (2001) Predicting cotton nematode distribution utilizing soil electrical conductivity. In: Richter D (ed) Proc Beltwide Cotton Conf, National Cotton Council, Memphis

Khalilian A., Mueller JD, Han YH et al (2003a) Performance of variable rate nematicide application systems. Proc Beltwide Cotton Conf National Cotton Council, Memphis

Khalilian A, Mueller JD, Han YJ et al (2003b) Soil texture as determinant of variable rate application of nematicides in cotton. ASAE Meeting Paper No. 031122

Khalilian A, Mueller JD, Han YJ, Kirkpatrick T (2004) Crop management applications of soil electrical conductivity in precision agriculture. ASAE Technical Paper No. 04-1093, ASAE, St. Joseph, MI 49085.

Kinloch RA, Rich JR (1998) Responses of cotton yield to soil applications of aldicarb and 1,3-D in Florida. J Nematol 30:639–642

Koenning SR, Kirkpatrick TL, Starr JL et al (2004) Plant-parasitic nematodes attacking cotton in the United States: old and emerging production challenges. Plant Dis 88:101–113

Koenning SR, Overstreet C, Noling JW et al (1999) Survey of crop losses in response to phytoparasitic nematodes in the United States for 1994. J Nematol 31(Suppl):587–618

Koenning SR, Walters SA, Barker KR (1996) Impact of soil texture on the reproductive and damage potentials of *Rotylenchulus reniformis* and *Meloidogyne incognita* on cotton. J Nematol 28:527–536

Lewis SA, Smith FH (1976) Host plant distribution and ecological associations of *Hoplolaimus columbus*. J Nematol 8:264–270

Li Y, Shi Z, Li F, Li HY (2007) Delineation of site-specific management zones using fuzzy clustering analysis in a coastal saline land. Comput Electron Agric 56: 174–186

Lund ED, Christy CD, Drummond PE (1999) Practical applications of soil electrical conductivity mapping. In: Stafford JV (ed) Precision agriculture '99 - Proceedings of the 2nd european conference precision agriculture SCI, Sheffield, pp 771–779

Martin SB, Mueller JD, Saunders JA, Jones WI (1994) A survey of South Carolina cotton fields for plant parasitic nematodes. Plant Dis 78:717–719

McBratney AB, DeGruijter JJ (1992) A continuum approach to soil classification by modified fuzzy means with extragrades. J Soil Sci 43:159–175

Melakeberhan H, Dey J, Baligar VC, Carter TE Jr (2004) Effect of soil pH on the pathogenesis of *Heterodera glycines* and *Meloidogyne incognita* on *Glycine max* genotypes. Nematology 6:585–592

Monfort WS, Kirkpatrick TL, Rothrock CS, Mauromoustakos A (2007) Potential for site-specific management of *Meloidogyne incognita* in cotton using soil textural zones. J Nematol 39:1–8

Mueller JD, Khalilian A, Han YJ, Wolak FJ (2001) Using soil electrical conductivity to predict the distribution of cotton nematodes. Phytopathology 91:S139

Noe JP (1990) Efficacy of fumigant nematicides to control *Hoplolaimus columbus* on cotton. J Nematol (Suppl) 22:718–723

Noe JP, Barker KR (1985) Relation of within-field spatial variation of plant-parasitic nematode population densities and edaphic factors. Phytopathology 75:247–252

Ortiz BV (2008) Study of the spatial variability of the southern root-knot nematode (*Meloidogyne incognita*) and its impact on cotton yield. PhD thesis, University of Georgia, Athens

Robinson AF, Heald CM, Flanagan SL et al (1987) Geographic distributions of *Rotylenchulus reniformis*, *Meloidogyne incognita*, and *Tylenchulus semipenetrans* in the Lower Rio Grande Valley as related to soil texture and land use. J Nematol 1 (Suppl):20–25

Starr JL, Heald CM, Robinson AF et al (1993) *Meloidogyne incognita* and *Rotylenchulus reniformis* and associated soil textures from some cotton production areas of Texas. J Nematol 25:895–899

Starr JL, Koenning SR, Kirkpatrick TL et al (2007) The future of nematode management in cotton. J Nematol 39:283–294

Sullivan DG, Shaw JN Rickman D (2005) IKONOS imagery to estimate surface property variability in two Alabama physiographies. Soil Sci Soc Am J 69:1789–1798

Tarr AB, Moore KJ, Dixon PM et al (2003) Use of soil electroconductivity in a multistage soil-sampling scheme. Crop Mgmt 10:1094/CM-2003-1029

Thomason IJ (1987) Challenges facing nematology: environmental risks with nematicides and the need for new approaches. In: Veech JA, Dickson DW (eds) Vistas on nematology. Society of Nematologists, Inc., Hyattsville

Wheeler TA, Barker KR, Schneider SM (1991) Yield-loss models for tobacco infected with *Meloidogyne incognita* as affected by soil-moisture. J Nematol 23:365–371

Wheeler TA, Kaufman HW, Baugh B et al (1999) Comparison of variable and single-rate applications of aldicarb on cotton fields in fields infested with *Meloidogyne incognita*. J Nematol 31 (Suppl):700–708

Williams BG, Hoey D (1987) The use of electromagnetic induction to detect the spatial variability of the salt and clay contents of soils. Aust J Soil Res 25:21–27

Wrather JA, Stevens WE, Kirkpatrick TL, Kitchen NR (2002) Effects of site-specific application of aldicarb on cotton in a *Meloidogyne incognita*-infested field. J Nematology 34:115–119

Wyse-Pester DY, Wiles LJ, Westra P (2002) The potential for mapping nematode distributions for site-specific management. J Nematol 34:80–87

Chapter 25
Precision Disease Control in Bed-Grown Crops

Jan C. van de Zande, Vincent T.J.M. Achten, Huub T.A.M. Schepers, Arie van der Lans, Corné Kempenaar, Jean-Marie G.P. Michielsen, Hein Stallinga, and Pleun van Velde

Abstract Matching spray volume to crop canopy sizes and shapes can reduce the use of plant protection products, thus reducing operational costs and environmental pollution. Developments on crop adapted spraying for fungal control are highlighted in arable crop spraying. A plant-specific variable volume precision sprayer, guided by foliage shape and volume (canopy density sprayer; CDS) was developed for bed-grown crops to apply fungicides. Sensor selection to quantify crop canopy and spray techniques to apply variable dose rates are evaluated based on laboratory measurements. Based on the laboratory experience a prototype CDS sprayer was built using either a Weed-IT® or a GreenSeeker® sensor to detect plant place (fluorescence) or size (reflectance). Variable rate application was either done with a pulse width modulation nozzle or a switchable four-nozzle body. Spray volume could be changed from 50 to 550 l ha^{-1} in 16 steps. Spray deposition, biological efficacy and agrochemical use reduction were evaluated in a flower bulb and a potato crop during field measurements using a prototype CDS sprayer. Spray volume savings of a prototype plant-specific sprayer are shown to be more than 75% in early late blight (*Phytophthora infestans*) control spraying in potatoes. In flower bulbs (lily) it was shown that in *Botrytis* blight control on average spray volume could be reduced by 45%. In a potato crop biological efficacy was maintained at the same good level as of a conventional spraying. In a flower bulb crop biological efficacy of the CDS was lower than of conventional spraying, which means that spray strategy and dose algorithms need further research.

1 Introduction

In crop spraying the goal is to achieve a uniform spray deposition all over the crop canopy structure or soil surface. Losses to the soil underneath the crop and outside the field, through spray drift are to be minimised. It is known that sprayer

---

J.C. van de Zande (✉)
Wageningen UR – Plant Research International, 6700 AP, Wageningen, The Netherlands
e-mail: jan.vandezande@wur.nl

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_25,

settings are important for spray distribution in crop canopy. Matching spray volume and direction to crop size and shape can reduce chemical application, thus reducing operational costs and environmental pollution. Manual or sensor actuated sprayers have shown potential reductions in agrochemical use of 30% and more. Sensors quantifying crop parameters such as quantity of biomass and photosynthesis activity are already commercially available. Sensors to evaluate the plant stress (MLHD 2004, Polder 2004) or spectral analysis of the crop canopy parameters (Bravo et al. 2003, Schut 2003, Vrindts et al. 2003, Scotford and Miller 2004, 2005) open the potential for more target oriented spraying in crop protection. Spray systems treating individual plants based on fluorescence (Weed-IT®, Rometron, Doorwerth, NL) as used on pavements (Kempenaar et al. 2006) or canopy reflection information (GreenSeeker®, Ntech Industries, Ukiah, USA) used for fertilising are already developed. Precise application techniques recently developed able to vary dose rates are obtained by Pulse Width Modulation nozzles (Weed-IT®) and multi-nozzle holders (VarioSelect®, Lechler, Metzingen, D) with switchable number of nozzles varying in flow rate (Dammer and Ehlert 2006); respectively in a continuous (50–300 l ha^{-1}) and a stepwise way (50–600 l ha^{-1} in 16 steps). Based on these possibilities smaller units of treatment can be achieved in the field. In spraying crop protection products this will lead from a full boom width treatment to section wise and even nozzle wise variable applications.

An example in which the different elements of precision farming are combined is a Canopy Density Sprayer for bed-grown crops like flower bulbs and potatoes (Zande and Achten 2005). This chapter presents an overview of recent developments and introductions in agricultural practice of crop adapted spraying for crop protection in bed-grown crops.

2 Potential Use Reduction

In order to quantify the potential of crop adapted spraying in arable crops an inventory of crop development in flower bulb growing was made. For a bed-grown crop like lilies it is obvious that easiest savings in spray volume can be made by not spraying the paths between the beds. As beds are created at 1.50 m spacing and the planted area of the bed is 1.0 m wide, about 30% of the area should not to be sprayed against fungal diseases. Canopy development and potential spray volume saving for the 2002 growing season of a lily crop (var. Stargazer) is shown for crop coverage on the bed and between beds on the paths and crop height on the bed (Fig. 25.1). Potential spray volume savings in the early season are possible by only spraying the individual plants. More than 90% is not to be treated at first sprayings against leaf blight (*Botrytis* spp.) based on green area coverage. This reduction potential decreases as the canopy develops to about 25% when the bed is fully covered with green canopy and only the paths in between the beds are not treated. Based on canopy height, savings can be generated up until the maximum height of the crop is reached which is the moment of removing the flowers. As the crop is grown to

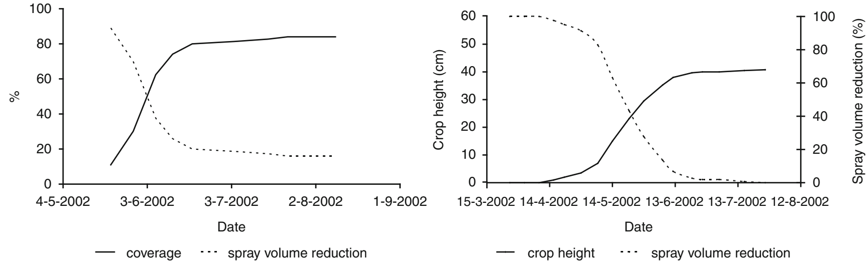

Fig. 25.1 Coverage with crop canopy (lily cv. Stargazer) of the bed and the path between the beds during the growing season and potential spray volume reduction by only spraying green parts (*left*) and crop height during the growing season and potential spray volume reduction (*right*) by adapting spray volume to crop height (full dose at maximum crop height)

produce flower bulbs the flowers are cut after initiation of flowers. Based on crop height the potential reduction in spray volume could be more than 90% for the early sprayings and on average around 45% for the entire growing season (Fig. 25.1).

To verify spray volume reduction in practice, a field experiment was performed applying the reduced spray volumes before full growth situation at reduced doses. Normally from the first spraying onwards a full dose is applied (1.6 l ha^{-1} Allure®; active ingredients chlorothalonil + prochloraz). First spraying was reduced to 0.1, 0.2, 0.4 or 0.8 l ha^{-1} and then doubled at each of the next group of applications until full dose was attained. This scheme showed that even starting the first spraying in the season with only 1/16th of the recommended dose did not affect average lily bulb weight significantly (Table 25.1). Nor was average disease infected leaf area at harvest time significantly affected except with the lowest starting dose of 1/16th of that recommended. Similar results were obtained for a tulip crop in three growing seasons. These measurements show the potential of using lower doses at early sprayings. Automating the adaptation of dose to the crop canopy density would be a challenge.

Sensors on the market, currently used for advising on fertilizer use could be utilized also for canopy density characterization. Therefore in the laboratory different plant densities and heights of a lily crop were used to evaluate a GreenSeeker® sensor for determining the reflection of different canopy densities. Results of the Normalised Differential Vegetation Index (NDVI) are presented in Table 25.2 for the three crop heights and two plant densities. There is little difference in NDVI for the middle and high crop irrespective of plant density. Only the low crop height shows a difference in reflection between plant densities.

The laboratory results show that the GreenSeeker® sensor is limited in use for adapting the dose to canopy density or crop height. The high values for the low crop height suggests an influence of soil surface (organic matter) on reflectance. However the sensor can be used in the early growth stages to adapt spray dose based on its canopy reflection signal (NDVI).

Table 25.1 Effect of crop adapted spraying against *Botrytis* blight on yield (relative bulb weight) of a lily crop and infected leaf area at harvest time (%) with reduced doses at early spraying and increasing dose to full dose (Allure®, 1.6 l ha^{-1}) at flower cutting (maximum crop height 60 cm)

	Fungicide application [l ha^{-1}]					2006		2007		
Treatment	1st/ 2nd	3rd	4th/ 5th	6th/ 7th	8th/ etc.	Bulb	Leaf	Bulb	Leaf	Aver. leaf
Height (cm)	10	20	30	40	60					
1	0	0	0	0	1.6	99	53 d[a]	100	43 cd	48 d
2	0	0.2	0.4	0.8	1.6	92	33 c	98	45 d	39 cd
3	0.1	0.2	0.4	0.8	1.6	96	30 bc	99	40 bcd	35 bc
4	0.2	0.4	0.8	1.6	1.6	96	18 ab	105	23 a	20 a
5	0.4	0.8	1.6	1.6	1.6	96	20 abc	103	30 abc	25 ab
6	0.8	1.6	1.6	1.6	1.6	95	20 abc	109	28 ab	24 a
7 Standard	1.6	1.6	1.6	1.6	1.6	100	15 a	100	30 abc	23 a
8 Control	0	0	0	0	0	79	100 e	74	95 e	98 e
LSD (0.05)						6	6	6	7	10

[a]same letter in column means no significant difference.

Table 25.2 NDVI values for a lily crop with different plant densities and crop heights in a laboratory test measured with a GreenSeeker®

Plant density [plants m^{-2}]	Crop height		
	Low	Medium	High
120	0.72	0.88	0.88
180	0.80	0.89	0.89

3 Canopy Density Spraying in Practice

A Canopy Density Sprayer for bed-grown crops like flower bulbs and potatoes is under development. This CDS prototype spraying system combines detailed crop information (fluorescence and spectral reflectance) with very accurate application techniques. The system sprays only when there are crop plants under the spraying nozzle(s) (Fig. 25.2). When leaves emerge from the soil only the leaves are sprayed: i.e. the sprayer operates as a patch sprayer. When the crop develops it forms rows and the CDS becomes a band sprayer. When the crop canopy covers the whole bed, only the bed will be sprayed but not the paths in between. When the crop develops to its maximum height (flowering) spray volume will be adapted to crop height or total leaf area to cover total leaf area with spray liquid uniformly. Expected reductions in agrochemical use vary from 25% in the full-developed canopy to more than 90%

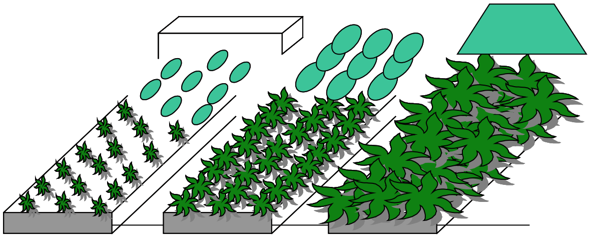

Fig. 25.2 Schematic presentation of the development of a Canopy Density Sprayer for bed-grown crops

in the initial leaf stage based on crop growth development evaluations during the growing season of flower bulb crops grown on beds (Zande et al. 2008).

Canopy adapted spraying systems are momentarily tested in prototype versions in potato and flower bulb crops to apply fungicides against late blight in an early potato crop and *Botrytis* blight in a lily flower bulb crop.

4 Plant-Specific Spraying Against Late Blight in Potatoes

The first experiments with plant-specific spraying against late blight in potatoes were done in autumn 2007 (WUR-PPO experimental farm, Lelystad) and were repeated in the 2008 and 2009 growing season. It was shown how much fungicide can be saved by switching on and off nozzles when spraying against late blight (*P. infestans*) and whether the biological efficacy remained comparable with conventional application. A prototype using Weed-IT® sensor-spray elements was built for this purpose enabling the spray to be placed in 10 cm bands with 5 cm length direction accuracy. The machine was prepared to work at a width of 2.25 m, on the top of three potato ridges (Fig. 25.3, left). The conventional spraying machine (Fig. 25.3, right) used TeeJet XR11004 nozzles (3 bar spray pressure) at 50 cm nozzle spacing

Fig. 25.3 Canopy density spraying with pulse width modulation nozzles (*left*), and conventional sprayer applying 300 l ha^{-1}

applying a spray volume of 300 l ha^{-1} (5 km h^{-1}). Boom height between the soil and the crop canopy was 75 cm. The fungicide applied (Shirlan®, active ingredient fluazinam) was prepared as a tank mix in a jerry can and placed on a 'Spider 15' balance with an accuracy of ten grams. The amount of spray volume used was determined by weighing the jerry can with the chemicals before and after every treated field (2.25 × 10 m). The average used dosage (l ha^{-1}) of every field was compared to that used in conventional spraying.

The experiment contained seven treatments; untreated, plus six treatments sprayed with fluazinam to protect the crop against *P. infestans*. Fields were sprayed with both conventional and Weed-IT® spray techniques at dose rates of 75% (0.3 l ha^{-1}) and 25% (0.1 l ha^{-1}) of recommended dose (0.4 l ha^{-1}).

After the treatments, leaves were picked to analyze them in the laboratory for protection against late blight. The leaves were inoculated with a few drops of a *Phytophthora* spore suspension and *Phytophthora* development on the leaves was visually evaluated after 6 days.

First experiments of late planted potatoes in autumn 2007 showed that the measured quantity of sprayed volume during applications on the different dates varied between 75 and 84%. These savings coincided with measured crop coverage of the soil surface. No differences in protection against late blight were found between the spray techniques and dose rates, except for the Weed-IT® 75% dose on October 23 which was significantly lower than the other techniques. From these first experiments it was concluded that individual plant spraying gave equally good protection against late blight with use of less than 25% of the standard applied amount of fungicide.

In the 2008 experiments early season sprayings resulted in a reduction of sprayed volume of the Weed-IT® application of between 25 and more than 50% for individual sprayings (Fig. 25.4) compared to the conventional applications.

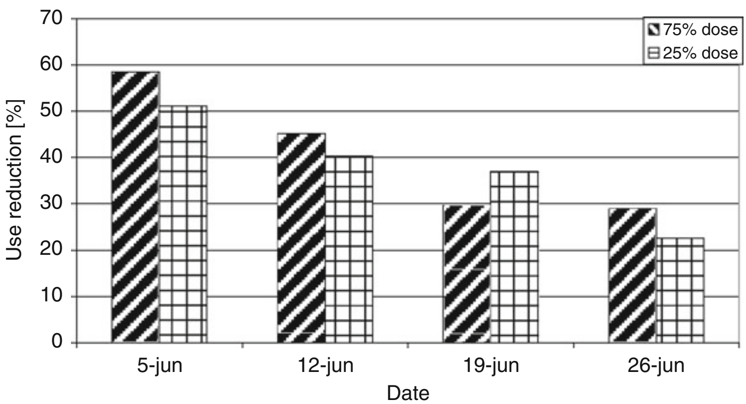

Fig. 25.4 Use reduction of fungicide (% compared to conventional) in early potato late blight control using a Weed-IT® sprayer for plant specific application

Table 25.3 Spray deposition for conventional and plant specific Weed-IT® application of fungicides in potatoes early in the season on different places of the plant, top of plant canopy and on the soil surface underneath

	Spray deposition [µl/cm^2]								
	On plant							Soil surface	
Spray technique	Front	Centre	Left	Right	Back	Sum	Above crop canopy	Top ridge	Between ridge
Conventional	0.89	1.00	0.82	0.78	0.72	0.85	1.34	0.55	1.08
Weed-IT®	0.65	0.78	0.65	0.46	0.62	0.63	0.36	0.40	0.49

Measured spray deposition on the plant canopy differed between the Weed-IT® application and conventional spraying as average spray deposition was lower (Table 25.3). However variation between deposits on plant parts related to the switching of the nozzles of the Weed-IT® showed no larger variation than of the conventional spraying. As expected spray deposit on the soil surface was lower for the Weed-IT® spray system.

There was no difference in biological efficacy in late blight control during early sprayings between conventional and Weed-IT® sprayings for the 75% dose (Table 25.4). The 25% dose gave a lower protection level for both applications techniques after the first treatment. After two additional sprayings the difference in protection level was less for the conventional spraying but still effective for both dose rates of the Weed-IT® sprayings. This suggests that at reduced dose rates there is a higher risk of blight infection with the plant-specific spraying, which probably is related to the difference in spray deposit. Further research is needed on this subject to determine optimised dose-effect algorithms based on sensor output. However, using the recommended dose will give no reduced efficacy of the CDS compared to the conventional spraying.

Table 25.4 Protection against late blight (*Phytophthora infestans*) expressed as % infected potato leaf area for conventional and Weed-IT® plant-specific application of 75 and 25% of recommended dose (0.4 l ha^{-1}) of Shirlan® (fluazinam) at early season spraying dates

	Percent infected leaf area			
Treatment	5 June	12 June	19 June	26 June
Untreated	99.7	98.6	97.8	99.1
Conventional 75%	12.1	13.9	3.4	0.6
Conventional 25%	22.9	29.8	5.8	3.1
Weed-IT® 75%	20.0	14.5	3.8	1.6
Weed-IT® 25%	23.4	29.5	10.8	7.4
$LSD_{0.05}$	6.8	7.1	3.8	2.8

5 Plant-Specific and Canopy Reflection Dependent Spraying Against Botrytis Blight in Flower Bulbs

In the flower bulb crop lily (at WUR-PPO, Lisse, NL) a prototype CDS sprayer was used to apply the fungicide Allure® (1.6 l/ha) in a plant-specific way using Weed-IT® elements and a canopy density manner using a SensiSpray element of 1.5 m wide working width (Fig. 25.5, Zande et al. 2009). Maximum dose rates were varied between full dose and half dose by adapting tank mix concentration. In the Weed-IT® sprayer TeeJet® 400067 flat fan nozzles were used with a nozzle spacing of 0.10 m. Individual plants were sprayed based on the Weed-IT® green detection sensor. The SensiSpray sprayer was equipped with VarioSelect® nozzle bodies at 0.50 m spacing containing 4 Lechler ID9001 venturi flat fan nozzles, able to switch and therefore apply spray volumes in steps of 130, 260, 390 and 520 l ha^{-1} depending on the measured NDVI of the GreenSeeker® sensor. For the conventional application one of the nozzles of each VarioSelect® nozzle body was replaced with a TeeJet® XR11004 flat fan nozzle. All systems operated at 3 bar spray pressure. Driving speed was 3.6 km h^{-1} for the conventional and SensiSpray applications and 3.0 km h^{-1} for the Weed-IT®, thereby all applying around 530 l ha^{-1}.

During the growing season crop protection against *Botrytis* blight sp. was done with weekly scheduled fungicide applications of the conventional, Weed-IT® and SensiSpray spray techniques at two maximum dose rates with 4 replications. Used spray volume per individual field (1.5×7 m) was quantified by weighing the sprayed amount on the sprayer. *Botrytis* spp. infection was monitored during the growing season using a 0–10 scale; 10 = no infection, 9 = 5% of plants infected, 6 = 40% of plants infected, and 0 = complete desiccated crop, with no green area left.

The prototype CDS sprayer equipped both with a Weed-IT® and a SensiSpray spray boom was used in 2008 for a season long spraying of fungicides against *Botrytis* blight in a lily crop. The canopy related dosing of both systems was active throughout the season. For all applications between early June and mid August spray

Fig. 25.5 Prototype canopy density sprayer for bed grown crops used in a lily crop; *left* in early growth stage with individual plants; *right* in late growth stage with fully covered bed

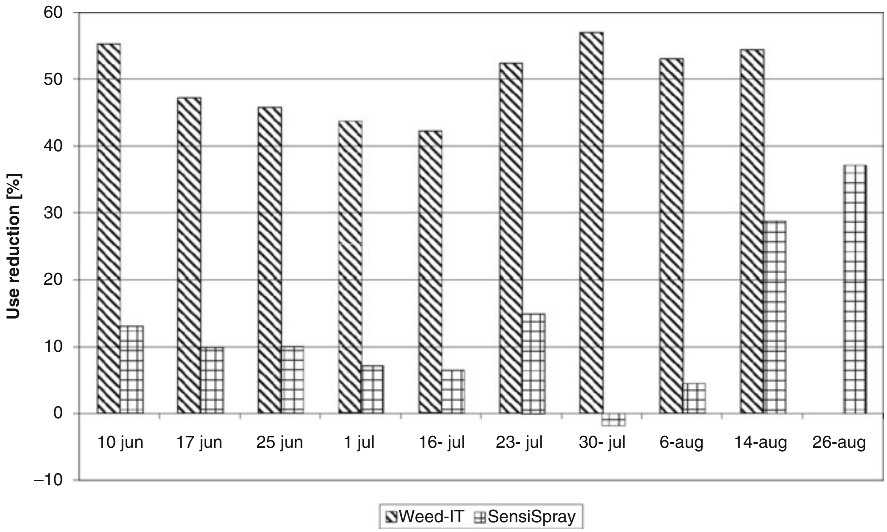

Fig. 25.6 Spray volume reduction in percent compared to conventional 530 l ha^{-1} for Weed-IT® and SensiSpray CDS spray techniques during the 2008 growing season of a lily crop

volume reduction (Fig. 25.6) for the Weed-IT® system was between 40 and 55% compared to conventional application (530 l ha^{-1}). The two late August sprayings could not be done because no green tissue was left.

The SensiSpray system resulted in a 10% reduction in spray volume during early season sprayings. The set NDVI (GreenSeeker®) and dose relation (spray volume) algorithm turned out to be inappropriate for lily crop development. Also at final sprayings in August there was an increase in spray volume reduction because of a decrease of green leaf tissue at the end of the season. Desiccation of the lily crop was however greater for both the Weed-IT® and the SensiSpray applications than for the conventional applications.

Spray deposition (μl cm^{-2}) in the lily crop was measured in early July when crop height and soil coverage was maximum. On top of the canopy there was little difference between the spray techniques (Fig. 25.7). In the middle leaf level the Weed-IT® had a higher sprayer deposition than the conventional spraying and the SensiSpray was lowest. At the lowest leaf level spray deposition of the Weed-IT® and the conventional spraying were comparable and the SensiSpray lowest.

Biological efficacy was evaluated throughout the growing season. First detection of *Botrytis* blight was late July in all plots (Table 25.5). In the Weed-IT® and SensiSpray fields there was a rapid decline in green area because of *Botrytis* blight infestation.

This resulted at harvest time in lower average bulb weights, especially of the SensiSpray system. As the dose-spray volume algorithm of the SensiSpray was used throughout the season it is now considered possible for adaption in order to improve

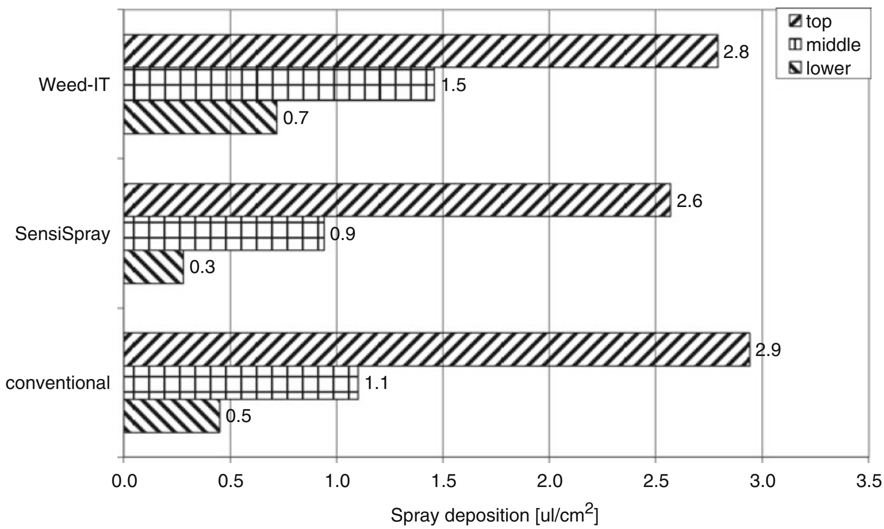

Fig. 25.7 Spray deposition in a lily crop divided in *top*, *middle* and *bottom* leaf layers for a conventional spraying, and Weed-IT® and SensiSpray CDS spray techniques

Table 25.5 Protection against *Botrytis* blight expressed as scale infected lily leaf area for conventional, SensiSpray and Weed-IT® plant-specific application of 100 and 50% of recommended dose (1.6 l ha^{-1} Allure®) at last season spraying dates and relative bulb yield

Spray technique	Dose (%)	*Botrytis* blight development 25 June	23 July	14 Aug	26 Aug	Bulb yield [rel.]
Untreated control		no disease	9.8	1.8	0.0	77
Conventional	100		9.8	8.5	6.8	100
Conventional	50		9.8	8.8	7.5	97
Weed-IT®	100		9.8	6.5	2.0	89
Weed-IT®	50		9.8	7.3	4.0	87
SensiSpray	100		9.8	7.8	5.5	51
SensiSpray	50		9.8	8.0	6.8	50

spray deposition depending on growth stage and GreenSeeker® NDVI signal. This is subject for further research.

6 Future Developments

Canopy Density Spraying on bed-grown crops, like potatoes and flower bulbs, have shown a potential reduction in use of plant protection products, especially with first sprayings of the crop early in the growth season. Furthermore, when the crop covers the soil surface completely but the crop still develops in height and leaf mass, a reduction in pesticides is possible while maintaining biological efficacy. Further development of Canopy Density Spray systems and more target oriented spraying can be realised when diseases are detectable before the development of visual symptoms. Sensor evaluation shows potential in this direction. The evaluation of combinations of sensor and spray systems on the market show that the potential of Canopy Density Spray system for effective application is close to practical use (Zande et al. 2008). First field tests of a prototype plant-specific fungicide application with a CDS-prototype (Weed-IT®) show a reduction of 75–84% in agrochemical use for the first three fungicide applications while maintaining good control of late blight in potato. Potato plants were still individually standing and crop coverage during these applications was around 30%. In lily flower bulb spraying use reductions were obtained between 10 and 50%. However biological efficacy of CDS spraying decreased compared to conventional spraying. Algorithm development to improve relations between crop reflection measurements and required dose need further research.

7 From Prototype to Practice

In order to deal with variations in crop development and site-specific variations in the field, the sensor-based spray technology system SensiSpray was developed. The system was built on a boom sprayer and consists of sensors to detect crop variation and a spray system to automatically change spray volume and therefore pesticide dose depending on the sensor signal (Fig. 25.8) and an application specific dosing model. The sensors used were GreenSeeker® sensors that measure crop reflection. The NDVI output signal of these sensors was used (Schwab et al. 2005). A control unit, electronics and software were developed to use this output signal of the GreenSeeker® sensors to adapt spray volume. To vary the spray volume VarioSelect® nozzle bodies were used fitted with four different low-drift venturi flat fan nozzles (Böttger and Langner 2003). Seven sensors were placed on a 27 m

Fig. 25.8 Varioselect® nozzle holder (*upper right*) and GreenSeeker® sensor placed on the spray boom (*bottom right*), sprayer sprays a high volume above green grass (*right* in *left* picture,) and a low volume above desiccated grass (*left*)

working width boom sprayer. Each sensor controlled the spray volume of a boom section 3–4.5 m wide.

Spray deposition measurements (Zande et al. 2009) were performed to test the sprayer's accuracy in adapting spray volume based on the crop reflection signal per section. A grassland field was prepared in 24 m wide strips next to each other with differences in biomass production by extra N fertilization, mowing and herbicide treatment. Treatments resulted in distinct differences in biomass and vegetation colour and therefore reflection. The sprayer passing across the strips at an angle of 45° at a speed of 6 km h^{-1} gave a clear view on the individual section changes on the sprayer boom. Measured spray deposit using a fluorescent dye (Brilliant Sulpho Flavine) added to the water in the spray tank showed that the individual section sensor reacts on the change in reflection and spray volume was adapted per boom section at an accuracy of 1 m in the driving direction.

To demonstrate the potential use of the SensiSpray system in practice it was used in potato haulm killing spraying (Kempenaar and Struik 2007). The variation in the field of the greenness (amount and activity of green biomass) of the potato canopy at desiccation spraying before harvest was used to vary spray volume of the herbicide used. The spray volume and dose adaptation was based on dosing algorithms of the Minimum Lethal Herbicide Dose Potato Haulm Killing system (MLHD PHK) relating reflection measurements with minimum dose needed to kill off potato canopy (Kempenaar et al. 2004). In the 2007 and 2008 season different potato fields were sprayed and a general use reduction in pesticides for potato haulm killing was circa 50%.

The experienced variation in crop canopy and NDVI reflection resulted in dose variation sprayed for a high and a low variable field of potatoes. Average dose for the high variation potato field was 0.85 l ha^{-1} of herbicide and for the low variation field 0.77 l ha^{-1}. Lowest dose was 0.5 l ha^{-1} for both fields and the highest dose 1.9 l ha^{-1} for the high variation field and 1.5 l ha^{-1} for the low variation field, respectively, resulting in coefficients of variation of 25 and 20% respectively. Conventional dose of potato haulm killing herbicide for the field was 2 l ha^{-1} because of the desiccation stage of the crop canopy whereas the label dose was 3 l ha^{-1}.

During the 2008 season tests were conducted in late blight control in potatoes adapting spray volume to crop development at the beginning of the growing season. Spray volume and dose was reduced for the first three fungicide applications. No difference occurred in disease development between conventional spraying and canopy adapted dose spraying with the SensiSpray system, both giving good control of late blight.

The NDVI measurements in the SensiSpray project yielded much information on spatial and temporal variation of crop biomass in potato, wheat, tulip and onion crops. How to use this information successfully in a site specific pesticide dosing system needs more research on the development of dose-effect algorithms for sensor based systems

Inputs of plant protection products for Canopy Density Spraying systems are lower than for conventional systems. Risk to the environment therefore, is also reduced as less pesticide is deposited besides the target and less is emitting as spray drift. The variation in spray drift increases alongside the field boundary due to the variation in spray volume but will in general be lower than for conventional spraying as spray volume is lower with similar tank concentrations. Canopy Density Spraying systems have a significant potential for reducing agrochemical inputs while maintaining biological efficacy.

Acknowledgement Research presented in this paper is part of a project financed by the Dutch Ministry of Agriculture, Nature and Food safety (LNV), SenterNovem (SMT programme) and the EU-project ENDURE. Homburg Machinehandel and Rometron are acknowledged for providing sensors and spray equipment and assisting in the development of the prototype CDS sprayer. Field employees of the experimental farms of WUR-PPO in Lelystad and Lisse are thanked for their work in the field.

References

Böttger H, Langner HR (2003) New technology for variable rate pesticide application. Landtechnik 58:142–143

Bravo C, Moshou D, West J, McCartney A, Ramon H (2003) Early disease detection in wheat fields using spectral reflectance. Biosys Eng 84:137–145

Dammer KH, Ehlert D (2006) Variable-rate fungicide spraying in cereals using a plant cover sensor. Prec Agric 7:137–148

Kempenaar C, Groeneveld RM, Uenk D (2004) An innovative dosing system for potato haulm killing herbicides. Proceedings of the 12th international conference on weed biology, Dijon, 31 August to 2 September, 2004: AFPP-Conference Proceedings, pp 511–518

Kempenaar C, Groeneveld RMW, Uffing AJM (2006) Evaluation of Weed IT model 2006 MKII: spray volume and dose response tests. Plant Research International, Note 418, Wageningen

Kempenaar C, Struik PC (2007) The canon of potato science: 33. Haulm killing. Potato Res 50:341–345

MLHD (2004) Minimum Lethal Herbicide Dose, MLHD online; manual for the herbicide dose calculation module V2.0. Opticrop, Plant Research International, Wageningen. 2004. http://mlhd.opticrop.nl/

Polder G (2004) Spectral imaging for measuring biochemicals in plant material. PhD Thesis, Wageningen Agricultural University, Wageningen. 150 pp

Schut AGT (2003) Imaging spectroscopy for characterization of grass swards. PhD Thesis, Wageningen University, Wageningen, 264 pp

Schwab GJ, Pena-Yewtukhiw EM, Wendroth O et al. (2005) Wheat yield population response to variable rate N fertilization strategies using active NDVI sensors. In: Stafford JV (ed). Precision agriculture '05. Wageningen Academic Publishers, Wageningen, pp 235–242

Scotford IM, Miller PCH (2004) Combination of spectral reflectance and ultrasonic sensing to monitor the growth of winter wheat. Biosys Eng 87:27–38

Scotford IM, Miller PCH (2005) Vehicle mounted sensors for estimating tiller density and leaf area index "(LAI) of winter wheat. In: Stafford JV (ed) Precision agriculture '05. Wageningen Academic Publishers, Wageningen, pp 201–208

Vrindts E, Reyniers M, Darius P et al (2003) Analysis of soil and crop properties for precision agriculture for winter wheat. Biosys Eng 85:141–152

Zande JC van de, Achten VTJM (2005) Precision agriculture in plant protection technique. Annu Rev Agric Eng 4:217–228

Zande JC van de, Achten VTJM, Michielsen JMGP et al (2008) Towards more target oriented crop protection. International advances in pesticide application. Asp Appl Biol 84: 245–252

Zande J.C. van de, Achten VTJM, Kempenaar C et al. (2009) SensiSpray: site-specific precise dosing of pesticides by on-line sensing. In: van Henten EJ, Goense D, Lokhorst C (eds) Precision agriculture '09. Wageningen Academic Publishers, Wageningen, pp 785–792

Chapter 26
Economic Evaluation of Precision Crop Protection Measures

Jan Ole Schroers, Roland Gerhards, and Martin Kunisch

Abstract This chapter analyzes the economic benefits of precision crop protection based on experimental data for site-specific application of herbicides in winter cereals, maize and sugar beets in Western Europe. Despite of additional costs for weed sensing and application technology, site-specific weed control resulted in higher economic return compared to conventional uniform applications even over periods of several years.

1 Introduction

An important effect of technological progress may be a decrease in the production costs per unit. The reduction of unit costs can either be attained with lower operating input with the same yield level or with a higher yield level with the same operating input.

The objective of precision herbicide application is to save operating inputs, by treating only subareas of a field where the economic weed threshold has been exceeded. Areas below the economic weed threshold, i.e. with low or no weed infestation remain untreated.

Furthermore, weed species can be controlled selectively with different herbicides and herbicide mixture can be varied during the application with a multiple tank sprayer or direct injection system (Miller et al. 1995, Heisel et al. 1996, Gutjahr et al. 2008, Gerhards and Oebel 2006, Timmermann et al. 2003).

J.O. Schroers (✉)
Association for Technology and Structures in Agriculture (KTBL), Bartningstrasse 49, D-64289 Darmstadt, Germany
e-mail: j.schroers@ktbl.de

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9_26,

2 Subject of Investigation – Description of Process Flows

For winter wheat, maize and sugar beet the costs of chemical weed control using three different methods – conventional uniform application (C), map-based site-specific (MB) and sensor-based site-specific (SB) were investigated (Table 26.1).

Every weed control method includes a sampling process and an application process. In the conventional weed sampling process only the average weed density and the weed species observed are measured based on approximately 20 counts per hectare in a 0.1 m^2 sampling frame. The disadvantages of conventional technology compared to precision farming technologies are that spatial and temporal variations in weed populations cannot be taken into account for weed management decisions. The advantages of conventional technology compared to precision farming technologies are that no additional technology – sprayer, camera system, GIS etc. – is required and no separate passage for site-specific weed sampling is needed in the map-based process.

As described in Chapters 2, 15, and 22, a three-chamber sprayer with three separate tanks, each filled with a different herbicide, which is applied via a separate spray line, is used for herbicide application in a map-based approach. Weeds are sampled in this approach in a separate work process. A camera system, mounted on the carrier vehicle, samples information about quantity and distribution of various weed species through high-resolution images during passage. The information is processed with image processing software and transformed into a digital geo-referential weed distribution map.

Before application the geo-referenced information on the distribution and quantity of weed classes is transferred to the sprayer controlling software. Based on this, the site-specific and selective treatment is carried out in combination with the

Table 26.1 Machinery – sprayers and spray booms in different systems for herbicide application (interest rate 4% per year)

Process:		Conventional application		Map-/Sensor-based application	
Name/type	Unit	Sprayer without boom	Single spray boom	Three-chamber sprayer without boom	Threefold spray boom
Tank volume	l	3,000	–	800/300/300	–
Working width	m	–	24	–	24
New price	€	23,000	16,000	46,000	32,000
Useful life	a	10	10	10	10
Useful employment	ha	18,000	9,600	18,000	9,600
Repair costs	€ ha^{-1}	0.55	0.50	0.95	1.50
Annual use	ha a^{-1}	1,800	1,800	1,800	1,800
Variable costs	€ ha^{-1}	0.55	0.50	0.95	1.50
Fixed costs	€ ha^{-1}	1.53	1.07	3.07	2.13
Total costs	€ ha^{-1}	2.08	1.57	4.02	3.63

GPS system installed on the tractor, which determines the sprayer position. The disadvantages of map-based technology compared to conventional technology are the additional costs for weed sampling and site-specific application of herbicides. The advantage of the map-based compared to conventional technology is that less herbicides are used resulting in less costs and less risk for the environment.

In the sensor-based process the three-chamber sprayer with three spray booms, which reacts to the signals of the controller software is also used. However, weed identification, image processing and site-specific treatment are performed within one passage. A sensor system on the camera for automatic weed identification delivers information of weed density, weed cover and species. A decision for real-time weed control separately for each weed class is calculated and realized in one passage. Weed species are grouped into grass weeds, annual broadleaved weed species and other weeds such as perennials. The advantage of the sensor-based process compared to the map-based is that no separate work process for site-specific weed sampling and map-based spaying is needed. Therefore, also a GPS system is not required. The disadvantages of the sensor-based process compared to the map-based are that it cannot be calculated how much herbicide solutions are used before filling the sprayer. Therefore, direct injection technology with premixing and central water tank would be beneficial.

The various processes in precision crop protection generate different costs, which can be deducted from the technology applied and the working time involved. The derivation of costs per measure will be explained in the following chapter.

3 Costs of Precision Crop Protection Technology

The costs of a plant protection measure consist of the herbicide costs and operating costs (labour, machinery) for the work processes of sampling and application (KTBL 2008/2009). The monetary output of the precision crop protection technology is equivalent to the herbicides saved. In this investigation it is assumed that with all processes the same efficacy is achieved.

The technical and economic parameters of the technology being applied in the respective processes of sampling and application significantly determine the operating costs and are presented in Table 26.1. Since the three-chamber sprayer used in the map-based and in the sensor-based processes is not commercially available yet, but available as prototype, the price was calculated based on the machine elements (water tank, control software, spray boom, etc.).

For the application the following technology is used with the specified technical and economic parameters shown. The costs for the sprayer are 3.65€ ha^{-1} in the conventional method and 7.64€ ha^{-1} in the precision crop protection methods.

For weed sampling in the sensor-based and map-based processes, a system of high resolution bi-spectral cameras is used for weed identification. In the map-based process the images and image processing software create a digital weed distribution map. In the sensor-based method the information is directly processed by the image processing system and is transferred to the control system of the three-chamber sprayer.

The machine costs for the site-specific weed imaging are derived from the investment and camera costs, including the image processing software, and for the map-based method additionally for the GPS and GIS software which results in the digital weed distribution map. The software for controlling the sections of the sprayer boom is included in the sprayer costs. The parameters for assessing the machine costs in the sampling methods are listed in Table 26.2.

The operating costs for the sampling processes consist of the labour requirements and machine costs (tractors, carrier vehicles, sprayers with the appropriate spray booms), implements, hardware and software (Table 26.3). A wage rate of 15€ man-hour^{-1} is assumed for all processes. All prices do not include value-added tax.

The working time in the map-based process consists of the labour requirements for weed sensing and additional 0.125 man-hours/ha for evaluating and creating

Table 26.2 Machinery – hard and software for weed sampling

Process:		Map-/Sensor-based application	Map-based application
Name/type	Unit	Camera system with image processing	GPS + GIS software for weed mapping
Working width	m	24	–
New price	€	25,000	5,000
Useful lifetime	a	5	10
Useful employment	ha	5,000	50,000
Repair costs	€ ha^{-1}	3.00	0.00
Annual use	ha a^{-1}	1,000	1,000
Variable costs	€ ha^{-1}	3.00	0.00
Fixed costs	€ ha^{-1}	5.50	0.60
Total costs	€ ha^{-1}	8.50	0.60

Table 26.3 Work processes – operating costs of weed sampling (wage rate 15€/man-hour)

Sampling process:		Conventional	Map-based	Sensor-based
Name:		Visual sampling	Camera offline	Camera online
Labour requirements	Man-hours ha^{-1} measure^{-1}	0.16	0.25	0
Variable machine costs	€ ha^{-1} measure^{-1}	0.46	9.00	3.00
Fixed machine costs	€ ha^{-1} measure^{-1}	3.99	11.07	5.50
Operating costs	€ ha^{-1} measure^{-1}	6.85	23.82	17.00

the weed distribution map. The additional GIS software and the GPS mounted on the tractor cause higher machine costs in the map-based sampling procedure. The sampling in the sensor-based process has no labour requirements, because it is completely included in the same application work process.

In Table 26.4 the labour requirements and machine costs of the specific application processes are itemised.

The higher labour requirements for applying the precision weed control processes result from the marginally higher assumed preparation time (importing the weed distribution map, etc.) and by probably having to fill the tanks more often, because of the smaller tank volume of the three-chamber sprayer, which is generally not completely compensated for by the reduced consumption of the herbicide mixture.

The operating costs for crop protection processes consist of the labour and machine costs for weed sampling and herbicide application. In Table 26.5, the operating costs of the processes are summarized and the additional costs of the map-based and sensor-based processes are compared to the conventional reference method. A sampling process is allocated to each application method. In practice, a maximum of two applications can be based on the result of one sampling process.

Table 26.4 Work processes – operating costs of herbicide application (wage rate 15€ man-hour^{-1})

Application process:		Conventional	Map- or sensor-based
Labour requirements	Man-hours ha^{-1} measure^{-1}	0.19	0.30
Variable machine costs	€ ha^{-1} measure^{-1}	3.54	6.69
Fixed machine costs	€ ha^{-1} measure^{-1}	3.29	5.35
Operating costs	€ ha^{-1} measure^{-1}	9.68	16.54

Table 26.5 Work processes – operating costs of various weed control technologies (wage rate 15€ man-hour^{-1})

Weed control process		Conventional	Map-based	Sensor-based
Labour requirements	Man-hours ha^{-1} measure^{-1}	0.35	0.55	0.30
Variable machine costs	€ ha^{-1} measure^{-1}	3.75	14.35	8.35
Fixed machine costs	€ ha^{-1} measure^{-1}	7.53	17.76	12.19
Operating costs	€ ha^{-1} measure^{-1}	16.53	40.36	25.04
Additional costs	€ ha^{-1} measure^{-1}	–	23.83	8.51

It is apparent that the sensor-based process results in significantly lower costs, compared to the map-based process, by saving an extra passage. Additionally there are no costs for the GPS system attached to the carrier vehicle and no costs for the following creation of a digital geo-referential weed distribution map.

In assessing the economic profitability of different weed control strategies, the output of precision plant protection strategies in the form of herbicide reduction should – at least – compensate for the additional operating costs.

4 Output of Precision Weed Control Technologies

Herbicide savings result from leaving areas untreated where the weed population is below the economic weed threshold and from applying selective herbicides with only active ingredients against one group of weed species (monocotyledonous weeds, dicotyledonous weeds, etc.).

These statements on herbicide savings in the individual treatment for maize (one herbicide application), winter wheat (two herbicide applications) and sugar beet (three herbicide applications) are based on evaluations of various investigations on precision weed control (Oriade et al. 1996, Schwarz and Wartenberg 1999, Miller et al. 1995, Timmermann et al. 2003). The savings potential depends widely on the types of other crop management practices (e.g. type of tillage: inversion tillage, reduced tillage and no-till), on the crop rotation and weed infestation level and spatial variability. In each individual field there can be significant deviations from the assumptions made here.

In Table 26.6 the assumed costs for herbicides for uniform applications and site-specific chemical weed control in maize for the weed species grouped into grass weeds, annual broadleaved weeds and bindweeds (*Convolvulus* spp.) are listed.

It is apparent that the savings in herbicide quantities for maize can be attained for grass weeds and for bindweeds. The figures imply that annual broad-leaved weeds occur more homogeneously. All in all, 41.55€ ha^{-1} herbicide costs can be saved by applying herbicides site-specifically.

Table 26.6 Herbicide costs in maize (1 application in May/June)

Product group controlling	Conventional application	Map- or sensor-based application	
	Product costs [€ ha^{-1}]	Treated area [%]	Product costs [€ ha^{-1}]
Grass weeds	30.00	40	12.00
Annual broad-leaved weeds	55.00	85	46.75
Bindweeds	18.00	15	2.70
Product costs, total	103.00		61.45
Savings			41.55

Table 26.7 Herbicide costs in winter wheat (1 application in autumn, 1 application in spring)

Product group controlling	Conventional application	Map- or sensor-based application	
	Product costs [€ ha^{-1}]	Treated area [%]	Product costs [€ ha^{-1}]
Application in autumn:			
Grass weeds	15.00	60	9.00
Annual braod-leaved weeds	20.00	50	10.00
Special weeds (e.g. *Galium aparine*)	15.00	10	1.50
Product costs, total	50.00		20.50
Savings			29.50
Application in spring:			
Grass weeds	35.00	60	21.00
Product costs, total	35.00		21.00
Savings			14.00
Overall product costs	85.00		41.50
Overall savings			43.50

In winter wheat, one herbicide is applied in October and one in March. The weeds are sampled once in autumn, shortly before application. Herbicide savings are summarized in the Table 26.7. Altogether herbicide costs of 43.50€ ha^{-1} were saved through site-specific application.

The highest herbicide savings were attained through intensive chemical weed control with precision crop technology in sugar beet production (Table 26.8). Weeds were sampled in the beginning of March and at the end of April/beginning of May. Special herbicide savings were made by controlling grass weeds and creeping thistle (*Cirsium arvense*) site-specifically. For sugar beet, site-specific weed control resulted in savings of 77€ ha^{-1} for herbicides.

5 Economic Evaluation – Results

Precision weed control is assessed with a crop-specific cost benefit analysis (Schwarz and Wartenberg 1999, Wagner 2000). Map-based processes are basically more expensive than online applications. Compared to the conventional method, online-sensor technology for weed sampling and patch spraying increased operating costs by 8.51€ ha^{-1} application^{-1}. Map-based technology, due to the additional passage and the GPS – GIS technology needed, had operating costs of 23.83€ ha^{-1} application^{-1} higher than the conventional method. Since one weed sampling can be used for several applications, the sampling costs can be divided between a maximum of two applications.

Table 26.8 Herbicide costs in sugar beets (three herbicide applications in a growth period)

Product group controlling	Conventional application	Map- or sensor-based application	
	Product costs [€ ha^{-1}]	Treated area [%]	Product costs [€ ha^{-1}]
Herbicide application 1:			
Annual broad-leaved weeds (soil-active herbicide)	20.00	90	18.00
Annual broad-leaved weeds (leaf-active herbicide)	20.00	90	18.00
Product costs, total	40.00		36.00
Savings			4.00
Herbicide application 2:			
Broad-leaved weeds (soil-active herbicide)	20.00	80	16.00
Broad-leaved weeds (leaf-active herbicide)	20.00	80	16.00
Grass weeds	30.00	15	4.50
Product costs, total	70.00		36.50
Savings			33.50
Herbicide application 3:			
Weeds (soil-active herbicide)	20.00	80	16.00
Weeds (leaf-active herbicide)	20.00	80	16.00
Creeping thistle	35.00	10	3.50
Product costs, total	75.00		35.50
Savings			39.50
Overall product costs	185.00		108.00
Overall savings			77.00

The lower cost of online-sensor technology increases the monetary benefit of site-specific weed control. For winter wheat the monetary benefit for map-based technology is 12.81 and 28.14€ ha^{-1} for online-sensor technology. For maize the benefit for map-based technology is 17.72 and 33.04€ ha^{-1} for online-sensor technology. For sugar beets the benefit for map-based technology is 22.48 and 53.13€ ha^{-1} for sensor technology.

6 Critical Overview and Conclusions

The economic benefit of precision weed control technology depends on a series of plant site-specific and technical-economic parameters. The most important effect are the savings of herbicides, which depend on spatial and temporal weed variability, crop yield potential and prices of herbicides.

Technology costs for weed sampling and patch spraying are another important factor. More investigations in efficient application technologies for patch spraying (e.g. direct injection systems) in combination with online-weed detection system would reduce operation costs for site-specific weed control. In addition, this technology would make chemical weed control safer for the farmer and consumer and reduce the herbicide load into the environment.

The economical use of highly complex and expensive technology requires sufficient machine utilisation. In the calculations presented above, an annual utilisation rate of 1,800 operating hectares is assumed (KTBL 2008/2009). Due to multiple applications per hectare farmland per year, this is equivalent to a 600–900 ha cropping area or to a contractor with a moderate to good annual utilisation of the technology (Table 26.9).

With sufficient utilisation an investment in map-based technology can be economically advisable, even when the price for the plant protection technology is twice as high as the price of a conventional sprayer. Savings of herbicides of 25€ ha^{-1} per application would make the investment in the map-based technology listed above (three-chamber sprayer with appropriate boom, soft and hardware for weed sampling) worthwhile.

Table 26.9 Production process – economic key figures for winter wheat, maize, and sugar beet

Economic key figures	Map-based application		Sensor-based application
Winter wheat:			
Number of samplings		1	
Number of applications		2	
Additional operating costs [€ ha^{-1}]	30.69		15.36
Savings of herbicides [€ ha^{-1}]	43.50		43.50
Benefit of precision control [€ ha^{-1}]	12.81		28.14
Maize:			
Number of samplings		1	
Number of applications		1	
Additional operating costs [€ ha^{-1}]	23.83		8.51
Savings of herbicides [€ ha^{-1}]	41.55		41.55
Benefit of precision control [€ ha^{-1}]	17.72		33.04
Sugar beet:			
Number of samplings		2	
Number of applications		3	
Additional operating costs [€ ha^{-1}]	54.52		23.87
Savings of herbicides [€ ha^{-1}]	77.00		77.00
Benefit of precision control [€ ha^{-1}]	22.48		53.13

A ready-to-use sensor technology, which makes site-specific weed control possible in one passage, under the assumption stated above, would be profitable with herbicide savings of about 9€ ha^{-1} per application and would increase the economic efficiency of the crop production processes investigated.

References

Gerhards R, Oebel H (2006) Practical experiences with a system for site-specific weed control in arable crops using real-time image analysis and GPS-controlled patch spraying. Weed Res 46:185–193

Gutjahr C, Weis M, Sökelfeld M et al (2008) Erarbeitung von Entscheidungsalgorithmen für die teilflächenspezifische Unkrautbekämpfung. J Plant Dis Prot XXI (special issue): 143–148

Heisel T, Christensen S, Walter AM (1996) Weed managing model for patch spraying in cereal. In: Robert, PC, Rust, RH, Larson, WE (eds) Precision agriculture. Proceedings of the 3rd international conference on precision agriculture, Minneapolis, pp 999–1007

KTBL (2008/09) Datensammlung Betriebsplanung Landwirtschaft 2008/09. Kuratorium für Technik und Bauwesen in der Landwirtschaft, Darmstadt

Miller PCH, Stafford JV, Paice MER, Rew LJ (1995) The patch spraying of herbicides in arable crops. In: Brighton crop protection conference: weeds, Brighton, pp 1077–1086

Oriade CA, King RP, Forcella F, Gunsolus JL (1996) A bioeconomic analysis of site-specific management for weed control. Rev Agric Econ 18:523–535

Schwarz J, Wartenberg G (1999) Wirtschaftlichkeit der teilflächenspezifischen Herbizidanwendung. Landtechnik 54(6):334–335

Timmermann C, Gerhards R, Kühbauch W (2003) The economic impact of the site-specific weed control. Prec Agric 4:249–260

Wagner P (2000) Problems and potential economic impact of precision farming. In: Conese, C, Falchi, M (eds) Proceedings of the 7th international congress computer technology in agriculture, Florence, pp 241–249

Index

E.-C. Oerke et al. (eds.), *Precision Crop Protection - the Challenge and Use of Heterogeneity*, DOI 10.1007/978-90-481-9277-9,