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Short-range sensing for fruit tree water stress detection and monitoring in orchards: a review

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Abstract

Water is critical to the health and productivity of fruit trees. Efficient monitoring of water stress is essential for optimizing irrigation practices and ensuring sustainable fruit production. Short-range sensing can be reliable, rapid, inexpensive, and used for applications based on well-developed and validated algorithms. This paper reviews the recent advancement in fruit tree water stress detection via short-range sensing, which can be used for irrigation scheduling in orchards. Thermal imagery, near-infrared, and shortwave infrared methods are widely used for crop water stress detection. This review also presents research demonstrating the efficacy of short-range sensing in detecting water stress indicators in different fruit tree species. These indicators include changes in leaf temperature, stomatal conductance, chlorophyll content, and canopy reflectance. Short-range sensing enables precision irrigation strategies by utilizing real-time data to customize water applications for individual fruit trees or specific orchard areas. This approach leads to benefits, such as water conservation, optimized resource utilization, and improved fruit quality and yield. Short-range sensing shows great promise for potentially changing water stress monitoring in fruit trees. It could become a useful tool for effective fruit tree water stress management through continued research and development.

Keywords: fruit tree water stress, near-infrared, orchard, spectroscopy, thermal imaging

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Introduction

In agriculture, water management involves using water to maximize productivity, ensure the global food supply, and safeguard natural resources. The global population is estimated to increase by approximately 2.3 billion people between 2010 and 2050 (UN, 2015), and the food demand is expected to double during this time. Concurrently, climate change will trigger extreme weather incidents with indications of representative and long-term heat waves and droughts (IPCC, 2018). It is predicted that within the next 50 years, the annual mean global temperature and the demand for crop water will increase.

Water stress, also called drought stress, is one of the most severe environmental stresses worldwide. Water stress is the insufficient supply of water from the soil to crops/trees and results in plant physiological conditions caused by lack of available soil water or a high evaporative demand of the atmosphere. It highly affects crop growth and production with quality. For trees, two kinds of stresses typically occur: biotic and abiotic stresses (Fig. 1). Among the abiotic stressors, water stress is the most devastating stressor that results in limiting plant growth, yield, and deteriorating quality (Gull et al., 2019). It is well known that extreme water deficits impair many physiological processes and considerably affect yields. Mild water deficits, which are not easy to identify, may also negatively affect yields (Cramer et al., 2011).

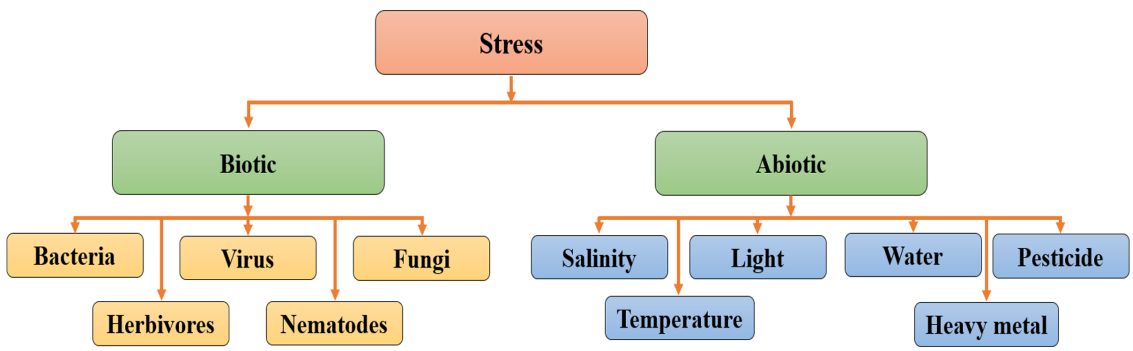

Fig. 1. Map of the different types of stress that occur in crops/trees (modified from Kochhar and Gujral, 2020).

High-valued crops, especially fruit trees, are very sensitive to water deficits. When water is limited to these crops, irrigation must be controlled to maximize water productivity while retaining yield and economic return for farmers. Evaluating the efficiency of irrigation systems and improving water management in precision agriculture are essential features. The assessment of tree water status with irrigation management is simple, and it requires cost-effective and user-friendly tools that could track crop water status over large areas. Both the quality and quantity of fruits depend on water. Excessive water contributes to increased vegetative growth and yield. Moreover, quality parameters, such as sugar content, pigment formation, acidity, and maturation, are adversely affected (Vijitha and Mahendran, 2012).

Conventional measurements of tree water stress are typically based on soil water content, plant water potential, and atmospheric water demand. The water status of the tissues of plants is generally measured in terms of the water potential, and plant-based measurements provide more direct insight into plant status than soil and atmospheric-based measurements (Jones, 2013). While these methods accurately measure plant water status, they are extremely time-consuming and labor-intensive, resulting in insufficient sampling (Gonzalez-Dugo et al., 2012). In addition, inside a field, evapotranspiration (ET) models assume a common growth with the same cover and soil type, which readily transpires. These strategies require time and yield point information that provides poor indicators of the general field condition. Many other techniques that classify the state of plant water include in situ soil water content, measurement of stomatal conductance, leaf water potential, and others. These methods, however effective, are still challenging, work-intensive, disruptive, and unfit for automation (Ihuoma and Madramootoo, 2017).

Considering the limitations of the existing methods, non-contacted spectroscopic sensing methods offer an alternative and are real-time, state-of-the-art techniques. They can monitor plant changes even before the appearance of visual symptoms (Bayat et al., 2016). Notably, methods based on drones, airplanes, and satellites are very common because, compared to terrestrial approaches, they can cover a larger region. Nevertheless, when the aim is to study individual trees, concentrating on the architecture concealed under the surface of the leaf canopy, this advantage becomes a downside. In particular, satellite imagery poses two key drawbacks: the resolution problem and the return frequency. Thus, imagery is not always possible for several satellites because of these issues (Gómez-Bellot et al., 2015). Hence, it is important to reduce the water used per unit yield for trees/crops, considering the need to save water and enhance agricultural productivity. Moreover, early detection of water stress is essential before it causes massive damage and yield losses. This paper reviews the recent advancement in the detection of fruit tree water stress using short-range sensing, which can be used for irrigation scheduling in orchards and large-scale applications. This article will contribute to the scientific understanding of water stress in fruit trees, provide practical solutions for orchard management, assess the effectiveness of sensing technologies, and serve as an educational resource for various stakeholders in the agriculture field.

Effect of water stress on fruit trees

Crop water stress is a physiological response that occurs due to a reduction in water supply to plants. Plants consume root zone water to satisfy their ET and reduce the water availability in the soil. Water deficiency results in different biochemical and physiological changes, such as osmotic active substances aggregation, increased high-molecular-weight hydrocarbon concentrations (Lodish et al., 2016), cuticle thickening (Patumi et al., 2002) and decreased photosynthetic pigments, stomatal conductance, and the photosynthetic rate (Bacelar et al., 2007). Increased lipid peroxidation and decreased levels of photosynthetic pigments, stomatal conductance, and the photosynthetic rate are also linked to water stress. Thus, water stress results in some damaging symptoms, such as leaf wilting, stunted growth, and leaf area reduction, which lead to a reduction in biomass, yield, and quality of crops (Aladenola and Madramootoo, 2014).

Water stress induces stomatal closure, decreasing evaporative cooling and increasing the leaf temperature (Parkash and Singh, 2020). The stomatal response is generally considered related to the content of soil water rather than leaf water. This means that stomata are most likely caused by chemical signals, such as abscisic acid (ABA) accumulation in dehydrated roots, rather than reduced cell turgor (Saradadevi et al., 2017). Pierantozzi et al. (2013) biochemically and physiologically studied water relationships and the yield of olive trees under water stress during the pre-flowering–flowering period. Under stressed conditions, plants undergo physiological, biochemical, cellular, and molecular alterations. Fig. 2 shows the plant condition in different organs during water stress. Plants have evolved different pathways to deal with these abnormal physiological disorders.

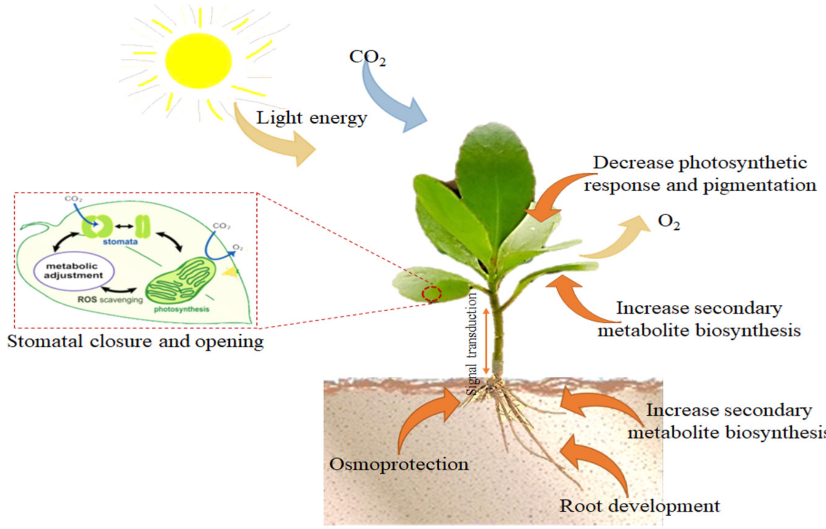

Fig. 2. Plant conditions during water stress (modified from Zingaretti et al., 2013; Osakabe et al., 2014).

Physically, when a plant tissue loses water, it reflects a reduction in the water potential of the plant cells, which means either cell turgor or osmotic potential decreases. As a result, many important plant processes, such as expansive growth of the stomatal opening, depend on cell turgor (Tardieu et al., 2011). In the case of fruit trees, water stress responses in multiple phenological stages have been observed. In the early stages of peach growth, water supply reduction has little effect on fruit size and production, but in the final stage of rapid fruit growth, these become more susceptible (Boland et al., 1993). The quality of fruit also affects fruit size and the amount of total soluble solids (Seo et al., 2018). Even if environmental conditions would otherwise lead to high crop yields, if water is scarce during low rainfall months, vegetable growth is often stopped, and yields decrease.

Water content indicators for fruit trees

The water quantity in fruit trees and plants is typically expressed as water potential. This can be measured from the leaf water potential (LWP), a direct measure of plant water stress. Different authors have mentioned other indicators for the measurement of water stress in fruit trees and plants, such as leaf water content (LWC), chlorophyll content, chlorophyll fluorescence (Chaerle et al., 2007), stem diameters, and xylem vessel characteristics (Pou et al., 2014). These indicators are partially beneficial for measuring water stress in trees but are time-intensive, expensive, and not ideal for use in large areas. Plant and canopy temperatures are two key parameters that have been recently used to show stomatal conductance, indicating water stress. The crop water stress index (CWSI) is one of the most well-known indicators for calculating the water stress of fruit trees and plants based on canopy temperature (Pou et al., 2014). Stomatal closure induced by water deficits (even for a very short time) reduces the transpiration rate, resulting in a reduction in evaporative cooling and an increase in leaf temperature (Buckley, 2019). Tree canopy temperature and air temperature are used to calculate the CWSI using equation (1) as follows (Gonzalez-Dugo et al., 2014):

$$\mathrm{CWSI}=\frac{(T_c-T_a)-(T_c-T_a)_{LL}}{(T_c-T_a)_{UL}-(T_c-T_a)_{LL}} \tag{1}$$

where T_c denotes the canopy temperature, T_a denotes the air temperature, $(T_c\text{-}T_a)_{LL}$ refers to the lower limit of the difference between the canopy and air temperatures, and $(T_c\text{-}T_a)_{UL}$ indicates the difference in canopy temperature where transpiration is discontinued.

Another important vegetation water measure is canopy water content (CWC), which is defined as total foliage water per unit area. CWC is related to plant water potential and relative water content for plant water stress detection (Cheng et al., 2014).

Short-range sensing of fruit tree water stress

Short-range sensing techniques are well adapted for the field and can be used flexibly for agricultural activities, such as monitoring, estimation, and mapping. Short-range sensing is highly reliable, inexpensive, and based on well-developed and validated algorithms and a wider range of applications, but it is time-consuming. Recent methods, such as helicopters and unmanned aerial vehicles (UAV) platforms, have provided much higher resolution but increased prices, constraints on coverage, and/or technological sophistication.

Short-range sensing methods based on spectral vegetation indices and infrared thermometry are widely used to determine crop water stress. Remote sensing has become a useful and cost-effective technique for the acquisition of spectral and thermal information of canopies compared to more time-consuming and laborious field techniques. However, remote sensing also has some disadvantages. For example, satellite imagery suffers from low-quality results with cloud cover and expensive sensors set up within crop fields to collect data from several plots (Anderson and Gaston, 2013). Thus, short-range sensing can be used to diagnose crop features, such as water stress, with improved and inexpensive knowledge of the vegetative status. Imagery sensing technologies largely focus on the visible wavelength reflectance of canopies, such as red, green, and blue, and non-visible spectrum ranges, such as near infrared (NIR). Monitoring these particular spectral ranges is typically carried out using visible, multispectral, and hyper-spectral cameras (Baluja et al., 2012). Recently, researchers have focused on monitoring plant physiological and structural statuses, gathering information from multispectral or hyperspectral cameras or sensors equipped with different platforms and comparing them to field measurements.

Thermal imaging

Thermal imaging provides continuous spatial monitoring through digital images and false-color thermal maps, surpassing the point-specific limitations of traditional temperature measurement methods (Huang et al., 2020). Objects above absolute zero emit infrared radiation with information about their characteristics. In thermal imaging, the infrared detector absorbs this radiation and converts it into a voltage or current, allowing visualization of object temperatures (Meola and Carlomagno, 2004). This technology is crucial for plant disease detection (Calderón et al., 2015), plant phenotyping (James and Sirault, 2012), plant stress, and water management (García-Tejero et al., 2018).

Currently, remote sensing platforms with thermal sensing imagery are widely available for studying fruit tree water stress (Meron et al., 2013). Fig. 3 illustrates thermal imaging and processing of fruit tree images for water stress detection. The leaf temperature drops as transpiration occurs on the leaf stomata. However, with water stress, transpiration does not occur due to stomata closure, which leads to a temperature increase in the leaf due to heat dissipation (Gates, 1964). Several CWSI approaches (Osroosh et al., 2016; Quebrajo et al., 2018) have been used to assess plant water stress using near-ground or proximal platform-based thermal imagery. With the advancement of light sensors and improved fields of view, infrared technologies are more capable of providing higher spectral information, improving the ability to monitor vegetation surface temperature (Lu et al., 2020).

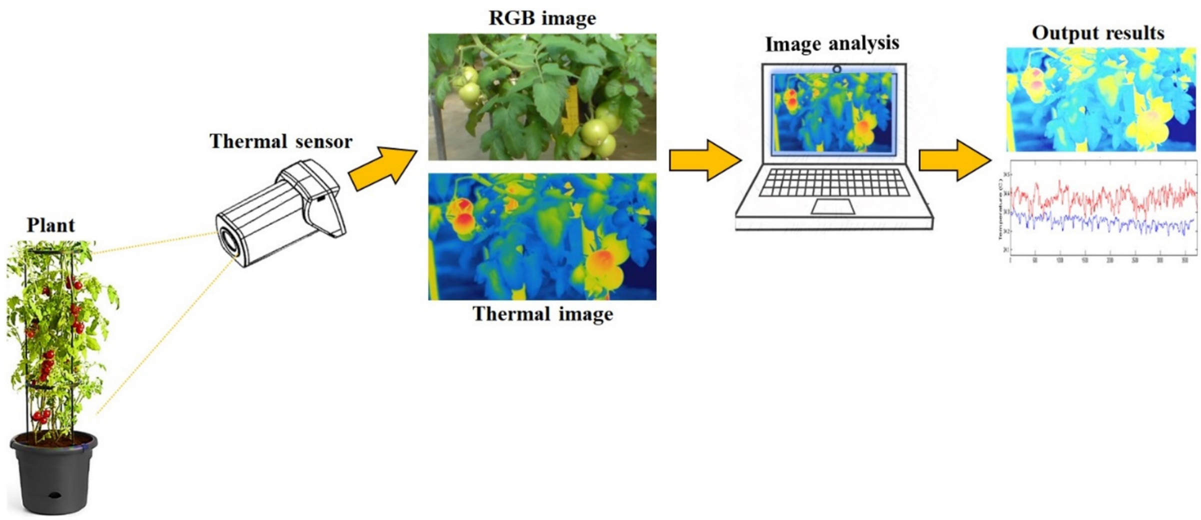

Fig. 3. Illustration of thermal imaging and processing.

The CWSI has been one of the most popular tools for detecting water stress in plants/trees since the 1970s. This prominent indicator is the difference between canopy temperature and air temperature, $\Delta t = (T_c - T_a)$, normalized by the vapor pressure deficit (VPD) (Jackson et al., 1981). The VPD normalization deals with the Δt based on (a) a lower limit at maximum transpiration (i.e., under well-watered conditions) and (b) an upper limit under no transpiration. The linear regression between Δt and VPD is the non-water stress baseline (NWSB), and both these techniques have been used to obtain a CWSI map from high-resolution thermal imagery. Zhou et al. (2022) developed a non-invasive method using thermal-RGB images to assess water stress in grapevines at the canopy level (Fig. 4a). By isolating pure canopy pixels and calculating the CWSI, they found a significant correlation ($R^2 = 0.67$) between CWSI and leaf water potential. This indicates that thermal imagery can effectively evaluate crop water status in grape production. Ben-gal et al. (2009) explored irrigation management effectively for optimal yield and oil quality using thermal imagery. Soil, plant, and remote sensing data, including the CWSI, were assessed by applying different irrigation levels (30 to 125%). The findings showed a consistent non-linear response in soil, plant water status, and the CWSI, with fewer changes at high irrigation levels. Interestingly, the analytical CWSI method performed comparably to the empirical one, suggesting its practical preference. Testi et al. (2008) introduced a method combining regulated deficit irrigation (RDI) and thermal imaging to detect the water stress of pistachio trees. They observed that the CWSI significantly increased during the day when pistachio canopies experienced water stress but remained stable in unstressed canopies. The most reliable CWSI values for assessing irrigation needs were found between 1,200 and 1,500 h when stressed pistachio canopies exhibited their highest diurnal CWSI values. During the stress period, RDI values reached 0.8 - 0.9, indicating a considerable water deficit. Egea et al. (2017) estimated the tree water status using the CWSI from high-resolution thermal imagery of a highly dense olive orchard. They installed a thermal camera on a mini remote-piloted aircraft system (RPAS) to acquire the images and used a segmentation algorithm to select the vegetation pixels. The Δt and VPD showed a high correlation ($R^2 = 0.74$) during the morning, but it was not consistent throughout the growing season. Moreover, the canopy temperature was measured only for the central trees in the plot, and the method was affected by the solar angle, which needed to be calibrated.

Canopy temperature is one of the most important tools for measuring water stress in fruit trees and is a statistical mean of the leaf temperature distribution. It is inversely related to leaf stomatal closure and transpiration. Stomatal closure occurs as a result of water stress, which then decreases the transpiration rate of plants. A low transpiration rate reduces plant cooling. Thus, the canopy temperature rises and acts as a water stress indicator. A canopy can be assumed to be a single homogeneous virtual leaf covering the entire plant surface. Trees with larger leaf sizes have a higher canopy resistance that increases canopy temperature. Ballester et al. (2013) demonstrated canopy temperature as an indicator of water stress by measuring it using a handheld thermographic camera with persimmon and citrus trees under deficit irrigation conditions. They also demonstrated a strong correlation between canopy temperature, fruit weight, and stomatal water potentials. However, the method is influenced by the leaf size and wind velocity, which affects the temperature of the leaves. For thermal imaging, a histogram gradient thresholding technique for canopy pixels was proposed by Salgadoe et al. (2019) for monitoring changes in water status caused by abiotic and biotic influences in individual plants. To avoid non-canopy-dependent pixel details, two histogram methods based on temperature intensity and the standard deviation were used. The approach demonstrated that measuring the canopy temperature is strongly comparable with typical methods. However, the process requires considerable time and will result in inaccuracies if the surfaces are not uniform or cannot stabilize with the environment.

Stem water potential is a recent state-of-the-art method used to measure crop stress in individual crops, and canopy temperature is inversely proportional to stomatal conductance (Sepulcre-Cantó et al., 2006). In the case of measuring leaf-level water stress, heterogeneity of canopy temperature and stomatal conductance within the tree crown is an important factor to be considered with the different stress levels of different irrigation conditions (Gonzalez-Dugo et al., 2012). A significant factor is the optimal time to perform thermal imaging during the day. It is assumed that water stress appears during solar noontime as plants are usually subject to maximum solar radiation during this time. Struthers et al. (2015) proposed a model that tracks changes in stomatal conductance and canopy temperature in pear trees over time. This model uses the VPD and air temperature as factors to account for varying weather conditions. Elevated ambient temperature and VPD induce fluctuations in stomatal behavior. Water-stressed trees exhibit greater variability in canopy temperature, and stomatal conductance changes more rapidly than canopy temperature. The threshold values of thermal indices with physiological parameters under deficit water irrigation in olive trees were demonstrated by García-Tejero et al. (2017) to test crop water status. The Pearson correlation coefficients between thermal indices with physiological parameters were observed at different times of the day to identify the more effective thermal index regarding the best sampling time. They showed that thermal readings taken at 12.00 GMT (Greenwich Mean Time) in the down part of the canopy gave a comparatively better thermal index. In contrast, Romero-Trigueros et al. (2019) found that the data obtained at 10.00 GMT showed the best spatial variability in grapefruit treated with deficit irrigation upon determination of the crop water stress index via infrared thermometry.

High-resolution airborne thermal imagery allows the evaluation of discontinuous canopies because it is possible to target pure tree crowns and is suitable for mapping water stress over large areas (Gonzalez-Dugo et al., 2013). Bellvert et al. (2016) presented a high-resolution airborne platform to estimate CWSI from fruit orchards to assess the spatial variability in the water status. The CWSI was estimated with a 640 $\times$ 480-pixel resolution thermal sensor mounted in an aircraft. Image pixel size is one of the drawbacks of thermal imaging. The relationship between the leaf water potential and CWSI decreases ($R^2 = 0.76$ to $R^2 = 0.28$) with an increased pixel size. They showed a pixel size of 0.6 to 0.8 m was required for precise leaf water potential mapping. Park et al. (2017) proposed a UAV-based thermal imaging method to estimate crop water stress in peach orchards. The edge detection method was used to extract the pure tree canopy from the images. The method showed a strong linear correlation between adaptive CWSI and stem water potential and stomatal conductance. However, the method showed limitations in the case of a narrow canopy temperature range. In addition, different varieties and environmental variables considerably influenced the method. Matese et al. (2018) found a relationship between the CWSI and vine water status, confirming the effectiveness of thermal remote sensing in evaluating vineyard water conditions. The fine spatial resolution of thermal imagery allowed for individual vine identification, facilitating a comparison between CWSI map data and physiological measurements. In another study, Bellvert et al. (2015) showed that a minimum pixel size of 0.30 m was optimal for grapevines. Santesteban et al. (2017) used CWSI from thermal images on a clear day and compared it with stem water potential and stomatal conductance at 14 vineyard sites. They applied spatial modeling to assess within-vineyard water status patterns. Table 1 summarizes the recent studies on thermal imaging to detect and analyze water stress conditions for fruit trees in orchards.

Table 1. List of thermal imaging studies for detecting water stress in fruit trees.

Fruit species	Spectral range (μm)	Detected parameters	Indices	Performance evaluation	References
Avocado	7.5 - 13	Canopy temperature	Surface temperature	$R^2 = 0.95$	Salgadoe et al. (2019)
Olive	7.5 - 13	Water status	CWSI	-	Ben-Gal et al. (2009)
Citrus	7.5 - 13	Stem water potential	Canopy temperature difference	$R^2 = 0.42 - 0.76$	Ballester et al. (2013)
Vineyard	7.5 - 13	Net photosynthesis	CWSI	R = -0.80	Matese et al. (2018)
Peach	7.5 - 13	Stem water potential	CWSI	$R^2 = 0.72 - 0.82$	Park et al. (2017)
Pistachio	8 - 14	Leaf water potential	CWSI	$R^2 = 0.83$	Testi et al. (2008)
Vineyard	7.5 - 13	Leaf water potential	CWSI	$R^2 = 0.63 - 0.72$	Bellvert et al. (2015)
Almond	7.5 - 13	Leaf water potential	Canopy temperature CWSI	$R^2 = 0.81$ $R^2 = 0.73$	Garc ía-Tejero et al. (2018)
Pear	8 - 12	Stomatal conductance	Canopy temperature	-	Struthers et al. (2015)
Olive	7.5 - 13.5	Stem water potential Stomatal conductance	CWSI Canopy temperature	$R^2 = 0.60 - 0.73$ $R^2 = 0.91$	Egea et al. (2017)
Vineyard	7.5 - 13	Stem water potential Stomatal conductance	CWSI Canopy temperature	$R^2 = 0.69$ $R^2 = 0.71$	Santesteban et al. (2017)
Almond	8 - 12	Stem water potential	CWSI Canopy temperature difference	$R^2 = 0.67$ $R^2 = 0.65$	Gonz alez-Dugo et al. (2013)
Peach	8 - 12	Stem water potential	CWSI Canopy temperature difference	$R^2 = 0.92$ $R^2 = 0.65$	Gonz alez-Dugo et al. (2013)
Apricot	8 - 12	Stem water potential	CWSI Canopy temperature difference	$R^2 = 0.64$ $R^2 = 0.65$	Gonz alez-Dugo et al. (2013)
Vineyard	17	Stem water potential	CWSI, Jones index	$R^2 = 0.62 - 0.65$	Gutiérrez et al. (2018)

CWSI, crop water stress index.

Thermal images provide canopy-related temperature, but non-canopy temperatures, such as that of soil, or mixed pixels of the canopy and non-canopy background cause errors in measuring an accurate canopy temperature from thermal imaging. A consistent process is also required for data acquisition and image analysis. Pou et al. (2014) used visible digital images (RGB) simultaneously with infrared thermal images for their analysis using ThermaCAM Researcher Pro 2.9 software (Teledyne FLIR LLC, USA). Gonzalez-Dugo et al. (2013) used algorithms developed in QuantaLab/IAS-CSIC (Quantalab, https://quantalab.ias.csic.es/) for data acquisition and image storage. Smartphone-based thermal imaging is a promising tool for enhancing the water stress monitoring process. With the advent of short-range sensing, the smartphone can be attached to one thermal camera with a mixture of digital and thermal sensors. Different studies showed the use of smartphones for water stress monitoring and the detection process. García-Tejero et al. (2018) demonstrated a thermal imaging system connected to a smartphone to assess the water stress in almond trees. Significant correlations were identified between thermal indexes from the thermal camera and CWSI. Furthermore, non-water stressed baselines for almond crops were established, revealing key associations with plant physiological parameters, such as leaf water potential and stomatal conductance. In addition, Petrie et al. (2019) tested the precision of a customer thermal camera and smartphone device using the CWSI and stomatal behavior to evaluate grapevine water status. Pichon et al. (2021) developed ApeX-Vigne (L'Institut Agro Montpellier, France), a free mobile app for monitoring vine water status in France. It relies on visually observing vine apices and categorizing them into three classes associated with vine water status.

Artificial neural network (ANN) models are also powerful tools for forecasting tree water stress. Gutiérrez et al. (2018) developed an on-the-go method for vineyard water status estimation using thermal imaging and machine learning. They conducted experiments and captured thermal images from a moving vehicle at a height of 1.0 m above the ground, as shown in Fig. 4b. Measurements on both sides of the canopy were used to create models by incorporating reference temperatures for calculating the thermal indices. With reference temperatures included, the best models achieved R^2 values of 0.65 for cross-validation and 0.62 for prediction. This study highlights the potential of thermal imaging for rapid and reliable vineyard water status estimation, possibly without the need for supervised reference temperature collection. Romero et al. (2018) developed a machine-learning model to estimate stem water potential from a UAV platform. ANN models were trained using different vegetation indices, and a high correlation was found between estimated and actual stem water potential. With the resolution of sensors used in short-range sensing, a large amount of data can be collected that describe whole plant physiology. However, the response of plants does not always show a linear relationship with water stress. For this reason, ANN can be used to deal with large and complex tasks due to its ability to model linear and nonlinear systems. Zúñiga et al. (2016) reported using UAV-based thermal infrared and multispectral images to schedule irrigation and characterize plant responses under several irrigation conditions.

Thermal imaging techniques for fruit orchards present a promising avenue for early stress detection and comprehensive orchard assessment. The non-invasive and remote-sensing nature of thermal imaging allows for efficient monitoring, enabling proactive management of potential issues. However, susceptibility to environmental factors, limited depth perception, and the associated costs pose significant challenges. Addressing these requires advancements in image processing, integration with complementary technologies, and efforts to educate orchard owners about the nuances of thermal imaging. Despite its limitations, ongoing research and technological innovations hold the potential to enhance the accuracy and practicality of thermal imaging, making it an increasingly valuable tool for sustainable orchard management.

VIS-NIR techniques

Visible-near-infrared (VIS-NIR) spectrometers have gained popularity for their ease of collecting spectral data (Huang et al., 2020). VIS-NIR spectroscopy, a non-destructive method, exploits variations in reflection and radiation among substances in the same spectral range. It utilizes electromagnetic waves in the range of 400 - 2,500 nm (Xie et al., 2016). Substances with hydrogen-based components, such as C-H, O-H, and N-H groups, absorb energy in the VIS-NIR range, causing changes in the reflected or transmitted spectrum (Arendse et al., 2018). Variations in sample composition produce distinct spectral curves, often featuring broad bands resulting from overlapping absorptions (Huang et al., 2020). Fig. 5a shows the possible light pathways as light interacts with a sample using a single incident ray. Fig. 5b presents the interactance and transmission measurements in the VIS-NIR range.

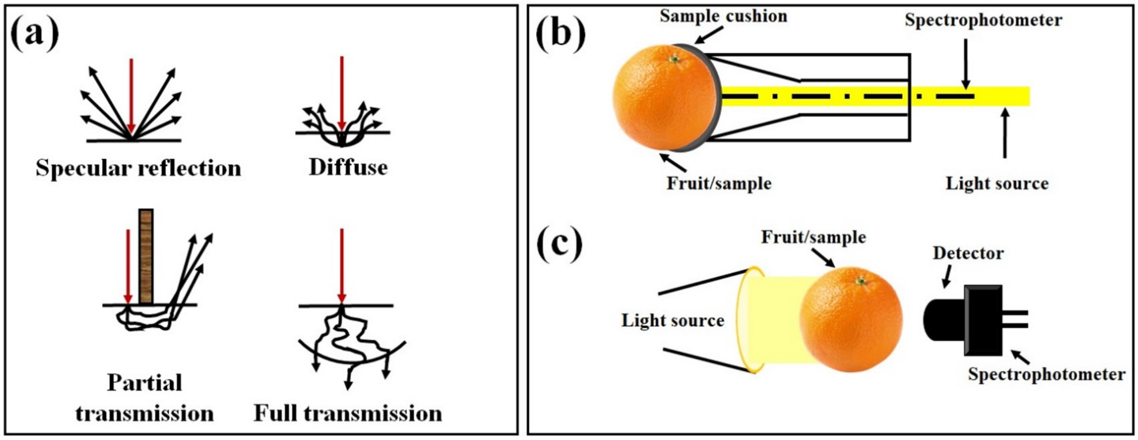

Fig. 5. (a) Possible light pathways as light interacts with a sample using a single incident ray (Zahir et al., 2022) and (b) diagram showing how interactance and transmission measurements are recorded using a visible-near-infrared (VIS-NIR) sensor (modified from Maniwara et al., 2014).

When crop water stress occurs, the internal structure of the leaf influences the reflectance in the red and NIR spectral regions. To measure crop water stress, we can examine water spectral absorption bands near 970, 1,200, 1,450, and 1,940 nm using NIR and shortwave infrared (SWIR) techniques (Olsen et al., 2013). In addition, visible region reflectance provides information about pigments, such as chlorophyll, carotenoids, anthocyanin, and plant photosynthesis. Extracting different vegetation indices acquired from multispectral and hyperspectral images in short-range sensing is a common and widely used approach to analyze crop spectral signatures. Moreover, with the advancement of an increased number of wavebands to predict crop-related parameters, partial least squares regression (PLSR) based on multivariate statistical techniques has been extensively considered for fast and non-destructive detection of water status. Dzikiti et al. (2011) quantified the seasonal dynamics of the canopy reflectance of citrus trees. The canopy reflectance showed a clear seasonal trend influenced by the position changes of the sun. Tree water use changed by 13% when canopy reflectance varied over the seasonal range of values. Up to 25% of the daily total transpiration was extracted from the internal water storage of the tree, detectable through spectral indices derived from the canopy reflectance. Monthly citrus canopy reflectance differed in summer and winter, demonstrating the potential of canopy reflectance for assessing citrus tree water status. Rallo et al. (2014) assessed leaf water potentials using high-resolution spectral reflectance upon optimization of vegetation indices, such as the normalized difference greenness vegetation index (NDGI), the green index (GI), the moisture spectral index (MSI), and the normalized difference water index (NDWI) families that could be used at the leaf or tree canopy level. A multivariate analysis, PLSR, was also tested using full spectral measurements in the visible infrared-shortwave infrared (VIR-SWIR) (350 - 2,500 nm) region to predict leaf water potential accuracy. Regarding spectral data, red wavelength (R) and NIR can be useful indicators of water potential, photosynthesis, and stomatal conductance. González-Fernández et al. (2015a) used field spectroscopy to estimate the leaf water content at the individual leaf level in a commercial vineyard. They revealed varying results based on grape variety, with Tempranillo showing the most accurate estimates due to its higher leaf water content. The estimates using continuum removal (CR) were the best, according to the vegetation indices. Among the spectral data, the band area centered at 1,450 nm was the most effective for assessing water content in vineyards. Zhang et al. (2012) identified spectral regions at approximately 1,400 and 1,900 nm, with the highest correlation with leaf composition variables.

Field spectro-radiometry can assess leaf-level water content in vineyards, but applying it to canopy-level water status in complex vineyards may be challenging. Pôças et al. (2015) proposed a statistical approach that validated the effectiveness of visible domain vegetation indices (VIs) for monitoring vineyard water status. VIs combining red, green, and blue spectral regions, such as the visible atmospherically resistant index (VARI), red : green ratio index (RGRI), photochemical reflectance index (PRI), NDGI, and GI yielded the best results when optimized with specific wavelength combinations. These VIs showed consistent performance in correlation with leaf water potential from post-flowering to harvest. Three bands and two bands, derived from sensors with visible bands, proved practical for estimating leaf water potential, considering the increasing availability of handheld spectroradiometers and hyperspectral sensors. This approach could result in improved irrigation management in vineyards but warrants further testing across diverse grape varieties and regions. Future research should explore non-linear or full-spectrum techniques and investigate the response to nighttime transpiration on leaf water potential. Tardaguila et al. (2017) used portable NIR spectroscopy to assess grapevine water status reliably for various conditions and varieties. Principal component analysis (PCA) and modified partial least squares (MPLS) were used to interpret the spectral models, which showed strong correlations for stem water potential (R = 0.77 - 0.93) and leaf relative water content (R = 0.66 - 0.81). The research also discussed the model performance differences between abaxial and adaxial spectra, affirming the effectiveness of non-invasive NIR spectroscopy for field assessments of grapevine water status. Diago et al. (2017) aimed to assess grapevine water status in a vineyard using a non-contact, vehicle-mounted NIR sensor. Spectra were acquired from leaves of water-stressed and non-stressed Riesling vines at two different times during the season (Fig. 6b). The calibration and cross-validation models achieved R^2 values of 0.95 and 0.88, respectively, for estimating stomatal conductance. These results indicate the potential of NIR spectroscopy for on-the-go assessment of plant water status, although further research is needed for full validation. Diago et al. (2018) aimed to validate a non-destructive method for assessing vineyard water status distribution using on-the-go, contactless NIR spectroscopy. The study compared various cross-validation strategies and models constructed from east-acquired spectra and resulted in the best results for both seasons. The determination coefficient of prediction (R^2) ranged from 0.68 to 0.85. Fernández-Novales et al. (2018) employed on-the-go proximal NIR spectroscopy to assess water regimes in a commercial vineyard. Spectra were collected from a moving vehicle during the period from veraison to harvest in a Tempranillo vineyard, as shown in Fig. 6a. Midday stem water potential and leaf stomatal conductance were measured concurrently as reference indicators of plant water status. Partial least squares (PLS) models achieved strong prediction results with R^2 values exceeding 0.86 for stem water potential and 0.66 for leaf stomatal conductance.

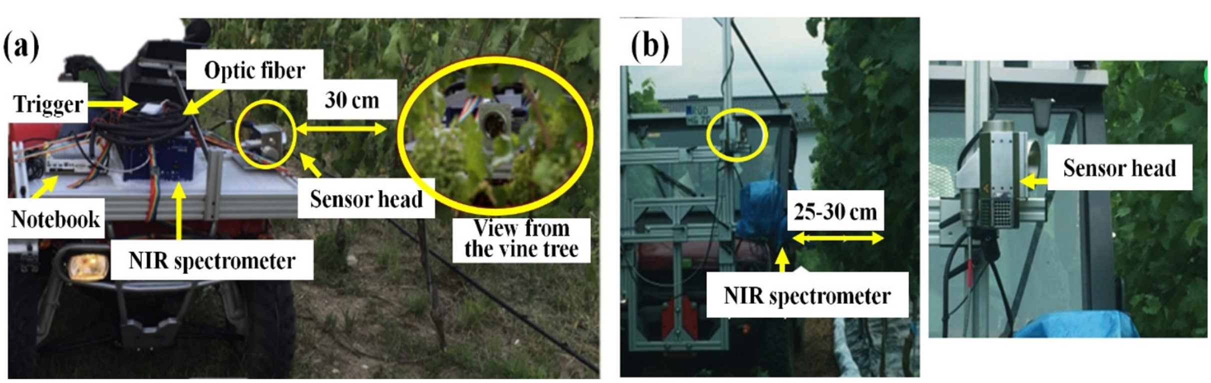

Fig. 6. Use of portable, contactless near-infrared (NIR) spectroscopy to validate a non-destructive approach for assessing water status distribution in vineyards; modified from (a) Fernández-Novales et al. (2018) and (b) Diago et al. (2017).

Kandylakis et al. (2020) introduced a UAV-based integrated SWIR and multi-spectral sensor system to estimate the water stress of four fruit vine varieties. A multispectral sensor with a resolution of 1,280 × 960 pixels with four different bands (R, G, RedEdge, and NIR) and a SWIR single band sensor with a resolution of 640 × 512 pixels were used to acquire data. The finding showed a good correlation ($R^2 > 0.80$) between SWIR and stomatal conductance in one variety but no strong correlation between the different varieties. More in-depth studies are needed to utilize the proposed approach for additional study areas with common varieties, soil conditions, and irrigation practices. Diurnal studies demonstrated good fluorescence recovery potential and consistent fluorescence estimates using the in-filling technique applied to airborne imaging (Zarco-Tejada et al., 2009). Moreover, the new structurally robust photochemical reflectance index (PRI) that uses 515 nm as the reference band (PRI515) and the chlorophyll ratio have been compared against the normalized difference vegetation index (NDVI), renormalized difference vegetation index (RDVI) and modified triangular vegetation index (MTVI) for their performance in tracking water status and the effects of sustained water stress on fruit quality at harvest (Stagakis et al., 2012).

For fruit quality assessment, Gamon et al. (1992) introduced PRI as a pre-visual indicator of water stress associated with the de-epoxidation state of xanthophyll pigments linked to photosynthesis. It is the difference between the xanthophyll pigment absorption band at 530 nm and a reference band at 570 nm. Recently, for crop water stress measurement, the visible spectral region with PRI index has been suggested by Suárez et al. (2009). The PRI is also sensitive to solar-induces chlorophyll fluorescence emission due to the correlation between steady-state chlorophyll fluorescence and stomatal conductance, and several studies have assessed the relationship between chlorophyll fluorescence and plant physiological status (Kalaji et al., 2018). Zarco-Tejada et al. (2013) proposed a normalized PRI in which the standard PRI is normalized by an index related to the canopy structure and by a red edge index related to the chlorophyll content using narrow-band multispectral (10 cm) and thermal (20 cm) imagery in four airborne campaigns over experimental vineyards. They demonstrated that normal PRI performed better than the standard PRI against stomatal conductance ($R^2 = 0.79$) and leaf water potential ($R^2 = 0.77$). Although the crown temperature was acquired from the trees, the established method for sensing water stress in the high-resolution PRI time series showed a good correlation with fruit quality (Suárez et al., 2009). They also measured the epoxidation state of the xanthophyll cycle with the destructive method and compared it with the PRI index, which showed a significant correlation ($R^2 = 0.81$). While NIR and SWIR have been successfully used in numerous trees and plants for water stress measurements, some studies have reported spectral measurements and water deficits in fields. The canopy temperature and reflectivity have been examined for apple trees (Facini et al., 2003), mandarin and peach fruits (Kriston-Vizi et al., 2008), grapevine (De Bei et al., 2011), and vineyard water statues (Serrano et al., 2012) as markers for water stress. Table 2 summarizes the recent studies on VIS-NIR spectroscopy for detecting and analyzing water stress conditions in fruit trees in orchards.

Table 2. List of visible-near-infrared (VIS-NIR) spectroscopy studies for detecting water stress in fruit trees (continued).

Fruit species	Spectral range (nm)	Detected parameters	Indices	Performance evaluation	References
Vineyard	900 - 1,700	Stomatal conductance	NDVI	$R^2 = 0.80$	Kandylakis et al. (2020)
Citrus	350 - 2,500	Water status	-	$R^2 = 0.89$	Dzikiti et al. (2011)
Olive Peach	670 - 775	Chlorophyll fluorescence extraction	NDVI	$R^2 = 0.57$ $R^2 = 0.54$	Zarco-Tejada et al. (2009)
Olive	350 - 2,500	Water potentials	NDGI MSI GI NDWI	$R^2 = 0.57$ $R^2 = 0.48$ $R^2 = 0.45$ $R^2 = 0.45$	Rallo et al. (2014)

Table 2. List of visible-near-infrared (VIS-NIR) spectroscopy studies for detecting water stress in fruit trees.

Fruit species	Spectral range (nm)	Detected parameters	Indices	Performance evaluation	References
Vineyard	350 - 2,500	Equivalent water thickness	-	$R^2 = 0.68$	González-Fernández et al. (2015a)
Grapevine	325 - 1,075	Predawn leaf water potential	VARI	$R^2 = 0.79$	Pôças et al. (2015)
			NDGI	$R^2 = 0.79$	
Grapevine	1,600 - 2,400	Water potential	-	$R_{cv} = 0.77 - 0.93$	Tardaguila et al. (2017)
		Relative water content	-	$R_{cv} = 0.66 - 0.81$	
Grape	1,100 - 2,100	Stomatal conductance	-	$R^2 = 0.95$	Diago et al. (2017)
Vineyard	1,100 - 2,100	Water potential	-	$R^2 = 0.86$	Fernández-Novales et al. (2018)
		Stomatal conductance	-	$R^2 = 0.66$	
Grape	1,100 - 2,100	Water potential	-	$R^2 = 0.68 - 0.85$	Diago et al. (2018)
Orange	500 - 800	Stem water potential	PRI	$R^2 = 0.69$	Stagakis et al. (2012)

NDVI, normalized difference vegetation index; NDGI, normalized difference greenness vegetation index; MSI, moisture spectral index; GI, green index; NDWI, normalized difference water index; VARI, visible atmospherically resistant index; PRI, photochemical reflectance index; R_{cv}, standard error of cross-validation.

One advantage of the VIS-NIR method is determining information on the plants' biochemical composition, aiding early stress detection and yield prediction. The non-destructive nature of VIS-NIR allows for repeated measurements without harming plants, facilitating long-term monitoring. However, there are critical challenges, such as limited depth penetration, particularly in dense canopies, which may lead to incomplete assessments of the entire plant. Additionally, the accuracy of this method can be affected by factors, such as sunlight intensity, atmospheric conditions, and shadows, potentially compromising the reliability of collected data. Interpreting VIS-NIR data also requires advanced analytical methods, necessitating a level of technical expertise that may be a barrier for some farmers. Moreover, the initial cost of acquiring suitable equipment and the need for periodic calibration could limit widespread adoption.

Other techniques

In the southern region of China, Luo et al. (2004) monitored the leaf temperature in cucumber plants using thermocouple technology. However, this method, which involved direct touch, resulted in significant measurement mistakes. The non-contact monitoring of leaf temperature has been made possible by infrared radiation thermometers, as scientists have capitalized on the swift advancements in infrared technology. González-Fernández et al. (2015b) highlighted the effectiveness of PLSR and CR analysis in predicting water content in leaves in commercial vineyards. They utilized hyperspectral data collected using a spectroradiometer and a plant probe. PLSR models incorporating CR reflectance were more precise, with the wavelength range of 1,265 to 1,668 nm found to be optimal for estimating water content in the vine leaves. Fernández-Novales et al. (2021) proposed on-the-go hyperspectral imaging with a push broom camera (400 - 1,000 nm) mounted on a motorized platform moving at 5 km/h in a Tempranillo vineyard. They used PLSR to predict grape composition parameters, achieving results with R^2 values of 0.55 to 0.88. This innovative methodology offers a non-destructive, in-field grape quality assessment during ripening. Kalyar et al. (2013) conducted measurements of leaf temperature and utilized the attributes of leaf gas exchange to determine the heat resistance of sunflower plants. Over the past few years, certain contemporary companies, such as Apogee, have successfully developed infrared radiometers of exceptional quality, characterized by a remarkable response time of 0.6 s (Yu et al., 2016). The infrared radiometer is ideal for measuring plant leaf temperature due to its high accuracy, high sensitivity, and diverse field of view. The combination of the ET model with the remote sensing data-based method was introduced by Bellvert et al. (2018) to assess the water status for irrigation in fruit orchards. The regressions between CWSI and stem water potential were determined from a remote sensing thermal-based method, and a Landsat-8 driven vegetation index was used to estimate the basal crop coefficient. The measured and actual ET showed a high correlation (R^2 > 0.70), and CWSI and stem water potential showed a high correlation (R^2 = 0.54 to 0.82) between them. However, operational constraints, expenses, and image acquisition throughout the season revealed major limitations. The ET at the canopy scale with the water loss in apple orchards was investigated by Odi-Lara et al. (2016). The basal crop coefficient and the soil-adjusted vegetation index (SAVI) were determined from satellite imagery and integrated into the daily root soil water balance. The results indicated a high correlation (R^2 = 0.78) between measured and modeled ET. Paço et al. (2014) also estimated ET from the reference ET and a standard crop coefficient in olive orchards. Zhang et al. (2018) used a combination of solar-induced fluorescence and PRI to monitor water stress in cotton leaves. PRI had positive correlations with the net photosynthetic rate (PN), stomatal conductance, transpiration rate, and quantum yield of the photosystem but a negative correlation with non-photochemical quenching. PRI was more effective for assessing PN during early water stress (R^2 = 0.86) than at all stress stages (R^2 = 0.54). It also correlated better with the relative water content and photosynthetic parameters indicator for evaluating cotton water status.

Future Perspectives and Limitations

Short-range sensing of fruit tree water stress will reshape modern agriculture in the future. This technology will empower farmers with real-time, precise data on individual plant water status, enabling highly efficient irrigation and resource management. Integrating remote sensing, artificial intelligence, and automation will lead to more sustainable and productive farming practices. It also has the potential to mitigate the impacts of climate change by enhancing crop resilience. However, as these technologies advance, there will be a need for robust regulatory frameworks, data privacy safeguards, and farmer education to ensure responsible and widespread adoption. Short-range sensing is a transformative tool that will drive the future of agriculture toward greater efficiency, sustainability, and resilience, even with evolving environmental challenges.

However, several limitations should be considered. The accuracy of short-range sensing can be influenced by environmental factors. The penetration depth into plant tissues is limited, which may restrict water stress detection in deeper layers. Furthermore, scalability and affordability remain challenges, especially for small and resource-constrained orchard owners who may find the initial investment and maintenance costs prohibitive.

Addressing these limitations necessitates ongoing research and development. Future innovations may focus on refining the accuracy and reliability of short-range sensing technologies, overcoming environmental interference, and making these tools more user-friendly and economically viable for different orchard sizes. Collaborative initiatives between researchers, technology developers, and farmers will be crucial for successfully integrating short-range sensing into mainstream orchard management practices. As precision agriculture continues to evolve, the synergistic combination of different sensing technologies and the establishment of best practices for their application will be essential for realizing the full potential of short-range sensing in addressing water stress in fruit orchards.

Conclusion

Conventional water stress measurements typically depend on soil water quality, plant water capacity, and atmospheric water demand. Fruits are highly valued crops and are particularly vulnerable to water deficits. Early water stress detection is important for fruits before causing significant harm and production losses. In this article, we reviewed the recent advances in fruit tree water stress detection using short-range sensing. Several studies have demonstrated CWSI measurements from thermal imagery, one of the major water stress indicators. Different techniques and methods have been used to evaluate the CWSI, the canopy temperature, and stomatal conductance. Results have shown that the CWSI has a high correlation (R^2 = 0.7 to 0.9) with the water stress of trees. In addition, some studies used NIR and SWIR techniques to estimate water stress. Additionally, a few studies have shown that these methods can be used to evaluate physiological conditions associated with plant–water interactions and irrigation scheduling in the field. The non-invasive and remote sensing nature of thermal imaging and VIS-NIR techniques allow for efficient monitoring, proactive management of potential issues, and repeated measurements without harm to the plants, facilitating long-term monitoring. Short-range sensing accuracy is affected by environmental factors, and its ability to penetrate plant tissues is limited, limiting water stress detection in deeper layers. Future research should focus on integrating advanced short-range sensing methods to evaluate the cost efficiency and commercial supply for precise detection of water stress in fruit trees. For this, we need efficient, inexpensive, and readily available advanced data analysis methods available for farmers and better implementation of irrigation scheduling for poor water quality regions.

Conflict of Interests

No potential conflict of interest relevant to this article was reported.

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