Biological Forum – An International Journal 15(2): 382-387(2023)

ISSN No. (Print): 0975-1130
ISSN No. (Online): 2249-3239

Remote Sensing for Crop Management: A Comprehensive Review

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(Received: 14 December 2022; Revised: 26 January 2023; Accepted: 01 February 2023; Published: 13 February 2023)
(Published by Research Trend)

ABSTRACT: Diseases, pests, weeds, and other biotic or abiotic factors can cause significant financial losses to crops. It is crucial to detect these problems early to take preventive measures. Vegetation monitoring and precision agriculture are necessary for assessing crop health and identifying crop pests in terms of environmental risk assessment. Although remote sensing can give helpful data for agricultural production, there are a few challenges in employing this technique. The outcomes from remote sensing investigations might be difficult to comprehend. Various crops and cultivation environments may necessitate different forms of analysis, and identifying trends and patterns in data can be challenging. Precision agriculture remote sensing is based on indirectly assessing reflected radiation from soil and crops in agricultural fields. Remote sensing indices such as NDVI, LSWI, TVDI, SAVI, WDI, and others can be used to determine crop development and soil moisture from satellite imagery. Remote sensing is a cost-effective, comprehensive, simple, and rapid method of gathering information suitable for monitoring plant stress and disease by providing multitemporal and multispectral information. Thus, it can deliver accurate details continuously at a minimum cost, making it a valuable tool.

Keywords: Remote Sensing, Crop Assessment, Biotic Stresses, Abiotic Stresses, Vegetation Indices.

INTRODUCTION

Plant stress is the stimulus that inhibits plant growth, metabolism, and development in response to various environmental conditions, including abiotic and biotic stressors (Atafar *et al.,* 2009). Abiotic stressors, such as insufficient or excessive water supply, extreme temperatures, heavy metals, ultraviolet radiation, and salinity, can cause significant damage to plant development and growth, leading to a substantial reduction in agricultural productivity worldwide (Fahad *et al.*, 2017, Fich *et al.,* 2016). Biotic stress is a biological component such as diseases, insects, and other pests subjected to agricultural plants (Gimenez *et al.*, 2018). Specific stressors harm plants. These plants suffer from various metabolic abnormalities (Godoy *et al.*, 2021).

With the global population projected to reach 8 billion by 2023, meeting the demand for food production becomes increasingly challenging (World Economic Forum, 2021). Predictions suggest that cereal production needs to increase to almost 3 billion tonnes by 2050, up from 2.1 billion tonnes, and meat production needs to rise by over 200 million tonnes to 470 million tonnes (FAO, 2009). India's total food grain consumption is expected to rise to 215 million tonnes by 2033-34 (According to research released by the NITI Aayog in 2019), with a significant increase in demand for other food products like edible vegetable oil, milk, sugar, eggs, fish, meat, fruits, and vegetables.

Crop damage due to various reasons, such as diseases, pests, weeds, and other biotic or abiotic stressors, results in significant losses in crop yield, which may range from 20-32% in the case of weeds (Mongia *et al.,* 2005), 35-42% in the case of diseases, and total loss in severe infections, insects damage ~14% ranging from 10-20% losses (Pimentel, 1997). Early detection of crop infestations and stress associated with moisture deficiencies, insects, fungal, and weed infestations is critical to mitigating these losses. Vegetation monitoring and precision agriculture using remote sensing can provide farmers with frequent, rapid, and multispectral information to assess the health of crops and detect infestations.

Crop assessment is a crucial task for agricultural development, and it plays a vital role in improving crop productivity and ensuring food security. Crop damage due to natural disasters, pests, and diseases is a significant problem faced by farmers worldwide. Traditional methods for crop assessment, such as field surveys and ground-based measurements, are time-consuming and labour-intensive. Remote sensing technology has emerged as an effective alternative for crop damage assessment and progress monitoring. Remote sensing refers to data collection from a distance without direct contact with the measured object. The technology uses sensors on various platforms such as satellites, drones, or aircraft. Remote sensing for precision agriculture relies on the indirect measurement of reflected radiation from soil and crops in the agricultural field, providing accurate information on plant stress and disease monitoring through multitemporal and multispectral data. This approach is cost-effective, comprehensive and suitable for continuously monitoring crops. To ensure good agricultural productivity, remote sensing imagery should be provided at least once a week and delivered to farmers within two days.

A. Remote sensing and its Types

Remote sensing is a technique used to identify, measure, and analyse specific objects, areas, or phenomena without direct contact with them, allowing for informed decision-making. It involves continuously monitoring the physical characteristics of a region by measuring it's reflected and emitted radiation from a distance, typically from aircraft or satellites.

1. Active remote sensing. Active remote sensing uses radar in the microwave section of the electromagnetic spectrum, which has wavelengths between 1mm and 1m. Synthetic Aperture Radars (SARs) are sophisticated radar sensors that can enhance spatial resolution mathematically and discern the polarisation of electromagnetic energy they transmit and receive, providing more information about surface features (Brown and Porcello 1969; Sarder, 1997). At microwave wavelengths, the atmosphere is transparent, and radar wavelengths are strong enough to penetrate clouds, allowing for imaging even in adverse weather conditions.

2. Passive remote sensing. Passive remote sensing includes satellite or airborne remote sensing. The three types are satellite-based remote sensing, ground-based remote sensing, and unmanned aerial vehicle (UAV)-based remote sensing. In UAV-based remote sensing, detectors for monitoring are installed on the UAVs. UAV-based imaging provides high spatial, spectral, and temporal resolution and is less expensive than conventional remote sensing platforms.

Radiometers are carried on two types of satellites: geostationary and polar-orbiting. Geosynchronous satellites are located in a high orbit near the equator, while polar-orbiting satellites orbit the Earth at lower altitudes, almost perpendicular to the equator. Polar-orbiting satellites pass over a different region of the planet on successive orbits as the Earth rotates (Cracknell and Hayes 1991).

Smart agriculture has extensively used unmanned aerial vehicles (UAVs) to monitor crop health indicators such as drought stress, disease infection detection, nutritional status, biomass, crop vigour monitoring, and yield prediction.

3. Spectral Remote Sensing. Spectral remote sensing involves using sensors to measure the reflection of light from the target. The sensors measure the intensity of light reflected by the crop in different wavelengths, which can be used to estimate various crop parameters such as chlorophyll content, leaf area index, and biomass. Spectral remote sensing can be further classified into multispectral and hyperspectral remote sensing.

A. Multispectral Remote Sensing: Multispectral remote sensing involves using sensors that measure radiation in several specific wavelength bands. Multispectral remote sensing data are widely used for vegetation monitoring, crop mapping, and yield estimation.

B. Hyperspectral Remote Sensing: Hyperspectral remote sensing involves using sensors that measure radiation in several narrow and contiguous spectral bands. Hyperspectral remote sensing provides more detailed information on crops' biochemical and physiological characteristics.

4. Thermal Remote Sensing. Thermal remote sensing involves using sensors that measure the temperature of the target. The temperature of the crop is an essential indicator of crop stress and water availability. Thermal remote sensing can estimate crop water stress, transpiration rates, and irrigation requirements.

5. Radar Remote Sensing. Radar remote sensing involves using sensors that emit microwave radiation and measure the backscatter signal reflected from the target. Radar remote sensing can estimate crop height, biomass, and canopy structure. It is also valuable for mapping crop areas, identifying crop types, and monitoring crop growth.

B. Indices of Remote Sensing and Signification

Various types of data are needed to estimate crop progress, including environmental factors like air temperature, relative humidity, and precipitation, as well as surface conditions like soil moisture content and temperature. Remote sensing techniques using satellite imagery can provide helpful information for crop monitoring by calculating specific indices such as the Normalised Difference Vegetation Index (NDVI), Land Surface Water Index (LSWI), Temperature-Vegetation Dryness Index (TVDI), Soil Adjusted Vegetation Index (SAVI), Water Deficit Index (WDI), and others. These indices can be used to assess crop growth and soil moisture levels.

1. Spectral Vegetation Indices. Remote sensing vegetation indices (SVIs) (Lyon *et al.,* 1998) often utilise the fact that plant pigments, including chlorophyll and carotenoids, absorb light in the visible red wavelengths (corresponding to AVHRR channel 1), while mesophyll tissue reflects light in the near-infrared range (Corresponding to AVHRR channel 2) (Tucker and Sellers, 1986). Healthy plants appear darker in the visible spectrum and brighter in the near-infrared range than sick or senescent plants. As foliage coverage increases, more red light is absorbed due to increased pigmentation, and more near-infrared radiation is reflected due to increased internal leaf dispersion of mesophyll (Curran and Williamson 1986). Soil reflectance is more straightforward than that of plants, with a general increase in reflectance with wavelength depending on soil texture, structure, water content, organic carbon, and iron oxide concentration (Huete and Escadafal 1991). These properties are used to differentiate between plants and soil, as they have distinct spectral properties. SVIs aim to increase reflectance contrast and detect vegetation in remote sensing imagery.

The ratio vegetation index (RVI) or simple ratio index (SRI) is the most basic SVI. Other SVIs, such as the

Normalised Difference Vegetation Index (NDVI), was developed to address reflectance from typically dark or reddish soil backgrounds by dividing the difference between the two channels by their total. (Tucker, 1979):

$$NDVI=(Ch2-Ch1)/(Ch2+Ch1)$$

The NDVI has an ideal range of -1 to +1, but it typically ranges from 0.0 to 0.8, as noted by Tucker (1979). As with all red/near-infrared indices, the NDVI is a specific measure of chlorophyll quantity and light absorption, according to Myneni *et al.* (1995a).

In regions with sparse vegetation growth, NDVI measurements are instrumental since they provide a more comprehensive dynamic range than simpler SVIs like RVI. Conversely, in areas with complete coverage, such as forests, the NDVI becomes saturated, as Huh (1991) observed.

To address some of these issues, various indices, such as the soil-adjusted vegetation index (SAVI), have been proposed, as noted by Leprieur *et al.* (1996) and Huete (1988). However, they have been less frequently used for ecological and epidemiological purposes and are not being investigated further. Primicerio *et al.* (2012) utilised a multispectral camera mounted on a UAV to assess vine health by calculating the normalised difference vegetation index (NDVI). Similarly, Gennaro *et al.* (2016) determined the GLSD-infected vine by estimating the NDVI based on UAV multispectral data, even in cases where the disease-infected vine was in the early stages of the illness and could not be diagnosed visually.

Table 1: Main spectral vegetation indices used in agriculture.

Index	Equation	Usefulness	Reference
N.G.	G/ (NIR+R+G)	Carotenoids, anthocyanins, xanthophylls	Sripada *et al.*, 2006
NR	R/ (NIR+R+G)	Chlorophyll	Sripada *et al.,* 2006
DVI	NIR-R	Soil reflectance	Tucker, 1979
GDVI	NIR-G	Chlorophyll, N status	Tucker, 1979
NDVI	(NIR-R)/ (NIR+R)	Vegetation cover	Rouse *et al.,* 1973
GNDVI	(NIR-G)/ (NIR+G)	Chlorophyll and photosynthesis, N status	Gitelson *et al*., 1996

Abbreviation: A=adapted, D=difference, G=green, N=normalized, NIR=near-infrared, R=red, RVI=Ratio Vegetation Index, VI= Vegetation Index.

2. Atmospheric Moisture Indices. As Dalu (1986) outlined, an approach has been established to estimate the overall water content in the atmospheric column, known as total precipitable water. The method employs atmospheric radiative transfer models over the ocean, assuming a surface relative humidity of 80% due to the balance between evaporation and diffusion. The estimates were validated against ship-collected data. To determine the total precipitable water content of the atmospheric column, U (kg m^2), a correction factor, a, is derived and the varying atmospheric path length as a function of the scan angle is considered, as per the technique suggested by Dalu (1986).

$$U = a \times (Ch4 - Ch5) \times \cos\theta$$

3. Rainfall Indices. As per Emanuel (1994), convective processes tend to dominate weather patterns in tropical latitudes with substantial reserves of potential energy from cyclical heating. The most vigorous convection currents produce the greatest updrafts, leading to clouds with a higher water content that is more likely to produce rainfall, as noted by Ba and Nicholson (1998). These convection currents form dense clouds with frigid, elevated tops that emit shallow thermal infrared radiance values. While it is possible to measure temperatures at the tops of clouds, the specific threshold temperature associated with rain-bearing clouds and the amount of rainfall they produce vary over time and space and must be determined through empirical analysis, according to Grimes *et al*. (1999).

Remote sensing can aid in creating a temporal developmental profile of crops throughout their life cycle. By retrieving environmental components and remote sensing indices, it becomes possible to discern the crop growth model, the relationships between them, and the influence of relevant variables on crop development. Remote sensing is a valuable tool for assessing crop development at local and large scales, relying on prior data and tests. By incorporating ecological, surface, and crop status data obtained via remote sensing approaches, as well as soil station data, the model's ability to determine crop condition is enhanced.

C. Role of Remote Sensing in Crop Progress Assessment

The theoretical framework known as crop growth or crop progress analysis is used to determine the relationship between genotype and environmental factors on the growth and development of plants. In natural habitats, growth and development cycles must be completed within a specific time frame due to environmental factors such as light, moisture, and nutrition, which can limit genetic potential. The physiological phases of crop development from planting to harvest are called crop phenology. Precise information on agricultural phenology is required during the growing season for crop growth management and yield estimation (Walthall *et al.,* 1935). The impact of water stress on crop yield varies depending on the growth stage (Anderson *et al.,* 2016). Some plant species naturally increase, while others grow more slowly. Fast-growing species have higher rates of photosynthesis but also use respiratory energy more efficiently for maintenance, growth, and ion uptake. While photosynthetic activity rates are higher in fast-growing species, they also utilize respiratory energy more effectively for maintenance, development, and ion absorption.

Growth indices in summary: Five key indices are commonly derived as an aid to understanding growth responses. Mathematical and functional definitions of those terms are summarised below**.**

Table 2: Key plant growth indices (Source: Charles Price and Rana Munns).

Growth Index	Units	Functional definition
Relative growth rate (RGR)	d^{-1}	Rate of mass increase per unit mass present
Net assimilation rate (NAR)	$g\ m^{-2}\ g^{-1}$	Rate of mass increase per unit leaf area
Leaf area ration (LAR)	$m^{2}\ g^{-1}$	Ratio of leaf area to total plant mass
Specific leaf area (SLA)	$m^{2}\ g^{-1}$	Ratio of leaf area to leaf mass
Leaf weight ratio (LWR)	unitless	Ratio of leaf mass to total plant mass

D. Role of Remote Sensing in Crop Damage Assessment

Remote sensing technology has potential applications in farming for assessing crop area and detecting crop status, especially in water stress or pest infestation cases. A hypothesis based on the reflectance of plants suggests that healthy crops have a higher near-infrared reflectance but a lower visible reflectance. In contrast, plants affected by illness have higher reflectivity in the visible band and lower reflectivity in the infrared. By examining the differences in spectral ranges between healthy and diseased plants, scientists can determine the stress potency of green leaves.

Diseased plants with reduced chlorophyll quantity and changes in internal structure can absorb incident sun ray modifications in the visible and near-infrared range. (Carter and Knapp 2001). Spectral reflectance is crucial in the red area and falls in the Near-Infrared range, depending on the contamination potency. Plants under stress also exhibit varying degrees of internal morphological alterations, decreasing spectrum reflectance in the Near-Infrared array. The foliar internal makeup of green trees is primarily responsible for their strong spectral reflectance in the Near-Infrared array. These spectral properties of foliage are the cornerstone for remote sensing of disease-stressed plants.

Various types of stresses can impact plant function, and there are several approaches to identifying the effects of these stresses through remote imaging. Instead of visualizing the stress, scientists typically examine the plant's natural response to stress. For example, changes in the stomatal aperture can affect leaf temperature, which can be reviewed to determine the effects of different stressors, such as drought, floods, salinity, temperature, or infection.

1. Drought. According to scientists, water or drought stress is when plants experience physiological reactions due to insufficient water availability, either from soil water deficit or high atmospheric evaporative demand. This stress leads to dehydration and affects plant cells' ability to maintain appropriate water concentrations, making it one of the crucial abiotic stressors that can impact crop growth, output, and food quality (Hopkins, 2009). However, plants may already be significantly damaged before any visible symptoms of water stress are observed (Jones, 2008). To avoid severe crop loss, detecting physiological changes in plants before they become apparent is essential. Hyperspectral imaging can provide a comprehensive spectrum of data that can reveal the relationship between spectral properties and plant conditions (Pinter, 2003). Multi-/hyperspectral remote sensing techniques, such as thermal imaging (TIR; 8–14 μm), visible, near-, and shortwave infrared reflectance (VNIR/SWIR; 0.4–2.5 μm), and sun-induced fluorescence (SIF 0.685 and 0.74 μm), are used to detect plant responses to external stress.

2. Salinity. Osmotic pressures and high quantities of sodium and chloride cause salt damage to crops. As soil sodium levels increase, sodium ions are more likely to be absorbed by the humus complex. Excess salt also hardens and compacts the soil, preventing water from reaching the root zone and remaining at the soil surface. In addition, extra salt raises soil pH, which sequesters certain soil nutrients and makes them inaccessible to plants, ultimately impacting productivity in tsunami-affected regions by inhibiting crop uptake of potash minerals through the cation exchange capacity (Tchiadje, 2007). Remote sensing (R.S.) data and geographic information systems (GIS) techniques have been used to assess floods, tidal waves, and other catastrophic events. NDVI, a vegetative activity metric derived from satellite data, can be used to quantify the impact of salt on crops and other vegetation. Under salt stress, crop canopy reflectance increases in the visible range (e.g., 450–700 nm) but decreases in the near-infrared region (e.g., 770–900 nm). However, remote sensing of salinity over large areas based on plant analysis has shown disappointing results because other stressors, such as water stress and pests, also generate significant changes in canopy reflectance (Goto, 2015).

3. Temperature. Several research studies have demonstrated that satellite-based land surface temperature measurements can estimate mean and maximum daily air temperatures. To estimate daily mean air temperature, Guo *et al.* (2017) established a correlation between air temperature data collected from meteorological stations and Land Surface Temperature (LST) data derived from remote sensing sources. By integrating remote sensing data on planting areas, phenology, daily mean air temperature, and maximum air temperature, it is possible to generate maps highlighting areas of agricultural damage caused by high temperatures.

4. Disease. Studies have shown that plant diseases, and pests can cause significant crop loss, with diseases alone accounting for at least 10% of global food production (Strange and Scott, 2005). Pesticides are often used excessively to protect crops, increasing production costs and the risk of hazardous residue in agricultural products. Changes in pigment, chemical concentrations, cell structure, nutrition, water absorption, and gas exchange can alter the colour and temperature of the plant canopy and its reflectance properties. Remote sensing can detect these changes, allowing for the safe, quick, and cost-effective detection and quantification of crop stress caused by various biotic and abiotic factors (Raikes and Burpee 1998).

The reflectance of plant leaves varies depending on the state of health and vitality of the plant, with healthy leaves exhibiting low reflectance at visible wavelengths due to strong absorption by photoactive pigments and high near-infrared reflectivity in the leaf's interior tissue due to repeated scattering at the air-cell contacts. Absorption by water, proteins, and other carbon components results in low reflectance in wide wavebands in the shortwave infrared. The difference in spectral properties between healthy and diseased plants can be used to track disease occurrence and severity. Hyperspectral remote sensing is a modern and practical disease surveying and mapping tool. However, distinguishing diseases from everyday nutritional stressors, such as nitrogen deficiency or overuse, can be difficult. They may have similar spectrum responses resulting in comparable biochemical characteristics and plant morphology alterations.

5. Insect Pest. Plant protection experts have utilized various approaches to detect and quantify crop damage caused by insect pests and diseases in crops like rice, cotton, wheat, sugarcane, legumes, and vegetables. One such method involves using a hyperspectral spectroradiometer to measure the spectral reflectance at the canopy level and compare data from healthy and pest-infested plants. Reflectance data from healthy and infected plants in different spectral bands such as blue, green, red, and near-infrared (NIR) are subjected to mathematical analysis to create vegetation indices that aid in identifying and quantifying agricultural losses.

Researchers Yang and Cheng (2001) demonstrated that canopy reflectance spectra acquired using a spectroradiometer could readily distinguish six stages of rice plant hopper infestation, particularly within the 737-925 nm range of the spectrum. Greenbug-infested wheat canopies showed more reflectivity in the visible range and less in the near-infrared sections of the spectrum than undamaged canopies. Several spectral vegetation indices were generated and linked to green bug density and the percentage of reflectance comparison. In contrast to previous findings, Reisig and Godfrey (2007) found that spider mite and aphid-infested cotton leaves increased reflectance in the near-infrared wavelength of around 850 nm compared to uninfected leaves.

CONCLUSIONS

Thus, the paper discusses the benefits of remote sensing as a tool for detecting and measuring both abiotic and biotic stressors in plants. It highlights the ease, cost-effectiveness, and comprehensiveness of remote sensing and notes that integrating information from various sensors can improve the sensitivity of detecting and measuring stressors. The paper also notes that remote sensing is already used for crop production forecasting, yield modelling, and stress detection in India. Finally, the passage emphasizes the usefulness of spectral remote sensing for the non-destructive estimation of plant growth and biophysical parameters.

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How to cite this article: Surbhi Pachori, Sunny Thakur, Akash Barela, Anamika Tomar, Sachin Prakash Nagre, Kumar Jai Anand, Teena Patel and S. K. Sharma (2023). Remote Sensing for Crop Management: A Comprehensive Review. *Biological Forum – An International Journal, 15*(2): 382-387.