www.ThePharmaJournal.com

The Pharma Innovation

ISSN (E): 2277-7695
ISSN (P): 2349-8242
NAAS Rating: 5.23
TPI 2023; 12(2): 1124-1130

www.thepharmajournal.com
Received: 23-12-2022
Accepted: 25-01-2023

Akash Barela
Department of Plant Breeding & Genetics, Jawaharlal Nehru Krishi Vishwa Vidyalaya, Jabalpur, Madhya Pradesh, India

Sunny Thakur
Department of Plant Breeding & Genetics, Jawaharlal Nehru Krishi Vishwa Vidyalaya, Jabalpur, Madhya Pradesh, India

Surbhi Pachori
Department of Plant Breeding & Genetics, Jawaharlal Nehru Krishi Vishwa Vidyalaya, Jabalpur, Madhya Pradesh, India

Shivangi Rahangdale
Department of Plant Breeding & Genetics, Jawaharlal Nehru Krishi Vishwa Vidyalaya, Jabalpur, Madhya Pradesh, India

Vinod Kumar Goyal
Department of Plant Breeding & Genetics, Jawaharlal Nehru Krishi Vishwa Vidyalaya, Jabalpur, Madhya Pradesh, India

Sumit Kakade
Department of Entomology, Jawaharlal Nehru Krishi Vishwa vidyalaya, Jabalpur, Madhya Pradesh, India

MK Shrivastava
Department of Plant Breeding & Genetics, Jawaharlal Nehru Krishi Vishwa Vidyalaya, Jabalpur, Madhya Pradesh, India

Corresponding Author:
Akash Barela
Department of Plant Breeding & Genetics, Jawaharlal Nehru Krishi Vishwa Vidyalaya, Jabalpur, Madhya Pradesh, India

Applications of proximal remote sensing in agriculture: A review

Akash Barela, Sunny Thakur, Surbhi Pachori, Shivangi Rahangdale, Vinod Kumar Goyal, Sumit Kakade and MK Shrivastava

Abstract
Agriculture meets humanity's most fundamental needs: food and fibre. New farming practices introduced during the last century (for example, during the Green Revolution) have helped agriculture keep up with rising demand for food and other agricultural goods. However, increased food consumption, a growing population, and rising income levels are all projected to place extra strain on natural resources. With an increasing awareness of agriculture's negative environmental implications, new techniques and approaches should be able to fulfil future food demands while preserving or lowering agriculture's environmental imprint. Emerging technologies such as geospatial technology, the Internet of Things (IoT), Big Data analysis, and artificial intelligence (AI) might be used to make more educated crop management decisions. The use of remote sensing technologies for PA has grown substantially over the last few decades. The unprecedented availability of high resolution (spatial, spectral, and temporal) satellite imagery has encouraged the use of remote sensing in a wide range of PA applications, including crop monitoring, irrigation control, fertilizer application, disease and pest management, and yield prediction. We present an overview of remote sensing systems, methodologies, and vegetation indices, as well as their recent (2015-2020) applications in PA in this study. Remote sensing-based PA technologies, such as variable fertilizer rate application technology in Green Seeker and Crop Circle, are already in use in commercial agriculture. Unmanned aerial vehicles (UAVs) have grown in popularity over the last decade due to their low cost and flexibility in acquiring high-resolution (cm-scale) photographs. At the same time, academics are investigating cutting-edge data storage and processing methods like cloud computing and machine learning due to the accessibility of a significant volume of satellite data. It is crucial to investigate and design an easy-to-use but dependable workflow for the real-time use of remote sensing in PA given the complexity of image processing and the quantity of technical knowledge and skill required. Wider usage of remote sensing technologies in commercial and non-commercial PA applications is anticipated to arise from the development of accurate yet simple-to-use, user-friendly systems.

Keywords: Big data analysis, disease and pest management, nutrient management, satellite remote sensing, UAV, vegetation indices, water management

Introduction
In the twenty-first century, sustainable agricultural systems depend heavily on precision agriculture (PA) (Delgado *et al.*, 2019 and Berry *et al.*, 2003) [17, 9]. Although PA has been defined in a variety of ways, the fundamental idea has not changed (Srinivasan *et al.*, 2006) [64]. In order to improve crop production while lowering water and nutrient losses and adverse environmental effects, PA entails a management strategy that uses a variety of cutting-edge information, communication, and data analysis techniques in the decision-making process (application of water, fertilizer, pesticide, seed, fuel, labour, etc.). Other terms used interchangeably with PA include information-based management, site-specific crop management, target farming, variable rate technology, and grid farming (Srinivasan *et al.*, 2006 and Koch *et al.*, 2004) [64, 34]. In addition to crop production, PA has been employed in the management and production of pasture, livestock, viticulture, and horticulture (Gebbers *et al.*, 2010 and Hedley *et al.*, 2014) [24, 28].

Section 2 describes the types of remote sensing systems covering various sensors and platforms used for PA applications. Section 3 provides a brief overview of remote sensing applications in agriculture with a focus on PA. Section 4 describes some commonly used vegetation indices derived from remote sensing data and their applications in PAs. Section 5 covers remote sensing in PAs for (i) irrigation water management, (ii) nutrient management, (iii) disease management, (iv) weed management, and (v) crop monitoring and yield.

It contains five subsections describing recent applications of Specifically, Section 5 will focus on research published between 2015 and 2020 for review/discussion. The final section of the paper describes the progress achieved, needs and challenges of remote sensing applications in PA.

Applications

Irrigation Water Management

Application time and rate of irrigation play an important role in mitigating crop water stress and achieving optimum crop growth and yield. A variety of irrigation management practices are used by farmers depending on many factors including water availability, existing water management infrastructure at the farm (e.g storage and conveyance system, type of irrigation system), local/regional water laws, economic status, size of the farm, knowledge of farmer, and others (Uphoff *et al.*, 2018 and Pardossi *et al.*, 2009) [69, 49]. Many farmers apply uniform irrigation at regular intervals based on their prior knowledge or experience of farming, soils, and climate at the location (Boland *et al.*, 2006) [10]. Large commercial farmers deploy soil moisture monitoring systems (wired or wireless moisture sensors) to irrigate (automatically or manually operation mode) based on the measured soil moisture data and crop/plant water requirements (Thompson *et al.*, 2007 and Holt *et al.*, 2019) [68, 30]. Local and regional agricultural agencies may provide irrigation advisory services based on the observed climate and weather conditions in the area (Eching *et al.*, 2002 and Smith *et al.*, 2002) [19, 63]. Almost all of these conventional farming practices do not consider the variability within a field and use a uniform irrigation rate for the entire field. Remote sensing data can help discern the variability within the field and apply variable rate irrigation with commonly used irrigation systems such as a center pivot. Variable rate application can help mitigate water stress arising from extreme wet and dry conditions to achieve uniformly high yields in all parts in the field while reducing water and nutrient losses (Evans *et al.*, 2013 and McDowell *et al.*, 2017) [21, 43]. Remote sensing images, collected multiple times during a growing season, are used to determine various indicators of crop water demand such as ET, soil moisture, and crop water stress. These indicators are used to estimate crop water requirement and schedule irrigation precisely.

Water Stress

Remote sensing products, either optical, thermal, or microwave, have been used to develop and test multiple indicators and techniques for precise water management (Amani *et al.*, 2016) [3] (Table 2). For example, normalized differential vegetation index (NDVI) and soil-adjusted vegetation index (SAVI) generated from optical images can be used to diagnose water stress and soil moisture conditions in many crops (Table 2). These indicators can be used in combination with weather forecast data for irrigation planning, as shown in Table 2. The Crop Water Stress Index (CWSI) based on thermal remote sensing is a common indicator used for estimating and planning irrigation water demand (Khanal *et al.*, 2017) [13].

$$CWSI = \frac{(Tc - Ta) - (Tc - Ta)LL}{Bio(Tc - Ta)UL - (Tc - Ta)LL}$$

where Tc is the canopy temperature extracted from the thermal image and Ta is the air temperature. LL and UL indicate the upper and lower temperature difference between cap and air. Conceptually, the lower limit (LL) corresponds to when the canopy is sweating at its potential rate and the upper limit (UL) corresponds to when transpiration from the canopy stops. Several methods have been used to calculate the UL and LL of the canopy-to-air temperature difference, each with its own advantages and disadvantages (Khanal *et al.*, 2017) [13]. CWSI is widely used for precise irrigation management in orchards (Maes *et al.*, 2019 and Egea *et al.*, 2017) [40, 20]. (Katsigiannis *et al.*, 2016) [32] developed CWSI maps for kiwi, pomegranate, and vineyard irrigation planning and management using a multisensory (multispectral and thermal) autonomous UAV system. However, some studies suggest that more research is needed to establish climate-, soil- and crop-specific triggers/thresholds to enable the use of CWSI for irrigation planning. has been shown (Quebrajo *et al.*, 2018) [52].

Table 1: Spatiotemporal resolutions of the satellite sensors used for precision agricultural (PA) applications. Satellites that provide high spatial (<30 m) and temporal resolutions (e.g., daily) are more suitable for PA.

Satellite (Years Active)	Sensor (Spatial Resolution)	Temporal Resolution	Application in Agriculture
Landsat 1 (1972–1978)	MS (80 m)	18 days	Crop growth (Leslie *et al.*, 2017) [36].
AVHRR (1979–present)	MS (1.1 km)	1 day	Nutrient management (Seelan *et al.*, 2003) [59].
Radar SAT (1995–2013)	C-band SAR (30 m)	1–6 days	Crop growth (McNairn.2002) [45].
VIIRS Suomi-NPP (2011–present) VIIRS-JPSS-1 (2017–present)	MS (IR Radiometer, 375 m and 750 m)	16 days (repeat)	Crop management (Skakun *et al.*, 2018) [62].
Sentinel-2 (2015–present)	MS (10 m–V and NIR, 20 m–Red edge and SWIR, 60 m–2 NIR)	2–5 days	Yield (Martínez-Casasnovas *et al.*, 2019) [42]; N management (Wolters *et al.*, 2019) [72].

Soil Moisture

Remote sensing data collected in multiple bands such as light, heat and microwave have been used to estimate soil moisture worldwide (Zhou *et al.*, 2016, Verstraeten *et al.*, 2008 and Zhang *et al.*, 2016) [78, 70, 76]. Optical and thermal remote sensing data have been widely used for soil moisture and ET estimation in an approach called the 'triangle' or 'trapezoid' or land surface temperature vegetation index (LST-VI) method (Zhang, K *et al.*, 2016, Carlson. 2007, Zhu *et al.*, 2017 and Babaeian *et al.*, 2018) [76, 13, 79, 5]. The Triangle or LST-VI method is based on the physical relationship between surface temperature (and thus soil moisture and latent heat flux) and vegetation cover properties. In this method, estimation of soil moisture is based on interpretation of pixel distribution within the LST-VI plot space. When there are enough pixels in the image to cover the full range of soil moisture and vegetation density, and clouds, surface water, and other outliers are removed, the LST-VI space resembles a triangle or trapezoid (Carlson *et al.*, 2007) [13]. One end of the LST-VI triangle or trapezium is sloping towards high temperatures, representing the dry end (low soil moisture) and the opposite end representing the wet end (high soil moisture). (Petropoulos *et al.*, 2009) [51]. The triangular or trapezoidal shape of LST-VI space is formed due to the low sensitivity of LST to soil moisture under dense vegetation conditions. This contrasts with the high sensitivity of LST to soil moisture under exposed soil or sparse vegetation conditions. Theoretically, once the upper and lower moisture contents of the wet and dry edges are determined, the soil moisture of the remaining pixels can be estimated using interpolation techniques. The triangulation method uses a simple parameterization approach and does not require additional atmospheric or surface data for soil moisture estimation (Carlson *et al.*, 2007 and Carlson *et al.*, 2019) [13-14]. However, the subjective determination of wet and dry limits in the triangulation method can introduce significant uncertainties in soil moisture estimation, especially for relatively uniform land surface areas (e.g., the LST-VI triangle forming variation in soil moisture (Zhu, W *et al.*, 2017) [79]. Moreover, traditional triangulation methods require separate parameterization for each observation, which is a time-consuming and computationally intensive process (Sadeghi *et al.*, 2017) [56]. Conventional triangulation requires both optical and thermal data, but in some cases (such as Sentinel-2) these data may not be available.

Nutrient Management

Applying the right fertilizer at the right time is essential to optimize crop growth and yield while minimizing environmental damage from nutrient loss to groundwater and surface water. Generally, the recommended fertilizer rates are applied evenly during planting and subsequent growth stages of the crop. However, crop fertilizer needs vary spatially and temporally (between and between seasons) due to differences in soil, management, topography, weather, and hydrology (Hendricks *et al.*, 2019 and Melkonian *et al.*, 2008) [29, 46]. Mapping such variability in plant nutritional status/needs for PA application can be difficult with commonly used tools such as chlorophyll meters. Several vegetation indices (NDVI, SAVI, etc.) derived from remote sensing data have been shown to be significantly correlated with plant chlorophyll content, photosynthetic activity, and plant productivity (Table 2). Mapping these indices can therefore help us understand spatial variations in plant trophic status that are important for PA. Recently, several tractor-mounted remote sensors have become available that can measure crop nutrient status for real-time application of spatially varying fertilizer rates.

Green Seeker, Yara N-Sensor, and Crop Circle are examples of commercially available handheld and tractor-mounted remote sensors that use crop reflectance data to determine and apply real-time, spatially-varying fertilizer rates is (Ali *et al.*, 2017) [2]. In tractor mounted systems, the remote sensor is usually mounted in front of the sprayer boom. Nitrogen (N) application rates in these systems are determined based on calculated vegetation indices (such as NDVI) and further transmitted to nutrient applicators/dispensers for real-time fertilizer application. Various algorithms are used to convert the measured vegetation index to the recommended N coverage rate. Generally, the N application rate is calculated by comparing the vegetation index measured on the target field with the reference vegetation level measured on a well-fertilized (N-rich) plot/strip representative of the target field. increase. The result revealed that maximum variation was recorded in flag leaf attitude of blade (late) followed by flag leaf attitude of blade (early), leaf pubescence of blade surface, gelatinization temperature through alkali spreading value, panicle curvature of main axis, spikelet density of pubescence of lemma, panicle exertion, decorticated grain shape (in lateral view) and culm attitude (Rahangdale *et al.*, 2022) [53]. Several fertilizer dose calculation algorithms (such as the nitrogen fertilizer optimization algorithm) (Raun *et al.*, 2005 and Bushong *et al.*, 2016) [54, 12] have been developed and successfully implemented in these commercial sensors to determine the vegetation index based on the seasonal N demand of many plants. (Franzen *et al.*, 2016 and Scharf *et al.*, 2011) [23, 58].

Table 2: Some recently used vegetation indices for remote sensing applications in precision agriculture *.

Index	Definition/Equation	Applications (References)
Normalized difference vegetation index (NDVI)	$\frac{RNIR - Rred}{RNIR + Rred}$	Biomass (Schaefer *et al*., 2016) [57]; breeding, phenotyping (Duan *et al*., 2017) [18]; yield (Hassan *et al*., 2019) [27]; disease (Yuan *et al*., 2016) [75]; n-management (Amaral *et al.*, 2015) [4]; soil moisture (Ihuoma *et al*., 2019) [31]; water stress (Ballester *et al*., 2018) [6].
Plant senescence reflectance index (PSRI)	$\frac{R680 - R550}{R750}$	Disease; yield; biomass (Zhou, L *et al*., 2016) [78].
Chlorophyll vegetation index (CVI)	$\frac{RNIR}{RGreen} * \frac{Rred}{RGreen}$	Crop yield (Meng *et al*., 2015) [47]; crop growth-chlorophyll content (Shang *et al*., 2015) [60]; yield (Martínez-Casasnovas *et al*., 2019) [42].
Chlorophyll index (CI)	$\frac{RNIR}{RRedEdge} - 1$	Chlorophyll and N-content (Taskos *et al*., 2015) [67].
Photochemical reflectance index (PRI)	$\frac{R531 - R570}{R531 + R570}$	Disease (Abdulridha *et al*., 2019) [1]; leaf water stress (PRInorm), canopy temperature and yield (PRI550) (Ihuoma *et al*., 2019) [31]; water stress (PRI, PRI550–515, PRInorm (Ballester *et al*., 2018) [6].
Normalized water index (NWI)	$\frac{R970 - R900}{R970 + R900}$	Soil moisture and crop yield (Ihuoma *et al*., 2019) [31].

*This list is an effort to compile some recently used vegetation indices, it is not meant to be a comprehensive list as there are many more indices that have been used in PA applications.

Crop Monitoring and Yield

Monitoring crop growth and yield is necessary to understand crop responses to the environment and agricultural practices and to develop effective management plans for field operations and/or corrective actions (Peng *et al.*, 2019) [50]. LAI and biomass are her two key indicators of plant health and development (Zhou *et al.*, 2016) [78]. LAI is also used as input for many crops growth and yield prediction models (Kross *et al.*, 2015) [35]. In situ methods of LAI estimation (physical and optical), like the destructive field methods used for biomass estimation, are time consuming and labor intensive. Similarly (Barela *et al.*, 2022a) [7] found that with increased radiation dose, the incidence of chromosomal damage may increase, resulting in reduced germination potential and plant growth and survival. Furthermore, these methods do not provide maps of spatial variability in plant growth and biomass. Remote sensing data on plant growth (e.g., LAI) and biomass can be used to analyze site-specific characteristics (e.g., soil, topography), management (e.g., water, nutrients and other inputs), various biotic and abiotic stressors (e.g., disease, weeds, water and nutrient stress). Similarly, remote sensing data can be used to map differences in tillage and residue management and their effects on crop growth. Several studies have used hyper spectral imagery and various machine learning and classification techniques to map farmland tillage and crop residues. Such information on growing conditions and tillage methods can help develop site-specific management plans, including application of different water, nutrients and pesticides, to increase production and management efficiency.

First, biophysical parameters (such as LAI) derived from remote sensing data are used in plant models to estimate plant yield and biomass. Second, statistical (e.g., regression) or empirical relationships between remotely detected crop parameters/indicators (NDVI, LAI, etc.) and observed crop yield and biomass in representative fields are developed. increase. Developed regression models or empirical relationships can then be used to map yields of target crops. Crop modeling is a data-intensive approach that requires a large amount of information such as model input parameters, weather data, observed yield and biomass data.

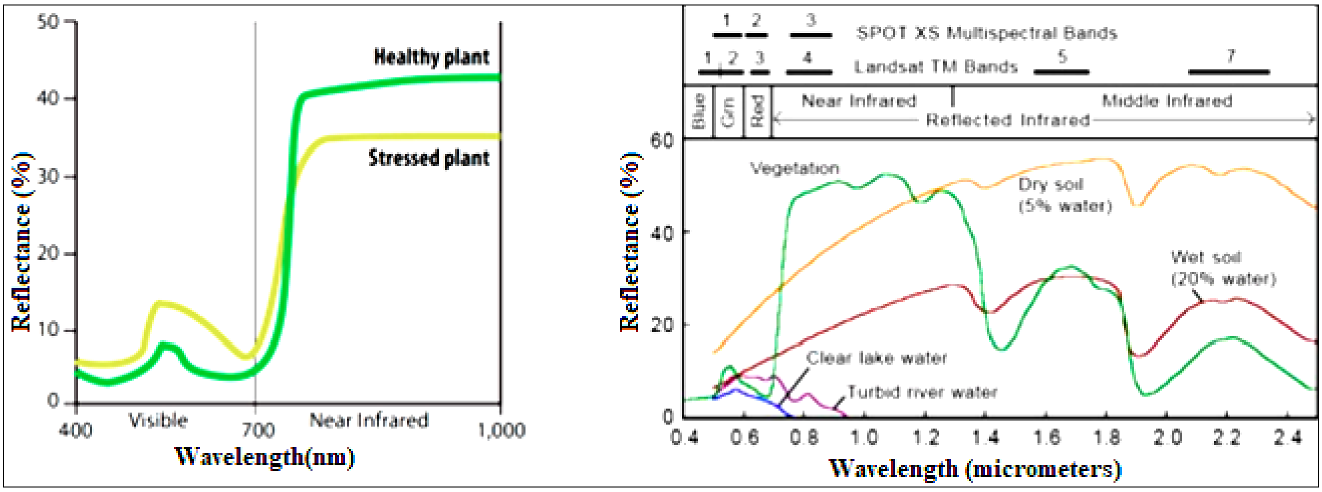

Fig 1: Typical reflectance spectrum of (A) a healthy and a stressed plant (taken from Govaerts and Verhulst (Govaerts *et al.*, 2010) [25]) and (B) soil, water, and vegetation (taken from Mondal (Mondal *et al.*, 2009) [48].

Vegetation index Solar radiation reflected by plants depends on the chemical and morphological characteristics of the plant. Plant type, water content, and canopy characteristics affect reflected light differently in each spectral band. Reflected light measured in the ultraviolet, visible (blue, green, red), near-infrared and mid-infrared regions of the spectrum provides useful information about plant structure and condition for developing different vegetation indices. It has been commonly used (Xue *et al.*, 2017) [74] (Table 2). A vegetation index is a mathematical formula that combines measured reflectance in many spectral bands to produce a value that helps assess plant growth, vigor, and various other vegetation characteristics such as biomass and chlorophyll content. (McKinnon *et al.*, 2017) [44]. Morphological characters were also revealed that Climate change, like every other crop, has a significant impact on soybean production. They found a lot of variation in the soybean genotypes for DUS characters (Barela *et al.*, 2022b) [8]. Mapping these indices helps to understand spatio-temporal variations in harvesting conditions that are important for PA applications. Widely used vegetation indices (Table 2) such as Normalized Differential Vegetation Index (NDVI), Green NDVI (GNDVI), and Ground-adjusted Vegetation Index (SAVI) take advantage of the fact that vegetation has low reflectance in the visible range. doing. It is the peak of the spectrum in the blue and red regions and peaks in the green region (Figure 2). Plant pigments, mainly chlorophyll and carotenoids, strongly adsorb in the visible part of the spectrum, excluding the green part. However, such strong adsorption does not occur in the near-infrared region of the spectrum, causing high reflectance in the near-infrared region of green, healthy plants (Figure 2). NDVI uses reflectance values measured in the red and NIR regions to provide valuable information on plant growth (LAI, biomass), vitality, and photosynthesis (Table 2). NDVI values range from -1 to 1, with positive values indicating increased greenness (LAI and vitality) and negative values indicating non-vegetated surfaces such as urban areas, bare/land, water, and ice. increase. External factors of vegetation conditions such as the sun and visibility geometry, surface soil and crop residues, and atmospheric effects can cause interference in spectral signals (Rondeaux *et al.*, 1996) [55].

NDVI is sensitive to confounding effects caused by soil, atmosphere, clouds and canopy shadows, which can lead to misinformation about crops and crop conditions (Carlson *et al.*, 1997 and Chen *et al.*, 2019) [15, 16]. Furthermore, NDVI is also known to be insensitive to changes in LAI and biomass after reaching a threshold (saturation), especially under dense plant conditions (Hashimoto *et al.*, 2019 and Tan. 2020) [26, 66]. A number of alternative indices have been developed to address these shortcomings of NDVI, the Atmospheric Tolerance Vegetation Index (ARVI), and the Wide Dynamic Range Vegetation Index (WDRVI). Red-edge-based vegetation indices, such as Red-Edge NDVI (RNDVI), Normalized Difference Red-edge (NDRE), and Red-Edge Difference Vegetation Index (REDVI), exist in plant vegetative status, LAI, and late growth in maize. biomass in dense vegetation conditions (LI, F *et al.*, 2014, Shaver *et al.*, 2017, Xie *et al.*, 2018 and Lu, J *et al.*,2015) [37, 61, 73, 39]. Remote Sens. 2020, 12, x FOR peer review 9/32 These constraints are the Soil Adaptive Vegetation Index (SAVI), Atmospheric Tolerance Vegetation Index (ARVI), and Wide Dynamic Range Vegetation Index (WDRVI). Red-edge-based vegetation indices, such as Red-Edge NDVI (RNDVI), Normalized Difference Red-edge (NDRE), and Red-Edge Difference Vegetation Index (REDVI), exist in plant vegetative status, LAI, and late growth in maize. biomass in dense vegetation conditions (LI, F *et al.*, 2014, Shaver *et al.*, 2017, Xie *et al.*, 2018 and Lu, J *et al.*, 2015) [37, 61, 73, 39].

$$CWSI = \frac{(Tc - Ta) - (Tc - Ta)LL}{Bio(Tc - Ta)UL - (Tc - Ta)LL}$$

Author declaration

The authors declare no conflicts of interest.

References

1. Abdulridha J, Ampatzidis Y, Kakarla SC, Roberts P. Detection of target spot and bacterial spot diseases in tomato using UAV-based and benchtop-based hyperspectral imaging techniques. Precis. Agric. 2019;21:955-978.
2. Ali MM, Al-Ani A, Eamus D, Tan DKY. Leaf nitrogen determination using non-destructive techniques-A review. J Plant Nut. 2017;40:928-953.
3. Amani M, Parsian S, MirMazloumi SM, Aieneh O. Two new soil moisture indices based on the NIR-red triangle space of Landsat-8 data. Int. J Appl. Earth Obs. Geoinf. 2016;50:176-186. [CrossRef]
4. Amaral LR, Molin JP, Portz G, Finazzi FB Cortinov L. Comparison of crop canopy reflectance sensors used to identify sugarcane biomass and nitrogen status. Precis. Agric. 2015;16:15-28. [CrossRef]
5. Babaeian E, Sadeghi M, Franz TE, Jones S, Tuller M. Mapping soil moisture with the Optical TRA pezoid Model (OPTRAM) based on long-term MODIS observations. Remote Sens. Environ. 2018;211:425-440. [CrossRef]
6. Ballester C, Zarco-Tejada PJ, Nicolás E, Alarcón JJ, Fereres E, Intrigliolo DS, *et al*. Evaluating the performance of xanthophyll, chlorophyll and structure-sensitive spectral indices to detect water stress in five fruit tree species. Precis. Agric. 2018;19:178-193. [CrossRef]
7. Barela A, Jain S, Tiwari S, Rahangdale S, Singh P. Impact of gamma radiations on seed germination and morphological characteristics of pea (Pisum sativum L.) The Pharma Innovation Journal 2022(a);11(8): 464-467.
8. Barela A, Shrivastava MK, Mohare S, Rahangdale S, Jawarkar S, Amrate PK, *et al*. Morphological Characterization and Recognition of New Traits of Soybean [*Glycine max* (L.) Merrill] International Journal Environment and Climate Change 2022(b);12(12):1497-1504.
9. Berry JK, Delgado JA, Khosla R, Pierce FJ. Precision conservation for environmental sustainability. J Soil Water Conserv. 2003;58:332-339.
10. Boland A, Bewsell D, Kaine G. Adoption of sustainable irrigation management practices by stone and pome fruit growers in the Goulburn/Murray Valleys. Aust. Irrig. Sci. 2006;24:137-145. [CrossRef]
11. Bongiovanni R, Lowenberg-DeBoer J. Precision agriculture and sustainability. Precis. Agric. 2004;5:359-387. CrossRef]
12. Bushong JT, Mullock JL, Miller EC, Raun WR, Arnall DB. Evaluation of mid-season sensor-based nitrogen fertilizer recommendations for winter wheat using different estimates of yield potential. Precis. Agric. 2016;17:470-487. [CrossRef]
13. Carlson T. An overview of the Triangle Method for estimating surface evapotranspiration and soil moisture from satellite imagery. Sensors. 2007;7:1612-1629. [CrossRef]
14. Carlson TN, Petropoulos GP. A new method for estimating of evapotranspiration and surface soil moisture from optical and thermal infrared measurements: The simplified triangle. Int. J. Remote Sens. 2019;40:7716-7729. [CrossRef]
15. Carlson TN, Ripley DA. On the relation between NDVI, fractional vegetation cover, and leaf area index. Remote Sens. Environ. 1997;62:241-252. [CrossRef]
16. Chen S, She D, Zhang L, Guo M, Liu X. Spatial downscaling methods of soil moisture based on multisource remote sensing data and its application. Water. 2019;11:1401.
17. Delgado J, Short NM, Roberts DP, Vandenberg B. Big data analysis for sustainable agriculture. FSUFS. 2019;3:54.
18. Duan T, Chapman SC, Guo Y, Zheng B. Dynamic monitoring of NDVI in wheat agronomy and breeding trials using an unmanned aerial vehicle. Field Crops Res. 2017;210:71-80.
19. Eching S. Role of technology in irrigation advisory services: The CIMIS experience. In Proceedings of the 18th Congress and 53rd IEC meeting of the International Commission on Irrigation and Drainage (ICID), FAO/ICID International Workshop on Irrigation Advisory Services and Participatory Extension Management, Montreal, QC, Canada, 24 July 2002, 24.
20. Egea G, Padilla-Díaz CM, Martinez-Guanter J, Fernández JE, Pérez-Ruiz M. Assessing a crop water stress index derived from aerial thermal imaging and infrared thermometry in super-high density olive orchards. Agric. Water Manag. 2017;187:210-221. [CrossRef]
21. Evans, R.G.; LaRue, J.; Stone, K.C.; King, B.A. Adoption of site-specific variable rate sprinkler irrigation systems. Irrig. Sci. 2013, 31, 871–887. [CrossRef]
22. Forkuor G, Hounkpatin OKL, Welp G, Thiel M. High resolution mapping of soil properties using remote sensing variables in southwestern Burkina faso: A comparison of machine learning and multiple linear regression models. PLoS One. 2017;12:e0170478. [CrossRef]
23. Franzen D, Kitchen N, Holland K, Schepers J, Raun W. Algorithms for in-season nutrient management in cereals. Agron. J. 2016;108:1775-1781. [CrossRef]
24. Gebbers R, Adamchuk V. Precision agriculture and food security. Science. 2010;327:828-831. [CrossRef]
25. Govaerts B, VerhulstN. The Normalized Difference

Vegetation Index (NDVI) Green Seeker TM Handheld Sensor: Toward the Integrated Evaluation of Crop Management; CIMMYT: Mexico City, Mexico; c2010. p. 13.
26. Hashimoto N, Saito Y, Maki M, Homma K. Simulation of reflectance and vegetation indices for Unmanned Aerial Vehicle (UAV) monitoring of paddy fields. Remote Sens. 2019, 11, 2119.
27. Hassan MA, Yang M, Rasheed A, Yang G, Reynolds M, Xia X, *et al*. A rapid monitoring of NDVI across the wheat growth cycle for grain yield prediction using a multi-spectral UAV platform. Plant Sci. 2019;282:95-103.
28. Hedley C. The role of precision agriculture for improved nutrient management on farms. J Sci. Food Agric. 2014;95:12-19. [CrossRef]
29. Hendricks GS, Shukla S, Roka FM, Sishodia RP, Obreza TA, Hochmuth GJ, *et al*. Economic and environmental consequences of over fertilization under extreme weather conditions. J Soil Water Conserv. 2019;74:160-171.
30. Holt N, Sishodia RP, Shukla S, Hansen KM. Improved water and economic sustainability with low-input compact bed plasticulture and precision irrigation. J Irrig. Drain. Eng. 2019;145:04019013. [CrossRef]
31. Ihuoma SO, Madramootoo CA. Sensitivity of spectral vegetation indices for monitoring water stress in tomato plants. Comput. Electron. Agric. 2019;163:104860. [CrossRef]
32. Katsigiannis P, Galanis G, Dimitrakos A, Tsakiridis N, Kalopesas C, Alexandridis T, *et al*. Fusion of spatio-temporal UAV and proximal sensing data for an agricultural decision support system. In Proceedings of the Fourth International Conference on Remote Sensing and Geoinformation of the Environment RSCy 2016, Paphos, Cyprus. 2016 Aug 12;9688:96881R.
33. Khanal S, Fulton J, Shearer S. An overview of current and potential applications of thermal remote sensing in precision agriculture. Comput. Electron. Agric. 2017;139:22-32.
34. Koch B, Khosla R, Frasier WM, Westfall DG, Inman D. Economic feasibility of variable-rate nitrogen application utilizing site-specific management zones. Agron. J. 2004;96:1572-1580. [CrossRef]
35. Kross A, McNairn H, Lapen D, Sunohara M, Champagne C. Assessment of Rapid Eye vegetation indices for estimation of leaf area index and biomass in corn and soybean crops. Int. J Appl. Earth Obs. Geoinf. 2015;34:235-248. [CrossRef]
36. Leslie CR, Serbina LO, Miller HM. Landsat and Agriculture-Case Studies on the Uses and Benefits of Landsat Imagery in Agricultural Monitoring and Production; US Geological Survey Open-File Report; US Geological Survey: Reston, VA, USA. 2017;1034:27.
37. LI F, Miao Y, Feng G, Yuan F, Yue S, Gao X, *et al*. Improving estimation of summer maize nitrogen status with red edge-based spectral vegetation indices. Field Crops Res. 2014;157:111-123.
38. Liou Y, Kar SK. Evapotranspiration estimation with remote sensing and various surface energy balance algorithms-A review. Energies 2014;7:2821-2849. [CrossRef]
39. Lu J, Miao Y, Huang Y, Shi W, Hu X, Wang X, *et al*. Evaluating an Unmanned Aerial Vehicle-based Remote Sensing System for Estimation of Rice Nitrogen Status. In Proceedings of the Fourth International Conference on Agro-Geoinformatics (Agro-geoinformatics), Istanbul, Turkey 20 July; c2015. p. 198-203.
40. Maes WH, Steppe K. Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture. Trends Plant Sci. 2019;24:152-154. [CrossRef]
41. Marino S, AlvinoA. Hyperspectral vegetation indices for predicting onion (*Allium cepa* L.) yield spatial variability. Comput. Electron. Agric. 2015;116:109-117. [CrossRef]
42. Martínez-Casasnovas JA, Uribeetxebarría A, Escolà A, Arnó J. Sentinel-2 vegetation indices and apparent electrical conductivity to predict barley (*Hordeum vulgare* L.) yield. In Precision Agriculture; Wageningen Academic Publishers: Wageningen, The Netherlands; c2019. p. 415-421.
43. McDowell RW. Does variable rate irrigation decrease nutrient leaching losses from grazed dairy farming? Soil Use Manag. 2017;33:530-537. [CrossRef]
44. McKinnon T, Hoff P. Comparing RGB-based vegetation indices with NDVI for drone based agricultural sensing. AGBX. 2017;021:1-8. Available online: https://agribotix.com/wp-content/uploads/2017/05/AgribotixVARI-TGI-Study.pdf (accessed on 23 September 2020).
45. McNairn H, Ellis J, Van Der Sanden JJ, Hirose T, Brown RJ. Providing crop information using RADARSAT-1 and satellite optical imagery. ISPRS J. Photogramm. Remote Sens. 2002;23:851-870. [CrossRef]
46. Melkonian JJ. ES, H.M.V. Adapt-N: Adaptive nitrogen management for maize using high resolution climate data and model simulations. In Proceedings of the 9th International Conference on Precision Agriculture, Denver, CO, USA; c2008 20-23 July.
47. Meng J, Xu J, You X. Optimizing soybean harvest date using HJ-1 satellite imagery. Precis. Agric. 2015;16:164-179.
48. Mondal P, Basu M. Adoption of precision agriculture technologies in India and in some developing countries: Scope, present status and strategies. Prog. Nat. Sci. 2009;19:659-666. [CrossRef]
49. Pardossi A, Incrocci L, Incrocci G, Malorgio F, Battista P, Bacci L, *et al*. Root zone sensors for irrigation management in intensive agriculture. Sensors. 2009;9:2809-2835. [CrossRef] [PubMed]
50. Peng Y, Li Y, Dai C, Fang S, Gong Y, Wu X, *et al*. Remote prediction of yield based on LAI estimation in oilseed rape under different planting methods and nitrogen fertilizer applications. Agric. For. Meteorol. 2019;271:116-125. [CrossRef]
51. Petropoulos G, Carlson TN, Wooster MJ, Islam S. A review of Ts/VI remote sensing-based methods for the retrieval of land surface energy fluxes and soil surface moisture. Prog. Phys. Geogr. 2009;33:224-250. [CrossRef]
52. Quebrajo L, Perez-ruiz M, Perez-Urrestarazu L, Martinez G, Egea G. Linking thermal imaging and soil remote sensing to enhance irrigation management of sugar beet. Biosyst. Eng. 2018;165:77-87. [CrossRef]
53. Rahangdale S, Singh Y, Parte D, Barela A, Gour L. Phenotypic Study of JNPT Lines of Rice (*Oryza sativa* L.) Derived from Indica x Japonica Sub species Frontiers in Crop Improvement. 2022;10(5):2603-2608.

54. Raun WR, Solie JB, Stone ML, Martin KL, Freeman KW, Mullen RW, *et al*. Optical sensor-based algorithm for crop nitrogen fertilization. Commun. Soil Sci. Plant Anal. 2005;36:2759-2781.
55. Rondeaux G, Steven M, Baret F. Optimization of soil-adjusted vegetation indices. Remote Sens. Environ. 1996;55:95-107. [CrossRef]
56. Sadeghi M, Babaeian E, Tuller M, Jones SB. The optical trapezoid model: A novel approach to remote sensing of soil moisture applied to Sentinel-2 and Landsat-8 observations. Remote Sens. Environ. 2017;198:52-68. [CrossRef]
57. Schaefer MT, Lamb DW. A combination of plant NDVI and LiDAR measurements improve the estimation of pasture biomass in tall fescue (Festuca arundinacea var. Fletcher). Remote Sens. 2016;8:109.
58. Scharf PC, Shannon DK, Palm HL, Sudduth KA, Drummond ST, Kitchen NR, *et al*. Sensor-based nitrogen applications out-performed producer-chosen rates for corn in on-farm demonstrations. Agron. J. 2011;103:1684-1691. [CrossRef]
59. Seelan SK, Laguette S, Casady GM, Seielstad GA. Remote sensing applications for precision agriculture: A learning community approach. Remote Sens. Environ. 2003;88:157-169. [CrossRef]
60. Shang J, Liu J, Ma B, Zhao T, Jiao X, Geng X, *et al*. Mapping spatial variability of crop growth conditions using RapidEye data in Northern Ontario, Canada. Remote Sens. Environ. 2015;168:113-125.
61. Shaver TM, Kruger GR, Rudnick DR. Crop canopy sensor orientation for late season nitrogen determination in corn. J Plant Nutr. 2017;40:2217-2223.
62. Skakun S, Justice CO, Vermote E, Roger JC. Transitioning from MODIS to VIIRS: An analysis of inter-consistency of NDVI data sets for agricultural monitoring. Int. J Remote Sens. 2018;39:971-992. [PubMed]
63. Smith M, Munoz G. Irrigation advisory services for effective water use: A review of experiences. In Proceedings of the Irrigation Advisory Services and Participatory Extension in Irrigation Management Workshop Organized by FAO-ICID, Montreal, QC, Canada; c2002 24 July.
64. Srinivasan A. (Ed.) Handbook of Precision Agriculture: Principles and Applications; Food Products Press, Haworth Press Inc.: New York, NY, USA; c2006. ISBN 978-1-56022-955-1.
65. Sun Y, Ren H, Zhang T, Zhang C, Qin Q. Crop leaf area index retrieval based on inverted difference vegetation index and NDVI. IEEE Geosci. Remote. 2018;15:1662-1666.
66. Tan C, Zhang P, Zhou X, Wang Z, Xu Z, Mao W, *et al*. Quantitative monitoring of leaf area index in wheat of different plant types by integrating nDVi and Beer-Lambert law. Sci. Rep. 2020;10:929.
67. Taskos DG, Koundouras S, Stamatiadis S, Zioziou E, Nikolaou N, Karakioulakis K, Theodorou N. Using active canopy sensors and chlorophyll meters to estimate grapevine nitrogen status and productivity. Precis. Agric. 2015;16:77-98.
68. Thompson RB, Gallardo M, Valdez LC, Fernadez MD. Using plant water status to define threshold values for irrigation management of vegetable crops using moisture sensors. Agric. Water Manag. 2007;88:147-158. [CrossRef]
69. Uphoff N. Improving International Irrigation Management with Farmer Participation: Getting the Process Right; Routledge: London, UK; c2018.
70. Verstraeten WW, Veroustraete F, Feyen J. Assessment of evapotranspiration and soil moisture content across different scales of observation. Sensors. 2008;8:70-117. [CrossRef] [PubMed]
71. With KA. Essential of Landscape Ecology; Oxford University Press: Oxford, UK; c2019.
72. Wolters S, Söderström M, Piikki K, Stenberg M. Near-real time winter wheat N uptake from a combination of proximal and remote optical measurements: How to refine Sentinel-2 satellite images for use in a precision agriculture decision support system. In Proceedings of the 12th European Conference on Precision Agriculture, Montpellier, France, Wageningen Academic Publishers: Wageningen, The Netherlands; c2019. p. 415-421.
73. Xie Q, Dash J, Huang W, Peng D, Qin Q, Mortimer H, *et al*. Vegetation indices combining the red and red-edge spectral information for leaf area index retrieval. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2018;11:1482-1493.
74. Xue J, Su B. Significant remote sensing vegetation indices: A review of developments and application. J Sens; c2017. [CrossRef]
75. Yuan L, Pu R, Zhang J, Wang J, Yang H. Using high spatial resolution satellite imagery for mapping powdery mildew at a regional scale. Precis. Agric. 2016;17:332-348. [CrossRef]
76. Zhang D, Zhou G. Estimation of soil moisture from optical and thermal remote sensing: A review. Sensors. 2016;16:1308. [CrossRef]
77. Zhang K, Kimball JS, Running SW. A review of remote sensing based actual evapotranspiration estimation. WIREs Water. 2016;3:834-853. [CrossRef]
78. Zhou L, Chen N, Chen Z, Xing C. ROSCC: An efficient remote sensing observation-sharing method based on cloud computing for soil moisture mapping in precision agriculture. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 2016;9:5588-5598. [CrossRef].
79. Zhu W, Jia S, Lv A. A universal Ts-VI triangle method for the continuous retrieval of evaporative fraction from MODIS products. J Geophys. Res. Atmos. 2017;122:206-227. [CrossRef]