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APPROACHES OF REMOTE SENSING IN PRECISION AGRICULTURE: A REVIEW

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ABSTRACT

Remote sensing in precision agriculture is established with sensors to analyze soil organic matter. Nowadays a variety of spectral indices are available that can be used for various precision agriculture applications. The spatial resolution of various remote sensing images has improved from 100's of meters to centimeter accuracy, granting assessment of various soil and crop properties but at the expense of increased data storage and processing requirements. In the past, optical remote sensing was used as an integral part of precision agriculture for crop and soil monitoring. However, in the present-day, work is being done on the development of thermal and hyperspectral remote sensing techniques. The applications of remote sensing in agriculture discussed here include soil characteristic mapping, precision farming practices, soil salinity detection, disease and pathogen detection, crop-water stress monitoring**,** crop monitoring, irrigation scheduling, soil texture analysis, soil moisture detection and soil texture analysis.

KEYWORDS: remote sensing, hyperspectral remote sensing, optical remote sensing, thermal remote sensing, UAVs stress monitoring, soil characteristics mapping etc.

1. INTRODUCTION

Agriculture is the primary source of food and a dominant factor in the development of the economic condition. Precision agriculture (PA) is being practiced commercially since the 1990s and revolutionized agriculture completely (Crookston, 2006). Due to a drastic increase in population, urbanization and industrialization (Vibhute and Gawali, 2013), the demand for food supply has increased, hence, there is an immediate need to enhance the agriculture practices into extremely resource-efficient systems that can benefit the world commercially along with the environmental sustainability (Donner and Kucharik, 2008; Zhang et al., 2015; Zillén et al., 2008). PA is a special type of agriculture practice that has become a frontier area in agriculture (Zhang et al., 2016) and focuses on the right management practice with the right place at right time (Gebbers and Adamchuk, 2010). PA tends to improve crop productivity and farm lucrativeness through meliorate management inputs (Zhang, Wang and Wang, 2002; Larson et al., 1991) and by using intensive data and information collection and processing (Harmon et al., 2005) that certainly leads to a better environment (Mulla et al., 2003; Mulla, 1993). By the passage of time, the technologies like global positioning systems (GPS), variable rate technologies (VRT), sensor networks and remote sensing have developed and assisted the farmers to identify and implement site specific farming practices (Khanal et al., 2017). In PA, data collection-cum-analysis is involved with proper information management and it also involves the technological development in sensor design, remote sensing, data processing techniques, and their monitoring (Mulla and Bhatti, 1997).

Remote sensing along with the geographical information system (GIS) and other types of data sets is helpful for farmers to decide on agricultural strategies (Soni, 2011). For commercial-scale monitoring and analysis in agriculture, remote sensing is the most cost-effective technology present today. It is non-destructive and can cover a large area for phenotypic crops (Yang et al., 2017). It utilizes visible, near-infrared (NIR) and short-wave infrared (SWIR) sensors for agriculture purposes. Thermal sensors are extensively used in the areas of intelligence (Hinz and Stilla 2006), food processing (Vadivambal and Jayas, 2011) and medicine (Ring and Ammer, 2012). The various applications of thermal remote sensing in the field of agriculture are (1) irrigation scheduling and harvesting, (2) monitoring crop stresses, crop diseases and soil water stress. In the future, the sensors could be mounted on satellites (Bausch and Khosla, 2010), UAVs (Berni et al., 2009), tractors (Adamchuk et al., 2004), mobile robots or airplanes to investigate the crop height, leaf reflectance, soil water stress and other properties which can help the farmers to quantify the fertilizers and pesticides. The objectives of this paper are to review and summarize the potential applications of remote sensing in the field of precision agriculture.

2. Remote sensing in precision agriculture

In PA, various remote sensing applications are used for collecting-cum-analyzing data about the crop and soil characteristics by using different types of sensors. It is based on the interaction of electromagnetic (EM) radiation with soil and plant material. Remote sensing applications in agriculture mainly focus on the reflected radiations and are least considered about the transmitted/absorbed radiations (Mulla, 2013). In addition to it, the plant leaves also emit fluorescence (Apostol et al., 2003) or thermal emission (Cohen et al., 2005) which provides essential information about the temperature variations and other factors like energy fluxes (Weng, 2009; Quattrochi and Luvall, 1999). Various factors stated by (Ben-Dor et al., 2008) that influence the applications of remote sensing in precision agriculture: (1) type of platform (satellite, air, or ground), (2) region of the EM spectrum (visible, infrared, or microwave), (3) spectral bandwidths and their number (panchromatic, multispectral or hyperspectral), (4) spatial resolution (low, medium, high), (5) temporal resolution, (6) radiometric resolution and (7) energy source (active or passive). Figure 1 shows a schematic diagram to illustrate about the cropping cycle involved in precision agriculture (Chantarat et al., 2007; Gebbers and Adamchuk, 2010).

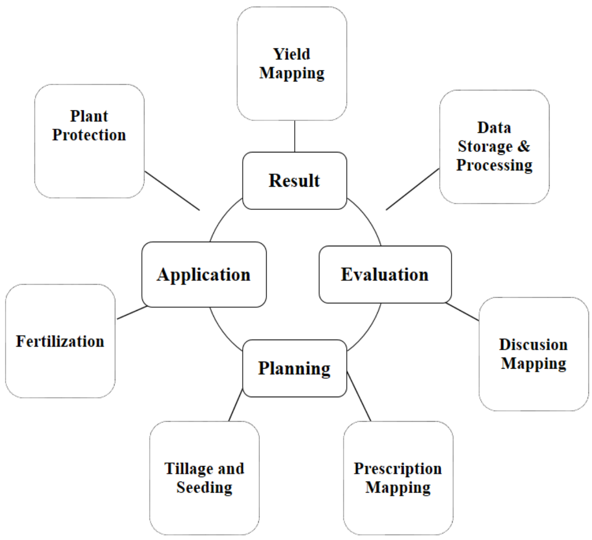

Figure 1: Precision agriculture information flow in crop production (Gebbers and Adamchuk, 2010).

2.1.Optical remote sensing in precision agriculture

Optical remote sensing is the most exploited remote sensing system in the field of agriculture which utilizes visible, NIR and SWIR sensors (Prasad and Bruce, 2011). In general, optical remote sensing is associated with the radiations reflected from the target object (Sabins Jr, 1996). By the advancement in remote sensing technology, different vegetative indices have been developed which are based on the combination of different bands to estimate various plant parameters like leaf area, biomass, chlorophyll content, etc. (Starkbet al. 2014; Anderson et al., 2013). Due to the cloud cover, the images from satellite and aerial platforms are severely limited while ground-based remote sensing is least affected (Moran et al. 1997).

2.2. Hyperspectral remote sensing in precision agriculture

Hyperspectral remote sensing (also known as imaging spectroscopy or spectrometry) is the acquisition of images in hundreds of contiguous spectral bands (forms hyperspectral cube) to obtain high-resolution data for each pixel (Galvão et al., 2018; Goetz et al., 1985). It is based on the ability of the sensors to capture narrow absorption bands instead of taking a greater number of bands. In 1987, an airborne visible/infrared imaging spectrometer (AVIRIS), the first hyperspectral sensor was launched. The technological advancement in hyperspectral remote sensing in agriculture leads to a significant enhancement over conventional remote sensing, resulting in improved modeling and mapping of agricultural attributes like as (1) crop type/species (Thenkabail et al., 2014; Thenkabail et al., 2013), (2) use of water and its productivities (Thenkabail et al., 2013), (3) management of stress factors (nitrogen deficiency, moisture deficiency, drought conditions (Delalieux et al., 2009; Gitelson, 2013; Thenkabail et al., 2014; Slonecker et al., 2013), and (4) biophysical and biochemical quantities (Galvão et al., 2018; Clark and Roberts, 2012). Imaging spectroscopy is different from multispectral imaging in terms of continuity of spectrum, range and spectral resolution of bands. Hyperspectral vegetation indices (HVIs) are used to target studies on crop characteristics such as leaf area index (LAI), biomass, pigments, moisture status, stresses, etc. (Haboudane et al., 2004; Galvão et al., 2018; Thenkabail et al., 2014; Bian et al., 2010; Goel et al., 2003; Zarco-Tejada et al., 2004). Hyperspectral remote sensing data is interpreted by using advanced statistical methods for chemometric analysis of reflectance spectra which included partial least squares (Rossel et al., 2006; Lindgren et al., 1994; Geladi, 2003; Alchanatis and Cohen, 2016), principal components analysis (Geladi, 2003; Alchanatis and Cohen, 2016), pattern classification and recognition techniques (Stuckens et al., 2000), classification techniques like decision tree (Wright and Gallant 2007) and object-oriented classification (Frohn et al., 2009). A variety of hyperspectral indices used in precision agriculture are mentioned in Table 1.

Table 1: Vegetation indices (modified from (Mulla, 2013).

Index	**Definition**	**Reference**
Multispectral broadband vegetation indices		
NG	G/(NIR+R+G)	(Sripada et al., 2005)
NR	R/(NIR+R+G)	
RVI	NIR/R	(Jordan, 1969)
GRVI	NIR/G	(Sripada et al., 2005)
DVI	NIR-R	(CJ, 1979)
GDVI	NIR-G	(CJ, 1979)
NDVI	(NIR-R)/(NIR+R)	(Rouse et al., 1974)
GNDVI	(NIR-G)/(NIR+G)	(Gitelson et al., 1996)
SAVI	1.5*[(NIR-R)/(NIR+R+0.5)]	(Huete and Escadafal, 1991)
GSAVI	1.5*[(NIR-G)/(NIR+G+0.5)]	(Sripada et al., 2005)
OSAVI	(NIR-R)/(NIR+R+0.16)	(Rondeaux et al., 1996)
GOSAVI	(NIR-G)/(NIR+G+0.16)	(Sripada et al., 2005)
MSAVI2	$0.5*[2*(NIR+1)-SQRT((2*NIR+1)^2-8*(NIR-R))]$	(Qi et al., 1994)
Hyperspectral narrowband vegetation indices		
Green index (G)	R_{554}/R_{677}	(Smith et al., 1995)
SR1	NIR/red = R_{801}/R_{670}	(Daughtry et al., 2000)
SR2	NIR/green = R_{800}/R_{550}	(Buschmann and Nagel, 1993)
SR3	R_{700}/R_{670}	(McMurtrey Iii et al., 1994)
SR4	R_{740}/R_{720}	(Vogelmann et al., 1993)
SR5	$R_{675}/(R_{700}*R_{650})$	(Chappelle et a., 1992)
SR6	$R_{672}/(R_{550}*R_{708})$	(Datt, 1998)
SR7	$R_{860}/(R_{550}*R_{708})$	
DI1	R_{800} -R_{550}	(Buschmann and Nagel, 1993)
NDVI	$(R_{800}-R_{680})/(R_{800}+R_{680})$	(Lichtenthaler et al., 1996)
GNDVI	$(R_{801}-R_{550})/(R_{800}+R_{550})$	(Daughtry et al., 2000)
PSSR(a)	R_{800}/R_{680}	(Blackburn, 1998)
PSSR(b)	R_{800}/R_{635}	
NDI1	$(R_{780}-R_{710})/(R_{780}-R_{680})$	(Datt, 1999)
NDI2	$(R_{850}-R_{710})/(R_{850}-R_{680})$	
NDI3	$(R_{734}-R_{747})/(R_{715}+R_{726})$	(Vogelmann et al., 1993)
MCARI	$[(R_{700}-R_{670})-0.2(R_{700}-R_{550})](R_{700}/R_{670})$	(Daughtry et al., 2000)
TCARI	$3*[(R_{700}-R_{670})-0.2*(R_{700}-R_{550})(R_{700}/R_{670})]$	(Haboudane et al., 2002)
OSAVI	$(1+0.16)(R_{800}-R_{670})/(R_{800}+R_{670}+0.16)$	(Rondeaux et al., 1996)
TCARI/OSAVI		(Haboudane et al., 2002)
TVI	$0.5*[120*(R_{750}-R_{550})-200*(R_{670}-R_{550})]$	(Broge and Leblanc, 2001)
MCRI/OSAVI		(Zarco-Tejada et al., 2004)
RDVI	$(R_{800}-R_{670})/SQRT(R_{800}+R_{670})$	(Roujean and Breon, 1995)
MSR	$(R_{800}/R_{670}-1)/SQRT(R_{800}/R_{670}+1)$	(Chen, 1996)
MSAVI	$0.5[2R_{800}+1-SQRT((2R_{800}+1)2-8(R_{800}-R_{670}))]$	(Qi et al., 1994)
MTVI	$1.2*[1.2*(R_{800}-R_{550})-2.5*(R_{670}-R_{550})]$	(Haboudane et al., 2004)
MCARI2	$\frac{1.5[2.5(R_{800}-R_{670})-1.3(R_{800}-R_{550})]}{\sqrt{(2R_{800}+1)^2-(6R_{800}-5\sqrt{R_{670}})-0.5}}$	

2.3. Thermal remote sensing in precision agriculture

Thermal remote sensing is based on the principle that everybody which has a temperature above absolute zero i.e. 0 K or -273.15 °C emits radiations in the infrared region of the electromagnetic spectrum (Prakash, 2000; Ishimwe et al., 2014; Khanal et al., 2017). Hence, it is associated with the thermal infrared region of EM spectrum which is helpful in data acquisition, processing and interpretation (Prakash, 2000). It measures the radiations emitted from the surface of the object. Although, the thermal wavelength region ranges from 3µm to 35µm but still only 8µm to 14µm region is taken into consideration for thermal remote sensing as due to overlap with solar reflection in day imagery from 3µm to 5µm wavelength, data interpretation becomes complicated and the investigation of the 17µm to 25µm is in the development phase (Kant et al., 2009). With the advancement of remote sensing technology, various airborne and satellite-based thermal sensors (Table 2) have been developed and are being used in agricultural applications either directly or indirectly.

Table 2: Thermal infrared sensors {modified from (Khanal et al., 2017).

Sensors	Wavelength (µm)	Waveband (thermal)	Spatial Resolution (m)	Temporal resolution (days)	References
Satellite					
AATSR/ ENVISAT	11.0–12.0	6–7	1000	1	(Llewellyn-Jones et al., 2001)
ABI/GOES-R	10.1–13.6	13–16	2000	Hourly	(GOES-R, 2020)
ASTER	8.125–11.65	10–14	90	16	(NASA, 2020a)
AVHRR	3.5–3.93	3	1100	0.5	(NOAA, 2020)
	10.50–12.5	4–5			
CBERS	10.4–12.5	4	80	26	(CBERS, 2020)
Landsat 4-5TM	10.40–12.50	6	120	16	(USGS 2020)
Landsat 7 ETM+	10.40–12.50	6	60		
Landsat 8	10.60–11.19	10	100		
	11.5–12.51	11			
MODIS	3.66–4.55	20–25	1000	1	(NASA, 2020b)
	8.4–14.08	29–35			
Airborne					
ATLAS	8.32–12.02	10–15	10	-	(Lo et al., 1997)
TIMS	8.2–12.2	1–6	50	-	(Kealy and Hook, 1993)

3. UAVs in precision agriculture

With the development of unmanned aerial vehicles (UAVs) or drones, remote sensing in agriculture became easier and cheaper and come under the reach of most of the farmers providing unaltered datasets of high spatial, temporal and spectral resolution (Colomina and

Molina, 2014). Yamaha developed the first UAV for agricultural purpose and continued its production till 2007 (Giles and Billing, 2015). The hardware implementations of UAVs in agriculture depend on several major aspects like weight, payload, range of flight, configuration and their costs (Mogili and Deepak 2018). These are efficient to cover hectares of fields in a single flight. Thermal and multispectral cameras are used to record the reflectance of the canopy (Bendig et al., 2012; Colomina and Molina, 2014). Figure 2 discusses the schematic overview of various platforms used in precision agriculture. The suitability of sensors in UAV remote sensing in the field of precision agriculture is summarized by (Maes and Steppe, 2019) in Table 3.

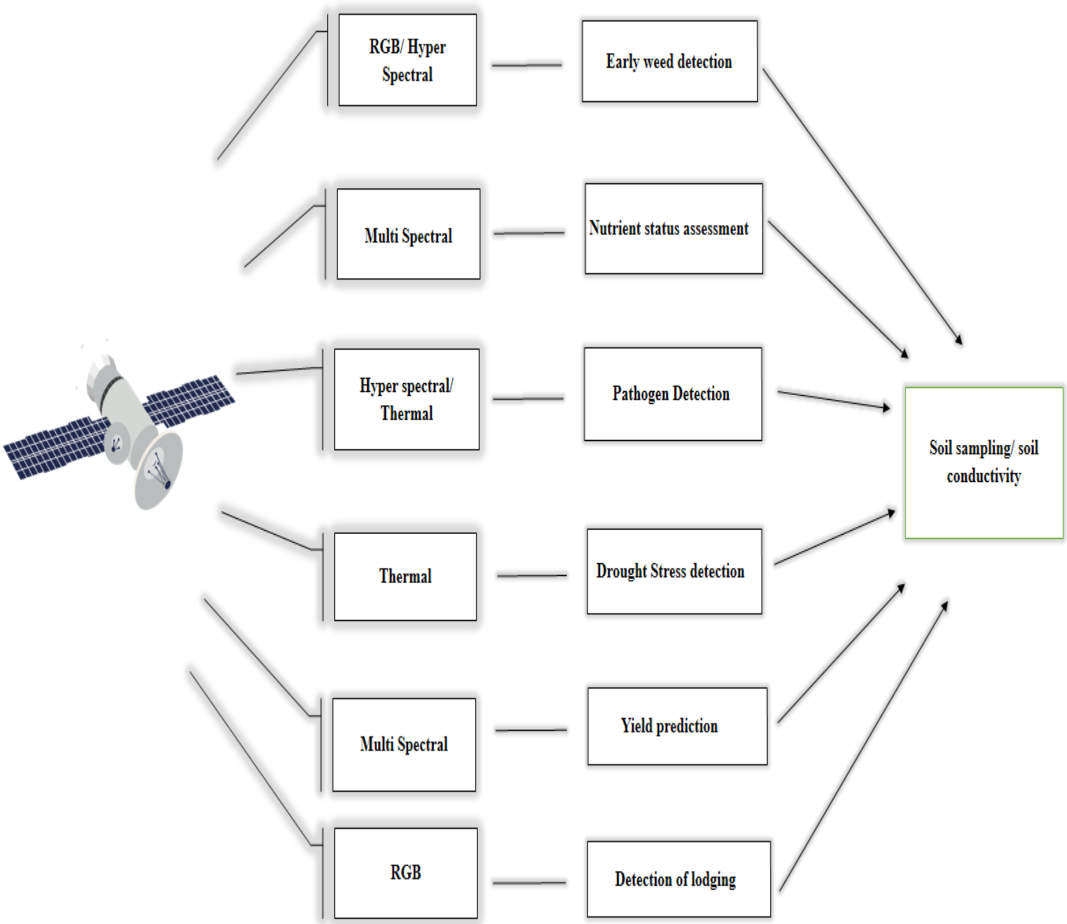

Figure 2: Schematic overview of various platforms used in precision agriculture (Maes and Steppe 2019)

Table 3: Overview of Applications and Suitability of Different Sensors (modified from Maes and Steppe (2019).

Application		**Type of sensor/camera**			
		RGB	**Multispectral (broadband)**	**Hyperspectral (narrowband)**	**Thermal**
Drought stress	**Detection in early stages**	-	-	-	highly suited
	Long-term consequences	-	highly suited	highly suited	suited
Pathogen detection	**Detection in early stages**	-	-	highly suited	highly suited
	Severity of infection	highly suited	highly suited	highly suited	suited
Weed detection	**Spectral discrimination**	-	suited	highly suited	-
	Object-based	highly suited	highly suited	-	-
Nutrient status	**-**	suited	highly suited	highly suited	suited
Growth vigor	**Growth stage**	highly suited	-	-	-
	Canopy height and biomass	highly suited	highly suited	-	-
	Lodging	highly suited	-	-	suited
Yield prediction	**-**	suited	highly suited	-	-

4. Applications of remote sensing techniques in agriculture

Remote sensing techniques are used in the field of agriculture for various purposes like crop classification, monitoring, yield estimation, identifying soil characteristics and precision farming practices. It is based on the interaction between sensors that can detect electromagnetic radiation and objects. The spectral reflectance curve of remotely sensed images helps in crop monitoring, yield area estimation and crop identification (as each crop has its spectral signature). The remote sensing applications in agriculture are mainly classified based on the platform used for the sensors (such as satellite, aerial, ground-based platforms).

4.1. Crop identification

Crop identification and its classification are done to prepare maps with different crop types which are beneficial for crop production inventory and crop acreage (Sesha Sai et al., 2013). For the identification of crops multispectral and multitemporal data are used with supervised or unsupervised classification techniques. Through accurate crop maps, agricultural monitoring and decision-making can be done at wider spatial scales (Kussul et al., 2015; Löw and Duveiller, 2014) to improve cropland management and support in policymaking

(Davidson et al., 2017). Various vegetation indices are used with the multi-temporal image classification (Hentze et al., 2016; Liu et al., 2016; Siachalou et al., 2015; Yan et al., 2015) to identify croplands and crop types (Hao et al., 2016; Marais Sicre et al., 2016; Ghazaryan et al., 2018).

4.2. Crop monitoring

For sustainable use and preservation of food, it is necessary to monitor the crop condition precisely and frequently (Kalpana et al., 2003). Crop monitoring is an advancement in remote sensing. It is mainly focused on the individual's physical parameters and different indices of the crop (Nellis et al., 2009). It helps the farmers in detecting the places where the growth is moderate or slow and allows them to take adequate measures. It, thus, not only increase productivity but also reduces the input cost. Images acquired throughout the crop season will not only help in detecting the problem but also monitor the success ratio of the treatment done on it.

4.2.1. Nursery monitoring

A nursery is a place where plants are grown in open fields or greenhouses till their maturing age. Seed monitoring through remote sensing allows the farmers to identify the individual viable and non-viable seeds before use (Kranner et al., 2010). The thermal profile of seeds is used to detect pernicious changes in temperature which varies with feasibility. This enables the detection of viable seeds from non-viable seeds (Kranner et al., 2010; Zhang et al., 2012). In nurseries, infrared thermography can be applied to detect seedlings viability, physical damage, disorders and evaluation of the growth progress of seeds, seedlings and plants (Hellebrand, Beuche, and Linke 2002; Kim and Lee 2004; Ljungberg and Joensson 2002; Ishimwe, Abutaleb, and Ahmed 2014).

4.2.2. Bruise detection

Damages on the surface of fruits and vegetables due to any external factors like transportation and handling (Manickavasagan et al. 2005) which cause a physical change in texture, color, smell and taste is termed as a bruise (Mohsenin 1986). Multispectral and hyperspectral NIR-based techniques can be used efficiently for bruise detection (Quansheng and Vittayapadung, 2008; Wen and Tao, 2000). Thermal imaging is preferred over NIR-based detection as it may get affected by the varied skin color or illumination setup (Varith et al., 2003).

4.2.3. Crop-water stress monitoring

Using thermal images, crop-water stress can be identified by monitoring canopy temperature and conductance. To detect crop water stress, (Jackson et al. 1981) evaluated the crop water stress index (CWSI).

$$CWSI = \frac{(T_c - T_a) - (T_c - T_a)_{LL}}{(T_c - T_a)_{UL} - (T_c - T_a)_{LL}}$$

Here, T_a denotes air temperature, T_c denotes canopy temperature, LL and UL are lower and upper limits respectively. Several formulations are there which vary according to the approach applied to determine UL and LL (Agam et al., 2013; Gonzalez-Dugo et al., 2014; Gonzalez-Dugo et al. 2013) recommended that temperature measurement of shaded leaves is much reliable indicator of leaf temperature.

4.2.4. Disease and pathogen detection

It can prove crucial for farmers and agricultural managers if plant diseases and insect infestation is detected early. It can reduce the loss due to these threats and erstwhile support the economy (Teke et al., 2013). The physiological state of the infected tissue during pathogenic infection is altered and causes changes in photosynthesis rate, transpiration, stomal conductance and can even cause cell death (Xu et al., 2006). Foliar pathogens such as leaf spots or rusts which often influence the entire plant or plant organs (Mahlein, 2016) can be directly detected by advanced optical sensor technology. For pre-symptomatic diagnosis of biotic stresses, thermal imaging is an exceptional choice for providing information before the emergence of visible necrosis on leaves by visualizing and analyzing the difference in temperature between infected and non-infected leaves (Ishimwe, Abutaleb, and Ahmed, 2014). Thermal sensors are way far effective in the detection of disease-induced early changes in plants respiration, transpiration and leaf temperature as compared to optical, multispectral and hyperspectral sensors (Mahlein, 2016; Mahlein et al., 2012; Stoll et al., 2008). However, hyperspectral remote sensing is an economical and powerful option for learning the spatial distribution of invasive plant species (Evangelista et al., 2009). The structure and chemical composition of the tissues during pathogenesis is highly pathogen-specific and thus influences the reflectance (Maes and Steppe, 2019).

4.3. Soil characteristic mapping

It is beneficial in agricultural management and development to understand various characteristics of the soil. In past, soil sampling and analysis were done to study the soil characteristics which were very slow and unable to provide required information efficiently (Zribi et al. 2011). Some of the soil quality parameters are explained below.

4.3.1. Soil salinity detection

Soil salinity causes severe degradation in the environment that disrupts crop growth and global-regional production (Abbas et al., 2013). For augmentation of soil affected with salinity, it is requisite to identify the soil type, exact location and affected area. It is expedient in interpreting salt-affected areas through optical remote sensing techniques (Saha, 2011). However, thermal imageries can also be used for the extraction of soil salinity as emitted radiance can provide subsoil information that cannot be harnessed through reflected radiation (Ben-Dor et al., 2008).

4.3.2. Soil moisture detection

Soil serves as a solvent as well as a carrier of nutrients needed for plant growth, it also regulates temperature, influences farm operations, supports microbial activities and performs as a nutrient itself. Hence, monitoring soil moisture from time to time is a necessity (Ramachandra, 2006). (Shafian and Maas, 2015) used raw digital count data in the visible-red, NIR and thermal bands from Landsat satellite images to develop the perpendicular soil moisture index (PSMI) which is correlated with observed soil moisture.

4.3.3. Soil texture analysis

Soil texture is a property of soil that can indicate other physical and chemical properties of soil like soil grain structure, hydraulic properties, porosity, nutrient retention ability, etc. that influence crop productivity. It also influences soil water content which in turn affects the land surface temperature (Mattikalli et al., 1998). (Wang et al., 2015; De-Cai et al., 2012) demonstrated the use of thermal remote sensing to evaluate soil texture at a regional extent by analyzing the differences in land surface temperature in a relatively similar climatic condition.

4.4. Precision farming practices

Precision agriculture is the management of farms by observing and giving responses to various changes in the intra field to increase the returns on inputs without changing the resources. It helps to locate the exact position of the field and is based on remote sensing technology, GIS and GPS/GNSS technology. Precision agriculture opposes conventional farming practices of equally applying the herbicide, pesticide and fertilizers in the whole area without observing the variability within the area. The advancement of remote sensing technology and reduction in the cost of sensors enabled the farmers to harness precision agriculture practices. NASA accentuated the importance of these technologies in the early decade of the current century and emphasized commercializing geospatial technologies and developing tools for producers and agricultural managers (Nellis et al., 2009).

4.4.1. Irrigation scheduling

Agricultural production needs water to meet crop water demand which is done through irrigation as non-availability of rainfall in every season (Pinter Jr et al., 2003) By maintaining the irrigation efficiency, farmers can maximize their profit. There are primarily four factors that quantify the need for irrigation i.e. crop water need, amount of precipitation, the efficiency of irrigation system and soil moisture (Rhoads and Yonts, 2000). (Panigada et al., 2014) states that by combined use of hyperspectral indices, fluorescence and thermal images good results can be insured for irrigation scheduling and crop-water stress identification.

4.4.2. Crop yield estimation

Estimation of crop yield is one of the most significant sectors of precision farming techniques that can offer the greatest benefit. It can help farmers with decision-intensive work like crop insurance, harvesting, storage requirements and cashflow budgeting (Khanal et al., 2017). Crop yield is closely related to the electrical conductivity of soil which further determines the characteristics and texture of soil (Bajcsy and Groves, 2004). The studies done by (Yang, 2009) showed that airborne multispectral and hyperspectral images can be used efficiently in the determination of the spatial patterns in the plants’ growth and yield before harvesting. Airborne images give better results than satellite images due to their finer spatial resolution (Teke et al., 2013).

5. CONCLUSION

This review paper has concisely discussed the current advancement and potential application of remote sensing in precision agriculture. These potential applications are soil characteristic mapping, precision farming practices, soil salinity detection, disease and pathogen detection, crop-water stress monitoring**,** crop monitoring, irrigation scheduling, soil texture analysis, soil moisture detection and soil texture analysis. Precision agriculture can potentially reduce the use of chemicals in crop production, efficient use of water resources, and helps in cost reduction in various agricultural processes by combined use of remote sensing GIS and GPS technology. UAV technologies and stress to achieve greater precision in agriculture act as a catalyst for increased integration of remote sensing in agricultural decision-making.

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