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Crop water stress monitoring through precision technologies: A review

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Abstract
Rapid population growth associated with climate change has a significant impact on both agricultural and human health, primarily due to water scarcity. According to UNICEF, nearly two-thirds population of the world is affected by severe water scarcity at least one month of every year. Water stress has an adverse impact on crop physiology predominantly in photosynthetic capacity. Thus, crop water optimization in farming systems requires advancement in the monitoring of water stress at different times of the season in order to prevent plant physiological damage and maximise crop water use. Precision agriculture enabled by technical enhancement is able to solve this problem. Precision technologies such as Geographical Information Systems (GIS), Remote Sensing (RS), UAV Imagery (UAV), Wireless Sensor Networks (WSN) and Machine Learning & Artificial Intelligence (ML & AI) can be used to efficiently detect crop water stress. This article addresses current advancements in crop water stress monitoring and how they could be enhanced further in the near future.

Keywords: Climate change, machine learning, UAV, water stress, WSN

Introduction

In context of climate change and its effects on plant physiology, maximising water use efficiency (WUE) is essential for better crop production. Among the different resources, irrigation water is recognised as a basic and necessary resource for agriculture which plays important role in food security. Insufficient irrigation water cause crop water stress at different stages of crop development. Specifically, water stress at reproductive stage of crop is very much critical. Only 20% of the world's arable land is used for irrigated agriculture, which supplies 40% of the world's food supply [5]. Due to water scarcity, irrigation is difficult to implement in many countries. Future food and water supplies are also jeopardised as a result of growing drought situations in a major part of the world and rapid population growth. Climate change, frequent droughts, rising global water scarcity and devastating flooding pose concerns to agricultural water supply security. Plants under water stress close their stomata to conserve water, which restricts the pathway for the exchange of oxygen and carbon dioxide thus reducing overall photosynthetic potential. Reduced photosynthesis is caused mostly by a loss in leaf area as well as a decrease in PSII activity. Thus, assessment of crop water stress is important [2]. Precision irrigation techniques are based on accurately detecting water stress in crops and understanding crop water stress.

Using conventional ground-based sample techniques to measure crop water status is extremely challenging since it is a time-consuming, laborious process that is not feasible for agriculture on a larger scale. Along with it is also destructive for plants. Similarly, different evapotranspiration models assume that the reference crop in a field is a freely transpiring plant with homogeneous soil type and cover. These procedures are time-consuming and produce point data that is not representative of the state of the field as a whole.

Effective scheduling of irrigation is essential for enhancing water use efficiency as well as agricultural sustainability. Recent research has focused on the use of precision technology as an alternative to traditional field measurements of plant stress indicators since it provides information on spatial and temporal variability [8]. Thus, in light of climate change these precision technologies such as wireless sensor networks, unmanned aircraft, remote sensing, machine learning & deep learning play a crucial role in development of sustainable goals. Spectral reflectance indices from high resolution sensors now been popular in recent years because they enable non-invasive and fast monitoring of plant water stress dynamics. This paper explored the current developments in crop water stress monitoring by precision technologies, that could be applied to improve irrigation scheduling.

Crop Water Stress Assessment

Crop water stress monitoring in agriculture must be strengthened at distinct periods of the growing season in order to minimise crop physiological damage and yield loss by deficit of water. Timely detection of plant water status is important for implementing scheduling of irrigation and optimising crop water use.

Crop Water Stress Mapping Through Remote Sensing

The advent of hyperspectral remote sensing has enabled the determination of leaf chemistry in vegetation canopies. The three types of indices that are present predominantly are xanthophyll indices (Photochemical Reflectance Index, Normalized Photochemical Reflectance Index), structural indices (Normalized Difference Vegetation Index, Renormalized Difference Vegetation Index, Optimized Soil Adjusted Vegetation Index) and water indices (Normalized Difference Water Index, Simple Ratio Water Index). The leaf xanthophyll cycle is the basis for xanthophyll indices. Structural Indices are calculated based on how well leaves reflect visible and near-infrared light. The 970 nm trough of the reflectance spectrum tends to disappear and move to lower wavelengths when plants are under water stress, and this idea was used to construct a reflectance water index [6]. Table 1 summarizes these subsequent indices. With the emergence of high-resolution and high-frequency remote sensing (e.g., MODIS) technology that can monitor spatial changes in crop water use variability and evapotranspiration, crop water use variability and evapotranspiration could be stimulated from the whole plant to the whole field or crop scale.

Table 1: Spectral vegetation indices that has been correlated to plant water stress

Reflectance indices	Major features	Formula	Plant water stress indicators
Photochemical Reflectance Index (PRI)	These are Xanthophyll indices that are sensitive to the epoxidation state of the pigments in the xanthophyll cycle	$\frac{R570 - R531}{R570 + R531}$	Chlorophyll fluorescence and Stomatal conductance
Normalized Photochemical Reflectance Index (NPRI)		$\frac{PRI}{[RDVI * \left(\frac{R700}{R670}\right)]}$	Chlorophyll fluorescence and Stomatal conductance
Normalized Difference Vegetation Index (NDVI)	These are structural indices that quantify water stress by measuring reflectance indices in the VIS and NIR spectral ranges.	$\frac{R800 - R670}{R800 + R670}$	Stomatal Conductance, Leaf water potential
Renormalized Difference Vegetation Index (RDVI)		$\frac{R800 - R670}{\sqrt{R800 + R670}}$	Stomatal Conductance, Leaf water potential
Optimized Soil Adjusted Vegetation Index (OSAVI)		$\frac{(1 + 0.16)R800 - R670}{(R800 + R670) + 0.16}$	Stomatal Conductance, Leaf water potential
Normalized Difference Water Index (NDWI)	These are water indices which measures the reflectance trough in the near-infrared region to assess the water stress	$\frac{R860 - R1240}{R860 + R1240}$	Leaf water potential
Simple Ratio Water Index (SRWI)		$\frac{R860}{R1240}$	Leaf water potential

Crop Water Stress Mapping Through UAV Imagery

Recent advancements in Unmanned Aerial Vehicles (UAVs) have expanded the use of remote sensing in precision agriculture research. As demonstrated in Figure 1, unmanned aerial vehicles (UAVs) can monitor crop water stress using imagery. Multispectral UAV remote-sensing systems are more cost-effective, accessible and efficient crop water stress trackers because they incorporate high-resolution pixel sensors that can precisely analyse crop water stress [1]. The use of multispectral UAV remote sensing also aids in the estimation of crop water stress index (CWSI) models, which are used to detect crop water stress. However, the Water Deficit Index (WDI) based on imaging from Unmanned Aerial Vehicles (UAVs) is increasingly being utilized as the soil background is a key issue in establishing CWSI data, particularly during early development stage canopy temperature data. Therefore, the WDI is a better index compared with the CWSI for exact estimations of crop water status, and the WDI maps thus give accurate irrigation maps. WDI index has the unique feature to be applicable both when the land surface is partly composed of bare soil and crops on the land surface are senescing. WDI can be computed by-

$$WDI = 1 - \frac{\lambda Eact}{\lambda Epot}$$

where λEact is the actual latent heat flux density, λEpot is the potential latent heat flux density

Thermal infrared systems detect crop water stress by assessing canopy temperature and field air temperature. Thermal imaging systems use both cooled and uncooled cameras. Cooled infrared cameras detect minor temperature differences via highly sensitive data. These systems detect crop water levels and monitor crop water stress. In contrast, uncooled cameras are employed to collect infrared thermal and microwave images from crop and canopy sources. The camera is based on the focal plane array (FPA) detector, which generates high-resolution images using a single sensor camera. Thermal sensors in combination with near-infrared (NIR) and visible sensors are used to filter non-leaf products from all samples and determine canopy temperature [1].

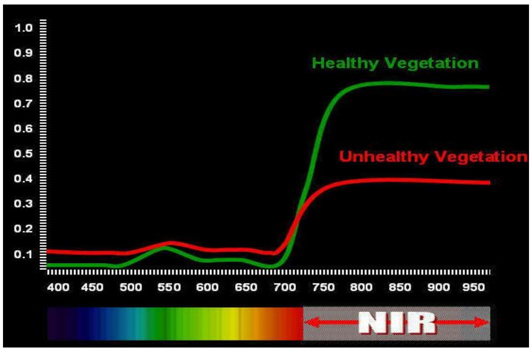

Fig 1: Estimation of crop water stress using a multispectral UAV system [1]

Crop Water Stress Mapping Through LiDAR

LiDAR system is a revolutionary technology for analysing field crop water stress. LiDAR provides accurate 3D data by delivering precise pulses at a target and measuring the pulse that bounces back in order to acquire data about the object (Figure 2) [3]. Furthermore, the recent development of accurate 3D LiDAR imagery together with natural colour, chlorophyll fluorescence, photochemical reflectance index and leaf temperature images is demonstrated which provide water stress information. Lidar can provide an accurate estimation of water stress through 3D modelling, as well as the exact location of water stress. The targeted short-band laser light effectively penetrates the crop canopy and is less impacted by the infiltrated light, which makes it an excellent tool for estimating crop water stress in the field. Along with LiDAR, algorithms and geometric regulations can be used to precisely deliver crop water stress and its connection to crop characteristics. The LiDAR system used to detect leaf water stress in several crops and the results demonstrated a strong link between leaf water stress and the number of LiDAR points acquired [1].

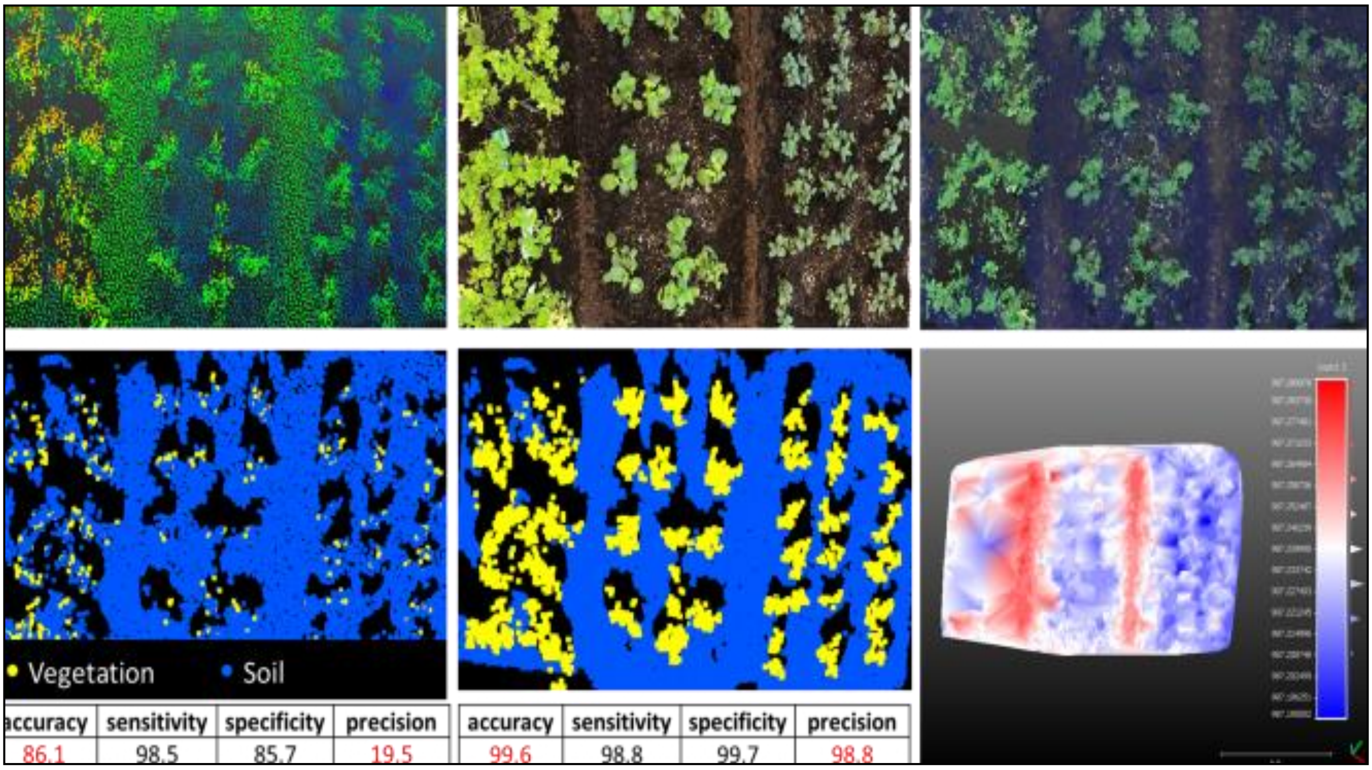

Fig 2: Application of LiDAR sensor in agriculture (source: gim-international.com)

Crop and Soil Water Stress Mapping Through Wireless Sensor Networks

A wireless sensor network (WSN) is a sensing system that consists of a group of spatially distributed sensors that monitor physical or environmental parameters such as weather, water status, soil status etc automatically and wirelessly. Deploying and maintaining ground-based sensors at field is a time-consuming task thus wireless sensor networks (WSN) are regarded as a trustworthy, efficient and cost-effective solution to this issue as they have the capacity to generate continuous, real-time, in-situ measurements under different operation situations. A WSN is made up of sensor nodes spread across a geographical area, with each sensor node capable of wireless communication [4]. A WSN, in conjunction with cellular communication infrastructure and internet technologies, provides significant capacity for remote measurement, transmission and access to information. The use of wireless sensor networks to assess soil parameters eliminates the requirement for sensors to be removed for field operations such as ploughing, allowing for long-term measurements without multiple disturbances to soil structure. Wireless sensors also eliminate the need for above-ground wiring, minimising the risk of equipment damage and data loss. Real-time communication between sensors, actuators and human users is simple using locally accessible telecommunications infrastructure and interfaces can be implemented on mobile hand-held devices [12]. Wireless underground sensor networks (WUSNs), on the other hand, are characterised as a system in which all sensors and communication components are buried underground. A single underground node and an above-ground hub comprise the most basic WUSN design (Figure 3). Advanced WUSNs can be made up of many subterranean nodes linked to a single above-ground hub or a wide-area network made up of multiple underground nodes linked to multiple above-ground hubs [10].

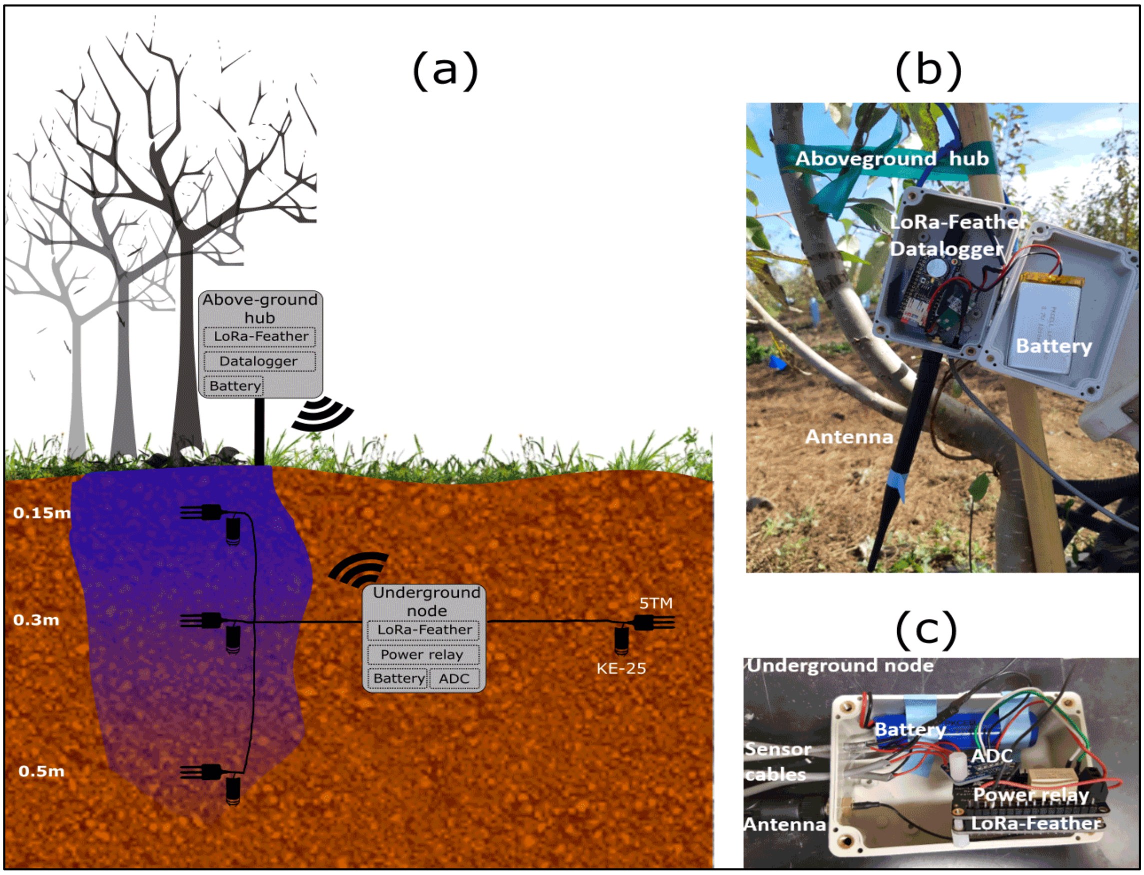

Fig 3: WUSN field experimentation setup [10]

Crop Water Stress Mapping Through Machine Learning and Deep Learning

Machine learning (ML) algorithms can resolve complicated, nonlinear issues by combining several sensors and datasets from multiple sources. Traditional image processing involves a substantial amount of variability in image acquisition, which increases the complexity of image processing. In ML, however, the user extracts key features from the collected image using knowledge and domain expertise. The diagnosis of water stress is much easier when these features are integrated with image processing. Moshou *et al*. (2014) attempted to assess water stress utilizing optical multisensory fusion and a support vector machine (SVM) classifier with the linear model [11]. They designed a hybrid classification algorithm that detected water stress in wheat using a multisensory fusion system and a least squares support vector machine (LSSVM) with an accuracy of 98.9%. artificial neural machine (ANN) is a popular ML approach for detecting water stress. ANN can calculate water potential, ET requirements with high accuracy The system ultimately collects information from crop, soil and environmental elements, sends it to a computerised irrigation-controlled algorithm and generates crop, soil and environmental stress analysis. ANN collects data using a wireless sensory network and compute water levels using infrared thermometers (IRTs) [1]. On the other hand, a convolutional neural network (CNN) based on deep machine learning is applied to thermal images for recognition and classification of water status. Deep Convolutional Neural Network (DCNN) delivers accurate and rapid stress phenotyping in real time. Among the various DCNN, GoogLeNet is effective for monitoring water stressed conditions. These models can be used to create a real-time image-based system for detecting crop water stress as well as scheduling irrigation.

Variable Rate Irrigation

Adapting to climate change can be accomplished through a variety of management options and technology improvements. Strategies like as variable rate irrigation (VRI) can assist producers in reducing the risks associated with climate change while also improving water-use efficiency. Due to natural variances in soil type or topography, most fields are not uniform. When water is applied consistently to a field, certain sections may become overwatered while others remain dry. VRI as illustrated in Figure 4, entails providing variable amounts of water to different zones of the field rather than applying a single uniform irrigation rate to the entire field based on the specific management zones within a field [7]. The VRI system integrates GPS positioning into a control system and may be installed into existing canter pivot systems. To achieve the required application rates within different management zones, the control system cycles through individual sprinklers or groups of sprinklers, turning them on and off and regulating travel speed. Variable rate irrigation techniques that rely on soil property characterisation for zoning result in the creation of prescription maps for precision irrigation applications. VRI management zones are created utilising the farmer's knowledge of the field, aerial images from online sources and maps of the land. The benefits of VRI are as follows:

- Boost yields by applying precise irrigation to all regions of the field.
- Reduce runoff, over-watering and under-watering, which benefits soil health and the environment; and
- Improve water and chemical application efficiency

Fig 4: VRI installed in centre pivot system of irrigation (source: valleyirrigation.com)

Micro Irrigation

The changing climate situation exacerbated the pressure of water shortages and competition for water from other commercial and environmental users. In this scenario micro irrigation could become the saver. It is the process of slowly applying water by hydraulic emitters or applicators installed at specific locations along water delivery lines in the form of discrete, continuous drops, tiny stream, or micro sprays. Micro-irrigation systems provide extensive control over water applications. Drip irrigation is a common type of micro-irrigation in which water is constantly given drop by drop directly to the root zone using drippers, resulting in a low volume of water, at low pressure and hence minimal energy costs [13]. Potential benefits and disadvantages of micro irrigation systems include:

- Improved plant development and productivity
- Improved plant growth and productivity by making better use of available water.
- Reduced the risk of salinity to plants.
- Improved fertiliser formulations and other chemical applications
- Reduced operating labour.

Decision Support System and Precision Irrigation

Decision support systems (DSS) are ML applications that integrate human knowledge to learn irrigation schedule patterns and mimic human decision-making activities. It is also a software based interactive system that supports decision-makers in assembling useful information from a variety of raw data, papers and personal skills in order to identify the problems and make the best decision (Figure 5). DSS architecture is composed of database (or knowledge base), the model (i.e., the decision context and user criteria) and the user interface. The combination of several sensor arrays with a web-based decision support tool measures real-time soil moisture data and direct transmission to a server allows farmers to monitor their fields in real time. Sensors put in the field collect data on crop features, soil type, irrigation network hydraulic properties, climate (historical and forecasted data) and information on water availability and crop production in order to produce an ideal weekly irrigation schedule [9]. Furthermore, DSS detects the amount of water used by crops in real time during the growing season to acquire an exact and employs many irrigation management indicators to assess irrigation water efficiency. Furthermore, the web-based decision support tool's smart programming enables the entire system to make quick irrigation recommendation calculations.

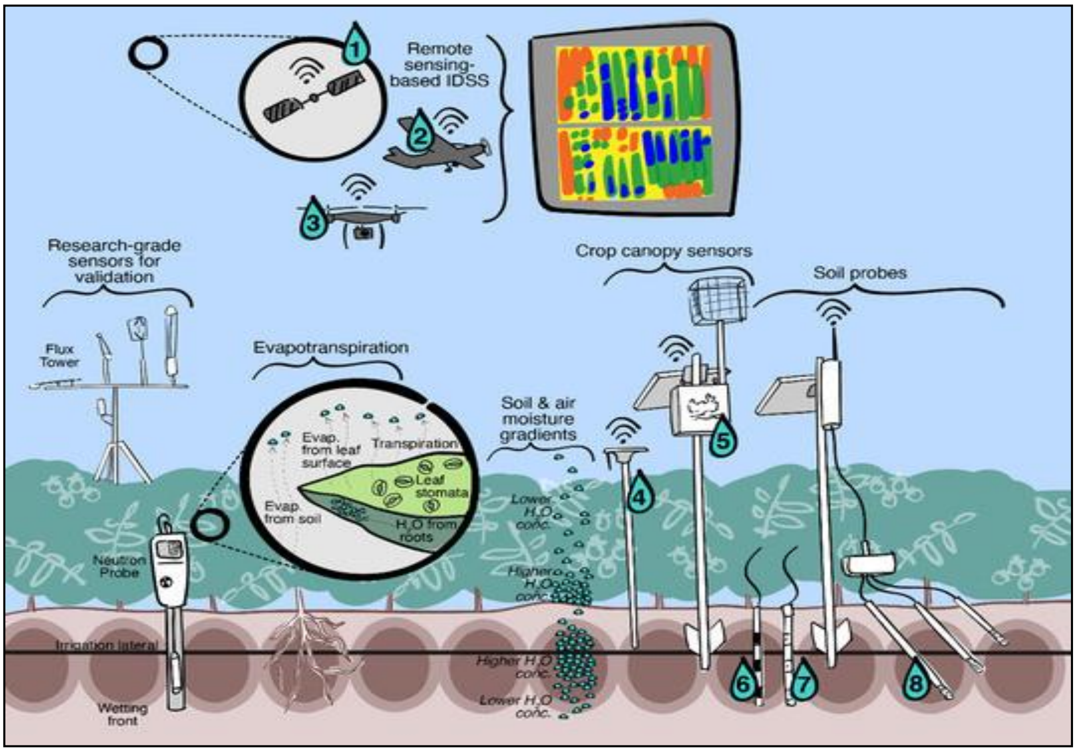

Fig 5: Conceptual illustration of DSS [9]

Conclusions and Future Scopes

Implementing an appropriate irrigation scheduling approach is essential in order to meet the demand for increased global food production while dealing with limited water resources. Thus, technical advancement in the irrigation sector through remote sensing, machine learning, deep learning, wireless sensor network for assessing crop water stress undoubtedly increase water use efficiency. Future study on the merging of thermal and narrow-band hyperspectral images to provide more precise plant water status information would be profitable.

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