Leaf water status assessment of olive by vegetation indices

Pedro Marques[1,2], Luís Canas[1], Eduarda Mateus[1], Anabela Fernandes-Silva[1,2]

[1]University of Trás-os-Montes e Alto Douro, Quinta dos Prados, 5000-801 Vila Real, Portugal; pedro.marques@utad.pt (P.M.); al62695@utad.eu; al62633@utad.eu; anaaf@utad.pt

[2]Centre for Research and Technology of Agro-Environment and Biological Sciences, University of Trás-os-Montes e Alto Douro, Quinta dos Prados, 5000-801 Vila Real, Portugal

Abstract

Information of plant water status, such as Relative Water Content (RWC) and Leaf Water Potential (LWP), during crop development are important for optimizing crop production and irrigation management. However, these methods are traditionally estimated by destructive and time-consuming in situ.

In the past decades, many relationships between spectral data from remote sensing observations and various biophysical and physiological crops parameters have been proposed. A common and widely used approach to analyse crop spectral signatures acquired from remote sensing platforms is based on the extraction of Vegetation Indices (VIs).

This study aims to assess the relationship between VIs with RWC and LWP in a drip irrigated olive orchard located in Alfândega da Fé, Portugal. Three irrigation strategies were implemented: well-watered (WI), sustained deficit irrigation (SDI) and farmer-managed irrigation (FMI). Spectral measurements (400 to 1000 nm) at leaf level were obtained with a spectroradiometer and the corresponding RWC and LWP were acquired in situ. A total of 23 VIs most commonly used in olive-growing were used and a good agreement were found. Transformed Chlorophyll Absorption Reflectance Index (TCARI) and TCARI divided by Optimized Soil Adjusted Vegetation Index (OSAVI) were the VIs with the higher correlation with LWP and RWC, R^2=0.71 and R^2=0.77, respectively.

Thus, the use of VIs poses as a good alternative for the traditional destructives methods for estimating RWC and LWP.

Keywords: Cv. Cobrançosa, irrigation, leaf reflectance, remote sensing, relative water content, leaf water potential

1. Introduction

Water is a major factor that limits plant production being an essential resource to ensure food supply for an increasing human population. Nowadays, agriculture consumes by irrigation about 70% of fresh water worldwide [1]. Thus, in a global warming scenario, irrigation management is important for optimization of water use in agriculture [2] and adoption of deficit irrigation (DI)strategies allows save water with a minimum impact in reduction of productivity being suitable for regions where water is scarce and improving water productivity is a goal [3].

Scheduling DI requires knowledge of soil water capacity, plant water needs and suitable and reliable water stress indicators [4]. Relative Water Content (RWC) [5] and Leaf Water Potential (LWP, Ψ) [6] are two methods wildly used to evaluate plant water status. The former is a sensitive indicator of water stress, that quickly responds to environmental conditions such as temperature, light, humidity, and water supply [5]. This indicator correlates closely with a plant's physiological activities and soil water status and is a reliable trait, e.g., for screening for drought tolerance of different genotypes [6, 7]. It is largely demonstrated that either predawn and midday LWP are variables considered reliable as water status indicators for irrigation scheduling purposes and are mandatory in research studies [8,9]. For example, for olive trees [7] reported a abruptly decline in both predawn LWP and RWC for available soil water content (AWC) below 30%, reaching minimum values of -6.1 MPa and 59 %, respectively, for AWC≈ 0. However, these two types of measurements are destructive as it is necessary to cut off the branches and leaves of plants and cannot be intensively performed [10,11].

Thus, it is necessary to create new non-destructively methods able to estimate plants water status that provides information related with RWC and LWP. This way, with the advancement of technology, authors suggested using spectral information of leaves and calculating Vegetation Indices (Vis) to estimate these plant water stress indicators. VIs consists in arithmetic operations applied at different spectral reflectance's in order to obtain a single value related to the vegetation [12]. They can be used to estimate: leaf area index, biomass, stomatal conductance, water stress indicators, chlorophyll, xanthophyll, among others parameters [13,14]. [10] used a near infrared (NIR) spectroscopy to estimate LWP in grapevines, and they founded a good relationship. Photochemical Reflectance Index (PRI) were used to distinguish between well-watered and stressed plants of *Chenopodium quinoa* Willd [11]. The authors reported that PRI can discriminate between two different water regimes in plants and can be considered to be a reliable water-stress index. Also, they stated that it may provide a non-destructive, low cost, non-contact optical tool for the assessment of drought intensity.

Therefore, the aim of this study was to evaluate the performance of different vegetation indices to estimate the water status indicators of RWC and LWP, in order to replace these destructive methods with indirect and non-destructive methods in olive trees.

2. Material and methods

In this section it is described the olive orchard studied and its irrigation strategies, the methodology used for field data acquisition and the acquisition of spectral reflectance data. Finally, the list of VIs used is described with the corresponding expression. All data was acquired in early autumn of 2019.

2.1 Study area description

The studied is carried out in a commercial olive orchard (*Olea europaea* L. cv "Cobrançosa") located at Vilariça Valley, near Alfândega da Fé, Portugal (Vilarelhos: 41.33º N, 7.04º W; 240 m altitude) a typical olive growing area of Northeast Portugal. The climate is typically Mediterranean with an average annual rainfall of 520 mm concentrated mainly from autumn to spring. Olive orchard area is about 1.6 ha with olive tree spacing 6 m x 6m apart and was submitted to three irrigation regimes (Figure 1): Well-Watered (WI), sustained deficit irrigation (SDI) and farmer-managed irrigation (FMI). Well-Watered regime was divided in two water treatments, while one was irrigated with an equivalent amount of water to supply 100% estimated crop water requirements (WR), the other supplied 120% of WR. Sustained deficit irrigation regimes also include two treatments, supplying 60% and 30% of WR. To estimate the crop water requirements, the approach described in [15] was followed for this orchard.

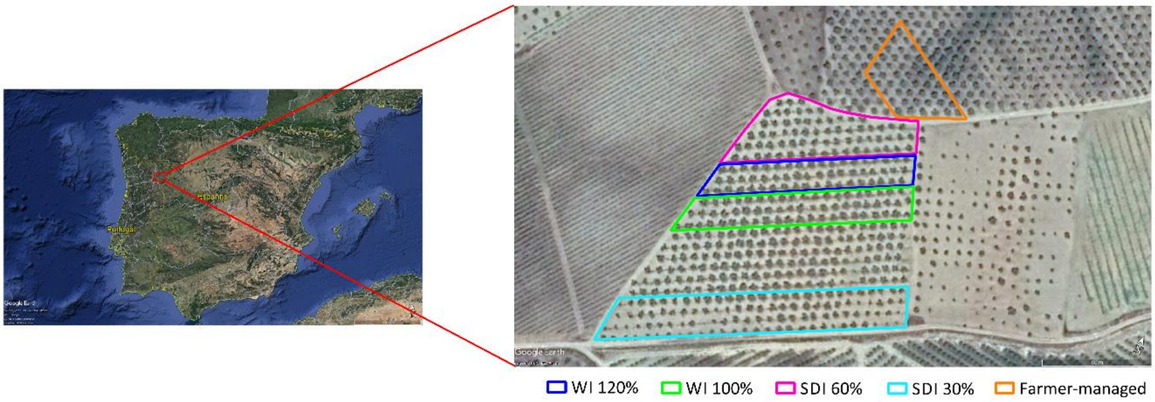

Figure 1 Irrigation treatments in a commercial olive orchard of cv. Cobrançosa, located at Vilariça Valley (Vilarelhos: 41.33º N, 7.04º W; 240 m altitude).

2.2 Field data

For field data acquisition five olive trees of each irrigation strategy were randomly selected. Measurements of midday shoot water potential (Ψ), were used to evaluate tree water status. A young leafy shoot per tree was collected, from a sunny position at the crown, from 5 replicate trees per treatment. After cutting, the small leafy shoot was immediately enclosed in a plastic bag to avoid any loss of water and quickly placed into the pressure chamber (model PMS 1000, Oregon, Corvallis, USA).

Concerning RWC measurements, for each selected tree, three leaves of the year were removed and placed in a glass tube, which was sealed, placed in a cold container and transported to the laboratory. The sample was weighed on a precision balance to obtain fresh mass (FM). Afterwards, cold distilled water was placed into the glass and after 48 h in the dark and stored at 4 °C the leaves were again weighed to obtain the Turgid Mass (TM). Finally, the leaves were placed in a ventilated oven-drying at approximately 70ºC for 48 hours and weighed again – Dry Mass (DM). The RWC were calculated as shown in the Eq. (1).

$$RWC = 100 \times \frac{(FM-DM)}{(TM-DM)} \quad (1)$$

2.3 Spectral reflectance data and vegetation indices

From each selected tree, three leaves were randomly cut, placed in sealed bags and transported to the laboratory in a refrigerate container. They were then analysed in the laboratory using a spectoradiometer device (HR2000, OceanOptics, UK), with an wavelength range between 200 and 1100 nm (Figure 2).

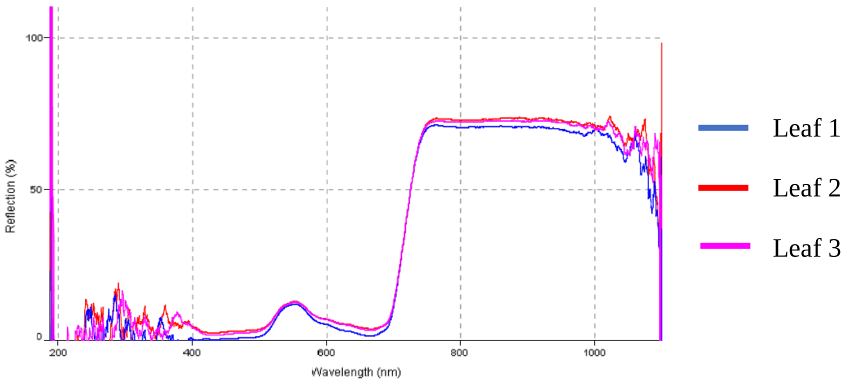

Figure 2. Example of reflectance of three leaves

Afterwards, with the spectral reflectance extracted from the leaves, a list of 23 different Vegetation Indices (VIs) was calculated in order to study their relationship with data collected from the field to assess leaf water status (RWC and LWC). Table 1 shows the VIs that are the most common used in olive trees [16–18].

Table 1. List of vegetation indices

Name	Formula	Name	Formula
BGI 1	$\frac{R400}{R550}$	**OSAVI**	$(1+0.16)\times\left(\frac{(R800-R670)}{(R800+R670+0.16)}\right)$
BGI 2	$\frac{R450}{R550}$	**PRI 515**	$\frac{R515-R531}{R515+R531}$
EVI	$2.5\times\frac{R800-R670}{(R800+6\times R670-7.5\times R450)+1}$	**PRI 570**	$\frac{R570-R531}{R571+R531}$
GI	$\frac{R554}{R677}$	**RDVI**	$\frac{R800-R670}{\sqrt{R800+R670}}$
GNDVI	$\frac{R800-R550}{R800+R550}$	**RE 750/710**	$\frac{R750}{R710}$
MCARI 1	$((R700-R670)-0.2\times(R700-R550))\times\left(\frac{R700}{R670}\right)$	**SRWI**	$\frac{R860}{R1000}$
MCARI 2	$1.5\times\frac{2.5\times(R800-R670)-1.3\times(R800-R550)}{\sqrt{(2\times R800+1)^2-(6\times R800-5\times\sqrt{R670})-0.5}}$	**TCARI**	$3\times\left((R700-R670)-0.2\times(R700-R550)\times\frac{R700}{R670}\right)$
MSI	$\frac{R1100}{R820}$	**TCARI/ OSAVI**	$\frac{3\times\left((R700-R670)-0.2\times(R700-R550)\times\frac{R700}{R670}\right)}{(1+0.16)\times\left(\frac{(R800-R670)}{(R800+R670+0.16)}\right)}$
MTVI 1	$1.2\times(1.2\times(R800-R550)-2.5\times(R670-R550))$	**TVI**	$0.5\times(120\times(R750-R550)-200\times(R670-R550))$
NDGI	$\frac{R550-R670}{R550+R670}$	**VOG**	$\frac{R740}{R720}$
NDVI	$\frac{R800-R670}{R800+R670}$	**WI**	$\frac{R900}{R970}$

R: Reflectance

3. Results and discussion

In this section the results are presented and correlated with field measurements. For the correlation purposes, the coefficient of determination R^2 was used to measure the proportion of variability between the values obtained with the VIs calculated through the spectroradiometer with the water status indicators measured in the field.

Regarding the RWC, in Figure 3 it is possible to verify that, on average, in WI (120% and 100%) and FMI, values are of approximately 88% (± 3), while SDI 60% and SDI 30% obtained 76% (± 3) and 62% (± 4), respectively, a reduction of 14% and 30%, thus indicating that WI and FMI had more water on the leaf. Concerning the LWP, it is also possible to verify that WI (120% and 100%) and FMI had higher values (LWP> -3.0 MPa, ±0.2) than SDI 60% and SDI 30% with -5.0 MPa (± 0.3) and -5.9 MPa (± 0.2) respectively, showing that plant is in sever water stress conditions, due to the cumulative effect of water deficit and accumulation of drought conditions in the early autumn. With a similar behaviour, the vegetation index TCARI indicated significant differences between these irrigation strategies. While WI (120% and 100%) and FMI had values of approximately of 15.9 (± 1.5), the SDI 60% and SDI 30% had higher values of 23.5 (±2.6) and 30.7 (±4.1) respectively, an increase of 33% and 49%. As this VI is related with the amount of chlorophyll on the leaf [19], where higher values means less chlorophyll, it shows that WI and FMI had more chlorophyll than SDI irrigation strategies.

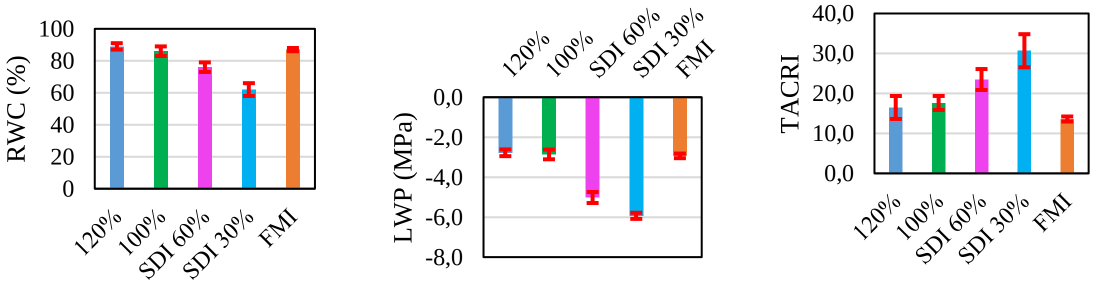

Figure 3. Average values of the five irrigation strategies. On the left the RWC values, on the centre the LWP values and, on the right, the vegetation index TCARI values.

Following the calculation of the 23 VIs shown in Table 1, these were correlated with the RWC and LWP field measurements through a linear regression line. Concerning the correlations with the RWC, the VIs TCARI, TCARI/OSAVI, TVI, MTVI 1 and GNDVI were the VIs with the best performance with $R^2 > 0.70$. However the vegetation index TCARI was the VI with the higher performance $R^2 = 0.77$ (Figure 4). Regarding the relationship between LWP, the VIs TCARI/OSAVI, TVI and MTVI 1 were the VIs with the best performance $R^2 > 0.70$ ($P<0.001$), being the vegetation index TCARI/OSAVI (Figure 4) the best one with R^2 = racio 0.71 ($P<0.001$)

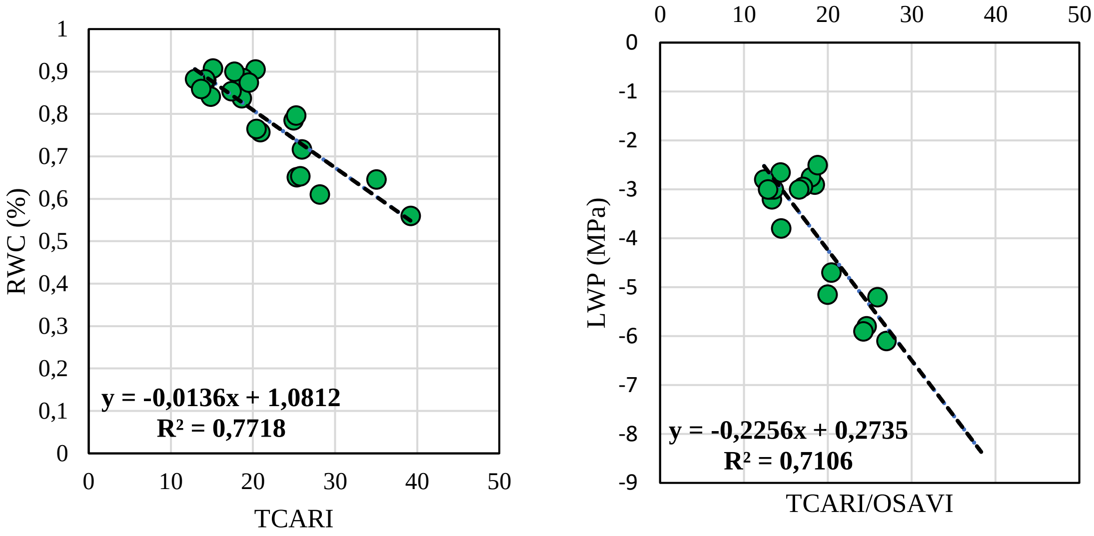

Figure 4. Results of the VIs with best performance. On the left the relationship with relative water content (RWC) and Transformed Chlorophyll Absorption Reflectance Index (TCARI) and on the right the relationship between the racio of Transformed Chlorophyll Absorption Reflectance Index and Optimized Soil -adjust Vegetation Index (TCARI/OSAVI) and leaf water potential (LWP).

The vegetation indices mentioned above consisted of the best performing indices, standing out from the others, since they are directly related to the chlorophyll in the leaf, which varies according to the amount of water available in the plant. In addition, GNDVI also had good correlations with RWC, since this index is directly related to the greenness of the leaf [20], which appears brighter green when well hydrated.

4. Conclusion

In this work, several correlations were made between vegetation indices and plant water indicators, in this case, RWC and LWP. For this, 23 vegetation indices were selected, which are the most used in the area of olive growing. It was possible to conclude that the chlorophyll and leaf greenness indices were the best performing indices. This is because the amount of water available on the plant significantly changes these values. Among them, the TCARI index showed the best performance when correlated with the RWC with R^2=0.77. On the other hand, in correlation with the LWP, the TCARI / OSAVI index corresponded to the index with the best performance with $R^2 = 0.71$.

Thus, VIs poses as a good alternative to the traditional methods to estimate water indicators in olive trees, being non-destructive, fast and effective.

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