On-the-go NIR spectroscopy and thermal imaging for assessing and mapping vineyard water status in precision viticulture

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Abstract. *New proximal sensing technologies are desirable in viticulture to assess and map vineyard spatial variability. Towards this end, high-spatial resolution information can be obtained using novel, non-invasive sensors on-the-go. In order to improve yield, grape quality and water management, the vineyard water status should be determined. The goal of this work was to assess and map vineyard water status using two different proximal sensing technologies on-the-go: near infrared (NIR) reflectance spectroscopy and thermal imaging. On-the-go spectral and thermal measurements were acquired at solar noon, on east side of the canopy in a Tempranillo (Vitis vinifera L.) commercial vineyard. A spectrometer (1100-2100 nm) and thermal camera operating at 0.30 m and 1.20 m respectively from the canopy were mounted on a ATV which moved at 5 km/h. Midday stem water potential (Ψ_s) was used as reference method. Spectral, thermal and physiological measurements were acquired over several dates from July to September, in seasons 2015 and 2016. Partial least squares (PLS) was used as the algorithm for the training of the water stress spectral prediction models. In the cross- validation, all determination coefficients (R^2) were above the 0.89 marks for Ψ_s. Moreover, canopy temperature and the crop water stress index (CWSI) were correlated to stem water potential (Ψ_s), with a R^2 value of 0.79. Vineyard water status was mapped using both near infrared reflectance spectroscopy and thermal imaging technologies and enabled the identification and delineation of zones with homogeneous grapevine water status to steer precise and optimized irrigation schedules in the context of precision and sustainable viticulture. These results suggest that both near infrared reflectance spectroscopy and thermal imaging can be used to non-destructively assess and map the vine water status in commercial vineyards. In conclusions, both new sensing proximal technologies show the potential applicability for assessing and mapping of vineyard water status in precision viticulture.*

Keywords. *new technologies, proximal sensing, stem water potential, CWSI*

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Introduction

Water is a key resource in viticulture. Water status affects vegetative growth and yield in grapevines, as well as grape and wine composition. New technologies are desirable in viticulture to assess vineyard water status and to improve irrigation management. Implementation of precision irrigation systems could contribute to saving water and to optimizing the impact on vine growth, yield and grape quality. Greater precision in irrigation can be obtained using plant-based sensing technologies (Jones, 2004). Most of these tools can monitor only a single plant at a time in the field and/or are time-consuming; therefore, new non-invasive proximal or remote technologies are needed to detect and map vineyard water status. In precision viticulture the usefulness and convenience of high-spatial resolution information provided to determine plant water status zones within-vineyards was suggested by several authors (Acevedo-Opazo et al., 2010; Baluja et al 2012; Cohen et al., 2016).

Canopy temperature has been recognized as an indicator of plant water status (Costa et al., 2010, 2013; Jones 1999, 2004). In fact, canopy temperature has been used as a tool for irrigation scheduling (Cohen et al., 2005, 2016; Meron et al., 2010). Thermal stress indices, such as the Crop Water Stress Index (CWSI) (Idso et al., 1981) and the Conductance index (Ig) (Jones et al., 2002) have been developed to assess crop water status, reducing the impact of environmental fluctuations. Recent studies have also shown the effectiveness of these canopy temperature based indices computed from high-resolution imagery acquired either by hand-held thermal cameras (Pou et al 2014; Grant et al., 2016) or mounted on unmanned aerial vehicles (Baluja et al., 2012; Bellvert et al., 2014, 2015; Cohen et al. 2017). A vineyard is typically a discontinuous crop, as vines are planted in rows, trained to vertically shoot positioned trellis system in most grapegrowing regions worldwide. Proximal thermal imaging could be taken on-the-go for monitoring vineyard water status and characterizing the spatial variability in the commercial vineyards (Gutierrez et al., 2018).

Near-infrared (NIR) spectroscopy is a powerful technology that provides a non-destructive analytical method. Non-destructive remote spectroscopy has enabled the definition of spectral indices from the combination of specific wavelengths, that are sensitive to changes in plant water status (Rodriguez-Perez et al., 2007). However, the use of NIR spectroscopy for the assessment of plant water status has not been extensively addressed. Likewise, estimation of grapevine water status based on NIR spectroscopy has been recently reported (Diago et al., 2017; 2018; Fernandez-Novales et al., 2018). Nevertheless, it is desirable the implementation of non-invasive NIR technology on-the-go to assessing and mapping the water status in commercial vineyards.

The goal of this work was to assess and map the water status of a commercial vineyard using two different proximal sensing technologies on-the-go: near infrared (NIR) reflectance spectroscopy and thermal imaging.

Materials and Methods

The field experiment was conducted in a commercial vineyard located in Tudelilla, La Rioja, Spain over two consecutive seasons from June to end of September 2015 and from July to August 2016. The vineyard was planted in 2002 with grapevines of (*Vitis vinifera* L.) Tempranillo (Clone 776), grafted on rootstock R-110. The vines were trained to a vertically shoot-positioned (VSP) trellis system on a double-cordon Royat. Vine spacing was 2.60 m between rows and 1.20 m in the row in a north-south orientation.

With the aim of creating a considerable variability of grapevine water status, a completely randomized block design (Hinkelmann and Kempthorne, 2007) with four blocks and three different water regimes was set, from no irrigation to full irrigation. This made up a total of 12 treatment replicates in three different vine rows. Each treatment replicate comprised 25 plants.

Midday stem water potential (ψ_s) was used as the reference indicator of the plant water status and it was measured around solar noon, (between 14:00 – 15:00 GMT+1). For each treatment replicate, the first five and last five plants were excluded, in order to avoid edge effects. The plants monitored were the 15 middle ones in each field replicate. These were sorted into three groups (five vines per group) and from each group a random one was marked. One adult leaf of the mid-upper part of the canopy was selected per vine and its stem water potential measured using a Schölander pressure bomb (Model 600, PMS Instruments Co., Albany, USA). Prior to the Ψ_s measurement, the selected leaves were covered with aluminum foil to drive them into dark adaptation for one hour.

NIR spectroscopy measurements

On-the-go spectral measurements were also acquired at solar noon (between 14:00 – 15:00 GMT+1) on five different days from June to September 2015. A NIR spectrometer (PSS 2120, Polytec GmbH, Waldbronn, Germany) working in the 1100-2100 nm spectral range, at a 4 nm resolution and 28 Hz of acquisition rate was used. The instrumentation was mounted to and carried on an all-terrain vehicle (ATV) (Trail Boss 330, Polaris Industries, Minnesota, USA), aiming to the left and capable of making spectral acquisitions controlled by a physical trigger while the vehicle was in motion (Fig 1A). The sensor head was installed at a height of 0.95 m from the ground, in order to cover the densest part of the vineyard's canopy (Fig 1B and 1C). Spectral measurements of the east side of the canopy were carried out contactless (at 25 to 30 cm from the canopy), from a moving vehicle moving at a speed of 5 km/h.

Fig 1. (A) General display of the all-terrain vehicle mounting thermal imaging and NIR sensing technologies for assessing vineyard water status. (B) Detail of the NIR head sensor. (C) Industrial computer, control tablet and NIR processing unit and head sensor. (D) Detail of the thermal camera. (E) Industrial computer and control tablet for the thermal camera.

Chemometric analysis was performed with algorithms programmed in MATLAB (version 8.5.0, The Mathworks Inc., Natick, MA, USA). PLS_Toolbox (version 8.1, Eigenvector Research, Inc., Manson, WA, USA) was used for principal component analysis (PCA) and partial least square regression (PLS).

After removal of spectral and reference outliers, the remaining samples were divided into two independent datasets: calibration dataset (comprising 80% of total data), and external data set (involving the remaining 20% of initial data) for mapping purposes.

As spectral pre-treatments, the Standard Normal Variate (SNV) plus Detrending (DT) (Barnes et al., 1989) procedure was used to remove the multiplicative interferences of scatter. In addition to a first or second derivative mathematical treatment, different window-wise filtering was applied. Partial Least Square (PLS) regression was tested for the prediction of Ψ_s using the on-the-go spectra acquired from the east side of the canopy. To prevent over-fitting, the assessment of the calibration model was performed by a six-fold cross-validation. In this method, the set of calibration samples was divided into ten groups, using one of them to check the results (prediction) and the remaining (nine groups) to build the calibration model. The model was repeated as many times as groups were (ten in total), in such a way that all the samples were used in both the calibration and prediction sets. The following statistics were used to select the most adequate models: determination coefficient of calibration (R^2_c), cross-validation (R^2_{cv}), and the root mean square error of calibration (RMSEC), cross-validation (RMSECV) and the number of latent variables (LVs).

Thermal imaging measurements

On-the-go thermal imaging was performed at solar noon (between 14:00 – 15:00 GMT+1) on two different days during summer 2016. A thermal camera (FLIR A35, FLIR® Systems, Inc., Bilerica, MA, USA) was used. The device was mounted on the same all-terrain vehicle (ATV) (Trail Boss 330, Polaris Industries, Minnesota, USA) used for NIR measurement (Fig 1A) and focused to the left at a distance from the canopy of approximately 1.2 m and with 48° × 39° horizontal and vertical field of views (FOV), respectively (Fig 1A). This distance and FOVs provided images covering canopy scenes of 1.07 m horizontally and 0.85 m vertically, approximately (Fig1D and 1E). Acquisition of the thermal images, at 60 frames per seconds (FPS), was performed in the east side of the canopy at an average speed of 5 km/h. Lower and upper boundary temperatures (T_{wet} and T_{dry}, respectively) were acquired using two artificial leaves (Evaposensor, Skye Instruments Ltd, UK): a wet reference (artificial leaf covered with a black cotton wick and receiving continuous water absorption) and a dry reference (dry artificial leaf).

Thermal images were not processed in their full dimensions to avoid the influence of other than canopy elements. A constant, automated crop out was performed to all the frames before their analysis. To remove large portions of sky, 35 pixels at the top were discarded, while the influence of soil and fruiting zone was prevented by removing 86 pixels at the bottom of the thermal images. Hence, only the middle section was taken into account in the analysis, named region of interest (ROI). While the total image resolution was 320×256 pixels, the ROI covered a total of 320×135 pixels (1.07×0.45 m of the canopy), a 52.7% of the original area. From the ROI, a segmentation process was carried out by picking only those pixels whose temperature values ranged between T_{wet} and T_{dry}, and afterwards the average temperature (T_{canopy}) was computed. Additionally, from the ROI, Crop Water Stress Index was calculated as follows:

$$CWSI = \frac{T_{canopy} - T_{wet}}{T_{dry} - T_{wet}} \tag{1}$$

Correlation analyses between the two thermal indices and Ψ_s were carried out.

Mapping

Maps of the predicted values of ψ_s in the monitored vineyard plots using the NIR spectroscopy and thermography models were built using a multilevel b-spline interpolation with QGIS 2.18 (Free Software Foundation, Boston, MA, USA).

Results and Discussion

A wide range of plant water status, from non-stress to severe water stress, as shown by the values of ψ_s was found varying from -0.76 to -2.20 MPa in season 2015 (Table 1). The best models obtained for ψ_s estimation were selected by statistical criteria, choosing those that presented the lowest value of SECV (0.157 MPa) and highest values of R^2_{cv} (0.89). Moreover, a reduced number of PLS factors was used for the development of the cross validation model on the east side of the canopy under field conditions.

Table 1: Calibration and cross-validation statistics of the best model obtained to predict stem water potential (Ψ_s, expressed in MPa) on east side of the vineyard canopy under field conditions from on-the-go NIR spectroscopy.

Season		Calibration								Cross validation	
	Spectral pre-processing	n	Min	Max	Mean	SD	LV	R^2_c	RMSEC	R^2_{cv}	RMSECV
2015	SNV + D1W15	126	-2.20	-0.76	-1.28	0.48	8	0.93	0.131	0.89	0.157

SNV: standard normal variate. D1W15: Savitzky-Golay filter with first-grade derivative, window size of 15. n: number of samples. Min: minimum. Max: Maximum. SD: standard deviation. LV: number of latent variables of the PLS model. RMSEC: root mean square error of calibration (MPa). R^2_c: determination coefficient of calibration. RMSECV: root mean square error of cross-validation (MPa). R^2_{cv}: determination coefficient of cross-validation.

In the case of thermal imaging, a wide variability in the plant water status was also observed in season 2016. Likewise, Ψ_s ranged between -1.87 to -0.87 MPa (Table 2). The average value was found as -1.28 MPa with a standard deviation of 0.236 MPa. The processing of the thermal images, along with the computation of the CWSI values, cast a determination coefficient of 0.79 when correlating the thermal index with the Ψ_s.

Table 2: Correlation statistics between Crop Water Stress Index (CWSI) and stem water potential (Ψ_s, expressed in MPa) on east side of the vineyard canopy under field conditions from on-the-go thermal imaging.

Season	Statistical summary of Ψ_s (in MPa)					Correlation between CWSI and Ψ_s
	n	Min	Max	Mean	SD	R^2
2016	23	-1.87	-0.87	-1.28	0.236	0.79

Min: minimum. Max: Maximum. SD: standard deviation.

The obtained results allow to assert that both NIR spectroscopy and thermal imaging were successfully capable of providing a very good estimation of the grapevine water status. NIR spectroscopy responded with slightly higher accuracy for water status estimation when compared to thermal imaging, taking into account that two different seasons were evaluated. In practical terms NIR technology has the advantage of removing the need of measuring reference temperatures, but on the other hand thermal cameras can be found at sensitively lower cost than NIR spectrometers. The results obtained in this work are in good agreement with those reported for on-the-go NIR spectroscopy (Diago et al. 2108; Fernández-Novales et al. 2018) and thermal imaging (Gutiérrez et al. 2018) for on-the-go vineyard water status appraisal, and open a totally new way of assessing crop water status to help in decision taking regarding irrigation management. However, further research is needed in order to gain a wider range of grapevine cultivars, seasons and locations to improve the accuracy and robustness of the predictive results.

The spatial variability of the vineyard water status at two given dates of season 2015 (Fig 2A) and 2016 (Fig 2B) was calculated and presented as maps from the predicted values of Ψ_s obtained using the external prediction models from the NIR spectra acquired on-the-go and the prediction of the second day using the equation from the first day by thermal imaging. In 2015, the most stressed vines (with more negative Ψ_s. values) were found on the west side of the plot and toward the north east, while the plants in the east and north-west parts of the plot exhibited little to no water stress.

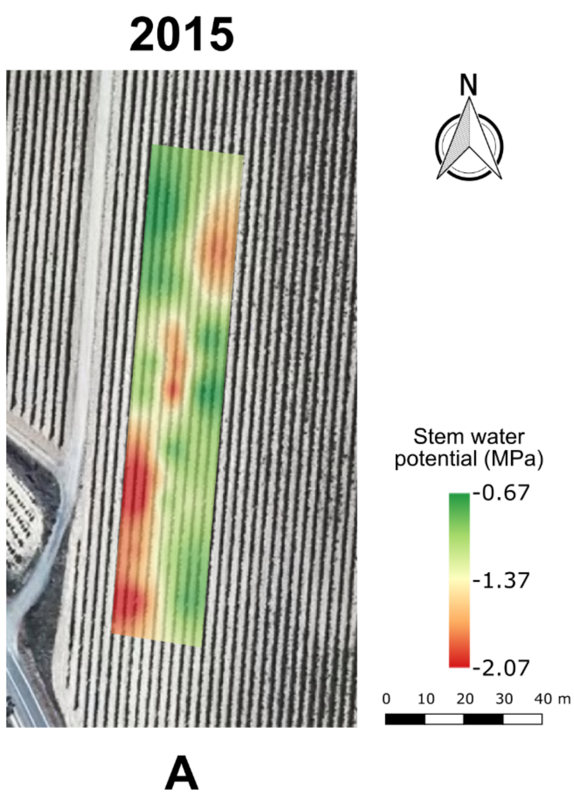

Fig 2. Maps of the predicted values of midday stem water potential using NIR spectroscopy (A) and Thermal imaging (B).

The presented results showed two innovative, non-destructive on-the-go technologies that allow the characterization of the water status of a vineyard, able to measure and predicting a huge amount of points within the plot for the precise monitoring of vine water status. Additionally, this large amount of information let for maps to be generated, and, from them, a few discretized zones can be defined for homogeneous irrigation treatments within them, leading to a more efficient and sustainable use of water.

Conclusions

On-the-go assessment of vineyard water status using NIR spectroscopy and thermal imaging thermography offers a pathway forward for the sustainable viticulture, particularly in the current worldwide scenario of increased water scarcity. The obtained results confirm the notable accuracy that both technologies reached in the estimation of the vineyard water status over two different seasons. Moreover, these non-destructive technologies allow to monitor rapidly large commercial vineyards becoming useful tools for irrigation scheduling in the decision-making process.

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