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Review

Recent advances in crop water stress detection

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ABSTRACT

In order to meet the demand for increased global food production under limited water resources, implementation of suitable irrigation scheduling technique is crucial, particularly in irrigated basins experiencing water stress. Optimizing water use in agriculture requires innovations in detection of plant water stress, at various stages of the growing season to minimize crop physiological damage, and yield loss. Remotely sensed plant stress indicators, based on the visible and near-infrared spectral regions, have the advantage of high spatial and spectral resolutions, low cost, and quick turnaround time. This paper outlines recent developments in monitoring crop water stress, for scheduling irrigation, some of the constraints experienced, and future research needs.

Contents

1. Introduction

Irrigated agriculture is essential to global food production, utilizing only 20% of cultivated land to provide 40% of the world's food supply (Garces-Restrepo et al., 2007). However, climate change, increasing worldwide shortages of water, frequent droughts, and global warming (Hirich et al., 2016) are threatening the reliability of irrigation water supplies. While the human population and demands for freshwater resources are increasing, drought and regular water scarcity can put global food security at risk (Lei et al., 2016), by severely disrupting agricultural production. The challenge is to meet rising productivity demands by improving methods of crop management (Behmann et al., 2014), and this requires a deeper understanding of plant response to abiotic stresses.

Conventional methods for monitoring crop water stress rely on in situ soil moisture measurements and meteorological variables to estimate the amount of water lost from the plant-soil system during a given period (González-Dugo et al., 2006). Regular sampling of soil to assess water depletion from the plant root zone assumes that the water holding capacity of the entire soil is uniform, so only

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a few point measurements are used to represent water retention characteristics (Clarke, 1997). The method is time consuming, assumes uniform plant density, and the same rate of transpiration, over an entire field, which is rarely the case. Similarly, evapotranspiration models assume a freely transpiring reference crop with uniform cover and soil type within a field. These methods are time consuming and produce point information that give poor indications of the overall status of the field. Other methods of detecting plant water status involve soil water balance calculations, direct and indirect measurement of plant water status, via stomatal conductance and leaf water potential. These approaches, though reliable, are labour intensive, destructive, and unsuitable for automation, due to heterogeneity of soil and crop canopy.

In order to increase water savings and enhance agricultural sustainability, implementation of suitable irrigation scheduling methods is essential (Osroosh et al., 2015), and requires early detection of water stress in crops, before it causes irreversible damage and yield loss. Recently, studies have focused on the use of remotely sensed data as an alternative to traditional field measurements of plant stress parameters, as this provides information about the spatial and temporal variability of crops (Dangwal et al., 2015; Leroux et al., 2016; Panigada et al., 2014; Rossini et al., 2013; Suárez et al., 2010; Zarco-Tejada et al., 2013; Zhao et al., 2015). Spectral reflectance indices obtained from high resolution hyperspectral sensors, onboard small Unmanned Aircraft Systems (sUAS), can be used in precision agriculture for monitoring crop water status and scheduling irrigation (Berni et al., 2009a, 2009b; Gago et al., 2015). However, due to several confounding factors affecting the vegetation indices (VIs) at the canopy and landscape scales, and that the threshold for water stress detection is crop specific, a general agreement for their use as a pre-visual indicator of water stress is yet to be achieved. This paper reviews the recent advances in crop water stress detection that can potentially be applicable to improve irrigation scheduling of vegetable crops and aims to identify the most promising approach for large-scale application.

2. Plant response to water stress

Crop water stress is a deficiency in water supply, detected as a reduction in soil water content or from the physiological responses of the plant to water deficit. Plants absorb root zone soil water to meet their evapotranspiration needs, and this depletes soil available water. Under limiting soil moisture conditions, chemical and hydraulic signals are transmitted to the plant leaf through xylem pathways (Limpus, 2009), which leads to physiological responses such as stomatal closure and reductions in photosynthesis rate. Wang et al. (2015) indicated that water stressed crops have reduced evapotranspiration, and manifest other symptoms such as leaf wilting, stunted growth, and leaf area reduction. Also, water stress adversely affects the physiological and nutritional development of crops, leading to reduced biomass, yield, and quality of crops (Aladenola and Madramootoo, 2014; Rossini et al., 2013; Zhang et al., 2017a, 2017b). Plant water status measures the response of a plant to the combined effects of soil moisture availability, evaporative demand, internal hydraulic resistance, and uptake capacity of the plant-root interface. It is a more sensitive indicator of stress than soil moisture (Jones, 2010). Plant response to water stress depends on environmental conditions and crop evapotranspiration needs, as irrigation must replenish soil moisture deficit from evapotranspiration losses. FAO-56 defines the irrigation water requirement for a well-watered crop as water loss through evapotranspiration of a disease-free crop under non-limiting soil conditions (Allen et al., 1998). Measures of plant water status are required to better understand the mechanisms of plant response and adaptation to water stress, and for the optimisation of crop production (Osakabe et al., 2014), through precision irrigation.

Similarly, evapotranspiration (ET) models are used to predict how changes in weather parameters can affect plant water status (Osroosh et al., 2016). The frequently used ET models are the Penman-Monteith (PM) (Allen et al., 1998) and Hargreaves (Hargreaves and Samani, 1985) equations. The Hargreaves model needs fewer data than the PM model and can estimate ET using air temperature as only input. Other researchers have used the CROPWAT-8, which is based on the Penman-Monteith method, to assess reference evapotranspiration (ETo), crop evapotranspiration (ETc), and irrigation water requirements (Bouraima et al., 2015; Patel et al., 2017; Surendran et al., 2017). The most common and practical approach widely used for estimating crop water requirement, and the operational monitoring of soil-plant water balance is the FAO-56 method. In the FAO-56 approach, crop evapotranspiration is estimated by the combination of ET_o and crop coefficients. There are two different FAO-56 approaches: single and dual crop coefficients. The single crop coefficient approach is used to express both plant transpiration and soil evaporation combined into a single crop coefficient (Kc). The dual crop coefficient approach uses two coefficients to separate the respective contribution of plant transpiration (Kcb) and soil evaporation (Ke), each by individual values (Allen et al., 2005). Kcb is multiplied by water stress coefficient (Ks) (range 0–1) to account for the reduction of ET due to soil moisture depletion. It has been shown that Ks is related to crop water stress index (CWSI) according to Eq. (1).

$$K_s = 1 - CSWI \tag{1}$$

Several researchers have evaluated the accuracy of water stress coefficient methods for estimating crop ETc under different levels of deficit irrigation. For instance, Bausch et al. (2011) successfully used a ratio of canopy temperature (Tc) as a substitute for the soil moisture based Ks. Kullberg et al. (2017) observed that using appropriate Ks method has the potential to improve irrigation scheduling to properly manage stress and ensure optimum crop yield under limited irrigation water supply. The main methods that are used for monitoring plant water stress have been summarized in Table 1, and are discussed below.

2.1. Plant-based approach

Stress quantification from plant-based approaches include the direct measurement of leaf water potential with a pressure chamber (Scholander et al., 1965). Leaf water potential is assumed to represent the mean soil water potential next to the plant roots (Ameglio et al., 1999), and provides good indication of leaf water status. It is widely adopted for scheduling irrigation in various crops (Alchanatis et al., 2010; Ameglio et al., 1999; Bellvert et al., 2016; Zarco-Tejada et al., 2012). However, the approach is slow and destructive, with limited temporal and spatial resolution, and is not suitable for strongly isohydric crops, which maintain a stable leaf water status over a wide range of evaporative demand or soil water supplies (Limpus, 2009). The amount of water in plant leaves can be measured by laboratory analysis, using Relative Water Content (RWC) and Equivalent Water Thickness (EWT) (Colombo et al., 2011). The EWT is the hypothetical thickness of a single layer of water averaged over the whole leaf area and can be computed in laboratory by measuring Fresh Weights (*FW*) and Dry weights (*DW*) and the one-sided leaf Area (*A*), as shown in Eq. (2).

$$ETW = \frac{FW - DW}{A} \tag{2}$$

Table 1
A summary of the methods for monitoring plant water stress, indicating their main advantages and disadvantages.

Methods	Description	Advantages	Disadvantages
1. Soil water measurement			
(a) Gravimetric method	Sampling of soil, which is weighed, oven-dried and reweighed to estimate the amount of water lost from the plant-soil system	It is reliable and serves as a guide on the amount of water to apply during irrigation	The method is labour intensive, destructive, and time consuming
(b) Soil moisture sensors			
(I) Neutron probe	Based on the emission of high energy neutrons by a radioactive source into the soil	Fast, non-destructive, and repetitive	Requires adequate operator training, storage, licencing, and inspection, due to its radioactive source
(II) TDR and FDR	Based on the difference between the dielectric constant of water and soil	Precise and easy to apply in practice. Estimates soil water levels at different depths along the soil profile. Readings can be logged automatically	Several sensors are required for an entire field. High cost of installation of sensors
(III) Tensiometers	Measures soil water potential	Easy to use for irrigation scheduling	Useful in coarse textured soils or in high frequency irrigation only. Used for a narrow range of available soil water
2. Soil water balance approach	Indirect estimate of soil moisture status based on soil water balance calculations	Good indicator of the amount of irrigation water and easy to apply	Not very accurate and requires calibration with actual soil measurements. Requires estimate of evaporation, rainfall, and irrigation events
3. Plant-based approaches			
(a) Stomatal conductance	Indirect indicator of plant water stress by measuring the stomata opening	Good measure of plant water status. Used as benchmark for most research studies	Labour intensive and unsuitable for automation and commercial application. Not very accurate for anisohydric crops
(b) Leaf water potential	Direct measurement of leaf water content	Widely accepted reference technique	Slow, destructive, and unsuitable for isohydric crops
(c) Relative water content	Direct measurement of leaf water status	Good indicator plant water status, requiring less sophisticated equipment	Destructive and time consuming
(d) Sap flow measurement	Measures the rate of transpiration through heat pulse	Sensitive to stomatal closure and water deficits. Adapted for automated recording and control of irrigation systems	Needs calibration for each tree and is difficult to replicate. Requires complex instrumentation and expertise
(e) Stem and fruit diameter	Measures fluctuation in stem and fruit diameters in response to changes in water content	Sensitive measure of plant water stress	Not useful for the control of high-frequency irrigation systems
4. Remote sensing methods			
(a) Infrared thermometry	Measures canopy temperature, which increases as a result of water stress	Reliable and non-destructive	Based on only a few point measurements. Does not account for soil and crop heterogeneity
(I) CWSI	Uses the difference between canopy and air temperatures to quantify crop water stress	Sensitive to stomatal closure and crop water deficit	Influenced by cloud cover, requires different baselines for different crops
(II) DANS, DACT, and Tc ratio	Measure single canopy temperature for quantifying water stress	Require less data than CWSI for detecting water stress. Tc ratio gives quantitative water stress coefficient (Ks) for calculating crop ET	Difficult to scale up to large cropped fields.
(b) Spectral vegetation indices			
(i) Structural indices	Measures reflectance indices within the VIS and NIR spectral range (NDVI, RDVI, OSAVI, TCARI) to indicate canopy changes due to water stress	Non-destructive with high temporal and spectral resolution	Requisite image analysis is still a challenging task. Precision reduces from leaf scale to canopy scale
(ii) Xanthophyll indices	Measures PRI and PRI_{norm}, which are sensitive to the epoxidation state of the xanthophyll cycle pigments	Account for physiological changes in photosynthetic pigment changes due to water stress	More work is needed to convert raw imagery to user-friendly irrigation application
(iii) Water indices	Measures the reflectance trough in the near-infrared region (WI, SRWI, and NDWI) used to represent canopy moisture content	Rapid and non-destructive measure of leaf water content	Problem of scaling up to canopy level

At the canopy level, Equivalent Water Thickness (EWT_{canopy}) (shown in Eq. (3)) can be obtained by scaling the EWC with Leaf Area Index (LAI), defined as the one-sided green leaf area per unit ground surface area (LAI = leaf area/ground area, cm^2/cm^2).

$$EWT_{canopy} = LAI * EWT \tag{3}$$

The RWC compares the water content of a leaf with the maximum water content at full turgor and can be considered as an indicator of vegetation status. It can be obtained from laboratory measurements of leaf weight and leaf Turgid Weight (TW) according to the following expression:

$$RWC = \frac{FW - DW}{TW - DW} * 100(\%) \tag{4}$$

Both RWC and EWC are good indicators of plant water status, and have been successfully used for scheduling irrigation in various crops (Danson et al., 1992; Jones, 2004; Panigada et al., 2014; Wang et al., 2015). The approaches require less sophisticated equipment, but are also destructive and time consuming.

Several other approaches are available that give indirect indications of stress such as measurement of stomatal conductance (Agam et al., 2013; Ballester et al., 2013; Lorenzo-Minguez et al., 1985; Maes et al., 2011), measurement of fruit and stem diameter (Gallardo et al., 2006; Huguet et al., 1992), and sap-flow measurement (Giorio and Giorio, 2003; Granier, 1987; Singh et al., 2010). Most plants exercise some measure of control over their leaf water status, by minimizing changes in leaf water status as the soil dries, through stomatal closure. Therefore, stomatal conductance is a very sensitive plant response to soil water deficit (Jones, 2004), except for some anisohydric species, which have less effective control of leaf water status under declining soil moisture conditions. The recognition that water stressed plants tend to close their stomata, which leads to increase in leaf temperature, has been used to develop thermal sensing methods, for the detection of plant stress (Idso et al., 1981). The approach provides a good indication of irrigation needs in many crops. However, measurements of stomatal conductance are tedious, and large leaf-to-leaf variation of the plant canopy requires much replication to obtain reliable data for irrigation scheduling.

The sap flow technique is used to assess transpiration rates of plants, by measuring the rate at which sap ascends stems using heat pulse. In this approach, short pulses of heat are applied in the stem, and the mass flow of sap is determined from the velocity of the heat pulses moving along the stem. The changes in transpiration rate indicated by sap flow are mainly determined by changes in stomatal opening. Singh et al. (2010) used sap flow sensors to schedule irrigation in corn field, but noted that the approach only gives indirect estimates of changes in conductance, as flow is also dependent on atmospheric conditions such as humidity. Therefore, changes in sap flow can occur without changes in stomatal aperture. Several other studies used sap-flow measurement for irrigation scheduling and control in a diverse range of crops, including grapevine (Eastham and Gray, 1998), fruit and olive trees (Ameglio et al., 1999; Giorio and Giorio, 2003) and even greenhouse crops (Ehret et al., 2001), with varying degrees of success. However, Jones (2004) stated that sap flow method requires a heat source, complex instrumentation, technical expertise, and needs calibration for each crop and for definition of irrigation control thresholds.

The use of plant-based indicators for irrigation scheduling requires the definition of threshold values, beyond which irrigation is essential. Therefore, it is important to regularly check the plant water status to avoid exceeding the reference values (Ballester et al., 2013). The threshold values, which are determined for plants growing under a well-watered condition, are difficult to obtain in a changing environment (Fereres and Goldhamer, 2003). Another limitation of plant-based approaches is that they do not usually provide information on the quantity of irrigation water to apply at any time, but only indicates that irrigation is required. This implies that soil moisture measurements or other estimation procedures are needed to determine the quantity of water to apply to optimize crop water use (Stockle and Dugas, 1992). A general drawback of both direct measurements of soil water status and plant-based approaches is the costs of installation of sensors or the difficulty with obtaining representative measurements, with single point sampling that would adequately account for soil and crop heterogeneity (Ballester et al., 2013; Jones, 2012).

2.2. Environmental canopy sensing

Infrared thermometry and thermal imagery, along with additional environmental measurements, have been acknowledged as an alternative approach to soil moisture based methods of plant water stress detection (Berni et al., 2009a; Cohen et al., 2005; Jones, 2010; Osroosh et al., 2015). Water stress detection based on canopy temperature measurements is probably the most widely used plant-based approach for remote sensing that is applicable to irrigation scheduling of several crops. As plants absorb solar radiation, canopy temperature increases, but is cooled when that energy is used for evapotranspiration.

Water stressed plants have reduced transpiration and higher leaf temperature compared to non-stressed crops. González-Dugo et al. (2006) used variability of canopy temperature to indicate water stress, and emphasised the need to quantify the complex relationship between canopy temperature, water stress, and spatial water availability. Collaizzi et al. (2012) revealed that canopy temperature-based algorithms are strongly correlated to crop outputs such as yield, water use efficiency, irrigation rates, seasonal evapotranspiration, and midday leaf water potential. Many indices have been established for evaluating water stress using infrared canopy temperature (Idso et al., 1981; Jones, 2004; Nielsen and Gardner, 1988; Osroosh et al., 2015; O'Shaughnessy et al., 2012; Payero and Irmak, 2006). Most of the indices use crop canopy temperature as a main driver for evaluation, typically as a single daily measurement at an assumed peak stress time, or by evaluating time above a temperature threshold. The approach is sensitive to small stresses, and relies on stomatal closure as an early indicator of water deficits.

2.2.1. Canopy temperature based crop water stress index (CWSI)

The CWSI derived from canopy temperature has been largely adopted as a tool to indicate plant water status and schedule irrigation in many crops (Aladenola and Madramootoo, 2014; Alchanatis et al., 2010; Bellvert et al., 2016; Yildirim et al., 2012). CWSI theory is based on the principle that transpiration cools the leaf surface and as root zone soil moisture is depleted, stomatal conductance and transpiration decrease and leaf temperature increases. The concept of using CWSI for improving irrigation scheduling gained popularity when Idso et al. (1981) observed a linear relationship between canopy temperatures measured using infrared thermometry and air temperature and vapour pressure deficit, and developed an empirical method of quantifying crop water stress. The empirical CWSI (Eq. (5)) uses two baselines. The lower baseline represents canopy Temperature (T_c) minus air Temperature (T_a) of a well-watered crop transpiring at maximum potential rate and the upper baselines represents (T_c–T_a) of a non-transpiring crop.

$$CWSI = \frac{[(T_c - T_a) - (T_{nws} - T_a)]}{[(T_{dry} - T_a) - (T_{nws} - T_a)]} \tag{5}$$

where, T_c: canopy Temperature (°C), T_a: air Temperature (°C), T_{nws}: non-water stressed canopy Temperature (°C), and T_{dry}: water-stressed canopy Temperature (°C).

Within the past few years, there have been improvements in the use of CWSI for monitoring water stress and scheduling irrigation in different crops (Berni et al., 2009a, 2009b; Gonzalez-Dugo et al., 2014; O'shaughnessy et al., 2011; Paltineanu et al., 2013). O'Shaughnessy et al. (2012) incorporated a Time-Temperature Threshold (TTT) into a theoretical index (CWSI-TTT), and used it to successfully automate irrigations of grain sorghum. The study however, reported an under-irrigation problem during the growing season, caused by cloud cover and the influence of changing crop aspect on infrared thermometer measurements. Osroosh et al. (2015) developed an adaptive irrigation scheduling algorithm relying on a theoretical CWSI. This, unlike the traditional CWSI algorithm where the threshold is a constant value, uses a dynamic threshold determined by following the CWSI trend. However, large discrepancies in their thermal readings, attributed to infrared thermal and microclimatic measurements, resulted in dissimilar values of measured temperature and midday CWSI.

Recent studies have evaluated additional indices based on infrared thermometry that require less information than CWSI for detecting crop water stress. Bausch et al. (2011) investigated the use of a ratio of canopy temperature (Tc ratio) measured over fully irrigated and water-stressed corn as a substitute for the Ks presently used in the reference ET-crop coefficient. The result indicated that the Tc ratio is a reasonable quantitative estimate of Ks for calculating crop ET under water stress conditions and that the ratio allows application of the crop coefficient method for scheduling deficit irrigation. Taghvaeiana et al. (2014) indicated that the Degrees Above Non-Stressed (DANS), which is based solely on canopy temperature, was effective in monitoring water stress and scheduling irrigations in deficit-irrigated sunflower in arid/semi-arid regions. DeJonge et al. (2015) recommended the Degrees Above Canopy Threshold (DACT) as a suitable index that requires a single canopy temperature measurement for quantifying water stress in maize. Kullberg et al. (2017) compared four thermal remote sensing indices based methods for estimating crop evapotranspiration coefficients: CWSI, DANS, DACT, Tc ratio, and observed that thermal indices DANS and DACT are responsive to crop water stress, comparable to more data intensive methods such as CWSI.

While canopy temperature measurements by infrared thermometers are reliable and non-invasive (Cohen et al., 2005), they are usually based on only a few point measurements. Therefore, uniformity of soil water content and of plant canopy for large areas is assumed. Most researchers, however, assume that weather conditions are constant if the measurements required to locally calibrate the baselines are made close to solar noon and under clear sky conditions. This assumption is problematic because weather conditions change with location, time of day and day of the year, and the baselines for the same crop will consequently change with weather conditions (Payero and Irmak, 2006). Researchers from different places have, therefore, reported different baselines for the same crop (Idso et al., 1981; Irmak et al., 2000; Nielsen and Gardner, 1988; Payero and Irmak, 2006; Steele et al., 1994; Yazar et al., 1999). The lack of transferability of the baselines, together with the restriction of having to make required measurements close to solar noon and under clear sky conditions, are major drawbacks of using the empirical CWSI method for irrigation scheduling (Alves and Pereira, 2000).

3. Remote sensing methods

Even though the usefulness of canopy temperature, measured from infrared thermometry, has been established in several studies for monitoring plant water stress, there are physiological and operational concerns that support the development of alternative narrow-band indices, based on the visible and red edge spectral region for detecting water stress in crops (Berni et al., 2009b; Dangwal et al., 2015; Panigada et al., 2014; Rossini et al., 2013; Wang et al., 2015; Zarco-Tejada et al., 2013; Zhao et al., 2015). In some plants, the diurnal fluctuations in stomatal conductance are such that the relationships between canopy temperature and stress levels are not clear-cut. An increase in evaporative demand due to high vapor pressure deficits induces a constant decline in leaf conductance, even when the crops are well watered (Zarco-Tejada et al., 2012). Again, monitoring of large cropped fields requires appropriate imagery at high spatial and spectral resolutions, as well as short revisit periods (Berni et al., 2009b). Although the use of remote sensing in agriculture was proposed few decades ago, it has not been widely adopted until recently, mainly because of the widespread adoption of emerging technologies that integrate high-resolution thermal cameras on board UAS (Berni et al., 2009a; Elston, 2016; Suárez et al., 2010; Zarco-Tejada et al., 2013). The potential applications of UAS in agriculture include; crop scouting, mapping canopy coverage, determining plant stresses, measuring soil moisture, managing variable-rate irrigation, and crop yield estimation (Ehsani et al., 2016).

Recent researchers have proposed the integration of remotely sensed data with soil water balance method to improve irrigation water management. For instance, Campos et al. (2016) estimated total available water in soil by integrating evapotranspiration data and multispectral imagery. Filion et al. (2016) used remotely sensed image to map soil moisture in the Mediterranean regions to support water management and agricultural practice. Zhang et al. (2017a, 2017b) integrated airborne imagery data into a soil water balance model to improve the estimation of soil water deficit for maize and sunflower grown under full and deficit irrigation treatments. Therefore, UAS will be a vital tool for growers soon, because they can cover large areas, and take advantage of new sensing, mapping and data analytic technologies. Image resolution is improving and costs are also decreasing with time. Real time mapping and rapid image analysis also provide for early detection of plant water stress for timely irrigation scheduling, due to the potential to scale up information from the leaf to canopy/field levels (Gago et al., 2015)

3.1. Spectral reflectance indices

The focus on indicators other than thermal infrared indices for monitoring water stress is because leaf temperature, though a direct indicator of plant transpiration, does not directly account for other physiological changes such as photosynthetic pigment changes or non-stomatal reductions of photosynthesis under water stress conditions (Zarco-Tejada et al., 2013). The spectral vegetation indices that have been correlated to plant water stress are given in Table 2. The Photochemical Reflectance Index (PRI) (Gamon et al., 1992), and solar-induced chlorophyll fluorescence emission (Flexas et al., 2002; Moya et al., 2004), are pre-visual indicators of water stress which serve as an indirect means for water stress detection (Berni et al., 2009b; Suárez et al., 2010).

The PRI is sensitive to the epoxidation state of the xanthophyll cycle pigments and to photosynthetic efficiency (Gamon et al., 1992; Suárez et al., 2010). The functional basis of the PRI is based on its sensitivity to rapid changes in carotenoids through the de-epoxidation of the xanthophyll pigments (Magney et al., 2016), and to heat dissipation increasing under water stress conditions (Panigada et al., 2014). When the light absorbed by plants exceeds their photosynthetic demand, energy dissipation occurs to avoid damage to the tissues (Rossini et al., 2013). The plants dissipate this excess energy non-destructively through re-emission of photons as fluorescence (radiative dissipation), and by conversion of light energy into heat in the pigment bed (thermal dissipation).

Table 2
Spectral vegetation indices that has been correlated to plant water stress.

Reflectance indices		Formula	References	Plant water stress indicators
Names	Abbreviations			
Xanthophyll indices				
Photochemical Reflectance Index	PRI	$\frac{(R_{570} - R_{531})}{(R_{570} + R_{531})}$	Gamon et al. (1992)	Chlorophyll flourescence and Stomatal conductance.
Normalized Photochemical Reflectance Index	PRI_{norm}	$\frac{PRI}{[RDVI * (R_{700}/R_{670})]}$	Berni et al. (2009a, 2009b)	Chlorophyll flourescence and Stomatal conductance.
Structural indices				
Normalized Difference Vegetation Index	NDVI	$\frac{R_{800} - R_{670}}{R_{800} + R_{670}}$	Rouse et al. (1974)	Stomatal Conductance, Leaf water potential
Renormalized Difference Vegetation Index	RDVI	$\frac{R_{800} - R_{670}}{\sqrt{R_{800} + R_{670}}}$	Rougean and Breon (1995)	Stomatal Conductance, Leaf water potential
Transformed Chlorophyll Absorption in Reflectance Index	TCARI	$3[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550}) * (R_{700}/R_{670})]$	Haboudane et al. (2002)	Stomatal Conductance, Leaf water potential
Optimized Soil Adjusted Vegetation Index	OSAVI	$\frac{(1 + 0.16)(R_{800} - R_{670})}{(R_{800} + R_{670}) + 0.16}$	Haboudane et al. (2002)	Stomatal Conductance, Leaf water potential
	TCARI/OSAVI	$\frac{3[(R_{700} - R_{670}) - 0.2(R_{700} - R_{550}) * (R_{700}/R_{670})]}{(1 + 0.16)(R_{800} - R_{670})/(R_{800*}R_{670} + 0.16))}$	Haboudane et al., 2002	Stomatal Conductance, Leaf water potential
Water indices				
Normalized Difference Water Index	NDWI	$\frac{(R_{860} - R_{1240})}{R_{860} + R_{1240}}$	Gao et al. (1996)	Leaf water potential
Simple Ratio Water Index	SRWI	$\frac{R_{860}}{R_{1240}}$	Zarco-Tejada et al. (2003)	Leaf water potential
Water Index	WI	$\frac{R_{900}}{R_{970}}$	Zarco-Tejada et al. (2003)	Leaf water potential

Where R represents the reflectances at the respective wavelengths, nm.

Previous studies have demonstrated that the interconversion of the xanthophyll cycle pigments can be detected in leaves as subtle changes in reflectance at 531 nm (Gamon et al., 1992, 1997).

Recently, researchers have shown the sensitivity of PRI for crop water stress detection over short time scales (Gamon et al., 1997; Suárez et al., 2009, 2010; Zarco-Tejada et al., 2012, 2013), whereas studies conducted over longer time scales reported contrasting results, at the leaf and canopy scales (Gamon, 2015; Magney et al., 2016; Rahimzadeh-Bajgiran et al., 2012). The studies generally observed that there are certain issues with the index, such as leaf biomass, background reflectance, sensor spectral responses, and viewing-illumination geometry effects. Therefore, different researchers proposed new formulations for the index, using alternative reference bands (Hernández-Clemente et al., 2011). Zarco-Tejada et al. (2012) obtained higher correlations in a citrus orchard with PRI_{515} for stomatal conductance (g_s) and leaf water potential (Ψ). Panigada et al. (2014) showed a high corelation between PRI_{586} and EWT_{canopy}, for cereal crops. Berni et al. (2009a, 2009b) normalized the standard PRI using the Renormalized Difference Vegetation Index (RDVI), an index that is sensitive to canopy structure, and a red edge index that is sensitive to chlorophyll content (R_{700}/R_{670}). The new index (PRI_{norm}) not only detects xanthophyll pigment changes as a function of water stress, but also normalizes for the chlorophyll content level and canopy leaf area reduction induced by stress. The PRI_{norm}, showed an improved capacity for water stress detection (correlated with leaf stomatal conductance, g_s and leaf water potential, Ψ) in comparison with other greenness and structural indices (Gago et al., 2015). Several other researchers have used the PRI and PRI_{norm} for water stress detection as an alternative to thermal measurements, with varying degrees of success (Behmann et al., 2014; Cheng and Wang, 2014; Colombo et al., 2008; Dangwal et al., 2015; Meroni et al., 2008, 2009; Panigada et al., 2014; Peñuelas et al., 2011; Rossini et al., 2013; Suárez et al., 2009, 2010; Wang et al., 2015; Zarco-Tejada et al., 2009, 2013). Rossini et al. (2013) revealed the feasibility of mapping water stress using spectral vegetation indices, taking advantage of the high spatial resolution capabilities that are more difficult in the thermal region. The studies revealed the potential applicability of remote sensing data in precision agriculture for improving irrigation scheduling. Nevertheless, the sensitivity of PRI measured at the crop canopy level requires further investigation, including an assessment for a new index formulation for high value vegetable crops, in order to optimise yield and productivity.

3.2. Structural indices

Structural Indices are based on the reflectance of leaves in the visible and near-infrared bands of the electromagnetic spectrum. The Normalized Difference Vegetation Index (*NDVI*) is the best-known vegetation index, used as a numerical indicator of vegetation greenness (Leroux et al., 2016; Zhao et al., 2015). The *NDVI* is an indication of the amount of chlorophyll and fraction of green cover. It is used in irrigation studies for mapping of crop cover as a means for estimating crop coefficients (Kc) for use in the conventional FAO-56 method (Allen et al., 1998), and for irrigation scheduling (Jones, 2012). Previous studies have also shown that NDVI has a linear relationship with the basal crop coefficient for ET (Kcb), because Kcb primarily depends on the dynamics of plant canopies (cover fraction, LAI, greenness). Based on this, several researchers have used NDVI to predict Kcb for various agricultural crops (Allen et al., 2005; Choudhury et al., 1994; Irmak et al., 2011; Kamble et al., 2013; Kullberg et al., 2017; Jayanthi et al., 2000).

Roujean and Breon (1995) and Haboudane et al. (2002) showed that empirically derived NDVI products are unstable, because they are affected by soil reflectance and sun view geometry. In an attempt to improve *NDVI*, the Renormalized Difference Vegetation Index (*RDVI*), Optimised Soil Adjusted Vegetation Index (*OSAVI*), and Transformed Chlorophyll Absorption in Reflectance Index (*TCARI*), were developed to minimize soil brightness influences from spectral vegetation indices involving red and Near-Infrared (NIR) wavelengths and to reduce the variability of the photosynthetically active radiation due to the presence of diverse non-photosynthetic materials. Subsequently, *TCARI*/*OSAVI* was established (Haboudane et al., 2002) to make accurate predictions of crop chlorophyll content from hyperspectral remote sensing imagery. The ratio has been shown to be relatively insensitive to canopy cover variations, even for very low LAI values. Apart from their use in yield estimation, structural indices (*NDVI*, *RDVI*, *OSAVI*, *TCARI*, and *TCARI*/*OSAVI*) are useful in plant stress monitoring to capture the changes in canopy structures caused by water stress (Haboudane et al., 2002; Roujean and Breon, 1995; Zarco-Tejada et al., 2012), and this is due to their positive correlations with stomatal conductance and leaf water potential (Gago et al., 2015). For instance, NDVI and TCARI/OSAVI were clearly related to the stem water potential (Ψ_{stem}) and g_s in vineyards cv. Tempranillo (Baluja et al., 2012). However, in *Citrus* orchards the indices were less correlated with g_s (Zarco-Tejada et al., 2012). Usually, most structural indices are more related to plant vigor than the plant physiological status, and might correlate well in crops where the biomass proportionally increases in parallel to photosynthesis. While the studies demonstrated the feasibility of narrow-band indices obtained from hyperspectral sensors onboard UAVs for monitoring plant water stress, the results indicate that the sensitivity of the indices at the plant canopy level needs further study, before they could be adopted for precision irrigation water management.

3.3. Water indices

Typically, the water-absorption bands in the 1300–2500 nm region show the highest sensitivity to leaf water concentration in most crops (Carter, 1991). However, the absorption by water in this region is very strong, so that infrared bands are inadequate for measuring the water concentration of the plant canopies (Peñuelas and Filella, 1998). Therefore, a reflectance trough in the near-infrared region at 950–970 nm, corresponding to a weaker water absorption band has been shown to be effective for representing the total plant or canopy moisture content (Peñuelas et al., 1997). When plants are water stressed, the 970 nm trough of the reflectance spectrum tends to disappear and to shift towards lower wavelengths (Peñuelas and Filella, 1998), and this concept was used to develop a reflectance water index (*WI*) and simple ration water index (*SRWI*) (Zarco-Tejada et al., 2003). The reflectance at 900 nm is used as a reference because there is no absorption by water at this wavelength, but it is subjected to the same changes in sample structure as the reading at 970 nm. This water index has been found to be highly correlated with plant water content in several crops (Peñuelas et al., 1997; Dawson et al., 1999; Wang et al., 2015). Peñuelas et al. (1997) observed a strong correlation between greenness and moisture content, and proposed the *WI* : *NDVI* ratio as a better indicator of canopy water content than the water index itself.

Gao (1996) used the Normalized Difference Water Index (*NDWI*) to monitor changes in water content of leaves using NIR (Near Infrared) and SWIF (Short Wave Infrared) at a wavelength of approximately 860 nm, and the other at 1240 nm, respectively. The SWIR reflectance reflects changes in both the vegetation water content and the spongy mesophyll structure in vegetation canopies, while the NIR reflectance is affected by leaf internal structure and leaf dry matter content but not by water content. The combination of the NIR with the SWIR removes variations induced by leaf internal structure and leaf dry matter content, thereby, improving the accuracy in retrieving the vegetation water content (Wang et al., 2015). However, Gao (1996) noted that *NDWI* is responsive to changes in water content of plant canopies, but is less sensitive to atmospheric aerosol scattering effects than *NDVI*. It is therefore, complementary to, not a substitute for *NDVI*. Nevertheless, previous studies have shown the relevance of water indices (*WI*, *SRWI*, *NDWI*, and *WI* : *NDVI*) for monitoring plant water stress in wheat and maize crops. For instance, Panigada et al. (2014) obtained a significant correlation between WI and EWT_{canopy}; Rossini et al. (2013) showed a high correlation between WI : NDVI and RWC; while Wang et al. (2015) obtained a good relationship between NDWI and leaf water content, and concluded that the narrow bands at 780 and 1750 nm are sensitive to the water parameters of spring wheat. The interest in reflectance indices is to use them to scale-up to satellite imagery since the use of thermal imagery is unreliable due to its poor resolution, which obtains mixed information from the plant and the soil background. The researchers showed the possibility of mapping plant water stress using hyperspectral indices, but observed that the translation of this finding in accurate irrigation scheduling requires further investigations.

4. Concluding remarks and future perspectives

Conventional irrigation scheduling techniques rely on soil moisture measurements, climatic data, and physiological measures of plant response to assess water stress. The approach is inadequate due to the high costs of sensors and their installation, and the difficulty with obtaining measurements, especially for heterogeneous soil and crop canopies. Plant indicators commonly used to determine crop water status are leaf water potential and stomatal conductance, but their measurements are either destructive, labour intensive or unsuitable for automation, which make it difficult for irrigators to adopt. Thus, automated techniques for monitoring crop water status that would provide non-destructive, rapid, and reliable estimates of plant water status are needed.

Spectral vegetation indices acquired from hyperspectral sensors onboard UAS have been identified as a valuable tool for monitoring plant water status and improving irrigation water management. Generally, most physiological studies on plant water stress report relatively significant relationships (with R^2 values of 0.5 or less) between a remotely sensed parameter such as NDVI or PRI and a measure such as leaf area index, stomatal conductance, and leaf water potential. Unfortunately, this sort of precision is inadequate to allow the use of single measurements of the parameters (e.g., NDVI or PRI) for estimation of plant water status. Therefore, innovative data management techniques that would integrate data from soil-based and plant-based approaches are needed to widen the scientific knowledge on the use of crop stress parameters to schedule irrigation, and provide irrigators with advanced tools for decision making.

Even though spectral reflectance indices have been proposed for water stress detection in various crops, most of these studies focused on different species of tree and cereal crops. To our knowledge, the use of narrow-band optical indices for detecting water stress and scheduling irrigation has not been extensively investigated for high value vegetable crops in water stressed regions and environments, and growing conditions. Furthermore, since VIs for water stress detection are crop and climate specific, it is imperative to investigate the spectral VIs needed to improve the productivity and yields of vegetable crops. The potential is enormous based on recent advances in sensor technologies, image analysis and processing, computer based decision making, and in the measurement of hyperspectral indices from UAS.

Again, leaf spectral properties are not solely dependent on plant water status. Factors such as soil background, canopy structure, leaf thickness, leaf age, differences in surface properties of leaves, and variations in leaf angle could influence the correlation between spectral response of leaves and plant water status. Future research should focus on the integration of thermal and narrow-band hyperspectral imagery to provide more precise information about plant water status, and the real-time data analysis and detection of plant water stress using advanced data analysis techniques that would be cost-effective and commercially available to farmers.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.compag.2017.07.026.

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