HYPERSPECTRAL IMAGING AND CNN FOR ON-THE-GO, NON-DESTRUCTIVE ASSESSMENT OF GRAPE COMPOSITION IN THE VINEYARD

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Abstract:
Context and purpose of the study- Knowledge of the spatial-temporal variation of the grape composition within a vineyard may assist decision making regarding sampling and vineyard management, especially if selective harvest is aimed. To have a truthful picture of the spatial-temporal dynamics of grape composition evolution during ripening in a vineyard, a huge amount of measurements at different timings and spatial positions are required. Unfortunately, the quick in-field measurement of a vast number of samples is very hard for simple variables such as total soluble solids (TSS), and impossible in the case of analyzing secondary metabolites, like anthocyanin concentrations. The goal of this study was the in-field assessment and mapping of the TSS, acidity parameters and anthocyanin concentrations in a Tempranillo (*Vitis vinifera* L.) vineyard, using non-destructive, on-the-go hyperspectral imaging (HSI).
Material and methods- HSI of grapevine canopies was carried out using a line-scan hyperspectral camera working in the Vis-NIR range (400-1000 nm) installed in all-terrain-vehicle, moving at 5 km/h in a commercial Tempranillo (*Vitis vinifera* L.) vineyard, under natural illumination conditions. Measurements were carried out at several dates during the ripening period over two consecutive seasons in 2017 and 2018. TSS, titratable acidity (TA), pH and anthocyanin concentrations analyses were also performed using gold standard, wet chemistry methods for model building and validation purposes. Convolutional neural networks (CNN) were applied for the development of regression models. The prediction results from the regression models were used for mapping (using GIS software) the evolution and distribution of grape composition in time–several datesand space–the vineyard plot.
Results- Prediction models were generated for the different grape composition parameters, yielding determination coefficients (R^2) above 0.85 for TSS and TA and ~0.70 for pH and anthocyanin concentrations respectively. The built maps illustrated the seasonal dynamics of TSS and anthocyanin accumulation in the studied vineyard. The obtained results evidenced the potential of hyperspectral imaging acquired on-the-go for the non-destructive, robust and massive assessment of TSS and total anthocyanin contents in grape berries in the vineyard. HIS may become a useful tool for decision-making on harvest selection and berry fate for winemaking.
Keywords: spatial-temporal variability, total soluble solids, berry anthocyanins, Vis-NIR spectral range, acidity parameters, prediction models.

1. Introduction

Wine quality is directly linked to the compounds present in grapes (Kennedy 2010). Berry ripening is frequently tracked by measuring the amount of TSS and acidity parameters, and, in the case of red grapes, the anthocyanin concentration of berries also. The balance between the sugar and acidity values is widely used to decide about harvest timing and together with the anthocyanin content (red varieties) are relevant to fix grape prices in many wineries and cooperatives worldwide (Bramley et al. 2011).
Current methods to determine the TSS, acidity variables, such as pH and titratable acidity, as well as the anthocyanin contents in grapes are destructive, require manual berry sampling in the vineyard and in general terms are time and labour demanding (Iland et al. 2004). Therefore, it would be desirable and relevant to the wine industry to have rapid, robust and non-destructive methods to assess the concentration of the main compositional parameters in grape berries along ripening. Moreover, the knowledge of the spatial–temporal variation of grape composition in fruit within a vineyard could be helpful to improve berry sampling, vineyard management and enable selective harvesting. This would require a large number of measurements, which is not feasible with the current analytical methods.
In the last years, hyperspectral imaging (HSI) has emerged as a powerful technology for non-destructive

analysis in several agricultural, food and safety applications (Sun 2010, Park and Lu 2015). HSI combines the potential of spectroscopy modelling with two-dimensional digital imaging, providing a vast amount of relevant information of the imaged samples. In order to convert the obtained spectral data into useful knowledge and results of grape composition, advanced computing solutions, such as machine learning (Jordan and Mitchell 2015) and deep learning (LeCun et al., 2015) algorithms are required. Convolutional Neural Networks (CNNs) are the most common implementation of deep learning (LeCun et al., 2015), being extensively used in the last years in many scientific and industrial fields. In agriculture, for instance, the huge potential of CNNs in computer vision has been employed for fruit detection and yield estimation in different crops (Sa et al. 2016).

The goal of this study was the in-field assessment and mapping of the TSS, acidity parameters and anthocyanin concentrations in a Tempranillo (*Vitis vinifera* L.) vineyard, using non-destructive, on-the-go hyperspectral imaging (HSI) and the development of predictive models for these compositional variables using CNNs.

2. Material and methods

Experimental layout and HSI acquisition

The experiment was carried out in two consecutive seasons, 2017 and 2018 in two different commercial vineyards. In 2017, HSI was acquired along four dates between veraison and harvest in vineyard site #1. This was a 0.7 ha commercial vineyard located in Ábalos, La Rioja, Spain (latitude 42_34045.700, longitude −2_42027.7800, 628 m asl). *Vitis vinifera* (L.) cultivar Tempranillo grapevines were planted in 2010, on rootstock R-110 and trained to a vertically shoot positioned (VSP) trellis system. Rows were oriented northeast–southwest and row and vine spacing was 2.2 and 1.0 m, respectively. In 2018, HSI measurements were carried out between veraison and harvest in three distinct dates in vineyard site #2. This was a commercial Tempranillo (*Vitis vinifera* L.) vineyard located in Tudelilla, La Rioja, Spain (Lat. 42◦18'18.26'', Long. −2◦ 7' 14.15'', 515m asl). Grapevines were planted in 2002 (north-south orientation) with vine spacing of 2.60m between rows and 1.20m between vines, and trained to a vertically shoot-positioned trellis system on a double-cordon Royat.

In both plots, three rows were selected and within each row 12 blocks of ~5 m containing five vines each were chosen for HSI acquisition and grape berry sampling and analysis. Hyperspectral images were acquired on-the-go at 5 km/h (from the eastern side of the canopy, which was partially defoliated around the fruiting zone) using a push broom Resonon Pika L ViS-NIR hyperspectral imaging camera (Resonon, Bozeman, MA, USA) that was mounted on an all-terrain vehicle (ATV) (Trail Boss 330, Polaris Industries, MN, USA). The spectral resolution of the camera was 2.1 nm (300 bands from 400 to 1000 nm), with 300 pixels of spatial resolution. The camera was placed at 2.0 m of distance from the canopy, and performed a vertical recording line of 1.32 m (field of view of 36.5º) which comprised the whole vine canopy, including the fruiting zone. Prior to hyperspectral imaging, both dark and white reference measurements were manually conducted. For the dark reference, the inherent electronic noise was measured, while for the white reference, a Spectralon (with a reflectance > 95%) was presented to the camera simulating the same position and distance to the canopy. The spectral light intensity values collected by the camera for the references and canopy measurements were converted into reflectance values. Hyperspectral images were georeferenced using an Ag Leader 6500GPS receiver (Ag Leader Technology, Ames, IA, USA) with RTK correction installed in the ATV.

Grape composition analysis

In both seasons, for each five-vine block a number of exposed clusters (between 3 and 5 per vine) were identified. In season 2017, for each visible cluster, a total of 10–15 visible berries were removed and placed in labelled plastic bags for subsequent chemical analysis. On average, 200 grape berries per block were collected at each date. In season 2018, the whole visible cluster was manually picked and placed into a plastic bag. Berry (2017) or cluster (2018) samples were then transported, in portable refrigerators, to the laboratory. In 2017, berries were stored at −20ºC until chemical analysis of TSS and anthocyanin concentrations were completed. In 2018, upon arrival to the laboratory each cluster was manually destemmed, berries counted and weighted and split into two subsamples of 50 berries each. One of them was used to determine the TSS, pH and titratable acidity, while the other one was stored at −20ºC until analysis of the anthocyanins. TSS, pH and TA analysis of berries were carried out following the OIV methods (OIV 2009). Anthocyanins were determined after Iland et al. (2004) and expressed as mg/g of berry.

Image processing and model development

From each hyperspectral image, spectra belonging to grape clusters were selected using a "signature" of a grape reference spectrum, which was manually acquired by selecting grape spectra from all the images (regions of approximately 200 spectra) and then averaging them. The signature spectrum was compared pixel-wise (spectra by spectra) for each image, and the Pearson's correlation coefficient between both spectra was computed. If this correlation surpassed the 0.87 mark, the image spectra was labeled as grape spectra. All images were processed using this methodology for grape spectra identification.

In each season the data set used for model development was composed by the grape berry spectra images and the values of the measured grape composition parameters. In 2017, 139 samples were collected, while the 2018 data set comprised 143 samples. Regression models were developed using CNNs. Unlike other CNN usages with RGB imaging, the networks implemented in this study convolved over one dimension (the spectral one), and no padding was used. The architecture of the CNNs was designed based on that from Windrim et al. (2016), that already proved to be useful in other HSI applications in agriculture (Wendel et al., 2018; Gutiérrez et al., 2019). The architecture comprised two convolutional layers and two fully connected layers, and the network was trained through 50 iterations (batch size of 5) using an RMSprop optimizer. The data set were split into train sets (80% of the original data set) and external validation sets (20%). The latter was used as validation data for score computing during the training of the networks.

Mapping

Interpolated TSS and anthocyanin concentration prediction maps for season 2017 were generated using kriging interpolation (Oliver and Webster 1990) implemented in ArcMap 10.5 (ArcGIS Desktop: Release 10. Redlands, CA, USA: Environmental Systems Research Institute).

3. Results and discussion

This two-year study introduces an innovative solution for the non-destructive, in-field estimation of relevant grape compositional parameters using on-the-go HSI in the vineyard.

For the grape composition variables measured in the two seasons, the prediction results of the TSS and anthocyanin models developed using the CNNs are shown in Figure 1a and 1b, respectively. For both parameters, the two-year model yielded determination coefficients (R^2) around to or above 0.75, and the regression lines were close to the 1:1 line with an even distribution of results. These results agree with those reported in a previous work (Gutiérrez et al. 2019) in which a different machine learning approach (Support Vector Machine) was used to develop predictive models. However, the RMSE values in the present work were found to be larger (Figure 1).

Titratable acidity (TA) and pH are probably the two most widely measured grape and must acidity variables for ripening assessment. The developed models using CNNs from HSI data acquired in season 2018 yielded R^2 values ~0.70 for pH (Figure 2a) and 0.93 for TA (Figure 2b) with RMSE values of 0.229 and 1.103, respectively. These are very remarkable outcomes, as it has to be highlighted that HSI measurements were taken contactless (~1m away) from the clusters hanging on the vines. While predictions of TSS and anthocyanins from on-the-go HSI had been reported in a previous work (Gutiérrez et al. 2019) the capability of this non-destructive spectral technique, in combination with a state-of-the-art artificial intelligence algorithm, like the CNNs, to successfully estimate pH and TA along maturation is for the first time (to the best of our knowledge) presented in this study.

Several works have evidenced that the assessment of key berry composition variables throughout ripening is feasible using spectroscopy on intact fruit samples (Cao et al. 2010, González-Caballero et al. 2010, Bellincontro et al. 2011), with values of R^2 and RMSE comparable to those found in the present research. However, in those works, spectral measurements were conducted mostly under laboratory conditions, where sample position, ambient temperature and lighting conditions can be controlled and homogeneous. On the other hand, in-field monitoring of grape composition using spectroscopy has been less often reported (Barnaba et al. 2014; Urraca et al. 2016), and in most cases using portable manual devices to yield discrete measurements. The step towards contactless, on-the-go grape composition monitoring in the vineyard can be facilitated by the use of HSI, as demonstrated in this research.

Since the hyperspectral images were georeferenced, it was also possible to map the spatial-temporal dynamics of the grape compositional variables along the ripening process. As an example, the prediction maps for TSS and anthocyanins in the four measuring dates of season 2017 are shown in Figure 3. The accumulation of TSS (Figure 3a) followed an increasing trend until the third date (18th September). The maximum TSS concentrations (26 °Brix) were reached in the latter stages of ripening but during the last ten days between the third and fourth sampling date only a slight increase in TSS occurred. The south area of the vineyard was the fastest to ripen. In the case of the anthocyanin concentration, large increments were detected across the four dates, from little variation (from 0.07 to 0.30 mg/g berry) on 11 August, to a plot with higher anthocyanin concentration and variability on 28th September (from 1.07 to 2.28 mg/g berry). Differently from the TSS, anthocyanins kept accumulating in the berries along the four dates, as evidenced by an increase of 0.40-0.60 mg/g berry, between the third and fourth date of September. The differential spatial-temporal pattern of accumulation between TSS and anthocyanins, which are primary and secondary metabolites, respectively, has been successfully revealed by the use of HSI on-the-go in junction with a powerful deep learning method, such as the CNNs.

The methodology developed in this work could also be deployed in specific, human-driven, other common agricultural machinery (also concurrently during tilling or mowing operations) or even on agricultural robots. It could even be feasible to integrate HSI sensors, GPS monitoring and computing into a single platform capable of performing real-time assessment in the vineyard, making use of powerful data analysis algorithms, (e.g. the CNNs) as it has been shown in recent studies (Sandino et al. 2018, Gutiérrez et al. 2019).

4. Conclusions

The obtained results evidenced the potential of hyperspectral imaging acquired on-the-go, in combination with the convolutional neural networks, for the non-destructive, robust and massive assessment of TSS, pH, titratable acidity and total anthocyanin contents in grape berries in the vineyard. HIS may become a useful tool for decision-making regarding harvest scheduling and selection as well as berry fate for winemaking.

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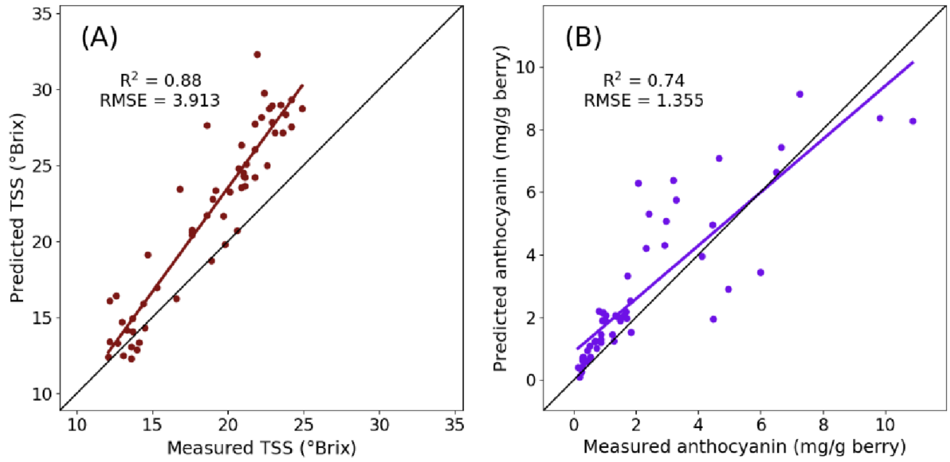

Figure 1. Regression plots for the external validation or prediction for the grape berry (A) Total soluble solids (TSS), and (B) the anthocyanin concentrations models, developed using hyperspectral imaging acquired on-the-go and convolutional neural networks (CNNs) in years 2017 and 2018 in two different commercial Tempranillo vineyards (Sites #1 and #2). Dark red line (A) and blue line (B) refer to the regression lines of the samples and the black solid line represents the 1:1 trend in both plots.

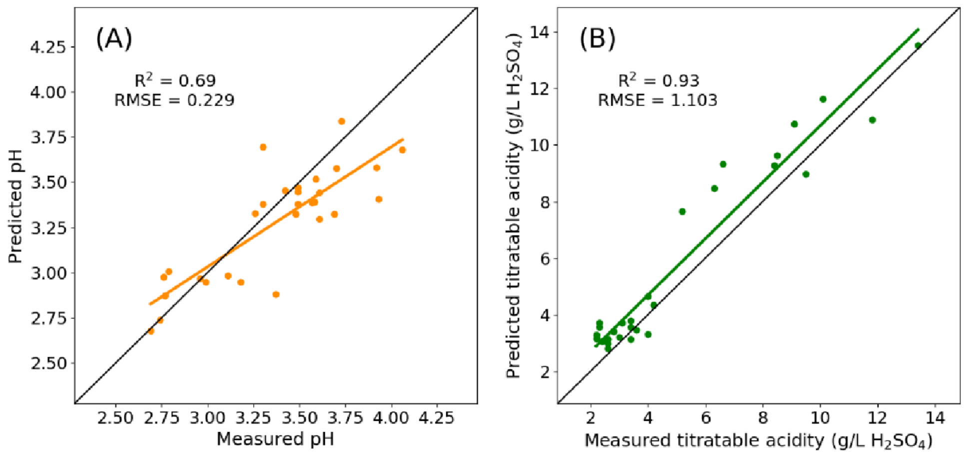

Figure 2. Regression plots for the external validation or prediction for the grape berry (A) pH, and (B) titratable acidity models, developed using hyperspectral imaging acquired on-the-go and convolutional neural networks (CNNs) in year 2018 in a commercial Tempranillo vineyard (site #2). Orange line (A) and green line (B) refer to the regression lines of the samples and the black solid line represents the 1:1 trend in both plots.