



# **Applications of Vegetative Indices from Remote Sensing to Agriculture: Past and Future**

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Abstract: Remote sensing offers the capability of observing an object without being in contact with the object. Throughout the recent history of agriculture, researchers have observed that different wavelengths of light are reflected differently by plant leaves or canopies and that these differences could be used to determine plant biophysical characteristics, e.g., leaf chlorophyll, plant biomass, leaf area, phenological development, type of plant, photosynthetic activity, or amount of ground cover. These reflectance differences could also extend to the soil to determine topsoil properties. The objective of this review is to evaluate how past research can prepare us to utilize remote sensing more effectively in future applications. To estimate plant characteristics, combinations of wavebands may be placed into a vegetative index (VI), i.e., combinations of wavebands related to a specific biophysical characteristic. These VIs can express differences in plant response to their soil, meteorological, or management environment and could then be used to determine how the crop could be managed to enhance its productivity. In the past decade, there has been an expanded use of machine learning to determine how remote sensing can be used more effectively in decision-making. The application of artificial intelligence into the dynamics of agriculture will provide new opportunities for how we can utilize the information we have available more effectively. This can lead to linkages with robotic systems capable of being directed to specific areas of a field, an orchard, a pasture, or a vineyard to correct a problem. Our challenge will be to develop and evaluate these relationships so they will provide a benefit to our food security and environmental quality.

**Keywords:** reflectance; vegetative indices; phenology; crop productivity; crop stress; spatial variation; temporal variation; growth

# 1. Introduction

Remote sensing has been available to us for as long as we have had sight. Through our eyes, we are able to determine a wide range of characteristics of any object, e.g., size, color, or shape, within the wavelength spectrum of 380–700 nm. With the advent of remote sensing equipment, it is often said that we now have "eyes in the skies" with a broader wavelength range; however, challenges remain in the application of this information for agricultural assessment and decision making. A number of popular articles depict the application of remote sensing to precision agriculture, as well as the combination of remote sensing with artificial intelligence to guide field-scale management. The application of these methods provides producers and land managers with spatial information that is difficult to obtain on the ground. Over the past fifty years, remote sensing research has provided a variety of tools that have proven valuable to agriculture. Hatfield et al. [1] summarized the state of knowledge on the

application of remote sensing to agriculture, and earlier Hatfield and Hart [2] developed a special issue of *Photogrammetric Engineering and Remote Sensing* to summarize the state of knowledge and advances in research during the early applications of remote sensing to agriculture and range science. Huete et al. [3] completed an analysis of products from the MODIS satellite and demonstrated the value these products have for agriculture. Remote sensing applications and approaches have changed over time, and in this article, we highlight how the past work builds a foundation for the future applications of remote sensing to guide more informed decision-making at the field scale. We will examine the traditional approaches to using remotely sensed data, the use of temporal patterns of variability to assess field-scale changes, and future applications of remote sensing to agricultural assessment.

### 2. Traditional Approaches

The application of remote sensing to agriculture has its roots in research relating the optical properties of leaves (e.g., reflectance, transmittance, and absorbance of light impinging on a leaf) from crop plants to morphological features [4,5]. Throughout the years, technological advancements and a better understanding of these relations have been refined to enhance the value of remotely sensed data to agronomic assessment [6,7]. These agronomic applications were discussed in detail by Hatfield et al. [1] to provide a background for the current state of knowledge in remote sensing. From the early work describing the optical properties of leaves and canopies, current applications have largely focused on the concept of a vegetation index (VI), which provides an estimate of a plant biophysical feature (e.g., ground cover, biomass, leaf area, or yield) based on reflectance from different combinations of wavebands [8].

Since one of the earliest VIs was developed in the late 1960s when Jordan [9] related leaf area to the ratio of near-infrared to red reflectance measured at the forest floor, many VIs have been developed that relate to different plant parameters. Table 1 provides a list of VIs and parameters that they are used to estimate, including leaf chlorophyll status, canopy photosynthesis, leaf area index (LAI), ground cover, above ground biomass, plant and crop water status, abiotic plant stress, and grain yield. These different VIs are used to provide an evaluation of the plant status at a point within the growing season with the intended purpose of providing an assessment of the plant canopy. Thenkabail et al. [10] evaluated hyperspectral observations over crop canopies and found a strong relationship between crop canopy characteristics and reflectance in the red (650 to 700 nm) wavebands, green (500 to 550 nm) wavebands, a portion of the near-infrared wavebands (900–940 nm), and in the wavebands sensitive to the moisture content (975 nm, 1215 nm). These are the same wavebands where previous research has found strong relationships with broad waveband classes available on satellites, aircraft, and unmanned aerial vehicles (UAVs). Hatfield and Prueger [11] provided examples of how these VIs change over the season and the dynamics in the different indices. For example, many chlorophyll indices have been related to leaf or canopy chlorophyll content, as shown in Table 1.

For canopy photosynthesis, photosynthetic efficiency was related to the photochemical reflectance index (PRI) [12] and shows a rapid increase in the beginning of the growing season and changes during the season, with a shift in values during mid-season for a maize (*Zea mays* L.) canopy (Figure 1). The abrupt changes in PRI values are not indicative of a decline in photosynthetic efficiency but are caused by the emergence of the tassels as a morphological structure at the top of the canopy. These changes are not evident in crops without morphological features to change the reflectance patterns.

VI Family	Index	Wavebands	Application	Reference
- - - - Plant biophysical indices		$R_{800} - R_{680}$	Biomass	[9]
	Difference Indices	R <sub>800</sub> - R <sub>550</sub>	Biomass	[13]
		R <sub>550</sub>	Chlorophyll	[14]
			Chlorophyll	[15]
		log(1/R <sub>737</sub> )	Chlorophyll	[16]
	Simple Ratio	$R = R_{NIR}/R_{red}$	Biomass, LAI, vegetation cover	[9,17]
	Ratio Vegetation Index	$RVI = R_{red}/R_{NIR}$	LAI	[18]
	Difference Vegetation Index	$DVI = m \times R_{NIR} - R_{red}$	LAI	[18]
	Weighted Difference Vegetation Index	$WDVI = R_{NIR} - m \times R_{red}$	LAI	[19]
	Photochemical Reflectance Index	$PRI = (R_{531} - R_{570})/(R_{531} + R_{570})$	Light capture efficiency	[12]
	Pigment-specific normalized difference	$PSNDc = (R_{800} - R_{470})/(R_{800} + R_{470})$	LAI	[20]
	Normalised Ratio Vegetation Index	NRVI = (RVI - 1)/(RVI + 1)	LAI	[21]
	Normalized Difference Vegetation Index	$NDVI = (R_{NIR} - R_{red})/(R_{NIR} + R_{red})$	Intercepted PAR, vegetation cover	[22]
-	Green NDVI	$GNDVI = (R_{NIR} - R_{green})/(R_{NIR} + R_{green})$	Intercepted PAR, vegetation cover	[13,23,24]
-	Red Edge NDVI	$NDRE = (R_{NIR} - R_{red edge})/(R_{NIR} + R_{red edge})$	Intercepted PAR, vegetation cover	[23]
	Corrected NDVI	$\begin{aligned} \text{NDVIC} = \text{NDVI} \times (1 - ((\text{R}_{\text{MIR}} - \text{R}_{\text{MIR}\_\text{min}})/(\text{R}_{\text{MIR}\_\text{max}} - \text{R}_{\text{MIR}\_\text{min}}))) \end{aligned}$	Intercepted PAR, vegetation cover	[25]
	Transformed Vegetation Index	$TVI = (NDVI + 0.5)^{1/2}$	Intercepted PAR, vegetation cover	[26]
	Corrected Transformed Vegetation Index	$CTVI = [(NDVI + 0.5)/( NDVI + 0.5 )]^*( NDVI + 0.5 )^{1/2}$	Intercepted PAR, vegetation cover	[27]
	Perpendicular Vegetative Index	$PVI = (R_{NIR} - aR_{red} - b)/(1 + a^2)^{1/2}$	LAI	[18]
	Wide Dynamic Range Vegetation Index	$WDRVI = (0.1R_{NIR} - R_{red})/(0.1R_{NIR} + R_{red})$	LAI, vegetation cover, biomass	[21]
	Soil Adjusted Vegetation Index	$SAVI = (R_{NIR}-R_{red})(1+L)/(R_{NIR} + R_{red} + L)$	LAI	[28]
	Modified Soil Adjusted Vegetation Index	$\begin{aligned} \text{MSAVI} = (2 \times (\text{R}_{\text{NIR}} + 1) - ((2 \times \text{R}_{\text{NIR}} + 1)^2 - 8 \times (\text{R}_{\text{NIR}} - \text{R}_{\text{red}}))^{1/2})/2 \end{aligned}$	LAI	[29]
	Transformed Soil Adjusted Vegetative Index	$TSAVI = a(R_{NIR} - aR_{red} - b)/(R_{red} + aR_{NIR} - ab)$	LAI, biomass	[30]
	Enhanced Vegetation Index	$EVI = 2.5(R_{NIR} - R_{red})/(R_{NIR} + 6R_{red} - 7.5R_{blue} + 1)$	Biomass	[3]

Table 1. Summary of	f selected vegetation	indices, wavebands,	, applications, a	and citations.
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Table 1.	Cont.
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VI Family	Index	Wavebands	Application	Reference
- - Plant biophysical indices -	Two-band Enhanced Vegetation Index	$EVI2 = 2.5(R_{NIR} - R_{red})/(R_{NIR} + 2.4 \times R_{red} + 1)$	Biomass	[31]
	Triangular Vegetative Index	$TVI = 0.5[120(R_{750} - T_{550}) - 200(R_{670} - R_{550})]$	Leaf area	[32]
	Specific Leaf Area Vegetation Index	$SLAVI = R_{NIR} / (R_{red} + R_{MIR})$	Specific leaf area	[33]
	Global Environmental Monitoring Index	GEMI = $\eta \times (1 - \eta \times 0.25) - [(R_{red} - 0.125)/(1 - R_{red})]$		[34]
		$\eta = (2 \times (R_{\rm NIR}^2 - R_{\rm red}^2) + 1.5 \times R_{\rm NIR} + 0.5 \times R_{\rm red})/(R_{\rm NIR} + R_{\rm red} + 0.5)$		
	Canopy Structure Index	$CSI = 2sSR - sSR^2 + sWI^2$	Photosynthetic tissue area	[35]
		$sSR = (R_{800}/R_{680} - 1)/(R_{800}/R_{680} - 1)max$		
		$sWI = (R_{900}/R_{1180} - 1)/(R_{900}/R_{1180} - 1)$		
-	Visible Atmospherically Resistant Indices	$VARI_{green} = (R_{green} - R_{red})/(R_{green} + R_{red})$	Green vegetation fraction	[36]
	, i i i i i i i i i i i i i i i i i i i	$VARI_{red edge} = (R_{red edge} - R_{red})/(R_{red edge} + R_{red})$	Green vegetation fraction	[37]
-	Plant Senescence Reflectance Index	$PSRI = (R_{680} - R_{500})/R_{750}$	Change in plant chlorophyll	[38]
Leaf or canopy chlorophyll - indices	Chlorophyll Indices	$CI_{green} = (R_{NIR}/R_{green}) - 1$	LAI, GPP, chlorophyll	[39-41]
	1 5	$CI_{red edge} = (R_{NIR}/R_{red edge}) - 1$	LAI, GPP, chlorophyll	[39-41]
	Normalized Pigment Chlorophyll Ratio Index	$NPCI = (R_{660} - R_{460}) / (R_{660} + R_{460})$	Crop canopy chlorophyll	[38]
	8 1 1	$NPCI = (R_{680} - R_{430})/(R_{680} + R_{430})$	Crop canopy chlorophyll	[42]
-	Modified Chlorophyll and Reflectance Index	$MCARI = [(R_{700} - R_{670}) - 0.2 \times (R_{700} - R_{550})] \times (R_{700}/R_{670})$	Canopy chlorophyll	[43]
Water Content Indices	Water Balance Index	WBI = $R_{970}/R_{900}$ or $R_{905}/R_{980}$	Water Content	[44]
	Normalized Difference Water Content	$NDWI = (R_{800} - R_{680}) / (R_{800} + R_{680})$	Water content	[45]
	Shortwave Infrared Water Stress Index	$\begin{aligned} \text{SIWSI} = (\text{R}_{1628} \text{ to } \text{R}_{1652}) - (\text{R}_{841} \text{ to } \text{R}_{876}) / (\text{R}_{1628} \text{ to } \text{R}_{1652}) + \\ (\text{R}_{841} \text{ to } \text{R}_{876}) \end{aligned}$	Water content	[46]
-	Relative Water Content	$RWC = R_{1483}/R_{1650}$	Relative water content	[47]
	Relative mater content	$RWC = R_{1100}/R_{1430}$	Relative water content	[48]

R = reflectance at different wavelengths or wavebands; R<sub>red</sub>, R<sub>green</sub>, R<sub>blue</sub> = reflectance in the visible red, green, and blue waveband, respectively; R<sub>NIR</sub>, R<sub>MIR</sub> = reflectance in the near and middle infrared waveband, respectively; m = slope of bare soil line.



**Figure 1.** Seasonal trajectory of the photochemical reflectance index (PRI) for maize during the 2016 growing season in Ames, Iowa. Symbols are the mean of two fields and with the standard error of the observations shown as the bars.

One application critical to plant assessment has been leaf area duration. Araus et al. [49] observed that VIs could be used to determine leaf area index (LAI) at intervals during the growing season as a way to estimate how well canopies were maintaining leaf area. One of the most widely used VIs for estimating leaf area has been the NDVI. However, at approximately an LAI of 4, the canopy closes and NDVI values become saturated; this saturation limits the usefulness of this index for leaf area. Upon reaching this saturation point, as Hatfield et al. [50] and Asrar et al. [51] point out, NDVI becomes an effective tool for measuring light interception and can be used to assess radiation use efficiency [52,53]. Estimates of leaf area after canopy closure are better suited with alternative VIs, such as SAVI or CSI [35]. However, VIs using hyperspectral reflectance (e.g., MCARI and TVI) were better at estimating leaf area than other VIs, with RMSE values of 0.28 for soybean (*Glycine max* (L.) Merr.), 0.46 for maize, and 0.85 for wheat (*Triticum aestivum* L.) [31]. The RMSE values for soybean and maize are similar to values observed using destructive sampling. These findings suggest that approaches that utilize NDVI as the product derived from various platforms should be treated with caution, especially when NDVI values exceed 0.75.

Another important application of remote sensing has been quantifying crop residue cover on soil to assess the resistance to water and wind erosion [54]. Bannari et al. [55] provide one of many examples of how mapping residues could be achieved with remote sensing data. In a recent analysis, Quemada et al. [56] refined the approach to estimate crop residue by combining the normalized difference tillage index, the shortwave infrared normalized residue index, and the water index to develop a more robust method for crop residue determination that accounted for the differences caused by variable soil moisture.

Estimates for crop yield using remote sensing data is one of the most sought-after parameters, and several approaches have been proposed. One recent integrated approach used Landsat imagery to develop a time series of LAI and assimilated those estimates into crop models for estimation of crop yield [57]. Earlier, Liu et al. [58] found it was possible to develop regional estimates of green LAI values by using Landsat images across multiple growing seasons. They found that NDVI was the least satisfactory of the indices to estimate leaf area but found that other indices, such as EVI, produced satisfactory results. Jay et al. [59] found that the use of UAV technology could provide centimeter resolution for sugar beets (*Beta vulgaris*) and suggested that these types of platforms could open new potential for the assessment of crop canopies.

The agronomic utility of remote sensing and VIs can be applied to not only vegetation but also describing soil conditions. Several different research groups have been working to relate soil properties to remotely sensed data [60–67]. One of the major limitations to using remote sensing to assess soil properties is that the soil must be bare to obtain only reflectance from the soil. Further, reflectance is only a function of the surface (i.e., it does not describe the rest of the soil profile), and the correlation of surface properties to properties in the soil profile is often weak. Nonetheless, detection of soil properties via remote sensing has successfully used different VIs to estimate soil organic carbon (e.g., [68]). A combination of 11 wavebands from Sentinel-2 data were used to compute 18 different indices from these data to develop predictive models of soil carbon and soil texture within the topsoil. Compared to laboratory observations, they found that the remote sensing estimates of soil organic carbon were satisfactory; however, estimation of soil texture classes was not possible. The benefit of using the soil organic carbon estimates from remote sensing was in that it readily upscaled to large spatial assessments [68]. Similarly, assessment of soil salinity using remote sensing data was shown by Scudiero et al. [69] in the San Joaquin Valley of California, with results that identified areas of agricultural land threatened by salinity. Another large-scale assessment was outlined by Seutloali et al. [70], in which they propose a process for the estimation of soil erosion using a combination of remotely sensed data combined with soil erosion models.

VIs have also been used in combination to provide a more comprehensive assessment of agricultural crops [71,72]. They used the compact airborne spectral imager (CASI) to derive VIs capable of estimating leaf area, nitrogen concentration, and photosynthetic efficiency across multiple crops in a region. The value of multiple VIs to estimate different crop parameters can provide regional assessments of crops and their productivity. These VIs could be used to estimate these same parameters using UAVs, aircraft, or satellites and the values used to control technologies that apply nutrients, water, pesticides, or other treatments in very specific areas of the field. Another interesting approach on the development of VIs was proposed by Atzberger [73] to use neural nets coupled with radiative transfer models to evaluate the intercorrelations among wavebands. This type of approach could result in VIs with greater precision and accuracy. In the next sections, we will expand on how remote sensing can be used in field management to taken even greater advantage of these VIs.

#### 3. Field-Scale Variability

Agricultural fields, orchards, groves, and vineyards all exhibit variation caused by differences in soil, crop growth, pest infestation, inconsistent distribution of nutrients or any combination of reasons. We can use VIs to assess that field variability and, more important, identify changes in field variability over time. Changes in patterns of variability throughout the growing season may signal problems within the field and indicate the need for management intervention. For example, Hatfield et al. [74] found that surface temperature variability was related to soil water availability and, when the field variability increased above a given threshold, it signaled the need for irrigation.

Several VIs have been developed to quantify crop water status, and this status is critical because variation in water availability in crops can determine the final crop productivity. These include the water balance index (WBI) by Peñuelas et al. [44], normalized difference water index (NDWI) by [45], shortwave infrared water stress index (SIWSI) by [46], and relative water content (RWC) by [47,48]. The wavebands

used in these indices are shown in Table 1. Champagne et al. [75] employed hyperspectral data to derive an index similar to RWC to estimate the canopy water thickness with an accurate prediction across a range of crops. A feature of the VIs estimating water status or water content is the use of near-infrared wavebands more sensitive to water adsorption. To evaluate the effects of flooding on crop production, Chen et al. [76] used the EVI derived from MERIS data to evaluate the difference between EVI and peak EVI as a measure of flood occurrence. They were able to use these data to assess the impact of flooding on agricultural productivity by monitoring changes in spatiotemporal patterns.

Remote sensing data can also be applied to determine variability in crop phenology, the progression of crop stages of development throughout the life cycle of a given plant. Boschetti et al. [77] developed a method of automatically extracting spatiotemporal data from MODIS to develop a phenological calendar for rice (Oryza sativa L.). This method proved useful for regional scale monitoring of the rice crop in different areas. Canisius et al. [78] used multi-temporal Radarsat-2 data to estimate phenology of canola (Brassica napus) and spring wheat (Triticum spp.) using the polarimetric feature of this satellite platform where they found plant height was positively related to the Alpha angle and LAI related to the Beta angle of the synthetic aperture radar (SAR) polarimetric parameters. This approach proved valuable in tracking the phenological development of these two crops. McNairn et al. [79] found that SAR could be used to estimate canola phenology with accurate results. Their approach used a dynamic filtering framework to provide a daily estimate of phenological development. Using MODIS data with a two-step filtering approach, Sakamoto et al. [80] found that the satellite estimates agreed with the reported crop progress across eastern Nebraska. Using a similar approach, Pichierri et al. [81] used SAR data to estimate biomass, water status, and structure of a range of agricultural crops in Canada. A combination of satellites with visible and near-infrared wavebands coupled with synthetic aperture radar may be necessary to obtain sufficient temporal resolution to be of value in crop monitoring [82].

The collection of remote sensing data describing field variability in a series of parameters can be incorporated into a management plan. An approach developed based on sequential observations of fields in the Midwest is shown by the diagram depicted in Figure 2. These sequential observations may not always be conducted at regular intervals, because reflectance values of multi-spectral or hyperspectral data collected via aircraft or satellite are affected by cloud cover. An initial observation is conducted to assess variability with a bare soil image. Agricultural fields consist of several different soils within a given field and these will provide different reflectance values. Huete [28] demonstrated that the SAVI index was useful for detecting these differences among soils. In this approach, we found the ratio of red/green ( $R_{670}/R_{550}$ ) provided an assessment of the change in growth. As the season progresses and crops begin to cover the soil surface, the field appears more uniform than the soil background. If that variability is still present or increases with a mid-season vegetative growth image, it is a signal that there is a problem in the field, which could be diagnosed with another image using different wavebands sensitive to nutrient or water stress. These more complex platforms would only be used after the initial diagnosis because they require more processing than a ratio which could be done with a simple camera. If the field is more homogenous, the next data collection could be at midto late grain-filling stage. If the variability is increasing at that time, the pattern would indicate that there is some factor limiting grain yield. Some examples of these factors could be insufficient nutrient supply or water stress, which could be determined using VIs sensitive to these problems (Table 1). This approach would allow for efficient use of UAV platforms and provide a set of information to producers that could prove valuable in assessing each field for management problems. Figure 3 shows an example of seasonal and in-field variability in the spatial patterns across a flight transect in a central Iowa maize field.



**Figure 2.** Diagram for a decision tree to evaluate problems in the field using a minimum of three remote sensing observations over a field during a growing season.



**Figure 3.** Variability of red/green ratio over a maize field in central Iowa at the tasseling stage and at the late grain-fill stage.

One of the future applications of remote sensing that can be linked to UAV and artificial intelligence is to develop systems that could utilize spatial variability within the management zone linked to sequential observations and then trained to provide an alert on a specific management problem. We can utilize the different VIs in innovative ways to assess agricultural systems and these need to be employed with new methods to capture the spatial and temporal variation.

## 4. Application of Thermal Remote Sensing to Agriculture

Thermal infrared is a measure of the temperature of an object and has been used in agricultural applications for crop water stress detection and water management. One of the recent reviews was provided by Khanal et al. [83] and is based on the previous work by many different research groups. The basis for the use of thermal infrared and plant stress can be traced back to Tanner [84] who

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observed that plant temperatures were different than air temperature. These observations have led to the application of thermal remote sensing to estimate crop water stress and evapotranspiration [1]. The most cited index has been the crop water stress index (CWSI) developed in empirical form by Idso et al. [85] and in theoretical form by Jackson et al. [86].

To overcome some of the problems with incomplete ground cover, there has been the integration of thermal with various VIs. The VIs have been used to determine the extent of ground cover. One example of this integration was provided in the development of the water deficit index (WDI) by Moran et al. [87] where they used a trapezoid to cover the range of well-watered to completely stressed vegetation across the range of canopy sizes based on the ratio of actual to potential evaporation. This has proven to be useful in extension from ground-based to airborne or satellite observations. A technique applicable to robotics and AI is the utilization of the variation of canopy temperature within a field. As the plant becomes water limited, the canopy temperatures will increase. Hatfield et al. [74] and Byrant and Moran [88] found that changes in the standard deviation of canopy temperatures within a field were a reliable estimator of soil water availability. Utilizing this approach offers potential for the use of thermal infrared into agricultural applications.

### 5. Future Applications of Remote Sensing to Agriculture

Many future applications incorporating remote sensing into agronomic management will build upon the foundations of the traditional approaches. One of the underdeveloped capabilities in remote sensing is the value of combining different VIs to estimate crop productivity [89]. Individual VIs have been shown to describe spatiotemporal patterns in crops and soils, but that data may need to be paired with other data sources, such as crop models or meteorological data, to provide meaningful information for management decisions. An example of this approach is provided by Claverie et al. [90] for maize and sunflower (Helianthus annuus L.), where they combined the seasonal patterns of green leaf area with plant biomass over the course of the growing season. They combined the growth and senescence phase of development to estimate crop yield based on the use of remotely sensed data to incorporate into a crop growth model. The agreement with the observed yields was acceptable for sunflower but showed considerable difference for the maize crop. While Guan et al. [91] found various wavebands could estimate crop yields, pairing that data with meteorological data was required to estimate crop growth parameters. Zarco-Tejada et al. [92] examined the use of chlorophyll fluorescence to estimate net photosynthesis as a foundation of precision agriculture decisions. Gross primary productivity has been examined by a number of researchers over time [93] and one of the recent efforts has been to combine chlorophyll with a photochemical reflectance index [94]. One of the major limitations to the use of remote sensing tools centers on the fact that crop development leaves a large amount of soil exposed until the crop completely covers the soil. Prior to the crop completely covering the soil, the VIs represent a combination of plant and soil reflectance. Utilization of the chlorophyll index to estimate crop nitrogen status has been the subject of several studies that have utilized more narrow band reflectance values [43,95–101].

One of the emerging applications of remote sensing is in its capacity to support large-scale estimation of energy, carbon [102] and water fluxes [103]. Some of the original work was based on the observations by Hatfield et al. [104] who showed that incorporation of surface temperature into the energy balance provided a reliable estimate of evapotranspiration. This was further developed by Bastiaanssen [105] using a surface energy balance approach and then extended by Allen et al. [106] and applied to agriculture and irrigation management by Allen et al. [107]. These efforts have been expanded into more regional scale models using work by Anderson et al. [108,109], with application shown in Anderson et al. [110,111]. This research has been applied and refined by He et al. [112] using products from the MODIS platform and further evaluated by Guzinski and Nieto [113] using the high resolution data from Sentinel-2 and -3 data sources. These approaches provide field scale estimates of crop water use for use in regional scale assessments of the impact of cropping systems and potential changes in land management or monitoring of drought [114–117]. One of the avenues for

future research in this area would be to couple the water use estimates with carbon fluxes to derive large-scale estimates of the carbon balance from remote sensing.

Another future application of remote sensing is for global scale assessments of vegetation [118]. Moreno-Martínez et al. [119] demonstrated the possibility of producing 500 m resolution maps of leaf area, leaf dry matter content, leaf nitrogen and phosphorus content and leaf nitrogen/phosphorus ratio. They utilized machine learning algorithms to develop these relationships on a global scale. The use of remote sensing can be extended beyond annual crops to perennial crops, and Peña and Brenning [120] demonstrated this potential for fruit trees to apply to crop inventory and changes in crop distribution. Pringle et al. [121] used time series modelling to evaluate productive agricultural lands in Australia as a means of determining land classification and protection of agricultural lands.

Implementation of many applications is often slowed by issues relating to spatial resolution compatibility and data management. Duveiller and Defourny [122] addressed difficulties with spatial resolution by developing a diagnostic approach capable of: (i) guiding users in the process of choosing the most appropriate imagery for their application, (ii) evaluating the adequacy of existing remote sensing systems for monitoring agricultural systems, and (iii) providing guidelines for designing future instruments capable of effective and efficient agricultural monitoring. Additionally, Huang et al. [123] provided an example of data management using a five-layer, fifteen-level data management structure to provide a range of sizes of information available from various platforms. This type of structure has the potential for effective cataloging and retrieval of data from a range of remote sensing but can also accommodate information collected at the field scale, e.g., crop yields, soil, and topography. Development of remote sensing tools that utilize the full suite of available data from the spectral range including microwave, radar, lidar along with the visible, near-infrared, shortwave infrared, and thermal wavebands offer a large amount of information. The development of tools that can be used in precision agriculture will begin to realize the potential often ascribed to remote sensing. The review of the application of remote sensing to precision agriculture by Brisco et al. [124] highlighted some of this potential; however, the development and deployment of UAVs has now made the future prospects closer to reality. They concluded that the future application of remote sensing would require continued development of tools that assessed the state of the vegetation with the field. One of those applications is the potential use of radiative transfer models to derive VIs rather than empirical observations [125,126] by using the radiative models to estimate plant canopy reflectance values [127].

Future applications of remote sensing to agricultural problems will begin utilizing artificial intelligence and machine learning to develop relationships to capture the information content in the spatiotemporal attributes of remotely sensed data. The use of artificial intelligence has begun to emerge in remote sensing, and it may be used to improve the interface of remote sensing data with other data sources, as well as improve upscaling of remotely sensed data. An example of machine learning applied to the remotely sensed data is provided by Debats et al. [128]. They used a random forest approach to classify land area and applied this approach across a wide range of field sizes and land covers to assess agricultural fields in Sub-Saharan Africa. This type of approach can be applied to assess.

Unmanned aircraft systems (UASs) have become readily available to support applications and have the potential to be equipped with a range of radiometric sensors capable of collecting data over a range of wavebands. These systems will have advantages for agriculture [129,130]. These units can detect problem areas in a field, evaluate areas with potential yield loss, or provide information for management decisions. These systems are extremely flexible in terms of the areas that data can be obtained from; however, they are also limited in terms of the area that can be covered in data collection. To take full advantage of UAS technology in the future, the linkage of the observed data with some type of control system will have to be developed and these control systems could be developed and would be of value in high value crops, e.g., vegetables, fruit, or grapes. The continued development of technology to link the pieces between observation and control technology will bring the future into reality.

The products developed from remote sensing data have great potential to help agronomic management practices through the interface with robotics, but that has largely been untapped. Some possibilities for application could be application of nutrients to specific plants or trees, regulating irrigation systems for specific tr ees or vines, or pesticide application to specific areas of a field. Management systems incorporating remote sensing, artificial intelligence, and robotics could conceivably be developed to independently collect data on the status of crops and soils, identify abnormal growth conditions, and take corrective action to maximize agronomic efficiency and profitability.

## 6. Conclusions

Remote sensing has progressed over the past decades from being an observational tool to being an integral part of the decision process in agricultural management. There are still challenges in terms of providing temporal coverage sufficient for decision-making with the timely feedback required from the time of acquisition to the delivery of the results to the decision-maker. Processing of the data often remains a limitation and we would suggest that to overcome this challenge, simple Vis should be used to assess the land surface. Then, if a deviation from the expected pattern occurred, the more complex algorithms should be evaluated. One major area of investigation is the comparison among sensors in the estimation of VIs and this will become increasingly important with the deployment of UAVs with potential assessment of a variety of canopy parameters. There are many different Vis, each with a specific application, and the application of machine learning to develop new algorithms linked to biophysical properties of agricultural plants would yield improved capabilities in assessment. One aspect that has not been evaluated and remains a challenge is the optimal temporal resolution of data for decision-making. The integration of the visible and near-infrared platforms with synthetic aperture radar has now increased the capability of obtaining data without clouds being a limiting factor.

Application of artificial intelligence into agriculture via remote sensing is a promising opportunity. Linking crop simulation models with remote sensing has already proven valuable in terms of providing information on crop development and projected productivity. The next level of opportunity is to develop systems capable of reducing the stress on the plant via a management intervention and determining if the treatment had the desired effect. The future promises both challenges and opportunities and the progress that remote sensing has made in the past 40 years offers solutions to revolutionize agriculture in the next decade.

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