Review Article

Remote sensing related tools and their Spectral indices applications for Crop management in Precision Agriculture

ABSTRACT

World population increasedrapidly has increased food demands for human and fulfill the food requirements with limited available resources of the planet is a big challenge for Agriculture. Farmers will need to increase the food production, either the increasing the agricultural land or enhancing crop productivity in agriculture by using different crop management practices and adopting new methods like precision farming. Concept of precision agriculture that involves integrating new technologies and field data to accomplish the right input at the right time in the right place. However, the agricultural sector is yet to adopt remote sensing technologies fully due to lack of knowledgeon their sufficiency, appropriateness andtechno-economic feasibilities. This study based on the research literature that focusedon the application of remote sensing tools in precision agriculture on different aspect of crop management from field preparation to crop harvesting, with the objective of contributing to the scientificunderstanding on the potential for RS technologies to support decision-making within differentproduction stages. Remote sensing tools and spectral vegetation index (normalized difference vegetation index& others) to support crop management and decisions making at different crop growth stages of crop production in precision agriculture, ranging from field preparation, weather, insect pest management, biotic & abiotic stress management and in-season crop health monitoring to harvest.

Keywords: Precision agriculture,Remote sensing, Vegetation indices, NDVI, Crop management.

1. INTRODUCTION

Precision agriculture is a novel idea in agriculture that combines numerous information-based technologies to improve precision in assessing farm variability and input application, resulting in higher farm profit and reduced environmental concerns [1]. The philosophy underlying the use of precision agriculture-based management systems is that all production inputs should be used only as needed depending on the field's spatial and temporal variability in order to achieve the most cost-effective crop yield. Precision agriculture aims to increase agricultural output while lowering production costs on the one hand and reducing environmental concerns related with crop production systems on the other, in order to accomplish the goal of sustainability [2].

- Precision agriculture is an approach where inputs are utilized in precise amounts to get increased average yields compared to traditional cultivation techniques.

- It is a management strategy that uses information, technologies to collect valuable data from multiple sources which factor into the decision-making process.

- Information and technology-based farm management system to identify, analyze and manage spatial and temporal variability within fields for optimum productivity and profitability, sustainability and protection of the land resources by minimizing the production costs [3].

2. PRECISION AGRICULTURE

Precision agriculture, often known as precision farming, is a concept that involves integrating new technologies and field data to accomplish the right thing at the right time in the right location [4]. In the 1980s, remote sensing was first employed in precision agriculture applications, and it is now widely used all over the world [5]. Precision agriculture collects and processes a lot of data and information in real time and location to make better use of farm inputs, which leads to better crop output and environmental quality [6]. Precision agriculture is based on advanced tools and information provided by modern technologies such as remote sensing (RS), global positioning system (GPS), geographic information systems (GIS), variable rate technologies for input applicators and yield mapping tools, soil, plant, and pest sensors, and soil, plant, and pest sensors [7].

Precision agriculture requires breakthroughs in computer processing, field positioning, yield monitoring, remote sensing, and sensor design, as well as data collection/analysis and information management [8]. More than 30% of future growth in US agribusiness (jobs, sales, exports, etc.) is expected to come from farmers' increased adoption of precision agriculture [9], including increased demand for both information management services and technological advances such as global positioning system (GPS) auto steer guidance (eg. Real Time Kinetic technology), variable rate irrigation, fertilizer and sprayer controllers, robotics, and real-time data [9].

Precision agriculture strives to maximized production while reducing environmental damage [10]. Precision agriculture is an integrated agricultural management system that uses a variety of technology instruments such as GPS, GIS, and remote sensing. Precision agriculture is intended to boost overall agricultural production efficiency while minimizing the negative effects of chemical use on the environment [11]. Specifically, Precision agriculture is a management strategy that employs information technology to improve agricultural quality and production. PA differs for traditional farming in the sense that this process accurately identifies variations and relates the spatial data to management activities. Precision agriculture involves five stages, namely, (i) data collection, (ii) diagnosis, (iii) data analysis, (iv) precision field operation, and (v) evaluation.

2.1 Prospects of precision agriculture in Indian agriculture situation

- India is over populated country and by precision agriculture we can produce more by using available resources to feed these populations not only in quantity but also can provide them nutritious food.

- Precision agriculture helps to produce and improve crops at minimum cost which is very essential for India as it is developing country where money or investment is a very big problem.

- In India, precision agriculture has great prospect as our country in highly natural calamity sensitive country and through it we can easily take measure to prevent our agricultural products from damage caused by natural calamities.

2.1.1 Agronomical perspective: Precise application of inputs as per the crop requirements leads to increases crop yield and quality. Further the use of agronomical practices like selection of suitable crop varieties, the application of optimum quantity of nutrients, pesticides and herbicides, and appropriate irrigation management to meet the demand of crops for optimum growth and development attributed to higher crop yield, especially in areas where traditionally practiced crop management practices were adopted.

2.1.2 Technical perspective: Precision agriculture allows efficient time management through acquire accurate information, which is processed and analyzed in decision making for land preparation, seeding, fertilizer, pesticide and herbicide application, irrigation and drainage, and post-production activities. Farmers can also accumulate knowledge about their farms and production systems to achieve better management.

2.1.3 Environmental perspective: The timely application of agrochemicals at ac curate rates avoids excessive residue in soils and water and thus reduces environmental footprints. Economical perspective: Application of precision farming can reduce cost of production by efficient use of farm inputs, labor, water etc.

2.2 Needs of remote sensing for Precision Agriculture

While remote sensing has been extensively and consistently utilized for large-scale crop inventory and production estimates [12], it has yet to make major inroads into precision farming. Precision farming necessitates the collection of crop condition data on a regular basis and at high spatial resolution throughout the growing season. Satellite sensors were insufficient until recently to give regular coverage at the resolutions necessary. Unlike large-scale crop inventory, the farmer is the one who is most interested in using pictures. Farmers have no idea what is accessible, how to interpret it, or how much it is worth. There are few cost-benefit analyses available to persuade the average farmer of the advantages of remote sensing. Crop advisors and extension agents are also ignorant of the technology. Because end consumers are rarely involved in product creation, there is a disconnect between what they want and what they get. Precision farmers are conversant with GIS and GPS technologies, but often lack the skills to extract data from imagery. Image-processing software is costly and created separately, resulting in compatibility issues with other geospatial tools. Most significantly, because agriculture is such a dynamic industry, satellite-derived products and information must be sent to farmers in near real time. This is a rare occurrence. Finally, the farmer's bottom line is profitability. The sooner new technologies are disseminated and used, the higher their potential profitability [13]. Precision agriculture has a lot of potential for merging historical remote sensing data with real-time data for better agricultural management [14].

3. REMOTE SENSING IN AGRICULTURE

The science of gaining information about an object through the analysis of data obtained by a device that is not in contact with the object is known as remote sensing [15]. In other words, remote sensing is the science of gathering and evaluating information about the environment using sensors that are not in physical touch with the environment (National Remote Sensing Centre - UK) [16]. The phrase "remote sensing" refers to a group of techniques for detecting the chemical or physical qualities of physical objects at any distance by recording, measuring, and interpreting images and digital representations of energy patterns generated by non-contact sensor systems [17].

The interaction of electromagnetic radiation released by the sun with soil and plant material is the basis for remote sensing in agriculture. Sensors are the instruments that are used to measure electromagnetic radiation. Sensors, film cameras, digital cameras, and video recorders may be used to collect data from various platforms such as satellites, aircrafts, drones, tractors, and in the form of manual handheld radiometers [5]. Some of the remote sensing satellites sensor and their application in agriculture was showing in table 1. Instead of measuring transmitted and absorbed electromagnetic radiation, optical remote sensing sensors monitor the incoming electromagnetic radiation from the sun and the present of electromagnetic radiation reflected by the earth's surface materials. The physical and chemical composition of the material existing on the earth's surface to which solar radiation is incident determines the degree of absorption, reflection, and transmission. Refection spectra, or characteristic refection curves, are the outcome of this. With the help of these spectra, which plot the refection against the wavelength of electromagnetic radiation, we may detect the materials present on the surface and partially characterize their condition.

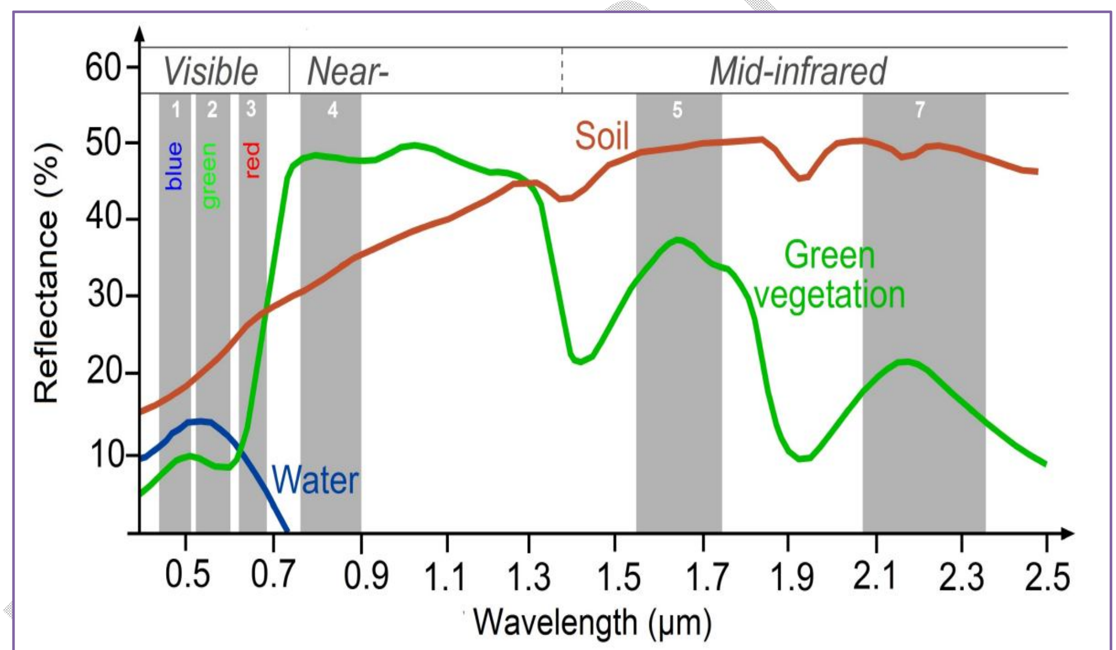

Fig. 1. Spectral response curve of clear water bodies, soil surface and greenvegetation as a function of different wavelengths ranges from visible to Mid-Infrared. (Source: SEOS project (http://www. seos-project.eu/home.html.))

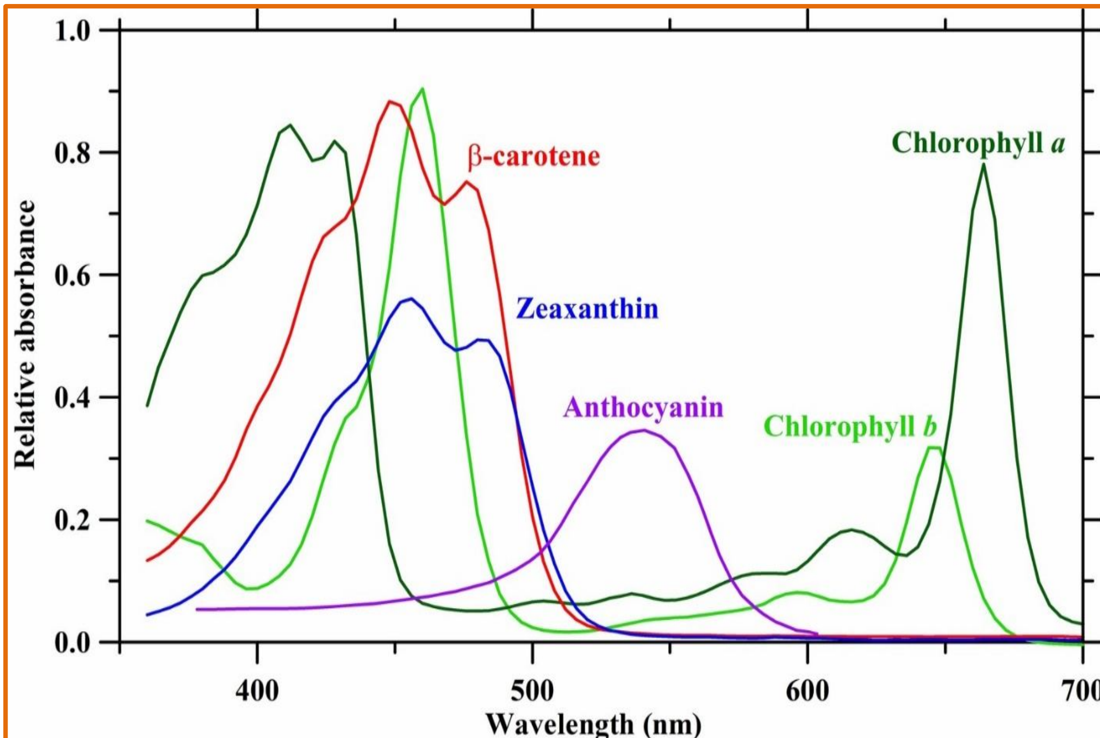

Fig. 2. Absorbance spectra of plant photosynthetic pigments at different wavelengths ranges [19]

Spectral signature of vital vegetation differs from dry vegetation, water and soil (Fig.1) showed that the water bodies were absorb more effectively all wavelengths longer than the visible range while the green vegetation surface has produced a very specific spectral signature. Spectral signature of vegetation is based on the amount of radiation reflected from plants is inversely related to radiation absorbed by plant pigments (chlorophyll a, chlorophyll b, carotenoids) and varies with the wavelength of incident radiation. Plant pigments such as chlorophyll absorb radiation strongly at the visible spectrum from 400 to 700 nm [18]. Figure 2 show the reflectance % is low in the visible range (400-700nm) due to higher absorbance of photosynthetic pigments (Fig.2). In contrast, plant reflectance is high in the near infrared (NIR 700 to MIR 1300 nm) region as a result of leaf density and canopy structure effects. The behavior of the NIR reflectance is also a function of leaf area index (LAI), cell turgor, leaf thickness, leaf internal air and water content.

Table 1. List of some of the sensors and their uses in Precision Agriculture

Satellite	Operational Year	Sensor (Spatial Resolution)	Temporal Resolution	Application in Precision Agriculture
Landsat-1	(1972–1978)	MS (80 m)	18 days	soil organic matter content wheat grain yield [20] Crop growth [21]
AVHRR	(1979–still Operational)	MS (1.1 Km)	1 day	Nutrient management [22]
Landsat 5 TM Landsat 7 Landsat 8 Landsat 9	(1984–2013) (1999-Operational) (2013-Operational) (2021-Operational)	MS and Thermal (120 m)	16 days	Biomass [23]; crop yield [24] Crop loss identification by using NDVI [25]
SPOT 1 SPOT-2	(1986–1990) (1990–2009)	MS (20 m)	2–6 days	Water management [24]
IRS 1A	(1988–1996)	MS (72 m)	22 days	crop identification and yield Assessment [26]
LiDAR	(1995)	VIS (10 cm)	N/A	nutrient Geography management [27]
Radar SAT	(1995–2013)	C-band SAR (30 m)	1–6 days	Crop advancement [28]
IKONOS	(1999–2015)	MS (3.2 m)	3 days	N deficiencies & fungicide performance efficiency [29] nutrient management [22]; ET estimation [30]
EO-1 Hyperion	(2000–2017)		16 days	Disease screening [31,32]
Terra MODIS Aqua MODIS	(1999– still Operational) (2002- still Operational)	MS (Spectro Radiometer; 250–1000 m)	1–2 days	Plant yield [33]; crop growth [34], Drought assessment [35]
Terra-ASTER	(2000– still Operational)	MS and Thermal (15 m–V, NIR, 30 m–SWIR, 90 m–TIR)	16 days	Water of management [36]
QuickBird	(2001–2014)	MS (2.44 m)	1–3.5 days	Disease identification [37]
AQUA AMSR-E	(2002–2016)	MS (Microwave Radiometer; 5.4 km–56 km)	1–2 days	Water of management [38]

Spot-5	(2002–2015)	MS (V, NIR–10 m, SWIR–20 m)	2–3 days	Crop growth [39]
ResourceSat-1	(2003–2013)	MS (5.6m–V, 23.5 m–SWIR)	5 days	Nutrient management [40]
KOMPSAT-2	(2006- Operational)	MS (4 m)	5.5 days	Seed yield [41]
Radarsat-2	(2007-2020)	C-band SAR (1–100 m)	3 days	LAI and biomass accumulation [42]
Rapid Eye	(2008–2020)	MS (6.5 m)	1–5.5 days	Water supervision [43]; crop yield [44]; crop growth and chlorophyll [45] Leaf area Index[46]
GeoEye-1	(2008- Operational)	MS (1.65 m)	2.1–8.3 days	Nutrient monitoring [47]
WorldView-2	(2009- Operational)	MS (1.4 m)	1.1 days	Crop development [48]
Pleiades-1A Pleiades-1B	(2011–present) (2012– present)	MS (2 m)	1 day	Crop evolution [49,50]
VIIRS Suomi-NPP VIIRS-JPSS-1	(2011–present) (2017–present)	MS (IR Radiometer, 375 m and 750 m)	16 day (repeat)	Crop management (NDVI [51]
Spot-6 Spot-7	(2012–present) (2014–present)	MS (6 m)	1-day	Disease indication [52]
SkySat-1 SkySat-2	(2013–present) (2014–present)	MS (1 m)	sub-daily	Crop growth [53]
Worldview-3	(2014–present)	SS (1.24 m)	<1 days	Crop advancement [54]; weed management [47]
Sentinel-1	(2014–present)	C-band SAR (5–40 m)	1–3 days	Crop growing [53]
Sentinel-2	(2015–present)	MS (10 m–V and NIR, 20 m–Red edge and SWIR, 60 m–2 NIR)	2–5 days	Yield of plants [54]; N management [55]
KOMPSAT-3	(2012)	MS (2.8 m)	1.4 days	Crop development [56]
KOMPSAT-3A	(2015–present)	MS (V NIR–2.2 m, SWIR–5.5 m)		Disease [57]
SMAP	(2015–present)	L-band SAR (1–3 km) and radiometer (40 km)	2–3 days	Crop yield [58]; water management [59]
TripleSat	(2015–present)	MS (3.2 m)	1 day	Crop progress [60]
ECOSTRESS-PHyTIR	(2018 –present)	Thermal (38 × 69 m)	1–5 days	ET [61]
FORMOSAT-2	2004	MS (Blue,Green, Red, NIR)(2 m)	Daily	Nitrogen Status and leaf area index (LAI) [62]

Resourcesat-2 Resourcesat-2A	2011 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	Crop management [51]
Cartosat-1 Cartosat-2 Cartosat-2A	2005 2007 2009	Panchromatic (0.5–0.85 µm) Cartosat 1: (2.5m) Cartosat 2, 2A: (0.8 m)	5	Crop yield [58]

4. VEGETATION INDICES

VIs (vegetation indices) are mathematical combinations or ratios of spectral bands, primarily red, green, and infrared, that are used to establish functional correlations between crop features and remote sensing observations [63]. The interaction of solar radiation with crop photosynthesis greatly influences vegetation indices, which are indicative of the dynamics of biophysical parameters connected to crop state. However, at early stages of crop development, the impacts of soil reflectance have an impact on the values of various vegetation indices used to detect crop stress [64]. Vegetation indices are spectral indices that describe the volume, density, health, and vitality of vegetation. The normalized difference vegetation index (NDVI) scale ranges from -1 to +1, and it is favorably associated to a substantial amount of high-quality vegetation (the larger value of the NDVI, the more abundant and healthier the vegetation). Several studies reveled that the application of NDVI and other spectral indices for measuring the leaf chlorophyll content [65] and relative water content of crop plants, which can provide the data concerning the physiological status of a plant [65].

Daughtry et al. [66] classified vegetation indices into two categories: first, intrinsic vegetation indices that include the ratios of two or more bands in the visible and near-infrared wavelengths; these indices are sensitive to soil background reflectance and can be difficult to interpret at low Leaf Area Index (LAI) [66; 67]. The soil-line VIs is the second type, and they employ the information from a regression line in the NIR-Red space to lessen the effect of the soil on canopy reflectance. Some of vegetation index and their potential uses in precision agriculture showed in table 2.

Table 2. Some resent use of Spectral vegetation indices and their application in crop management and the related estimated morphological or physiological traits in precision agriculture.

Index	Formula	Applications in agriculture
Normalized Difference Vegetation Index (NDVI)	(R830 – R670)/(R830 + R670)	Physiology [68] Plant health, Yield [69]
Normalized difference red edge index (NDRE)	(RNIR−Rred edge)/(RNIR+Rred edge)	Plant stress detection [70], Nitrogen and water status [71]
Green Normalized difference vegetation index (GNDVI)	(R750-R550) / (R750 + R550)	Chlorophyll [72]
Ratio index (RI-1 dB)	R735/R720	Chlorophyll [73]
Photochemical Reflectance Index (PRI)	(R531 - R570)/(R531+R570)	Physiology Photosynthesis [74]
Normalized Photochemical Reflectance Index (PRInorm)	PRI / [RDVI×(R700/R670)]	Chlorophyll fluorescence Stomatal conductance [75,76]
Plant Senescence Reflectance Index (PSRI)	(R678 - R500)/R750	Chlorophyll/Carotenoids Senescence [77]
Modified Chlorophyll Absorption in Reflectance Index (MCARI)	[(R700 - R670) - 0.2 * (R700 - R550)]* (R700/R670)	Green leaf area index Chlorophyll [78]
Red edge Chlorophyll index (CI red-edge1)	[(R750-R800)/(R695-R740)]-1	Chlorophyll [79]
Normalized difference water index (NDWI)	(R857 – R1241)/(R857 + R1241)	Leaf water potential [80]

Green index (GI)	R554/R677	Crop greenness and stress identification [81]
Modified normalized difference vegetation index (mNDVI)	(R800 – R680)/(R800 + R680 – 2R445)	leaf pigment content [82]
Triangular vegetation index (TVI)	0.5 [120(R750 – R550) – 200(R670 -R550)]	green leaf area index and canopy chlorophyll density [83]
water index (WI)	R970/R900	Leaf water potential [84] Yield of wheat under water stress [85]
normalized water index-1 (NWI-1)	(R970−R900)/(R970+R900)	Grain Yield & biomass yield of wheat under water stress [85] LAI[86]
normalized water index-2 (NWI-2)	=(R970−R850)/(R970+R850),	Yield [85]
normalized water index-3 (NWI-3)	(R970−R920)/(R970+R920)	Yield [85]
Enhanced Vegetation Index (EVI)	2.5*(RNIR−RRed)/(RNIR+6RRed−7.5RBlue+1)	Disease [87] yield [69]
Plant Pigment ratio (PPR)	(Rgreen − Rblue)/(Rgreen + Rblue)	Chlorophyll [88]
photosynthetic vigour ratio	(R550−R650)/(R550+R650)	Identification of healthy and stressed plants
Gitelson and Merzlyak index (GMI)	R750/R550	Chlorophyll [89]
Carter index 1 (Ctr1)	R760/R695	Stress [90]
Copper Stress Vegetation Index (CSVI)	R550/R850 ×R700/R850	Copper content [91]

New Vegetation Heavy Metal Pollution Index (VHMPI)	DCR505 - DCR640/ DCR690 -DCR730	Copper content [92]
Heavy Metal Cd Stress-Sensitive Spectral Index (HCSI)	(R780-R712)/R678 × (R678/R550)	Cadmium content [93]
Heavy Metal Stress Sensitive Index (HMSSI)	CI(Red−edge)/PSRI	Cadmium, lead and mercury Contents [94]

5. APPLICATIONS OF REMOTE SENSING IN PRECISION AGRICULTURE

Crop condition and yield forecasting, acreage estimates of specific crops, detection of crop pests and diseases, disaster location and mapping, wild life management, water supply information and management, weather forecasting, range land management, and livestock surveys all benefit from remote sensing techniques [95]. When Bhatti et al. [96] used Landsat imagery of bare soil to estimate spatial patterns in soil organic matter content, which were then used as auxiliary data along with ground-based measurements to estimate spatial patterns in soil phosphorus and wheat grain yield, it was the first application of remote sensing in precision agriculture. Remote sensing of plant ripeness[97] can give the farmer the opportunity to make decisions about the optimal harvest time. The estimation of yield [98] and yield potential [99] are also useful applications in precision farming. In agricultural remote sensing, radar data can be utilized to make a variety of claims. Radar systems are not affected by cloud cover, and they actively broadcast a signal that is received after a variety of scattering. Radar data is utilized in agriculture for phenology determination [100], soil moisture determination [101], and biomass estimation [100; 102].

5.1 Mapping of Cropping area and Yield Forecasting

The cropping area was determined using remote sensing and satellite data, and the projected crop output was forecasted across a certain cropping area, as well as how much of the crop would be harvested under specific conditions. The quantity of produce in a specific farmland over a given period can be predicted using remote sensing data. Crop yields have been forecasted using remote sensing, generally based on statistical–empirical connections between yield and vegetation indices [103]. Walsh et al. [104] conducting research on winter wheat, using ground-based spectra to forecast yield at the beginning of shooting stage Many researchers are concluded their research that the developmental phase of plants, as a critical component of yield forecasting [105;106], Leaf area and evapotranspiration [107]. For instance, the most accurate yield forecasts of winter oilseed rape were achieved when the spectral measurements were performed in the phase of full budding of the crop [108]. However, Piekarczyk et al. [106] showed that the strongest relationship between the spectral data and the winter rape yield was obtained at the beginning of the flowering stage, while wheat yields were most accurately predicted when the plants were in the shooting phase.

Each plant species' yield is determined by a number of complicated elements, including crop type, soil type, weather events, soil fertility, water supply, nutrient supply, and the duration of sunlight throughout the season, as well as the quantity of seeds. The grain yield of cereals, for example, cannot be determined directly from satellite data, thus proxies such as biomass [109], leaf area index (LAI) [110; 111], or chlorophyll content are used instead [112; 113]. The Normalized Diference Vegetation Index (NDVI), Normalized Diference Red Edge Index and Enhanced Vegetation Index are commonly used to represent these proxies [114].

5.2 Abiotic Stress Identification

Plant stress detection is critical for enhancing agricultural yield and productivity so that enough food can be produced to sustain the world's rapidly growing population. Water stress, salinity, temperature, nutrient availability, pests, and diseases are all factors that affect plant productivity. Remote sensing and geographic information systems (GIS) are becoming increasingly important in agricultural drought detection, assessment, and management because they provide up-to-date information in a variety of spatial and temporal scales that is difficult and time-consuming to obtain using traditional methods such as field surveys and questionnaires [115]. Changes in vegetation cover and soil moisture, according to Wan et al. [116], were mostly attributable to changes in vegetation cover and soil moisture, and indicated that the surface temperature can rise fast with water stress at multiple scales (25m2 to 1.2km2). As a result, it's easy to see how the LST/NDVI ratio rises during droughts.

5.3 Application in Plant physiology

Chlorophyll content may be determined remotely, which is a useful tool for detecting physiological states and stress in plants [117]. Sellers [118] investigated the relationships between spectral vegetation indexes and leaf area index (LAI), absorbed Photosynthetically Active Radiation (PAR), and photosynthetic capability in canopies. When background reflectance (eg. soils, water) is minimal, ratios of near-infrared and visible reflectance’s (e.g. simple ratio or NDVI) are predicted to be a near linear indicator of minimum canopy resistance and photosynthetic capacity, but a poor predictor of Leaf Area Index or biomass, according to his research [119].

5.4 Identifying the Effect of Climate change on Agriculture

Climate change is currently one of the most complicated global challenges. Climate change has resulted in temperature shifts, heat waves as a result of increased greenhouse gas levels in the atmosphere, changes in weather patterns, and rainfall uncertainty, which has resulted in frequent droughts and higher precipitation. Agriculture sustainability has been harmed by global climate change, which has resulted in poorer agricultural yields, a threat to food security, and food and feed safety.

5.5 Irrigation Water Management

Agriculture farming systems serve a critical role in maintaining crop water status, reducing crop water stress, and attaining optimal crop growth and yield by controlling irrigation time and rate. Most small farmers use various irrigation water management practices in today's agricultural systems, which are influenced by a variety of factors such as irrigation water availability, irrigation system type, local/regional water laws, farmers' economic status, farm size, previous knowledge and experience with farmer soils, and climate at the location [120]. Irrigation water management is used by large landowners and commercial farmers, who install automatic or manual soil moisture monitoring systems based on measured soil moisture data and crop water requirements [121].

With commonly used irrigation systems like a Centre pivot, remote sensing data can help determine the variations within the field and apply variable rate watering. [122; 123] Variable rate application can assist minimize water stress resulting from extreme wet and dry conditions to generate uniformly high yields in all regions of the field while lowering water and nutrient losses. Various indicators of crop water status in plants and soil, such as ET [124], soil moisture [125], and crop water stress, are determined using remote sensing data and photos (collected multiple times over a growing season).

5.6 Integrated Disease and Pest management in Agriculture

Recent satellites with multispectral and hyperspectral sensors on board provide huge volumes of data in a cost-effective manner and at higher spatial and spectral resolution, which can be utilized to detect pests and disease infection. The most efficient uses of space data for pest identification are in forestry and some plantation crops where pest damage has a wide spatial spread. Several studies have shown that hyperspectral imaging may be used to diagnose pest and disease infestations in vegetable crops [126; 127], rice and castor [128], and citrus canker disease [128; 129]. Mirik et al. [130] used the maximum likelihood classifier method to distinguish between healthy and diseased (streak mosaic) wheat fields, with overall classification accuracy of 89.47–99.07 percent. Ji et al. [131] looked at how MODIS hyper spatial data may be used to track locust outbreaks in China and found that the NDVI could reliably distinguish between before and after damage for each type of damage. The areas where the NDVI dropped were clearly marked and classified as minor, moderate, or serious damage. The ability of the high-resolution QuickBird satellite to identify and map basal stem rot disease (Ganoderma boninense) in oil palms in a recent study by [132]. Vegetation indices derived from satellite hyperspectral data might be used to identify stress symptoms caused by the cypress aphid (Cinara cupressi Buckton) invasion in central Chile [133].

6. CONCLUSION

In conclusion, a review of prior works provided an extensive overview of Remote sensing tools and their Spectral indices applications in Crop management in Precision Agriculture temporally and spatially around the world, detailing the various applications of remote sensing and their vegetation index at various crop growth stages to predict the vegetation health to mapping the final yield of crop. We found that a majority of research findings were based on remote sensing satellite technologies conducted in developed countries. Recent research studies of remote sensing in agriculture were focused on hyperspectral sensors, followed by multispectral and visual sensors. Our review of prior studies showed the potential of remote sensing tools and spectral index to support crop management and decisions making at different crop growth stages of crop production in precision agriculture, ranging from field preparation, weather, insect pest management, biotic & abiotic stress management and in-season crop health monitoring to harvest.

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