Calibration Methodology of a Hyperspectral Imaging System for Greenhouse Plant Water Stress Estimation

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Abstract

Much progress has been made on optimizing plant water supply based on different methods for irrigation scheduling, in both open-field and greenhouse cultivations, such as real-time measurements of solar radiation and soil or substrate water content. However, only a limited number of methods use plant-based physiological indicators to detect plant water stress and adapt irrigation scheduling accordingly. In addition, even fewer indicators can be estimated by non-contact, remote sensors (RS) that do not affect plant development. Hyperspectral imaging could be an accurate remote way to detect plant water status, taking into account crop characteristics. In this work, a methodology of hyperspectral imaging calibration and acquisition is presented. The method uses the reflectance characteristics in hyperspectral bands from 400 to 1000 nm and incorporates the appropriate radiometric and geometric corrections. The basic statistical parameters of mean and standard deviation values are used to estimate spatial and spectral correlation of each band on the extracted areas/pixels of interest. Several statistical techniques are used for the selection of optimal features that will lead to the development of appropriate plant water stress indices that could be used for incipient water stress detection in optimal irrigation scheduling systems.

INTRODUCTION

Greenhouse irrigation management, especially in hydroponic systems, needs a series of short-time water applications (10-25 doses per day). Even though several methods are used to detect plant water deficit, only a few methods use plant-based physiological indicators. Katsoulas et al. (2006) stressed the need for the creation of a suitable method to control irrigation frequency and proposed a technique based on crop transpiration. However, that method implies the knowledge of a crop coefficient that varies for different planting periods.

Crop reflectance (Knipling, 1970), fluorescence (Norikane and Kurata, 2001) and thermal radiation transmittance (Jones and Schofield, 2008) are affected by plant water status. Several studies have attempted to detect and quantify water stress -through appropriate indices- using reflectance in the visible and the near infrared regions (Sellers, 1985; Peñuelas et al., 1993; Schlemmer et al., 2005). The use of a hyperspectral camera to identify plant reflectance variations related to leaf water deficit levels is a non-destructive and fast measurement method. Hyperspectral imaging technology could be used to study leaf reflectance changes caused by different water stress levels in more than one leaf, enhancing the reliability and sensitivity of plant water detection (Graeff and Claupein, 2007; Zhou et al., 2011).

The reflectance sensor collects such plant-based data from the spectrum, capturing the energy reflected and emitted by the plants, while this energy changes according to leaf chemical compounds and water content (Fig. 1). A typically healthy plant has a small pick in the green band, a small drop in the blue and red bands (due to chlorophyll absorption), a rising peak in the near infrared (NIR) band (due to scattering by air content in sponge cavities) and a falling peak in the middle infrared MIR band (due to water stored in thylakoids that absorbs more radiation at that spectrum). The plant reflectance signal varies according to water stress emergence and chemical compounds metabolics.

Until recently, the reflectance identity of the crop was defined by laboratory protocols and spectroradiometers that measured radiance reflectance coming from only a single point of the target. Even though this kind of sensors present low levels of equipment noise, they cannot give representative reflectance data of the canopy, due to leaf structure variability. Hyperpsectral imaging technology is capable of measuring reflectance in more than one leaves (or plants) and gives more reliable data for the canopy's reflectance identity. However, this optic technique includes a variety of equipment noises that should be taken into consideration before plant image acquisition. Different types of sensor noise include the detector dark current, the sensor temperature, the readout noise, the exposure shot noise and should eventually be removed with statistical techniques and special filters, using samples of known reflectance (Polder et al., 2003).

Even though this remote sensing technique has been successfully used for years in open field cultivations and relevant reflectance calculation models have been developed, it has not been extensively tested in the case of greenhouse crops. It has to be noted that open field methods cannot directly be applied in greenhouses due to difficulties arising mainly from shadows resulting from the greenhouse frame and equipment. The problems related to the greenhouse structure shadows or to other obstacles (like old leaves and soil background) could be eliminated by forming vegetation indices using the combination of data from two or more spectral bands (Jackson and Huete, 1991). According to Zakaluk and Sri Ranjan (2008), the most common forms of reflectance indices are the following: (1) reflectance ratios corresponding to the ratio of two spectral bands, which are referred to as "simple ratio" (SR) vegetation indices and (2) normalized difference (ND) vegetation indices, which are defined as ratios of the difference in reflectance between two spectral bands over the sum of the reflectance at the same bands.

Consequently, the aim of this work is to study the possibility of detecting plant water stress in greenhouses using a hyperspectral imaging methodology and furthermore, to study the effect of system settings on the reflectance measurements and the resulting plant water stress indices.

MATERIALS AND METHODS

The hyperspectral camera Imspec V10 (Spectral Imaging Ltd, Finland) was used, which operates in the visible and near infrared (VNIR) ranges of 400-1000 nm. It was used as a push broom line scan camera and provided full spectral information for each pixel. The hyperspectral camera was attached to a rotary scanning system, in which, scanning speed and angle were controlled. A spectral data acquisition software was used to set the operational parameters of the camera, to start data acquisition and to monitor on-going tasks. The camera's specifications and settings were: spectrograph: V10, spectral range: 400-1000 nm, spectral resolution (30 mm): 2.08 nm, spectral resolution peak: 435.8 nm (2.86 FWHM/nm), 696.5 nm (3.34 FWHM/nm), 912.3 nm (3.33 FWHM/nm), slit width: 8 mm, pixels in full frame: 1312 x 1024, exp. time range: 0.1-500 ms.

The camera system was placed on a moving cart, so that images of the vertical canopy axis could be obtained. The hyperspectral imaging system was calibrated inside a light-controlled growth chamber. Light intensity was controlled with high pressure sodium lamps, 600W each. The chamber included 24 lamps in total (6 lamps per light-intensity level) with a maximum light intensity of 240 W m^{-2}. For extra illumination of the target area (70 x 100 cm), four quartz-halogen illuminators (500 W each) were used to provide calibration wavelength from 400 to 900 nm. The optic system was placed at a distance of 1 m from the target (white panel or plant). A spectrally flat black surface was placed as a background, to ensure a constant field of view without any shadows.

The calibration of the hyperspectral imaging system requires geometric and radiometric calibration (Lawrence et al., 2003). Geometric calibration eliminates optical errors, such as curvature distortion of the spectral lines. The system was already geometrically calibrated by the supply company. Radiometric calibration includes the elimination of a variety of noise sources, such as photon noise, thermal noise, read out noise and quantisation noise. The proper number of lens aperture (f/) and exposure time (ms) ranges of the camera for the specific light signal conditions were evaluated, in order to achieve the most suitable readout values. The MATLAB software package (by MathWorks®) was used for image analysis. The acquired images were improved based on the above factors, by using the radiometric equation:

$$r = \frac{R - D_\lambda}{W_\lambda - D_\lambda} \quad (1)$$

where: r is the actual plant reflectance, R is the measurement of plant colour reflection, W_λ is the colour reflection of the white reference in the specific lighting conditions during measurements acquisition and D_λ is the black reference (Polder et al., 2003). Figure 2 shows the position of the hyperspectral imaging systemthat was used to eliminate light signal noise (white balance calibration), inside the growth chamber that simulates stable greenhouse conditions.

After the radiometric calibration, the instrument was ready to measure plant reflectance and exact color measurements of the leaf. Mainly, the reaction of plants reflectance identity was studied between the different time exposure values in order to evaluate the most effective reflectance indices for plant water stress detection based on greenhouse tomato (*Solanum lycopersicum*).

RESULTS

Images acquired with a hyperspectral camera contain noise from a variety of sources that are determined by the camera. Exposure time, frame rate and size of lens aperture are some of the camera's parameters that can be used to eliminate signal-to-noise errors and improve the image sharpness. Figure 3 shows the dark current estimation based on the digital number (i.e., captured light intensity) response to different exposure time and frame rate settings. As expected, dark current noise is proportional to exposure time values. As shown in the two scatter plots, it is confirmed that dark current noise is proportional to exposure time values (as the exposure time increases, the dark current noise increases too), while the dark current noise is decreased as the frame rate increases, with correlation coefficients of 0.99 and 0.88, respectively.

It was observed that the sensitivity of the CCD silicon detector is wavelength dependent (Fig. 5). Thus, the light signal showed low sensitivity in the blue part of the spectrum (high digital number values) and high sensitivity in the red and NIR parts (low digital number values). The lowest values of noise were observed when the lens aperture was at f/1.4 and the maximum values were observed at f/11. Another interesting point is the dependency of the noise on the sensor temperature. Figure 6 shows the relation between sensor temperature and black level noise expressed by digital numbers. From this graph, it is evident that black level noise increases when the sensor temperature increases, following a 2^{nd} degree polynomial trend line.

Before the acquisition of the hyperspectral images for the detection of water stress in plants, the readout digital numbers of illumination in white reference for different exposure times were recorded. It was observed that the light signal of halogen lamps had a peak between 700 and 800 nm and tended to decrease at the left and right sides of the spectrum, as a result of the low values of light signal in the blue and infrared spectrum. The sodium lamps improved the light signal in the green and red spectrum, but the light signal in the blue spectrum remained low (Fig. 6).

After all these procedures, the camera was used to measure plant reflectance and exact leaf color measurements. In addition, the speed of the scanner had to be determined in order to avoid the distortion of image size and spatial resolution. The experiments showed that the images were clearer when the exposure time was 130 ms and the speed of the scanner was at 0.16 mm/s with a frame rate of 500 Hz and a frame resolution of 800. The typical spectral signature of a healthy tomato plant is shown in Fig. 7, for two different exposure times. The spectral signature of tomato showed differences between the two exposure times tested, due to the amount of captured light intensity through the slit. These variations will be further minimized in the analysis process, using various spectral indices. The combination of more than one spectral region reduces additive and multiplicative errors associated with light conditions. Some of the most effective spectral indices for plant water stress assessment are NDVI $((R_{680}-R_{800})/(R_{680}+R_{800}))$, rNDVI $((R_{750}-R_{705})/(R_{750}+R_{705}))$, mrNDVI $((R_{750}-R_{705})/(R_{750}+R_{705}-2*R_{445}))$ and PRI $((R_{531}-R_{570}/R_{531}+R_{570}))$. NDVI and rNDVI indices use steeply sloped regions of red edge and (NIR) spectrum, which are more sensitive to smaller changes in vegetation physiology and are more suitable for hyperspectral sensors. NDVI and rNDVI showed the same index values between the different exposure time curves. The value of NDVI was 0.86 when the exposure time of the camera was at 140 ms, and 0.87 when the exposure time was at 130 ms.The values of rNDVI were 0.58 and 0.60, when the camera’s exposure time was at 140 and 130 ms, respectively. mrNDVI also gave stable index values between the two curves, at 0.68 and 0.66, respectively. On the other hand, PRI seems to be more sensitive to light intensity and to environmental conditions, with decreasing values from 0.07 to 0.04 when the exposure time changed from 140 ms to 130 ms.

$NDVI_{800}$ and rNDVI not only eliminated light signal noise, but they also showed good correlation with substrate water content, with R^2 values of 0.85 and 0.83, respectively. Figure 8 shows a reduction of $NDVI_{800}$ and rNDVIvalues as a function of substrate moisture content decrease. However these indices depend on the value of the leaf area index (LAI) of the cultivation (they are saturated in high LAI values) and further research is required (Asner, 1998; Mänd et al., 2010). Other indices with good correlation with substrate moisture content were mrNDVI and mrSRI, with R^2 values of 0.75 and 0.80, respectively. These indices also eliminate light signal noise and they are less influenced in high LAI values. However, mrNDVI and mrSRI vary greatly even among the plant of same specie and age due to the impact of the leaf structure. PRI showed medium correlation with soil moisture content, due to the low light intensity emitted by the sodium lamps in the blue and green spectral regions. Moreover, in greenhouse conditionswhere irrigation management includes at least 8-10 applications a day, PRI will not be able to detect short-time leaf water content variations, as it takes at least 3 days for actual plant water stress detection (Thenot et al., 2002, Sun et al., 2008; Tsirogiannis et al., 2010). PRI is more suitable for photochemical rate, de-oxidation cycle and crop canopy detection (Gammon et al., 1992; Suarez et al., 2009, Sarlikioti et al., 2010). The combination of PRI with fluorescence and canopy temperature, could lead to faster and thus more useful plant water stress detection.

CONCLUSIONS

In this work, a hyperspectral imaging system was developed, to perform acquisition of hyperspectral imaging data and to estimate the optimal characteristic wavelength in order to develop indices for greenhouse plant water stress detection. Different sources of hyperspectral camera's noise were investigated and the reflectance spectrum of greenhouse tomato was measured. Exposure time and lens aperture values were the camera's parameters that influenced the levels of dark current noise, which depended on light intensity. In addition, the dark noise current was increased by the increase of sensor temperature, following a 2^{nd} degree polynomial. It was validated that NDVI, rNDVI and mrNDVI indices are more sensitive to smaller changes in vegetation physiology and are more suitable for hyperspectral sensors. PRI is more sensitive to light intensity and environmental conditions.

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Figures

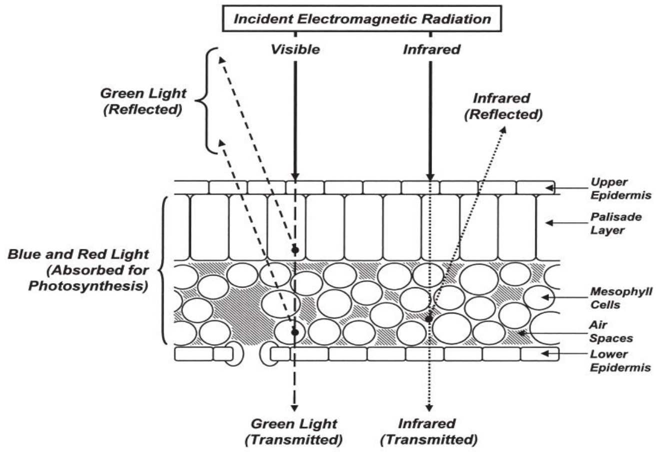

Fig. 1. Influence of electromagnetic spectrum based on the structure of a typical plant leaf. Diagram from Summy et al. (2003).

Fig. 2. Hyperspectral imaging system in a growth chamber.

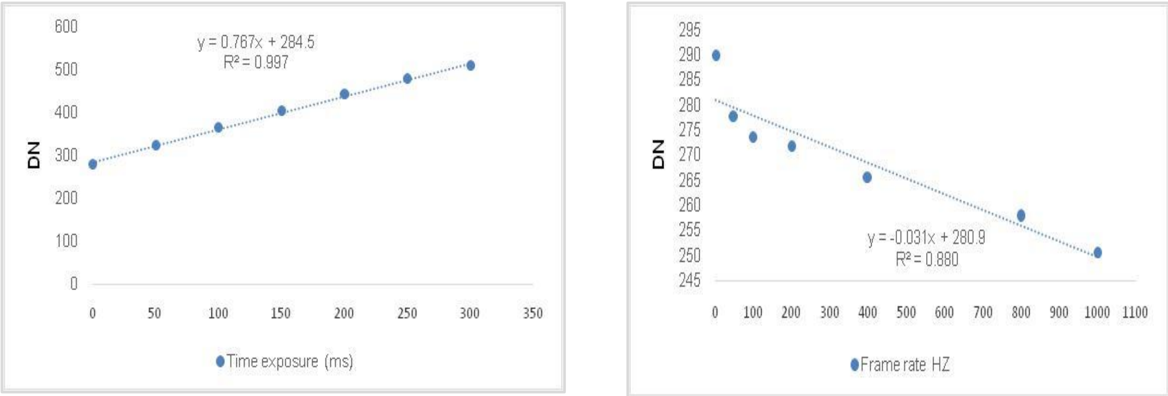

Fig. 3. Dark current noise estimation based on digital number response to different exposure times (left) and frame rates (right).

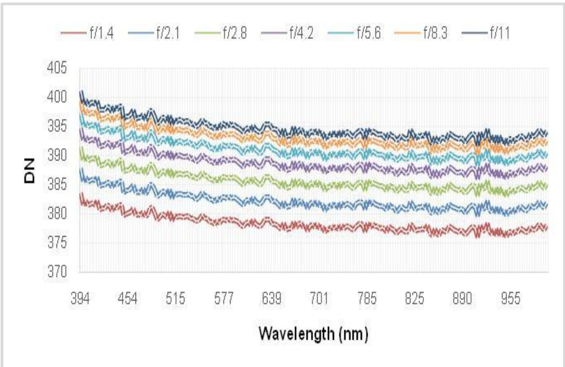

Fig. 4. Dark current noise development based on digital numbers response to different numbers of lens aperture.

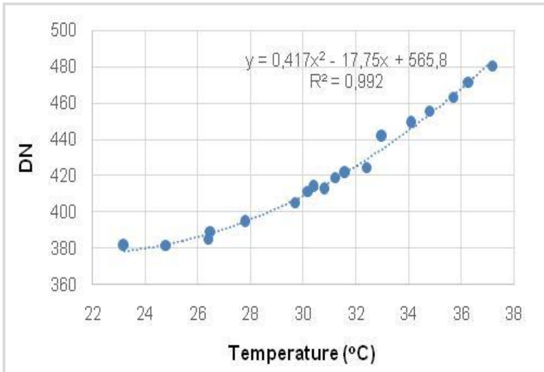

Fig. 5. Dark current development based on digital number response to different sensor temperatures.

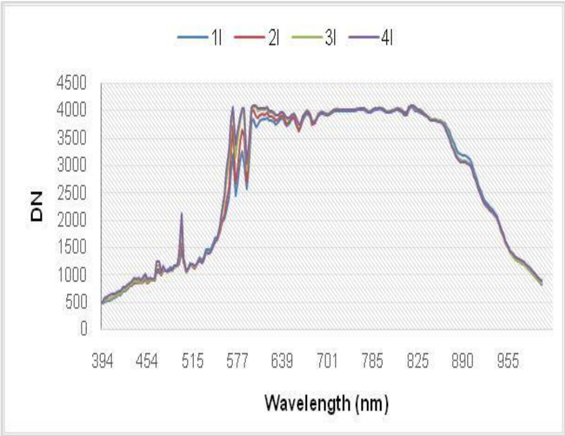

Fig. 6. Illumination reflectance for four different light levels (6 sodium lamps/level) at the same time, with 4 halogen lamps (Exposure time at 130 ms and lens aperture at f/2.1).

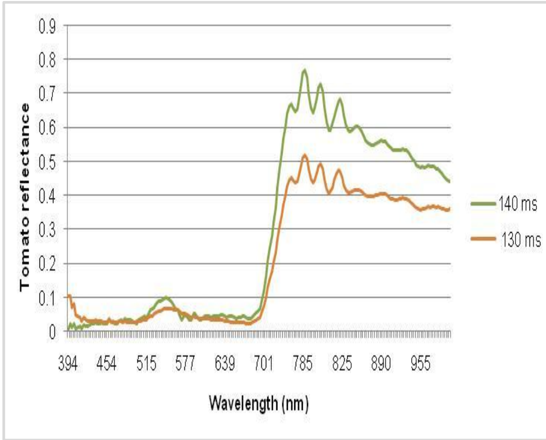

Fig. 7. Tomato reflectance based on the radiometric calibration method.

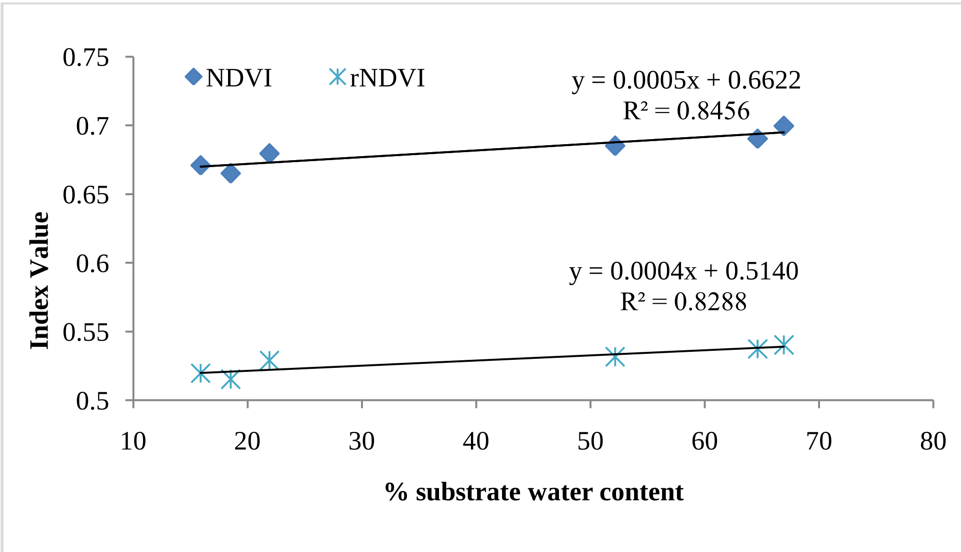

Fig. 8. $NDVI_{800}$ and rNDVI responses to substrate moisture content.