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Crop Water Stress Detection Using Remote Sensing Techniques †

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Abstract: To meet the demand for increasing global food production while using limited water resources, crop water stress must be improved in agriculture. Remote-sensing-based plant stress indicators have the benefits of high spatial resolutions, a cheap cost, and short turnaround times. This study discusses the current advancements in agricultural water stress monitoring and irrigation scheduling, some of the challenges that have been met, and the upcoming research needs. Remote sensing systems are prepared to handle the intricate and technical evaluations of agricultural productivity, security, and crop water stress quickly and effectively. We explore the use of remote-sensing systems in the evaluation of crop water stress by looking at the existing research, technologies, and data. This study examines the connection between relative water content (RWC), equivalent water thickness (EWT), and agricultural water stress. Using remote sensing, evapotranspiration, and sun-induced chlorophyll content are examined in connection to crop drought. Spectral indices, remote sensing satellites, and multi-spectral sensing systems, as well as systems that measure land surface temperature, are examined. This critical study focuses on cutting-edge techniques for assessing crop water stress.

Keywords: crop water stress; spectral indices; multi-spectral; remote sensing satellites; thermometric sensing

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1. Introduction

Arid regions have discovered creative solutions to meet their crop needs, based on their growth phases, kinds, and environmental circumstances, which has led to appreciable yield improvements. A deficiency of irrigation water will cause agricultural water stress at various times throughout the crop cycle, under various environmental conditions. Its primary impact is felt in the rate of photosynthesis, which further causes a disturbance in the rates of transpiration [1,2].

Remote sensing collects information from crops, soil, and ambient elements without direct physical contact [3]. Through the quick identification of crop growth changes that are frequently missed by conventional approaches, it has improved and optimized agricultural production [4]. A highly accurate determination of the crop temperature is made possible by remote sensing systems, which also provide particular information that is important in the study of irrigation scheduling, quantity, and duration [5]. Remote sensing systems can be divided into sensor-based and platform-based systems. In total, two types of sensors may record the reflectivity inside the electromagnetic (EM) spectrum: active sensors and passive sensors. The sensor is mounted onto a variety of remote sensing platforms, including ground vehicles, aircraft, satellites, and handheld devices [6].

Precision irrigation scheduling requires an assessment of crop water stress, which is one of the elements that characterize how a crop interacts with its environment [7]. The

CWS came to be recognized as a common indicator for evaluating this stress on the leaf and canopy scales. This was a more accurate technique to examine the water stress at the plot, regional, and global stages, as well as evapotranspiration. Implementing effective irrigation scheduling techniques is crucial to increase water savings and improve agricultural sustainability [8]. Remote sensing data can reveal information on the geographical and temporal variations of crops [9,10]. Precision agriculture uses spectral reflectance indices from high-resolution hyperspectral sensors on small, unmanned aircraft systems to monitor the crop water status and plan irrigation [11].

An assessment of the crop water deficit using remote sensing devices is the subject of this review. The paper supplies an overview of the many remote sensing systems that can be used to find crop water stress. Optical, thermometric, land-surface temperature, multispectral (spaceborne and airborne), hyperspectral, and LiDAR sensing systems are examined. A consensus about the use of vegetation indices (VIs) as pre-visual indicators of water stress has not yet been reached, due to several confounding factors that affect these VIs on the canopy and landscape scales. This research discusses the current developments in crop water stress monitoring that may be applied to enhance vegetable crop irrigation scheduling and seeks to figure out the most promising method for widespread implementation. To forecast the production conditions and schedule irrigation, the crop water stress needs to be detected during the various growing seasons. Distinguishing this agricultural water stress has been researched using several methodologies. These techniques rely on remote sensing, measurements of the soil water content, and plant responses. The study also considers the fact that different approaches are effectively used for different crops.

2. Comparison of Crop Water Stress Detection Methods

Table 1 provides an overview of various methods used for soil moisture measurement, including the gravimetric method, time domain reflectometer (TDR), neutron probe method, tensiometer method, vegetation indices method by remote sensing (VIs), water indices by remote sensing, water balance indices, remote sensing-based ET estimation by energy balance, CWSI by the infrared thermometer, and LST based CWSI. The table includes a brief description of each method, its advantages, disadvantages, and references. The methods vary in their precision, ease of use, cost, and sensitivity to different soil types and environmental conditions. Some methods require direct contact with soil, while others utilize remote sensing techniques. The choice of method depends on the specific research or application requirements.

Table 1. Comparison of crop water stress detection methods.

Methods	Description	Advantages	Disadvantages	References
Gravimetric Method	A straightforward technique that involves weighing a wet sample, drying it in an oven, reweighing it, and then estimating the amount of water loss as a percentage of the dry soil quantity	Highly precise and reliable technique with hardly any room for instrumental error, not affected by salinity or soil type	Time-consuming, dependent on mass measurements, destructive, and labor-intensive	[12,13]
Time domain reflectometer (TDR)	An electromagnetic method based on the idea that water and other materials, such as soil, have different dielectric constants	Less time-consuming and damaging than gravimetric techniques, reduced labor expenses	Environmentally sensitive, expensive equipment, and calibration dependent on soil texture	[12,13]
Neutron Probe method	Evaluates the soil's volumetric water content	High accuracy, permits observations at various depths, rather simple	Time-consuming monitoring and expensive equipment licensing are required.	[14]
Tensiometer method	Soil-water-potential-based	Cheap, affordable, easy to install, accurate, and for irrigation scheduling	Requires contact with soil and destructive	[14]
Vegetation indices method by remote sensing (VIs)	Indicators of vegetation are used to illustrate its properties	The high temporal and spectral resolution, non-destructive	Precision decreases from leaf scale to canopy scale and image analysis is a difficult task	[15,16]

Table 1. *Cont.*

Methods	Description	Advantages	Disadvantages	References
Water Indices by remote sensing	Determines the reflectance in the SWIR and near-infrared range, which is used to indicate the water content of the canopy. Typical indices include WI, SRWI, NDWI, and MSI	Leaf water content may be measured without causing damage. Excellent direct signs of water stress	The difficulty of ascending to the canopy level	[17]
Water balance indices	Monitors change in the chlorophyll fluorescence and water content of the leaves using the green and SWIR spectral bands. The calculated indices are WABI, WABI-1, and WABI-2	Exhibited excellent performance at the leaf and canopy levels	It is necessary to use an expensive single-spectrum instrument. The penetrability of the SWIR band through heavy atmospheric layers is a problem	[17]
RS-based ET estimation by Energy balance	The surface energy balance equation LE = Rn-G-H Latent Energy includes ET as a residual (LE), Rn = Net Sky Radiation, G = Ground to Air, H = Heat to Air	A single thermal band with the excellent resolution is sufficient and needed METRIC and SEBAL have good consistency and accuracy	It's challenging to determine whether ET is possible. As ET cannot be directly measured, high-resolution thermal imaging is crucial.	[18]
CWSI by infrared thermometer	The canopy temperature and its decrease with the ambient air temperature are used to calculate CWSI	Depends on the direct technique and VPD	Different baselines must be calculated for various crops; this takes time. To evaluate CWSI, many factors must be considered	[19]
LST based CWSI	Utilizing LST and the hot-and-cold pixels approach to calculate CWSI	Using only remote sensing methods Work and time are non-intensive	Depending on this method to calculate LST, LST computation is laborious and varies	[20]

3. Satellite-Based Crop Water Stress Detection

Table 2 provides information on various satellite applications and their advantages and limitations. It includes information on the type of satellite, its applications, the advantages of using it, and any limitations associated with it. Some examples of the satellites included in the table are AMSR-E, AMSR-2, NISAR, Tandem-L, Sentinel-1, and SMAP. The applications of these satellites range from analyzing soil moisture to vegetation status and dynamics observation. The advantages of using these satellites include high precision, excellent resolution, and data collection in all weather conditions, among others. However, some of the limitations include limited frequency ranges, high cost, and limited precision in field determination.

Table 2. Satellite-based crop water stress detection.

Satellite	Applications	Advantages	Limitations	References
AMSR-E	High-efficiency passive microwave soil moisture analysis with drought	Data collection for daily soil moisture measurement with a 12.5 km precision	Just two files every day, one for the day and one for the night	[21]
AMSR-2	Analysis of soil-water-related parameters and global observation of soil moisture (from the soil surface to a few centimeters depth)	More than 99% correct in capturing data both during the day and at night/good resolution and accuracy of data collecting	Only functions in certain frequency ranges, including 6.925, 7.3, 10.65, 18.7, 23.8, 36.5, and 89.0 GHz	[22]
NISAR	Global soil moisture maps with a time horizon of 6 to 12 days	Acquires soil moisture data in all weather conditions and with a precise resolution of 3–10 m	Product assessment in 12–24 h	[23]
Tandem-L	Worldwide soil moisture	Provides extremely accurate measured data with millimeter-level accuracy and excellent resolution between 20 m and 4 km	A significant premium over conventional satellite systems	[24]
Sentinel-1	Dynamics observation	With a precision resolution of 5 to 20 m, field determination is less precise	Easy to create new systems, incorporating sensor structures and application development models	[25]
SMAP	Analyzes the vegetation status and soil surface	High likelihood of mission failure with a 9 km precise resolution	SSM is captured by passive sensors for roughly 36 km	[26]

4. Crop Water Stress Detection Using Spectral Indices

Table 3 below lists several reflectance indices used to indicate plant stress and their respective formulas. Reflectance indices are measures of the amount of light reflected from vegetation at specific wavelengths and can be used to estimate plant health and stress. The plant stress indicators listed in the table are associated with different physiological processes related to plant water statuses, such as stomatal conductance, chlorophyll fluorescence, leaf water potential, and water content. The references listed provide additional information on the use and interpretation of each index.

Table 3. Crop water stress detection using spectral indices.

Reflectance Indices	Formula	Plant Stress Indicators	References
Photochemical Reflectance Index (PRI)	$\frac{R_{570}-R_{531}}{R_{570}+R_{531}}$	Stomatal conductance and chlorophyll fluorescence	[27]
Normalized Photochemical Reflectance Index (NPRI)	$\frac{PRI}{RDI*\frac{R_{700}}{R_{670}}}$	Stomatal conductance and chlorophyll fluorescence	[28]
Normalized Difference Vegetation Index (NDVI)	$\frac{R_{800}-R_{670}}{R_{800}+R_{670}}$	Leaf water potential and stomatal conductance	[29]
Renormalized Difference Vegetation Index (RDVI)	$\frac{R_{800}-R_{670}}{\sqrt{R_{800}+R_{670}}}$	Leaf water potential and stomatal conductance	[30]
Transformed Chlorophyll Absorption in Reflectance Index (TCARI)	$3[(R_{700}-R_{670})-0.2(R_{700}-R_{550})*\left(\frac{R_{700}}{R_{670}}\right)]$	Leaf water potential and stomatal conductance	[31]
Optimized Soil Adjusted Vegetation Index (OSAVI)	$\frac{(1+0.16)(R_{700}-R_{550})}{(R_{800}+R_{670})+0.16}$	Leaf water potential and stomatal conductance	[31]
Normalized Difference Water Index (NDWI)	$\frac{R_{860}-R_{1240}}{R_{860}+R_{1240}}$	Leaf water potential	[32]
Simple Ratio Water Index (SRWI)	$\frac{R_{860}}{R_{1240}}$	Leaf water potential	[33]
Water Index (WI)	$\frac{R_{860}}{R_{1240}}$	Leaf water potential	[33]

5. Crop Water Stress Detection Using Multispectral Sensing Systems

Table 4 provides information on different multispectral sensing systems, their descriptions, advantages, and references. The first system listed is a UAV remote multispectral sensing system called AIRPHEN Multispectral Camera, which has a high-resolution camera and precise CWS (crop water stress) detection. It is also low-cost, cheap, effective, and available with RGB color bands. The second system listed is a spaceborne multispectral sensing system that includes Landsat, Orb view, World view, IKONOS, and Quick bird. These systems are used to figure out agricultural water stress by collecting multispectral high-resolution data, which provides entire crop water stress temporal features.

Table 4. Crop water stress detection using multispectral sensing systems.

Multispectral Sensing Systems	Description	Advantages	References
UAV remote MS sensing system	AIRPHEN Multispectral Camera with a lens of 8 mm focal length, 1280 × 960 pixels, and spectral resolution 10 nm	High-resolution camera, precise CWS detection, low cost, cheap, effective, and available with RGB color bands	[34,35]
Spaceborne MS sensing system	Landsat, Orb view, World view, IKONOS, Quick bird SPOT-5	To figure out agricultural water stress, multispectral high-resolution data should be collected. This will give us entire crop water stress temporal features	[36,37]

6. Future Directions

The target water stress can be located using remote sensing technology. For applications including agricultural growth assessment and irrigation, as well as leaf and canopy phenotypic categorizations that detect crop losses, digital imaging technologies are used. Using information from digital photography, the water stress can be measured. The most recent methods for crop water stress assessment that used digital pictures from remote sensing have shown notable results. Most of the studies showed three degrees of agricultural water stress: minimal stress (optimum moisture), medium stress (mild drought stress), and severe stress (drought stress). With an accuracy that ranged from 83 to 99%, these methods produced encouraging findings for the estimation of agricultural water stress. Machine learning is crucial to raising the calibers and effectiveness of these systems. For an accurate evaluation of the crop water stress, a microcontroller-based signal processor (MSP430) integrated soil and ambient sensors. A dependable resource for examining these crop water levels, and soil water stress factors is an independent wireless sensor system that is made up of a gateway plus a wireless sensory node.

7. Conclusions

Traditional methods, such as measuring the soil moisture, have drawbacks in terms of their sensor costs and installations, and difficulty in obtaining estimates. Plant-based estimates are more dependable and accurate. There are significant relationships between the PRI and NDVI, and attributes such as the LWP, stomatal conductance, crop efficiency, and stem water potential. A crop water stress evaluation is a technical and intricate process in and of itself. Our study suggests new techniques that bring together farmers, researchers, and tech developers. Narrow-band optical indices could be used to plan the irrigation for high-value vegetable crops in water-stressed countries. Conventional irrigation scheduling methods use measurements of the soil moisture and weather, and physiological assessments of the plant response. These methods are ineffective because it is difficult to obtain these measurements, especially for varied soil and crop canopies. This assessment makes recommendations for remote sensing systems and sets the path for creating new facilities that assess a system's effectiveness in diverse environmental scenarios, such as multispectral/hyperspectral and thermal sensing systems that are based on remote sensing features.

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