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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 benefit of high spatial resolutions, cheap cost, and short turnaround times. This study discusses current advancements in agricultural water stress monitoring, irrigation scheduling, some of the challenges met, and upcoming research needs. Remote sensing systems are prepared to handle the intricate and technical evaluation of agricultural productivity, security, & crop water stress quickly and effectively. We explore the use of remote-sensing systems in the evaluation of crop water stress by looking at existing research, technologies, and data. The 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 multispectral 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, kind, and environmental circumstances, which leads to appreciable yield improvements. A deficiency of irrigation water will cause agricultural water stress at various times of the crop cycle and under various environmental conditions. The primary impact is felt in the rate of photosynthesis, which further causes disturbance in 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 crop temperature is made possible by the remote sensing system, which also gives particular information important in the study of irrigation scheduling, quantity, and duration [5]. Systems for remote sensing can be divided into sensor-based and platform-based systems. Two types of sensors may record reflectivity inside the electromagnetic (EM) spectrum: active sensors and passive sensors. The sensor is mounted on a variety of remote sensing platforms, including ground vehicles, aircraft, satellites, and handheld devices [6].

Precision irrigation scheduling requires the assessment of crop water stress, 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 stress on the leaf and canopy scales. This was a better way to analyze water stress at plot and regional scales, including evapotranspiration, on a greater scale. Implementing effective irrigation scheduling techniques is crucial for increasing water savings and improving 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 crop water status and plan irrigation [11].

The assessment of crop water deficit using remote sensing devices was 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 a pre-visual indicator of water stress has not yet been reached, due to several confounding factors affecting VIs at the canopy & landscape scales. This research discusses current developments in crop water stress monitoring that may be applied to enhance vegetable crop irrigation scheduling and looks to figure out the most promising method for widespread implementation. To forecast production conditions and schedule irrigation, crop water stress needs to be detected during various growth seasons. It has been researched how to distinguish agricultural water stress using several methodologies. These techniques rely on remote sensing, measurements of 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. 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 and reduce 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	Expensive equipment Licensing and monitoring required time-consuming	[12,14]
Tensiometer method	Soil water potential based	Cheap, affordable, easy to install, accurate, and for irrigation scheduling	Requires in contact with soil and destructive	[12,14]
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]
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 changes 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 & canopy level.	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.	Possible to derive ET is a difficult task. Since ET cannot be measured directly, Thermal imaging with high resolution is essential.	[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. Satellites Based Crop Water Stress Detection

Table 2. Satellites 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, 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	acquire 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 four 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	Analyze 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. 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)	$\frac{PRI}{[RDVI*(R_{700}/R_{670})]}$	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)	$3[(R_{700}-R_{670})-0.2(R_{700}-R_{550})*(R_{700}/R_{670})]$	Leaf water potential and stomatal conductance	[31]
Optimized Soil Adjusted Vegetation Index (OSAVI)	$\frac{(1+0.16)(R_{800}-R_{670})}{(R_{800}+R_{670})+0.16}$	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)	$\frac{R_{900}}{R_{970}}$	Leaf water potential	[33]

5. Crop Water Stress Detection Using the Multispectral Sensing Systems

Table 4. Crop Water Stress Detection Using the 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

Remote sensing technologies can be used to find target water stress. Digital imaging approaches are used for leaf & canopy phenotypic categorization to detect crop losses in addition to applications like crop growth evaluation, irrigation, and crop losses. Using information from digital photography, measure water stress. The most recent methods of crop water stress assessment using 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 accuracy ranging from 83 to 99%, these methods produced encouraging findings for the estimate of agricultural water stress. Machine learning is crucial for raising the calibers and effectiveness of systems. For the accurate evaluation of crop water stress, a microcontroller-based signal processor (MSP430) integrates soil and ambient sensors. A dependable resource for examining crop water levels and soil water stress factors is an independent wireless sensor system made up of a gateway plus a wireless sensory node.

7. Conclusions

Traditional methods, like measuring soil moisture, have drawbacks in terms of sensor costs, installations, and difficulty obtaining estimates. Plant-based estimates are more dependable and accurate. There are significant relationships between PRI and NDVI and attributes like LWP, stomatal conductance, crop efficiency, and stem water potential. 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 irrigation for high-value vegetable crops in water-stressed countries. Conventional irrigation scheduling methods use measurements of soil moisture, weather, and physiological assessments of plant response. The method is ineffective because it is difficult to get measurements, especially for varied soil and crop canopies. Narrow-band optical indices could be used to plan irrigation for high-value vegetable crops in water-stressed countries. This assessment makes remote sensing system recommendations and sets the path for creating new facilities that assess a system's effectiveness in diverse environmental scenarios. Such as multispectral/hyperspectral & thermal sensing systems based on remote-sensing features.

References

1. Chang, Y.N.; Zhu, C.; Jiang, J.; Zhang, H.; Zhu, J.K.; Duan, C.G. Epigenetic regulation in plant abiotic stress responses. *J. Integr. Plant Biol.* **2020**, *62*, 563–580.
2. Goldstein, A.; Fink, L.; Meitin, A.; Bohadana, S.; Lutenberg, O.; Ravid, G. Applying machine learning on sensor data for irrigation recommendations: Revealing the agronomist's tacit knowledge. *Precis. Agric.* **2017**, *19*, 421–444.
3. Tian, H.; Wang, T.; Liu, Y.; Qiao, X.; Li, Y. Computer vision technology in agricultural automation—A review. *Inf. Process. Agric.* **2020**, *7*, 1–19.
4. Aasen, H.; Honkavaara, E.; Lucieer, A.; Zarco-Tejada, P. Quantitative Remote Sensing at Ultra-High Resolution with UAV Spectroscopy: A Review of Sensor Technology, Measurement Procedures, and Data Correction Workflflows. *Remote Sens.* **2018**, *10*, 1091.
5. Long, D.S.; Engel, R.E.; Siemens, M.C. Measuring Grain Protein Concentration with In-line Near Infrared Reflectance Spectroscopy. *Agron. J.* **2008**, *100*, 247.
6. Mulyono, S. Nadirah Identifying Sugarcane Plantation using LANDSAT-8 Images with Support Vector Machines. *IOP Conf. Ser. Earth Environ. Sci.* **2016**, *47*, 12008.
7. Zhou, Z.; Majeed, Y.; Diverres Naranjo, G.; Gambacorta, E.M.T. Assessment for crop water stress with infrared thermal imagery in precision agriculture: A review and prospects for deep learning applications. *Comput. Electron. Agric.* **2021**, *182*, 106019.
8. Osroosh, Y.; Peters, R.T.; Campbell, C.S.; Zhang, Q. Automatic irrigation scheduling of apple trees using theoretical crop water stress index with an innovative dynamic threshold. *Comput. Electron. Agric.* **2015**, *118*, 193–203.
9. Dangwal, N.; Patel, N.R.; Kumari, M.; Saha, S. Monitoring of water stress in wheat using multispectral indices derived from Landsat-TM. *Geocarto Int.* **2015**, *31*, 1–26.
10. Leroux, L.; Baron, C.; Zoungrana, B.; Traoré, S.B.; Seen, D.L.; Bégué, A. Crop monitoring using vegetation and thermal indices for yield estimates: A case study of a rainfed cereal in semi-arid west Africa. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens*. **2016**, *9*, 347–362.
11. Gago, J.; Douthe, C.; Coopman, R.E.; Gallego, P.P.; Ribas-Carbo, M.; Flexas, J.; Escalona, J.; Medrano, H. UAVs challenge to assess water stress for sustainable agriculture. *Agric. Water Manag.* **2015**, *153*, 9–19.
12. Sharma, P.K.; Kumar, D.; Srivastava, H.S.; Patel, P. Assessment of different methods for soil moisture estimation: A review. *J. Remote Sens. GIS* **2018**, *9*, 57–73.
13. Tanriverdi, C.; Degirmenci, H.; Gonen, E.; Boyaci, S. A comparison of the gravimetric and TDR methods in terms of determining the soil water content of the corn plant. *Sci. Pap. Ser. A-Agron.* **2016**, *59*, 153–158.
14. Enciso, J., Porter, D., Peries, X.; et al. *Irrigation Monitoring with Soil Water Sensors (Spanish)*; Fact Sheet B-6194; Texas AgriLife Extension Service, Texas A&M System: College Station, TX, USA, 2007.
15. Romero, M.; Luo, Y.; Su, B.; Fuentes, S. Vineyard water status estimation using multispectral imagery from a UAV platform and machine learning algorithms for irrigation scheduling management. *Comput. Electron. Agric.* **2018**, *147*, 109–117.
16. Poblete, T.; Ortega-Farías, S.; Moreno, M.A.; Bardeen, M. Artificial Neural Network to Predict Vine Water Status Spatial Variability Using Multispectral Information Obtained from an Unmanned Aerial Vehicle (UAV). *Sensors* **2017**, *17*, 2488,
17. Rapaport, T.; Hochberg, U.; Shoshany, M.; Karnieli, A.; Rachmilevitch, S. Combining leaf physiology, hyperspectral imaging and partial least squares-regression (PLS-R) for grapevine water status assessment. *ISPRS J. Photogramm. Remote. Sens.* **2015**, *109*, 88–97,
18. Allen, R.G.; Tasumi, M.; Trezza, R. Satellite-Based Energy Balance for Mapping Evapotranspiration with Internalized Calibration (METRIC)—Model. *J. Irrig. Drain. Eng.* **2007**, *133*, 380–394.
19. Jackson, R.D.; Idso, S.B.; Reginato, R.J.; Pinter, P.J., Jr. Canopy Temperature as a Crop Water Stress Indicator. *Water Resour. Res.* **1981**, *17*, 1133–1138.
20. Veysi, S.; Naseri, A.A.; Hamzeh, S.; Bartholomeus, H. A satellite based crop water stress index for irrigation scheduling in sugarcane fields. *Agric. Water Manag.* **2017**, *189*, 70–86.
21. Kolassa, J.; Gentine, P.; Prigent, C.; Aires, F. Soil moisture retrieval from AMSR-E and ASCAT microwave observation synergy. Part 1: Satellite data analysis. *Remote Sens. Environ.* **2016**, *173*, 1–14.
22. Kaihotsu, I.; Asanuma, J.; Aida, K. Evaluation of the AMSR2 L2 soil moisture product of JAXA on the Mongolian Plateau over seven years (2012–2018). *SN Appl. Sci.* **2019**, *1*, 1477.
23. NISAR: The NASA-ISRO SAR Mission. Water: Vital for Life and Civilization. © 2019 California Institute of Technology. Government Sponsorship Acknowledged. Available online: https://nisar.jpl.nasa.gov/system/documents/fifiles/15_NISARApplications_SoilMoisture1.pdf (accessed on 16 July 2021).
24. DLR Tandem-L, Satellite Mission Proposal for Monitoring Dynamic Processes on the Earth's Surface. Cologne, April 2016. Reprinting or Other Use (Including Excerpts) is Only Permitted after Prior Agreement with DLR. DLR.de/HR. Available online: (accessed on 16 July 2021).
25. Harm-Jan, F.B.; van der Velde, R.; Su, Z. Sentinel-1 soil moisture content and its uncertainty over sparsely vegetated fields. *J. Hydrol. X* **2020**, *9*, 100066.

26. Abbaszadeh, P.; Moradkhani, H.; Gavahi, K.; Kumar, S.; Hain, C.; Zhan, X.; Duan, Q.; Peters-Lidard, C.; Karimiziarani, S. High-Resolution SMAP Satellite Soil Moisture Product: Exploring the Opportunities. *Bull. Am. Meteorol. Soc.* **2021**, *102*, 4–309.
27. Gamon, J.; Penuelas, J.; Field, C. A narrow-waveband spectral index that tracks diurnal changes in photosynthetic efficiency. *Remote Sens. Environ.* **1992**, *41*, 35–44.
28. Berni, J.A.J.; Zarco-Tejada, P.J.; Sepulcre-Cantó, G.; Fereres, E.; Villalobos, F. Mapping canopy conductance and CWSI in olive orchards using high resolution thermal remote sensing imagery. *Remote Sens. Environ.* **2009**, *113*, 2380–2388,.
29. Rouse, J.W.; Haas, R.H.; Schell, J.A.; Deering, D.W. Monitoring vegetation systems in the Great Plains with, E.R.T.S. In Proceedings of the Third ERTS-1 Symposium, Washington, DC, USA, 10–14 December 1973; NASA SP-351; Fraden, S.C., Marcanti, E.P., Becker, M.A., Eds.; NASA: Washington, DC, USA, 1974; pp. 309–317.
30. Roujean, J.-L.; Breon, F.-M. Estimating PAR absorbed by vegetation from bidirectional reflectance measurements. *Remote Sens. Environ.* **1995**, *51*, 375–384.
31. Haboudane, D.; Miller, J.R.; Tremblay, N.; Zarco-Tejada, P.J.; Dextraze, L. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. *Remote Sens. Environ.* **2002**, *81*, 416–426.
32. Gao, B. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sens. Environ.* **1996**, *58*, 257–266.
33. Zarco-Tejada, P.J.; González-Dugo, V.; Berni, J.A. Fluorescence, temperature, and narrow-band indices were acquired from a UAV platform for water stress detection using a micro-hyperspectral imager and a thermal camera. *Remote Sens. Environ.* **2012**, *117*, 322–337.
34. Jay, S.; Comar, A.; Benicio, R.; Beauvois, J.; Dutartre, D.; Daubige, G.; Li, W.; Labrosse, J.; Thomas, S.; Henry, N.; et al. Scoring Cercospora Leaf Spot on Sugar Beet: Comparison of UGV and UAV Phenotyping Systems. *Plant Phenomics* **2020**, *2020*, 9452123.
35. Okujeni, A.; Jänicke, C.; Cooper, S.; Frantz, D.; Hostert, P.; Clark, M.; Segl, K.; van der Linden, S. Multi-season unmixing of vegetation class fractions across diverse Californian ecoregions using simulated spaceborne imaging spectroscopy data. *Remote Sens. Environ.* **2021**, *2021*, 112558.
36. Ibrahim, E.; Monbaliu, J. Suitability of spaceborne multispectral data for inter-tidal sediment characterization: A case study. *Estuarine Coast. Shelf Sci.* **2011**, *92*, 437–445.
37. Navarro, A.; Rolim, J.; Miguel, I.; Catalão, J.; Silva, J.; Painho, M.; Vekerdy, Z. Crop Monitoring Based on SPOT-5 Take-5 and Sentinel-1A Data for the Estimation of Crop Water Requirements. *Remote Sens.* **2016**, *8*, 525.