ASSESSING AND MAPPING VINEYARD WATER STATUS VARIABILITY USING A MINIATURIZED NIR SPECTROPHOTOMETER FROM A MOVING VEHICLE

Authors: Maria Paz DIAGO[1,2*], Wenchao SHENG[1], Ignacio BARRIO[1,2], Fernando RUBIO-ORDOYO[1], Juan FERNANDEZ-NOVALES[1,2]

[1]*Department of Agriculture and Food Science, University of La Rioja, Madre de Dios 53, 26007 Logroño, Spain*
[2]*Instituto de Ciencias de la Vid y del Vino (Universidad de La Rioja, CSIC, Gobierno de La Rioja) Finca La Grajera, Ctra. Burgos Km 13, 26007 Logroño, Spain*

*Corresponding author:maria-paz.diago@unirioja.es

Abstract:

Context and purpose of the study - In the actual scenario of climate change, optimization of water usage is becoming critical in sustainable viticulture. Most of the current approaches to assess grapevine water status and drive irrigation scheduling are either destructive, time and labour consuming and monitor a small, limited number of plants. This work presents a novel methodology using a contactless, miniaturized, low-cost NIR spectrometer to monitor the vineyard water status variability from a moving vehicle, to provide reliable information towards precision irrigation.

Material and methods - Spectral measurements were acquired using a NIR micro spectrometer, operating in the 900–1900 nm range, from a ground vehicle moving at 3 km/h. Spectra acquisition was carried out on the northeast side of the canopy across six dates in 2021 season and five dates in 2022, in two VSP commercial vineyards of *Vitis vinifera* L. Tempranillo and Graciano in the Rioja Appellation Board (Spain). Grapevines were monitored at solar noon using stem water potential (Ψs) as reference indicator of plant water status. At each date, 36 and 27 measurements of Ψs were taken in the Tempranillo and Graciano vineyards, making a total of 396 and 297 data respectively. Partial least squares (PLS) regression and the Variable Importance in the Projection (VIP) method were used to build calibration and prediction models using the pooled data from the two seasons for each variety. Multiple Linear Regression (MLR) was also applied to build simplified estimation models using 8 and 10 spectral bands with the highest VIP scores (always >1). Determination of coefficient (R^2) and root mean square error (RMSE) were computed to assess model performance.

Results - Remarkable cross-validation models were built using the whole spectrum (117 wavelengths) with R^2_{cv} ranging from 0.62 to 0.80, and RMSECV between 0.115-0.138 MPa in Tempranillo and Graciano vineyards, respectively. With the aim of simplifying model building, the 8 and 10 spectral bands showing the highest VIP scores, with values above 1 in all instances, were selected to build MLR cross validation models of stem water potential. In both varieties MLR8 and MLR10 (MLR models built with 8 and 10 wavelenghts only respectively) yielded R^2_{cv} ranging from 0.45-0.59 and RMSECV ~ 0.156-0.171 MPa. Although lower performance was achieved with the simplified models they could still be utilized to classify and map the vineyard plots into three different water status zones, susceptible of precise, differentiated irrigation.

Keywords: water stress, stem water potential, proximal sensing, partial least squares, multiple linear regression

1. Introduction

Optimization of water usage is becoming critical in sustainable viticulture. In order to implement smart irrigation, that is to provide vines under different water requirements with distinct irrigation doses, the utility of high-spatial resolution information of plant water status within a vineyard plot has been reported (Acevedo-Opazo et al. 2010; Cohen et al. 2017). Most of the current methods to assess grapevine water status (Rienth & Scholasch 2019) are either destructive, time and labour consuming and monitor only a small, limited number of plants.

Near infrared (NIR) spectroscopy (from 800-2500 nm) is a technique that provides rapid and non-destructive data acquisition and has proven successful to monitor plant water status at leaf and canopy level in several species including grapevines (Cozzolino 2017; Cottrozzi et al. 2017; Diago et al. 2018). Water is a primary constituent of grapevine leaves. In the NIR range the O-H second overtone shows around 978 nm, the O-H stretch first overtone at 1454 nm, and the combination bands of O-H bonds in hydroxyl groups around 1930-1940 nm (Tugnolo et al. 2021).

NIR spectral sensors (covering the range from 1200-2100 nm) mounted on ground vehicles have demonstrated good capability to estimate grapevine water status with determination coefficient of prediction (R^2_P) reaching values between 0.68-0.85 and root mean square error of prediction (RMSEP) ranging from 0.131 – 0.190 MPa (Diago et al. 2018; Fernández-Novales et al. 2018). However, these devices are expensive, big sized and heavy. Towards increased implementation of NIR spectroscopy in vineyard operations, more compact, miniaturized spectral sensors, of lower cost, that facilitate spectra collection, in an easier and more affordable way are required.

This work presents a novel methodology using a contactless, miniaturized, low-cost NIR spectrometer to monitor the vineyard water status variability from a moving vehicle, to provide reliable information towards precision irrigation.

2. Material and methods

Vineyard plots. The experimental work was conducted in two commercial vineyards located in Tudelilla, La Rioja, Spain during the summer months of July, August, September and October over two consecutive seasons, 2021 and 2022. The Tempranillo (*Vitis vinifera* L.) (TE) vineyard was planted in 2002 following a north-south orientation (Lat. 42°,18’ 18.26’’, Long. -2°,7’ 14.15’’, Alt. 515 m) while the Graciano (*Vitis vinifera* L.) (GR) vineyard was planted in 2016 following a northwest-southeast orientation (Lat. 42°,18’ 30.52’’, Long. -2°,7’ 05.17’’, Alt. 497 m). Both varieties were grafted on rootstock R-110 and trained to a vertically shoot-positioned (VSP) trellis system on a double-cordon Royat with vine spacing of 2.60 x 1.20 m.

Solely with the aim of generating a wide array of vine water status, three water regimes were established in a completely randomized block design in each vineyard plot. The following irrigation treatments were implemented: *T0, full irrigation*. Two water pipelines irrigating 6 L h^{-1} two hours per day, five days a week; *T1, moderate irrigation*. A single water pipeline irrigating half the amount in T0, and *T2, no irrigation*. Four and three replicates per irrigation treatment were applied in the TE and GR plots, respectively. Each replicate was composed by three rows, of which only the middle row was monitored to avoid the edge effects. Each replicate was represented by three consecutive sections of five plants, making a total of15 plants per replicate.

Spectral and vine water status measurements. Spectral measurements were acquired on-the-go, from a moving vehicle (3 Km h^{-1}) in which a NIR micro spectrometer (Insion 1.7 NT/H spectrometer, Insion Gmbh, Obersulm, Germany) operating in the 900–1860 nm spectral range, at 8.2 nm resolution and 12.5 Hz acquisition rate was installed. An integrated 20 W tungsten halogen lamp was also used as external lighting source. The moving vehicle was a modified brushcutter (940 Sherpa 4WD XL, AS-motor, Bühlertann, Germany) also equipped with an industrial computer (controlled via wifi by a tablet) and an RTK GPS receiver (AG Leader 6500 with RTK relay) with centimetric precision and 20Hz refresh rate.

Spectral measurements were conducted at solar noon (between 14:00 – 15:00 GMT+1) on the east side of the TE canopy and on the northeast side of the GR canopies along six dates in 2021 season and five dates in 2022. The spectrometer collimator and light source were placed at a height of 1.0 m from the ground, pointed to the canopy on a lateral point of view at 0.30 m of distance. The stem water potential (Ψ_s) was chosen as the plant water status reference method. The 15 plants in each replication were divided into three sets of 5 vines each. In each set one leaf from the mid-upper part of the canopy of a random vine was selected and its stem water potential measured using a Schölander pressure bomb (Model 600, PMS Instruments Co., Albany, USA) at the same time as on-the-go spectral measurements were acquired. Prior to the Ψ_s measurement, the selected leaves were covered with aluminium foil to drive them into dark adaptation for at least one hour.

Spectral processing and data analysis. Spectral processing was conducted according to the methodology described in Diago et al. (2018) and Fernández-Novales et al. (2018). It consisted of the following steps: (i) allocation of spectra to each field replication; (ii) spectra comparison and filtering of the measurements acquired on-the-go against a grapevine leaf spectral signature collected under the same environmental conditions (this is done to avoid the spectral information corresponding to canopy elements other than leaves, such as gaps, wires, wood, clusters, etc.). After averaging the filtered grapevine leaf spectra and removal of light scattering effects, they were linked to their corresponding Ψ_s values. Spectral processing was conducted with Matlab (version 2019a, The Mathworks Inc., Natick, MA, USA)). Calibration (c) and cross-validation (cv) models for grapevine water status were built using the PLS Toolbox (version 8.1, Eigenvector Research, Inc., Manson, WA, USA) software in conjunction with MATLAB (version 2019a, The Mathworks Inc., Natick, MA, USA). Partial Least Squares (PLS) regression was used as the algorithm for training the plant water status prediction models. The Variable Importance in the Projection (VIP) method (Wold et al. 1993) was applied to assess the relative importance of each wavelength in the best PLS models, considering influential wavelengths those with VIP scores greater than 1. Multiple Linear Regression (MLR) was also applied to build simplified estimation models using 8 and 10 spectral bands with the highest VIP scores (always >1). The determination coefficient of calibration (R^2_c) and cross-validation (R^2_{cv}), and the root mean square error of calibration (RMSEC) and cross-validation (RMSECV) were calculated as performance metrics of the models.

Mapping. Maps of the actual (measured) and predicted values of Ψ_s (using the PLS models) were built using empirical Spline interpolation (Earls and Dixon 2007), implemented in ArcGis 10.3 (Environmental Systems Research Institute, Redlands, CA, USA).

3. Results and discussion

A summary of the Ψs data gathered across the two seasons for the two vineyards is presented in Table 1. As shown in the table, the range of grapevines monitored and used to build the estimation models expanded from no stressed vines (Ψ_s>-1.0 MPa) to highly stressed vines (Ψ_s<-1.4MPa), particularly in the case of the Tempranillo vineyard. Such a wide variation is necessary to build robust estimation from the spectral information. Likewise,
calibration and cross-validation models were built using the whole spectrum (117 wavelengths) with R^2_{cv} ranging from 0.62 to 0.80, and RMSECV between 0.115-0.138 MPa in Tempranillo and Graciano vineyards, respectively.
These performance metrics are in good agreement with those reported in previous works using more expensive (up to 10-fold) and more sophisticated spectrometers (Diago et al. 2018). Towards simplification of model generation, a discrete number of spectral bands showing the highest VIP scores (data not shown), with values above 1 in all instances, were selected to build MLR calibration and cross validation models of Ψ_s. In both cultivars MLR8 and MLR10 (MLR models built with 8 and 10 wavelenghts only respectively) yielded R^2_{cv} ranging from 0.45-0.59 and RMSECV ~ 0.156-0.171 Mpa (Table 1). Although lower performance was achieved with the simplified models compared to the partial least squares (PLS) model created using the whole spectra, they could still be utilized to classify the vineyard plots into two-three different water status zones of low, medium and high water stress, susceptible of precise, differentiated irrigation. As observed in Figure 1, in all three types of models, the values adequately spread across the regression line in both cultivars and the two years of study.

In Figure 2, an example of maps of the variability of the reference (measured) and estimated Ψ_s (using the PLS model) for one of the sampling dates in the Tempranillo and Graciano vineyards is shown. Increased and more variation of water stress (intra-plot) was detected in the Tempranillo vineyard as compared to the Graciano one. Good correspondence between the reference and estimated maps can also be observed, which supports the potential usability of this non-destructive, spectral-based methodology to assess vineyard water status and to help in the definition of differentiated irrigation subzones within a given vineyard.

From a practical standpoint, once the model has been built for a given vineyard (using data for at least several seasons), a cost between 25-40 €/ha can be estimated, including data acquisition in the vineyard and processing. This value may be reduced depending on the size of the plot and the possibility of increasing the speed of the on-the-go spectral acquisition (from the current 2 km/h to increased values). An initial scanning of the vineyard variability degree, for example, using a map of NDVI from the vineyard acquired in a previous season may help to decide whether all rows need to be scanned or scanning every other 3 or more rows would be enough to capture the variability in plant water status. This can vary from one plot to another, and will certainly have an impact in the final cost of the operation. Further research is certainly needed to find out the largest time windows in which in-field monitoring is not substantially affected by environmental changes. In any case, the capability of monitor a large number of vines in comparison to current discrete measurements of a very limited plants is unique and highly relevant in terms of the representativeness of vineyard water status monitoring.

4. Conclusions

This work has opened a new field of research involving the testing and in-field validation of a lower cost spectral device to assess the spatial variability of vineyard water status in a semi-automated, non-destructive way, that may become affordable in the mid term to become implemented in the grapegrowing industry to support decision making regarding optimized vineyard irrigation, hence to increase watering sustainability.

5. Acknowledgments

This work has received funding from project PID2019-108330RA-I00 funded by MCIN/AEI/ 10.13039/501100011033 (Spain). The authors acknowledge Rubén Martínez and Fernando Rubio for their help with the measurement of the stem water potential. Special thanks to Bodegas Vivanco for providing the vineyards to conduct the study and Luis Angel García for his technical support.

6. Literature cited

Acevedo-Opazo, C., Ortega-Farias, S., Fuentes, S. 2010. Effects of grapevine (*Vitis vinifera* L.) water status on water consumption, vegetative growth and grape quality: An irrigation scheduling application to achieve regulated deficit irrigation. Agricultural Water Management 97, 956–964.

Cohen, Y., Alchanatis, V., Saranga, Y., Rosenberg, O., Sela, E., Bosak, A. 2017. Mapping water status based on aerial thermal imagery: comparison of methodologies for upscaling from a single leaf to commercial fields. Precision Agriculture 18, 801–822.

Cotrozzi, L., Couture, J. J., Cavender-Bares, J., Kingdon, C. C., Fallon, B., Pilz, G., Pellegrini, E., Nali, C., Townsend, P. A. 2017. Using foliar spectral properties to assess the effects of drought on plant water potential. Tree Physiology 37, 1582e1591.

Cozzolino, D. 2017. The role of near-infrared sensors to measure water relationships in crops and plants. Applied Spectroscopy Reviews, 52, 837e849.

Diago, M. P., Fernández-Novales, J., Gutiérrez, S., Marañón, M., Tardaguila, J. 2018. Development and validation of a new methodology to assess the vineyard water status by on-the-go near infrared spectroscopy. Frontiers in Plant Science, 9:59.

Fernández-Novales, J., Tardaguila, J., Gutiérrez, S., Marañón, M., Diago, M. P. 2018. In field quantification and discrimination of different vineyard water regimes by on-the-go NIR spectroscopy. Biosystems Engineering 165, 47–58.

Rienth, M., Scholasch, T. 2019. State-of-the-art of tools and methods to assess vine water status. Oeno One 53, 619–637.

Tugnolo, A., Giovenzana, V., Malegori, C., Oliveri, P., Casson, A., Curatitoli, M., Guidetti, R., Beghi, R. 2021. A reliable tool based on near-infrared spectroscopy for the monitoring of moisture content in roasted and ground coffee: A comparative study with thermogravimetric analysis. Food Control 130, 108312.

Wold, S., Johansson, E., Cocchi, M. 1993. PLS: partial least squares projections to latent structures. In H. Kubinyi (Ed.), Methods and applications (p. 759). Netherlands, Leiden: Kluwer ESCOM Science Publisher.

Table 1. Summary of data of stem water potential (Ψ_s) of Tempranillo and Graciano vineyards in the two years of study (2021 and 2022). Performance metrics of the partial least squares (PLS) and Multiple Linear Regression (MLR) models using eight (MLR8) and ten (MLR10) most relevant wavelengths as determined by the highest Variable in Importance Projection (VIP) method. Values of Ψ_s expressed in MPa.

Variable	Tempranillo			Graciano		
n	396			297		
Minimum	-2.15			-1.65		
Maximum	-0.80			-0.10		
Model type	**PLS**	**MLR8**	**MLR10**	**PLS**	**MLR8**	**MLR10**
R^2_C	0.83	0.57	0.61	0.78	0.61	0.64
RMSEC	0.103	0.167	0.159	0.124	0.157	0.164
R^2_{CV}	0.80	0.55	0.59	0.62	0.46	0.51
RMSECV	0.115	0.171	0.163	0.138	0.164	0.157

n: number of data; R^2_c: determination coefficient of calibration; R^2_{cv}: determination coefficient of cross validation; RMSEC: root mean square error of calibration (MPa); RMSECV: root mean square error of cross validation (MPa).

Figure 1: Best Partial Least Squares (PLS) (a, b); Multiple Linear Regression with 10 spectral bands (MLR10) (c, d) and Multiple Linear Regression with 8 spectral bands (MLR8) (e, f) models of cross validation for Ψs estimation in Tempranillo (a, c, e) and Graciano (b, d, f) vineyards over the two seasons (2021 and 2022).

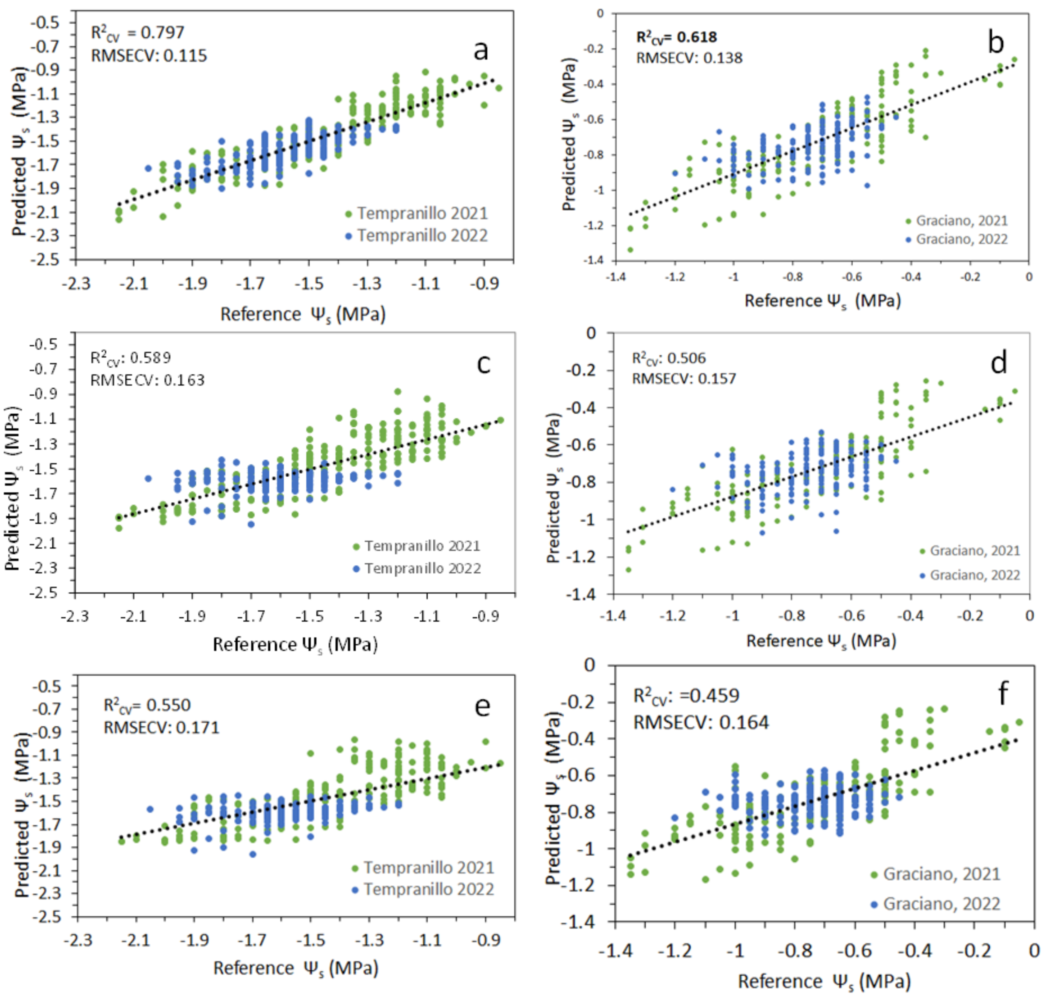
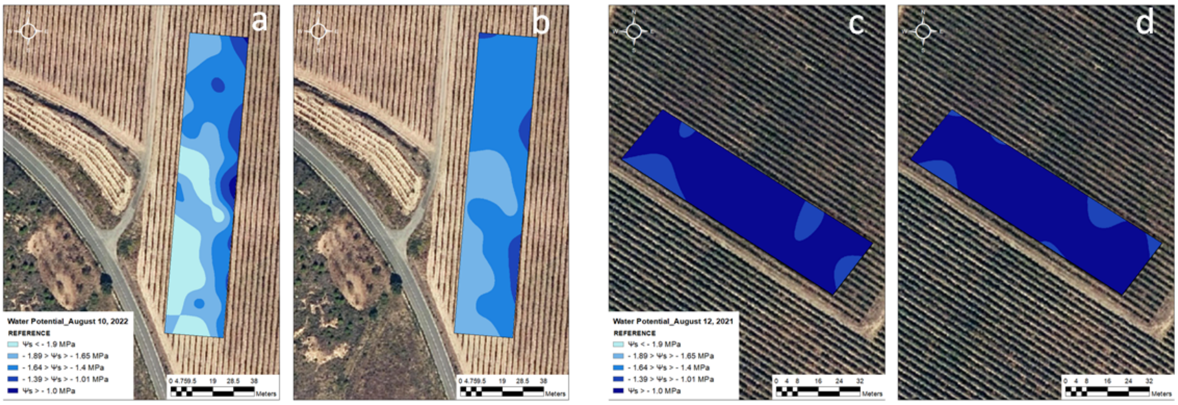


Figure 2. Example maps of (a, c) reference and (b, d) predicted values of stem water potential (Ψ_s) in the Tempranillo (a, b) and Graciano (c, d) vineyard respectively on the 10th and 12th August 2021.


a
b
c
d
Water Potential_August 10, 2022
REFERENCE
Ψs < - 1.9 MPa
- 1.89 > Ψs > - 1.65 MPa
- 1.64 > Ψs > - 1.4 MPa
- 1.39 > Ψs > - 1.01 MPa
Ψs > - 1.0 MPa
0 4.759.5 19 28.5 38
Meters
Water Potential_August 12, 2021
REFERENCE
Ψs < - 1.9 MPa
- 1.89 > Ψs > - 1.65 MPa
- 1.64 > Ψs > - 1.4 MPa
- 1.39 > Ψs > - 1.01 MPa
Ψs > - 1.0 MPa
0 4 8 16 24 32
Meters