MAPPING GRAPE COMPOSITION IN THE FIELD USING VIS/SWIR HYPERSPECTRAL CAMERAS MOUNTED ON A UTV

Authors: Luca BRILLANTE[1,2*], Eve LAROCHE-PINEL[1,2], Brent SAMS[3], Benjamin CORALES[1,2], Kaylah VASQUEZ[1,2], Vincenzo CIANCIOLA[1,2]

[1] *Department of Viticulture & Enology, California State University Fresno, Fresno, CA, USA*
[2]*Viticulture and Enology Research Center, California State University, Fresno CA, USA*
[2]*Winegrowing Research Department, E&J Gallo Winery, Modesto, CA, USA*

*Corresponding author: luca.brillante@csufresno.edu

Abstract:

Context and purpose of the study – Assessing grape composition is critical in vineyard management. It is required to decide the harvest date and to optimize cultural practices toward the achievement of production goals. The grape composition is variable in time and space, as it is affected by the ripening process and depends on soil and climate conditions. This variability makes an appropriate assessment of the overall grape composition of a vineyard block complicated and time-consuming. Our work focused on developing a system to assess and map grape composition directly in the field through the application of machine-vision models to hyperspectral images acquired on the go in a vineyard with sprawling canopies, where the fruit tends to be hidden by the foliage.

Material and methods – For this study, a UTV was specially adapted to lift the canopy and expose the fruits, two hyperspectral cameras (a Senop HSC VIS/NIR and a Specim NIR/SWIR) were mounted with GPS systems and halogen lights for night imaging. We imaged a Merlot vineyard located in Madera, California, four times during the 2022 growing season. At the same time, we sampled grapes from 160 vine locations which were analyzed in the laboratory to assess anthocyanin, soluble solids, pH, and titratable acidity. A total of ~1,000 samples were collected. For the analysis, the images needed to be segmented to extract the grape's signal from sampled vines. Then, the reflectance of the grapes was used to look for correlations with grape composition using machine learning models. Evaluation and interpretation of models were performed using RMSE, R^2. Interpretation of the model was conducted through feature importance and partial dependence plots to understand the relationship between wavelength predictors and the outcome. This project is the first to use a SWIR camera mounted on a UTV to assess grape composition.

Results – Our results demonstrate that SWIR images can be used to perform a classification to extract grape signal with a mean error of 2.2% using the spectral signature of each class represented in the image (grape, leaves and background). The prediction of grape compounds from the refined spectral signal shows promising results. This project aims to help growers to monitor grape composition in the field rapidly and spatially to inform variable rate management.

Keywords: Precision viticulture, grape composition, hyperspectral imaging, mapping, machine-learning

1. Introduction

The key to successful grape growing for wine, table, and raisins lies in the ability to evaluate grape composition and use this information to make optimal harvesting decisions and adjust viticulture techniques such as canopy management and fertilization to enhance grape quality.

Laboratory investigations have demonstrated that spectroscopy methods are effective in assessing grape and fruit composition (Fernandes et al., 2011; Lin & Ying, 2009). Efforts have been made to apply these methods in the vineyard, including mounting spectroscopy sensors (spectrometers) on UAVs and harvesters, and developing commercial tools such as Spectron by Pellenc and Multiplex by ForceA that are specifically adapted to grapes (Bramley et al., 2011; Fernández-Novales et al., 2019; Gutiérrez et al., 2018).
Combining features of both imaging and spectroscopy, hyperspectral imaging can assess the presence of different components simultaneously while also identifying the spatial distribution of those components in the products being examined. When used to assess grape composition, hyperspectral imaging can isolate grape pixels from the background in an image and use the spectral information from those pixels to determine their composition.
The preliminary findings on using hyperspectral images to evaluate grape composition indicate that this technique is appropriate for estimating Brix and color content in grapes in both laboratory and field settings, as evidenced by studies conducted by Gutiérrez et al. (2018) and Hernández-Hierro et al. (2013). The objective of this project is to test this method in the West Coast environment, which is characterized by high radiation levels and unique trellis systems. To enhance the technology's capabilities, the project will expand the measurement to the SWIR region of the spectrum and utilize artificial intelligence for the first time to analyze hyperspectral data to assess grape composition and improve the reliability and accuracy of the results. The project will also lay the groundwork for developing a more straightforward sensor by identifying the wavelengths that provide the most informative data for evaluating sugars, titratable acidity, and color in grapes.

2. Material and methods

Experimental design - 160 vines were identified, marked, and precisely located with GNSS technology in an 8-row Merlot vineyard situated in Madera, California.

Plants measurements - The sampling procedure involved collecting grapes from both sides of the selected vines. The berries were stripped of their skin, which was subsequently frozen for analysis through HPLC. The flesh of the grapes was extracted and crushed to determine the total soluble solids (sugar content) using a refractometer, and titratable acidity was assessed through automatic titration using NaOH. Furthermore, the skins were freeze-dried and powdered before being subjected to extraction for 24 hours with a mixture of methanol, water, and hydrochloric acid (in a 70:29:1 ratio), followed by measurement through reverse phase HPLC with a gradient of acetonitrile and formic acid, as previously described by Martínez-Lüscher et al. (2019).

Images acquisition - For this study, a UTV was customized to lift the canopy and expose fruits, and fitted with two hyperspectral cameras operating in the VIS/NIR (500 to 900 nm) and NIR/SWIR (950 to 1710 nm) domains, along with GPS systems and halogen lights for night imaging. Using this setup, both sides (North and South) of the 8 rows were captured four times throughout the growing season at the same time as the sampling. Reflectance standards were also captured before the beginning of the acquisitions.

Analysis - A custom computer with 2 GPU NVIDIA GTX 2080 Ti and 128Gb of Ram was used to analyze the data cubes. The grapes were extracted from the background, which could be the plants or the conveyor belt, and then supervised machine-learning algorithms were employed to predict Brix, TA, total anthocyanins, and individual anthocyanins.

3. Results and discussion

The NIR/SWIR camera captured over 800GB of images, while the VIS/NIR camera captured 190GB. The images were manually labeled and the PerClass Mira software utilized the specific spectral signature of each category in the image to perform classification and extract grape signals, as illustrated in Figure 1.

Preliminary findings using the SWIR images indicate that it is feasible to accurately extract the grape signal by classifying the images based on the unique spectral signature of each category present. Table 1 displays the classification results for the image depicted in Figure 1, indicating a mean class error of 2.2%.

The extraction of grape signal using a pre-labeled image has shown promising results, and additional research will be conducted to investigate the feasibility of using the model trained on one image to predict results for another image. The prediction modeling is still being investigated as further preprocessing of the images is required to correct reflectance and match the corresponding berry analysis.
The VIS/NIR camera images will be processed after since the NIR/SWIR domain is the main focus of this study.

4. Conclusions

The initial findings of the study indicate that it is possible to use this method to monitor grapes, as the grape signal was accurately extracted with an average error of 2.2%. However, further research is still being conducted to predict grape composition based on this signal.

5. Acknowledgments

The authors thank the CSU-Agriculture Research Institute and the American Vineyard Foundation for their generous funding.

6. Literature cited

BRAMLEY, R. G. V., LE MOIGNE, M., EVAIN, S., OUZMAN, J., FLORIN, L., FADAILI, E. M., HINZE, C. J., & CEROVIC, Z. G. (2011). On-the-go sensing of grape berry anthocyanins during commercial harvest: Development and prospects. *Australian Journal of Grape and Wine Research*, *17*(3), 316–326. https://doi.org/10.1111/j.1755-0238.2011.00158.x

FERNANDES, A. M., OLIVEIRA, P., MOURA, J. P., OLIVEIRA, A. A., FALCO, V., CORREIA, M. J., & MELO-PINTO, P. (2011). Determination of anthocyanin concentration in whole grape skins using hyperspectral imaging and adaptive boosting neural networks. *Journal of Food Engineering*, *105*(2), 216–226. https://doi.org/10.1016/j.jfoodeng.2011.02.018

FERNÁNDEZ-NOVALES, J., TARDÁGUILA, J., GUTIÉRREZ, S., & PAZ DIAGO, M. (2019). On-The-Go VIS + SW - NIR Spectroscopy as a Reliable Monitoring Tool for Grape Composition within the Vineyard. *Molecules*, *24*(15), 2795. https://doi.org/10.3390/molecules24152795

GUTIÉRREZ, S., TARDAGUILA, J., FERNÁNDEZ-NOVALES, J., & DIAGO, M. P. (2018). On-the-go hyperspectral imaging for the in-field estimation of grape berry soluble solids and anthocyanin concentration. *Australian Journal of Grape and Wine Research*, *25*(1), 127–133. https://doi.org/10.1111/ajgw.12376

HERNÁNDEZ-HIERRO, J. M., NOGALES-BUENO, J., RODRÍGUEZ-PULIDO, F. J., & HEREDIA, F. J. (2013). Feasibility study on the use of near-infrared hyperspectral imaging for the screening of anthocyanins in intact grapes during ripening. *Journal of Agricultural and Food Chemistry*, *61*(41), 9804–9809. https://doi.org/10.1021/jf4021637

LIN, H., & YING, Y. (2009). Theory and application of near infrared spectroscopy in assessment of fruit quality: A review. *Sensing and Instrumentation for Food Quality and Safety*, *3*(2), 130–141. https://doi.org/10.1007/s11694-009-9079-z

MEYERS, J. M., DOKOOZLIAN, N., RYAN, C., BIONI, C., & VANDEN HEUVEL, J. E. (2020). A New, Satellite NDVI-Based

Sampling Protocol for Grape Maturation Monitoring. *Remote Sensing*, *12*(7), 1159. https://doi.org/10.3390/rs12071159

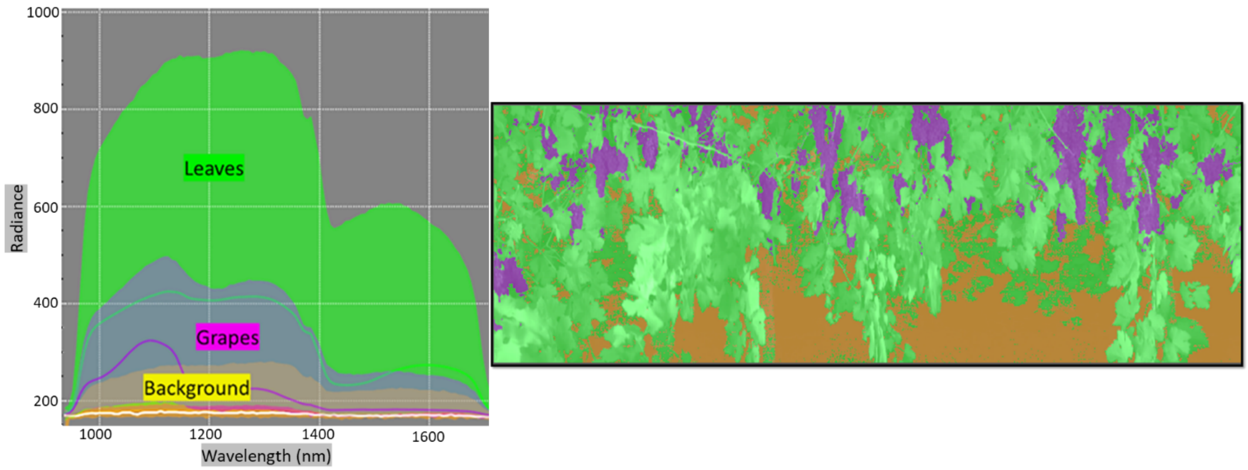

Figure 1: Illustration of the segmentation of the NIR/SWIR image after classification

Table 1: Confusion matrix with accuracy, precision and error in percentage for the segmentation of the image illustrated in Figures 2 and 3.

		Labelled			Class error
		Background	Leaves	Grapes	
Predicted	Background	97.5	2.5	0	2.5
	Leaves	1.8	98.2	0	1.8
	Grapes	0.4	1.8	97.8	2.2
Precision		97	97	1	2.2