International Journal of Agricultural and Applied Sciences, June 2024, 5(1): 101-111
https://www.agetds.com/ijaas
ISSN: 2582-8053
https://doi.org/10.52804/ijaas2024.5114

Review Article

OPEN ACCESS

Advancements in Remote Sensing Technologies for Assessing Abiotic Stress in Plants: a Comprehensive Review

T. D. Warik[1], G.S. Pawar[1], G.U. Shinde[3], H.V. Kalpande[1], S.M. Gambhire[1], A.B. Pillewad[1]
[1]*Department of Agricultural Botany, College of Agriculture, Parbhani, VNMKV, Parbhani, Maharashtra.*
[2]*Department of FMPE, VNMKV, Parbhani, Maharashtra.*
**Corresponding author e-mail: tejuwarik@gmail.com*
(Received: 03/03/2024; Revised: 25/05/2024; Accepted: 30/05/2024; Published: 30/06/2024)

ABSTRACT
One of the key elements influencing crop production across the globe is abiotic stress. Early detection and corrective action in this regard can help to lessen the effects of stresses on crop growth and output. Recent advances in remote sensing hold a vital role in the early identification of abiotic stress across a broader area with less involvement of money, time, and labour. Remote sensing technology has become an indispensable tool in the field of agriculture, particularly for detecting abiotic stress in plants. This paper reviews the application of remote sensing techniques for the assessment of abiotic stress factors such as drought, flood, salinity, and nutrient deficiency. Furthermore, the review explores the critical aspects of data acquisition, processing, and analysis, underscoring the importance of machine learning and artificial intelligence techniques in enhancing the accuracy of stress detection.
Keywords: abiotic stress, remote sensing techniques, stress detection.

INTRODUCTION

Many environmental elements have an ongoing impact on plants. These include biotic and abiotic stresses. Abiotic stress factors included extreme temperatures (heat, cold, and freezing), too-high or too-low irradiation, water logging, drought, inadequate mineral nutrients in the soil, and excessive soil salinity. Biotic environmental factors are other organisms like symbionts, parasites, pathogens, herbivores, and competitors; and wind, ionizing radiation, or pollutants (Schulze *et al.* 2002). Abiotic stress is defined as any departure from these ideal external circumstances, meaning that there is an excess or variation in the chemical or physical environment that negatively impacts plant growth, development, and productivity (Bray *et al.* 2000). Each abiotic factor's number or intensity determines how it affects the plant. The plant needs a specific amount of each abiotic environmental element for optimum growth.

The earth's climate is changing quickly, according to the most recent scientific research. Due to global warming, the already poor situation will soon get significantly worse as desertification continues to rise and the annual loss of arable land might treble by the end of the century. (Evans 2005; Vinocur and Altman 2005). The main abiotic stresses—high salt, heat, cold, and drought—have a 70% negative impact on the survival, biomass production, and yields of key food crops. (Vorasoot et al. 2003).

In the contemporary global landscape, plant stress detection is regarded as one of the most important topics for improving crop productivity. With this wide-ranging view, there are numerous options for technology. Qualitative techniques like fluorescence, thermography, and VIS/NIR reflectance offer a non-disruptive picture of how stresses are affecting plants, even over vast regions. The effects of stress can be seen at different spatial scales, ranging from the DNA level (nanometers) to the cell (micrometres), the entire plant (millimeters to meters), and the field (kilometers). Only qualitative methods can be used to greater scales. (Galieni *et al.*, 2021).

As one of the large data sources, remote sensing uses platforms from satellites, manned and unmanned aircraft, and ground-based structures to provide earth-observation data and analytical findings regularly. The advancement of satellite remote sensing technology in particular has allowed for the availability of vast amounts of remotely sensed data for study and other uses. (Liu 2015; Chi et al. 2016).

Currently, there are over a thousand operational satellites orbiting the planet, many of which are used for remote sensing. Typically, these satellites' sensors continuously take pictures of the earth's surface at various temporal and spatial resolutions. (Rosenqvist et al. 2003; Anonymous 2015).

Remote Sensing:

Remote sensing can be defined as learning something about an object without touching it. The field of remote sensing can be divided into two general categories: analog remote sensing and digital remote sensing. Analog remote sensing included use of film to record the electromagnetic energy. Digital remote sensing included use of some type of sensor to convert the electromagnetic energy into numbers that can be recorded as bits and bytes on a computer and then displayed on a monitor. Modern tiny satellites, which revolutionized the satellite paradigm in the late 1980s, created new opportunities for space applications.

From 1957 to 1969, the first microsatellites were launched. A total of 238 mini-satellites and 249 micro-satellites were launched between 1980 and 1999 from various countries across the world, such as China, India, Germany, Japan, Korea, Saudi Arabia, China, Algeria, and Malaysia. In 1999, a special issue on tiny satellite engineering was released. (Swinerd 1999). The International Workshop on Earth Observation Small Satellites for Remote Sensing Applications took place in Kuala Lumpur, Malaysia from November 13–16, 2007. Based on Dr. Kramer's presentation at that Workshop (Kramer 2007), Kramer and Cracknell (2008) have produced an overview of tiny satellites in remote sensing.

Steps involved in remote sensing included:

Digital Image Analysis: It is the process by which the selected imagery is converted/processed into information in the form of a thematic map. Digital image analysis is performed through a series of steps. These steps include (1) image acquisition/selection, (2) pre-processing including image enhancement, (3) classification, (4) post-processing, and (5) accuracy assessment.

Image Acquisition/Selection: The application of the study and the budget come first when choosing or purchasing suitable remotely sensed imagery.

Pre-processing: Pre-processing is defined as any technique performed on the image before the classification.

Classification: Only spectral information (tone/color) used to classify digital data.

Post-processing: Post-processing can be defined as those techniques applied to the imagery after it has been through the classification process.

Change Detection: Images can be used to simply identify binary “change versus no-change” or “from-to change”

Accuracy Assessment: Accuracy assessment is a vital step in any digital remote sensing project. (Congalton, R. G. 2010).

Remote Sensing in Precision Agriculture:

Since its establishment in the 1980s, precision agriculture has transformed agricultural operations by integrating remote sensing, geographic information systems (GIS), and global positioning systems (GPS). This approach was based on agricultural mechanization. Precision agriculture has changed over the last three decades from strategic monitoring based on satellite imaging for local decision-making to tactical monitoring and control guided by data from low-altitude remotely sensed data for site-specific treatment at the field level (Zhang et al. 2002).

Broad-band multispectral or narrow-band hyperspectral data capture, both imaging and non-imaging, is the primary use of sensors. To accommodate sensors aboard manned and unmanned aircraft, space-borne platforms are utilized, whereas ground-based platforms are best suited for laboratory and field sensors that need to be deployed quickly. Agricultural remote sensing is an extremely specialized subject that produces extremely complicated and large volumes of pictures and spectral data to inform agricultural development decisions. To enhance decision-making regarding fertilization, irrigation, and pest management for crop production, remote sensing is used in agricultural areas to monitor crop stress and soil parameters. Early plant stress detection offers the chance to make early management changes to enhance crop output and quality. (Kim et al., 2010).

Remote Sensing Qualitative Methods for Abiotic Stress Detection:

A healthy leaf emits fluorescence when stimulated by UV radiation. The wavelengths of radiation are blue (440 nm), green (520 nm), red (690 nm), and far-red (740 nm). The electromagnetic signal that is reflected by the plant leaves during reflectance-based remote sensing is used to record the data. Changes in leaf components are the parameters tracked in reflectance-based remote sensing for plant stress. (Chaerle *et al.* 2002).

Firstly, plants and electromagnetic radiation interact, which is the basis of most of the processes involved. Plants can undergo a wide range of intricate physiological and biochemical reactions to stressful situations, including changes in stomatal conductance, pigment content, and biochemistry. In the previous few decades, agricultural sciences primarily relied on reflectance (in the thermal (in the thermal infrared, TIR, 7.0–20.0 µm region), fluorescence (at 0.68 and 0.74 µm wavelengths), and near-infrared (NIR, 0.7–1.3 µm and short wave-infrared, SWIR, 1.3–2.5 µm) sensors. Additionally, sensors can be categorized according to how they are used in (i) non-imaging techniques (such as VIS, multispectral and hyperspectral imaging, thermal imaging, fluorescence imaging, and x-ray imaging) and (ii) imaging techniques (such as VIS, multispectral and hyperspectral imaging, and fluorescence imaging). Since non-imaging sensors do not give spatial information, they are generally better suited for measurements made at lab or leaf scales. The great resolution of the sensors that are currently on the market aids in identifying potential relationships between minute processes occurring at the tissue level and plant electromagnetic patterns after exposure to stress. (Thomas et al., 2017, 2018). The spatial resolution is a crucial component in gathering data on plant responses to stress at the canopy or landscape levels. For instance, proximal hyperspectral imaging is more effective than hyperspectral remote sensing in the field of characterizing a particular disease. (Kuska and Mahlein, 2018). Every sensing approach has a unique level of efficacy in identifying and detecting stress, which varies depending on the level of technical advancement attained and the inherent features of the technology being used. It depends on (i) the kind of stressful conditions and (ii) its magnitude early identification of stressful conditions is important In the event of water stress, for instance, temperature-based indices offer a suitable pre-visual identification of plant reactions. (Gerhards et al., 2019).

Secondly, Plant genotype is connected to spectrum responses to stress exposure within the same sensing vegetation technology and stressful circumstances. To produce indicators or parameters for certain demands, this element could require a thorough investigation of particular stress-genotype combinations together with an understanding of the physiological and biochemical mechanisms that lead to changes in the spectrum feature.

Thirdly, data collection procedures should take into account the plant canopy and leaf structural architecture, as well as the measuring environment. Enhancements are required for (i) pre-processing data, (ii) integrating calibrating systems on automated systems, and (iii) utilizing multiple sensors. platforms with 3-D shape sensors installed as well. (Mishra et al., 2020).

Fourthly, the identification of specific stressors can be challenging, particularly in open-field conditions where a multi-stress scenario can occur, because certain plant responses which may be detectable for stress diagnosis may be shared among various stresses (e.g., drought, salinity, temperatures, mineral toxicity, or pathogen infection). Single-sensing techniques have the potential to identify individual stress signals with high specificity in experimental settings. However, a comprehensive and integrated approach is necessary to identify potential multiple causes in agricultural applications (Jones and Schofield, 2008). The aforementioned factors provide a fresh foundation for the development of vegetation sensing for stress detection by utilizing existing methods and introducing and enhancing cutting-edge imaging techniques that are useful for the agricultural industry. (Mishra et al., 2017; Khan et al., 2018; Gerhards et al., 2019; Gorbe and Calatayud, 2012; Murchie and Lawson, 2013).

Fluorescence Spectroscopy:

A specific wavelength of light is absorbed by fluorescent molecules, which then change their electronic shell and eventually return to their original state while releasing some of the absorbed energy as an electromagnetic wave. Every molecule has unique wavelengths for absorption and emission. For example, chlorophyll fluorescence (ChlF) has two peaks in the far-red (735 nm) and red (680 nm) wavelength ranges of its natural emission, which fall between 650 and 800 nm. Variations in the chlorophyll content of leaves can be detected by variations in the shape of the fluorescence spectra and the ratio of the two maxima emission peaks (F685/F735). (Buschmann, 2007; Pandey et al., 2015). Following plant exposure to both biotic and abiotic stressful circumstances, ChlF and ChlF parameters are commonly used to quickly assess any mutation of Photosystem II.

Vis/NIR Spectroscopy:

With both active and passive sensors, leaf and/or canopy reflectance has been extensively studied under a variety of biotic and abiotic stressful situations. While the latter rely on sunlight as their light source, the former are equipped with light-emitting components. Since reflectance in the VIS, NIR, and SWIR is predominantly controlled by photosynthetic pigments, cell structure, and water content, respectively, the principal applications in plant health detection are based on spectral wavelengths ranging from 400 to 2,500 nm. In reality, when plants develop in poor settings, these features can undergo significant alterations. (Mishra et al., 2017).

Reflectance spectroscopy is generally utilized to sense a variety of stressful situations. The assessment of crops' nitrogen status is a topic covered in some of the more current work on this subject. (Stellacci et al., 2016), the effects of salinity on crop growth and yield (Boshkovski et al., 2020); the plant changes brought on by drought (Stagnari et al., 2014; Maimaitiyiming et al., 2017; Sylvain and Cecile, 2018); the accumulation of particular secondary metabolites in plant tissue (Couture et al., 2016); and the phenotyping of plants (Garriga et al., 2017; Ge et al., 2019), the macro- and micro-nutrient deficiencies (Galieni et al., 2015). These days, the majority of reflectance spectroscopy technologies are based on hyperspectral sensors, which allow for massive data collection by allowing images to be acquired in some tiny (<10 nm) and contiguous spectral bands.

Thermal Imaging:

Because of the strong correlations between foliar surface temperature (Tleaf) and leaf gas exchange (CO_2 and H_2O fluxes controlled by stomatal closure or aperture) or stomatal conductance (gs), it can be effectively used in the identification of stressed circumstances (Gutirrez et al., 2018). Well-known and extensively studied subjects include the physical rules governing body emission in the TIR region and the atmospheric and environmental factors influencing the Tleaf-gs connection. (Valu et al., 2013; Vialet-Chabrand and Lawson, 2019; Jones and Schofield, 2008). Its primary uses are in agriculture and phenotyping, specifically in the establishment of irrigation schedules and sensing for crop water stress detection (Gutirrez et al., 2018).

Fluorescence Imaging

The emergence of novel technologies has made it possible to construct an image by simultaneously accumulating a large number of punctual fluorescence spectroscopic signals, each of which is encoded with a color-value connection. Typically, the system consists of a charge-coupled device (CCD) camera and a UV light source to excite the fluorescent molecules. (Sankaran et al., 2010). Moreover, fluorescence imaging is a helpful tool for examining stressful situations caused by nutrient deficiencies (Wang et al., 2018c), extreme temperatures (Dong et al., 2019; Lu and Lu, 2020), drought and/or salinity (Yao et al., 2018; Sun et al., 2019).

Multi- and Hyperspectral Imaging and Thermal Hyperspectral Remote Sensing for Stress Characterization:

The classification of spectral sensors is based on the resolution of the measure (i.e., the density of wavebands in the measure). Multi- and hyperspectral sensors can load data from a continuous and wider VIS/NIR band, usually between 400 and 1,000 nm, with the most sophisticated systems reaching the 350–2,500 nm band (Stellacci et al., 2016; Maes and Steppe, 2019). The spectral resolution of multispectral sensors is approximately 50 nm, whereas hyperspectral sensors have a resolution of 1 to 10 nm (Mahlein, 2016; Stellacci et al., 2016). Nevertheless, because they are more widely available and less expensive, multi-spectral sensors are currently beneficial only in agricultural applications.

Because the spectrum information is combined with the spatial and temporal dimensions in the image-based VIS/NIR technique, it is possible to assess the occurrence of stressful situations even at the landscape scale (Zhang et al., 2019a). Real-time monitoring of the water state, biomass and yield, nutrient status, disease, and pests is facilitated by spaceborne, aerial, and ground-based systems (Xue and Su, 2017; Maes and Steppe, 2019; Zhang et al., 2019a; Caballero et al., 2020).

Until recently vegetation spectra in the mid-and thermal-infrared region (MIR: 2.5–6.0 μm and TIR: 8.0–14.0 μm) have been considered featureless. Most spectral features of plant leaves in the TIR domain have been overlooked due to lack of equipment, poor signal-to-noise ratio and the complex nature of the spectral characteristics of vegetation (Ribeiro da Luz and Crowley 2007). However, recent advances in TIR application led to the discovery that the spectral signatures of fresh plants are dominated by epidermal materials of leaves (i.e. cell wall and cuticle) (Salisbury, 1986). The reflectance spectra of green leaves taken by high-resolution sensors in the TIR region revealed a broad range of distinctive spectral features (Salisbury 1986; Salisbury and Milton 1988). The spectral response of fresh and completely dried leaves measured in the mid-to thermal-infrared region revealed significant variation in the mid-infrared spectral response, emphasizing the potential use of mid-infrared for leaf water content quantification (Gerber et al. 2011). Remotely sensed data using TIR radiation has been successfully used to detect water-deficit stress even before visual symptoms of the same appeared (Möller et al. 2006). Fresh leaves showed the lowest MIR and TIR reflectance, and with the decrease in leaf water content, reflectance increased. In the MIR, the variation in reflectance was more prominent between 2.5 and 3.0 μm (maximum reflectance of about 30%) and 3.5–5.8 μm (maximum reflectance of about 16%). The absorption characteristics at 3.05 μm and 4.65 μm are related to the leaf water content (Ribeiro da Luz 2006; Fabre et al. 2011). Cheng *et al.* (2011) reported better retrieval of leaf water content retrieval from the MIR to TIR spectra (R2 ¼ 0.88) than that obtained from VNIR to SWIR spectra (R2 ¼ 0.77). The correlation between leaf water content and spectral response over the entire MIR region was reported to be negative (Ullah *et al.* 2013).

Abiotic Stress Monitoring:

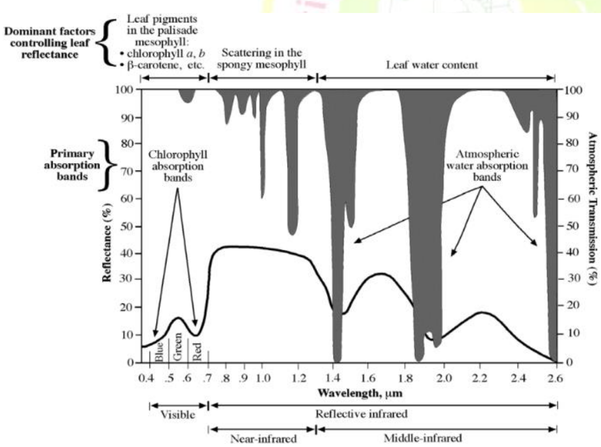
Water-Deficit Stress Monitoring:

A variety of approaches with differing degrees of precision and application have been tried, such as assessing the water content of soil or plants, the concentrations of pigments or nitrogen, dry matter, and the leaf area index (LAI) (Carter 1993; Peñuelas *et al.* 1994). Scientists concluded sensors can accurately detect the water-deficit stress that is being applied. (Sinclair and Ludlow 1985). Leaf water content can effectively indicate the health and vigour of a plant along with its photosynthetic efficiency (Harry, 2006). The selection of suitable genotypes in breeding for water-deficit stress tolerance provides advanced prediction for monitoring the physiological status of any vegetation (Harry, 2006). Apart from these, precise estimates of plant water content can be used for drought risk assessment (Bauer et al. 1986). Plant water deficit stress or drought stress is one of the major limiting factors which affects yield and is usually detected only after it becomes visually apparent. So, an accurate estimation of plant water status or relative water content (RWC) is a major factor in the decision-making process regarding general land use, crop irrigation and drought assessment (Peñuelas *et al*. 1997). RWC can be defined as the ratio of the volume of water present in a leaf to the water volume of the leaf at fully turgid conditions (Hunt and Rock 1989). Assessment of water-deficit stress can be done by taking plant canopy or leaf level reflectance measurements, as they show change in response to changing RWC of the plant (Gutierrez *et al*. 2010). Different species may exhibit different symptoms of water-deficit stress; however, one of the common effects of water-deficit stress across all the species is the change in plant's spectral (Peñuelas *et al*. 1993). The water absorption bands can be of good use in the estimation of the plant's RWC.

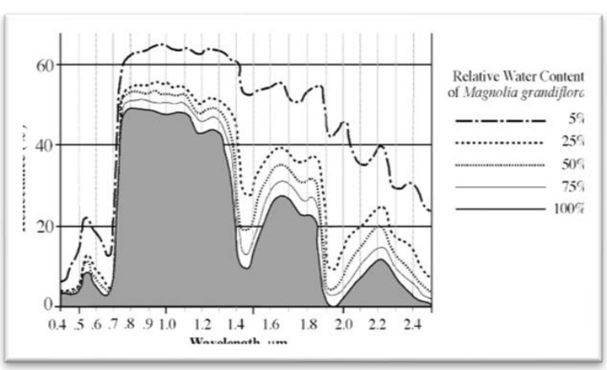
The reflectance of plant leaf or canopy particularly beyond visible spectral range is mostly governed by leaf water content. Therefore, it can indirectly be used for non-destructive in-situ evaluation of plant water status. Canopy reflectance obtained from hyperspectral sensors besides offering quick and easy measurements enables the estimation of some additional parameters through a series of different spectral indices (e.g., chlorophyll content, LAI, intercepted radiation and photosynthetic capacity) (Araus *et al.* 2001). Of its versatile nature, canopy reflectance is a very useful tool for high-throughput phenotyping (Montes *et al*. 2007; Chapman 2008).

Effect of Stress on Plant's Spectral Signature:

Recognizing an object in isolation from its surroundings is remote sensing's main goal. It is referred to as spectrum reflectance if this is accomplished through reflectance measurements. In the wavelength range of 400-2700 nm, the spectral reflectance of the vegetation varies with wavelength and can be split into three primary wide zones. (Gates *et al.* 1965). The response is dominated by the pigmentation of leaves, specifically chlorophyll, carotene, and xanthophylls, in the visible spectrum (400–700 nm). Low reflectance and high absorbance, particularly at blue and red wavelengths, define this region. (Gausman 1974). The NIR region has two weak water absorption features at wavelengths 950–970 and 1150–1260, respectively (Sims and Gamon 2002). There are three main water absorption bands are present at 1400 nm, 1900 nm, and 2700 nm. The response in the shortwave infrared (SWIR) spectrum (1300-2700 nm) is primarily influenced by the water content of the same leaves. The visible-near-infrared (VNIR) and SWIR spectra have been extensively explored for determining leaf water content (Ceccato *et al*. 2002; Cheng *et al.* 2011). Water molecules present in leaves weakly absorb radiation in the NIR (720–1000 nm) region and strongly absorb in the SWIR (1400–1900 nm) region (Datt 1999).



Typical spectral reflectance pattern of leaf. Source: Jensen (2009).



Source: Jensen (2009)

than the NIR region for measuring leaf water content (Datt 1999). Numerous investigations found a significant relationship between leaf water content and reflectance and derivative spectra between 1400 and 1900 nm. (Ceccato *et al*. 2001, 2002; Champagne *et al*. 2003). If the chlorophyll content decreases as a result of biotic and abiotic stressors, the reflectance in the visible region increases. The reflectance in the NIR region of the electromagnetic spectrum will be reduced if disease or pests harm the leaves.

Spectral Indices for Characterizing Stress:

The vegetation indices (VIs), which highlight a certain aspect of the vegetation, are combinations of spectral responses in several wavebands. (Wiegand *et al*. 1991). Composite indices are more capable of detecting changes in a plant's biophysical and biochemical characteristics brought on by biotic and abiotic stressors than individual spectral bands (Asrar *et al.* 1984). The indexes also attempt to minimize the complexity of the multispectral/hyperspectral data and standardize the representation of crop spectral responses, which aids in comparing crops across regions. (Malingreau 1989). The NDWI was created to evaluate the condition of the water using airborne hyperspectral imaging with a considerably greater spatial resolution (Gao, 1996). NDWI is a reasonably accurate indicator of vegetation water content because it is less subject to atmospheric scattering caused by water vapours. It can also function using the 1640 nm and 2130 nm water absorption bands (Chen *et al.* 2005). According to Zarco-Tejada *et al.* (2003), the simple ratio water index (SRWI; R860/R1240) can be used to estimate plant water content concerning LAI, equivalent water thickness (EWT), and leaf biomass. The difference between the reflectance spectra of two spectral bands serves as the basis for the VIs, also known as simple ratio and normalized difference indices (Rouse *et al*. 1974). Spectral indices, such as WI or NDWI, use straightforward ratios of the reflectance at a wavelength within the water absorption bands and another wavelength from outside the water absorption bands, ideally used as a control, to identify changes in plant water content. (Sims and Gamon 2002). Indicators such as the red edge inflexion point (REIP) and the normalized differential vegetation index (NDVI) make use of wavelengths that are impacted by changes in the cellular makeup or pigment content of leaves. (Horler *et al.* 1983). The majority of the indices currently in use, such NDWI and WI, employ wavelengths in the near-infrared (NIR, 700-1300 nm) range. Even though numerous research has demonstrated the existence of meaningful connections between these indices and plant water status. (Peñuelas *et al*. 1997; Serrano et al. 2002; Pu *et al.* 2003; Asner and Martin 2008). It has been suggested that wavelengths in the SWIR rather than the NIR could more accurately depict changes in plant water status. (Tucker 1980). The SWIR wavebands located in the range of 1500–1750 nm have been identified as useful for monitoring plant water content (Ceccato *et al.* 2002; Chen et al. 2005; Eitel *et al.* 2006).

Characterization of Stresses through Plant Pigment Assessment:

Under stressful conditions, the amount of leaf chlorophyll drops, which reduces the amount of light that is absorbed overall in the visible spectrum (Zarco-Tejada *et al.,* 2001). The usual spectral reflectance pattern of plants is altered as a result of these alterations, which results in a decrease in green reflection and an increase in red and blue reflections. The location and form of the spectral red edge are significant indications of plant water status when chlorophyll content is utilized as a measure of plant water-deficit stress (Horler *et al*. 1983). The (R850 R710)/(R850 R680) index was proposed by Datt (1999) utilizing the leaf reflectance of 21 Eucalyptus species. Sims and Gamon (2002) created some indices using a sizable database that included over 400 leaves and a variety of functional categories, leaf structures, and developmental stages. They then compared these indices to ones that were already in use. They discovered that when it came to connection with chlorophyll concentration, indices mSR705 and mND705 were far superior to others.

According to Gitelson and Merzlyak (1994), chlorophyll-a absorbs light at a wavelength of 670 nm with the highest sensitivity of reflectance. They concluded that the wavebands with the greatest sensitivity to chlorophyll-a levels were 550–560 nm and 700–710 nm. For pigment estimation, Blackburn (1999) identified the optimal individual wavebands, e.g., 680, 635 and 470 nm for chlorophyll-a, chlorophyll-b and carotenoids, respectively. Concentrations of both chlorophyll-a and chlorophyll-b in bracken (Pteridium aquilinum) were found to be best correlated with 676 nm (Blackburn 1998). Chlorophyll-a displayed the strongest connection with 680 nm wavelength at senescence in the same study. Gitelson and Merzlyak (1997) obtained an inaccuracy of less than 4.2 g cm^2 while predicting leaf chemicals using an algorithm created from leaf optics and verified over nine species with a range of 0.27 to 62.9 g cm^2 of chlorophyll.

Remote Sensing of Water Stress:

Remote sensing offers a quick, affordable, non-destructive, and spatio-temporal measure of a variety of physiological, biochemical, and structural crop parameters at various scales (ground, airborne, and satellite). Plants may experience permanent damage before observable signs of water stress arise. (Mahajan et al. 2005, Yardoanov et al. 2003, Jones et al. 2008). So, a pre-symptomatic or pre-visual identification of physiological changes in plants can essentially help to prevent serious crop damage. (Chaerle et al. 2000). With its continuous spectrum data, hyperspectral photography can provide more light on the connection between spectral traits and related plant states. (Pinter et al. 2003).

Challenges and Future Perspectives:

For the assessment and tracking of stress, imaging technologies have emerged as a crucial tool that helps physiologists, breeders, and agronomists with both in-field and lab research. Stress can be seen on many different length scales, from the tiny cellular level to the macroscopic level in plants and fields. In agricultural applications, whole-field sensing is inherently appealing. Qualitative remote sensing technologies and techniques have the tremendous advantage of being able to detect quickly and provide indications on a wide range of scales, from the microscopic to the landscape. Furthermore, the use of robotic platforms makes it possible to continuously monitor vegetation.

Owing to its great versatility, the most significant limitations, however, are associated with the accurate definition of protocols for measurements, processing, and pre-processing of data collected; these steps should account for the variability of environmental conditions that arise during measurements, as they have the potential to impair the accuracy and dependability of the results obtained. Improved decision-making about the application of water and other nutrients is possible for farmers through the combination of remote sensing and plant physiological investigations (Jones et al., 2004).

CONCLUSION

In summary, this review emphasizes an overview of the crucial role that remote sensing plays in the detection and management of abiotic stress in plants. Remote sensing is a significant quick, and affordable method for monitoring and managing abiotic stress in plants, ultimately promoting sustainable agriculture and food security. Remote sensing helps to establish sustainable agricultural practices and mitigate the problems associated with food security in a constantly changing climate by expanding our understanding of how plants react to environmental stressors. We covered the main abiotic stressors in this study, including salinity, drought, and nutrient deficiencies, as well as how multispectral and hyperspectral data can be used to detect stress-induced responses, such as changes in leaf reflectance, chlorophyll content, and hydration status. To make it easier to identify areas of stressed plants, we investigated several indices and algorithms used to extract useful information from the collected picture. We also investigate accurate identification depending on understanding how abiotic stressors affect plants' spectral signatures.

Remote sensing can be used to record and analyse changes in reflectance patterns, chlorophyll content, and water status as a result of stressors such as drought, salt, and nutrient deficiency. The ability to recognize these spectrum variations is a crucial component of stress detection. Physiological aspects are also included in it. Researchers and practitioners can better understand how plants respond to stress by fusing spectral data with physiological models. The assessment of the health of the plant, the degree of the stress, and the creation of specialized management techniques are all made possible by this method.

In conclusion, the interaction between remote sensing technology and physiological aspects of plant response to abiotic stresses holds great promise for improving our capacity to monitor and manage stressors, resulting in more sustainable agriculture, ecological management, and informed decision-making in a changing world.

CONFLICT OF INTEREST

The author here declares that there is no conflict of interest in the publication of this article.

REFERENCES

Anderson, M.; Zolin, C.; Sentelhas, P.; Hain, C.; Semmens, K.; Tugrul Yilmaz, M.; Gao, F.; Otkin, J.; Tetrault, R. 2016. The Evaporative Stress Index as an indicator of agricultural drought in Brazil: An assessment based on crop yield impacts. *Remote Sens. Environ*., **174**, 82–99.

Anonymous. 2015. The 10 countries are most active in space. [2017- 10-25]. http://www.aerospace-technology.com/features/ feature the-10-countries-most-active-in-space-4744018/

Asrar GQ, Fuchs M, Kanemasu ET, Hatfield JL 1984. Estimating absorbed photosynthetic radiation and leaf area index from spectral reflectance in wheat 1. *Agron J* **76**:300–306

Bauer ME, Daughtry CST, Biehl LL et al 1986. Field spectroscopy of crops. IEEE Trans Geosci Remote Sens GE-24:65–75. https://doi.org/10.1109/TGRS.1986.289589

Blackburn GA 1998. Spectral indices for estimating photosynthetic pigment concentrations: a test using senescent tree leaves. *Int J Remote Sens* **19**:657–675. https://doi.org/10.1080/ 014311698215919

Blackburn GA 1999. Relationships between spectral reflectance and pigment concentrations in stacks of deciduous broadleaves. *Remote Sens Environ* **70**:224–237

Borel, C. 1997. Iterative Retrieval of Surface Emissivity and Temperature for a Hyperspectral Sensor. In Proceedings of the Proceedings for the First JPL Workshop on Remote Sensing of Land Surface Emissivity, Pasadena, CA, USA, 6–8 May 1997.

Borel, C.C. 2003. ARTEMISS—An Algorithm to Retrieve Temperature and Emissivity from Hyper-Spectral Thermal Image Data. In Proceedings of the 28th Annual GOMACTech Conference, Hyperspectral Imaging Session, Tampa, FL, USA, 31 March–3 April 2003; pp. 3–6.

Boshkovski, B., Tzerakis, C., Doupis, G., Zapolska, A., Kalaitzidis, C., and Koubouris, G. 2020. Relationships of spectral reflectance with plant tissue new avenues towards tailoring food crop quality. Agronomy 8:138. doi: 10.3390/agronomy8080138

Bray EA, Bailey-Serres J, Weretilnyk E 2000) Responses to abiotic stresses. In: Buchanan BB, Gruissem W, Jones RL (eds) Biochemistry and molecular biology of plants. American Society of Plant Physiologists, Rockville, pp 1158–1203

Buschmann, C. 2007. Variability and application of the chlorophyll fluorescence emission ratio red/far-red of leaves. *Photosynth. Res*. **92**, 261–271. doi: 10.1007/s11120-007-9187-8

Caballero, D., Calvini, R., and Amigo, J. M. 2020. "Chapter 3.3: Hyperspectral imaging in crop fields: precision agriculture," in Hyperspectral Imaging Data Handling in Science and Technology, ed J. M. Amigo (Amsterdam: Elsevier), 453–473. doi: 10.1016/B978-0-444-63977-6.00018-3

Ceccato P, Flasse S, Grégoire J-M 2002. Designing a spectral index to estimate vegetation water content from remote sensing data. Remote Sens Environ 82:198–207. https://doi.org/10.1016/ S0034-4257(02)00036-6

Ceccato P, Flasse S, Tarantola S et al 2001. Detecting vegetation leaf water content using reflectance in the optical domain. *Remote Sens Environ* 77:22–33. https://doi.org/10.1016/ S0034-4257(01)00191-2

Chaerle L, De Boever F, Van Der Straeten D 2002. Infrared detection of early biotic and wound stress in plants. *Thermol Int* **12**:100–106

Champagne CM, Staenz K, Bannari A et al 2003. Validation of a hyperspectral curve-fitting model for the estimation of plant water content of agricultural canopies. *Remote Sens Environ* **87**:148–160. https://doi.org/10.1016/S0034-4257(03)00137-8

Chapman SC 2008. Use of crop models to understand genotype by environment interactions for drought in real-world and simulated plant breeding trials. *Euphytica* **161**:195–208

Chen X, Vierling L, Deering D 2005. A simple and effective radiometric correction method to improve landscape change detection across sensors and across time. *Remote Sens Environ* **98**:63–79

Cheng T, Rivard B, Sánchez-Azofeifa A 2011. Spectroscopic determination of leaf water content using continuous wavelet analysis. *Remote Sens Environ* **115**:659–670. https://doi.org/10.1016/ j.rse.2010.11.001

Cheng W, Yagi K et al 2005. Influence of elevated concentrations of atmospheric CO2 on CH4 and CO2 entrapped in rice-paddy soil. *Chem Geol* **218**:15–24

Chi M, Plaza A, Benediktsson J A, Sun Z, Shen J, Zhu Y. 2016. Big data for remote sensing: Challenges and opportunities. Proceedings of the IEEE, **104**, 2207–2219.

Congalton, R. G. 2010. Remote sensing: an overview. *GIScience & Remote Sensing*, **47**(4), 443-459.

Couture, J. J., Singh, A., Nason, K. F. R., Serbin, S. P., Lindroth, R. L., and Townsend, P. A. 2016. Spectroscopic determination of ecologically relevant plant secondary metabolites. *Methods Ecol. Evol*. **7**: 1402–1412. doi: 10.1111/2041-210X.12596

Datt B .1999. Remote sensing of water content in eucalyptus leaves. *Aust J Bot* **47**:909. https://doi.org/10.1071/BT98042

Dong, Z., Men, Y., Li, Z., Zou, Q., and Ji, J. 2019. Chlorophyll fluorescence imaging as a tool for analyzing the effects of chilling injury on tomato seedlings. Sci. Hortic**.** **246**, 490–497. doi: 10.1016/j.scienta.2018.11.019

Eitel JUH, Gessler PE, Smith AMS, Robberecht R 2006. Suitability of existing and novel spectral indices to remotely detect water stress in Populus spp. *For Ecol Manag* **229**: 170–182.
https:// doi.org/10.1016/j.foreco.2006.03.027

Evans LT 2005. Is crop improvement still needed? *J Crop Improv* 14:1–7

Fabre S, Lesaignoux A, Olioso A, Briottet X 2011. Influence of water content on spectral reflectance of leaves in the 3–15- µm domain. *IEEE Geosci Remote Sens Lett* **8**:143–147. https://doi.org/10.1109/LGRS.2010.2053518

Gago, J.; Douthe, C.; Coopman, R.E.; Gallego, P.P.; Ribas-Carbo, M.; Flexas, J.; Escalona, J.; Medrano, H. 2015. UAVs challenge to assess water stress for sustainable agriculture. Agric. Water Manag. **153**, 9–19.

Galieni, A., D'Ascenzo, N., Stagnari, F., Pagnani, G., Xie, Q., & Pisante, M. 2021. Past and future of plant stress detection: an overview from remote sensing to positron emission tomography. *Frontiers in Plant Science*, **11,** 609155.

Galieni, A., Mattia, C. D., Gregorio, M. D., Speca, S., Mastrocola, D., and Pisante, M. 2015. Effects of nutrient deficiency and abiotic environmental stresses on yield, phenolic compounds and antiradical activity in lettuce (*Lactuca sativa* L.). *Sci. Hortic*. 187, 93–101. doi: 10.1016/j.scienta.2015.02.036

Gamon, J.; Peñuelas, J.; Field, C. 1992. A narrow-waveband spectral index that tracks diurnal changes in photosynthetic efficiency. *Remote Sens. Environ*. **41**: 35–44.

Gao B-C 1996. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sens Environ* **58**:257–266. https://doi.org/10.1016/S0034-4257(96)00067-3

Garriga, M., Romero-Bravo, S., Estrada, F., Escobar, A., Matus, I. A., and del Pozo, A. 2017. Assessing wheat traits by spectral reflectance: do we really need to focus on predicted trait-values or directly identify the elite genotypes group? *Front. Plant Sci*. **8**:280. doi: 10.3389/fpls.2017.00280

Gausman HW 1974. Leaf reflectance of near-infrared. *Photogramm Eng* **40**:183–191

Ge, Y., Atefi, A., Zhang, H., Miao, C., Ramamurthy, R. K., and Sigmon, B. 2019. High-throughput analysis of leaf physiological and chemical traits with VISNIR-SWIR spectroscopy: a case study with a maize diversity panel. *Plant Methods* **15**, 1–12. doi: 10.1186/s13007-019-0450-8

Gerber F, Marion R, Olioso A et al 2011. Modeling directional–hemispherical reflectance and transmittance of fresh and dry leaves from 0.4µm to 5.7µm with the PROSPECT-VISIR model. *Remote Sens Environ* **115**:404–414. https://doi.org/10.1016/j.rse.2010.09.011

Gerhards, M., Schlerf, M., Mallick, K., and Udelhoven, T. 2019. Challenges and future perspectives of multi-/hyperspectral thermal infrared remote sensing for crop water-stress detection: a review. Remote Sens. 11:1240. doi: 10.3390/rs11101240

Gerhards, M.; Schlerf, M.; Rascher, U.; Udelhoven, T.; Juszczak, R.; Alberti, G.; Miglietta, F.; Inoue, Y. 2018. Analysis of Airborne Optical and Thermal Imagery for Detection of Water Stress Symptoms. *Remote Sens*. **10**, 23.

Gitelson AA, Merzlyak MN 1997. Remote estimation of chlorophyll content in higher plant leaves. Int J Remote Sens 18:2691–2697

Gorbe, E., and Calatayud, A. 2012. Applications of chlorophyll fluorescence imaging technique in horticultural research: a review. *Sci. Hortic*. **138**, 24–35. doi: 10.1016/j.scienta.2012.02.002

Grant, O.M.; Chaves, M.M.; Jones, H.G. 2006. Optimizing thermal imaging as a technique for detecting stomatal closure induced by drought stress under greenhouse conditions. Physiol. Plant. 127, 507–518.

Gutierrez M, Reynolds MP, Klatt AR 2010. Association of water spectral indices with plant and soil water relations in contrasting wheat genotypes. *J Exp Bot* **61**:3291–3303

Gutiérrez, S., Diago, M. P., Fernández-Novales, J., and Tardaguila, J. 2018. Vineyard water status assessment using on-the-go thermal imaging and machine learning. PLoS ONE 13:e0192037. doi: 10.1371/journal.pone.0192037

Harry V 2006) Principles of soil and plant water relations. *Geoderma* 133:478

Hecker, C.; Hook, S.; van der Meijde, M.; Bakker, W.; van der Werff, H.; Wilbrink, H.; van Ruitenbeek, F.; de Smeth, B.; van der Meer, F. 2011. Thermal infrared spectrometer for Earth science remote sensing applications-instrument modifications and measurement procedures. Sensors 11, 10981–10999.

Hecker, C.A.; Smith, T.E.L.; da Luz, B.R.; Wooster, M.J. Thermal Infrared Spectroscopy in the Laboratory and Field in Support of Land Surface Remote Sensing. In Thermal Infrared Remote

Sensing; Kuenzer, C., Dech, S., Eds.; Springer: Dordrecht, The Netherlands; pp. 43–67.

Horler DNH, Docray M, Barber J .1983. The red edge of plant leaf reflectance. *Int J Remote Sens* **4**:273–288. https://doi.org/10.1080/01431168308948546

Idso, S.B.; Jackson, R.D.; Pinter, P.J.; Reginato, R.J.; Hatfield, J.L. 1981. Normalizing the stress-degree-day parameter for environmental variability. *Agric. Meteorol*. **24**: 45–55.

Jensen JR 2009. Remote sensing of the environment: an earth resource perspective 2/e. Pearson Education India, Chennai

Jones, C. L., P. R. Weckler, N. O. Maness, M. L. Stone, and R. Jayasekara, 2004. Estimating water stress in plants using hyperspectral sensing. 2004 ASAE/CSAE Annual International Meeting. Ottawa, Ontario, Canada.

Jones, H., and Schofield, P. 2008. Thermal and other remote sensing of plant stress. *Gen. Appl. Plant Physiol*. **34**:19–32.

Khan, M. J., Khan, H. S., Yousaf, A., Khurshid, K., and Abbas, A. 2018. Modern trends in hyperspectral image analysis: a review. *IEEE Access* **6**, 14118–14129. doi: 10.1109/ACCESS.2018.2812999

Kim, Y., D. M. Glenn, J. Park, H. K. Ngugi, and B. L. Lehman, 2010. Hyperspectral image analysis for plant stress detection. 2010 ASABE Annual International Meeting. Pittsburg, Pennsylvania.

Kramer, H.J. and Cracknell, A.P., 2008. An overview of small satellites in remote sensing. International Journal of Remote Sensing, 29, pp. 4285–4337

Kramer, H.J., 2007. An overview of small satellite in remote sensing. In Proceedings of International Workshop on Earth Observation Small Satellites for Remote Sensing Applications, Kuala Lumpur, Malaysia, 2007 CD, Universiti Teknologi Malaysia, Johor Bahru.

Liu P. 2015. A survey of remote-sensing big data. *Frontiers in Environmental Science*, **3**: 1–6.

Lu, Y., and Lu, R. 2020. Enhancing chlorophyll fluorescence imaging under structured illumination with automatic vignetting correction for detection of chilling injury in cucumbers. Comput. *Electron. Agric*. **168**:105145. doi: 10.1016/j.compag.2019.105145

Maes, W. H., and Steppe, K. 2019. Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture. *Trends Plant Sci*. **24**: 152–164. doi: 10.1016/j.tplants.2018.11.007

Mahlein, A. K. 2016. Plant disease detection by imaging sensors-parallels and specific demands for precision agriculture and plant phenotyping. *Plant Dis*. **100**: 241–251. doi: 10.1094/PDIS-03-15-0340-FE

Maimaitiyiming, M., Ghulam, A., Bozzolo, A., Wilkins, J. L., and Kwasniewski, M. T. 2017. Early detection of plant physiological responses to different levels of water stress using reflectance spectroscopy. *Remote Sens*. **9:**745. doi: 10.3390/rs9070745

Malingreau JP 1989. The vegetation index and the study of vegetation dynamics. In: Toselli F (ed) Applications of remote sensing to agrometeorology. Springer, Dordrecht, pp 285–303

Meerdink, S.; Roberts, D.; Hulley, G.; Gader, P.; Pisek, J.; Adamson, K.; King, J.; Hook, S.J. 2019. Plant species' spectral emissivity and temperature using the hyperspectral thermal emission spectrometer (HyTES) sensor. *Remote Sens. Environ*. **224**: 421–435.

Meroni, M.; Rossini, M.; Guanter, L.; Alonso, L.; Rascher, U.; Colombo, R.; Moreno, J. 2009. Remote sensing of solar-induced chlorophyll fluorescence: Review of methods and applications. *Remote Sens. Environ*. **113**: 2037–2051.

Mishra, P., Asaari, M. S. M., Herrero-Langreo, A., Lohumi, S., Diezma, B., and Scheunders, P. 2017. Close range hyperspectral imaging of plants: a review. *Biosyst. Eng*. **164**: 49–67. doi: 10.1016/j.biosystemseng.2017.09.009

Möller M, Alchanatis V, Cohen Y et al 2006. Use of thermal and visible imagery for estimating crop water status of irrigated grapevine. J Exp Bot 58:827–838

Montes JM, Melchinger AE, Reif JC 2007. Novel throughput phenotyping platforms in plant genetic studies. *Trends Plant Sci* **12**:433–436

Murchie, E., and Lawson, T. 2013. Chlorophyll fluorescence analysis: a guide to good practice and understanding some new applications. *J. Exp. Bot*. **64**: 3983–3998. doi: 10.1093/jxb/ert208

Pandey, P., Ramegowda, V., and Senthil-Kumar, M. 2015. Shared and unique responses of plants to multiple individual stresses and stress combinations: physiological and molecular mechanisms. *Front. Plant Sci*. **6**:723. doi: 10.3389/fpls.2015.00723

Peñuelas J, Gamon JA, Fredeen AL et al 1994. Reflectance indices associated with physiological changes in nitrogen- and water-limited sunflower leaves. *Remote Sens Environ* **48**:135–146. https://doi.org/10.1016/0034-4257(94)90136-8

Peñuelas J, Gamon JA, Griffin KL, Field CB 1993. Assessing community type, plant biomass, pigment composition, and photosynthetic efficiency of aquatic vegetation from spectral reflectance. *Remote Sens Environ* **46**:110–118. https://doi.org/10.1016/0034-4257(93)90088F

Pinter, P.J., Jr.; Hatfield, J.L.; Schepers, J.S.; Barnes, E.M.; Moran, M.S.; Daughtry, C.S.; Upchurch, D.R. 2003. Remote Sensing for Crop Management. Photogramm. Eng. *Remote Sens*. 69, 647–664.

Rascher, U.; Alonso, L.; Burkart, A.; Cilia, C.; Cogliati, S.; Colombo, R.; Damm, A.; Drusch, M.;

Guanter, L.; Hanus, J.; et al. 2015. Sun-induced fluorescence - a new probe of photosynthesis: First maps from the imaging spectrometer HyPlant. *Glob. Chang. Biol*. **21**: 4673–4684.

Ribeiro da Luz B, Crowley JK 2007. Spectral reflectance and emissivity features of broad leaf plants: prospects for remote sensing in the thermal infrared (8.0–14.0 µm. *Remote Sens Environ* **109**:393–405. https://doi.org/10.1016/j.rse.2007.01.008

Ribeiro da Luz, B. 2006. Attenuated total reflectance spectroscopy of plant leaves: a tool for ecological and botanical studies. *New Phytol*. 172, 305–318.

Rosenqvist A, Milne A., Lucas R, Imhoff M, Dobson C. 2003. A review of remote sensing technology in support of the Kyoto Protocol. *Environmental Science & Policy*, **6**, 441–455.

Rossini, M.; Nedbal, L.; Guanter, L.; Aˇc, A.; Alonso, L.; Burkart, A.; Cogliati, S.; Colombo, R.; Damm, A.; Drusch, M.; et al. 2015. Red and far-red Sun-induced chlorophyll fluorescence as a measure of plant photosynthesis. *Geophys. Res. Lett*. 42, 1632–1639.

Rouse JW, Haas RH, Schell JA et al 1974. Monitoring the vernal advancements and retrogradation. Texas A M Univ, Texas

Salisbury JW 1986. Preliminary measurements of leaf spectral reflectance in the 8-14 µm region. *Int J Remote Sens* **7**:1879–1886

Salisbury JW, Milton NM 1988. Thermal infrared 2.5-to 13.5-µm) directional hemispherical reflectance of leaves. *Photogramm Eng Remote Sensing* 54:1301–1304

Sankaran, S., Mishra, A., Ehsani, R., and Davis, C. 2010. A review of advanced techniques for detecting plant diseases. *Comput. Electron. Agric*. **72**, 1–13. doi: 10.1016/j.compag.2010.02.007

Schulze ED, Beck E, Müller-Hohenstein K 2002. Pfl anzenökologie. Spektrum Akademischer, Heidelberg

Sims DA, Gamon JA 2002) Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages. *Remote Sens Environ* **81**:337–354. https://doi.org/10.1016/S0034-4257(02)00010-X

Sinclair TR, Ludlow MM 1985. Who taught plants thermodynamics? The unfulfilled potential of plant water potential. *Funct Plant Biol* 12:213–217

Stagnari, F., Galieni, A., Speca, S., Cafiero, G., and Pisante, M. 2014. Effect of light and water supply on morphological and physiological leaf traits of red beet. *Agron. J*. **106**, 459–468. doi: 10.2134/agronj2013.0293

Stellacci, A. M., Castrignana, A., Troccoli, A., Basso, B., and Buttafuoco, G. 2016. Selecting optimal hyperspectral bands to discriminate nitrogen status in durum wheat: a comparison of statistical approaches. *Environ. Monit. Assess*. **188**, 1–15. doi: 10.1007/s10661-016-5171-0

Suárez, L.; Zarco-Tejada, P.J.; Berni, J.A.J.; González-Dugo, V.; Fereres, E. 2009. Modelling PRI for water stress detection using radiative transfer models. Remote Sens. *Environ*. **113**, 730–744.

Sun, D., Zhu, Y., Xu, H., He, Y., and Cen, H. 2019. Time-series chlorophyll fluorescence imaging reveals dynamic photosynthetic fingerprints of SOS mutants to drought stress. *Sensors* **19**:2649. doi: 10.3390/s19122649

Swinerd, G., 1999, Special issue on small satellite engineering. Proceedings of the Institution of Mechanical Engineers. Part G – *Journal of Aerospace Engineering*, G4, pp. I–II.

Sylvain, T., and Cecile, L.-G. 2018. “Chapter 8: Disease identification: a review of vibrational spectroscopy applications,” in Vibrational Spectroscopy for Plant Varieties and Cultivars Characterization Comprehensive Analytical Chemistry, eds J. Lopes and C. Sousa (Amsterdam: Elsevier), 195–225. doi: 10.1016/bs.coac.2018.03.005

Tucker CJ 1980. Remote sensing of leaf water content in the near infrared. *Remote Sens Environ* **10**:23–32. https://doi.org/10.1016/0034-4257(80)90096-6

Ullah S, Skidmore AK, Groen TA, Schlerf M 2013. Evaluation of three proposed indices for the retrieval of leaf water content from the mid-wave infrared 2–6µm) spectra. *Agric For Meteorol* **171–172**:65–71. https://doi.org/10.1016/j.agrformet.2012.11.014

Van Der Tol, C.; Verhoef, W.; Timmermans, J.; Verhoef, A.; Su, Z.; Observations, E. 2009. An integrated model of soil-canopy spectral radiances, photosynthesis, fluorescence, temperature and energy balance. *Biogeosciences* **6**, 3109–3129.

Vialet-Chabrand, S., and Lawson, T. 2019. Dynamic leaf energy balance: deriving stomatal conductance from thermal imaging in a dynamic environment. *J. Exp. Bot*. 70, 2839–2855. doi: 10.1093/jxb/erz068

Vinocur B, Altman A 2005. Cellular basis of salinity tolerance in plants. *Environ Exp Bot* **52**:113–122

Vorasoot N, Songsri P, Akkasaeng C, Jogloy S, Patanothai A 2003. Effect of water stress on yield and agronomic characters of peanut. *Songklanakarin J Sci Technol* **25**(3):283–288.

Wang W, Vinocur B, Altman A 2003b. Plant responses to drought, salinity and extreme temperatures: towards genetic engineering for stress tolerance. *Planta* 218:1–14.

Wang, X., Hou, L., Lu, Y., Wu, B., Gong, X., Liu, M., et al. 2018c. Metabolic adaptation of wheat grain contributes to a stable filling rate under heat stress. *J. Exp. Bot*. 69, 5531–5545. doi: 10.1093/jxb/ery303

Wiegand CL, Richardson AJ, Escobar DE, Gerbermann AH 1991. Vegetation indices in crop assessments. *Remote Sens Environ* **35**:105–119.

Wieneke, S.; Ahrends, H.; Damm, A.; Pinto, F.; Stadler, A.; Rossini, M.; Rascher, U. 2016. Airborne based spectroscopy of red and far-red sun-induced chlorophyll fluorescence: Implications for improved estimates of gross primary productivity. *Remote Sens. Environ*. **184**, 654–667.

Xue, J., and Su, B. 2017. Significant remote sensing vegetation indices: a review of developments and applications. *J. Sens.* 1–17. doi: 10.1155/2017/1353691

Yao, J., Sun, D., Cen, H., Xu, H., Weng, H., and Yuan, F. 2018. Phenotyping of Arabidopsis drought stress response using kinetic chlorophyll fluorescence and multicolor fluorescence imaging. *Front. Plant Sci.* **9**:603. doi: 10.3389/fpls.2018.00603

Young, S.J.; Johnson, B.R.; Hackwell, J.A. 2002. An in-scene method for atmospheric compensation of thermal hyperspectral data. *J. Geophys. Res*., **107**, 4774.

Zarco-Tejada PJ, Miller JR, Noland TL et al 2001. Scaling-up and model inversion methods with narrowband optical indices for chlorophyll content estimation in closed forest canopies with hyperspectral data. *IEEE Trans Geosci Remote Sens* 39:1491–1507. https://doi.org/10.1109/36.934080

Zhang N, Wang M, Wang N. 2002. Precision agriculture -a worldwide overview. Computers and Electronics in *Agriculture*, **36**, 13–132.

Zhang, J., Huang, Y., Pu, R., Gonzalez-Moreno, P., Yuan, L., and Wu, K. 2019a. Monitoring plant diseases and pests through remote sensing technology: a review. *Comput. Electron. Agric*. **165**:104943. doi: 10.1016/j.compag.2019.104943

Citation: T. D. Warik, G.S. Pawar, G.U. Shinde, H.V. Kalpande, S.M. Gambhire, A.B. Pillewad 2024. Advancements in Remote Sensing Technologies for Assessing Abiotic Stress in Plants: a Comprehensive Review. *International Journal of Agricultural and Applied Sciences*, 5(1): 101-111. https://doi.org/10.52804/ijaas2024.5114