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Review

Crop reflectance monitoring as a tool for water stress detection in greenhouses: A review

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Multisensory platforms for remote sensing measurements offer the possibility to monitor in real-time the crop health status without affecting the crop and environmental conditions. The concept of the speaking plant approach, and plant response based sensing in general, could be valuable providing a better understanding of the interactions between the microclimate and the physical conditions of the plants. Early detection of plant stress is critical, especially in intensive production systems, in order to minimise both acute and chronic loss of productivity. Non-contact and non-destructive sensing techniques can continuously monitor plants and enable automated sensing and control capabilities. This paper reviews past research and recent advances regarding the sensors and approaches used for crop reflectance measurements and the indices used for crop water and nutrient status detection. The most practical and effective indices are those based on ground reflectance sensors data which are evaluated in terms of their efficiency in detecting plant water status under greenhouse conditions. Some possible applications of this approach are summarised. Although crop reflectance measurements have been widely used under open field conditions, there are several factors that limit the application of reflectance measurements under greenhouse conditions. The most promising type of sensors and indices for early stress detection in greenhouse crops are presented and discussed. Future research should focus on real time data analysis and detection of plant water stress using advanced data analysis techniques and to the development of indices that may not be affected by plant microclimate.

1. Introduction

1.1. Background

Plant stress is caused by biotic or abiotic factors that adversely affect plant growth and significantly reduces productivity. Plant stress is expressed in the plant canopy in many types of symptoms. Water stress, for example, closes stomata and impedes photosynthesis and transpiration, resulting in changes in leaf colour and temperature (Nilsson, 1995, p. 146) but other symptoms of water stress include morphological changes such as leaf curling or wilting due to loss of cell turgidity. Early detection of plant stress is very critical

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Nomenclature

ARVI	Atmospherically resistant vegetation index
AVI	Average vegetation index
C	Sensors that measure plant reflectance in contact with the leaf
ChF	Chlorophyll fluorescence
Chl	Chlorophyll content
CO_2	Carbon dioxide
CWSI	Crop water stress index
DVI	Difference vegetation index
ETc	Crop evapotranspiration
EVI	Enhanced vegetation index
eNDVI	Enhanced normalised difference vegetation index
F	Fluorescence
FOV	Field of view
FR	Fluorescence ratio
Fwbi	Floating position water band index
GNDV	Green normalised difference vegetation
GNDVI	Normalised difference vegetation index on greenness
g_s	Stomatal conductivity
GVI	Green vegetation index
LAI	Leaf area index
LED	Light emitting diode
MIR	Middle infrared region
mNDVI	Modified normalised difference vegetation index
MNDVI8	Modified normalised difference vegetation index
Macc01	Maccioni index
D	Derivative Reflectance at D690
DD	Datt Derivative
mrNDVI	Modified red edge normalised difference vegetation index
mrSRI	Modified red edge simple ratio index
MSI	Moisture stress index
MTCI	Merris terrestrial chlorophyll index
N	Nitrogen
ND	Normalised difference
NDII	Normalised difference infrared index
NDVI	Normalised difference vegetation index
NDWI	Normalised difference vegetation index
NIR	Near infrared region
NPh	Non phosphorylated thylakoids
NPQI	Normalised phaeophytinization index
NPQ	Non photochemical quenching
NWI	Normalised water index
OSAVI	Optimization soil adjusted vegetation
PAR	Photosynthetic active radiation
PRI	Photochemical reflectance index
PSII	Photosystem II
PSRI	Plant senescence reflectance index
PWC	Plant water content
RI	Reflectance index
rNDVI	Red edge normalised difference vegetation index
rNDVI	Red normalised difference vegetation index
RS/CAM	Remote sensing based on imaging systems
RS/FOV	Remote sensing based on spectroradiometer that measures in specific field of view of the target
RS	Remote sensing
RVI	Red vegetation index
RWC	Relative water content
SAVI	Soil adjusted vegetation index
SB	Single band
SIPI	Structure independent pigment index
SIWSI	Shortwave infrared water stress index
sNDVI	Similar normalised difference vegetation index
Sp	Spectroradiometer in laboratory
sPRI	Similar photochemical reflectance index
SR	Simple ratio
SR	Simple ratio
SWC	Soil water content
Tc	Canopy temperature
TCARI	Transformed chlorophyll absorption in reflectance index
VI	Vegetation index
VIS	Visible spectrum
VOG REI	Vogelman red edge index
VPD	Vapour pressure deficit
WI	Water index
Y	Yield
ΔPRI	Delta photochemical reflectance index

especially in intensive production systems in order to minimise both acute and chronic loss of productivity.

Plant water stress may be the result of a single parameter or a combination of environmental conditions (e.g. air temperature, relative humidity, solar radiation intensity, air velocity) root conditions (e.g. available water in the root, electrical conductivity in the root zone), the microclimate and plant genetic traits. Methods such as substrate water content (for soilless crops) or soil water tension, leaf water potential and sap flow, among others, have been widely used to help describe plant water status. However, soil or substrate water content indicates the availability of water in the root zone and that is not always directly correlated with the water status of the plant. In addition, although leaf water potential and sap flow measurements provide direct information about plant water status, they require plant contact or destructive sampling which is difficult to realise in commercial scale. Non-contact and non-destructive sensing techniques can continuously monitor plants and enable automated sensing and control capabilities (Ling, Giacomelli, & Russell, 1996).

The dynamic response of plants to the changes of their environment is often called 'speaking plant' (Takakura, Kozai, Tachibana, & Jordan, 1974). The concept of the speaking plant approach and plant response – based sensing is valuable to have a better understanding of the interactions between the microclimate and the physical conditions of the plants (Kacira, Sasae, Okushima, & Ling, 2005). Thus, in this approach, the physical responses of the plants to the environmental changes are monitored and the information is utilised to identify conditions which put plants under stress and to avoid the occurrence of these conditions or control greenhouse microclimate to achieve more efficient and optimal production.

Up to now, in most of the greenhouses climate control has been based on air temperature and relative humidity measurements carried out at a suitable representative single point located at the centre of the greenhouse, assuming complete homogeneity of greenhouse microclimate. However, this assumption is not valid in most greenhouses and particularly in present greenhouses since their size has greatly increased over the recent decades. Climate characterisations show that even in well-designed greenhouses large temperature gradients exist, for instance in a pad and fan-cooled greenhouse with length longer than 40 m, the air temperature gradients from pad to fan distance can be as high as 5 °C (Kittas, Bartzanas, & Jaffrin, 2003). These large temperature gradients not only cause non-uniform production and quality, but can also induce pest and diseases infestations (Fatnassi, Chaouachi, & Klibi, 2015). That is why some climate control systems suggest the installation of sensors in several positions inside the greenhouse or to manually perform measurements in different positions to adjust control strategies.

The greenhouse microclimate (air temperature, humidity and velocity) and crop (crop transpiration, stomatal and aerodynamic conductance) physiological response vary over different locations in the greenhouse not only due to the variation of outside weather conditions but also to the greenhouse climate control systems per se, i.e. by the use of heating, insulation, ventilation or cooling systems. Thus, direct and real-time monitoring of plant responses and processes along with monitoring of the local microclimate parameters can help to improve climate control and overall production.

For commercial production systems, it is more advantageous to develop a real-time plant canopy health, growth and quality monitoring system with multi-sensor platforms. This can be achieved by a sensing system equipped with a multi-sensor platform moving over the canopy and ultimately using plants as ‘sensors’ to communicate their true status and needs. Such systems could be used to detect crop deviations from normal development and crop stress.

1.2. Machine vision

Computer vision is a non-contact and non-destructive sensing technology that enables multi-dimensional sensing capabilities (Kacira & Ling, 2001). This technology can be used to extract various information from a targeted object including morphological (size, shape, texture), spectral (colour, temperature, moisture), and temporal data (growth rate, development, dynamic change of spectral and morphological states) (Story & Kacira, 2015).

Knowing the value-added benefits of the real-time plant monitoring systems, researchers have paved the way for the commercialisation of robotic machine vision systems to be implemented within greenhouses. To this effort, Bonstema (2015) developed the “SWEEPER” (http://www.sweeper-robot.eu) greenhouse harvesting robot, in which a side view image of the canopy is taken by a colour camera. Priva (De Lier, The Netherlands) (http://www.priva-international.com/) developed the Priva TopCrop Monitor that visualises crop activity in the greenhouse based on plant temperature measurements and estimations of plant transpiration. As noted by Story and Kacira (2015), the HortiMaX (http://www.hortimax.com) CropView system allows the grower to capture images of a single location in their plant canopy 24 h a day, 7 days a week and time-stamped the images to corresponding greenhouse climatic data and events. The grower can only view a handful of plants within the image, not the entire plant canopy. Also this system does not extract plant or canopy features to quantitatively determine overall plant growth and status over time. In other words, if there is a plant-related problem, the trend of this issue is not identified until the grower visually identifies the problem themselves, and this detection approach may not be timely.

The interaction of sunlight with crop canopies and plant leaves can be used to obtain valuable information about the plant growth and health status. Changes in plant colour, morphology, thermal features can be indicative of plant disease or stresses. Therefore, monitoring the crop and analysing these features in real time and providing qualitative and quantitative information to the growers can help them prevent damage to the crops and optimize resource use leading to improved overall production quality.

1.3. Basics in plant reflectance

Despite the fact that plant leaves often look similar, they vary widely in both shape and chemical composition, as far as the concentration of water in the leaf intercellular spaces is concerned. This results in continuously varied plant reflectance. Plant leaves absorb the majority of radiance in the visible band by plant pigments located in mesophyll (Fig. 1a) such as chlorophyll and xanthophylls, but reflect mostly in the near-infrared (NIR) band. In addition, water content in sponge cavities, carbon content in different forms (sugar, starch, cellulose and lignin) in mesophyll cells and nutrient compounds (N, P, K) in mesophyll cells and palisade parenchyma also affect leaf spectral properties.

Several authors (e.g. Datt, 1999; Grant, Brothers, & Bogan, 1987; Hodanova, 1985; Jackson & Huete, 1991; Jacquemoud & Baret, 1990; Jacquemoud & Ustin, 2008; Kacira et al., 2005; Knipling, 1970; Maracci, Schmuck, Hosgood, & Andreoli, 1991; Verdebout, Jacquemoud, & Schmuck, 1994; Vogelmann, Bornman, & Josserand, 1989) have reported that the different chemical and physical characteristics affect the leaf optical properties (Fig. 1b).

When a plant is under water stress, which can be experienced when the demand for water exceed the water supply in the root zone or plants capability to transport the water from root zone to the atmosphere, the photosynthesis rate is decreased due to xanthophyll oxidation. As a result, stomata close and lead to decreased CO_2 assimilation rate. Therefore, the light energy that is absorbed by the leaf, cannot be used to guide photosynthetic electron transport and a part of the solar radiation returns back to the atmosphere as reflectance radiation, while the other part is dissipated as heat or re-emitted as chlorophyll fluorescence. As with water stress, nutrient stress also influences the photosynthetic rate and consequently the electromagnetic energy that is absorbed by the

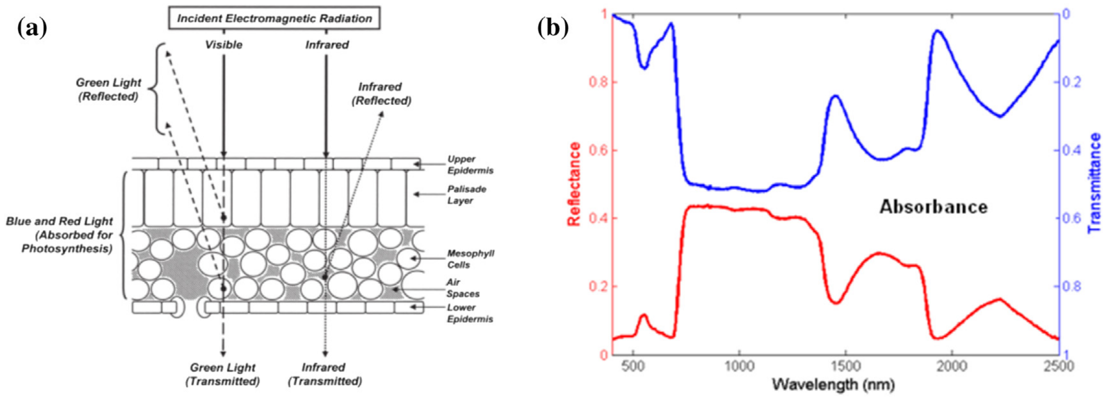

Fig. 1 – (a). Influence of electromagnetic spectrum based on structure of a typical plant leaf. From Summy et al. (2003). (b). Reflectance, absorbance and transmittance spectral of a plant leaf. From Jacquemoud and Ustin (2008).

leaf due to the nutrient's involvement in the photosynthetic process as a component of photosynthetic enzymes (such as ribulose bisphosphate carboxylase/oxygenase) and chlorophylls. Meanwhile, the high leaf absorption percentage of solar radiation in the visible range of the spectrum causes a rapid saturation of the reflected signal for a very low amount of canopy leaf area. This results in a reflectance light signal reduction (Soudani et al., 2012). That is why several reflectance indices, or regions in the spectrum that are based on visible light spectrum, are strongly dependent on ambient light.

The radiation with wavelength longer than 950 nm is usually absorbed by the leaf liquid while the radiation at ~1000 nm is absorbed by the leaf dry matter (carbon and nutrient compounds). The reflectance in the 680–750 nm wavelengths is also influenced by water and nutrient concentration, while the reflectance spectrum in 750–800 nm is varied mostly by leaf water content concentration.

Several researchers (Bandyopadhyay, Pradhan, Sahoo, Singh, & Gupta, 2014; Jain, Ray, Singh, & Panigrahy, 2007; Kim, Glenn, Park, Ngugi, & Lehman, 2010; Kruse, 2004, p. 69; Peñuelas, Gamon, Fredeen, Merino, & Field, 1994; Peñuelas, Filella, & Araus, 1997; Peñuelas, Filella, Biel, Serrano, & Savé, 1993; Ray, Das, Singh, & Panigrahy, 2006; Sclemmer, Francis, Shanahan, & Scepers, 2005) showed that the reflectance in the green and red bands under water or nutrient stress is increased due to leaf Chlorophyll concentration reduction (less absorbance radiation). Other studies (Amatya, Karkee, Alva, Larbi, & Adhikari, 2012; Jones, Weckler, Maness, Stone, & Jayasekara, 2004; Sclemmer et al., 2005; Vigneau, Ecarnotb, Rabatela, & Roumet, 2011) reported that the reflectance of stressed plants was increased in the near infrared region due to radiation scattering by air content risen in sponge cavities (less water content). Peñuelas et al. (1993) observed a significant decrease in the magnitude of the whole NIR reflectance of stressed plants only when the plant was close to wilting. Apparently, other factors such as leaf thickness, leaf age, leaf angle, leaf area index (LAI) and plant species can influence the leaf spectral response in a greater degree than the water stress during measurement (Fig. 2).

In contrast to NIR region, in the middle infrared region (MIR), more absorption and less reflectance and transmittance is observed in green leaves due to the fact that water absorbs more radiation in that spectrum (Fig. 1b). Thus, this region contains more information about sponge parenchyma that includes water, cellulose, nitrogen, lignin and starch. The

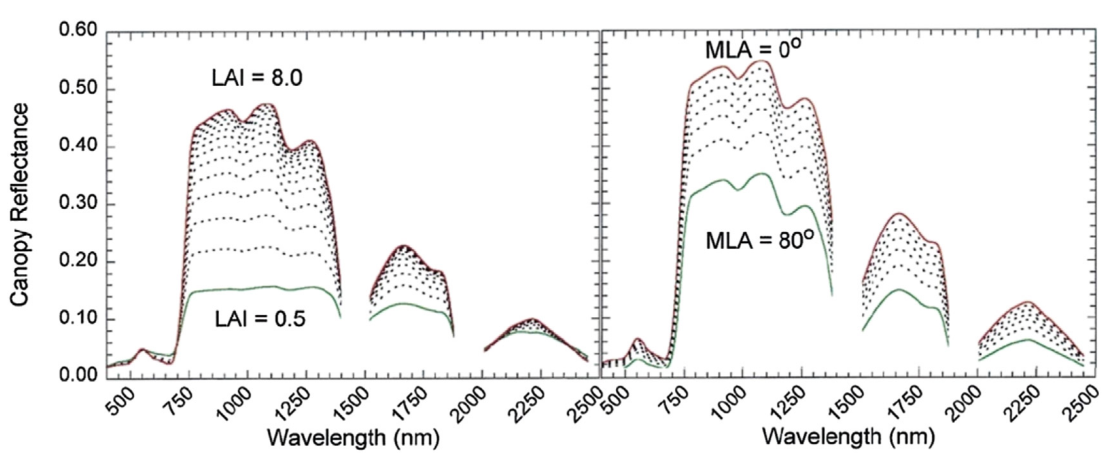

Fig. 2 – Effect of leaf area index (left) and mean leaf angle (right) increase on canopy reflectance. From Asner (1998).

basic absorption areas for leaf water status monitoring are located around 1450 nm, 1940 nm and 2500 nm and the overall shape of the MIR spectrum is largely influenced by water.

Nevertheless, Sun et al. (2008) indicated that although the 1450 nm wavelength is highly sensitive to fast and steep developing stress, it cannot be used for low stress cases. In addition, several authors (Bowman, Hubick, Von Caemmerer, & Farquhar, 1989; Cordon & Lagorio, 2007; Hunt & Rock, 1989; Jacquemoud & Ustin, 2008; Verdebout et al., 1994) have already concluded that the use of MIR is insufficient to estimate the leaf water status due to the fact that reflectance changes within a biologically meaningful range are too insignificant and the light signal at that spectrum is too low (high light signal noise). Thus, MIR has not been used extensively in plant water stress assessment, as more satisfactory results have been reported in the visible and NIR spectrum regions.

According to Köksal, Güngör, and Yildirim (2010), based on a first derivative analysis, certain parts of the spectrum can be selected for further study. Thus, in order to amplify the spectral differences detected and to provide additional details for stress detection, several authors have proposed combining the data from spectral bands into indices. Therefore, more than 150 vegetation indices (VI) have been presented during the last three decades (Asner, 1998; Borzuchowski & Schulz, 2010; Silleos, Alexandridis, Gitas, & Perakis, 2006). However, only a small subset of them have substantial biophysical basis or have been systematically tested for water stress. In addition, more than 20 VIs have been based on the visible and NIR spectrum. According to Aparicio, Villegas, Royo, Casadesus, and Araus (2004) and Zakaluk and Sri Ranjan (2008), the most common forms of reflectance indices are the following:

- reflectance ratios corresponding to the ratio of two spectral bands, which are referred to as simple ratio (SR) vegetation indices and
- normalised difference (ND) vegetation indices, which are defined as ratios of the difference in reflectance between two spectral bands to the sum of the reflectance at the same bands.

1.4. *Rationale for the current review paper*

Up to now, the majority of reflectance indices have been studied in open field and in a lab scale and not in the greenhouse conditions. The object of this paper is to provide a review of the most commonly used reflectance indices and spectrum areas that can be applied for early plan water and nutrient stress detection in green house conditions. The efficiency of the spectral indices in detecting water and nutrients stress is benchmarked with plant direct and indirect physiological measurements, such as leaf water potential, chlorophyll fluorescence, canopy temperature, stomatal conductance, transpiration, substrate water content and others.

In addition, objective of this manuscript is to briefly describe the most important technical specifications of ground-based remote sensors that are used for reflectance measurements. The most popular types of spectrometer sensors, such as hyperspectral and multispectral remote cameras are presented. Suggestions are made for specific guidelines to avoid errors in measurements during data acquisition.

2. Reflectance measurement technologies

2.1. *Sensors*

Several sensor systems are available and many ground-based remote sensing (RS) technologies have been used to obtain the required information (Lan, Zhang, Lacey, Hoffmann, & Wu, 2009). The progress of ground-based reflectance measurement techniques plays a critical role in accurate monitoring and assessment of plant reflectance. Different techniques for acquiring plant reflectance data have been used to determine qualitative and quantitative plant characteristics. Initially measurements were conducted in laboratory studies and later on, in satellite and airborne remote sensing. The development of non-imaging field spectroscopy gave the opportunity for a real-time and cost effective way to undertake large scale monitoring in open field and greenhouse covered canopy. Moreover, the improvement of non-imaging field spectroscopy to image remote sensing data acquisition lead to vast amount of plant reflectance data generation at higher spatial resolution (Liaghat & Balasundram, 2010). In this section, a classification of ground based (remotely or in contact) sensing techniques are presented.

Ground based sensors can be classified into three distinct categories: (a) spectrometers and radiometers (b) imaging and non-imaging and (c) active and passive. The basic characteristic of non-imaging (spot) field spectroscopy is the ability of the sensor to allow continuous sensing at a wide range of spectral bands (spectrometers) or at a smaller range which is limited to certain spectral bands (radiometers). The key feature which distinguishes a spectrometer from a multiband radiometer is the continuous measurement of the produced spectrum (Milton, 1987). A non-imaging sensor system can easily measure radiance reflectance by pointing the fibre optic input of the equipment at the point or at all points of the target, taking measurements of highly accurate locations and topographic profiles. The performance of these non-imaging sensors depends on an integrated artificial light source in order to collect the reflected radiation from the target and thus, these sensors are called ‘active sensors’. Milton (1987) first reviewed the principles of field spectroscopy parameters. Since then, different ground-based remote sensing techniques have been developed and used mostly in the open field.

Over the last decade, advances in sensors' technology have developed optic systems that made possible the simultaneous recording of several bands of different points of the target with a single acquisition. Imaging systems allow light to entering the sensor through the slit, impinge on the photosensitive area of the detector and give exact spatial and spectral resolution whereas each pixel receives light of different areas of the spectrum (Huang & Zeng, 2001). Based on different recording spectral bands (channels), the imaging reflectance sensors can be distinguished into panchromatic images (1 channel), colour images (3 channels), multispectral images (4–20 channels) and hyperspectral images (more than 20 channels) (Kozma-Bognár & Berke, 2010; Willoughby, Folkman, & Figueroa, 1996). The number and position of the bands in each system provide a unique combination of spectral information and are tailored to the sensor requirements that are designed to support (Fig. 3). Most hyperspectral and multispectral imaging systems work in a wavelength range from visible to infrared and usually are passive sensors using natural or external light sources. Thus, the imaging sensors require sufficient and accurate information from ambient air such as light intensity, direction of light and atmospheric effects.

The most recent technological machine vision systems are divided into scanning and framing systems. Hyperspectral image sensors usually use the scanning techniques in order to acquire the reflectance data from different parts of the target with one image recording. Some of such scanning methods are the whisk-broom, paddle-broom and push-broom techniques. Push-broom scanners have a linear array of thousands of detector elements aligned cross-track, which scan the full width of the collected data in parallel as the platform moves (Fig. 3). This scanning method is able to cover the sensing at variable angles and it scans point-by-point across the area of interest. In framing systems, images of the targets are taken frame by frame. Images can be described in terms of scale, which is determined by the effective focal length of the optics of the remote sensing device, altitude from which image is acquired and the magnification factor employed in the reproduced image. Further technical information about optical sensors can be found in Mouroulis (1999), Aikio (2001, p. 435), Lawrence, Park, Windham, and Mao (2003), Polder, Gerie van der Heijden, Paul Keizer, and Young (2003), Govender, Chetty, and Bulock (2007), Govender, Dye, Weiersbye, Witkowski, and Ahmed (2009), Schowengerdt (2007), Vagni (2007), Chung-Ru Ho (2008, p. 36), Panda (2012) and Li et al. (2013). For commercial production settings, it is more advantageous to develop a real-time plant canopy health growth and quality monitoring system with multi-sensor platforms (Kim et al., 2010; Story & Kacira, 2015).

Based on the data found in the manuscripts referred in this work, a presentation (Fig. 4) and analysis of the sensors used in the relative manuscripts is given below. It was found that 11% of the studies followed protocols based on laboratory conditions, by sampling detached leaves. These methods are time consuming and detect plant stress in leaf and not in plant or canopy level exclusively under stable conditions. The development of more light, handy ground based remote sensing methods, evaluates the reliability of field reflectance measurement and minimises the accuracy discrepancies arising from other methods. Thus, 14% of the researches used ground-based sensors in contact with the leaf to measure the plant reflectance variation in the field conditions. Despite these methods give real-time results of plant stress level, they are not suggested in greenhouse conditions as they cannot integrate in control systems or computer models. Also, quite enough measurements should be received from different leaves in order to determine stress in plant or canopy level. The majority of the studies (75%) applied methods based on remote sensing. However, the majority of the remote sensing studies (74%) used sensors that measure reflectance by the point or the mean of all the points of a small field of view of the target. Only the 26% of the remote sensing studies from 2000 and on, applied imaging spectrometers for plant stress detection mostly in open field conditions. The new generation of ground-based imaging spectrometers already provides a considerable improvement, availability and accurate information on crop conditions and cost-effectiveness to a stage where information from RS imagery is being used for large scale irrigation policy level decision in open field (Govender et al., 2009). Elsayed (2015) tested five spectral both passive and active reflectance sensors, including a hyperspectral passive machine vision in order to assess plant water stress.

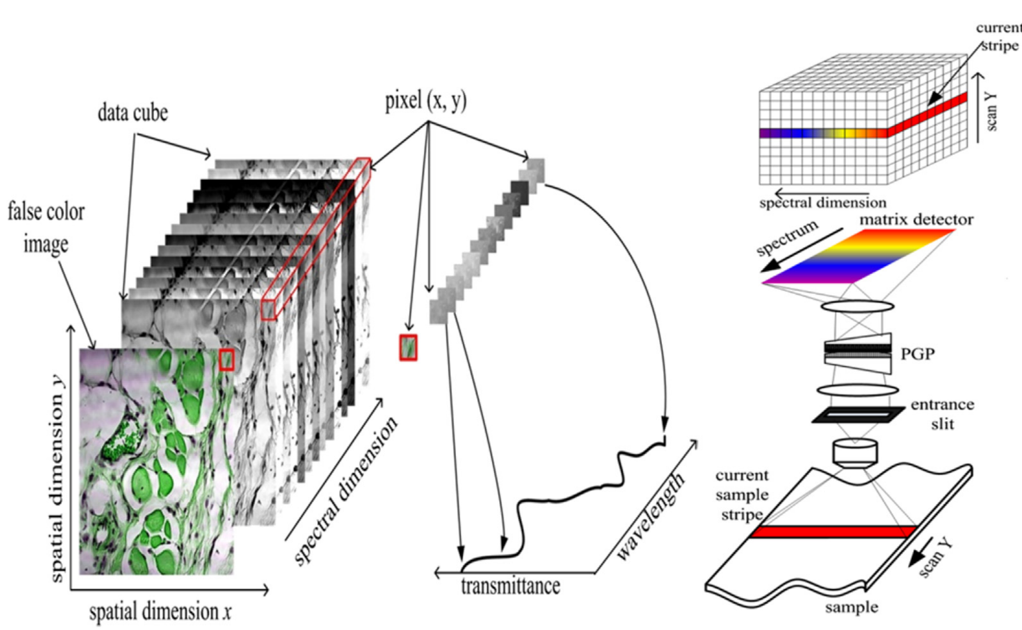

Fig. 3 – Hyperspectral cube captured by a spectral imaging system (left), Pushbroom scanner (right). From Li et al. (2013).

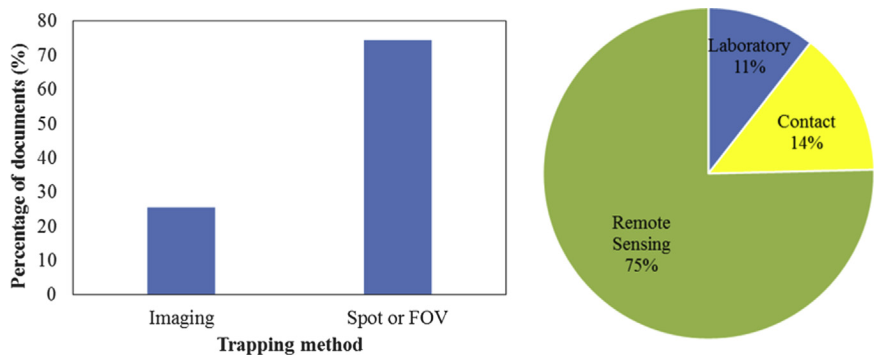

Fig. 4 – Classification of studies referred in the present manuscript that link different classes of ground based sensors or laboratory methodologies with different types of plant stress monitor and the development by the year of the documents that studied different types of plant stress based on machine vision sensors.

They concluded that passive hyperspectral machine vision had the highest correlation with substrate water content than other active sensors. However, machine vision is not possible to use direct reflectance measurements as a metric of leaf water concentration, as each wavelength has its own measurement error and requires good knowledge of the sensor's and ambient conditions such as light intensity, direction of light and other.

A list of ground based remote sensors used in the different studies referred in this work to monitor plant stress is presented in Table 1.

2.2. *Measurements and data processing in greenhouse applications*

Although sensor technologies have been considerably improved during recent years, crop reflectance measurement remains a difficult task. The accuracy of the measurement depends on several parameters related to:

- the sensor used (e.g. detector dark current, sensor temperature, readout noise, exposure shot noise, number of lens aperture, calibration variation) (Polder et al., 2003),
- the methodology followed during the measurement (e.g. the way the instrument was held (hand-held or supported), the distance from the target, the effective size and density of target area, the frequency of calibration) and view angle (Aparicio et al., 2004; Bastiaanssen, Molden, & Makin, 2000; Jackson & Huete, 1991),
- the environmental conditions (e.g. light conditions, proportion of shade in the target) (Polder et al., 2003), dust and aerosols in the air.

For optimal calibration of the imaging system, a first cycle has to be performed in the laboratory, using known or reference light sources. Thus, the responsiveness of the system to different spectral bands under different radiation intensities can be recorded and analysed in order to choose the appropriate camera settings (frame rate and exposure time) and decrease the signal-to-noise ratio (radiometric calibration). During this phase, the image noise characteristics are determined and the initial gain and offset are adjusted (Amatya et al., 2012; Arngren, 2011; Brunn et al., 2010; Hu et al., 2012). Furthermore, the response of the instrument is adapted to a polynomial to obtain the instrument response function and evaluate the nonlinear characteristics. Katsoulas, Elvanidi, Ferentinos, Bartzanas, and Kittas (2014) described a calibration methodology for a hyperspectral imaging system used to formulate appropriate reflectance indices for plant water stress detection.

Under greenhouse conditions, light intensity (and sometimes light quality) distribution is inhomogeneous. The illumination that each pixel receives depends on the weather conditions, the greenhouse structure, the surrounding surfaces (background, ground) and the density and architecture of the canopy. In addition, the reflectance in the red region is expected to be low in the morning and increase as the sun rises, because of the increasing amount of reflective white ground cover. The NIR region, however, is not affected as much as the red region, due to the high percentage of light that is transmitted through the canopy and reflected from the shaded ground (Aparicio et al., 2004; Eitel, Gessler, Smith, & Robberecht, 2006; Jackson & Huete, 1991).

To ensure a constant background and eliminate the effect of shade, a spectrally flat black surface could be placed as a background (Kittas et al., 2016; Mazzetto, Calcante, & Mena, 2009), while the use of artificial illumination could contribute to stabilise specular reflectance and simulate natural lighting (Graeff & Claupein, 2007; Katsoulas et al., 2014; Sun et al., 2008). Yet, the above modifications cannot eliminate shades created due to overlapping leaves and shades on the crop itself than the background. Nevertheless, due to the fact that the camera parameters are not constant, mathematic models could further eliminate the errors originating from different noise sources. Kim et al. (2010) mentioned that the calibration procedure with dark reference images was performed by covering the lens with a dark material, while white reference images were acquired by placing a white board in front of the lens under ambient illumination. The dark image was taken once for each imaging session and the reference image (white spectralon) was taken in different light conditions in order to minimise the influence of ambient outdoor natural light variations. Both the reference and normalised images must be obtained under the same light conditions

Table 1 – A list of ground based remote sensors involved in vegetation monitoring in field and laboratory conditions.

Type	Type of light source	Type of signal	Type of light source	Trapping image method	Type	Company	Spectral resolution	Reference
Laboratory	Non-imaging	Spectrometer	Active	Spot	GER IRIS	Mark IV	300–2500	(Maracci et al., 1991)
				Spot	Cary 5G UV–Vis–NIR	Agilent Technologies, Mississauga, Canada	250–2500 nm ± 1	(Noble & Li, 2012)
				Spot	UV5240	Beckman	400–2500 nm ± 2	(Peñuelas & Inoue, 1999)
	Imaging	Hyperspectral	Passive	Framing field of view (FOV) 45°	S1 PRO	Leica Germany	250–1300	(Graeff & Claupein, 2007)
				Scanning	XEVA-FPA-1.7-320	XenICs, Leuven, Belgium	900–1700 nm	(Zhou, Mao, & Zhang, 2011)
Sensors in contact	Non-imaging	Radiometer	Active	Spot	PMA-11	Hamamatsu, Photonics K.K., Japan	531, 570 nm	(Shahenshah, Yasuda, Mao-song, & Isoda, 2010; Inamullah & Isoda, 2005)
				Spot	Plant Pen PRI 200	Photon Systems Instruments Ltd., Brno, Chez Republic	500–600 nm	(Sarlikioti, Driever, & Marcellis, 2010)
		Spectrometer	Active	10 mm Spot	Field Spec Pro JR	Analytical Devices, Boulder, CO, USA	300–2400 nm ± 1	(Asner, 1998; Delalieux, Van Aardt, Keulemans, & Coppin, 2005; Jones et al., 2004)
				FOV	Field Spec FR	Analytical Devices, Boulder, CO, USA	350–2500 nm ± 1	(Bandyopadhyay et al., 2014; Zhao, Raja Reddy, Gopal Kakani, & Reddy, 2005)
				10° FOV	EKO MS-720	Eko Instruments	350–1050 nm ± 3.3	(Shimada, Funatsuka, Ooda, & Takyu, 2012)
Remote Sensing	Non-imaging	Radiometer	Active	FOV	Crop Circle ACS-470	Holland Scientific Inc., Lincoln, NE, USA	550, 670, 760 nm	(Elsayed, 2015; Kim et al., 2010; Padilla, Pérez-Rodríguez, Mougeot, Ludwig, & Redpath, 2014; Tsirogiannis, Katsoulas, Savvas, Karras, & Kittas, 2013)
				FOV	GreenSeeker	Ntech Industries, Ukiah, CA, USA	660 nm ± 12, 770 nm ± 12	(Elsayed, 2015; Jones et al., 2007)
			Passive	FOV	Skye UKIV51	Skye instruments, Powyd, UK	660, 730 nm	(King, Layzell, & Canvin, 1986)
				25° FOV	SKR 1800	Skye instruments, Powyd, UK	531, 570 nm	(Thenot, Méthy, & Winkel, 2002; Winkel, Thenot, & Méthy, 2002; Zarco-Tejada, González-Dugo, & Berni, 2011)
				20–30°	G1117 GaAsP/ S1226 44BK	Hamanatsu Photonics, Hmamakita, Japan	640, 720 nm	(Soudani et al., 2012)
				36°	SRS	Decagon, Pulman, WA, USA	532, 570 nm	(Magney, Vierling, Eitel, Huggins, & Garrity, 2016)
		Spectrometer	Active	Spot	Exotech-100	Exotech Inc., MD, USA	400–2400 nm	(Pinto Da Silva, Douglas, & Branton, 1971)
				Spot	Exotech-21	Exotech Inc., MD, USA	500–1100 nm	(Duggin, 1974)
				15° FOV	SE590	Spectron Engineering Inc., Denver, CO, USA	390–1100 nm ± 1.1	(Gammon, Peñuelas, & Field, 1992; Peñuelas, Filella, Elvira, & Inclan, 1995; Peñuelas et al. 1997, 1993)
				12° FOV	S2000 FL	Ocean Optics Inc. Duedin, FL, USA	400–950 nm	(Mänd et al., 2010)

(continued on next page)

Table 1 – (*continued*)

Type	Type of light source	Type of signal	Type of light source	Trapping image method	Type	Company	Spectral resolution	Reference
				Spot	Ocean Optics Maya 2000 Pro spectrometer	Ocean Optics, Dunedin FL, USA	350–1100 nm ± 5	(Noble & Li, 2012)
				25° FOV	FieldSpec Pro FR	Analytical Devices, Boulder, CO, USA	900–1350 nm	(Clevers, Kooistra, & Schaepman, 2008)
				30° FOV	Field Spec Pro 3	Analytical Devices, Boulder, CO, USA	350–2500 nm ± 1.4 (VIS, NIR ± 2 SWIR)	(Borzuchowski & Schulz, 2010; González-Fernández, Rodríguez-Pérez, & Marcelo, 2015; Liu, Jindra, Ueda, Hiromi, & Hirose, 2003; Yi, Bao, Wang, & Zhao, 2013)
				25° FOV	Field Spec Pro	Analytical Spectral Devices, Boulder, CO, USA	325–1075 nm ± 1	(Hernández, Melendez-Pastor, Navarro-Pedreño, & Gómez, 2014; Jain et al., 2007; Li et al., 2013; Marino et al., 2014)
				15° FOV	Li-1800	Licor Inc., Lincoln, NE, USA	300–1100 nm ± 2 or 650–1100 nm ± 10	(Daughtry & Biehl, 1985; Köksal, 2011; Köksal et al., 2010; Peñuelas et al., 1994; Suárez, Zarco-Tejada, Berni, González-Dugo, & Fereres, 2009; Zarco-Tejada, Miller, Mohammed, & Noland, 2000)
				Spot	MSR87	CropScan Inc., Rochester, NY, USA	400–1000 nm, Filters	(Gianquinto et al., 2011; Pederson & Nutter, 1982)
				10° FOV	Hand-held FieldSpect	Analytical Spectral Devices, Boulder, CO, USA	400–1000 nm	(Genc, Demirel, Camoglu, Asik, & Smith, 2011)
				18° FOV	FieldSpec UV/VNIR	Analytical Spectral Devices, Boulder, CO, USA	350–1050 nm ± 1.4	(Aparicio et al., 2004)
					ASEQ	LR1-T spectrometer	300–1000 nm ± 0.6	(Merlier, Hmimina, Dufrêne, & Soudani, 2015)
			Passive	Spot	Tec5	Obersursel Germany	300–1150 nm ± 3.3	(Li, Mistele, Hu, Chen, & Schmidhalter, 2014)
				Spot	Unispec	PP Systems, Haverhill, MA, USA	310–1100 nm ± 3	(Li, Wan, Zhou, Yang, & Qin, 2010)
	Imaging	Multispectral	Passive	Framing	MS3100	Duncan Tech, Auburn, CA, USA	400–1000 nm, Filters	(Jones et al., 2007)
					S1 PRO	Leica, Germany	250–1300 nm: Filters	(Graeff & Claupein, 2007)
					KP-D20AU	Hitachi, Tokyo, Japan	400–700 nm	(Story, Kacira, Kubota, Akoglu, & Lingling, 2010)
					DFK 23G445	Imaging Source, Charlotte, NC, USA	400–700 nm	(Story & Kacira, 2015)
					DMK 23G445	Imaging Source, Charlotte, NC, USA	850 nm	(Story & Kacira, 2015)
				Scanning	CV-M50 IR	Jai Co. Ltd., Japan	400–1000 nm, Filters	(Hsiao et al., 2010)
		Hyperspectral	Passive	Scanning	ImSpector V10E-ImSpec V10	Spectral Imaging Ltd., Finland	400–1000 nm ± 5	(Amatya et al., 2012; Kim et al., 2010)

HySpex VNIR 1600-160	Norsk Elektro Optikk, Norway	400–1000 nm ± 3.7	(Vigneau et al., 2011)
Micro-Hyperspec VNIR	Headwall Photonics, MA, USA	400–1000 nm ± 3.2/±6.4	(Zarco-Tejada et al., 2011)
Hyperspec VNIR 1003A-10143	Hadwall Photonics, Fitchburg, MA	400–1000 nm	(Amatya et al., 2012)
PCO 1600-ImSpec V10 spectrograph	PCO AG, Kelhein, Germany	400–900 nm	(Kittas, Elvanidi, Katsoulas, Ferentinos, & Bartzanas, 2016; Yao, Huang, Hruska, Thomson, & Reddy, 2012)
Imaging-2012 Spectrophotometer	University of Saskatchewan	450–1000 nm ± 5 nm	(Noble & Li, 2012)
Tec5	Oberursel, Germany	300–1700 nm	(Elsayed, 2015)
PHILLIS	Ocean PHILLIS	384–1000 nm	(Aguilar, Zinnert, Polo, & Young, 2012)

inside the greenhouse. Use of diffuse/haze greenhouse glazing can also be used as alternative approach to eliminate shades on the crop canopy and in the background in the ground surfaces.

3. Reflectance indices

3.1. *Crop water status assessment*

An increasing trend in the number of articles studying plant reflectance variation and its relationship to plant water status in open field or in greenhouse conditions is observed during the last 20 years (Fig. 5). The number of studies that have been conducted in greenhouses is relatively low and most of them have been performed after 2005, mainly due to advances in ground remote sensing. Based on this search, it can be seen (Table 2) that numerous successful case studies related to the reflectance indices, single bands or complex combinations for different species in different irrigation treatments, have been applied in open field while a few of them have been carried out in greenhouses. Crop reflectance characteristics and indices have been studied in correlation with several crop, climate or soil data such as plant water content (PWC), stomatal conductivity (g_s), chlorophyll fluorescence (ChF) and soil water content (SWC) in different plants with different ground based remote sensing, combining conventional methods, in the field, the greenhouse or the laboratory.

The photochemical reflectance index (PRI) and the normalised difference vegetation index (NDVI) are the most commonly used and analysed indices for crop water stress assessment (Fig. 5b). Other reflectance indices like the water index (WI), the modified normalised difference vegetation index (mNDVI), the red normalised difference vegetation index (rNDVI) and the Vogelman red edge index (VOGREI) have been used with a range of results.

3.2. *Promising RIs for crop water status assessment*

In this section, the studied reflectance indices that presented promising results are presented and analysed and their sensitivity on the environmental parameters, the canopy structure and the different crops are discussed.

3.2.1. *Photochemical reflectance index*

PRI has been used in several studies (e.g. Garbulsky, Peñuelas, Gamon, Inoue, & Filella, 2011; Magney et al., 2016; Mänd et al., 2010; Sarlikioti et al., 2010; Zarco-Tejada et al., 2011) using wavelengths from the spectrum around the green peak. Usually PRI is defined as:

$$PRI = (R531 - R570)/(R531 + R570)$$

PRI is related to rapid changes inde-epoxidation of the xanthophylls cycle. The xanthophylls cycle can be triggered at differing light intensities based on the photosynthetic potential of a plant (Magney et al., 2016; Sun et al., 2008; Van Gaalen, Flanagan, & Peddle, 2007). Stress factors limit photosynthetic activity and lead to an excess of absorbed energy that is dissipated by plants to avoid damage linked to increased leaf

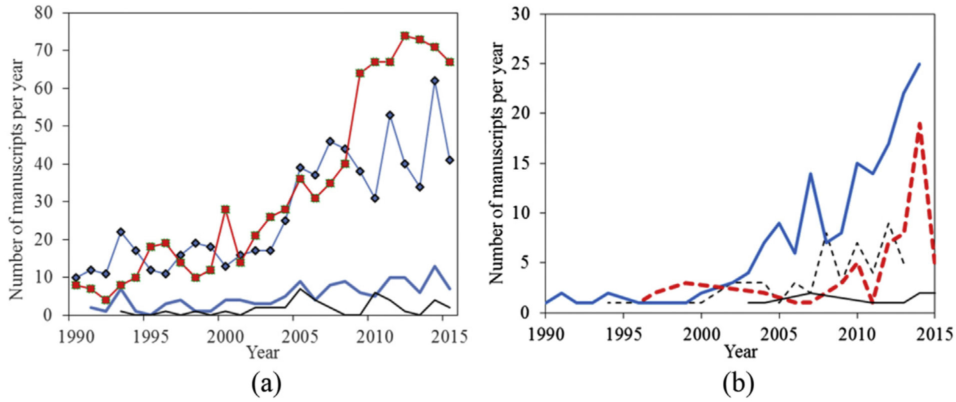

Fig. 5 – Evolution of documents found in Scopus related to (a) reflectance and remote sensing and (b) reflectance indices. Note: the search was based on the following terms: In (a) "remote sensing" and "plant" or "crop" or "leaf" (squares); "reflectance" and "plant" or "crop" or "leaf" (diamonds); "remote sensing" or "reflectance" and "plant" or "crop" or "leaf" and "water status" or "water stress" (thick line); "remote sensing" or "reflectance" and "plant" or "crop" or "leaf" and "nutrient status" or nutrient stress" (thin line); In (b): "NDVI" (Continuous thick line); "rNDVI" (Continuous thin line); "WI" (Discontinuous thick line); "PRI" (Discontinuous thin line).

temperature (Merlier et al., 2015). Also, PRI reflects long-term changes in the ratio of carotenoids/chlorophyll (Mänd et al., 2010). Thus, it is indirectly affected by water stress conditions due to the effects of water stress on the efficiency of photosynthesis (Gammon et al., 1992; Garbulsky et al., 2011; Inamullah & Isoda, 2005; Magney et al., 2016; Shimada et al., 2012; Suárez et al., 2007; Suárez, Zarco-Tejada, Gonzálelez-Dugo, Berni, & Fereres, 2008; Thenot et al., 2002; Tsirogiannis et al., 2013; Van Gaalen et al., 2007; Zarco-Tejada et al., 2011).

PRI is affected by leaf and canopy parameters such as chlorophyll content, dry matter, leaf thickness, LAI and leaf angle distribution (Garbulsky et al., 2011; Malenovský, Mishra, Zemek, Rascher, & Nedbal, 2009; Mänd et al., 2010; Sarlikioti et al., 2010; Suárez et al., 2009). According to Merlier et al. (2015), PRI values are mainly related to soil moisture content when the chlorophyll content is not a limiting factor. Magney et al. (2016), found that delta PRI (ΔPRI) derived from a midday or early morning PRI, demonstrated less sensitivity than an uncorrected PRI to LAI and leaf chlorophyll content throughout the growing season.

Gammon et al. (1992) were among the first who presented the physiological reflectance index and correlated the depoxidation state of the xanthophylls cycle pigments to water stress. Suárez et al. (2009) obtained a high determination coefficient between PRI and crown temperature for peach and olive trees demonstrating an indirect relationship between PRI and water stress. Van Gaalen et al. (2007) observed strong linear correlation between NPQ (non photochemical quenching) and PRI in *sphagnum moss*. Thenot et al. (2002) carried out experiments under greenhouse conditions (Photosynthetic Active Radiation-PAR level of 1800 μmol m^{-2} s^{-1}) and found that after withholding the water supply for 5 or 12 days in *Chenopodium quinoa*, a 20% and 52%, respectively, PRI was varied compared to control plants. Sarlikioti et al. (2010) noted that a good correlation (R^2>60%) between PRI and relative water content, CO_2 assimilation, stomatal conductance, operating efficiency of PSII (Photosystem II) and NPQ, was established in glasshouse tomato plants, only when light intensity was higher than 700 μmol m^{-2} s^{-1}. In PRI measurements with low light signal (Fig. 6), the relationship between the index and the RWCs percentage was poor in comparison to photosynthesis or fluorescence parameters that showed a high correlation to RWCs percentage. Magney et al. (2016) evaluated PRI with other environmental conditions. Their results showed that during the growing season, when water was plentiful, and when vapour pressure deficit (VPD) and air temperature were low, there is a small response of PRI. In addition, the study showed that PRI was sensitive to conditions where high VPD and air temperature limited stomatal conductance.

Tsirogiannis et al. (2013) used an index close to PRI [Water Deficiency Reflectance Index 1 WDRI1 = (R560 − R510)/(R560 + R510)] to detect water stress. They found no consistent relationship between irrigation treatment and WDRI1 was found, however three days after the initiation of deficit irrigation, when irrigation covered only 50% of plant evapotranspiration, a gradual variation of WDRI1 was detected and a good relationship between WDRI1 and crop water stress index (CWSI) was found (Fig. 7).

3.2.2. *Normalised difference vegetation index*

NDVI is a widely used index with different reflectance combinations (Table 2). Its mathematical formation incorporates wavelengths in green and near infrared region. Many researchers report high correlation with biomass, chlorophyll, leaf area and yield (e.g. Jones et al., 2004, 2007; Köksal, 2011; Liu et al., 2004), while Jones et al. (2004) explain that although $NDVI_{(800-640)}$ [= (R800 − R640)/(R800 + R640)] may be a good indicator of nitrogen content and biomass, it provides a medium estimate of plant water content. Several researchers (Genc et al., 2011; Kim et al., 2010) showed that $NDVI_{(800-680)}$ has good correlation with plant water status. Nevertheless, Amatya et al. (2012) showed that $NDVI_{(800-640)}$ in potato has higher correlation with soil water content than the $NDVI_{(800-680)}$, while Jones et al. (2004) and Köksal (2011) found

Table 2 – Reflectance indices evaluated for plant water stress assessment and correlated with the vegetation characteristics.

Acronym	Name	Equation (nm)	Vegetation	Species	Application	Method	Reference
SB	Single band	670, 770, 780, 820	PWC, ETc	Green beans, 51 different species leaf	Field, laboratory	RS based on spectroradiometer that measures in specific FOV of the target (RS/FOV)	Köksal (2011), Ceccato, Flasse, Tarantola, Jacquemoud, and Grégoire (2001)
SB	Single band	1450, 1950, 2250, 1600	PWC	Corn (maize), spinach, snap bean, 50 different species leaf	Greenhouse, laboratory	C	Jones et al. (2004), Ceccato et al. (2001)
AVI	Average vegetation	490 – 1300, 510 – 1300, 516 – 1300, 540 – 1300, 600 – 1300	PWC	Wheat	Laboratory	RS based on imaging systems (RS/CAM)	Graeff and Claupein (2007)
AVI	Average vegetation	1150 – 1260, 630 – 650, 950 – 979	PWC	Corn (maize), spinach, snap bean	Greenhouse	In contact (C)	Jones et al. (2004)
DVI	Difference vegetation	630 – 650	PWC	Corn (maize), spinach, snap bean	Greenhouse	C	Jones et al. (2004)
DVI	Difference vegetation	780 – 670, 820 – 670, 800 – 970, 770 – 670, 950 – 970	PWC, ETc	Green beans	Field, greenhouse	RS/FOV, C	Jones et al. (2004)
SR	Simple ratio	800/680, 900/680	PWC, ETc, SWC	Sugar beet, apple, potatoes	Field, greenhouse	RS/FOV, RS/CAM	Köksal et al. (2010), Köksal (2011), Kim et al. (2010), Amatya et al. (2012), Genc et al. (2011)
SR	Simple ratio	780/670, 770/670, 800/970, 820/670	PWC, ETc	Green beans	field	RS/FOV	Köksal (2011)
SR	Simple ratio	858/1240, 1070/1340, 678/1070, 880/1265	PWC	Cotton	field	C	Yi et al. (2013)
MSI	Moisture Stress Index	1600/820	PWC	52 different species leaf, cotton	Laboratory, field	Spectroradiometer in laboratory (Sp), C	Ceccato et al. (2001), Yi et al. (2013)
MSI	Moisture Stress Index	870/1350, 1650/835	PWC	Cotton, vineyard, cotton	field	C	Yi et al. (2013), González-Fernández et al. (2015)
WI	Water	900/970	PWC, g_s, CO2, NPQ, PSII, NPh, SWC,ChF, SF	Apple, potatoes, corn, spinach, snap bean, grass, wheat, pepper, bean, gerbera, olive, cotton, vineyard	Greenhouse, field, laboratory	RS/CAM, C, RS/FOV,	Kim et al. (2010), Amatya et al. (2012), Jones et al. (2004), Clevers et al. (2008), Liu et al. (2004), Peñuelas et al. (1993), Sun et al. (2008), Genc et al. (2011), Kittas et al. (2016), Panigada et al. (2014), Marino et al. (2014), Bandyopadhyay et al. (2014); Yi et al. (2013), González-Fernández et al. (2015)
FR	Fluorescence ratio	690/600, 740/800	PWC, g_s, ChF	Olive	Laboratory	RS/FOV	Sun et al. (2008)

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Table 2 – (*continued*)

Acronym	Name	Equation (nm)	Vegetation	Species	Application	Method	Reference
MSI	Moisture stress	1599/819		Wheat	Greenhouse, field	RS/FOV	Borzuchowski and Schulz (2010), Datt (1999)
VOG REI 1	Vogelman red edge index	740/720	SWC	Apple, potatoes, mandarin, orange	Greenhouse	RS/CAM	Kim et al. (2010), Amatya et al. (2012), Kittas et al. (2016)
VOG REI 2 or 3	Vogelman red edge index	(734 − 747)/(715 + 726), (734 − 747)/(715 + 720)	SWC	Apple, potatoes	Greenhouse	RS/CAM	Kim et al. (2010), Amatya et al. (2012), Kittas et al. (2016)
NDVI	Normalised difference vegetation	(800 − 680)/(800 + 680)	PWC, ETc, SWC, SF, CO_2	Apple, sugar beet, olive	Greenhouse., field	RS/CAM, RS/FOV, C	Kim et al. (2010), Köksal et al. (2010), Genc et al. (2011), Kittas et al. (2016), Marino et al. (2014)
NDVI	Normalised difference vegetation	(800 − 640)/(800 + 640)	PWC, SWC	Potatoes	Greenhouse	RS/CAM, C	Amatya et al. (2012), Jones et al. (2004)
NDVI	Normalised difference vegetation	(860 − 670)/(860 + 670)	PWC	Spring barley, sugar beet, orange, cereal	Greenhouse, field	RS/FOV	Borzuchowski and Schulz (2010), Liu et al. (2004), Panigada et al. (2014)
NDVI	Normalised difference vegetation	(900 − 680)/(900 + 680), (780 − 670)/(780 + 670), (820 − 670)/(820 + 670), (770 − 670)/(770 + 670), (920 − 670)/(920 + 670)	PWC	Green beans	Field	RS/FOV	Köksal (2011)
NDVI	Normalised difference vegetation	(780 − 670)/(780 + 670)	PWC, ETc	Green beans	Field	RS/FOV	Köksal (2011)
NDVI	Normalised difference vegetation	(490 − 620)/(490 + 620)	PWC	Hibiscus	Field	RS/CAM, C	Shimada et al. (2012), Kittas et al. (2016)
NDVI	Normalised difference vegetation	(490 − 610)/(490 + 610), (490 − 600)/(490 + 600), (850 − 650)/(490 + 590), (490 − 590)/(490 + 590), (858 − 645)/(858 + 645)	PWC	Hibiscus, vineyard	Field	C	González-Fernández et al. (2015)
NDVI	Normalised difference vegetation	(760 − 670)/(760 + 670), (760 − 730)/(760 + 730), (780 − 670)/(780 + 670), (780 − 510)/(780 + 510), (850 − 560)/(850 + 560), (810 − 740)/(810 + 740), (774 − 656)/(774 + 656)	Tc, Y	Barley	Field	RS/CAM, RS/FOV	Elsayed (2015)
NDVI	Normalised difference vegetation	(850 − 1650)/(850 + 1650), (835 − 1650)/(835 + 1650), (858 − 2130)/(858 + 2130), (860 − 1240)/(860 + 1240), (870 − 1260)/(870 + 1260), (858 − 648)/(858 + 648)	PWC	Cotton, vineyard	Field	C	Yi et al. (2013), González-Fernández et al. (2015)
NDVI	Normalised difference vegetation	(NIR − VIS)/(NIR + VIS)	Tc	Lettuce	Greenhouse	RS/CAM,	Story and Kacira (2015)
NDWI	Normalised difference vegetation	(860 − 1240)/(860 + 1240)	PWC,	Grass	Field	RS/CAM, RS/FOV	Clevers et al. (2008), Datt (1999)

NDWI	Normalised difference vegetation	(820 − 1240)/(890 + 1240)		Winter wheat	Field	C	Liu et al. (2004)
rNDVI	Red edge NDVI	(750 − 705)/(750 + 705)	SWC, CO_2, SF, PWC	Apple, potatoes, olive	Greenhouse	RS/CAM, RS/FOV	Kim et al. (2010), Marino et al. (2014), Amatya et al. (2012), Kittas et al. (2016)
sNDVI	Similar NDVI	(810 − 710)/(810 + 710), (810 − 560)/(810 + 560)	SWC		Greenhouse	RS/FOV	Tsirogiannis et al. (2013)
NPQI	Normalised phaeophytinization	(800 − 445)/(800 − 680)	PWC, g_s, Ch, F	Olive	Laboratory		Sun et al. (2008)
PRI	Photochemical reflectance	(531 − 570)/(531 + 570)	PAR, NPQ, PSII, NPh, SWC, PWC, g_s, ChF, Tc, CO_2, stem diameter	Apple, potatoes, wheat, tomato, soybean, cereal, olive	Greenhouse, field, laboratory	RS/CAM, RS/FOV, C	Kim et al. (2010), Sarlikioti et al. (2010), Borzuchowski and Schulz (2010), Suárez et al. (2009), Sun et al. (2008), Inamullah and Isoda (2005), Kittas et al. (2016), Panigada et al. (2014), Marino et al. (2014)
NWI	Normalised water index-1	(970 − 900)/(970 + 900), (970 − 850)/(970 + 850), (970 − 920)/(970 + 920), (970 − 880)/(970 + 880),	PWC, Tc, Y	Wheat, barley	Field	RS/CAM, RS/FOV, C	Bandyopadhyay et al. (2014), Elsayed (2015)
PRI_{620}	Photochemical reflectance 620 nm	(531 − 620)/(531 + 620)	PWC, Ch, F, CO2	Cereal	Field	RS/CAM	Panigada et al. (2014)
sPRI	Similar photochemical reflectance	(560 − 510)/(560 + 510)	Tc, SWC,ETc, CWSI		Greenhouse	RS/FOV	Tsirogiannis et al. (2013)
PSRI	Plant senescence reflectance	(680 − 500)/750	SWC	Apple, potatoes, wheat	Greenhouse	RS/CAM, RS/FOV	Kim et al. (2010), Amatya et al. (2012), Borzuchowski and Schulz (2010)
SIPI	Structure independent pigment	(800 − 445)/(800 − 680)	PWC, g_s, Chl	Corn (maize), spinach, snap bean, wheat, peanut, olive	Greenhouse, field, laboratory	C, RS/FOV, Sp	Jones et al. (2004), Peñuelas and Inoue (1999), Sun et al. (2008)
SIWSI	Shortwave IR water stress	(858 − 1640)/(858 + 1640)	PWC	Cotton	Field	C	Yi et al. (2013)
NDII	Normalised difference infrared index	(835 − 1650)/(835 + 1650)	PWC	Vine	Field	C	González-Fernández et al. (2015)
Fwbi	Floating-position water band	900/(930 − 980)	PWC	Cotton, vine	Greenhouse, field	C	Jones et al. (2004), Yi et al. (2013), González-Fernández et al. (2015)
mrNDVI	Modified red edge NDVI	(750 − 705)/ (750 + 705 − 2*445)	SWC	Apple, potatoes, wheat	Greenhouse	RS/CAM, RS/FOV	Kim et al. (2010), Amatya et al. (2012), Borzuchowski and Schulz (2010), Kittas et al. (2016)
eNDVI	Enhanced NDVI	[(NIR + GREEN) − 2*BLUE]/ [(NIR + GREEN)±2*BLUE]	Tc	Lettuce	Hreenhouse	RS/CAM	Story and Kacira (2015)
mrSRI	Modified red edge SRI	(750 − 747)/(705 − 445)	SWC	Potatoes	Greenhouse	RS/CAM	Amatya et al. (2012), Kittas et al. (2016)

(continued on next page)

Table 2 – (continued)

Acronym	Name	Equation (nm)	Vegetation	Species	Application	Method	Reference
WI/NDVI_4	Water/Norm. dif.	(970/900)/((900 − 680)/(900 + 680))	PWC	Peanut, wheat	Laboratory	Sp	Peñuelas and Inoue (1999)
SAVI	Soil adjusted vegetation	((800 − 680)/(800 + 680 + L))*(1 + L)	PWC, ETc, SWC	Green beans	Field	RS/FOV	Köksal (2011), Köksal et al. (2010)
EVI	Enhanced vegetation	(2.5*((800 − 680)/(800 + 6*680 − 7.5*450 + 1)))	SWC	Apple	Greenhouse	RS/CAM	Kim et al. (2010)
ARVI	Atmospherically resistant vegetation index	(800 − (2*680 − 450))/(800 + (2*680 − 450))	SWC	Apple	Greenhouse	RS/CAM	Kim et al. (2010)
OSAVI	Optimum soil adjusted vegetation	(1.5*(800 − 680))/(800 + 680)		Watermelon, cereal	Field	C/CAM	Genc et al. (2011), Panigada et al. (2014)
GNDV	Green normalised difference vegetation.	(474 − 537)/(747 + 537)		Watermelon	Field	C	Genc et al. (2011)
TCARI	Transformed chemical absorption reflectance index	3*[(700 − 670) − 0.2 (700 − 550)*(700/670)]	PWC, Ch, F, CO_2	Cereal	Field	CAM	(Panigada et al., 2014)
TCARI/OSAVI	Trans.Chemical Absorption Reference In./ optimal soil adjusted veg.	(3*[(700 − 670) − 0.2 (700 − 550)*(700/670)])/ [(1.5*(800 − 680))/(800 + 680)]	PWC, Ch, F, CO_2	Cereal	Field	CAM	(Panigada et al., 2014)

RS: remote sensing, RS/CAM: remote sensing based on imaging systems, RS/FOV: remote sensing based on spectroradiometer that measures in specific field of view of the target, Sp: spectroradiometer in laboratory, C:sensors that measure plant reflectance in contact with the leaf.

low correlation of $NDVI_{(800-640)}$ with leaf water content in corn, spinach and snap beans or green beans, and high correlation with transpiration and yield increase. According to Marino et al. (2014), a reliable correlation was found between canopy NDVI and leaf g_s. Shimada et al. (2012) showed strong correlation between $NDVI_{(490-620)}$ and leaf water potential. Kittas et al. (2016) explained that $NDVI_{(800-680)}$ had better correlation with soil moisture content than $NDVI_{(490-620)}$ in greenhouse tomato, while Katsoulas et al. (2014) supported that NDVI at 800 and 680 nm was invariable with environmental conditions variation and especially with light intensity. Usually, NDVI is not significantly related to variations in environmental conditions such as VPD and air temperature but it is weakly correlated to stomatal conductance and strong correlated to LAI (Aguilar et al., 2012; Magney et al., 2016).

3.2.3. *Red normalised difference vegetation index,* $rNDVI_{(705-750)}$

The $rNDVI_{(705-750)}$ is based on spectral parts suitable for potential water content and soil moisture estimation (Liu et al., 2004). This theory was confirmed by Kim et al. (2010) and Amatya et al. (2012), as they found high correlation between rNDVI and water stress in apple and potatoes, respectively. NDVI in the red region gives stable measurements in different species and it can be saturated less by dense vegetation conditions in comparison with other NDVI formations (Asner, 1998).

3.2.4. *Water index*

Water index (WI = R970/R900) reflects water absorption in the mesophyll and increases as relative water content decreases. WI has high variability due to the fact that leaf structure plays a crucial role on radiation absorption at 900 and 970 nm. Peñuelas and Inoue (1999) explained that WI decreased directly after water stress initiation in monocotyledonous plants (wheat), while in case of dicotyledonous plants (peanut) with double leaf water concentration due to leaf structure capacity, WI started to decrease when leaf water concentration reached 60%. Several authors (Amatya et al., 2012; Genc et al., 2011; Jones et al., 2004; Kittas et al., 2016), demonstrated that the spectral relative changes observed between 950 and 970 nm are correlated with the relative water content (RWC), provided that RWC, stomatal conductivity and leaf water potential values are lower than 85%, 0.075 mmol m^{-2} s^{-1} and −1.5 MPa, respectively (Peñuelas et al., 1993). It is noteworthy however, that WI values responded positively as g_s and water potential increased in olive trees, with better correlation coefficient than other reflectance indices (such as PRI and NDVI) (Marino et al., 2014). Meanwhile, Bandyopadhyay et al. (2014) and Elsayed (2015) used normalised water index NWI [Normalised water index = (R970 − R900)/(R970 + R900)] based on the WI for screening spring wheat genotypes for grain yield under well irrigated and water deficit conditions. For this study it was concluded that NWI values were significantly negatively correlated with the grain yield due to water or nutrient stress.

3.2.5. *Other indices*

The modified red (mr) edge index is categorised into the mrNDVI [modified red NDVI = (R750 − R705)/(R750 + R705-2*R445)] and mrSR [modified red Simple Ratio

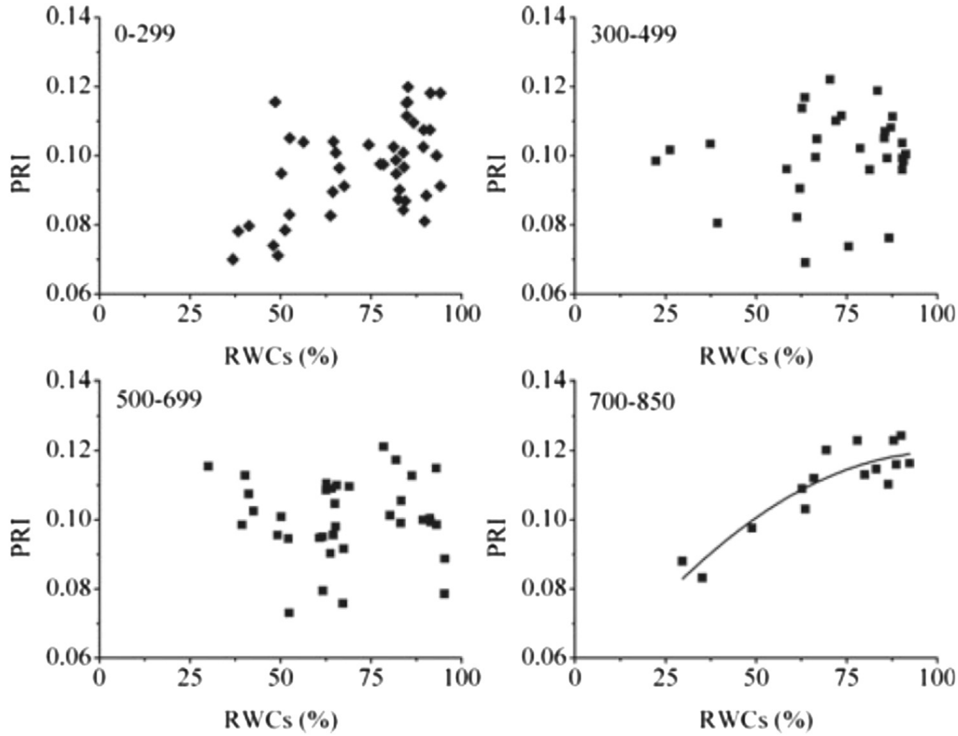

Fig. 6 – Correlation of photochemical reflectance index (PRI) and slab relative water content for light intensities varying from 0 to 299, 300–499, 500–699 and 700–850 μmol m^{-2} s^{-1}. From Sarlikioti et al. (2010).

Index = (R750 − R445)/(R705 − R445)]. Figure 8 shows a correlation of mrSR and mrNDVI with soil water content in a potato crop under four water treatment levels (10%, 15%, 20% and 25% soil water content). Similar results were found by Kittas et al. (2016) for a tomato crop in greenhouse. Merlier et al. (2015) supported that mrNDVI correlated directly with leaf chlorophyll content, values that corresponded with drought and high temperature evolution. Generally, mrNDVI and mrSRI are recently developed indices and further research in different conditions is necessary.

The Vogelmann red edge index was originally used to correlate the reflectance radiation at 720 and 740 nm with total chlorophyll content at leaf level (Vogelmann, Rock, & Moss, 1993). Kim et al. (2010), Amatya et al. (2012) and Kittas et al. (2016) found a good correlation of VOGREI (Table 1) with soil moisture content under greenhouse conditions. The index seems to be less influenced by differences in background conditions and light contamination than NDVI and VI. Generally, VOGREI is another newly developed reflectance index that should be further analysed for small scale water

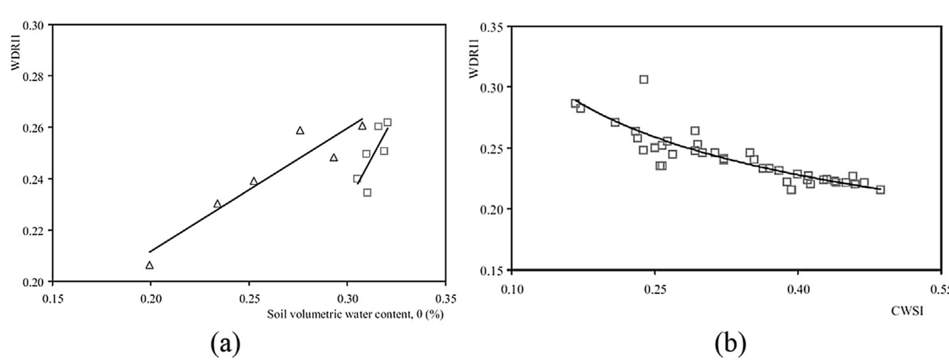

Fig. 7 – (a). Relationships between mean daily values of WDRI1 and soil volumetric water content (θ, m^3 water m^{-3} soil) as influenced by irrigation treatment; squares: 100% ET$_c$; triangles: 50% ET$_c$. Straight lines indicate the best fit of the linear relationships between the measured values of θ and WDRI1 (R^2 = 0.70 and 0.89 for 100% ET$_c$ and 50% ET$_c$, respectively). (b) Relationship between instantaneous values of WDRI1 and CWSI for the 100% ETc treatment during 28–30 July. The solid line indicates the best fit of the relationship between the measured values of CWSI and WDRI1 [WDRI1 = 0.178 CWSI-0.27 (R^2 = 0.76)]. From Tsirogiannis et al. (2013).

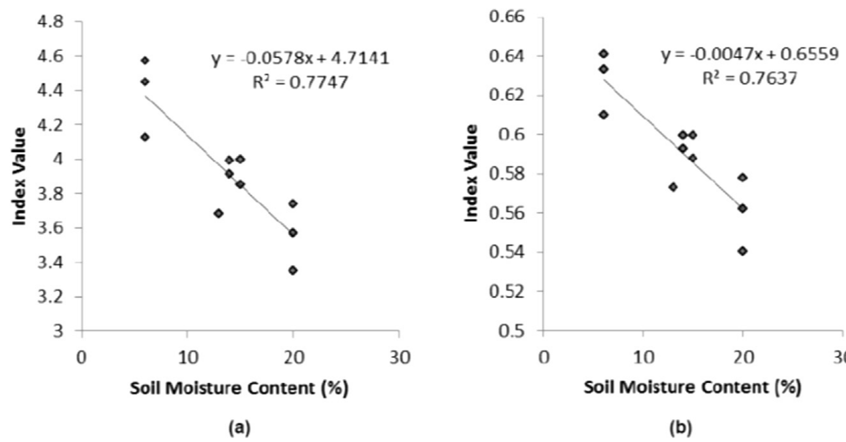

Fig. 8 – Correlation between soil moisture content and spectral indices, (a) with mrSRI and (b) mrNDVI in potatoes. From Amatya et al. (2012).

stress assessment inside the greenhouse, based on species variability and sample replicate stability.

3.3. *Nitrogen stress assessment*

Nitrogen is up taken by roots and stored to mesophyll cells of the leaves in order to synthesize proteins (which are integrated in structural components to constitute cell wall) or enzymes in metabolic pathways (Vigneau et al., 2011). Nitrogen that is allocated to leaves varies as the photosynthesis and the rubisco production rate (which represents about 50% of leaf nitrogen content) change (Gutschick, 1999; Vigneau et al., 2011). Leaves from healthy plants contain higher amounts of nitrogen, chlorophyll, rubisco, photosynthetic rate and lower starch content and leaf thickness than N-limited plants (Peñuelas et al., 1994). Rate limitations on N consumption causes low fractional content and high thickness, dry mass per unit area and long leaf lifetimes. Increase of leaf N content amount confers large water use efficiency by increasing the mesophyll conductance and decreasing the ration between the stomatal conductance and mesophyll conductance (Flexas et al., 2013). If mesophyll conductance decreases, the carboxylation rate per mass of rubisco enzyme declines, decreasing at the same time the CO_2 assimilation per mass of N. However, photosynthetic and rubisco production rate is strongly related to chlorophyll content (Chl) in leaf tissue (Sclemmer et al., 2005) while N is the only compound that influences the actual extracted chlorophyll content (Croft, Chen, & Zhang, 2014; Sclemmer et al., 2005; Silleos et al., 2006). Chlorophyll levels affect leaf area, leaf weight and plant size (Basyouni & Dunn, 2013, pp. 1–4). If N stress occurs, the chlorophyll content is decreased, the leaf is changed from green to yellow–green and less radiation is used by the plant, and as a result, the red and red-edge spectrum is increased. The greenness of the leaves represents the amount of chlorophyll found in the chloroplasts, which can be used as an indirect indicator for the photosynthetic processes of the plant to determine plant health and vigor (Basyouni & Dunn, 2013, pp. 1–4). Thus, reflectance at VIS (Visible spectrum) spectrum can provide a measure of stress that results in chlorophyll degradation and consequently to N concentration detection. Though, the correlation of N concentration to chlorophyll varies according to the environmental conditions, the cultivar and the growing season.

Chlorophyll in living leaves has absorbance peaks in two distinct regions: the blue region (400–500 nm) and the red region (600–700 nm), with no transmission in the NIR region (Basyouni & Dunn, 2013, pp. 1–4). Several authors (e.g. Jain et al., 2007; Sclemmer et al., 2005; Vigneau et al., 2011) observed a strong correlation between chlorophyll content and crop reflectance at 525–630 nm, 640–660 nm, around 705 nm, 730 nm and 930 nm. Based on Lepine, Ollinger, Ouimette, and Martin (2016), the vegetation index DVI [Difference Vegetation Index = (NIR − Red)] was strongly correlated with canopy N content. In fact, the correlations with N appeared to decline as indices became more complex, with NDVI [Normalised difference vegetation index = (NIR − Red)/(NIR + Red)] and EVI [Enhanced vegetation index = (2.5 × NIR − Red)/(1 + NIR + 6 × Red − 7.5 × Blue)] to be weakly correlated with canopy N. According to Lepine et al. (2016), these results indicate that the relationship between N and the indices in that analysis were driven more so by variation in NIR reflectance than by variation in visible reflectance. This observation supports the notion that the contribution of visible reflectance in some vegetation indices can add noise to an otherwise strong correlation between NIR reflectance and N. That is why canopy structural properties, such as LAI influences the reflectance in that spectrum area. Croft et al. (2014) used a number of reflectance indices based on Red and NIR spectrum area as well, such as MNDVI8 [Modified NDVI = (R755 − R730)/(R755 + 730)], MTCI [Meris terrestrial chlorophyll index = (R754 − R709)/(R709 − R681)], Macc01 [Maccioni 2001 = (R780 − R710)/(R780 + R680)], D [Derivative reflectance at D690 = D690] and DD [Datt derivative = D754/D704]. Figure 9 shows the relationship between reflectance indices (MNDVI8, MTCI, Macc01, D, DD) and leaf chlorophyll content (broad or needle site). Bajwa, Mishra, and Norman (2010) used reflectance indices based on NIR spectrum area {MSAVI [Modified soil adjusted vegetation

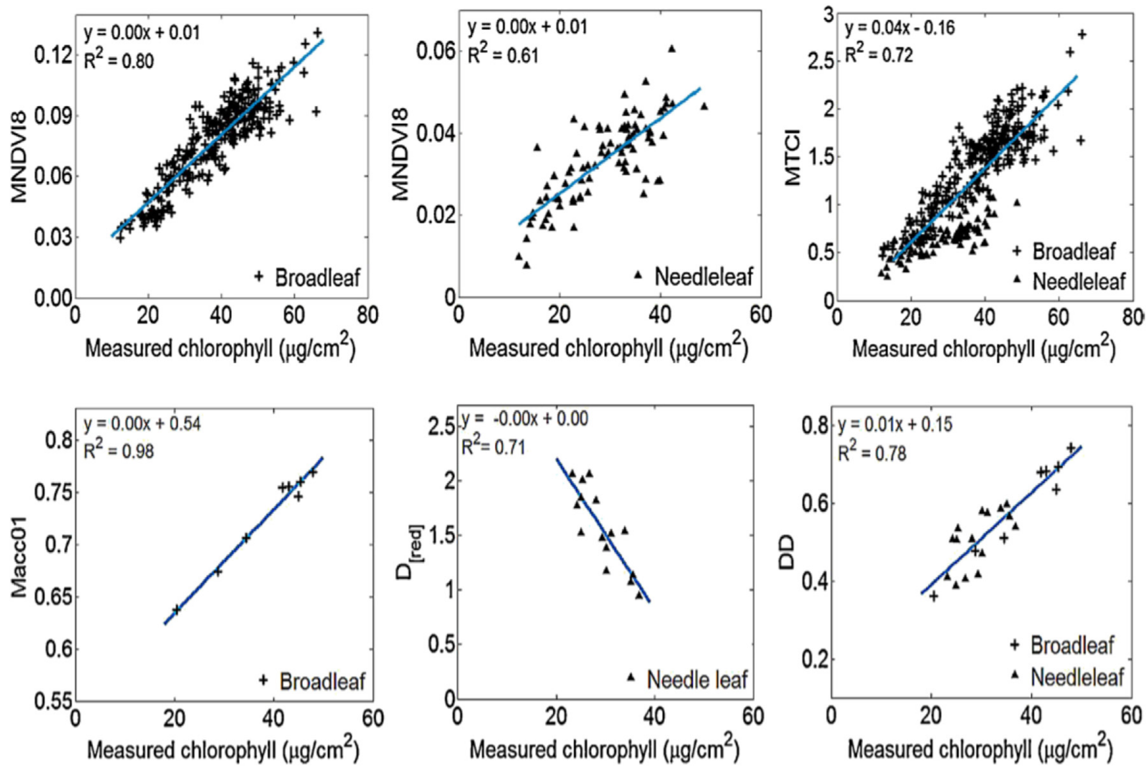

Fig. 9 – Relationship between reflectance indices (MNDVI8, MTCI, Macc01, D, DD) and leaf chlorophyll content (broad or needle site). From Croft et al. (2014).

index = 1/2 × (2 × (R810 + 1) − (√(2 × R810 + 1) 2 − 8 × (R810 − R690))], WDRVI = [Wide dynamic range vegetation index = (R810 − R690)/(R810 + R690)]} to predict green biomass ($R^2 > 0.70$). Peñuelas et al. (1995) had already studied SIPI index {SIPI = [Structural independent pigment index = (R800 − R445)/(R800 + R680)]} and found that it was highly correlated to the ratio of carotenoids/chlorophyll-a. Only when the index included reflectance measurements around 700 nm {NDRE [Normalised difference red edge = (R790 − R720)/(R790 + R720)]} lead to N status prediction (Bajwa et al., 2010). Zhao et al. (2005) reported that leaf N and Chl concentrations were linearly correlated with indices that include Blue or NIR reflectance measurements (R405/R715 and R1075/R735).

Among others who used reflectance indices based on Red, NIR spectrum area to correlate with N plant content, Hernández et al. (2014) concluded to a positive correlation between rNDVI and leaf N concentration. Vigneau et al. (2011) also noted that VOGREI was highly correlated to leaf N content while Padilla et al. (2014) showed that $NDVI_{(NIR\text{-}RED)}$[$=(R_{NIR} - R_{RED})/(R_{NIR} + R_{RED})$], GNDVI [Normalised difference vegetation index on greenness $= (R_{NIR} - R_{GREEN})/(R_{NIR} + R_{GREEN})$], RVI [Red vegetation index $= (R_{NIR}/R_{RED})$] and GVI[Green vegetation index - $= (R_{NIR}/R_{GREEN})$] showed high correlation with N concentration. On the other hand, Nigon et al. (2015) found MTCI [Merris terrestrial chlorophyll index = (R751 − R713)/(R713 − R679)] to be the most promising reflectance index for determining N stress level for variable rate application of N fertilizer over a broad range of conditions. Consequently, it was concluded that reflectance measurements around to 700 nm are capable to lead to N stress prediction.

4. Discussion

4.1. *How to improve accuracy in measurements*

The level of technology used in hyperspectral sensors has been significantly increasing during the last decade. However, even the most advanced hyperspectral sensors present some instability in measurement over time, due to the intense effects of solar radiation in the target area (Tuominen & Lipping, 2011). Illumination is important in optical reflectance applications, especially in the hyperspectral camera in which a uniform spatial distribution is crucial.

Specialised lighting devices that emit stable and smooth light are efficient and affordable. Such illumination sources must have intensity peaks in the area of interest of the reflectance measurement (Noble & Li, 2012). Figure 10 shows the spectral response in a broad-spectrum of several common light sources compared with sunlight, over the typical range of a silicon-based detector of hyperspectral cameras (Lawrence et al., 2003). Sunlight emits high energy in the visible spectrum and low energy in the near-infrared spectrum. Typical halogen lamps emit low energy in the blue region and high energy in the red region. In addition, fluorescence tubes give certain peaks in which reflectance sensors can measure, while high power LEDs do not have enough power to improve the light signal (Lawrence, Park, Heitschmidt, Windham, & Thai, 2007). A quartz-tungsten-halogen flood light could be a good option as it emits stable light in the visible and NIR spectral regions, without significant spectral peaks.

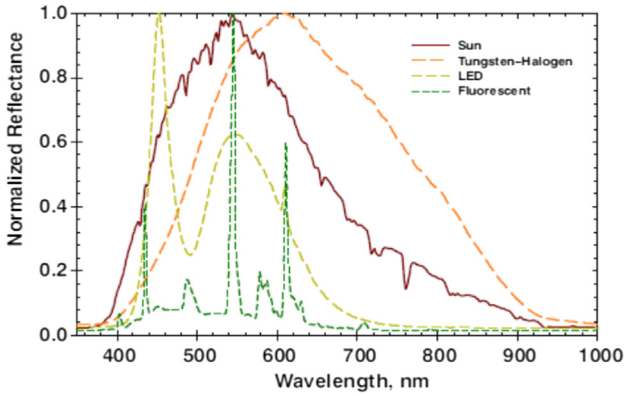

Fig. 10 – Typical mean spectral response of sunlight, tungsten-halogen lamps, white LEDs and fluorescent lamps. From Lawrence et al. (2007).

Several parameters affect the accuracy of reflectance measurements, a summary of the most important points to be noted in order to acquire accurate reflectance measurements is given below:

- A stable position for the optical system with an appropriate distance from the target and a fixed geometry between the sensor and the target are necessary. The appropriate distance between the sensor and the target varies according to the dimensions of camera's light detector and the target size that is needed to capture (angle view) (For instance, the hyperspectral ImspecV10 camera with 18° objective lens size has a field of view capacity that equals to 32° in case of 1550 spatial pixels). Camera angle view can be measured horizontally, vertically and diagonally. In case that an optical scanning system is used, the view angle calculation is influenced by the scanning distance.
- Before any image acquisition, the camera's settings (exposure time and number of lens aperture) must be corrected by measuring a white surface of known reflectance (spectralon) at the same position with the plant target. In this stage, the gain and the offset are adjusted according to the light signal.
- Placing a black material behind and below the target scene will help to avoid scattering of the neighbourhood materials and spectral interference from the ground.
- A light measuring sensor during the time of recording could help to correct errors from the primary image acquisition and effects of variable cloud coverage.
- For the signal-to-noise calculation, a dark image is acquired by covering the lens with dark material. After that, the resulting pictures are normalised with the dark and white reference images to generate a calibrated image without noise.

4.2. *Reflectance indices correlation to plant water and nutrient status*

According to the studies revised, it seems that PRI cannot be used to detect early plant water stress, since it was not able to detect changes for periods shorter than 3-d after stress initiation. PRI changed significantly (due to mechanism of xanthophylls) only when substrate or soil water content was reduced to half. However, PRI constitutes an effective water stress detection index in cases that the leaf relative water content proportion is smaller than some reference portion according to the leaf structure. Nevertheless, for greenhouse conditions where irrigation management includes at least 8–10 irrigation events per day (depending to plant growth stage), PRI seems not suitable to detect leaf water content variations for short-time scale. Probably the combination of PRI with fluorescence and canopy temperature, could lead to early plant water stress detection (earlier than three days after stress initiation) (Zarco-Tejada et al., 2013). However, due to the fact that the contribution of fluorescence signal (Fs) is very low, as it represents only 2–3% of leaf electromagnetic reflectance in red and near infrared spectrum, the reliability of this spectral index to detect water stress is also unknown. In addition, since PRI is affected by parameters such as soil type, sun angle and LAI, the above parameters have to be known and constant or their effect has to be taken into account in order the index to be used for crop water stress detection. Furthermore, it seems that the index cannot be correlated to plant water status at low light levels (<700 μmol m^{-2} s^{-1}), while ΔPRI (the difference of actual to an initial-reference value) signal is more sensitive to light conditions where water and nutrients are limited. Thus, to correlate reflectance indices to the gas-exchange and/or water status parameters, the values obtained from early morning and late afternoon measurements should be discarded (Marino et al., 2014).

The NDVI that is based on wavelengths from 670 to 690 nm (the index tends to saturate due to chlorophyll absorbance maximum) could be a suitable index for water stress detection only in certain species. Thus the index should be further evaluated in greenhouse crops, taking into account the leaf age and the LAI (as this type of NDVI gives quite satisfactory results in cases of low LAI). The $NDVI_{(490-620)}$ should be further analysed in order to prove whether it is an appropriate index for plant water stress detection, focussing on high and stable light conditions during the measurements, mostly in the blue region. If light signal is satisfactory, $NDVI_{(490-620)}$ can be more flexible in the environmental conditions of greenhouses and suitable for short-time scale irrigation. The $NDVI_{(800-620 \text{ or } 640)}$ can probably be used for water stress detection in greenhouse crop, especially with low LAI, while NDVI that includes the green spectral region varies its intensity as LAI increases. On the other hand, NDVI indices that include the spectrum at 740–800 nm are more influenced by leaf structure and less by LAI.

The indices mrNDVI and mrSRI identify the sensitivity of vegetation to small changes in foliage water content, a little faster than rNDVI. On the other hand, rNDVI identifies the plant water content sensitivity with less variability among replicates with leaves of the same level of water stress.

According to Aparicio et al. (2004), NDVI, SR and PRI were more effective during growth stages than WI, which was more effective during anthesis and maturity stages, during which, the first three indices seem to decrease, while WI increases. Moreover, some researchers believe that WI is not influenced by the relative shifts and the environmental conditions and is a more appropriate index for measuring reflectance at canopy level because the impact of leaf angle distribution on the relationship between the canopy reflectance and the canopy water content is minor (Aparicio et al., 2004; Clevers et al., 2008).

A summary of the advantages and disadvantages of the most commonly used reflectance indices for water stress assessment are given in Table 3.

VIS and the red edge spectrum could be used for either water or nutrient stress estimation. However, the nitrogen stress could be detected more rapidly in the blue and red spectrum due to the direct connection between nitrogen and chlorophyll contents. Thus, for nitrogen stress detection, reflectance indices that will include wavelengths at that spectrum area are proposed. However, in the case of leaf water stress detection, when the soil water content is low, the plant develops specific protection mechanisms. In that case, the plant exhibits a reduced transpiration rate in order to prevent the temperature increase, although the photosynthetic rate and the chlorophyll content remain stable for a lathe time interval.

Nevertheless, the full capabilities of these promising approaches are not yet entirely clear. Generally, a need to monitor the above indicators in real-time in all vegetation growth stages is observed. Also, there is a promising potential for combining information from a wide range of reflectance indices for the diagnosis and quantification of water or nutrient stress, during different time-scale periods and different environmental and vegetation stage conditions.

5. Concluding remarks and future perspectives

A possible future perspective could include the use of suitable reflectance indices for the real time detection of plant water stress for greenhouse crop requirements, from non-contact and destructive sensors. Unfortunately, the spectral properties of leaves are not only influenced by plant water status, but also by factors such as leaf age, sun versus shade leaf anatomy, leaf thickness, differences in leaf surface properties, soil background and non-water stress related variations in leaf angle, canopy structure and leaf area. These factors can introduce variations that reduce the correlation between water stress in greenhouse plants and leaf spectral response (Eitel et al., 2006).

The main effort of current research is to develop an index that will be not influenced by climatic conditions and sunlight that will give a more detailed information about plant water stress deficit, that will be used any time and in real time and finally that will be commercially available and cost-effective. r/mrNDVI or mrSRI seems to be the reflectance indices that could detect water stress level in greenhouse conditions but further analysis must be performed for different species and light conditions. In greenhouse cultivations, there is a need to detect plant reflectance changes in a level more than 60% of soil water content. However, reflectance indices measurements suffer from the background signal influence and the light intensity in the view of the remote sensor. The

Table 3 – Advantages and disadvantages of the most effective reflectance indices for water stress assessment.

Reflectance indexes	Advantages	Disadvantages
PRI	• Direct correlation with photosynthetic rate or canopy temperature and stomatal conductance • It is sensitive to water stress conditions through depoxidation state of xanthophylls • Closely efficiency at the leaf and canopy levels over a wide range of species	• Intensive to changes of different environmental condition • Indirect correlation with plant water content • Slow appearance of variability between control and water stressed plants, at least 3 days. It is dependent from the intensity of the leaf area and canopy structure
NDVI (800–680 or 640)	• Good indicator of nitrogen content, biomass, chlorophyll, leaf area index at the leaf and canopy level for different species • Good correlation to soil water content	• Slow appearance of variability between control and water stressed plants, at least 3 days • Poor to medium correlation with water treatment patterns at plant water content method • Saturated from the high LAI
NDVI (490–620)	• Good correlation to plant water content	• Variable of leaf age and grow maturity
rNDVI	• High correlation with soil moisture content and plant water content • Identifies small changes in foliage water content	• It must be studied more in case of heterogeneous species, illumination, canopy architecture and other parameters.
WI	• It is not influenced from the relative shifts and the environment condition • It starts to decrease with first water losses in proper species • Good correlation with PWC in simple leaf structure	• It may give differences among replicates with leaves at the same level of water stress • Include variation among species and different LAI at growth stages • It is influenced from the greenhouse covered condition (atmospheric water absorption and liquid water condense)
mrNDVI mrSRI	• High correlation with soil moisture content and plant water content • Captivity of small changes in canopy foliage water content in small time scale in more time scale requirements than rNDVI	• Plant variability among replicates with leaves at the same level of water stress
VOGREI	• Appears to be less influenced by differences in green leaf biomass, background conditions and light contamination	• Further study for the species variability and sample replicate stability

processing of reflectance measurements is the most important step for the acquisition of indices.

The normalised difference and ratio eliminate the background signal only in cases of a constant spectrum from one measurement to another. For this reason, the conventional reflectance indices are not capable of monitoring stable water deficit. Recently developed decision support systems that use information from one or the combination of several of the above mentioned spectral indices (Genc et al., 2011; Köksal, 2011; Loh, 2011; Ray et al., 2006; Zhou et al., 2011), have to be improved to optimise plant water stress detection. Also, for further studies, much work remains to be done to identify the change in composition of leaf pigments under water stress conditions, by combining the red and NIR regions based on existing or new reflectance index formation.

However, hyperspectral imaging of plant canopy reflectance can be a useful tool for water stress early detection, although the cost and the complexity are major disadvantages of hyperspectral techniques. Also, the calibration methods of optical sensors, especially the hyperspectral imaging system, reduce the wavelengths, noise and light errors. The performance of reflectance indices data can be improved by filtering the measurements form valid recording images. However, there are some parameters in the protocols of optical systems calibration methods in greenhouses, such as the light signal, that need to be further analysed to generate more stable data. Furthermore, the use of a stable light source is advisable for hyperspectral detection accuracy. The use of more stable light protocols is therefore necessary to generate comparative data in different greenhouse environment conditions.

The development of smart systems and technologies with automation and robotic applications can help improve the resource use efficiency and productivity in controlled environment agriculture systems. Autonomous systems with multi-sensor platforms moving around to sense the crop in a greenhouse system would aid to this effort. Additionally, plant monitoring requires more efforts in developing platforms to integrate multidimensional data (Bautista-Gallego et al., 2011) since plant interactions cannot be elucidated by a simple stepwise algorithm or a precise formula, particularly when the data set are complex, noisy, vague, uncompleted or formed by different kind of data.

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