EXTENDED ABSTRACT

Spectral discrimination between *Vitis vinifera* and *labrusca* by spectroradiometric techniques

Tainá Fragoso[1], José Eduardo Costa[1,2], Jorge Ducati[1]
*Corresponding author: ducati@if.ufrgs.br

[1] State Center for Research in Meteorology and Remote Sensing - Universidade Federal do Rio Grande do Sul. Brazil (CEPSRM/UFRGS).
[2] Physics Institute - Universidade Federal do Rio Grande do Sul. Brazil (IF/UFRGS).

Keywords: spectroradiometry, *Vitis labrusca*, spectral classifications

ABSTRACT

Context and purpose of the study. Brazil is one of the few countries where vineyards of *Vitis labrusca* and *Vitis vinifera* coexist in the same geographical spaces, due to complex processes of territorial occupation by successive waves of European settlers. This situation presently leads to difficulties in the monitoring of grape and wine production, a necessary task to enforce regulations on wine quality. As an alternative to vineyard inventories informed by farmers, detection and discrimination of both Vitis species can be performed by Remote and Proximal Sensing techniques.

Material and methods. Spectroradiometry was performed on living leaves of plants of *Vitis vinifera* and *labrusca*. Vineyards were separated by 200 meters to minimize confusion effects from environmental factors. Resulting reflectance spectra were analyzed by PCA and other statistical techniques, looking for wavelengths where both species can be discriminated.

Results. Spectral traits typical of each species are mainly located at visible and near-infrared wavelengths. Accuracies as high as 85% in discrimination were attained, characterizing these techniques as a potentially useful tool to vineyard monitoring.

INTRODUCTION

Brazil holds a unique position in the global viticulture landscape by contain, within the same geographical region, both *Vitis vinifera* and *Vitis labrusca* vineyards. This configuration arises from historical processes of territorial occupation, characterized by successive waves of migration and the local adaptation of grape varieties to diverse edaphoclimatic conditions (Protas *et al.*, 2024). Although this varietal richness is an important characteristic, it poses significant challenges for monitoring vineyard production, particularly with respect to traceability and standardization of wine quality.

Monitoring vineyards and assessing the spatial distribution of varieties represent critical challenges for crop management and limit the effectiveness of public policies, origin certification, and production planning. In light of these challenges, technologies based on remote sensing (RS) and proximal sensing offer promising non-invasive and systematic alternatives for crop detection and discrimination (Mazzia *et al.*, 2020).

Within this context, contact spectroradiometry—based on measurements of leaf reflectance of electromagnetic radiation—reveals spectral signatures that vary between grapevine varieties, enabling the exploration of these data to distinguish species and cultivars (Lacar *et al.*, 2001). This approach can enhance vineyard monitoring strategies, support precision viticulture, and advance techniques for mapping varieties in regions where multiple species coexist. By investigating the spectral behavior of grapevine leaves through contact sensing techniques, this study aims to contribute to the development of classification models that assist in territorial management and add value to viticultural production.

RESEARCH OBJECTIVES

The objective of this study is to assess the feasibility of using contact spectroradiometry to discriminate between *Vitis vinifera* and *Vitis labrusca* vines. It aims to identify the spectral regions with the greatest discriminative power between different cultivars and species by analyzing leaf reflectance spectra. For this purpose, statistical methods such as Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) will be applied, along with complementary techniques, to extract meaningful spectral features. This study proposes to contribute to the development of alternative varietal mapping methods, thereby reducing reliance on producer-reported information and strengthening traceability and quality control in grape and wine production.

MATERIAL AND METHODS

Data Collection

Spectral data were collected in vineyards located in the municipality of Mariana Pimentel, in the state of Rio Grande do Sul, Brazil, from samples including *Vitis vinifera*, *Vitis labrusca*, hybrids, and rootstocks.

Measurements were made with a handheld FieldSpec® 3 ASD spectroradiometer, operating over the 350 – 2500 nanometers (nm) range. The instrument was fitted with a Leaf Clip featuring an integrated light source, characterizing the technique as active-source contact spectroradiometry.

System calibration was performed using a Spectralon® white reference panel. Five plants per variety were sampled; one leaf was taken from each plant, except for Cabernet Sauvignon, for which two leaves per plant were measured. Leaves were collected from the mid-canopy region of the vines and measured immediately after harvesting.

For each leaf, five reflectance spectra were acquired at two distinct positions on the adaxial surface (upper and lower positions of the leaf), avoiding major veins. This strategy captures intra-leaf variability and produces more representative spectral curves. In the case of the Paulsen 1103 rootstock, only one measurement per leaf was taken, given the observed morphological homogeneity.

In total, 574 adaxial surface reflectance spectra were obtained from 60 leaves, covering the following varieties: Barbera, Cabernet Sauvignon, White Garganega, Merlot, Sangiovese, Syrah, Isabel, Niagara Branca, Niagara Rosada, Goethe, and Paulsen 1103.

Processing and Analysis

The methodology used here is based on previous studies by Pithan *et al.* (2021), Tsai and Philpot (1998), and Blackburn (2006), and involves calculation of mean reflectance spectra, spectral ratios, first derivatives, standard deviations, Linear Discriminant Analysis (LDA), and Principal Component Analysis (PCA) to identify wavelengths significant for discriminating grapevine varieties.

Preprocessing steps included detector level leveling correction, spectral smoothing, and normalization by the area under the spectral curve. The 350 - 399 nm band was excluded due to its high noise levels.

After preprocessing, mean reflectance spectra were computed for each variety from their respective spectral sets. The spectral ratio method was then applied: mean reflectance spectra were paired and divided to generate ratio curves that highlight subtle differences between groups (Pithan *et al.*, 2021). Next, first derivatives of their ratios were calculated to reveal spectral regions where curve slopes change most sharply, indicating potential discriminant bands.

Derivative variability was quantified via standard deviation, enabling identification of spectral regions with greatest instability. These data were used for a preliminary selection of wavelengths based on minimum inter wavelength distance and magnitude of spectral variation.

For classification and validation, Linear Discriminant Analysis (LDA) was combined with a forward-stepwise variable selection procedure, which progressively adds wavelengths to the model to maximize class separation accuracy and remove redundancies. LDA performance was assessed by 5-fold cross-validation.

Additionally, Principal Component Analysis (PCA) was employed as an exploratory tool for dimensionality reduction and assessment of overall variance, allowing comparison with the local discrimination emphasis of the spectral ratio approach.

RESULTS

Using a forward stepwise LDA on a 21-band preselection, we obtained a mean classification accuracy of 93 % (70 % training / 30 % testing). First, the spectral ratio method generated 55 pairwise combinations of varieties, highlighting regions where ratios deviate from 1 and thus exhibit high discriminative potential. We then calculated the first derivatives of these ratios and used their standard deviations to quantify spectral variability, preselecting seven wavelengths in each of the three regions—VNIR (400–1050 nm), SWIR1 (1051–1800 nm), and SWIR2 (1801–2500 nm)—while maintaining a minimum spacing of 25 nm between bands, for a total of 21.

Applying a forward-stepwise selection within LDA with 5-fold cross-validation allowed us to identify the ten most discriminative wavelengths (428, 497, 649, 674, 699, 724, 1408, 1515, 1540, and 1858 nm). Model performance analysis showed that adding spectral bands progressively increases accuracy up to a saturation point around 12 bands, suggesting an optimal band count that balances performance and overfitting risk.

The LDA confusion matrix demonstrated effective separation between varieties, with low error rates and strong within-group cohesion. Projection of samples into the discriminant component space revealed three main clusters: one comprising *V. vinifera* varieties, another containing hybrids and American species (*V. labrusca)*, and a third consisting of the Paulsen 1103 rootstock.

Tests using different minimum-spacing criteria for wavelength selection produced alternate sets, though concentrated in the same spectral regions. These results indicate that varietal discrimination predominantly occurs in specific spectral areas. Thus, even when different wavelengths within these regions are chosen, separation remains efficient, because these regions reflect leaf characteristics driven by morphological and biochemical factors.

PCA based selection—using the wavelengths with the highest loadings on the most significant components—produced a different set of wavelengths than the spectral-ratio approach, although they fall within the same regions, with more bands selected in the SWIR1 region. The accuracy for this PCA driven method was approximately 90 %, a reduction likely attributable to the method's tendency to capture broader variations rather than the most discriminative features.

CONCLUSION

These findings suggest that systematic variations exist among the spectral signatures of the varieties analyzed, and that these variations can be effectively explored through spectral analysis and combined statistical methods to identify regions with the greatest discriminative power between varietal groups. The adopted approach demonstrates potential to support varietal mapping strategies and the development of classification systems based on remote and proximal sensing.

ACKNOWLEDGEMENTS

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

REFERENCES

Blackburn, G. A. (2006), "Hyperspectral remote sensing of plant pigments", Journal of Experimental Botany 58(4), 855–867.

Lacar, F., Lewis, M. and Grierson, I. (2001), Use of hyperspectral reflectance for discrimination between grape varieties, in "Scanning the Present and Resolving the Future. Proceedings. IEEE 2001 International Geoscience and Remote Sensing Symposium (Cat. No.01CH37217)", Vol. 6, pp. 2878–2880.

Mazzia, V., Comba, L., Khaliq, A., Chiaberge, M. and Gay, P. (2020), "UAV and machine learning based refinement of a satellite-driven vegetation index for precision agriculture", Sensors 20(9).

Pithan, P. A., Ducati, J. R., Garrido, L. R., Arruda, D. C., Thum, A. B., and Hoff, R. (2021), "Spectral characterization of fungal diseases downy mildew, powdery mildew, black-foot and petri disease on vitis vinifera leaves", International Journal of Remote Sensing 42(15), 5680–5697.

Protas, J. F. d. S., Lazzarotto, J. J. and Machado, C. A. E. (2024), Panorama da vitivinicultura brasileira em 2022, Comunicado Técnico 233, Embrapa Uva e Vinho, Bento Gonçalves, RS, Brasil.

Tsai, F. and Philpot, W. (1998), "Derivative analysis of hyperspectral data", Remote Sensing of Environment 66(1), 41–51.

TABLE AND FIGURE

Table 1. Initial subset wavelengths and first derivative standard deviation values by region. Highlighted wavelengths were selected by the forward- stepwise method.

Region	Wavelength (nm)	Standard Deviation of Derivatives
VNIR	674	0.0164
	649	0.0087
	497	0.0072
	699	0.0054
	522	0.0037
	724	0.0036
	428	0.0028
SWIR1	1408	0.0022
	1383	0.0014
	1490	0.0009
	1515	0.0007
	1465	0.0007
	1433	0.0007
	1540	0.0005
SWIR2	1908	0.0078
	1883	0.0036
	1934	0.0028
	1973	0.0017
	1998	0.0016
	1858	0.0016
	2464	0.0014

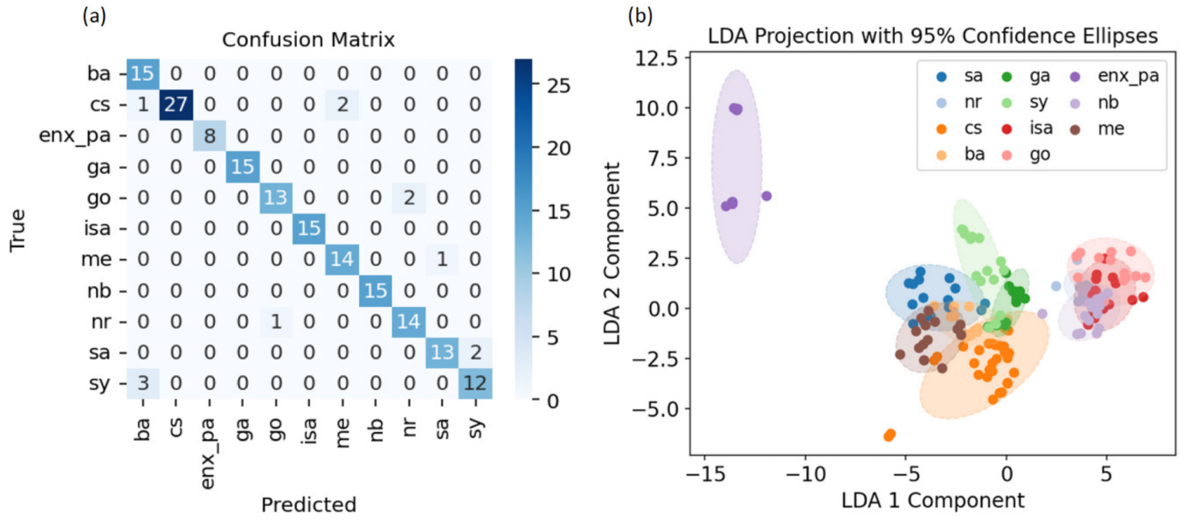

Figure 1. Results obtained through LDA using the final set of selected wavelengths. In (a) the model performance in discriminating between varieties. In (b) the projection of the samples in the space of two discriminant components obtained by LDA.

Read as:
ba: Barbera;
cs: Cabernet Sauvignon;
ga: White Garganega;
go: Goethe;
isa: Isabel;
me: Merlot;
nb: "Niagara Branca";
nr: "Niagara Rosada";
sa: Sangiovese;
sy: Syrah;
enx_pe: Paulsen 1103 Rootstock.