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

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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

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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 × 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

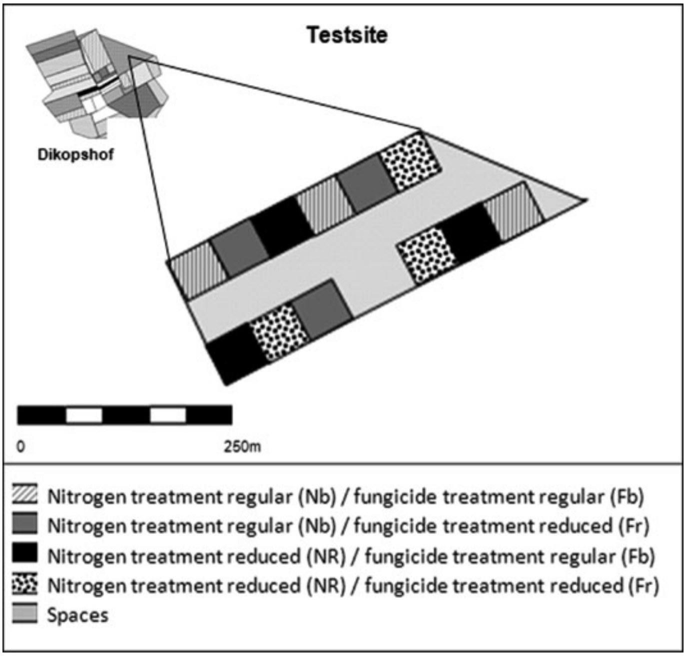

Fig. 7.1 Description of the Dikopshof test-site in 2001/2002

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)	$0 < \text{PLAND} \leq 100$	Class
Number of Patches (NP)	$\text{NP} \geq 1$	Class & landscape
Total Edge (TE)	$\text{TE} \geq 0$	Class & landscape
Area-Weighted Mean-Shape-Index (AWMSI)	1<=AWMSI<=2	Class & landscape
Patch Richness (PR)	$\text{PR} \geq 1$	Landscape
Mean Nearest-Neighbor Distance (MNN)	$\text{MNN} > 0$	Class & landscape
Contagion (CONTAG)	$0 < \text{CONTAG} \leq 100$	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

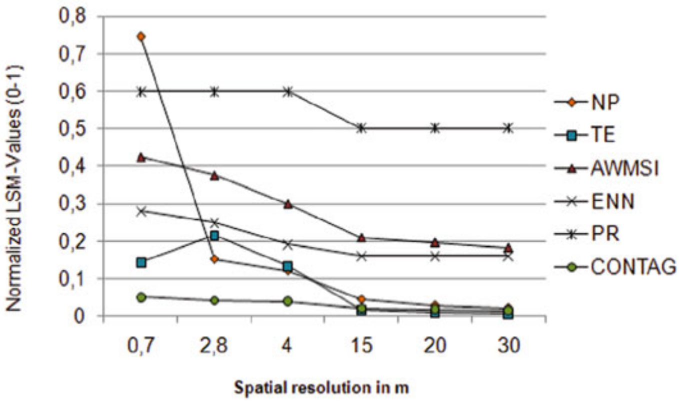

Fig. 7.2 Variation of selected landscape metrics by changing spatial resolution form 0.7 to 30 m (all calculations were performed on the landscape level and the results were normalized)

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

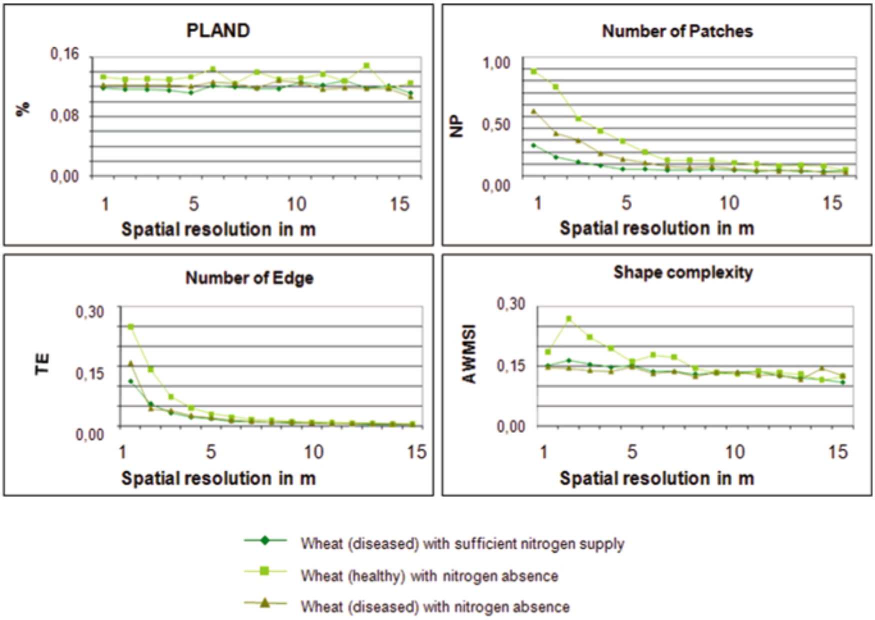

Fig. 7.3 Variation of the landscape metrics (LSM) by changing spatial resolution (class level) – LSM-Values are normalized between 0 and 1

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

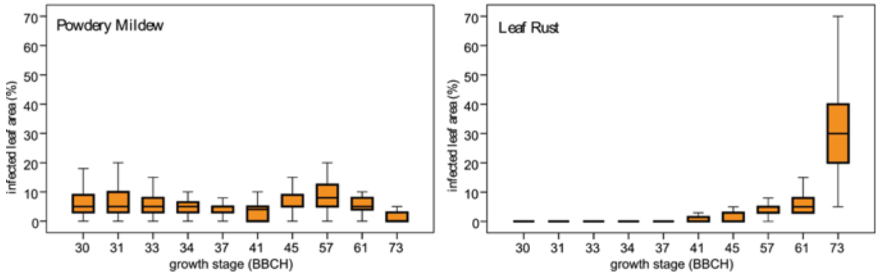

Fig. 7.4 Disease progress curves (boxplots with median, quartiles and extrema) of powdery mildew and leaf rust in wheat as observed at 28 sample points in a test plot where no fungicides were applied in 2005 (modified from Franke et al. 2009)

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.

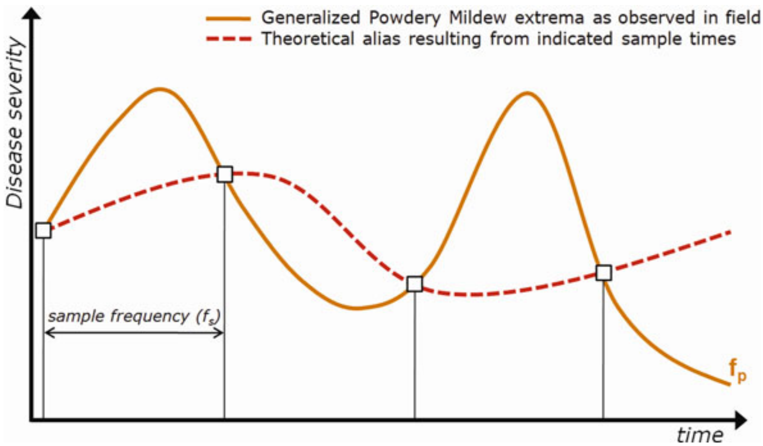

Fig. 7.5 Example for temporal aliasing. Generalized temporal frequency of powdery mildew severity *(f_p)* derived from in-field observed extremes in 2005 (*solid line*), and an alias (*dashed line*) that would result from exemplarily shown sample dates (*boxes*). The temporal sample frequency f_s (or 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 Li-cor 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

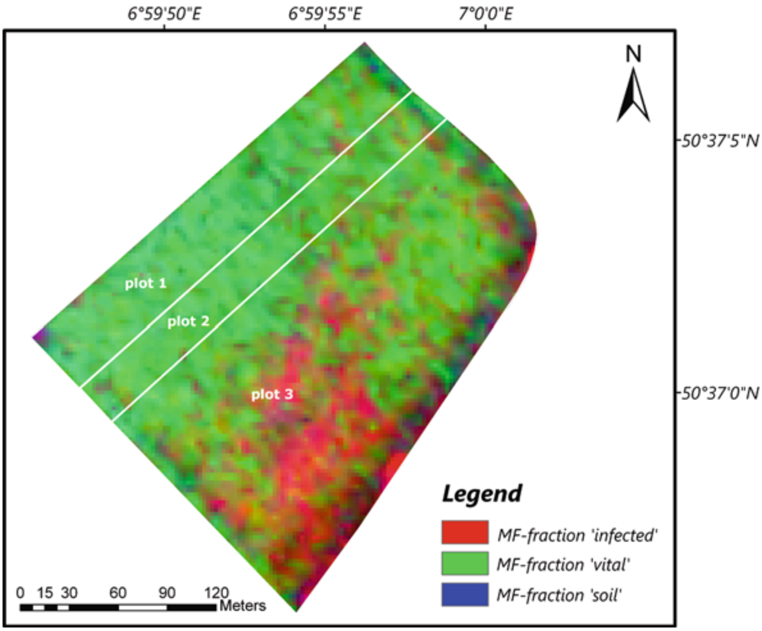

Fig. 7.6 False-color composite of an experimental field showing fractions of the spectral endmembers ‘infected wheat’ (R), ‘healthy wheat’ (G) and ‘soil’ (B) as estimated by the MTMF (Franke et al. 2008)

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.

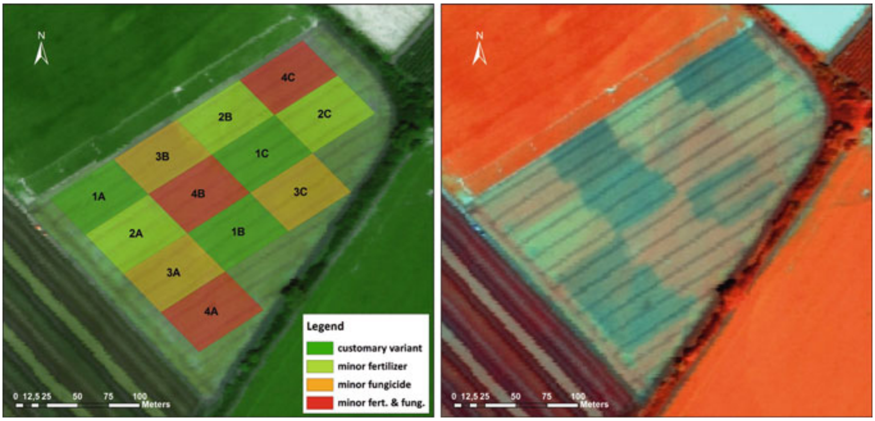

Fig. 7.7 Map of a winter wheat field with subplots differently treated with agrochemicals (vector data over true-colour RGB from AISA data) (*left*), false-colour AISA image taken on 01/07/2008 (R: 490 nm, G: 552 nm, B: 810 nm) (*right*). *Dark lines* represent the tractor lanes

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.

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