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In-field hyperspectral proximal sensing for estimating grapevine water status to support smart precision viticulture†

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Abstract: Predawn leaf water potential (Ψ_{pd}) is the main parameter to determine plant water status, and it has been broadly used to support irrigation management. However, the Scholander pressure chamber methodology is laborious, time-consuming and invasive. This study examined a low-cost hyperspectral proximal sensor to estimate Ψ_{pd} in grapevine (*Vitis vinifera* L.). For this, both Ψ_{pd} and spectral reflectance (340-850 nm) were accessed in grapevines in a commercial vineyard located in the Douro Wine Region, northeast Portugal. A machine learning algorithm was tested and validated to assess grapevine water status. The experiment was performed in a randomized design with 12 grapevines (cv. Touriga Nacional) per irrigation treatment: non-irrigated, 30% crop evapotranspiration (Etc), and 60% Etc. The dataset was analyzed using Principal Component Analysis (PCA), and the machine learning regression algorithm applied was Extreme Gradient Boosting (Xgboost). Results from the validation dataset (n = 108) for the Xgboost tested exhibited a root mean square error (RMSE) of 0.23 MPa, mean absolute error (MAPE) of 16.57% and an R^2 value of 0.95. These results demonstrate that the hyperspectral sensor and Xgboost algorithm show potential to predict Ψ_{pd} in vineyards regardless of plant water status.

Keywords: leaf water potential; machine learning; point-of-measurement; precision viticulture

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1. Introduction

Viticulture is a major economic importance activity in Mediterranean regions. However, climatic changes have affected wine production and quality over the years in these regions [1]. Because of that, irrigated vineyards have been increasing due to the necessity to reduce climatic changes' effects on viticulture [2]. Simultaneously, human habits demand water resources and pressure agriculture to reduce water waste and improve irrigation management [2,3].

The predawn leaf water potential (Ψ_{pd}) is an eco-physiological indicator used to assess grapevine's water status and support irrigation management in vineyards [4]. Commonly, it is measured using a Scholander pressure chamber. Nonetheless, this method is destructive, time-consuming, laborious, and depends on set of measurement points to represent large planting areas [5].

Technological advances such as optical sensors are a fast, cost-effective, and non-invasive method to estimate Ψ_{pd} with high accuracy [6]. Specifically, hyperspectral proximal sensors and machine learning algorithms showed good results in predicting Ψ_{pd} [7].

However, more studies are necessary to develop this technology, focusing on turning it economical and readily available to wine producers [8]. This study examined a low-cost hyperspectral proximal sensor to estimate Ψ_{pd} in grapevine (*Vitis vinifera* L.).

2. Materials and Methods

2.1. Test site:

The research was carried out in Quinta dos Aciprestes (41.21° N; 7.43° W; 145 m), a commercial vineyard (wine company Real Companhia Velha) in the Douro Wine Region, northeast of Portugal (Figure 1). The vines in test site follow a Bilateral Royat System, with canopy height around 1.5 m and plants spacing of 2.2 m x 1 m. The cultivar studied was Touriga Nacional, in a randomized design in 2 plots, with two replicate areas. Each plot includes three irrigation treatments: non-irrigated, irrigation to replace 30% of evapotranspiration (Etc) water volume, and 60% Etc, managed by the wine company. For each irrigation treatment there were considered six grapevines totaling 36 grapevines assessed.

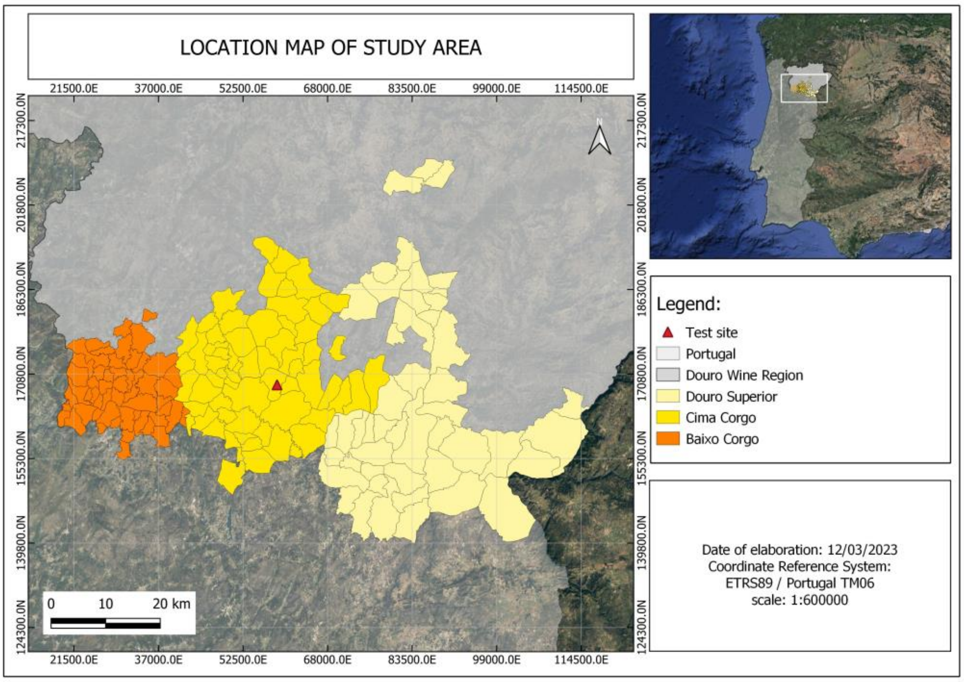

Figure 1. Location of study area in northeast of Portugal.

2.2. Predawn leaf water potential and spectroscopy methodology:

The predawn leaf water potential (Ψ_{pd}) was measured using a Scholander pressure chamber [9](PMS600, Albany, OR, USA) at predawn on one leaf from each vine per block sampled. The hyperspectral data were measured using a prototype directed vertically close to the leaf, which records reflectance signatures between 340 nm and 850 nm of the electromagnetic spectrum [10]. The Ψ_{pd} and hyperspectral data were measured in the same leaves during six consecutive weeks in 2022 after veraison (25 July) on evaluation dates: 28 July — 3 days after veraison (DAV) —, 4 August (10 DAV), 11 August (17 DAV), 19 August (25 DAV), 25 August (31 DAV) and 1 September (38 DAV), totalling 216 observations.

2.3. Statistical and principal component analysis:

A one-way analysis of variance (ANOVA) with a *p*-value associated with the Fischer test ($p \leq 0.05$) was performed to compare the means of Ψ_{pd} between the irrigation treatments and the evaluation dates.

A Principal Component Analysis (PCA) was performed to discover patterns that could explain the variance of spectral data on evaluation dates. The PCA considered three evaluation dates to represent the different stages of grape ripening: 28 July (3 DAY), 11 August (17 DAY) and 1 September (38 DAY).

2.3. Data processing and modelling:

A multiplicative scattering correction logarithm was applied in the hyperspectral reflectance to correct baseline and scattering artefacts in spectra data before algorithm processing [7].

The machine learning algorithm tested was Extreme Gradient Boosting (Xgboost). For Xgboost's application, the dataset was randomly split into two sub-datasets: 50% to calibration (n = 108 observations) and 50% to validation (n = 108 observations) [11]. The statistical analysis and machine learning algorithm were computed in R (version 4.2.3) [12].

Model performance in estimating Ψ_{pd} was evaluated based on the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAPE).

3. Results

Table 1 presents statistical results of the measured Ψ_{pd} and shows significant differences among all the evaluation dates and irrigation treatments. Considering the evaluation dates, non-irrigated grapevines presented a better statistical mean than irrigated grapevines. Due to a 1.6 mm precipitation on 10 August (16 DAV), the values of Ψ_{pd} since 4 August showed a variability, mainly in 30% Etc treatment.

Table 1. Statistical results of predawn leaf water potential (Ψ_{pd}, MPa) for the irrigation treatments in different evaluation dates during the stages of grape ripening.

Evaluation date	Non-irrigated	30% Etc	60% Etc	ANOVA F
28 July	-1.263 ± 0.226bA	-0.560 ± 0.072dB	-0.469 ± 0.119bB	5.72e-14 ***
4 August	-1.294 ± 0.185bA	-1.096 ± 0.231aB	-0.575 ± 0.020aC	7.12e-11 ***
11 August	-1.475 ± 0.116aA	-0.729 ± 0.090cB	-0.650 ± 0.122aB	<2e-16 ***
19 August	-1.490 ± 0.123aA	-0.717 ± 0.095cB	-0.433 ± 0.087bC	<2e-16 ***
25 August	-1.558 ± 0.095aA	-0.752 ± 0.155cB	-0.446 ± 0.075bC	<2e-16 ***
1 September	-1.538 ± 0.124aA	-0.958 ± 0.146bB	-0.390 ± 0.120bC	<2e-16 ***
Mean	-1.436A	-0.802B	-0.494C	<2e-16 ***
ANOVA F	1.08e-05***	4.04e-12 ***	7.48e-08 ***	

* ANOVA F is the p-value associated with the Fischer test performed in the ANOVA. Means with a p-value less than 0.05 are considered statistically different. Means followed by the same lowercase letter in the same column (among dates) or means followed by the same uppercase letter in the same line (among irrigation treatments) are not significantly different (α = 5%).

Figure 2 shows PCA that the spectral data in the evaluation dates indicate different cycle of leaf development. The first two principal components accounted for a variance > 75%. The figure represents the clustering according the dates of assessment suggesting that the leaf's ageing and abiotic stress (e.g., water stress) can be detectable through spectral data. The spectral data is grouped by evaluation date in a pattern related to the changes in the leaves composition caused by aging.

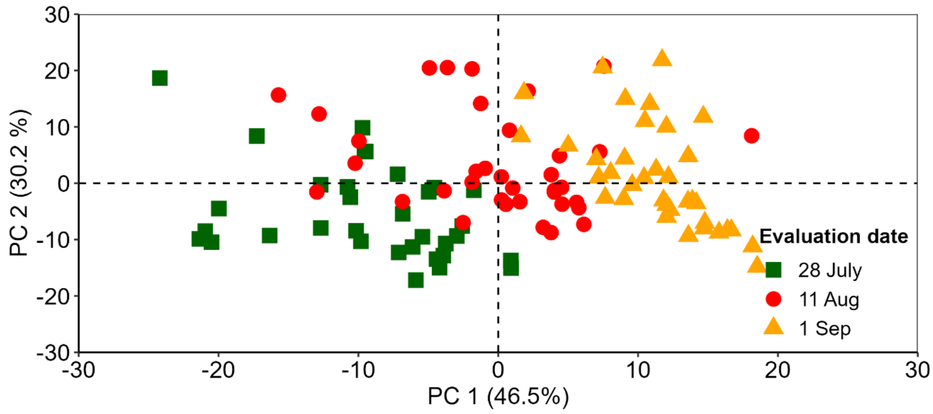

Figure 2. Principal component analysis of spectral data according to three evaluation dates: Beginning (28 July), Middle (11 August) and End (1 September) of the cycle of leaf development.

Table 2 and Figure 3 show the performance of the Extreme Gradient Boosting regression model. This model performed a variance of 0.95% in Ψ_{pd} prediction, the RMSE of 0.23 MPa and the MAPE of 16.57%. The R^2 of 1 and RMSE of 0.00 in the training dataset indicate that there is a tendency of overfitting behavior observed in data features, probably due to the structure of the data. Figure 3 supports the tendency of overfitting showing the good metric for the training dataset and the lower prediction in the validation dataset.

Table 2. Model performance metrics of training and validation dataset.

	Training dataset	Validation dataset	Total
R^2	1	0.89	0.95
RMSE (MPa)	0.00	0.32	0.23
MAPE (%)	0.09	33.36	16.57

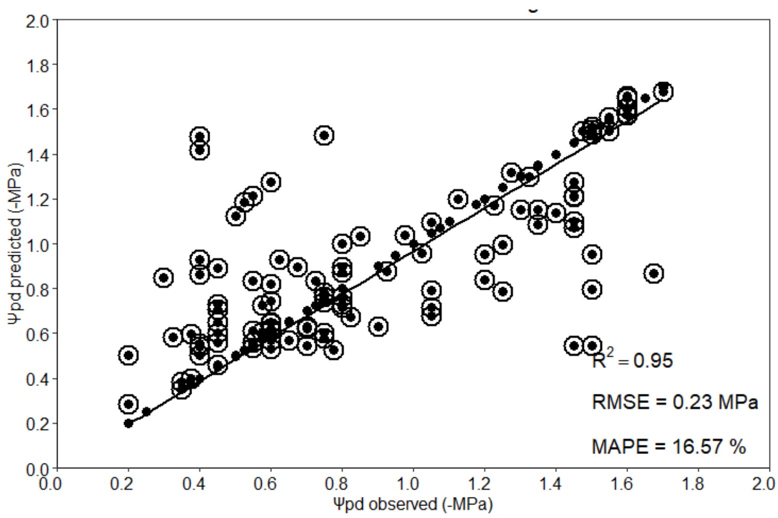

Figure 3. Extreme Gradient Boosting model for estimating predawn leaf water potential (Ψ_{pd}) with predicted and observed values measured using a Scholander pressure chamber. *Circled observations are the validation dataset (*n* = 108 observations).

4. Discussion

Low water regimes can induce water stress symptoms in grapevines and affect their phenology. Water stress causes stomata closure, in consequence, leaf temperature increase by reducing transpiration rates and reduces CO_2 concentration, along with photodamage to photosystem II (PSII) reaction centers [13]. Spectral sensors provide information about plant physiology before water stress impact on grapevine productivity.

The low-cost hyperspectral proximal sensor shows promising results in estimating Ψ_{pd} in grapevine. The prototype sensor predicted Ψ_{pd} considering a variance between -0.2 MPa and -1.7 MPa with an error of 0.23 MPa. These results allow the use of the sensor by grapevine producers that conduct their vineyard under deficit irrigation. In these areas, the irrigation schedule starts when vineyards present Ψ_{pd} values below -0.4 MPa [14], inside the range detected by the sensor studied.

Even though Scholander pressure chamber is a recognized method to access Ψ_{pd}, it is not widely applicable in large vineyards, besides of being time and labour consuming. Jointly, sensor and Extreme Gradient Boosting model, provide real time and reliable detection of plant water status. They can be used to support irrigation decisions by winegrower in an automated system that would allow adjustments of irrigation to the site-specific characteristics, according to yield and quality objectives [15].

5. Conclusions

This work shows the applicability of a low-cost hyperspectral proximal sensor and Extreme Gradient Boosting regression model in predicting Ψ_{pd} considering different evaluation dates and irrigation treatments. These results indicate the potential of this model and sensor to be applied in vineyards to support irrigation management.

There are other applications of this sensor to be studied, such as integrating this sensor in robots to optimize the measurements of Ψ_{pd} in vineyards, and quantifying berry quality parameters and leaves pigments.

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References

1. Jones, G.V.; Alves, F. Impacts of Climate Change on Wine Production: A Global Overview and Regional Assessment in the Douro Valley of Portugal. *International Journal of Global Warming* **2012**, *4*, 383–406. https://doi.org/.

2. Costa, J.M.; Vaz, M.; Escalona, J.; Egipto, R.; Lopes, C.; Medrano, H.; Chaves, M.M. Modern viticulture in southern Europe: Vulnerabilities and strategies for adaptation to water scarcity. *Agricultural Water Management* **2016**, *164*, 5–18. https://doi.org/10.1016/j.agwat.2015.08.021.
3. Finco, A.; Bentivoglio, D.; Chiaraluce, G.; Alberi, M.; Chiarelli, E.; Maino, A.; Mantovani, F.; Montuschi, M.; Raptis, K.G.C.; Semenza, F.; et al. Combining Precision Viticulture Technologies and Economic Indices to Sustainable Water Use Management. *Water* **2022**, *14*. https://doi.org/10.3390/w14091493.
4. Pôças, I.; Tosin, R.; Gonçalves, I.; Cunha, M. Toward a generalized predictive model of grapevine water status in Douro region from hyperspectral data. *Agricultural and Forest Meteorology* **2020**, *280*. https://doi.org/10.1016/j.agrformet.2019.107793.
5. Tosin, R.; Pôças, I.; Gonçalves, I.; Cunha, M. Estimation of grapevine predawn leaf water potential based on hyperspectral reflectance data in Douro wine region. *Vitis* **2020**, *59*, 9–18. https://doi.org/10.5073/vitis.2020.59.9-18.
6. Romero, M.; Luo, Y.; Sud, B.; Fuentes, S. Vineyard water status estimation using multispectral imagery from an UAV platform and machine learning algorithms for irrigation scheduling management. **2018**, *147*, 109–117. https://doi.org/.
7. Tosin, R.; Martins, R.; Pôças, I.; Cunha, M. Canopy VIS-NIR spectroscopy and self-learning artificial intelligence for a generalised model of predawn leaf water potential in Vitis vinifera. *Biosystems Engineering* **2022**, *219*, 235–258. https://doi.org/10.1016/j.biosystemseng.2022.05.007.
8. Mirás-Avalos, J.; Araujo, E. Optimization of Vineyard Water Management: Challenges, Strategies, and Perspectives. *Water* **2021**, *13*. https://doi.org/10.3390/w13060746.
9. Scholander, P.F.; Bradstreet, E.D.; Hemmingsen, E.A.; Hammel, H.T. Sap Pressure in Vascular Plants: Negative hydrostatic pressure can be measured in plants. *Science* **1965**, *148*, 339–346. https://doi.org/10.1126/science.148.3668.339.
10. Martins, R.C.; Barroso, T.G.; Jorge, P.; Cunha, M.; Santos, F. Unscrambling spectral interference and matrix effects in Vitis vinifera vis-nir spectroscopy: Towards analytical grade 'in vivo' sugars and acids quantification. *Computers and Electronics in Agriculture* **2022**, *194*. https://doi.org/.
11. Kuhn, M.; Johnson, K. *Applied predictive modeling*; Springer: New York, 2013; Volume 26.
12. R Core Team *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing: Vienna, Austria, 2023.
13. Maimaitiyiming, M.; Ghulam, A.; Bozzolo, A.; Wilkins, J.L.; Kwasniewski, M.T. Early Detection of Plant Physiological Responses to Different Levels of Water Stress Using Reflectance Spectroscopy. *Remote Sensing* **2017**, *9*. https://doi.org/10.3390/rs9070745.
14. Gonçalves, I. Impactes das Alterações Climáticas na Vitivinicultura da Região Demarcada do Douro e Medidas de Adaptação. Universidade de Trás-os-Montes e Alto Douro, 2021.
15. Fernandes de Oliveira, A.; Mameli, M.G.; Lo Cascio, M.; Sirca, C.; Satta, D. An Index for User-Friendly Proximal Detection of Water Requirements to Optimized Irrigation Management in Vineyards. *Agronomy* **2021**, *11*. https://doi.org/10.3390/agronomy11020323.

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