ESTIMATING GRAPEVINE WATER STATUS: A COMBINED ANALYSIS OF HYPERSPECTRAL IMAGE AND 3D POINT CLOUDS

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Abstract:

Context and purpose of the study

Mild to moderate and timely water deficit is desirable in grape production to optimize fruit quality for winemaking. It is crucial to develop robust and rapid approaches to assess grapevine water stress for scheduling deficit irrigation. Hyperspectral imaging (HSI) has the potential to detect changes in leaf water status, but the robustness and accuracy are restricted in field applications. The varying leaf orientations can significantly affect how light interacts with the plant, ultimately influencing the reflectance properties. This study focused on developing an approach for detecting grapevine water status using HSI and 3D data. Leaf orientation parameters derived from 3D point clouds were integrated with spectral signatures to address the spectral variance caused by variations in leaf orientation. A water status assessment model was developed based on multiblock partial least squares (MBPLS) to estimate leaf water potential (Ψ_L) using spectral signatures and leaf orientation parameters.

Material and methods

HSI and 3D point clouds of selected leaves were captured simultaneously in a vineyard during the 2021 growing season, and Ψ_L was measured as the groundtruth to assess the model performance. Mean spectral reflectance was derived from the hyperspectral images, while leaf orientation parameters were extracted from 3D point cloud data. The dataset was split randomly into 70% training/calibration and 30% test datasets.

Results

The test result shows that the model estimated the Ψ_L with R^2 = 0.8942, RMSE = 0.1153 MPa and MAE = 0.0894 MPa. The leaf orientation parameters derived from 3D point clouds acted as an enhancing component that explained the spectral variance caused by variations in leaf orientation and improved the underlying relationship between spectral reflectance and vine water status.

Keywords: Grapevine, Hyperspectral image, 3D point clouds, Leaf orientation, Data fusion.

1. Introduction

Wine grape cultivation in regions experiencing periodic droughts necessitates irrigation to provide sufficient water for plant growth. However, over-irrigation can negatively impact berry pigments and sugar content, reducing wine quality. Therefore, mild to moderate and timely water deficit is desirable for wine grape production to achieve an appropriate balance between grape yield and quality (Acevedo-Opazo et al., 2010; Martínez-Moreno et al., 2022). Ground-based hyperspectral imaging (HSI) techniques provide opportunities for non-destructive and high-resolution assessment of grapevine water status (Ryckewaert et al., 2022; Thapa et al., 2022). However, the varying leaf orientations can significantly affect how light interacts with the plant, thus influencing the reflectance properties and ultimately affecting the accuracy of the results (Liu et al., 2020). Consequently, quantifying the spectral variance caused by the variation in leaf orientations is important to properly interpret the underlying relationship between spectral reflectance and vine water status. Recent advancements in three-dimensional (3D) imaging technologies have enabled accurate estimation of leaf angle and determining leaf orientation (Xiang et al., 2023). This study combined spectral signatures and geometric information, derived from hyperspectral images and 3D point clouds, respectively, to develop a model for grapevine water status estimation. Specifically, a Multiblock Partial Least Squares (MBPLS) model was created using leaf spectral reflectance and the normal vector of the leaf surface as inputs to estimate the mid-day Ψ_L.

2. Material and methods

Experimental site and design - Experiments were conducted in a Washington State University research vineyard with own-rooted *Vitis vinifera* L. cv. Riesling vines planted in 2010. Soil is Warden silt loam with varying depths, and the regional climate is semi-desert with 200 mm annual precipitation. Eighteen vines were randomly selected and were irrigated to water-holding capacity at the start of grape ripening in 2021, and subsequent water was withheld to create a gradient of plant water status.

Water status and image data acquisition - Data was collected weekly for six weeks after the irrigation event. Healthy, sun-exposed, fully developed leaves were labeled in the west side of each data vine between 14:00 and 15:30 on experimental days for ground truth measurements. A hyperspectral camera (Nano-Hyperspec®, Headwall Photonics, Bolton, MA, USA) and a stereo camera (ZED 2, Stereolabs, CA, USA) were used to capture images from a ground-based sensing platform. The hyperspectral camera had a spectral range of 400 – 1000 nm with 274 spectral bands, while the stereo camera captured 3D point cloud data with a resolution of 2208 × 1242 within a depth range of 0.3 – 20 m. After image acquisition, Ψ_L was measured using a pressure chamber (Model 615 D, PMS Instrument Company, Albany, OR, USA).

Data analysis - Data analysis for this study was conducted in Python 3.9. The hyperspectral image processing involved reflectance correction, leaf segmentation, and spectra extraction. Reflectance was corrected using dark and white references. Leaf segmentation was performed manually, and the spectra of individual leaves were averaged to obtain a single observation for each leaf, denoted by a reflectance vector: $[\boldsymbol{r_1},\boldsymbol{r_2} \ldots \boldsymbol{r_{274}}]$. The 3D data processing included point cloud visualization, leaf segmentation, and plane fitting. A plane that had the largest number of points within distance threshold (10 mm) was selected to represent the leaf orientation (Zhou et al., 2018). This process returned the plane as an equation ax + by + cz + d = 0 in the default 3D coordinate system of the sensor. The leaf orientation was denoted by the normal vector: [a, b, c]. Multiblock Partial Least Squares (MBPLS) regression was used to combine leaf spectral reflectance and orientation parameters to construct a Ψ_L estimation model. The reflectance vector and the leaf orientation parameter vector were used as inputs to the MBPLS-based model to estimate the output variable (Ψ_L). The dataset was divided randomly into 70% training/calibration and 30% test datasets. Leave-one-out cross-validation was used in the model calibration process to evaluate model performance, and three metrics, including coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE), were used to assess the model's performance. In the end, an Partial Least Squares (PLS) model was built using only spectra data to compare the model performance.

3. Results and discussion

3.1. *Data visualization*

A total of 213 samples (individual leaves) were collected in this experiment from 18 vines, with each sample consisting of 274 spectral variables (X1 block), three geometric variables (X2 block) and one output variable (Y). Figure 1 (A) shows the distributions of Ψ_L in training/calibration (150 samples) and test (63 samples) datasets. Leaf water potential, Ψ_L ranged from -1.9 to -0.6 MPa, with the majority of the observations between -1.4 and -0.6 MPa, corresponding to no water stress (Ψ_L > -0.9 MPa) and mild to moderate water stress (-1.4 MPa ≤ Ψ_L ≤ -0.9 MPa). A few observations were found between -1.9 and -1.4 MPa, which indicated severe water stress (Ψ_L < -1.4 MPa) (Rienth & Scholasch, 2019). The leaf orientations were identified based on their respective normal vectors, which were subsequently categorized into two groups: those pointing toward the south and those pointing toward the north. Figure 1 (B) presents the distribution of leaf orientations, revealing that a roughly equal number of leaves were observed facing north or south. Figure 2 displays the average spectra for two orientation groups, namely south and north, separately. This approach allows for a clear visualization of the observed differences in spectral patterns. Additionally, the spectra of samples belonging to three different water stress levels were also displayed separately. Notably, for each water stress level, leaves facing south exhibited higher reflectance than those facing north. This finding can be attributed to the smaller angles between leaf plane normal and incident light in the southern orientation. These results emphasize the significance of accounting for both water status and leaf orientation when analyzing spectral reflectance in vine leaves.

3.2. *Estimating leaf water potential with an MBPLS-based model*

Figure 3 (A) shows the performance of the PLS model using only spectral variables. It was evaluated with the same test dataset as the MBPLS model. Figure 3 (B) displays the performance of the MBPLS model using both spectral variables and leaf orientation parameters, providing a basis for comparison. The green lines correspond to the equation y = x, which depicts the perfect/ideal alignment of the estimated Ψ_L with the measured ground truth data. On the other hand, the red lines denote the regression lines relating measured and estimated Ψ_L, which exhibit estimation error and deviations from the ideal relationship. By combining spectral reflectance and leaf orientation parameters, it was noticed that the R^2 between estimated and measured values was improved from 0.8259 to 0.8942, whereas the RMSE was reduced from 0.1205 to 0.1153 MPa, and the MAE was reduced from 0.0953 to 0.0894 MPa. The leaf orientation parameters derived from 3D point clouds had a modest contribution to estimating leaf water stress. However, it acted as an enhancing component that explained the spectral variance caused by variations in leaf orientation and improved the interpretation of the underlying relationship between spectral reflectance and vine water status. Overall, these findings demonstrate the importance of considering multiple factors and data sources when estimating vine water status. While the study offered valuable insights, one limitation was that the solar angle still varied since the data collection was conducted over several weeks. To enhance the accuracy and validity of future research, it is recommended to integrate the solar angle into the model to gain a more comprehensive understanding of the intricate interactions between sunlight and plant water status.

4. Conclusions

The fusion of spectral signatures and leaf orientation parameters, derived from HSI and 3D point clouds respectively, enabled an MBPLS-based model to estimate grapevine leaf water potential with an R^2 of 0.8942, RMSE of 0.1153 MPa and MAE of 0.0894 MPa. The leaf orientation parameters acted as an enhancing component that explained the spectral variance caused by variations in leaf orientation and improved the interpretation of the underlying relationship between spectral reflectance and vine water status.

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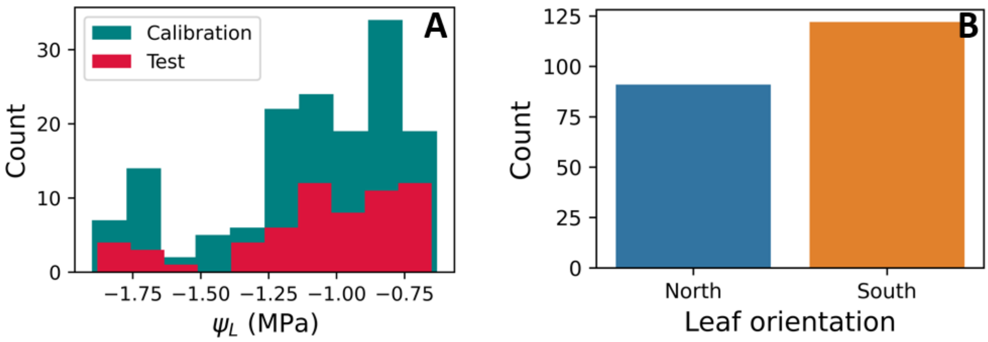

Figure 1: (A) Histogram of the output variable Ψ_L, displaying the frequency of observations for each value range. **(B)** Distribution of leaf orientations, displaying the frequency of observations for each orientation group.

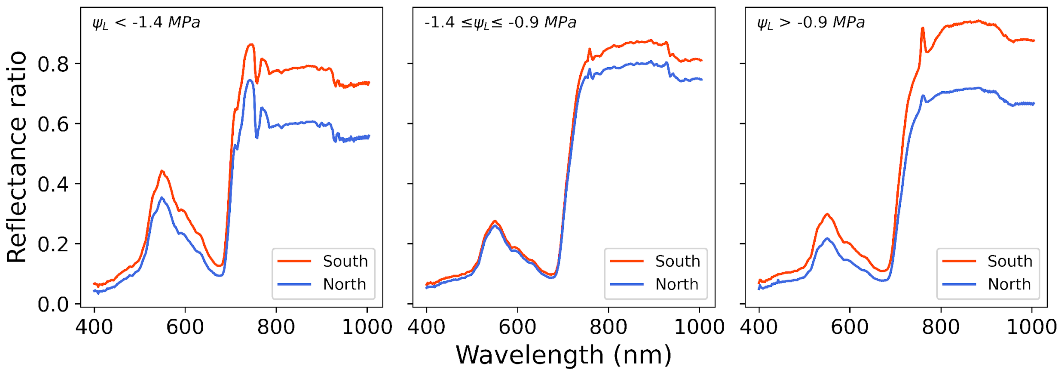

Figure 2: The spectra were averaged by water stress levels and leaf orientations, providing a visual representation of the observed differences in spectral patterns.

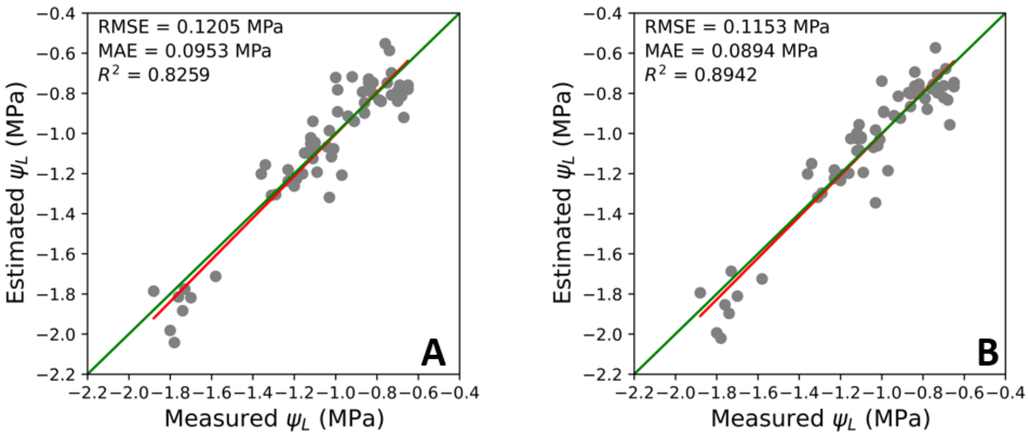

Figure 3: Comparing model performance on a test set for the estimation of Ψ_L using **(A)** spectral variables and **(B)** spectral and leaf orientation variables.