Chapter 2
Remote Sensing and Geographic Information System: A Tool for Precision Farming

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Contents

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Abstract The right time application of the right amount of input is a prerequisite to optimizing profitability and sustainability with a lesser impact on environmental degradation. Such can be achieved through precision farming (PF). It can offer a great potential to minimize the yield gap by optimizing food production using best management practices. It can also help to maintain the consumption of natural resources at an ecologically benign and environmentally sustainable level. PF is a holistic approach to enhance crop productivity with the aid of satellite-based technology and information technology (IT) to assess and manage the spatial and temporal variability of resources and inputs such as seeds, fertilizers, chemicals, etc. within the field. Application of remote sensing (RS) and geographic information system (GIS) shows a great promise to precision agriculture (PA) because of its role in monitoring spatial variability overtime at high resolution. This chapter highlights various applications of RS and GIS techniques in PA or smart agriculture.

Keywords Decision support system · Geographic information system · Remote sensing · Satellite farming

Abbreviations

AIEM	Advanced Integral Equation Model
ALI	Advanced Land Imager
ARVI	Atmospherically Resistant Vegetation Index
ASTER	Advance Spaceborne Thermal Emission and Reflection Radiometer
AVHRR	Advance Very High Resolution Radiometer
AVIRIS	Airborne Visible Infrared Imaging Spectrometer
AWS	Amazon Web Services
CASI	Compact Airborne Spectrographic Imager
DCNI	Double-peak Canopy Nitrogen Index
DEM	Digital Elevation Model
DGPS	Differential Global Positioning System
DSSAT	Decision Support System for Agrotechnology Transfer
DVI	Difference Vegetation Index
EO	Earth Observing
EOS	Earth Observing System
EROS	Earth Resources Observation and Science
ERS	European Remote Sensing satellite
FASAL	Forecasting Agricultural Output Using Space, Agrometeorology and Land Based Observations
FIS	Farm Information Systems
GDVI	Green Difference Vegetation Index

GI	Greenness Index
GIS	Geographic Information System
GNDVI	Green Normalized Difference Vegetation Index
GNSS	Global Navigation Satellite System
GOSAVI	Green Optimized Soil-Adjusted Vegetation Index
GPS	Global Positioning System
GRVI	Green–Red Vegetation Index
GSAVI	Green Soil–Adjusted Vegetation index
GWR	Geographically Weighted Regression
HH	Horizontal Transmit and Horizontal Receive
HNDVI	Hyperspectral Normalized Difference Vegetation Index
HV	Horizontal Transmit and Vertical Receive
HVI	Hyperspectral Vegetation Index
IEM	Integral Equation Model
IRS	Indian Remote Sensing
IRSS	Indian Remote Sensing Satellite
IT	Information Technology
JERS	Japanese Earth Resource Satellite
LAI	Leaf Area Index
LANDSAT	Land Satellite
LASSIE	Low-Altitude Stationary Surveillance Instrumental Equipment
LIDAR	Light Detection and Ranging
LORIS	Local Resources Information System
MCAR	Modified Chlorophyll Absorption Ratio
MCARI	Modified Chlorophyll Absorption Ratio Index
MODIS	Moderate-resolution Imaging Spectrometer
MSAVI	Modified Soil-Adjusted Vegetation Index
MSR	Modified Simple Ratio
MSS	Multispectral Sensor
MTVI	Modified Triangular Vegetation Index
MZ	Management Zone
NAOC	Normalized Area Over Reflectance Curve
NASA	National Aeronautics and Space Administration
NDI	Normalized Difference Index
NDNI	Normalized Difference Nitrogen Index
NDRE	Normalized Difference Red Edge
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NG	Normalized Green
NGNDVI	Normalized Green Normalized Difference Vegetation Index
NR	Normalized Red
NUE	Nitrogen Use Efficiency

OLS	Ordinary Least Square
OMNBR	Optimal Multiple Narrow Band Reflectance Indexes
OSAVI	Optimized Soil-Adjusted Vegetation Index
PA	Precision Agriculture
PCA	Principal Component Analysis
PF	Precision Farming
PFDC	Precision Farming Development Center
PLS	Partial Least Squares
PSSR	Pigment Specific Simple Ratio
PVI	Perpendicular Vegetation Index
RDVI	Renormalized Difference Vegetation Index
RGRI	Red–Green Ratio Index
RIICE	Remote Sensing–based information and Insurance for Crops in Emerging Economics
RISAT	Radar Imaging Satellite
RS	Remote Sensing
RVI	Ratio Vegetation Index
RVSI	Red-Edge Vegetation Stress Index
SAR	Synthetic Aperture Radar
SAVI	Soil-Adjusted Vegetation Index
SNR	Signal-to-Noise Ratio
SOC	Soil Organic Carbon
SOM	Soil Organic Matter
SPAD	Soil Plant Analysis Development
SPOT	Système Pour l’Observation de la Terre
SR	Simple Ratio
SRM	Satellite-based Rice Monitoring
SRTM	Shuttle Radar Topography Mission
SWIR	Shortwave Infrared Region
TCARI	Transformed Chlorophyll Absorption Reflectance Index
TKK	Tata Kisan Kendra
TM	Thematic Mapper
TVI	Triangular Vegetation Index
TVIMSR	Triangular Vegetation Index Modified Simple Ratio
UAV	Unmanned Aerial Vehicles
USDA	United States Department of Agriculture
VH	Vertical Transmit and Horizontal Receive
VNIR	Visible Near Infrared
VRT	Variable Rate Technology
VV	Vertical Transmit and Vertical Receive
WDVI	Weighted Difference Vegetation Index

2.1 Introduction

Innovative discoveries in the fields of science and technology and their subsequent application in the agriculture field have enabled farmers to utilize their valuable natural resources effectively and efficiently for obtaining maximum yield. These developments have further been greatly supported by the use of sophisticated machine, adoption of new planting practices, judicious use of manures and fertilizers, integrated pest management by using herbicides and pesticides, etc. (Andreo 2013). However, to meet up with the future challenges to feed the 9 billion people of the world, there is a need to stop the declining trend of the total crop productivity, minimizing the rate of degradation of natural resources, and enhancing farm incomes. Other constraints like fragmented land holdings, trade liberalization on agriculture, as well as global climatic variations have posed serious threats in agricultural growth and development. The role of newly emerged technology adoption might play major instruments to increase agricultural productivity in the future (Hakkim et al. 2016). Therefore, the success of large-scale farming depends on the culmination of information based on satellite remote sensing (RS) data with well-documented spatial maps obtained through geographic information system (GIS) which are the basis of precision farming (PF) (Brisco et al. 1998; Carr et al. 1991; Palmer 1996).

PA is defined as the "the application of technologies and principles to manage spatial and temporal variability associated with all aspects of agricultural production to improve crop performance and environmental quality" (Pierce and Nowak 1999). The efficient management of various farm inputs in a particular location requires a qualitative and quantitative assessment of the infield variability (both, spatial and temporal) (Khosla 2001; Patil and Bhalerao 2013). PF is considered as one of the breakthroughs in agriculture (Crookston 2006), ranking below conservation tillage, fertilizer and herbicide management, and improved crop genetics, and is a holistic approach to improve crop productivity with the aid of information technology (IT) and satellite-based technology (Finch et al 2014). The right time application of the right amount of input in right location is a prerequisite to optimizing profitability and sustainability with a lesser impact on environmental degradation (Mondal et al. 2004; Mondal and Tewari 2007). Linsley and Bauer (1929) were credited to drill the seed by adopting PF. However, the works of Johnson et al. (1983) and Matthews (1983) initiated the modern PF (Stafford 2000).

2.1.1 Concept and Principle of Precision Farming

Precision farming (PF) or precision agriculture (PA) is an integrated information– and production-based farming system utilizing adequate information, appropriate technology, and proper management. The goal of precision PA is to enhance long-term, site-specific and whole farm production efficiency, productivity, and net return without incurring any severe impact on the ecosystem of the surroundings (Earl et al. 1996; Andreo 2013). PF, as it is practiced today, had its beginnings in the mid-1980s with two contrasting philosophies, namely, farming by soil (Larson and Robert 1991) versus grid soil sampling for delineation of management zones (MZs) (Bhatti et al. 1991b; Mulla 1991, 1993; Mulla and Miao 2016).

PF is a breakthrough from the traditional management practice of soil and crop to sophisticated management considering spatial and temporal variability within the same field. It is a fine-tuning of total field management, where management decisions are considered according to the variations in resource conditions. The PF can be statistically represented as $P = 1-SD$, where, SD is standard deviation. If SD is 0, then $P = 1$, indicating a highly homogeneous field and if SD is 1, then $P = 0$, denoting maximum variability of field (Patil and Bhalerao 2013).

The basic principle of PF is to maximize the use efficiency of inputs considering spatial and temporal variability within a field and reflected by the quantity and quality of outputs. The five “R” concepts may be used in PA encompassing the “right amount of input at the ‘right place’ at the ‘right time, from ‘right source’ with ‘right manner’” (Khosla 2008). In this sense, PF can relate to an agricultural production system with a robust set of technologies, including RS, GIS, Global Positioning System (GPS), and Variable Rate Technology (VRT), which can propel agriculture into the computerized information–based world. The application of such technologies can optimize production efficiency, quality, reducing production costs, and reducing negative environmental impacts of farm practices – all at the location-specific, site-specific, zonal level (Earl et al. 1996; Andreo 2013).

Farm machinery and equipment for PF are available for various farm operations, including the tillage operation, sowing, transplanting, mechanical weeding, fertilizer distribution, as well as spraying of pesticides, etc. (Fig. 2.1). Nowadays global navigation satellite system (GNSS)–based vehicle guidance has been the most widely adopted PA technology in developed countries (Heraud and Lange 2009). GNSS-based navigation system auto steers the operation of tractors and other machinery to minimize gaps and overlaps on the predefined paths. Several aviation tools were used to guide operators to allow agricultural vehicles to use visual feedback such as light bars or graphical displays. However, nowadays auto-guidance systems steer agricultural vehicles under operation without direct input from operators. Autonomous agricultural vehicles known as Field Robots are the next logical step in the automation of crop production system (Gebbers and Adamchuk 2010).

PF offers several benefits, including improved efficiency of farm management inputs, increases in crop productivity or quality, and reduced transport of fertilizers and pesticides beyond the edge of a field (Mulla et al. 1996).

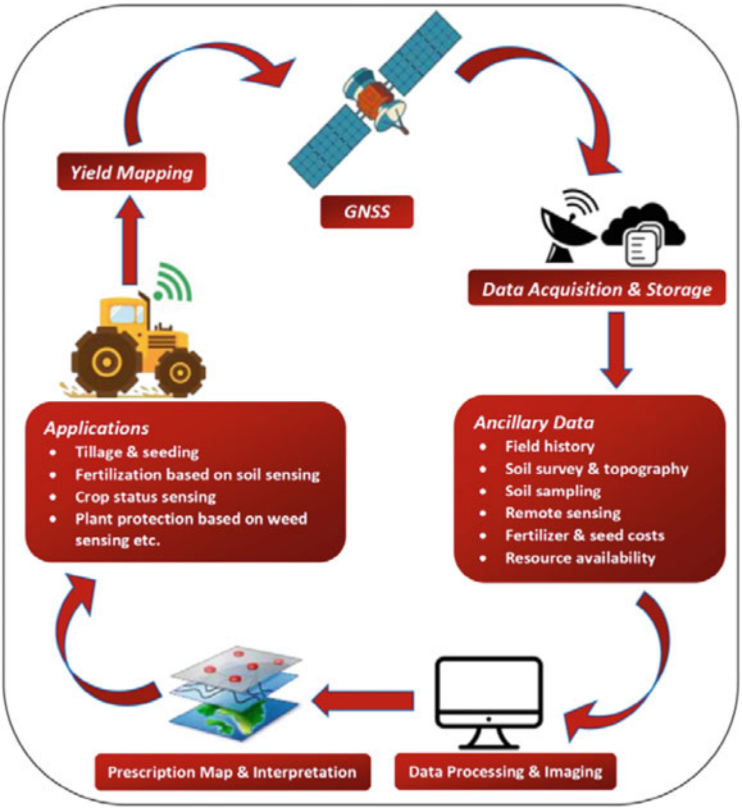

Fig. 2.1 Flow diagram depicting precision agriculture in crop production

2.1.2 Objectives of Precision Farming

2.1.2.1 Increased Profitability and Sustainability

Maximum profit can be obtained in each zone or site in a field by balancing precise amount of farm inputs (seeding rate, variety, herbicide, and insecticide) as per crop needs, which can be determined by weather, soil characteristics (nutrient availability, texture, and drainage) and historic crop performance. At the very same time, PF aims at sustaining this profitability (Van Evert et al. 2017; Nabi et al. 2017; Meena et al. 2018) PA has an advantage for both farmers and society as a whole. For the farming community, PA is expected to provide positive returns on investment, leading to an increase in profitability; while for society, PA is attractive because it may increase the sustainability of the farming (Pierce and Nowak 1999; Fleming et al. 2000; Gebbers and Adamchuk 2010; Foley et al. 2011; Banu 2015; Basso et al. 2016).

2.1.2.2 Production Efficiency Optimization

The basic objective of PF is to optimize economic returns across a field. There is a need to adopt the differential management approach to get optimum production at each site or within each "zone." The identification of variability in yield potential is a prerequisite of PF, assuming a uniform yield potential of the field (Nabi et al. 2017). MZs are used in PF to divide field regions which differ in their requirements for farm inputs (Mulla 1991, 1993; Mulla and Miao 2016). The response of fertilizer, irrigation, or pesticides can be delineated based on variations in crop yield, soil type, topography, and soil properties (moisture content, pH, organic matter, etc.). RS has been used to delineate MZs based on variations in soil organic matter (SOM) content (Mulla 1997; Fleming et al. 2004; Christy 2008). Boydell and McBratney (2002) used 11 years of Landsat Thematic Mapper imagery for a cotton field to identify MZs based on yield stability.

2.1.2.3 Optimizing Product Quality

Optimization of product quality is another important concern for PF. This can be achieved through sensors that detect the quality attributes of the crop and thus inputs are to be applied accordingly (Hakkim et al. 2016). If quality premiums exist in production systems, they may alter the quantity of input required to get optimum profitability and agronomic response (Pierce and Nowak 1999; Gebbers and Adamchuk 2010; Whelan and Taylor 2013; Nabi et al. 2017).

2.1.2.4 Efficient Use of Farm Inputs

PF involves efficient use of farm inputs, that is, fertilizer, chemicals, seeds, etc., according to the yield potential of the soil and judicious use of site-specific variable rate application (VRA) of these agrochemicals (i.e. herbicides, insecticides) where the problem appears (Nabi et al. 2017).

2.1.2.5 Soil Conservation, Water, Energy Surface, and Groundwater Protection

A comprehensive approach to PF begins from crop planning and thus includes such tillage practices that conserve the soil or disturb the soil to its minimum. Besides, water is efficiently applied through techniques like drip irrigation, etc. In all these cases, very less energy is used and thus PA leads to conservation of energy too (Nabi et al. 2017). PF aims at safeguarding the environment by way of efficient use of inputs like chemical fertilizers, etc. This prevents their leaching through groundwater or as runoff through surface water.

2.1.2.6 Minimizing Environmental Impact

In PF, farmers follow precise management practices which may reduce the environmental risk associated with uniform/blanket field treatments (Whelan and Taylor 2013). A better management decisions lead to judicious use of inputs to optimize production needs, resulting decrease in the net loss of any inputs to the environment. Though there may be possibilities of potential unintentional damages to the environment associated with the production system. However, such damage risk can be minimized through adoption of such a hi-tech method (Pierce and Nowak 1999; Gebbers and Adamchuk 2010; Nabi et al. 2017).

2.1.2.7 Minimizing Risk

Most of the farmers considered risk management from two contrasting points of view – assured income and environmental impact. Farmers frequently practice risk management by committing an error by applying extra low-cost inputs (Whelan and Taylor 2013). To ensure that the produce is harvested/sold on time and to get guaranteed assured returns, farmers often follow the practice of extra spraying of chemicals, extra fertilizer addition, buying more machinery, or hiring extra labor. PF attempts to offer a risk management solution that may allow both income and environment parameters to be considered. Thus, improved management strategy depends on a better understanding of the soil–plant–animal–environment interaction and more detailed use of emerging and existing information technologies (Pierce and Nowak 1999; Whelan and Taylor 2013; Nabi et al. 2017).

2.1.3 Components of Precision Farming

2.1.3.1 Remote Sensing Technique

The science that makes inferences about material object from measurement made at distance without coming into physical contact with the object under study is called RS. RS comprises sensors to collect the reflected radiation from the object and a platform such as an aircraft, balloon, rockets, satellite, or even a ground-based sensor-supporting stand onto which the sensors could be attached. Various aircraft and spacecraft imaging systems along with RS sensors are used nowadays. Indian Remote Sensing Satellites (IRSS), French National Earth Observation Satellite (i.e., SPOT), IKONOS, etc. are some of the recent notable imaging system used in spacecraft platforms. RS is a promising technology for PA as it effectively monitors spatial variability overtime at high resolution (Moran et al. 1997). Various researchers have reported the usefulness of RS technology to obtain spatially and temporally variable information in PF (Hanson et al. 1995; Moran et al. 1997). Moran et al. (1997) summarized the various application of RS as a source of various types of information for PF. However, there are several limitations found in using RS data for mapping. The major limitations are calibration of the instrument, atmospheric correction, and normalization of off-nadir effects on optical data. However, during the monsoon period, cloud screening for data and image processing from various airborne video and digital cameras also create a disadvantage of optical RS (Moran et al. 1997).

A relatively cheap, available and marketable RS technology for PA is the need of the hour in developing countries. Some of the pertinent requirements are as follows:

- Turnaround time should be low (24–48 h).
- Data cost should be less (~100 INR/acre/season).
- Spatial resolution should be high (minimum 2 m multispectral).
- Spectral resolution should be high (<25 nm).
- Temporal resolution should be high (minimum 5–6 data per season).

However, the delivery of analytical products in a simpler format may creat interest among the users to purchase it in developing countries (Ray et al. 2010; Sahoo 2011).

2.1.3.2 Geographic Information System

GIS could be referred to as a computerized data storage and retrieval system that could be used for managing and analyzing spatial data. GIS presents analyzed information in the form of maps that provides a better understanding of various crop growth factors and soil fertility, pests, weeds, and other factors determining yield. GIS map is useful for decision-making based on spatial relationship. Several GIS software with various functionality and price are available nowadays. Many farm information systems (FIS) are available where simple programs are used to produce a farm-level database. Local Resources Information System (LORIS) is one of such FIS. LORIS includes many modules capable of importing data, generating raster files through different gridding methods, storing raster data in a database, generating digital agro-resource maps, creating operational maps, etc. (Schroder et al. 1997).

A comprehensive farm GIS contains base maps of topography, soil types, and properties, etc. Information and data on yield, crop rotation, tillage, chemicals, fertilizers, etc. could be stored in the system for obtaining useful information. Thus, GIS could be useful for preparing the fertility and weed and pest intensity maps based on which further recommendations of application rates of inputs could be inferred.

2.1.3.3 Global Positioning System

GPS could be referred to as a satellite-based navigation system capable of locating any positions on the Earth. Real-time, three-dimensional data regarding positions, navigation, and timing could be obtained through GPS continuously (24 h/day). The development of GPS was primarily made for military applications, but it was made available for civilian use since the 1980s. No charges for subscription or setup are needed for using GPS. The system can be accessed with a GPS by anyone and can be used in any application that requires location coordinates. The public availability of the global positioning system (GPS) has opened many new avenues for spatial data analyses.

Nowadays farmers access the GPS to perform site-specific activities. In GPS, several satellites are involved in the identification of the actual position of farm equipment within the field. When detection is done in single receiver mode (autonomous navigation), the accuracy of the GPS could be degraded due to various errors. In PA, where a higher degree of accuracy is needed, the operation of the GPS has to be done in a differentially corrected positioning mode, for instance by Differential Global Positioning System (DGPS). DGPS is mostly used for yield mapping and VRA in PA. GPS plays a significant role to determine the precise location in the field for the study of spatial variability as well as for site-specific input applications. The positional accuracy of the GPS is around 20 m with location accuracy of 1 m and submeter could also be obtained by using DGPS. The availability of GPS approaches to the farming system will make all field-based variables to be integrated. The integration among field variables such as the intensity of weeds, soil moisture content, yield, and RS data could be achieved by the use of GPS more specifically by the use of DGPS.

2.1.3.4 Variable Rate Techniques

Variable Rate Technique is an equipment which is capable of altering the rate of application of fertilizers, seeds, irrigation, chemicals, etc. according to the site- and soil-specific requirement across the field. Adjustments in pesticides, herbicides, nutrients, lime, and even seeding rates could be done according to the status or problems of soils and the areas (Adamchuck and Mulliken 2005). VRT consists of a variable rate control system having application equipment that performs a site-specific application of inputs at the precise time. Management practices commonly used in PF include variable-rate fertilizer (Diacono et al. 2013) or pesticide application, variable rate seeding or tillage, and variable rate irrigation. Sylvester-Bradley et al. (1999) reported that VRT is best fitted where prior knowledge of identified large heterogeneity and predicted treatment zone is available. Besides, the lack of appropriate sensor is the major problem (Goulding 2002). Murrell (2004) observed that the application of variable N rates enhanced N use efficiency (NUE) over fixed rates, but did not respond to increase in yield. Farmers are more likely to accept those practices that increase yields as well as NUE (Murrell 2004; Olesen et al. 2004; Goulding et al. 2008).

2.1.3.4.1 Components of VRT

The VRT is consist of many technical components (Fig. 2.2). The basic component of a typical map-based variable rate system is a cab-computer of controller equipped with application software, an actuator that works according to the direction of computer and controls the input rates, and a DGPS receiver that helps in geo-referencing by providing the information about the position of the vehicle or cab. After receiving the positional information through DGPS, the computer sets the required application rate as a function of vehicle position by harmonizing with other preexisting information and then sends a setpoint signal to the controller that regulates the desired rate of application. Actual application rates for GPS position could also be recorded by a VRT (Sökefeld 2010), which could be stored as a record and could be reviewed further for future recommendation.

2.1.3.4.2 Variable Rate Application Methods

Variable Rate Application (VRA) methods could be classified into two groups based on the use of GPS system in it or not. The two methods are map-based VRA and sensor-based VRA (Table 2.1).

2.1.3.4.3 Map-Based VRA

This VRA method uses a GPS receiver and an electronic map or prescription map to control the rate of application. An electronic map, also known as a prescription map, is an electronic data file containing all important and specific information regarding the input rates required for a particular field or condition. With the movement of the applicator across the field (using the field position from GPS receiver), the input concentration changes by matching with the desired rate preset of the particular positions in the prescription map (by harmonizing the positions obtained from DGPS receiver). Map-based VRA also uses map-based previous measurements that are then implemented by employing several strategies which are based on crops, soils, and location-specific information like yield of crops, topography, soil properties, RS datasets, and others (Grisso et al. 2011).

2.1.3.4.4 Sensor-Based VRA

GPS or prescription maps are not used in this method. In this case, soil properties and crop characteristics are assessed by the sensors attached to applicators and the report

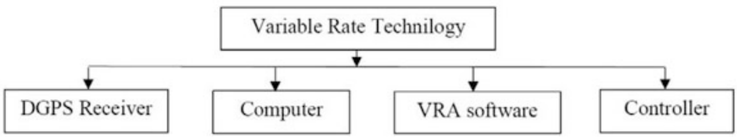

Fig. 2.2 Basic components of variable rate technology (VRT)

Table 2.1 Comparisons between map- and sensor-based VRA

S. No.	Parameter	VRA (map based)	VRA (sensor based)
1	Brief method of approach	Grid sampling followed by lab analysis and generation of site-specific maps. Finally the use of VRA	Field information based on real-time sensor, feedback control measures, and finally the use of VRA
2	Requirement of DGPS/GPS	Important	Not so important
3	Soil and plant sample analysis in laboratory	Required	Not required
4	Mapping	Important	Not necessary
5	Requirement of time	More	Less
6	Constraints	Cost of soil sampling and analysis	Lack of appropriate sensors to obtain soil- and plant-related data
7	Operation procedure	Difficult	Easy
8	Operation skills	Required	Required
9	Sampling size	2–3 acres	Individual spot
10	Acceptance among the farmers	It is popular in developing countries	It is popular in developed countries

Modified, Patil and Shanwad (2009)

is then transferred to the control system where calculations of input rates are made. The control system then relays the computed information of input rate to the controller, based on which the final inputs are done to the specific site. One of the notable advantages of sensor-based VRA is the use of real-time data using real-time sensors instead of previously collected data in map-based VRA.

2.2 Usefulness of Remote Sensing Data in Precision Farming

Applications of RS knowledge in the agricultural field have attracted a variety of endeavors (Moran et al. 1997; Mani 2000; Pinter et al. 2003; Adamchuk et al. 2004; Andreo 2013). The major endeavors are monitoring and mapping of soil properties like organic matter and clay content, moisture percentage, pH and salinity level (Corwin and Lesch 2003; Christy 2008; DeTar et al. 2008; Gomez et al. 2008); crop yield and biomass study of canola, corn, cotton, sorghum, and wheat (Lelong et al. 1998; Yang et al. 2000, 2001; Shanahan et al. 2001; Seelan et al. 2003; Warren and Metternicht 2005; Zhao et al. 2007); crop species classification (Rao 2008); crop nutrient and water stress (Lelong et al. 1998; Erickson et al. 2004; Clay et al. 2006;

Moller et al. 2007; Tilling et al. 2007); infestations of weeds and their monitoring (Lamb and Brown 2001; Thorp and Tian 2004; Scotford and Miller 2005; Gutierrez et al. 2008); and plant diseases and infestation of insects (Seelan et al. 2003).

2.3 Satellite Remote Sensing in Precision Farming

Since the early 1970s literature reveals that satellites have been successfully utilized for RS imagery in the field of agriculture (Bauer and Cipra 1973; Doraiswamy et al. 2003; Jewel 1989; Mulla 2013) (Table 2.2). Identification and inventorization of

Table 2.2 List of satellites and their suitability in precision agriculture

Satellite (year)	Spectral bands with spatial resolution	Return frequency (d)	Suitability in precision agriculture
LiDAR (1995)	VIS (vertical RMSE 10 cm)	N/A	High
Radar SAT (1995)	C-band radar (30 m)	1–6	Medium
IKONOS (1999)	Panchromatic, B, G, R, NIR (1–4 m)	3	High
Landsat 7 ETM + (1999)	B, G, R, NIR, 2 SWIR, Panchromatic, TIR (15, 30, 60 m)	16	Medium
SRTM (2000)	C/X-band radar (30 m)	N/A	Medium
Terra EOS ASTER (2000)	G, R, NIR and 6 MIR, 5 TIR bands (15–90 m)	16	Medium
EO-1 Hyperion (2000)	400–2500 nm, 10 nm bandwidth (30 m)	16	High
Rapid Eye (2008)	B, G, R, red edge, NIR (6.5 m)	5.5	High
World View-2 (2009)	P (0.5 m), B, G, Y, R, red edge, NIR (1.84 m)	1.1	High
Cartosat 1 and Cartosat 2, Cartosat 2A (2005, 2007, 2009)	Panchromatic (0.5–0.85 μm) Cartosat 1: 2.5 Cartosat 2, 2A: 0.8 m	5	High
Landsat 8 OLI (2013)	B, G, R, NIR, 2 SWIR (30 m), Panchromatic (15 m), 2 TIR (100 m)	16	Medium
SPOT 6 and 7 (2012 and 2014)	Panchromatic (1.5 m), B, G, R, NIR (6.0 m)	1–4	High
Resourcesat 2 and 2A (2011 and 2016)	AWiFS (56 m), LISS-III (23.5 m), LISS-IV (5.6 m), B, G, R, NIR, MIR	2–3, 12–13, 25–26	High
KOMPSAT 3 and 3A (2012 and 2015)	Panchromatic, B, G, R, NIR, MWIR (KOMPSAT 3A: 0.55 and KOMPSAT 3:0.70 m)	1.4	High
Sentinel 2A and 2B (2015 and 2017)	B, G, R (10 m), 3 red edge (20 m), 2 NIR (10, 20 m), 3 SWIR (20 and 60 m)	5	High

P = purple, B = blue, G = green, R = red, IR = infrared, NIR = near infrared, MIR = mid infrared, TIR = thermal infrared. Suitability classes L, M and H refer to low, medium and high respectively crops could be done with Landsat MSS and Thematic Mapper (TM) data within certain limits (Morain and Williams 1975; Hanuschak et al. 1980; Ryerson et al. 1985; Ehrlich et al. 1990; Oetter et al. 2000; Blaes et al. 2005), SPOT imagery (Buttner and Csillag 1989; Hanna et al. 2004; Xavier et al. 2005), and Indian Remote Sensing (IRS) satellite data (Dutta et al. 1994; Panigrahy and Sharma 1997). Satellite RS has created huge availability of remotely sensed data for research and various applications (Liu 2015; Chi et al. 2016). Their use was generally observed in large-scale classifications of crops (Bauer and Cipra 1973; Jewel 1989; Panigrahy and Sharma 1997), monitoring of impacts on tillage (Casady and Palm 2002), as well as to understand the effect of environmental factors like infestation and outbreaks of diseases (Yang et al. 2005). The measurement of reflectance from the surface soils with the help of Landsat TM data is a significantly efficient and accurate method for topsoil organic carbon (SOC) content estimation (Baumgardner et al. 1985; Henderson et al. 1989; Frazier 1989; Huang et al. 2007; Jaber and Al-Qinna 2011; Yang et al. 2015). Based on Landsat imagery of bare soil, initiation of use of RS data in PA was made to understand and study the spatial patterns of soil organic matter (SOM) content (Bhatti et al. 1991a; Frazier and Jarvis 1990; Wilcox et al. 1994). Mulla (1997) also reported the use of Landsat imagery data as auxiliary data coupled with ground truth information for assessing the spatial patterns of soil phosphorus as well as grain yield of wheat.

Satellite imaging systems with the fine spatial resolution with revisit cycles of a very short period are generally used in researches regarding PA (Table 2.2) (Mulla 2013). Images with high spatial resolution provide provisions of identification and area estimation of crops more accurately over the traditional practice. Attempts of preparing maps of SOC contents using satellite multispectral imagery have been made using 4-m IKONOS (Sullivan et al. 2005), and 10 and 20 m SPOT (Campbell 1996; Vaudour et al. 2013). In the past few years, the data of IKONOS and Quick Bird data have been used for several applications (Mumby and Edwards 2002; Sawaya et al. 2003; Wang et al. 2004). Notable operations including assessment of nitrogen (N) deficiency in sugar beet, the efficiency of fungicides in wheat, etc. have been made using IKONOS through spectral information of visible and near-infrared bands (Seelan et al. 2003). Bausch and Khosla (2010) estimated values of normalized green normalized difference vegetation index (NGNDVI) (Gitelson et al. 1996a, b) in irrigated maize from Quick Bird data which strongly correlates with spatial patterns in N sufficiency. Quick Bird images (spatial resolution of 2.4 m) were also found to be effective for determining olive plantation area, numbers of trees, spatial patterns of tree canopies in concerned area and yields of olive (García Torres et al. 2008; Castillejo-González 2018). Further, improvement in the processing capability was noted as a result of the incorporation of additional spectral information like the use of red-edge spectral wavelength (obtained from WorldView-2) in PA. Performance of simulated WorldView-2 red-edge-based spectral indices were used by Li et al. (2014) to assess concentration and uptake of N in summer maize (*Zea mays L*). Enhanced availability of high-resolution optical satellite data opens the avenues of new opportunities in PF through crop mapping and assessment (Turker and Ozdarici 2011; Yang et al. 2011; Drusch et al. 2012; Hornacek et al. 2012; Li et al. 2013; Esch et al. 2014; Qiu et al. 2014).

Several trends could be noted on the uses of satellite-based RS data (Table 2.2). First, the improvement is observed on spatial resolution from 80 m (Landsa) to submeter in GeoEye and WorldView (Mulla 2013). Secondly, the improvement on the frequency of revisit is noticed in WorldView as compared to Landsat which took 18 days. Third, an increase in number of spectral bands, that is, eight or more (bandwidths >40 nm) in WorldView from four in case of Landsat (bandwidths >60 nm) is observed. The introduction of hyperspectral sensors such as Hyperion has provided further superior spectral resolution, (400–2500 nm with interval of 10 nm). With the betterment of spectral and spatial resolution of satellite datasets, the use of reflectance data from these platforms has become more effective and reliable in PA (Table 2.2).

The suitability of various spectral and spatial images in case of PA depends on several factors like crop management practices, the capacity of farm equipment, variation in farm inputs, farm unit area, and water resources, etc. (Olson 1998; Al-Kufaishi et al. 2006; Lindblom et al. 2017; Friedl 2018; Neupane and Guo 2019). Improved spatial and spectral resolutions (1–3 m) are useful for estimating spatial patterns of crop biomass or yield than computing variable rate of fertilization (5–10 m). Accuracy of VRA of fertilizers is often limited by delay times of fertilizer spreader (Chan et al. 2004). Improved spatial and spectral resolutions (0.5–1 m) are generally useful in case of variable rate spraying of herbicides for spot weed control as compared to variable rate irrigation (5–10 m) (Chan et al. 2004). In developing countries mostly financially strong larger commercial farms are able to obtain higher spatial and spectral resolution RS datasets compared to smaller farms (Mulla 2013).

Normalized Difference Vegetation Index (NDVI)–based estimation of spatial patterns in crop biomass (Yang et al. 2000) and potential crop yield (Doraiswamy et al. 2003) is becoming familiar in PA. NDVI is calculated based on the ratios in the red and NIR portion of spectrum (Rouse et al. 1973) using the formula $\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{Red})/(\mathrm{NIR} + \mathrm{Red})$. It ranges from 0 to 1 as normalization processes are used to calculate the index. NDVI exhibits a sensitive response toward green vegetation even for areas with low vegetation covers (Xue and Su 2017). Hence, use of this index is often observed in the assessment of regional and global vegetation. NDVI shows a significant relation not only with the canopy structure and LAI but also with canopy photosynthesis (Gamon et al. 1995; Grace et al. 2007). Despite being used widely, various limitations are associated with NDVI (Thenkabail et al. 2010). Introduction of yield monitors capable to provide measurements of yield in finer-scale resolution across large spatial areas could augment the capacity of RS in the prediction of structural characteristics of crop, namely, LAI, biomass, and yield (Karnieli et al. 2010; Sripada et al. 2005; Zhang et al. 2012). However, calibration in RS is another important step as factors such as soil brightness, soil color, atmosphere, cloud, cloud shadow, and leaf canopy shadow could affect the values of NDVI (Xue and Su 2017).

Apart from NDVI, several broadband spectral indices (Table 2.3) have used in PA (Sripada et al. 2006, 2008; Miao et al. 2009). The normalized red (NR) index is

Table 2.3 Use of different multispectral, broadband vegetation indices in precision agriculture

Index	Definition	References
NG	G/(NIR + R + G)	Sripada et al. (2005)
NR	R/(NIR + R + G)	Sripada et al. (2005)
GRVI	NIR/G	Sripada et al. (2005)
GSAVI	1.5 × [(NIR − G)/(NIR + G + 0.5)]	Sripada et al. (2005)
GOSAVI	(NIR − G)/(NIR + G + 0.16)	Sripada et al. (2005)
NDRE	$(R_{790} - R_{720})/(R_{790} + R_{720})$	Barnes et al. (2000)
WDVI	NIR − (C.red)	Clevers (1997)
GNDVI	(NIR − G)/(NIR + G)	Gitelson et al. (1996a, b)
OSAVI	(NIR − R)/(NIR + R + 0.16)	Rondeaux et al. (1996)
ARVI	(NIR − RB)/(NIR + RB)	Kaufman and Tanre (1992)
MSAVI2	$0.5 \times [2 \times (\mathrm{NIR} + 1) - \mathrm{SQRT}((2 \times \mathrm{NIR} + 1)^2 - 8 \times (\mathrm{NIR} - \mathrm{R}))]$	Qi et al. (1994)
SAVI	1.5 × [(NIR − R)/(NIR + R + 0.5)]	Huete (1988)
DVI	NIR − R	Tucker (1979)
GDVI	NIR − G	Tucker (1979)
PVI	$\mathrm{SQRT}((\rho_{soil} - \rho_{veg})^2{}_{\mathrm{R}} - (\rho_{soil} - \rho_{veg})^2{}_{\mathrm{NIR}})$	Richardson and Weigand (1977)
NDVI	(NIR − R)/(NIR + R)	Rouse et al. (1973)
RVI	NIR/R	Jordan (1969)

Modified, Mulla (2013)
G = green reflectance, NIR = near infrared, and R = red reflectance, RB = difference between Blue and Red channel, C = ratio between NIR and red reflectance of soil

generally concerned with the portion of the spectrum where chlorophyll strongly absorbs radiation. Contrarily, the normalized green (NG) index is associated with the portion of the spectrum where absorption of radiation occurs through pigments other than chlorophyll. Ratio vegetation index (RVI) is the ratio of NIR to red reflectance (Jordan 1969) whereas the green–red vegetation index (GRVI) (Tucker 1979) is the ratio of NIR to green reflectance. There are two types of NDVI, one usually deals with NIR and R reflectance while the other is green normalized difference vegetation index (GNDVI), which deals with NIR and G reflectance (Gitelson et al. 1996a, b). The difference between reflectance in the NIR and R bands is generally considered to compensate for the effects of soil reflectance to formulate difference vegetation index (DVI) (Tucker 1979). Better performance of these indices was noted than NIR and R ratio indices such as NDVI and RVI where compensation of soil effects is not considered. According to Sripada et al. (2006), green difference vegetation index (GDVI) (NIR-G) exhibited a better correlation with an economically optimum N rate in corn than DVI (NIR-R). The main function of vegetation indices, other than NDVI, is a compensation of the effects factors like soil background and atmospheric conditions that hamper the vegetation spectral reflectance of crop characteristics such as type of crops, leaf area index (LAI), or canopy biomass (Bouman 1995). Exclusion of diminution of the effect of soil brightness (as the pixels in the image is a combination of vegetation and soil information) could be done by using distance-based vegetation indices in cases where vegetation is sparse (Huete and Jackson 1988). Perpendicular vegetation index (PVI) (Richardson and Weigand 1977) and SAVI are notable distance-based vegetation indices in recent days (Thiam and Eastmen 1999). Many other indices have also been reported that are capable to compensate the undesirable soil effects which include soil-adjusted vegetation index (SAVI) (Huete 1988), modified soil-adjusted vegetation index (MSAVI) (Qi et al. 1994), optimized soil-adjusted vegetation index (OSAVI) (Rondeaux et al. 1996), green soil-adjusted vegetation index (GSAVI, Sripada et al. 2005), green optimized soil-adjusted vegetation index (GOSAVI), etc. On the other hand, the atmospherically resistant vegetation index (ARVI) is another type of index capable of considering atmospheric effect (Kaufman and Tanre 1992).

Major challenges regarding the use of satellite RS in PA were summarized by Moran et al. (1997) and Yao et al. (2010), and according to them RS images in the visible and NIR bands are restricted to cloud-free days when irradiance is relatively consistent across time. Cloud cover could not affect only the radar imagery obtained from satellites or airplanes. Calibration of raw digital numbers to true surface reflectance, atmospheric corrections, geo-rectification of data by GPS-based ground control locations are other notable challenges regarding this.

2.3.1 Satellite-Based Rice Monitoring (SRM) – A Case Study

The combined knowledge of integrated RS, crop modeling, and ICT tools in the satellite-based rice monitoring (SRM) system (Fig. 2.3) is useful for the effective dissemination of near-real-time and accurate information of growth and yield of rice. Information regarding abiotic and biotic stresses under rice cultivation may be generated which will be useful for end-users. Remote Sensing–Based Information and Insurance for Crops in Emerging Economies (RIICE) technology is capable of providing timely and accurate is capable of providing information about rice-planted areas at village level. This information is about the start of the season and its variability with geography, expected and actual yield, and the impact of any disaster on specific rice-growing areas. The use of precise and real-time information obtained from RIICE in the implementation of crop insurance programs has become a trend in several countries (i.e., the Republic of India and the Socialist Republic of Vietnam). In rice cultivation, for monitoring, mapping, and forecasting purposes such projects have already shown significant success. A combination of RS, crop modeling, web geographic information system (GIS), smartphone, unmanned aerial vehicles (UAV), and Amazon Web Services (AWS) made such systems promising in various countries. In 2016, over 24.5 million hectares of land under rice cultivation have been monitored through these integrated systems with more than 85% accuracy while the coverage area was only 1.6 million ha in the initial stages in 2012 (Sylvester 2018).

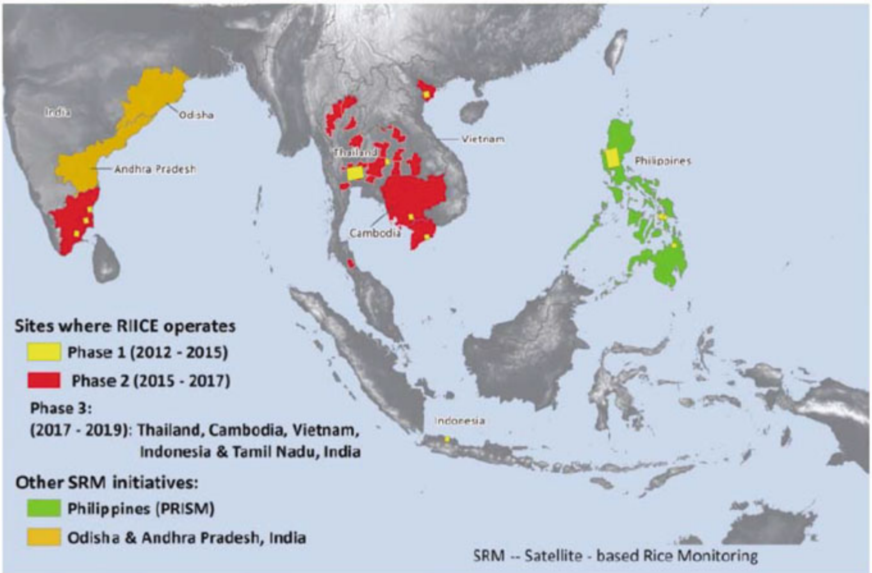

Fig. 2.3 Satellite-based rice monitoring (SRM) sites in South Asia and Southeast Asia. (Adopted, Sylvester (2018)

2.3.2 Proximal Remote Sensing of Crops in Precision Farming

To overcome the constraints of satellite-based RS, modern world is emphasizing on the use of proximal RS techniques in PA to assess the growth and stress of crops. Proximal RS is also an integrated system having components like sensors mounted on tractors, spreaders, sprayers, or irrigation booms which combinedly could monitor and conduct the real-time site-specific management of fertilizers, pesticides, or irrigation (Hummel et al. 1996). Schepers et al. (1992) were the pioneers of assessment of crop status through proximal sensing over RS where they had used a Minolta soil plant analysis development (SPAD) meter for determining chlorophyll contents of maize at silking stage under a range of N treatments by measuring leaf greenness. After that, a significant number of sensors and spectral indexes were invented for monitoring various crop properties (Table 2.4) associated with N stress in plants and to set the basis for VRT.

Unavailability of direct estimation of the amount of N fertilizer needed to overcome crop N stress is a notable constraint of the chlorophyll meter, Green Seeker, Yara N, and Crop Circle sensors (Samborski et al. 2009). To overcome this drawback, comparisons of sensor readings with reference strips values of crops receiving sufficient N fertilizer were made by scientists (Blackmer and Schepers 1995; Kitchen et al. 2010; Raun et al. 2002; Sripada et al. 2008). These data were used to develop N fertilizer response functions related to sensor readings to

Table 2.4 Developments in remote and proximal leaf sensing in precision agriculture

Year	Innovation	References
1992	SPAD meter (650, 940 nm) used to detect N deficiency in corn	Schepers et al. (1992)
1995	Nitrogen sufficiency indices	Blackmer and Schepers (1995)
1996	Optical sensor (671, 780 nm) used for on-the-go detection of variability in plant nitrogen stress	Stone et al. (1996)
2002	Yara N sensor	Link et al. (2002)
2002	Green Seeker (650, 770 nm)	Raun et al. (2002)
2002	CASI hyperspectral sensor–based index measurements of chlorophyll	Haboudane et al. (2002, 2004)
2002	MSS remote sensing of agriculture fields with UAV	Herwitz et al. (2004)
2003	Fluorescence sensing for N deficiencies	Apostol et al. (2003)
2004	Crop Circle (590, 880 nm or 670, 730, 780 nm)	Holland et al. (2004)
2004	LASSIE (Real-time images of crop and soil surfaces)	Lilienthal et al. (2004)
2005	Cropscan2000H – grain quality sensor	Long et al. (2005)
2006	Field Spec (325–1075 nm)	Rodriguez et al. (2006)
2010	CropSpec – Crop Canopy Sensor (735, 808 nm)	Reusch et al. (2010) Topcon.
2010	The Multiplex – fluorescence-based optical sensor	Ghozlen et al. (2010) FORCE-A, Orsay, France
2011	OptRx (670, 730, 780 nm)	Sudduth et al. (2011) AgLeader
2013	HandySpec (360–900 nm or 400–1100 nm)	Weis et al. (2013) HandySpec Field, Tec5, Oberursel, Germany
2013	Weedseeker – automatic spot spray system	Weis et al. (2013) N-Tech, Trimble
2014	ISARIA – real-time VR nitrogen sensor (670, 700, 740, 780 nm)	Haas (2014) Fritzmeier Umwelttechnik
2017	See and Spray – smart spraying by artificial intelligence	Chostner (2017) Blue River Technology, USA
2019	H-sensor artificial intelligence (deep and transfer learning)	Partel et al. (2019) Agricon GmbH, Germany

recommend the required amount of N fertilizer to mitigate N stress in crops (Scharf et al. 2011). Further experiments are still needed in this regard for getting superior crops, site, and climate-specific responses.

2.3.3 Hyperspectral Remote Sensing in Precision Farming

Hyperspectral imaging is widely known as imaging spectroscopy. According to Goetz et al. (1985), hyperspectral remote sensing (HRS) could be classically defined as "The acquisition of images in hundreds of continuous registered spectral bands such that for each pixel a radiant spectrum can be derived." Rather than the number of bands available in the image, the narrow and continuous wavelength nature makes it hyperspectral (Shippert 2004; Mohan and Porwal 2015). Reflectance data over a wide spectral range are generally collected at small spectral increments (typically 10 nm) in HRS (Goetz et al. 1985). Pointing out of the particular frequency is the crucial function in this technique with more number of bands to reduce the redundancy (Bandyopadhyay et al. 2017), which improves the capability to assess the spectral response of soils and vegetated surfaces in a more precise way. This opens the avenue of a detailed insight regarding the spatial and spectral variability of bare as well as vegetated surfaces (Mulla 2013).

National Aeronautics and Space Administration (NASA) launched the airborne visible/infrared imaging spectrometer (AVIRIS) in 1987, which was the first hyperspectral sensor (Goetz 1987; Tan 2017) and it was able to provide continuous imagery from 380 to 2500 in bands with a spectral resolution of 10 nm and spatial resolution of 20 m. AVIRIS became highly successful along the time, and in a majority of hyperspectral analyses it is the principal source of data nowadays (Vorovencii 2009) . In 2000, NASA launched a satellite-based Hyperion sensor (spectral coverage 0.40–2.50 μm), EO-1 for capturing hyperspectral images from space mainly with the primary issue of mineralogical mapping (Kruse 2003). However, these hyperspectral datasets are also very useful for crop- and soil-related studies. Datt et al. (2003) reported that hyperspectral data obtained from Advanced Land Imager (ALI) predicted spatial patterns in case of rice yield more precisely with the help of derivative indexes and red-edge position as compared to the predictions made by NDVI. Wu et al. (2010) in China observed that chlorophyll content in the canopy and leaf area index could be measured in a nondestructive way for a considerable range of crops by using vegetative indexes formulated based upon red-edge reflectance data collected by hyperspectral ALI. Again, for assessing the green leaf area index, the Compact Airborne Spectrographic Imager (CASI), an aerial hyperspectral imaging system has also been used (Haboudane et al. 2002, 2004). Some handheld, boom-mounted, hyperspectral, and multispectral imaging systems are also there in this regard, for example, The Crop Scan sensor (CROPSCAN Inc., Rochester, MN, USA) (Andreo 2013).

Continuity, range, and spectral resolution of bands are the main factors that make differences between hyperspectral and multispectral imaging. A number of plant and soil parameter such as chlorophyll, cellulose, LAI, carotenoids, crop biomass, soil moisture, soil nutrient, and organic matter can be sensed using hyperspectral data (Haboudane et al. 2002; Goel et al. 2003; Oppelt and Mauser 2004; Zarco-Tejada et al. 2004). A specific wavelength is most sensitive to a particular soil or crop parameters. The crop LAI and biomass can be retrieve with a red band centered at 687 nm, whereas crop moisture content can be assessed with a NIR band centered at 970 nm (Thenkabail et al. 2010). Thenkabail et al. (2010) reported linkages of 33 more hyperspectral reflectance bands with certain characteristics of soils and crops. Contrarily, there are limitations in the case of multispectral imaging which could analyze based on single broadband combinations. Hence it is insensitive to measure chlorophyll and others plant attributes at LAI values exceeding 3.0

(Thenkabail et al. 2000). Another problem of this constraint is the interference of the reflectance of bare soil at lower LAI values. According to Thenkabail et al. (2000), three general categories of predictive spectral indices could be formulated using hyperspectral data: (1) optimal multiple narrow-band reflectance indexes (OMNBR), (2) narrow band NDVI, and (3) SAVI. The requirement of narrow bands is only two to four in case of OMNBR to depict plant characteristics. However, the most important information regarding plant parameters can be obtaining from shorter green wavelength (500–550 nm), longer red wavelength (650–700 nm), red-edge (720 nm), and two NIR (900–940 and 982 nm), spectral bands. This band-based information is only available in narrow increments of 10–20 nm and cannot be sensed in broad multispectral bands that are associated with older satellite imaging systems. Improved statistical methods like partial least squares (PLS) (Viscarra Rossel et al. 2006) and principal components analysis (PCA) (Geladi 2003) were found useful for chemometric analysis of hyperspectral data. Besides, pattern recognition and classification such as object-based (Frohn et al. 2009) decision tree (Wright and Gallant 2007) approaches are also useful. A range of narrowband hyperspectral indexes (Table 2.5) have been used in PA (Haboudane et al. 2002, 2004; Li et al. 2010; Miao et al. 2007, 2009). Similar forms as broadband spectral indices have also observed among many of these but they vary in terms of reflectance bands for hyperspectral indices that are narrower. Such indices exhibited effective responses to the canopy or leaf attributes such as LAI, chlorophyll, specific pigments, or nitrogen stress etc. Along with the existing indices, continuous assessments and innovations are also being made for the development of new hyperspectral indices (Li et al. 2010; Thenkabail et al. 2011).

Several researchers (Yao et al. 2010; Thenkabail et al. 2011) studied promising applications of HRS in PA. These applications include a diverse range of crops and their biophysical and biochemical variables, such as yield (Wang et al. 2008), chlorophyll a and b (Zhu et al. 2007; Delegido et al. 2010), total chlorophyll (Haboudane et al. 2004), nitrogen content (Rao et al. 2007), carotenoid pigments (Blackburn 1998), plant stress (Zhao et al. 2007), plant moisture (Penuelas et al. 1995), aboveground biomass (Thenkabail et al. 2004a, b), and biophysical variables (Darvishzadeh et al. 2008; Thenkabail et al. 1994a, b; Alchanatis and Cohen 2010).

Application of HRS for variable-rate techniques, particularly nitrogen fertilization depending on spatial patterns in chlorophyll content, could be considered as its most concerning use in PF. As, in China, the performance of the MCARI/OSAVI705 index has been proved significantly superior over all other vegetation indexes in terms of chlorophyll content assessment of a diverse range of agricultural canopy types (Wu et al. 2010).

2.3.4 Microwave Remote Sensing in Precession Farming

Microwave remote sensing (MRS) can monitor the earth's surface, irrespective of atmospheric conditions and day/night which makes it more effective and useful

Table 2.5 Hyperspectral narrow-band vegetation indices commonly used in precision agriculture

Index	Definition	References
SR5	$R_{675}/(R_{700} \times R_{650})$	Chappelle et al. (1992)
SR2	NIR/green $= R_{800}/R_{550}$	Buschman and Nagel (1993)
DI1	$R_{800} - R_{550}$	Buschman and Nagel (1993)
NDI3	$(R_{734} - R_{747})/(R_{715} + R_{726})$	Vogelmann et al. (1993)
SR4	R_{740}/R_{720}	Vogelmann et al. (1993)
MSAVI	$0.5[2R_{800} + 1 - \mathrm{SQRT}((2R_{800} + 1)2–8(R_{800} - R_{670}))]$	Qi et al. (1994)
SR3	R_{700}/R_{670}	McMurtrey et al. (1994)
Greenness index (G)	R_{554}/R_{677}	Smith et al. (1995)
RDVI	$(R_{800} - R_{670})/\mathrm{SQRT}(R_{800} + R_{670})$	Rougean and Breon (1995)
HVI	R_{743}/R_{692}	Gitelson et al. (1996a, b)
MCARI	$[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})] (R_{700}/R_{670})$	Daughtry et al. (2000)
NDVI	$(R_{800} - R_{680})/(R_{800} + R_{680})$	Lichtenthaler et al. (1996)
NDWI	$(R_{857} - R_{1241})/(R_{857} - R_{1241})$	Gao (1996)
OSAVI	$(1 + 0.16) (R_{800} - R_{670})/(R_{800} + R_{670} + 0.16)$	Rondeaux et al. (1996)
MSR	$(R_{800}/R_{670} - 1) /\mathrm{SQRT}(R_{800}/R_{670} + 1)$	Chen (1996)
SR6	$R_{672}/(R_{550} \times R_{708})$	Datt (1998)
SR7	R860/(R550 × R708)	Datt (1998)
NDI1	$(R_{780} - R_{710})/(R_{780} - R_{680})$	Datt (1999)
NDI2	$(R_{850} - R_{710})/(R_{850} - R_{680})$	Datt (1999)
PSSRa	R_{800}/R_{680}	Blackburn (1998)
PSSRb	R_{800}/R_{635}	Blackburn (1998)
RVSI	$0.5(R_{722} + R_{763}) - R_{733}$	Merton and Hunting-ton (1999)
RGRI	R_{red}/R_{green}	Gamon and Surfus (1999)
SR1	NIR/red $= R_{801}/R_{670}$	Daughtry et al. (2000)
Green NDVI (GNDVI)	$(R_{801} - R_{550})/(R_{800} + R_{550})$	Daughtry et al. (2000)
TVI	$0.5 \times [120 \times (R_{750} - R_{550}) - 200 \times (R_{670} - R_{550})]$	Broge and Leblanc (2000)
TCARI	$3 \times [(R_{700} - R_{670}) - 0.2 \times (R_{700} - R_{550}) (R_{700}/R_{670})]$	Haboudane et al. (2002)

(continued)

Table 2.5 (continued)

Index	Definition	References
TCARI/OSAVI	$\frac{3 \times [(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})]\ (R_{700}/R_{670})}{(1 + 0.16)\ (R_{800} - R_{670})/(R_{800} + R_{670} + 0.16)}$	Haboudane et al. (2002)
NDNI	$\left[\frac{\log\ (1/R_{1510} - \log(1/R_{1680})]}{[\log\ (1/R_{1510} - \log(1/R_{1680})]}\right.$	Serrano et al. (2002)
MCARI/ OSAVI	$\frac{[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550})]\ (R_{700}/R_{670})}{(1 + 0.16)\ (R_{800} - R_{670})/(R_{800} + R_{670} + 0.16)}$	Zarco-Tejada et al. (2004)
MTVI	$1.2 \times [1.2 \times (R_{800} - R_{550}) - 2.5 \times (R_{670} - R_{550})]$	Haboudane et al. (2004)
MCARI2	$\frac{1.5[2.5(R_{800} - R_{670}) - 1.3(R_{800} - R_{550})]}{\sqrt{}\left[(2R_{800} + 1)^2 - \left(6R_{800} - 5\sqrt{}R_{670}\right) - 0.5\right]}$	Haboudane et al. (2004)
NAOC*	$\mathrm{NAOC} = 1 - \frac{\int_a^b \rho d\lambda}{\rho_{\max}(\mathrm{b-a})}$	Delegido et al. (2010)
DCNI	(R720 − R700)/(R700 − R670)/ (R720 − R670 + 0.03)	Chen et al. (2010)

R = reflectance at the wavelength (nm) in subscript. NIR = near-infrared reflectance. *(ρ refers to reflectance, λ the wavelength, $\rho_{\max=}$ maximum far-red reflectance, corresponding to reflectance at the wavelength "b," and "a" and "b" are the integration limits surrounding the chlorophyll well centered at ~670 nm)

(Navalgund et al. 2007). Electromagnetic waves having frequencies between 109 and 1012 Hz are generally considered as microwaves. Radar is an active MRS system (Reddy 2018) in which the terrain is illuminated using electromagnetic energy and the scattered energy returning from the terrain (known as radar return) is detected and recorded as images. In the case of both aircraft- and satellite-based systems, radar return intensity varies with characteristics of terrain and radar systems (Gupta and Jangid 2010). The various sensor parameters such as polarization, incidence angle, etc. (Henderson and Lewis 1998; Sahebi et al. 2002; Gupta and Jangid 2010) and physical parameters such as surface roughness, feature orientation, and electrical (dielectric constant) property of the target (Ulaby et al. 1978; Dobson and Ulaby 1986; Baghdadi et al. 2008; Sahebi and Angles 2010) generally governs the microwave signatures. Terrain properties affect the frequency of radar scattering (Reddy 2018). A given surface will appear very rough at higher frequency compared to a lower frequency. Usually, a rise in the backscattering coefficient occurs with an increase in frequency while the signal penetration depth rises with a rise in wavelength in the microwave region. Multifrequency data are capable of distinguishing types of roughness (Reddy 2018). The polarization of the incident wave also influences the backscattering. The multiple scattering and volume scattering from a complex surface, such as forest, cause depolarization. The radar backscattering coefficient is greatly influenced by the angle of the incident energy. This dependency of the backscattering coefficient toward the angle of the incident is mainly due to surface roughness (Ulaby et al. 1986; Fung 1994).

The soil moisture estimation using MRS is mostly based on the strong dependence of radar backscatter on the dielectric constant of soil. The dielectric constant of dry soil at microwave frequency is about 3, while it is about 80 for water. The radar backscattering coefficient ($\sigma°$) is strongly related to soil moisture due to high dielectric constant of a mixture of soil and water (Wang 1980).

The linear increase in the backscattering coefficient could be observed with the increase in soil moisture content. The development of a significant number of site-specific empirical models has been made based on the relationship between the backscattering coefficient and soil moisture content. The two factors that influence the backscattering coefficient are soil surface moisture and soil roughness (Panciera et al. 2013; Zhao et al. 2016; Huang et al. 2019). Many contradictions are there regarding the effects of soil surface roughness and soil moisture content on the backscattering coefficient where some consider that the effects of soil surface roughness are greater than that of soil moisture content while others consider them the same (Satalino et al. 2002; Rahman et al. 2008).

Several researchers effectively devoted their time in the incorporation of the effect of surface roughness and crop cover using a theoretical approach based on physical models (the integral equation model (IEM) (Fung et al. 1992; Fung 1994; Srivastava et al. 2006) and advanced IEM (AIEM) (Chen et al. 2003; Pettinato et al. 2013; Choker et al. 2017; He et al. 2017). The development of some semiempirical models over bare soils was also reported (Oh 2004; Dubois et al. 1995). The Oh model is dependent upon the ratios of the measured backscatter coefficients HH/VV and HV/VV for estimating volumetric soil moisture (mv) and surface roughness (Hrms). The backscatter coefficients in HH and VV polarizations to the soil's dielectric constant and surface roughness were used in the model proposed by Dubois (Baghdadi et al. 2016). Derivation of soil moisture over vegetated areas could be made by the models used in bare land along with the vegetation scattering models. Water Cloud Model is the most widely used vegetation scattering model (Lievens and Verhoest 2011). The generalization of these empirical models over a wide area results in problems of sensitivity limitation toward other target parameters, including soil texture, surface roughness, and vegetation cover (Bertoldi et al. 2014).

For accomplishing various applications, the aforesaid interaction of microwaves is widely used. Under rice cultivation, a distinctive pattern in backscatter could be noticed throughout the growth stage. This is might be due to the result of interaction between rice canopy structure, canopy water content, soils, and surface with SAR properties such as band, polarization, and incident angle (Le Toan et al. 1997; Chakraborty et al. 2005; McNairn and Shang 2016; Fikriyah et al. 2019). The estimation of rice area is generally made based on the physical basis formed, depending upon the characteristic temporal increase in backscattering coefficient from rice transplanting stage to maximum vegetative stage (Patel et al. 1995; Panigrahy et al. 1997, 2000; Parihar and Oza 2006). Three main mechanisms of scattering that could explain the interactions between SAR and rice canopy structure are (a) direct volume scattering from the rice canopy, (b) surface scattering from the ground, and (c) multiple scattering (double-bounce) from the interaction between the rice canopy and the ground surface (Bouvet and Le Toan 2011; Koppe et al. 2013). Quad-polarization (VH, VV, HH, and HV) data provided by RADARSAT-2 were found potent enough to retrieve parameters regarding rice canopy and to determine the biomass associated with the crop yield (Wu et al. 2011; Yang et al. 2012). For monitoring the rice phenology, the sensor acts as an ideal data source. The exploitation of the relationships of the backscattering coefficients and their combinations versus the phenology of rice helps to measure HH/VV, VV/VH, and HH/VH ratios, which are effective for monitoring of rice phenology (He et al. 2017).

In various studies where space and airborne SAR scatterometers and simulations model are involved are found efficient for retrieving soil parameters (roughness and moisture) and, to a lesser extent, the soil's textural composition (Shi et al. 1997; Oh 2004; Holah et al. 2005; Zribi et al. 2005; Baghdadi et al. 2006, 2007; Srivastava et al. 2006, 2009). In western Rajasthan, for detecting paleo-channel having high moisture content at a depth of 45–75 cm covered by dry sand, the subsurface penetration capability of radar has been used (Mehta et al. 1993).

Mohan et al. (1990) studied optimal sensor configuration based on different ground-based scatterometer data for application in soil moisture and vegetation purposes. However, radar signal obeys a logarithmic function with the soil-surface roughness irrespective of SAR configuration (Fung 1994; Ulaby et al. 1986). More sensitivity of SAR data toward soil roughness could be observed at a higher angle of incidence (Baghdadi et al. 2008; Baghdadi and Zribi 2006). Broadly, low frequency (C, L band) and low incidence angle (7°–17°) are associated with soil moisture applications.

The higher angle of incidence (>40°), higher the frequency (X, C) with multi-polarization (HH, VV and HV) capability is required for crop inventory. At the time of the monsoon period and flood inundation, the Radar Imaging Satellite (RISAT) has been effective for monitoring crops in PF (Das and Paul 2015). SAR interferometry merges two SAR images of the identical scene captured from variable positions and/or times required to map topography DEM generation and tracks out small coherent movements (differential interferometry). Numerous researchers have demonstrated the potential of SAR interferometry for various RS applications like plant density mapping, plant height estimation, and surface water extent in adverse weather conditions which could be used in PF. A few important findings of using SAR interferometry for agricultural crop studies are presented in Table 2.6. Synthetic aperture radar (SAR) images can be potentially used in the agricultural sector for identification of crops and the on-field conditions, soil moisture, tilled conditions, forecasting of yield and residue assessment, zone mapping and management, etc. (McNairn and Brisco 2004).

2.4 Utility and Applications of GIS

GIS operations and functionality were reviewed by several authors (Maguire et al. 1991; Martin 1991; Bernhardsen 1992 and Environmental Systems Research Institute 1993). Laurini and Thompson (1998) compiled 10 major functions of GIS as follows:

Table 2.6 Use of radar remote sensing for research in precision agriculture

SAR technique	Sensor parameters	Biophysical parameters of agricultural crop							Author(s)
	Frequency	LAI	Biomass	Yield	Density	Height	Water content	Crop inventory	
Backscatter coefficient	X, Ku, and Ka bands	√							Ulaby et al.(1984)
Backscatter coefficient	C and L bands		√						Ulaby et al. (1999)
Backscatter coefficient	X band						√		Qi et al. (2004)
SAR Interferometry	C band					√			Srivastava et al. (2006)
Backscatter coefficient	C and L bands				√				Patel et al. (2006a)
Backscatter coefficient	C band			√					Patel et al. (2006b)
Polarimetric SAR Interferometry	S, C, and X bands					√			Lopez-Sanchez et al. (2007)
Polarimetric SAR	L band							√	Tan et al. (2011)
Backscatter coefficient	C band		√			√			Wu et al. (2011)
Polarimetric SAR	C and L band							√	Skriver (2012)
Backscatter coefficient	C band							√	Jang et al. (2012)
Backscatter coefficient	X, C, and L bands						√		Kim et al. (2012)
Backscatter coefficient	C band	√	√					√	Moran et al. (2012)
Backscatter coefficient	L and X bands		√						Paloscia et al. (2012)
SAR Interferometry	C band							√	Engdahl (2013)
Backscatter coefficient	X band	√							Fontanelli et al. (2013)
Backscatter coefficient	X band	√	√						Inoue and Sakaiya (2013)
Polarimetric SAR	C band		√						Patel and Srivastava (2013)
Polarimetric SAR	C band		√			√			Haldar et al. (2014)

(continued)

Table 2.6 (continued)

SAR technique	Sensor parameters	Biophysical parameters of agricultural crop							Author(s)
	Frequency	LAI	Biomass	Yield	Density	Height	Water content	Crop inventory	
Backscatter coefficient	L, X, C, and Ku bands						√		Emmerik et al. (2015)
Polarimetric SAR	C band							√	Uppala et al. (2015)
Backscatter coefficient, SAR Interferometry, and Polarimetric SAR Interferometry	X band					√			Erten et al. (2016)
Polarimetric SAR	C band	√	√			√	√		Srivastava et al. (2016)
Backscatter coefficient	C band							√	Sonobe et al. (2017)
Polarimetric SAR	L band	√	√			√			Hariharan et al. (2018)
Polarimetric SAR	C and X band							√	Liu et al. (2019)
Backscatter coefficient	C band	√	√			√			Valcarce-Diñeiro et al. (2019)

Modified, Sivasankar et al. (2018)

(i) Automated Mapping: Replicating paper maps or toposheets into digital format
(ii) Thematic Mapping: Using target's information and demographic data
(iii) Map Overlay or Composite Mapping: Mapping from stacked data layers
(iv) Spatial Querying: Gathering information about particular condition from a database through identification
(v) Spatial Browsing: Searching information about particular condition from a database through identification
(vi) Spatial Problem-Solving: Using deductive reasoning or eliminating irrelevant spatial information for addressing the particular problem-solving and decision-making
(vii) Spatial Data Analysis: Testing the spatially explicit data for interpretation
(viii) Implementing Spatial Statistics: Using statistical tools for assessment of spatial attributes of interest
(ix) Spatial Statistical Analysis: Testing statistically the spatial attributes of interest
(x) Spatial Analysis: Carrying out simulation through a wide range of spatial statistical tools available for further representation of spatial phenomena (Foley et al. 1990; Laurini and Thompson 1992; Bonham-Carter 1994).

A typical GIS contains information about the usual features of a location, unique or discriminate features within that location, changing trend of particular observation parameters over time, spatial or landscape patterns of that location, and prediction of the target's change in future (Gangwar 2013). Its importance is widespread over various disciplines and implementation sectors like agriculture, IT sectors, telecommunication, mining and exploration, environmental and ecological exploration and maintenance, strategic studies for renewable energy resources, natural resource identification, and management, as well as any other particulars associated with earth's spatial dwelling. Some potential management and decision-making applications of GIS in the agricultural sector are in PF, addressing pests and diseases, land use planning, biodiversity assessment, resource identification, and mapping, crop area marking and yield prediction, watershed and irrigation management, genetic resources management, etc. (Mulla 1993; Mulla and McBratney 2000; Oliver 2010; Mulla and Khosla 2015). GIS application in natural resource management has already documented by many scientists such as forest pest impact modeling (White 1984), modeling of narcotic crop sites (Waltz and Holm 1986), waste disposal site modeling (Buckley and Hendrix 1986), water quality assessment (Welch et al. 1986), CO_2 effect analysis (Brekke 1986), etc. GIS enriches knowledge and reduces uncertainty to improve and expedite decision-making, prevent mistakes, and save cost. The integration of GIS with simulation modeling and RS tools ensures a high range of applications in different scientific fields.

2.4.1 Geostatistics: A Tool for Spatial Variability Assessment

Geostatistics has been evolved basically to characterize incompletely known spatial features of the earth by incorporating multiple numerical techniques through probabilistic models or pattern recognition techniques (Olea 2009). It always uses sampling location details to find out the spatial correlation between measurements, which makes it a distinct from classic statistical concepts. In the 1950s, the seminal idea about geostatistics was put forwarded by Danie Krige to address doubt during decision-making for carrying out expensive operations in mining and petroleum industries (Zhang 2011). Later, mining industries' data interpolation through geostatistics was proposed by Matheron (1962). Gradually, geostatistics has extended its prevalence in other earth science fields like forestry, soil mapping, meteorology, ecology, hydrogeology, geomorphology, hydrology, geophysics, geography, soil sciences, landscape ecology, epidemiology, environmental monitoring and assessment, oceanography, sedimentology, agronomy, geochemistry, atmospheric sciences, or any other discipline with spatial data (Myers 2008; Fischer 2015). In recent years, it has been successfully combined with RS and GIS for accelerating its efficiency and broad coverage in the scientific arena. The term "spatiotemporal statistics" (the scientific branch that analyses and interprets spatial and temporal data) is often synonymously used instead of geostatistics (Journel 1986). Geostatistics has specifically expressed interpolation of scalar values, such as strain ellipticity (Mukul 1998), soil properties, vectors treatments (Young 1987; Lajaunie et al. 1997), curvilinear geometrical analysis (Xu 1996), kriging interpolation for three-dimensional geometrics of earth surfaces (Lajaunie et al. 1997), etc. Certainly, geostatistics is different from conventional statistics. Conventional statistics provide analysis and interpretation of uncertainty occurrences due to limited and error sampling. It does not quantify the space, magnitude, or other factors associated with variability of uncertainty. It mainly considers discrete or individual data points. Conversely, apart from the data distribution, geostatistics further employs tools to determine spatial relationships, and thus provides accurate and bulk information from limited and error sampling. Additionally, it predicts the probability of spatial distribution of properties and minimizes uncertainty in data sampling. It mainly considers differences in value and spatial locations of data points. Geostatistics is based on the fact that at some scale autocorrelation of properties of an object occurs, that is, in close proximity, data has homogeneity. It measures the sample (called supports) to represent a population. This sample can be one or mean of several others.

Principles of geostatistics mostly rely on Kriging. Kriging is defined as a linear regression method for determining point values (or spatial means) at a random location of earth from observations of its value from adjacent locations. The concept of kriging was first put forward by Matheron (1962) for data points' interpolation and termed as an optimal prediction of a variable by interpolating its location with data points in close proximity (Cressie 1990). Unlike other regression models, kriging allows estimation of a single realization of the unbiased, random field.

Kriging method is divided into five major types: simple kriging, ordinary kriging (mostly used), anisotropic kriging (for analysis of geometric anisotropy), universal kriging (analysis of local pattern or trends), and co-kriging (analysis using two or more regionalized input variables) (Hendrikse 2000). Other types include indicator kriging, disjunctive kriging, and log-normal kriging. Simple kriging assumes stationarity of the first moment over the domain with known averages. Universal kriging assumes polynomial trend (three steps: removal of drift in a specified distance, kriging of secondary residuals, and outcome or estimated residuals from secondary residuals' kriging combined with a drift to determine properties of the real surface) while indicator kriging incorporates indicator functions either in separate form or in combination to predict transition probabilities. Disjunctive kriging is a nonlinear expression of kriging. Lognormal kriging uses a logarithmic technique to interpolate positive data. Ordinary kriging considers an unknown mean (constant) over neighborhood search for data estimation of the target location. Anisotropic kriging uses variogram surface inspection with various pixel sizes and the result varies with scale change. Co-kriging is a combination of ordinary kriging operations to identify and estimate poorly sampled variables (predict and) using well-sampled variables (co-variable). The co-variables should be correlated either positively or negatively. Studies conducted on the prediction of spatial variability in chemical properties by Nourzadeh et al. (2012) revealed that Cokriging was the best method for interpolating the chemical properties of soil. Kriging till date has spread its application in various disciplines like the spatial variability maps of soil properties (Franzen and Peck 1995; Hengl et al. 2004; Santra et al. 2008; Liu et al. 2008; García-Tomillo et al. 2017), environmental science (Lajaunie 1984; Zirschky 1985; Webster and Oliver 2007), hydrology (Mulla and Hammond 1988; Moslemzadeh et al. 2011; Danilov et al. 2018), mining (Pan et al. 1993), natural resources for the management of nutrients (Vieira et al. 2007; Chatterjee et al. 2015; Fathi and Mirzanejad 2015; Metwally et al. 2019), RS (Mulla 1991; Oliver 2010; Mulla 2016), and modeling of microwave devices. Kriging not only provides spatial autocorrelation, but also can replace stratified sampling if aggregates size is greater than the distance between two sampling points (Webster and Oliver 2007). It compensates for the data clustering and gives estimates of estimation error. Its uniformity in all types of sampling and properties has made its broad range of applications (Oliver and Carroll 2004; Oliver 2010, 2013). Oliver (2013) had conducted a case study on a field which has complex geography with variations in topography and soils in the Yattendon Estate in Berkshire. Based on variogram and kriging, he generated various digital maps related to yield of crops, soil properties to aid the farmer in decision-making, etc. He presented the short-range (30 m) and long-range (130 m) spatial variations in wheat yield through interpolation technique (Fig. 2.4).

The short-range variation is due to the management effects. However, the long-range variation in yield is mostly related with the soil texture, that is, sand and clay content and slope, hence the plateau area has the highest yield.

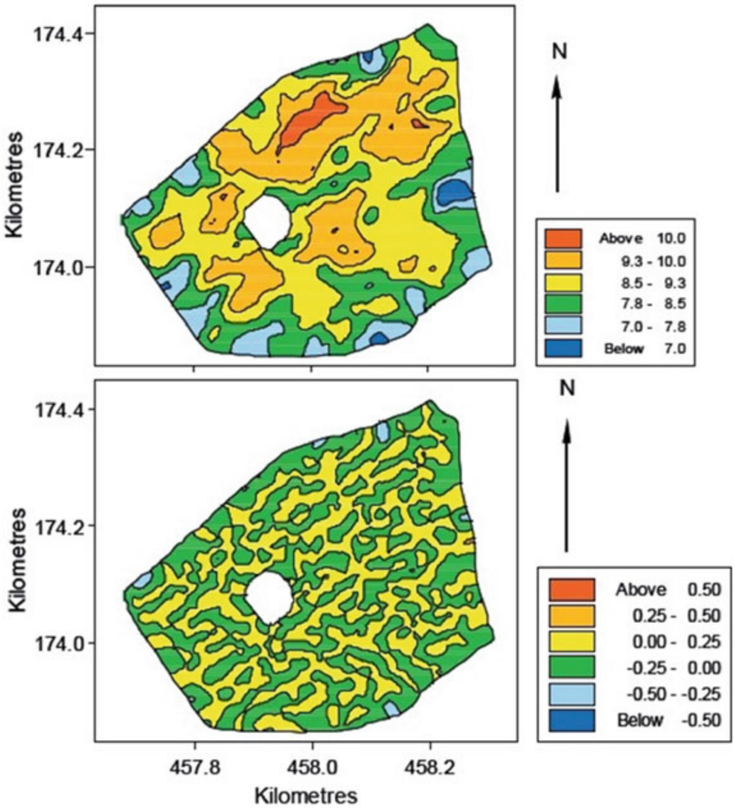

Fig. 2.4 The long-range (top) and short-range (below) spatial variation in yield. (Modified, Oliver 2013)

2.4.2 Spatial Econometry

Compared with the above mentioned, spatial econometry is relatively a new discipline in the scientific field (Arbia 2015). The idea was pioneered by Belgian economist Jean Paelinck just 40 years ago (Paelinck and Klaassen 1979). It has accelerated its speed from the last two decades due to the flood of problems associated with digitization and explosive revolution of data in information and technology and communication sectors. Spatial econometry is a scientific field that offers analytical techniques for identifying interdependence of geographically neighbor observations (areas or points) (LeSage 2005). This subfield of econometrics (i.e., application of statistical tools to make a quantitative analysis of actual economic phenomena based on observations and understanding to formulate inference about economic relationships) using regression models undergoes spatial autocorrelation and heterogeneity for cross-sectional and panel data (Paelinck and Klaassen 1979; Anselin 1988). Spatial interaction means a sample correlation about the location of observations. Spatial heterogeneity means the variability of econometric relationships according to space. It has been spreading the essence of success, as it recalls Gauss–Markov assumptions what the traditional econometrics forgot (LeSage 1999). Spatial econometrics though in adolescence stage, already has several application fields like regional economics, real estate, criminology, demography, agricultural economics, land use land cover, urban planning, industrial organization, political sciences, psychology, demography, epidemiology, managerial economics, education, economic development, health economics, public finance, innovation diffusion, history, labor, resources, energy economics, transportation, social sciences, food security, marketing, environmental studies, etc. (Arbia 2015). With the help of various geostatistical and spatial data analysis tools and models, spatial econometry interprets different economic phenomenon, namely interactions, spatial concentration, external factors, etc.

2.4.3 Spatial Regression

Regression is a statistical process to evaluate the relationship between a variable of interest (dependent) and one or more explanatory variables (predictors or independent variables). The spatial dependence of observations is determined through spatial autocorrelation (data attributes generated in response to the spatial pattern in values). The spatial pattern is estimated with the help of global (Moran's I, Geary's C, Getis/Ord Global G) as well as local (LISA and others) statistical methods. The regression model of such characteristics (i.e., spatial autocorrelation) is called a spatial regression model (Srinivasan 2015). Spatial autocorrelation is observed when observations that are closer to each other in space have related values. Spatial regression analysis aims to model, examine, and explore spatial relationships and explains factors responsible for the spatial pattern. Ordinary least square (OLS) is the best regression technique used so far. OLS provides a global model of variable or process for further interpretation and prediction (Arc GIS Pro, v. 10.7) using a single regression equation. Another important technique that has a long use in geography and other associated disciplines is the geographically weighted regression method (GWR). GWR provides a local model of variable or process for prediction or interpretation by fitting the regression equation to every aspect in the dataset (Kupfer and Farris 2007). Both OLS and GWR effectively estimate liner relationships (either positive or negative). Spatial regression has address two issues: (a) geographic features that are not spatially autocorrelated (Lark 2000) and (b) nonstationary nature of properties that user wants to model (Paciorek and Schervish 2006; Risser and Calder 2015; Risser et al. 2019).

2.4.4 Delineation of Management Zones

PF is a time- or location (site)-specific farming method that relies on four "R" principles: Right product, Right rate, Right time, and Right place. It aims in managing spatial soil variability by addressing only the requirements for soil and crop rather than the entire field (Doerge 1999; Mzuku et al. 2005). PF thus requires a practical management approach to delineate its MZs. Similar MZs are the homogeneous areas having an analogous trend of yield limitation or improvement through similar key factors in each case (Doerge 1999; Khosla and Shaver 2001; Fridgen et al. 2004; Basso et al. 2007). However, delineation of such subfields is hard as there exist strong interrelationships of biotic, abiotic, and climatic factors. Already several approaches such as topography, soil properties through survey maps (Carr et al. 1991), soil sampling (Mulla 1991), terrain features through DEM (McCann et al. 1996; Lark 1998; Nolan et al. 2000), aerial photography (Fleming et al. 2000) remotely sensed imageries (Bhatti et al. 1991b; Moulin et al. 1998), invasive (Mulla 1991) and noninvasive samplings (Johnson and Richard 2003), etc. are in practice to delineate management zones. Each management zone is unique (may it be in requirements or results). The most important spatial information for demarcating MZs has the characteristics of stability, quantitativeness (numerical), being rigorous and nonstop sampled and should pose a relationship with crop yield and performance directly. For the development of the management zone to carry out the PF, several data on previous crop history, previous years' yield map, soil properties, and fertility, drainage, microclimate, pest problem, etc. about every portion of the field is required. If some subregions of the field show similarity to each other, they are marked as a particular management zone and, thus, the entire field is separated by different types of management zones. As complex relationships among several factors are continuously occurring in the field, the constraint arises on maintenance and update of recorded data for making zone-wise application map for the next uses. The problem further arises with the combined use of more than one variable (say, for example, weed control and fertilizer management, organic nutrition and irrigation, etc.). Therefore, a good management zone always requires help from flexible and advanced GIS tools (Royal 1998). A proper combination of all types of collected field information, knowledge about marking MZs, and modification or change of formula with temporal variability of MZs are needed to address the challenge further. GIS users for determining MZs should be ready for change and flexible enough to convert the management layer in raster or vector format for running selected variable rate applicators. The most effective management zone strategy changes with region and growers. Available data on soil and crop conditions along with experience of farmers and profound knowledge of users in computer and software handling, etc., all help to select ideal management zone.

2.5 Geoinformatics in Precision Agriculture

Geoinformatics is part of scientific and technological field, which collects, differentiates, stores, analyses, depicts, and transfuses information about the structure and characteristic features of location in a secured way for the users to interpret well (Raju 2003). On the other hand, Ehlers (2003) has stated that it is not only a branch of science and technology, but also an art for acquiring spatial information to analyze, store, visually represent, and transfuse further. There are several coined definitions of Geoinformatics worldwide. Geoinformatics is a multidisciplinary field and consists of several disciplines such as RS for acquiring images through earth observation sensors, GIS for processing, interpretation of geoinformation, and visually depicting outcomes through sheets or digitally for decision-making. Besides, it provides an opportunity to prepare spatial databases, framing information systems, modeling through manual–digital interaction using various wired and wireless network interfaces. Geocomputation, cartographic technology, GPS, GIS, web-mapping, geodesy, RS, photogrammetry, and geo-visualization are used in Geoinformatics for geoinformation analysis. Geoinformatics is becoming more efficient and acceptable in several sectors due to combining the improved analytical efficiency, latest telecommunications opportunities, in a wide range of information, and recent upgradation of image processing tools such as RS, GPS and GIS. The flow chart of the working principle of Geoinformatics in a decision support system is presented in Fig. 2.5. Nowadays Geoinformatics provides benefit to many regular services such as urban planning and land uses, car transports, aviation, and maritime transports, public health, meteorology and climatology, environmental modeling and analysis, military, agriculture, oceanography, business planning, architecture, and archaeological studies, telecommunications, and many more. In industrial, environmental, commercial, and agricultural sectors and in various regional, national, and international public or private organizations, in the field of research, survey, mapping, emergency support, etc., currently Geoinformatics plays a crucial role in better decision-making and goal achievements.

2.5.1 *Yield Monitoring and Mapping*

Since yield is a major parameter representing the impacts of different on-field agronomic factors, monitoring, mapping, as well as their relationship with spatial and temporal variability of other agronomic attributes would help in the formation of future strategy (Mondal et al. 2004). Thus, yield monitoring and mapping consist of a vital and logical part for the system required for practicing PA. From the aspect of PA, yield monitoring could be simply defined as a technique capable of generating adequate information that could be used by the farmers for making better decisions in the field (Wang 1999). Grain yield could be assessed field- or load-wise by yield monitors. Some monitoring systems used in the case of forage crops collect

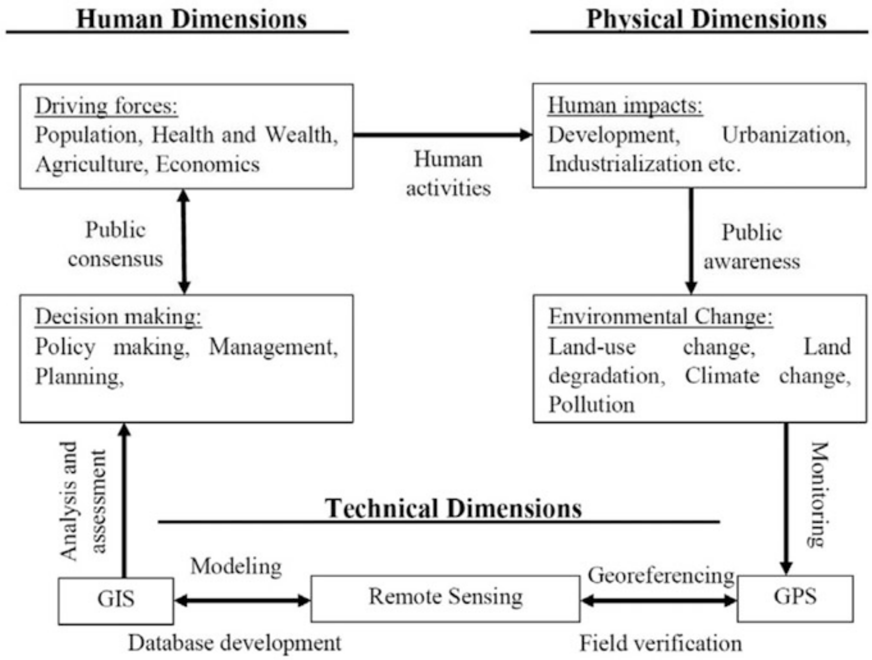

Fig. 2.5 Flowchart of the working principle of geoinformatics in a decision support system. (Modified, Murai 1999)

information such as weight, water content, and several other parameters bale wise (Davis et al. 2005).

2.5.1.1 Yield Monitoring in Precision Farming

The yield monitoring system provides the farmer with greater flexibility with instant information about the condition of the field and crops based on which farmers could take necessary steps (Thylen and Murphy 1996). In recent days, yield monitors enable farm equipment to acquire a large range of information of grain yield, moisture level, and soil properties and so on through their association with the equipment (Fig. 2.6) which eventually made the decision-making process easier for the farmers. So, the time of harvesting (Vellidis et al. 2001; Yang and Everitt 2002) fertilizer application, irrigations could be easily assessed along with the mitigation of potential threat through improved understanding of yield-related traits by analyzing geo-referenced data of particular field (Grisso et al. 2002). This information is generally collected in data storage devices, which could be further transferred and stored in personal computers in a variety of formats.

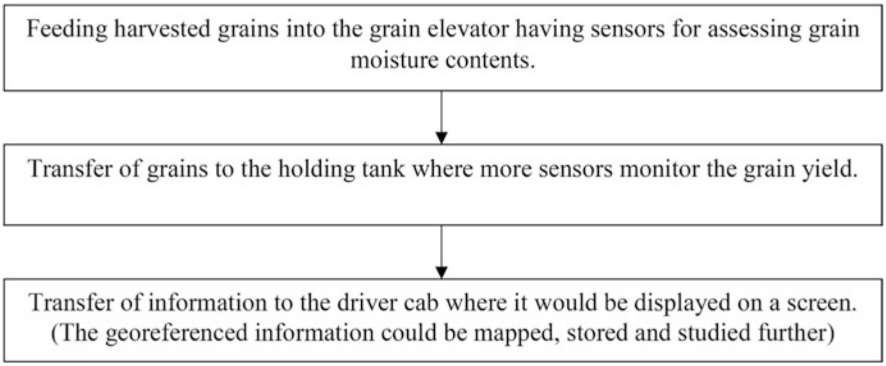

Fig. 2.6 Flowchart of the steps of yield-monitoring process

2.5.1.2 Yield Mapping in Precision Farming

The whole process of measurement, compilation, and presentation of georeferenced crop yield data and other parameters such as grain moisture content in a consolidated effective form such as in the form of a map is called yield mapping. Several sensors dedicated to several parameters are generally employed in this whole process. These sensors along with the DGPS receiver assess several sets of instantaneous data points of several parameters based on which yield maps are developed (Arslan and Colvin 2002; Fulton et al. 2018). Many automated elements are involved in this system. For instance, as a combine operator guides the farmers for crop cultivation and its harvesting only, yield data collection is an automated system in the process of yield mapping. So the flow of grain through the chute is continuously recorded along with the recording of the field position of the harvester. Georeferenced yield information is then transferred in a computerized system for interpolating with the help of special software to generate yield maps of the field. The binary format is most preferable as it is capable of storing digital data efficiently. But the conversion of this binary data into standard text format is necessary as most of the software cannot process the raw binary data. One cannot get the reason of yield variation from the yield map as it only offers the information depicting the superior and inferior parts of the field in terms of yield or it may provide an overview of variation of grain moisture content in the field which would help farmers to decide whether to harvest or not in that particular part of the field (Stoorvogel et al. 2016). Hence, farmers are asked to apply their experience, indigenous knowledge, and supplementary information to describe yield maps for upgrading their decision regarding crop management to get maximum profit. Thus, the PF system is mainly the assemblage of different elements and technologies in one effective system for performing successful PA (Pfost et al. 1998, 1999; Blackmore et al. 2003; Zhang et al. 2008; Colaco et al. 2015; Fulton et al. 2018).

2.5.2 Fertilizer Recommendation

Recommendations of fertilizers depending on the analysis of soil and plant are generally introduced for the betterment of productivity in agriculture as they are of high efficiency mainly focused on the practical scientific techniques that deal with the data obtained from the soil and plant analysis (Xia et al. 2011). The soil testing and fertilizer recommendation methods are commonly implemented to improve fertilizer efficiency for obtaining an augmented yield along with mitigating the detrimental effects of long-term fertilization for specific crops (Black 1992; Wang et al. 1998). The increase in crop growth due to better fertilization could also contribute to building soil organic carbon content, which in turn influences the distribution of nutrients in the soil as well as nutrient cycling. Thus, fertilizer recommendation based on soil and plant analyses not only helps in promoting crop productivity to meet the ever-increasing need of rising population but also helps to maintain environmental sustainability. Hence, the use of this essential and effective technique in modern agriculture not only ensures a steady production but also facilitates optimum use of fertilizers which makes it a source-efficient and environment-friendly approach (Xia et al. 2011; Wei and Qi 2013).

Traditionally over the years, the soil is sampled and tested in the laboratory for a recommendation of fertilizers which is not only uneconomical but also time-consuming. With the use of geospatial analysis, cost-saving and increment of work efficiency can be successfully achieved (Tang et al. 2007).

The wide use of computers as a computing device in experiments and researches regarding fertilizers was started between the 1970s and 1980s in the western world (Haynes 1986). An increase in concerns regarding the development and application of a various range of fertilizers was noted since the 1980s (Black 1992) and computer-based fertilization decision systems were established by several developed countries at that time. Auburn University coined a recommendation system containing 52 fertilization standard types while the Agro Services International Inc. starred to use a software-based system to determine the optimal nutrient requirement and were able to give consultancy regarding 11 nutrients for 140 numbers of crops. “Crop-environment resources information system” was developed by Richie and people got the recommendation of nitrogen-based on climates, crop varieties, physiological characteristics, moisture and nutrient status for wheat and corn cultivation (Haynes 1986; Black 1992). The emergence of the agricultural production decision system integrating several systems such as scientists’ expertise, simulation models, GIS, and RS took part in the development of technology. AE-GIS, a decision support system equipped with crop models and GIS, was developed by Florida State University agricultural and environmental studies. The Decision Support System for Agrotechnology Transfer (DSSAT) was then developed by the University of Hawaii, which was capable of assessing the effects of different environmental factors by using simulation models to help take appropriate decisions further regarding management practices. In a similar period, GPFARM developed by the United States Department of Agriculture (USDA) became a potent organization to support production decision-makers as it took economy, environment, and sustainability together into consideration.

Over time scientists developed expert systems on fertilizer recommendation for crops based on the soil nutrient status of the field. Previously soil samples had to collect in a scientific way, which was very cumbersome to the farmers (Ren et al. 2002; Wang et al. 2010). Application of Resource Information Database helped to overcome such problems to some extent. Thus, this system of scientists' expertise was able recommend fertilization by cutting down complicated and time-consuming procedures including soil sampling and analysis (Tang et al. 2007). Because of the mutation of the past few decades, a combination of spatial information with soil nutrient content database became necessary to study the distribution of nutrients in agricultural fields (Mao and Zhang 1991; Qi et al. 2009).

Latest interventions like high-resolution satellite information, GPS, GIS, and information technology hold good prospects of monitoring soil nutrient status and in fertilizer management, land use planning which can be sustained for the future. The satellite covers many types of information, namely landforms, geological features, soil categories, erosion, land use, groundwater, and soil moisture which increases the potential of the fertilizer recommendation process. The combined use of RS, GPS, and GIS imparts positively on digital analysis and mapping of the distribution of different nutrients in soils of a vast area quickly. RS, GIS and GPS in recent days could assess the spatial variance of soil nutrients where geostatistics forms the foundation of soil resource information database. Depending on laboratory analysis and previous literature, soil testing and fertilizer recommendation models and indices are made (Tang et al. 2007; Li et al. 2008). After indexing the nutrient status of a particular field in the database of soil resources, scientists' expertise concludes fertilizer recommendation, dose, and application scheme for a specific crop (Tang et al. 2007).

2.5.3 Digital Soil Mapping

Soil maps could be simply defined as mapping units where a specific type of soil having characteristic properties is believed to be located. Digital soil mapping with the assistance of computer-based systems covers various features or properties of soil in the generated maps (Kumar 2018). Thus, digital soil mapping is nothing but making databases of georeferenced information about the soil under certain resolution based on field observations and laboratory analysis along with environmental considerations. Statistical and mathematical models are generally used to combines soil observations and information dealing with correlation among RS data and environmental attributes. Unlike soil mapping, soil-landscape mapping delivers a land resource survey that deals with similar or associated soil types and repeating patterns of landscapes (Schoknecht et al. 2004). Soil-landscape mapping is an important tool for better and firm decision-making under variable management practices, as land resource interpretation lowers the risk of implication of various practices. It also enhances the better understanding of biophysical processes, and helps in strategies for land use planning in large-scale environmental regulation, trading, monitoring, and mapping of natural resources, such as distribution and prediction of soil carbon storage (Pieri 1997). Geospatial technologies in which satellite-based imageries are used for simple monitoring purposes, such as soil productivity, fertility, moisture status, etc., would help farmers to make future decisions precisely.

Soil and landscape analyses have been significantly influenced by the advancement of GIS-based digital terrain modeling (Mahmoudabadi et al. 2017). For soil characteristics prediction, development of soil-landscape models have also been made by combined use of both statistical modeling and digital terrain analysis (Moore et al. 1993; McSweeney et al. 1994). In these cases, images acquired through RS devices act as data source support for digital soil mapping (Ben-Dor et al. 2008; Slaymaker 2001). For analyzing and modeling the land surface as well as studying the relations between several components of the landscape such as topography, anthropogenic, hydrological, geological, and biological components, digital terrain analyses are generally used. Despite being a profitable and potent technology, soil spectroscopy has not still been regularly applied during survey or monitoring. With computer software's upgradation, digital elevation models (DEMs) have become popular. DEMs generally use remotely sensed data to produce 3-D landscape models that are capable of delineating geomorphological and land surface features in a precise way through visual interpretation. DEMs are also able to provide several information regarding elevation, slopes, aspect maps, etc. with the help of which efficiency of soil mapping can be augmented. Hence, for this purpose, logical integration of remotely sensed imagery, soil data obtained from sampling, and digital elevation models (DEMs) could upgrade the efficiency of the DSM system to interpret and predict the soil properties (Grunwald 2009), and automated soil mapping using DEMs has also been started. Significant positive correlation and predictive features among terrain attributes and different soil properties have been observed by Moore et al. (1993) and Gessler et al. (1995). Thus, the use of terrain attributes along with soil features can act as secondary variables that could enhance the interpolation accuracy of present soil information (Kumar and Singh 2016).

2.6 Modern Trend in Precision Farming: Use of Drones

The modern trend in monitoring natural resources, vegetation, and agrarian belts is to adopt drones, that is, unmanned aerial vehicles (UAVs) that possess miniaturized sensors (Jin et al. 2009; Wang and Wu 2010; Salami et al. 2014). They are rapid in turnaround and offer very high-resolution imagery because of the proximity of sensors to the surface to be monitored (Berni et al. 2009; Green 2013; Vanac 2014). As agriculture is the backbone for many developing countries like India, there is an urgent need to incorporate RS in this sector at a cheap cost (~100 INR/acre/season) with improved spatial (2 m multispectral or more), spectral (<25 nm),

Table 2.7 Differences of UAVs from various remote sensing tools

Tools	Field of view	Spatial resolution	Usability	Payload	Data acquisition cost
UAV	50–500 m	0.5–10 cm	#	X	*
Helicopters	0.2–2 km	5–50 cm	##	X	**
Airborne	0.5–5 km	0.1–2 m	##	√	***
Satellite	10–50 km	1–25 m	–	–	****

Modified, Candiago et al. (2015)
√: Unlimited, X: Limited, *Very low, **Medium, ***High, ****Very High, #Very good, ##Pilot mandatory

and temporal (minimum five to six times in each season) resolutions, reduced turnaround time (24–48 h) for delivering analytical observations in simple and easy to understand the way in case of PF (Hunt et al. 2005; Lelong et al. 2008; Nebiker et al. 2008; Rango et al. 2009; Hardin and Hardin 2010; Xiang and Tian 2011). Unmanned aerial systems (UAS) have a great potential of capturing images of spatial phenomena from a low altitude (Swain et al. 2007) and therefore this young technology is now gaining attention in the agricultural sector in place of others.

One of the most active emerging areas of research in PA uses cameras mounted on UAVs (Berni et al. 2009; Zhang and Kovacs 2012; Huang et al. 2018). An Unmanned Aerial Vehicle (UAV) can be fully automated or instructed to be automated or manually operated (Sylvester 2018). The development of UAV platforms linked with various sensors (image, position, range, etc.) can effectively capture multispectral images at a cm-level resolution which holds good prospects in PF (Lelong et al. 2008; Turner et al. 2011; Guo et al. 2012; Primicerio et al. 2012; Bendig et al. 2012; Lucieer et al. 2014; Nex and Remondino 2014; Colomina and Molina 2014; Bansod et al. 2017), agriculture, and forestry management (Grenzdörffer et al. 2008). Nowadays, UAVs are showing their potential in farm resource management by capturing quality images of various aspects of crop cultivation, especially monitoring the crop health at relatively cheaper expenditure over other RS tools (Primicerio et al. 2012). The UAVs are relatively inexpensive, can be deployed rapidly at low altitudes when crop stress is starting to appear, and have the flexibility to be flown during windy or partly cloudy conditions (Mulla and Miao 2016). In Table 2.7, differences of UAV from other RS tools are mentioned.

The successful use of UAVs or drones in PF is now gaining importance. For instances, UAVs have potential applications in tracking out small weed zones (in rangelands) (Hardin et al. 2007); crop water stress (Berni et al. 2009); biomass monitoring (Hunt et al. 2005; Swain et al. 2010); in figuring out vineyard vigor (Primicerio et al. 2012); in the identification of crop types such as rice (Swain et al. 2007, 2010), coffee (Johnson et al. 2004), wheat (Hunt et al. 2010), corn (Hunt et al. 2005), etc.; and in evaluating the effect of nutrient management on crops, etc. Reports from Hunt et al. (2005) and Swain et al. (2007) showed the evidence of identification capabilities of drones about the effects of the application of different doses of nitrogen on crops.

2.7 Major Challenges in Precision Farming

A well-documented improvement in crop yield, profitability, or environmental quality remains rare in scientific literature, despite a large number of success stories on PF. There are many technology-related, farm-related, data related, and organization related issues, which are associated with the adoption of PF. The major challenges as are follows:

- Technology-related issues involve compatibility and high cost of hardware and software, and a lack of understanding in the correct application of the technology.
- Lack of reliable and inexpensive sensors, cloud-free data, different data formats, etc.
- Most of the available sensors provide indirect measurement of soil and plant attributes; however producers are looking for sensors which can provide direct input for existing prescription algorithms (Dobermann et al. 2004).
- Issues with data interoperability: Farmers and researchers can easily collected huge information within short span of time, but assessment, interpretation, and transformation of these quality data into meaningful management decisions, beneficial potentialities, and related risks have proven to be a difficult task.
- The major constraints for implementation of technology in farmers' fields include lack of awareness about current policies, lack of skills, and their uneducated backgrounds.
- Inadaptability by the farmers at the grassroots: In developing countries, most of the farmers have small and marginal landholdings and they are financially weak, and thus afraid of the risks of change, so they reluctantly accept technological interventions.

2.8 Conclusions and Future Perspectives

Remote sensing technology has a great potential to acquire various spatial, spectral, and temporal resolution datasets which can be used as input for precision agriculture. Remote sensing data at optical, microwave, thermal, and hyperspectral domains prove to be a powerful tool to assess crop and soil properties in varying spatial and temporal scales with cost-effectiveness. Satellite RS coupled with GIS and mobile app-based positional information has emerged as an efficient tool for the sustainable development in precision agriculture resources by optimizing input resources, minimizing the cost of production, and risk of biotic/abiotic in nature. Modernization and advancement in space and information technologies have created a suitable environment for the implication of PF in many countries. In most of the developing countries, the problem of adoption of PF is due to small landholdings, so the adoption of precision farming through community farming approach would be a better option. The full potential of precision farming can only be exploited if the soil scientists, agronomists, agricultural economists, and engineers develop simple and robust methodologies and technologies for farmers.

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