ARTICLE IN PRESS
BIOSYSTEMS ENGINEERING XXX (XXXX) XXX

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journal homepage: www.elsevier.com/locate/issn/15375110

Research Paper

Optical specifications for a proximal sensing approach to monitor the vine water status in a distributed and autonomous fashion

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ARTICLE INFO

Article history:
Received 21 June 2021
Received in revised form
29 October 2021
Accepted 5 November 2021
Published online xxx

Keywords:
Grapevine
Optical device
Green technology
vis/NIR spectroscopy
Chemometrics
Wavelength selection

In agriculture, increasing attention is being paid to collect data in a non-destructive way using optical systems which can be field distributed in a completely interconnected network. To improve the irrigation scheduling management, the control of the plant's water status is crucial. This work focused on the definition of optical specifications (wavelength-selection in vis/NIR region) for the development of cost-effective sensors, giving an initial bulk of information to design optical devices to be used in a network of distributed field sensors. The analyses were performed on vines of cv. Pinot Blanc. Optical data were collected on leaves before the analysis of water potential and moisture content. Pearson-correlation analysis between predawn water potential (Ψ_{PD}) and moisture content was performed ($r = 0.47$ and p-value<0.05) highlighting a non-highly correlation between the two parameters. The optical data (350–2500 nm) were used to build a PLS-model with vis/NIR and Ψ_{PD} (RMSEP = 0.056 MPa, $R^2 = 0.7$). The study identified the most significant wavelengths related to the water potential at the leaf level to design a chemometric model that was compared to the model based on the whole spectra. Therefore, related VIP-scores were used to calibrate another PLS-model after the selection of most relevant optical bands (530 ± 20 nm, 700 ± 20 nm, and 1400 ± 20 nm). Good predictive performance was obtained with an RMSEP = 0.056 and an $R^2 = 0.60$. These results paved the ground for further development of integrated optical sensors capable to monitor vine water status in the field in a distributed and autonomous fashion.

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https://doi.org/10.1016/j.biosystemseng.2021.11.007
1537-5110/

1. Introduction

The fourth industrial revolution (Industry 4.0) overlaps automated and interconnected systems. The modern technologies classified as "enabling technologies", series of wide and multidisciplinary applications to different tasks, allow to develop of new solutions able to reduce human error, to increase production, to optimize energy consumption, and to produce reliable information. For example, in the wine industry, recent technological developments have provided a useful and efficient tool for remote and real-time monitoring of important variables involved in grape production, processing the data, and transmitting the required information to the users (Matese & Di Gennaro, 2015). Additionally, the long-term environmental sustainability of vineyards is dependent on strategic water management due to global water scarcity. These trends are increasing the pressure on grape growers to continually seek opportunities to maximize the efficient use of freshwater, highlighting the need for efficient and sustainable viticulture management in terms of the water resources (Pagay et al., 2016).

In the vineyard, the agronomic practices for water management include the selection of tolerant genetic material, the use of cover crops and the supply of water through irrigation (Dai et al., 2011; Linares Torres et al., 2018). Indeed, in several viticultural areas, irrigation is becoming an important strategy to support production and to maintain the quality of the grapes. A promising strategy to improve water management is represented by precision irrigation, which optimises the supply of water along the time and the space, increasing the water use efficiency at field scale (Ortuani et al., 2019). New technologies, for instance based on models from proximal and remote sensing data are required for precision irrigation to quickly detect the water status of the vineyard (Mirás-Avalos & Araujo, 2021). The introduction of new technologies for supporting vineyard management also allows the efficiency and quality of production, synergically reducing the environmental impact (Casson et al., 2020) in the viticulture sector. The key proxy to assess and manage irrigation practices is the plant water status. Water status varies due to vineyard practices and environmental factors, such as meteorological conditions, site topography, soil characteristics, which lead to variability in grape composition at harvest, compromising the wine composition (Yu & Kurtural, 2020).

In this context, water potential (Ψ) has been world widely accepted as a useful and reproducible parameter of the plant water status. Thresholds for grapevine water status have been defined in terms of water potential and they can be used to manage irrigation under different phenological stages (Ojeda et al., 2002). Nevertheless, the measurement of water potential requires destructive sampling, it is labour-intensive, time-consuming and potentially biased by the operator. One of the most promising approaches to disrupt these current methodological barriers is the use of optical-based strategies that are intrinsically non-destructive and reproducible on a large scale for completely interconnected IoT devices development.

In recent decades, optical instrumentation in the visible (vis), and in the near-infrared (NIR) have been used as technological tools for remote and proximal sensing. These tools are capable to manage the different agronomic operations, including the monitoring of water status (Seng et al., 2018). Although remote sensing is a current landmark for the agricultural sector (from an experimental point of view), it is still unable to fully embrace this technology in real production scenarios. Some reasons behind this include: (i) the techno-economic benefits of such technologies, (ii) the limited availability and training of remote sensing-based decision-support tools, (iii) the costs and, (iv) the interoperability of different tools and data sources (Khanal et al., 2020). Moreover, the discontinuous nature of grapevine canopies and their moderate cover causes noisy backgrounds and shadows, which influences the measured reflectance signals (Borgogno-Mondino et al., 2018). For these reasons, the use of proximal sensing techniques is a convenient option. Proximal sensors are placed directly in contact or close by (few meters) a specific target (e.g. soil, plant, crop, etc.). These sensors provide information related to the properties of the objects analysed through signals coming from physical measures. Therefore, spectroscopy (Fernández-Novales et al., 2018; Giovenzana et al., 2018; Cotrozzi et al., 2017; Cozzolino, 2017; Tardaguila et al., 2017; González-Fernández et al., 2015), multispectral and hyperspectral imaging (Kotsaki et al., 2020; Pôças et al., 2020; Loggenberg et al., 2018; Rapaport et al., 2015), and thermal imaging (Gutiérrez et al., 2018; Petrie et al., 2019) have been successfully used in different contexts for modelling the vineyard water status.

In order to design a future generation of real-time stand-alone sensors capable to estimate the water status, it is necessary to investigate different technical aspects that have to be combined with a suitable operation protocol. Regarding the sensors, several works have demonstrated the suitability of leaf reflectance to evaluate grapevine water status (De Bei et al., 2011; Rapaport et al., 2015; Pôças et al., 2020). However, to achieve integrated, miniaturized, and low-cost data assessment, variable (wavelength) selection has to be considered (Pasquini, 2018). Variable selection can also improve the prediction performance, make the calibration reliable, and provide a simpler interpretation of the results (Yun et al., 2019). Data mining strategies may be applied to grapevine data retrieved with new non-destructive devices, aiming for useful, reliable, and objective information (Gutiérrez et al., 2016).

Furthermore, some aspects related to the practical operation of the sensors also have to be studied. For example, environmental and uncontrolled light conditions could be cancelled out by performing signal acquisition during the night or by using light modulation strategies. Moreover, it has long been recognized that many important ecological processes vary with leaf age, the time elapsed since leaf budburst. During their lifetime, leaves exhibit variable photosynthetic rates, morphological, allocation and transformation of chemicals, epiphyll colonization, and defence against herbivory. Thus, leaf age is a critical parameter for interpreting leaf function over time and for understanding how leaf traits evolve over development (Wu et al., 2017). Accordingly, there is the need to develop a stand-alone, cost-effective, sensor and a relative operative procedure in a view of a network of distributed optical sensors to make a rational decision about irrigation scheduling towards a more sustainable grape and wine production.

The specific objectives of the study were to identify the most sensitive wavelengths to water status at the leaf level, by induction of stress under controlled conditions and to utilize these indicative bands to design a chemometric model and to compare the performance with the quantitative model using the whole spectra deriving from a commercial portable spectrophotometer.

2. Materials and methods

2.1. Sampling

The experimental activity was performed from the beginning of May to the end of July 2020 at the department of agriculture and environmental sciences of the University of Milan. The sampling was carried out in 8 sampling times on 24 grapevines of *cv*. Pinot Blanc, grafted onto two different rootstocks (1103 P and M4). The vines were 4 years old, grown in 60 L plastic pots and the substrate was composed of 70% sand and 30% peat, supplemented with a layer of expanded clay aggregate on the bottom of the pot to reduce water flooding. The training system was Guyot. During the phenological phase of budding, the plants were maintained in well-watered conditions in order to develop a well-expanded canopy. Moreover, phytosanitary status was controlled in order to keep the same sanitary conditions for each vine.

Soil water content was maintained at field capacity level till the beginning of the experiment, after that the irrigation was interrupted for the whole experimental period. The plants were divided into two groups (lines 1 and 2) based on the rootstock genotype at 0.5 m from each other.

For each rootstock, 11 plants were used as a test (test plant) and 1 plant was used as control (control plant), for a total of 22 test plants and 2 control plants as showed in Fig. 1.

The analyses were performed in predawn, from 03:00 to 05:30, when the water potential of leaves is in equilibrium with the water potential of the soil. One median leaf per plant of about 30 days old was chosen from a primary shoot at each sampling day. Therefore, each individual leaf was first submitted to the optical analysis followed by the water potential and moisture content analysis, which are described in detail in the next sub-sections.

2.2. Optical analysis

Optical data were collected (immediately after choosing the leaf without any dark room) using a portable full-range spectrophotometer (ASD Quality SpecTrek, Malvern Panalytical, UK) operating between 350 and 2500 nm. Each spectrum was acquired using a black pad positioned at the opposite side of the leaf acquisition surface. The black pad allows the acquisition of only reflectance data avoiding eventual transflection of the light. In a view of a future application of stand-alone sensors, this procedure won't be needed because no reflective surfaces (for transflectance analysis) should be present behind the leaf, and also no issues of moisture accumulation and leaf damage will arise.

Four averaged reflectance spectra for each leaf were acquired: two on the upper surface (adaxial) and two on the

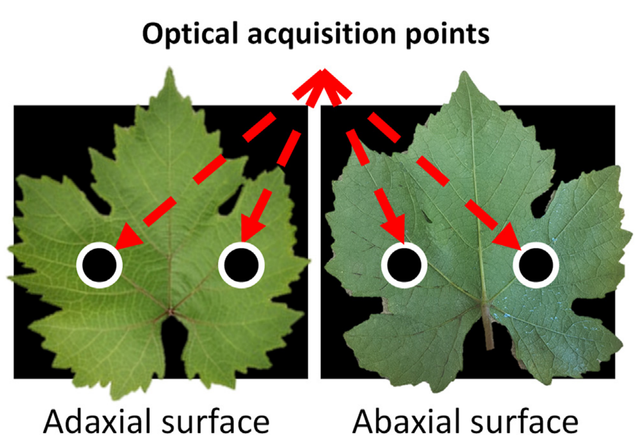

Fig. 2 – Spectral acquisition setup carried out on the leaf surfaces.

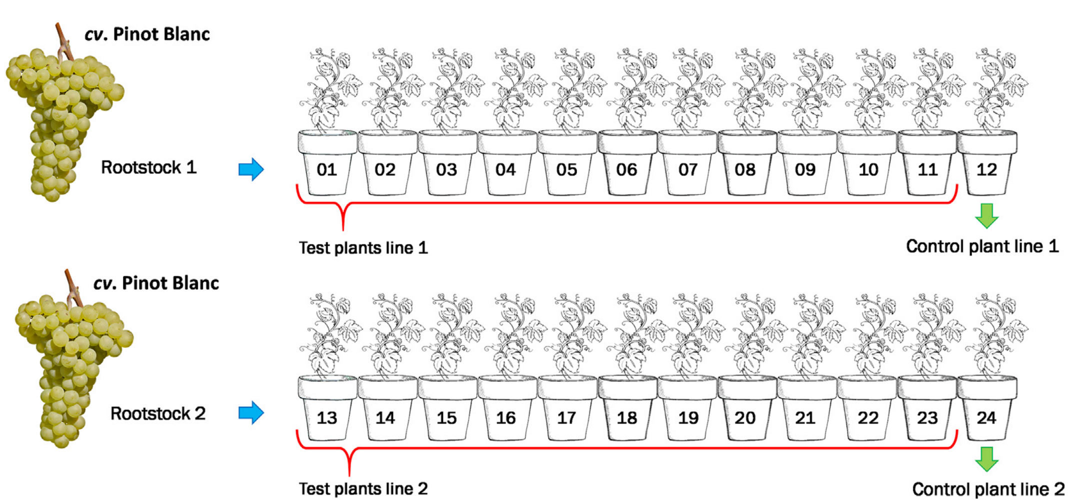

Fig. 1 – Organization of the samples analysed in controlled condition.

Please cite this article as: Pampuri, A et al., Optical specifications for a proximal sensing approach to monitor the vine water status in a distributed and autonomous fashion, *Biosystems Engineering*, https://doi.org/10.1016/j.biosystemseng.2021.11.007

lower surface (abaxial) as showed in Fig. 2. At the end of each acquisition, which takes about 30 s, the spectrum of each sample is automatically calculated as the average of 50 scans, to obtain a more representative spectrum of each side of the leaf.

2.3. Water potential and moisture content analysis

From the same leaf where the optical analysis was performed, the predawn water potential (Ψ_{PD}) was measured by using a Scholander pressure chamber (Scholander et al., 1965), produced by PMS Instrument Company, Corvallis, Oregon (USA).

Then, after optical and pressure analyses, to determine the moisture content (MC) each leaf was weighed (fresh weight) using an analytical balance (LAZ 30 P, Sartorius Lab Holding GmbH, Goettingen, Germany). Then the leaves were stored to be dried in an oven (UNB400, Memmert GmbH & Co, Schwabach, Germany) at 90 ± 1.5 °C for 48 ± 0.25 h and dried until constant weight. Once reached room temperature, leaves are re-weighed (dry weight) for the MC determination (Eq. (1)):

$$MC\ (\%) = \frac{(GW - DW)*100}{GW} \tag{1}$$

where:

$MC\ (\%)$ = percentage of moisture content;
GW = gross weight;
DW = dry weight.

2.4. Data analysis

The data analysis was performed in the Matlab® environment, version 2021a (The MathWorks, Inc., Natick, MA, USA) using both the PLSToolbox package (Eigenvector Research, Inc. Manson, Washington) and in-house functions. The data processing workflow included four steps: (i) the analysis of the relationship between Ψ_{PD} and MC, (ii) the development of a predictive model for predicting between Ψ_{PD}, (iii) the variable selection based Variable Importance in the Projection (VIP) scores and, (iv) the development of a simplified predictive model based on the variables previously selected.

The first part is focused on finding the correlation structure between Ψ_{PD} and MC using the Pearson correlation coefficient and the relative significance was evaluated by p-value calculation.

The second step was the calculation of the predictive model using optical data for the prediction of Ψ_{PD}. In order to reduce instrumental noise at the tails of the instrument spectral range, the spectra were cut from 480 to 2200 nm. Different pre-processing techniques were applied to highlight spectral differences related to Ψ_{PD} and the most performing one was identified in Savitzky and Golay second derivative (Der 2) with a second-degree polynomial order and a window size equal to 15. Considering the inhomogeneous physical structure of the samples, the Der 2 pre-treatment can correct the eventual baseline vertical shifts (offsets) and of the global intensity effects (typically arising from unwanted light scattering). Furthermore, the spectra were mean-centred focusing on the variability among the sample (Biancolillo & Marini, 2018; Oliveri et al., 2019). A latent variable modelling using the Partial Least Square (PLS) method, which maximizes the covariance among the vis/NIR spectra and Ψ_{PD}, was performed (Oliveri et al., 2020). To build calibration and validation datasets, leaves samples were averaged in pairs as described in Fig. 3. Therefore, considering the 8 sampling times, 10 samples were used for calibration and 2 samples were used for validation for a total of 80 calibration samples and 16 samples as an external validation set. In particular, the calibration model was built using only the test plants to have a wider variability to be used for the model building.

The models' accuracy was evaluated using the RMSE (root mean square error), as well as bias and R^2 (coefficient of determination); the lower the error and the bias and the higher the R^2 (as maximum equal to 1), the better the model performances. Besides, the RPD (ratio between the standard deviation of the response variable and RMSE) was calculated. An RPD between 1.5 and 2 means that the model can discriminate low from high values of the response variable; a value between 2 and 2.5 indicates that coarse quantitative predictions are possible, and a value between 2.5 and 3 or above corresponds to good and excellent prediction accuracy, respectively (Nicolai et al., 2007).

The third step included the variable selection, which was performed using Variable Importance in the Projection (VIP) scores. The VIP score is the squared function of the PLS weights taking into account the amount of explained y variance in each dimension. The VIP score value is calculated for each variable. Therefore, VIP scores provide information about the significance of each variable on the latent variables (LV). The greater the VIP scores, the more important the corresponding variable is. VIP score values greater than 1.0 are used as a threshold criterion for variable selection since the respective variables are considered to be the most influential in the model.

Therefore, as the final step, the model was rebuild using new optical variables applying Der 2 (as the full variable model) and Autoscaling. This column pre-processing eliminates systematic location and dispersion differences between heterogeneous variables, thereby giving all of them the same a priori importance (mean values equal to 0 and standard deviations equal to 1) and enhancing differences between the samples. In the case of signals in which all of the variables have different nature, measurement unit or spectral ranges, column autoscaling it is important if there are variables that are characterized by a relatively low mean value and/or standard deviation but which contain useful information (Oliveri & Downey, 2013).

3. Results and discussions

3.1. Reference data analysis

In order to bring the plants toward a more stressed condition and obtain enough variability to build a reliable multivariate model for the valuation of water potential, the test pots were covered by a plastic film from the beginning to the end of the sampling campaign. This covering procedure has prevented the infiltration of water during rainfalls. However, it avoided the evaporation of the water from the soil extending the time required to obtain the situation of stress.

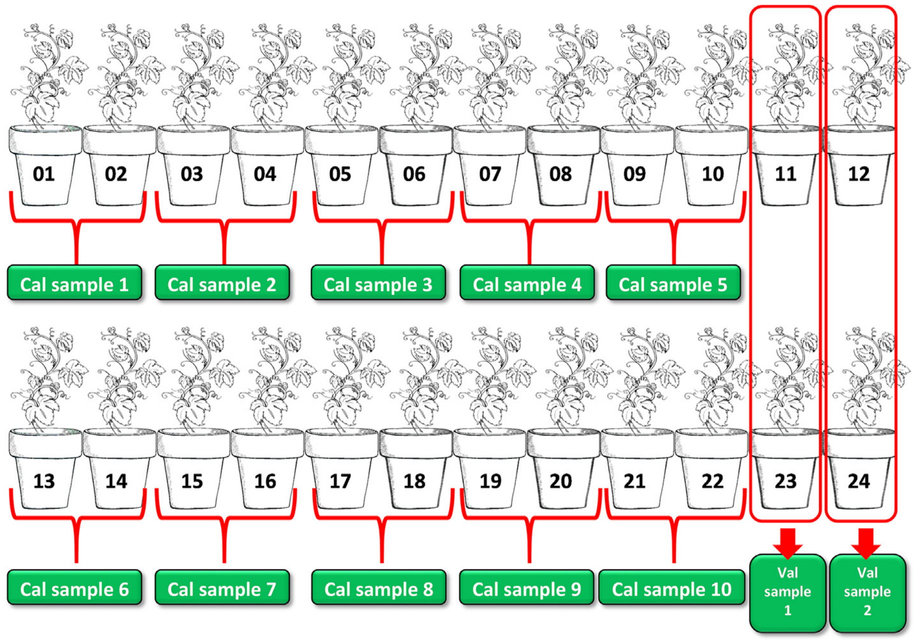

Fig. 3 — Dataset organisation for model construction.

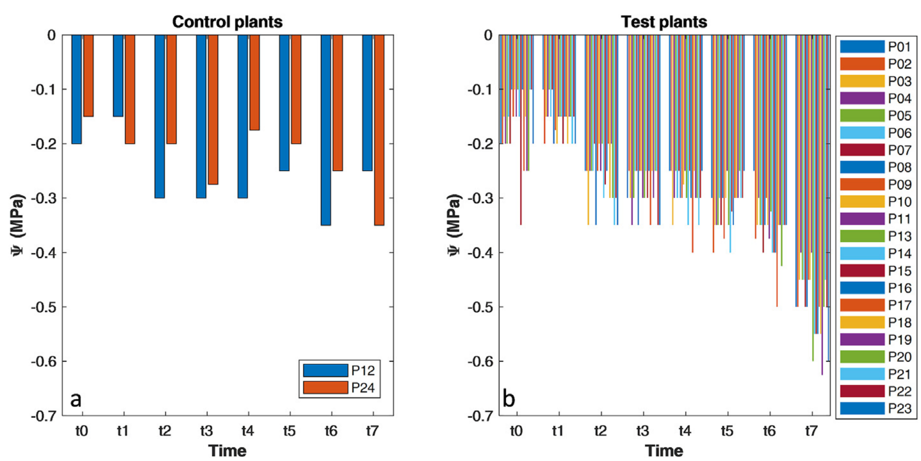

Fig. 4 — Water potential results for control plants (a) and test plants (b) for both rootstocks.

The predawn water potential is reported in Fig. 4. Overall, the control plants (P12 and P24, Fig. 4a) water status remain steady along the whole sampling period showing values of water potential of 0.25 ± 0.1 MPa. Instead, the plants used as test (Fig. 4b) show a general increasing trend (from about 0.15 to 0.55 MPa) caused by the decreasing water availability.

Though only one variety was considered (*cv.* Pinot Blanc) two rootstock genotypes have been used in this work. Fig. 5 shows the mean and the standard deviation of water potential of the test plants with rootstock 1 (Fig. 5a) and rootstock 2 (Fig. 5b). Overall, no significant differences in water potential have been highlighted from t0 to t5 in both rootstocks. While, concerning the samples measured in t6 and t7, a more pronounced condition of stress was expressed by rootstock 2. Moreover, considering the eleven vines (from each rootstock) as replicates, a direct estimation of the measurement error of the analysis with Scholander pressure chamber has been performed calculating the mean of the standard deviation obtained from each sampling time. The mean standard deviation showed a measurement error (in absolute value) of the reference method equal to 0.045 MPa.

In order to define the relationships between the predawn water potential and leaf water content, a Pearson correlation analysis was performed (Fig. 6). The plots matrix shows correlations among both variables considered (MC and Ψ). Histogram distribution plots of the variables appear along with the matrix diagonal and scatter plots of variable pairs appear in the off-diagonal. The slopes of the least-squares reference lines represent highly significant (p-value<0.05) correlation coefficients equal to 0.47. Even though the Pearson correlation shows that a significant link between the two parameters exists, it is clear that the water content of the leaf is not directly related to the water pressure and, thus, it can not be used as a proxy of water potential. This suggests that for a

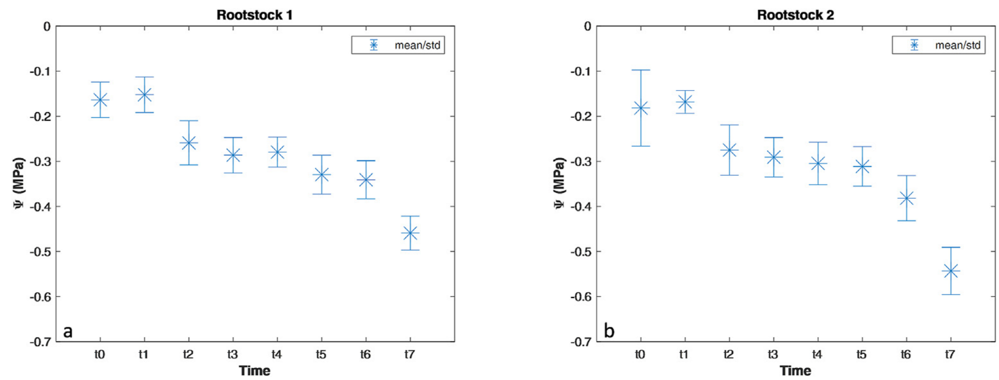

Fig. 5 – Mean and standard deviation of water potential for rootstock 1 (a) and for rootstock 2 (b).

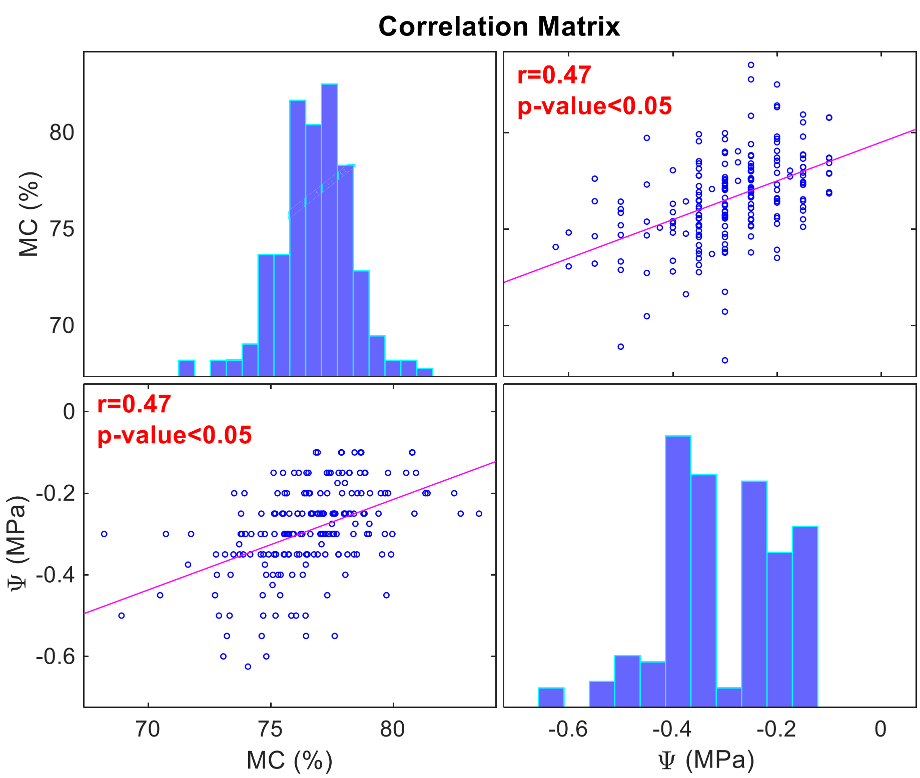

Fig. 6 – Pearson correlation analysis and frequency (on diagonal) plot for MC and ΨPD.

supervised modelization using optical data, the OH- bonds (highly related to the water absorption) need to be taken into consideration for the construction of a multivariate model.

3.2. *Spectra exploration*

Concerning the optical analyses, in order to reduce the physiological variability of leaves along the whole sampling campaign (Santesteban et al., 2019) the median leaf from the primary shoot was picked at each sampling day. This procedure guaranteed the reduction of the optical noise related to the leaf color change that is part of the ageing process. Furthermore, only the spectra acquired from the abaxial surface were used for the analysis. Even though the analysis was conducted in controlled conditions (keeping the sanitary status monitored and constant for all vines), the common treatments could affect the spectra acquisition on the adaxial surface producing optical noise. Considering the different types of sanitary treatments which can also be carried out in a real commercial vineyard, the adaxial surface is unsuitable to be used to obtain optical information related to water potential. Therefore, the use of only the abaxial surface is recommended to develop optical models for the estimation of this parameter.

Figure 7 shows the mean raw (Fig. 7a) and pre-treated spectra acquired from the abaxial surface of sampled leaves. The spectra have been labelled (from dark blue to yellow) according to the respective value of water potential measured with the Scholander pressure chamber.

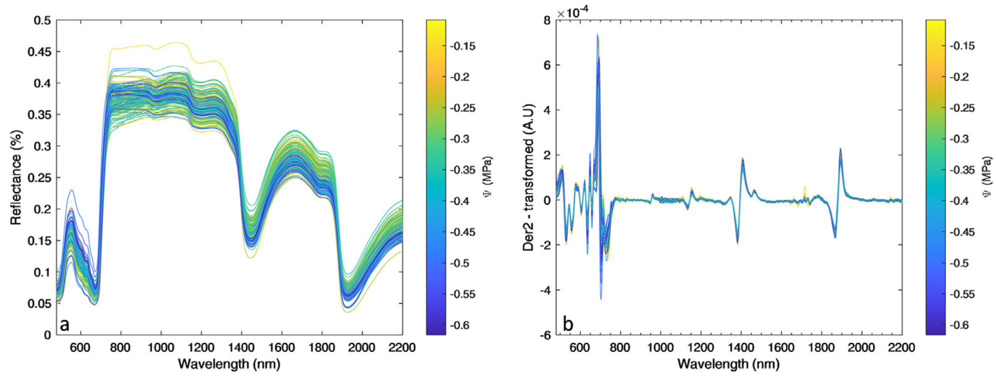

Fig. 7 – Raw (a) and second derivative pre-treated (b) spectra from leaves abaxial surface. Spectra were coloured according to Ψ_{PD} values.

From raw spectra (Fig. 7a), the water stress seemed to cause a progressive reflectance increasing trend in the green (530–550 nm) and red (700–750 nm) regions. While, in the pure NIR a decreasing reflectance trend was observed around the –OH bands (970–1000, 1380–1420, and 1900–2000 nm) which can be related to water absorption. The moisture content in grapevine leaves is higher than 60%. In this sense, the bands at 978, 1454, and 1930 nm are related to the OH second overtone, the OH stretch first overtone, and the harmonic and combination bands of OH bonds in hydroxyl groups, respectively (Tugnolo et al., 2021). The water content, besides altering the spectrum with changes in the strength of hydrogen bonds, causes other changes due to the combination of the OH-groups engaged in hydrogen bonds with other molecules. Water associates strongly with ions, organic monomers, and polymers by hydrogen bonds; therefore, water absorption bands in the near-infrared spectrum are influenced by the effects of other molecules with water (Büning-Pfaue, 2003).

However, especially in the NIR region (700–2200 nm), a clear scattering effect appears in the raw data causing significant repercussions in the global intensity of the optical signal. Therefore, the entire spectrum of each sample has been mathematically pre-treated using a Der 2 transformed (Fig. 7b). After pre-treating, a more in-depth visual analysis of the spectra was performed. The individuation of the most representative spectral ranges for the prediction of the water potential is crucial for a future application in low-cost optical devices for water potential evaluation. Three important optical ranges (two in the visible, the green and red regions, and one in the NIR, the–OH bond) were identified as the ones with higher variability when analysed together with Ψ values obtained from the reference method. Overall, the Der 2 transform improved the stability of the optical signal. However, the reference method error can affect the supervised modelling phase (0.045 MPa, deriving especially from the different manual operations necessary to carry out the analysis). Therefore, to reduce the associated error derived from the use of one leaf as one sample, an averaging process was performed. Indeed, the mean result from the analysis of two leaves (at least) was considered. No particular considerations were performed for the choice of the two leaves to be averaged. This procedure was performed at each sampling time. The mean value of water potential and the mean spectrum were obtained coupling the results from two plants as described in Fig. 3. Then, the second derivative transform was applied to the spectra. Fig. 8 shows the pre-treated spectra (used for calibration model) highlighting the main three ranges of the vis/NIR spectrum where a clear effect of water stress exists. Similar results were observed by Rapaport et al. (2015) that showed the existence of opposite reflectance trends (in hyperspectral data) at 530–550 nm and around 1500 nm (associated with independent changes in photoprotective pigment contents and water availability) indicative of stress-induced alterations in midday leaf water potential (Ψ_l) on plants of *Vitis vinifera* L. cv. Cabernet Sauvignon.

3.3. *Regression model and variables selection*

The spectral data (pre-treated with Der 2 transformed and then mean-centered) were used to build a PLS regression model to predict values of predawn water potential to evaluate the level of water stress of the grapevine. Fig. 9 shows the figures of merit and the regression model using the entire vis/NIR spectral range. The calibration, cross-validation and external validation results have been reported.

Overall, a good predictive performance was obtained with a low error (RMSE CV = 0.051 MPa, RMSEP = 0.056 MPa) and a satisfactory R^2 equal to 0.78 and 0.7 in cross-validation and prediction, respectively. Comparable results were obtained in cross-validation by De Bei et al. (2011) using spectral vis/NIR data, and in prediction by Rapaport et al. (2015) and Pôças et al. (2020) using hyperspectral vis/NIR data. These already promising results could be further improved by increasing the variability and the number of samples employed. However, the capability of the model to predict enough accurately the new samples (coming from the external validation set) left the floor to move toward a simplification of the model using few optical variables.

Therefore, with the view to developing a new concept of customized optical devices using few optical variables for water status evaluation, the VIP scores were calculated (Fig. 9b). The VIP revealed the most important variables used to predict the grapevine water potential and confirmed the spectral visual inspection. In particular, wavelengths in the visible around 530 nm and the NIR around 730, 1000, 1400, and

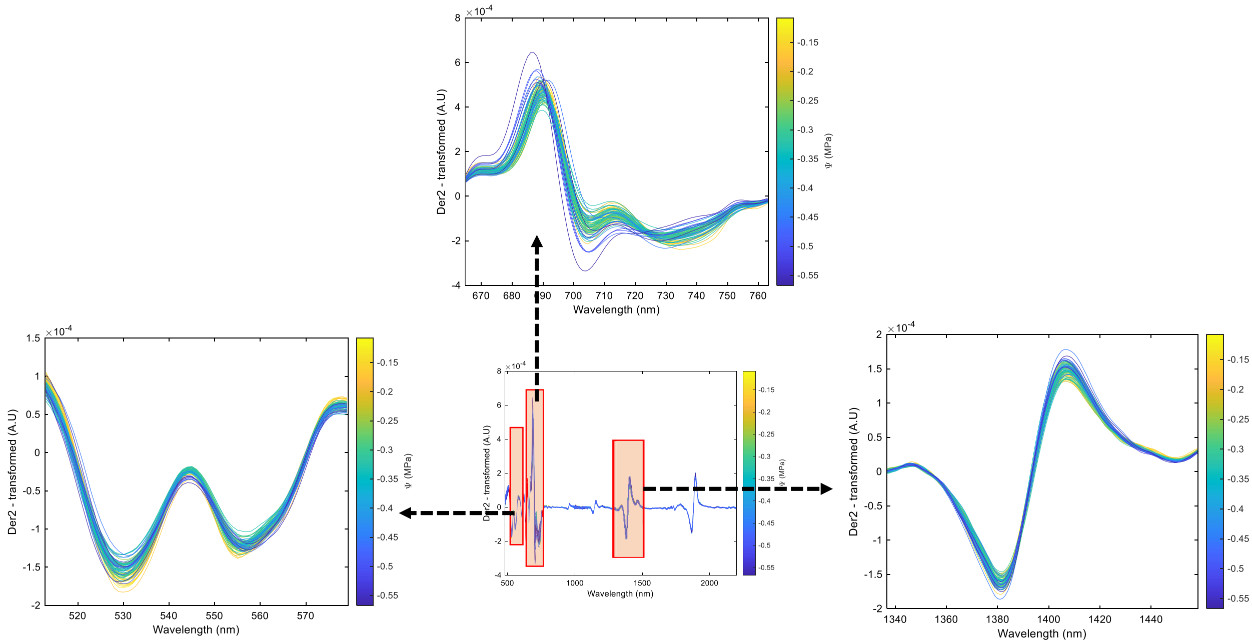

Fig. 8 — Spectral ranges where variations related to the Ψ_{PD} were highlighted after pre-treating with second derivative. Two ranges in the visible (from 520 nm to 570 nm and from 680 nm to 750 nm) region and one in the near-infrared (from 1380 nm to 1440 nm) region. Spectra were coloured according to Ψ_{PD} values.

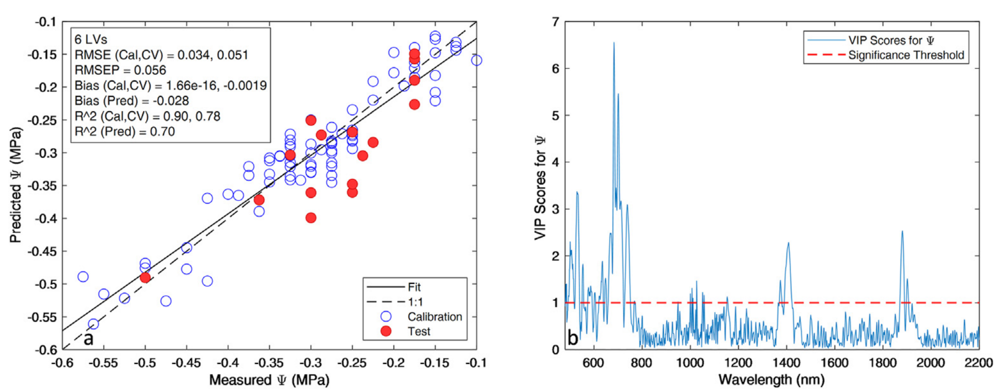

Fig. 9 — Figure of merits (a) of the PLS model built using the entire spectral range (from 480 nm to 2200 nm). Variable importance in projection (b) of the PLS model.

1900 nm were identified to be the most suitable for developing a new model with fewer variables.

Despite that, three main important spectral ranges were identified (from the visual spectral analysis and the VIP calculation) as more informative and technically (in terms of costs and engineering) more suitable for the development of customized optical systems with few wavelengths that could be applied directly on the leaf. The two ranges in the visible

Table 1 — Figure of merits (in cross-validation, RMSE-CV and R^2CV, and prediction RMSEP and R^2Pred) of the PLS models built using the full spectrum and the wavelengths selected from the VIP scores analysis. The mean and the standard deviation (SD) for Ψ_{PD} were reported. The number of latent variables (LVs), calibration (Cal) and prediction (Pred) samples were highlighted.

PLS models	Mean	SD	Ψ_{PD} (MPa) Range	LVs	Cal samples	Pred samples	R^2CV	RMSE-CV (MPa)	R^2Pred	RMSEP (MPa)	RPD
Full spectral range	−0.28	0.107	−0.1 < Ψ <-0.575	6	80	16	0.78	0.051	0.70	0.056	1.91
Selected spectral bands	−0.28	0.107	−0.1 < Ψ <-0.575	7	80	16	0.78	0.05	0.60	0.058	1.84

Table 2 – Strengths, weaknesses, opportunities, and threats related to the application of the experimental outputs and concepts of this work in the viticulture sector.

Positive	Internal		Negative
	Strengths	*Weaknesses*	
	Selection of vis/NIR bands easily available on the market	High variability of environmental conditions	
	Design a network of distributed proximal sensors characterized from 3 optical bands for real-time leaf water status evaluation	High variability of crops and soil	
	Design of operative procedure easily applicable infield contest	Difficult to positioning infield the stand-alone sensors	
	Opportunities	*Threats*	
	Monitoring of crop water status in a semi-continuous way	Research efforts in optimizing water potential estimation	
	Improvement of irrigation management	Strong link with traditional methods by wine operators Reduced orientation towards innovation by wine operators	
	External		

(530 ± 20 nm and 700 ± 20 nm) and one in the range related to the first OH- overtone (1400 ± 20 nm) were used to develop a new PLS regression model (Table 1). The same samples were used for calibration and prediction but, in this case, the data were pre-treated using Der 2 and scaled using autoscale, to give the same importance to all the optical variables included. Overall, a comparable error was obtained (both in cross-validation and prediction) using 7 LVs with respect to the PLS model using the entire spectral range.

3.4. *Potential field application*

Research has been focusing on the development of simplified systems (Dhillon et al., 2019; Pichon et al., 2021; Das et al., 2017) for the estimation of the water status of different crops (bib_Elvanidi_et_al_2017Elvanidi et al., 2017). In particular for sectors in which the product is characterized by a high added value as in the grape and wine sector.

Currently, no commercial cost-effective stand-alone devices capable to estimate rapidly the water status directly in the field are available on the market. However, the ongoing optical technology is ready to be used directly in the field without the presence of human resources.

The consumer electronics industry is driving the convergence of digital circuitry, wireless transceivers, and microelectro-mechanical systems (MEMS), which makes it possible to integrate sensing, data processing, wireless communication, and power supply into low-cost millimetre-scale devices (Sadowski & Spachos, 2020). The resulting miniaturization and cost reduction of electronic components is leaving space for a completely new method of data acquisition and management using wireless sensor networks (WSNs) based on small battery-powered nodes. A WSN consists of small and low-cost Internet-of-Things (IoT) devices in a network of peripheral nodes equipped with sensors and a wireless module for data transmission to an online database, where the data are stored and accessible to the end-user. These nodes are energy independent and could be installed in specific areas of the vineyard to provide more representative information of the entire vineyard variability (Dhillon et al., 2017).

To transfer this optical technology from a controlled condition (using full range spectrophotometer) in the real field conditions (using optical sensors with few wavelengths) it is important to respect different crucial aspects: (i) reproduce at best the controlled conditions in the field (analysis during the night on several plants of the same parcel), (ii) design a sampling campaign to maximize the variability of the whole vineyard related to the leaf water potential (iii), minimize the noise related to the leaf ageing and phytosanitary treatments and (iv) introduce into the optical dataset the data from sensors which monitor the vineyard environmental conditions (temperature, relative humidity, and leaf wetness). This work has been focusing on the definition of the optical specifications for the development of simplified and cost-effective sensors to be used in a network of distributed field sensors. In order to summarize the strengths, weaknesses, opportunities, and threats related to the application of the experimental outputs and concepts of this work in the viticulture sector, a SWOT table was created (Table 2).

4. Conclusions

In this preliminary work performed in controlled conditions, a model using optical data from a full range vis/NIR spectrophotometer (350–2500 nm) was proposed to predict leaf water status and relate with plant water stress in order to replace the traditional time-consuming destructive method (Scholander pressure chamber). The optical outputs (combined with a chemometric approach) have shown a good capability to be used as predictors of the PLS model for the prediction of the Ψ_{PD} (RMSEP = 0.056 MPa, $R^2 = 0.7$).

Moreover, to further simplify the computation of the PLS model, a variable selection strategy was proposed using the VIP scores obtained from the PLS model using the full vis/NIR range. The new model has shown comparable results (RMSEP = 0.058 MPa, $R^2 = 0.6$) using only three spectral bands (two in the visible and one in the NIR). This model simplification had the main goal to be implemented with a future simplified optical hardware. Indeed, the technology is in sharp development and is reaching a considerable level of miniaturization. Therefore, the development of a new generation of non-invasive IoT devices capable to monitor the leaf water status in a distributed and autonomous fashion in a cost-effective manner has the potential to revolutionize the

Please cite this article as: Pampuri, A et al., Optical specifications for a proximal sensing approach to monitor the vine water status in a distributed and autonomous fashion, *Biosystems Engineering*, https://doi.org/10.1016/j.biosystemseng.2021.11.007

vineyard irrigation management system, projecting the viticulture towards a new paradigm.

Funding

This research has been founded by European Horizon 2020, project i-GRAPE (grant Nº 825521) and Regione Lombardia 2018, project ADAM (grant Nº 4403).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors wish to thank Prof. Paulo Freitas and Prof. Claudio Gandolfi for the supervision of the research projects. The authors also acknowledge to the i-Grape consortium for the fruitful discussions and inputs.

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Please cite this article as: Pampuri, A et al., Optical specifications for a proximal sensing approach to monitor the vine water status in a distributed and autonomous fashion, *Biosystems Engineering*, https://doi.org/10.1016/j.biosystemseng.2021.11.007