USING NIR/SWIR HYPERSPECTRAL CAMERA MOUNTED ON A UAV TO ASSESS GRAPEVINE WATER STATUS IN A VARIABLY IRRIGATED VINEYARD

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Abstract:

Context and purpose of the study – Vineyards face climate change, increasing temperatures, and drought affecting vine water status. Water deficit affects plant physiology and can ultimately decrease yield and grape quality when it is not well managed. Monitoring vine water status and irrigation can help growers better manage their vineyards. However, when field measurements, such as stem water potentials (SWP), can be precise, they are time-consuming. In addition, they do not allow for easy assessment of spatial variability, which is a critical factor for water status management. Remote sensing tools can help map plant water status in space and time and streamline data acquisition over whole vineyards several times during the season. In this project, we monitored a variably irrigated vineyard several times during the season with a hyperspectral NIR/SWIR camera mounted on a UAV.

Material and methods – We worked in a Cabernet Sauvignon vineyard in the San Joaquin Valley of California equipped with an automated irrigation system. We created forty-eight independent watering zones and applied twelve different amounts of water replicated four times in a randomized block scheme. Water amounts were fractions of the grower allocation and applied as sustained and regulated deficit irrigation strategies. Hyperspectral images in 112 bands from 900 nm to 1700 nm were collected using a UAV every two weeks from June to harvest. Contemporarily, we measured vine water status through SWP, stomatal conductance (g_s) and net assimilation (A_N). For the analysis, the images were segmented to extract the canopy signal and converted to reflectance, then used to predict the field water status measurements using machine learning models. Models were evaluated using coefficients of determination (R^2), and root mean square error (RMSE). Feature importance was also computed to determine the importance of each band in the model.

Results – Field measurements of stem water potential ranged from -2.0 to -1.14 MPa. The canopy signal was segmented from the soil background using a classifier with an accuracy of 99.7%. We tested random forest, gradient boosting machine, and support vector machine algorithms in a preliminary analysis to predict SWP values. The most performant model was the random forest, and it was able to predict SWP values with an R^2 of 0.6 and an RMSE of 0.1 MPa as assessed in a 5-fold cross-validation procedure. The most important bands for model prediction were 1146 nm, 1153 nm, 1321 nm, 1363 nm, and 1434 nm, all situated in water absorption domains. These promising results demonstrate that SWIR images can monitor the field's vine water status and inform irrigation management with high resolution.

Keywords: Vine water status, hyperspectral imaging, drone, variable rate irrigation,

1. Introduction

Grapevine production is highly dependent on efficient water management, and traditional tools like the pressure chamber have been used for decades to make plant-based irrigation decisions (Levin et al., 2021). However, in recent years, sensing (Bellvert et al., 2015; Brillante et al., 2015) and modeling approaches (Brillante et al., 2016a) have gained popularity. It has been found that water status, regulated through deficit irrigation strategies, significantly affects grape quality and production performance (Brillante et al., 2017; Yu et al., 2020; Martinez-Luscher et al., 2017; Brillante et al., 2018). On the other hand, sustained deficit irrigation is a technique where vines are watered at a constant deficit regardless of their phenological stage. If executed optimally, deficit

irrigation can improve fruit quality and sustainability without negatively impacting yield (Edwards et al., 2013). Furthermore, novel systems that enable variable irrigation at the local scale can be used to adapt water schedules to individual rows, resulting in improved return on water usage. These systems require new solutions to determine the required amount of water for plants with higher spatial resolution.
Even though grapevines are capable of withstanding drought conditions, prolonged or severe irrigation deficiencies can cause physiological changes that affect their physical and chemical composition (Maimaitiyiming et al., 2020). Remote sensing imagery can be used to detect these changes, with alterations in cell structure observable in the NIR domain (De Bei et al., 2011) and changes in water content impacting the SWIR domain (Kandylakus et al., 2020). Hyperspectral imaging offers the combined power of spectral and spatial information, which can be leveraged to evaluate vine water status. Previous studies, such as Kandylakis et al. (2020), have shown that UAV-based SWIR reflectance is useful for measuring grapevine stomatal conductance. Additionally, Laroche-Pinel et al. (2021) found that satellite-based NIR and SWIR reflectance at 10-20 m resolution can be used to predict grapevine stem water potential, although better pixel resolution can be achieved through UAV acquisition. It is important to note that both studies were conducted outside of the United States, indicating a regional gap in the literature.
As the use of agricultural remote sensing continues to promote economic and environmental growth through improved resource management decisions, concerns remain regarding the interpretation, cost, and accuracy of unmanned aircraft vehicles (drones) and their corresponding sensors (Khanal et al., 2020). In this study, a commercial vineyard block was subjected to twelve irrigation regimes to introduce local-scale variability in water potentials. This added to a ground-based dataset of plant water potentials and their spectral signatures, which was then utilized to train a machine learning model to predict the water status of grapevine plants in hyperspectral images with 112 narrow band-wavelengths in both the Near-Infrared (NIR) and Short-Wave-Infrared (SWIR) domains.

2. Material and methods

Experimental design - The experiment was carried out in Cantua Creek, California (36.50745° N, 120.29715° W) on a commercial vineyard growing Cabernet Sauvignon grapes. The study area covered 144 vineyard rows, and the experimental design involved twelve treatments that were replicated four times in a randomized block design. Each block consisted of three rows with three buffer rows separating them. On each row, four treatments were applied to ten vines, and samples were collected from the four central vines. Four treatments were irrigated with sustained deficit irrigation at 100, 80, 60, and 40% of the adjusted control (grower allocation). The remaining eight experimental zones were subjected to regulated deficit irrigation treatments and were irrigated differently "pre" and "post" veraison. Variable deficit irrigation was applied in weekly sets ranging from 8-20 hours. All 192 experimental vines were GNSS sampled and tagged.

Plant measurements - The Stem Water Potential (SWP) was measured using a pressure chamber (Scholander et al., 1965) on one leaf per vine from a mature main shoot, which was bagged in Mylar® 30 minutes prior to removal to allow for leaf equilibration, following the sampling procedure in Brillante et al. (2016b). The plants were sampled three times between June 15, 2022, and August 3, 2022, with the 48 replicates measured on each of the three dates.

Images acquisition - Flight and ground data were conducted simultaneously. The DJI Matrice 600 Pro drone and the Specim AFX-17 hyperspectral camera, capable of capturing images in 112 bands from 900-1700 nm, were used in the study. The captured images were classified into three categories, namely, vine (99.7% accuracy), shadow, and inter-row using perClass Mira (perClass BV, NL). The vine class was then extracted from the classification mask and cropped to the extent of the 48 experimental zones. The mean radiance was then obtained from each zone for all three sampling dates.

Analysis - The extracted radiance was utilized to predict SWP values via a machine-learning model. The Random Forest (RF) selection function wrapped by Recursive Feature Elimination (RFE) was employed to determine the top-performing feature subsets (Kuhn., 2019). The predictor features were then evaluated for variable importance using a k-fold cross-validation resampling method conducted thrice.

3. Results and discussion

The plant's SWP values had a range of -1.74 to -1.18 MPa, with a mean of -1.55 MPa (Figure 1). Based on this initial investigation, the optimal model predicted SWP values with an R-squared (R2) of 0.52 and a root mean square error (RMSE) of 0.12 MPa (Figure 2).
Improvements can still be made in predicting SWP using SWIR hyperspectral data. Further work can be conducted to eliminate any potential noise in the hyperspectral data and to compute the conversion in reflectance using different methods. Moreover, larger datasets can lead to better training and prediction performance, and our research is still ongoing.
It may be possible to classify the observed and predicted SWP values into three categories based on their distribution: High stress (SWP < –1.6 MPa), stress (–1.6 MPa < SWP < -1.4 MPa), and no stress (SWP > -1.4 MPa).

The most significant features were the radiance values at 1433.76 nm, 1497.5 nm, 1504.59 nm, 1490.41 nm, 1525.89 nm, 1518.79 nm, and 1511.68 nm, as determined by the top five important features.
The model was able to select the most effective predictive feature wavelengths for estimating SWP, which are located within the water absorption domains as shown in previous research (Kandylakis et al., 2020; De Bei et al., 2011; Laroche-Pinel et al., 2021).

4. Conclusions

The initial findings of this study are encouraging, and ongoing efforts are being made to enhance the model. This research is one of the pioneering studies that employs SWIR hyperspectral data obtained from a UAV to forecast vine water status. To improve the predictive accuracy, it is necessary to collect more data by adding additional sampling dates during other growing seasons to validate and strengthen the predictive performance.

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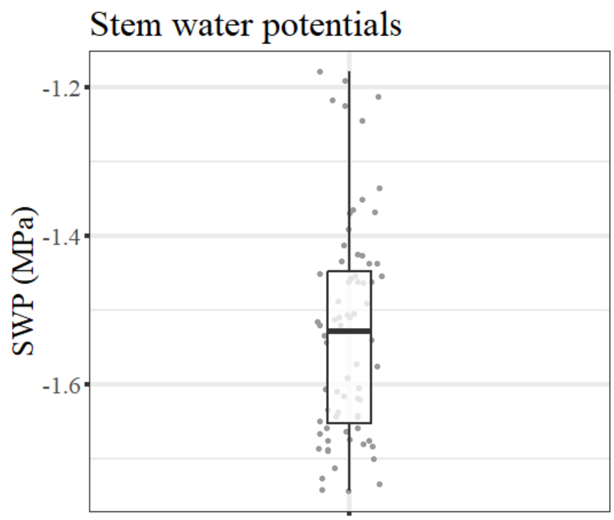

Figure 1: Variability of SWP values for full dataset

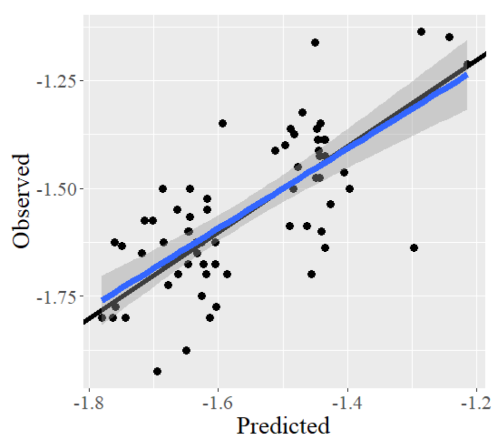

Figure 2: The predicted and observed SWP values for the repeated cross-validation