IMAGE BASED VINEYARD YIELD PREDICTION USING EMPIRICAL MODELS TO ESTIMATE BUNCH OCCLUSION BY LEAVES

Authors: Gonçalo VICTORINO* & Carlos M. LOPES

Linking Landscape, Environment, Agriculture and Food (LEAF), Instituto Superior de Agronomia, Universidade de Lisboa, Tapada da Ajuda, 1349-017 Lisboa, Portugal

*Corresponding author: gvictorino@isa.ulisboa.pt

Abstract:

Context and purpose of the study - Vineyard yield estimation brings several advantages to the entire wine industry. It can provide useful information to support decision making regarding bunch thinning practices, harvest logistics and marketing strategies, as well as to manage stored wine and cellar tanks allocation. Today, this estimation is performed mainly using manual methods based on destructive bunch sampling. Yield estimation using image analysis has the potential to perform this task extensively, automatically and non-invasively. However, bunch occlusion, caused mainly by leaves, presents a great challenge to this approach. This occlusion is highly dependent on canopy porosity, which in turn is affected by factors such as vigor, shoot density and leaf area, water availability, biotic and abiotic stresses, among others. In this work, the results of an image-based yield estimation method that estimates bunch occlusion by leaves using canopy porosity data, are compared with a manual approach.

Material and methods - The trial was carried out in two vineyards located within Lisbon winegrowing region, over four years (2018-21). Spur pruned vines trained on a vertical shoot positioning trellis system were used. In a first step, an empirical model was computed to estimate the fraction of bunches occluded by leaves based on the proven assumption in the literature that there is a relationship between canopy porosity and the fraction of exposed bunches. For this, images were captured from 1 m segments at two phenological stages (veraison and full maturation) in non-defoliated and partially defoliated vines of three grape varieties. This model was then used, in a second step, along with other image-based predictors of bunch weight, to estimate grapevine yield. The developed approach included image-based variables related to the visible bunch area and perimeter, berry number and bunch compactness, while considering canopy porosity to estimate the fraction of occluded bunch area. Results were compared to a manual method based on bunch counts and historical bunch weight, on six grape varieties, at veraison. All vine images were collected from a perspective perpendicular to the vine rows, by a static commercial RGB camera or a RGB camera installed on a terrestrial robot.

Results - The yield estimated with the developed algorithm showed a high correlation with the actual yield (R^2 = 0.86), with estimation errors ranging between -0.1% and 20.8%, depending on the variety and the year. In most cases, the proposed algorithm outperformed the manual method which was mostly impaired by variations of bunch weight that were not considered by historical data. The proposed image-based approach seems to be an accurate alternative to conventional yield estimation methods. It can be carried out using different image collection setups and has the advantage of being independent of historical data and able to be applied to much larger samples than those used in manual methods. Even though the occlusion estimation method worked well for most cases, further research is needed for modeling non-visible bunches in very dense canopies.

Keywords: Grapevine yield prediction, Bunch occlusion, Proximal sensing, Canopy porosity, Bunch pixels

1. Introduction

Timely vineyard yield estimation can be extremely advantageous for the winegrower, with impacts on the whole vine and wine production chain (Dunn & Martin, 2004). Current conventional methods of yield estimation consist of manually sampling grapevine yield components on random vines in the field (Whitty et al., 2017). This sampling is usually performed near lag phase, on the onset of veraison, and is then generalized to the whole vineyard plot. However, such methods are dependent on manual counts or destructive sampling, making them laborious and sensitive to spatial variability, especially in vineyards with high spatial variability where a higher number of samples is required for accurate results (Taylor et al., 2018).

Several efforts have been made to replace manual methods with automatic and non-invasive approaches. Recently, the most explored ones have been data driven models based on computer vision and image processing (Barriguinha et al., 2021). Overall, the automatic recognition of yield components in images collected in field conditions has proven successful (e.g. Millan et al., 2018; Hacking et al., 2019; Liu et al., 2020). However, apart from early-stage approaches, the majority of these research disregards the problem of bunch occlusion by performing partial or total defoliation in the fruiting zone prior to image collection (e.g. Dunn & Martin, 2004; Pérez-Zavala et al., 2018; Milella et al., 2019). However, such practices should be independent of yield estimation methods as they impact berry development and maturation and, particularly in warm climate viticulture regions, can be risky considering the higher chance of sunburn and berry dehydration. In non-disturbed canopies bunch occlusion by leaves can reach high values (e.g. 50% and 75% at veraison Victorino et al., 2020).

Visible bunch area and canopy porosity have been used to estimate the percentage of exposed bunches (Victorino et al., 2022a), considering the fact that a higher porosity also means that there's higher bunch exposure. This relationship enables to obtain an estimation of the total bunch area which then needs to be converted into mass. This conversion can be challenging considering its cultivar-dependency (Lopes & Cadima, 2021; Victorino et al., 2022b). The aim of this paper is to compare, in real field conditions, the accuracy of a non-invasive and multicultivar image-based yield estimation approach with a manual method based on bunch counts and historical bunch weight at harvest.

2. Material and methods

Plant material and growing conditions - Data was collected from two sites located within the Lisbon winegrowing region. In the first site – ISA, Lisboa – data was collected from the white varieties Alvarinho, Arinto and Encruzado which were spur pruned, drip irrigated, planted in 2006, spaced 1.0 m within and 2.5 m between N-S oriented rows. In the same site, data was also collected from the red variety Syrah, spur pruned, rainfed and planted in 1999 spaced 1.2m within and 2.5 m between N-S oriented rows. On the second site – Quinta da Amieira, Torres Vedras - data was collected from two varietal plots - red variety Castelão and white variety Chardonnay -, spur pruned, rainfed, planted in 2003 and spaced 1.0 m within and 2.5 m between N-S oriented rows. All plots were trained in a vertical shoot positioning trellis system with two pairs of movable wires. In total, it was used six subsets of data with different cultivar, season and site combinations. All data were collected between 2018 and 2021, on 1 m length vine segments at the onset of veraison (BBCH 81; Lorenz et al., 1995). A total of 213 vine segments were analyzed (30–40 per data set).

Image acquisition & processing - Images were collected with a blue background in order to facilitate image analysis. From each vine segment, the following variables were extracted: visible bunch projected area (vBA), visible bunch projected perimeter (vBP), visible berry number (vBe) and canopy porosity (POR). To assess these features, all images were processed as follows: i) images were scaled based on the physical scale present under the cordon of each vine segment; ii) images were cropped in order to include only a region of interest (fruit zone) that encompasses approximately 50 cm above the cordon; iii) bunches were manually segmented on each image in order to obtain the actual vBA, vBP and vBe from each vine segment; iv) to estimate POR, canopy gap pixels were classified using a static color threshold after converting the original image from RGB to HSV (Hue-Saturation-Value) color space for improved invariance to illumination conditions. This task was performed using OpenCV in PyCharm® while tasks i to iii were performed with the software Image J® (v1.53k, National Institutes of Health, EUA). For more details see (Victorino et al., 2022a; Victorino et al., 2022b).

Yield estimation At harvest, all bunches of the analyzed vine segments were counted and weighed. The final yield was compared to the output of the two methods of yield estimation: (i) the manual method, based on bunch counts and multiplication by historical bunch weight (Dami & Sabbatini 2011); (ii) an image analysis method following recent research (Victorino et al., 2022a) which considers visible bunch area and canopy porosity to estimate total bunch area (TBA), in order to overcome bunch occlusion by leaves. This was then followed by a conversion of bunch area into yield based on a combination of variables obtained via image analysis, selected via a stepwise regression model, which is fully described in the results section.

Data analysis - All cultivars' datasets were grouped into one original dataset, which was divided into a training set (with 50% of the data) and a validation set (with the remaining 50%) in a fully random way. Data analysis was divided into two parts. The first part consisted in the computation of a stepwise regression model (SAS® v9.3; SAS Institute, Cary, NC, USA) for yield estimation based on traits obtained via image analysis. The model was then validated on the validation set, and the coefficient of determination (R^2) and root mean squared error (RMSE) were used to evaluate its performance. The second part of data analysis consisted of comparing the output of the developed model with yield estimation obtained with manual methods. For this, to allow for a fair comparison, both approaches were used only on the validation data set, and estimation errors ($(Yield_{est} - Yield_{act})/Yield_{act}$) and trends were compared.

3. Results and discussion

Obtaining the best set of yield predictors - To find an appropriate set of independent variables to predict yield, a forward stepwise regression analysis between image-based features and actual yield was applied to the training set. Table 1 shows the summary of the stepwise regression. In the first step the variable $TBA \times CI^2$ was selected, corroborating previous work (Victorino, et al., 2022a) and underlying the importance of TBA in explaining grapevine yield. The variable CI is associated to TBA, allowing the differentiation between cases with the same TBA but with different bunch architecture, as bunch compactness is known to be a trait that influences bunch weight (Tello et al., 2016). The second selected variable was vBA/vBP (Table 1). In Victorino et al. (2022b), authors explored this ration in laboratory conditions, as a bunch with a higher percentage of holes in its structure will show a lower ratio. The final variable selected to enter the model (derived variable vBA/vBP×vBe) associates the ratio vBA/vBP with an indicator of bunch size (vBe), increasing model performance. Furthermore, the fact that vBe was considered by the model, even if included in a derived variable, goes in accordance with previous publications that elected vBe as an important yield estimator (e.g. Aquino et al., 2018; Millan et al., 2018; Liu et al., 2020). However, as previously reported (Lopes & Cadima, 2021; Victorino et al., 2022b), bunch weight estimation accuracy increases when vBe is not used as a single predictor but instead used along with other predictors.

The estimated values of the elected model fit very well with the actual yield, however, the residual plot (not shown) indicated that estimated yield variation was dependent on the values of the predictor variables. The violation of the constant variance assumption indicated the need for a variable transformation. A square root transformation of the response variable (yield) was performed which stabilized the variance and improved the linearity of the model (data not shown). Equation 1 shows the final model, after converting the rooted response back to the original scale. The final model presented an $R^2 = 0.86$ and a RMSE = 0.82 kg on the validation set.

$$\text{Est. yield}_{\text{image}}\,(\text{kg/m}) = \left(0.883 + 298\text{E}{-7} \times [TBA \times CI^2] + 0.0004 \times \left[\frac{vBA}{vBP} \times vBe\right] - 0.154 \times \frac{vBA}{vBP}\right)^2 \qquad (1)$$

For variable description see material and methods section.

Comparing the accuracy of Yield Estimation methods - Figure 1 shows the comparison between the observed yield per meter and the estimated yield via manual and image-based methods, for each variety. Both yield estimating methods presented the same overall correlation coefficient between estimated values and actual yield (r = 0.89), however under and overestimations can be observed in both cases. Regarding manual estimations, the lowest absolute error was observed on cv. Arinto (7.6 %) followed by cv. Castelão (10.0 %), while the highest was observed on cv. Syrah (124.2 %). Within manual estimations, only cv. Arinto presented an absolute estimation error below 10%, while cvs. Chardonnay and Syrah presented very high errors. The manual method explored in this work, despite being a highly accessible method to any winegrower, in some cases, showed extremely high estimation errors, mainly caused by differences between historical and actual bunch weight. In some cultivars, this error was almost twofold (e.g. observed bunch weight: 72.1 g against historical bunch weight: 119.5 g for cv. Syrah), likely due to the problems of the bad fruit set and water stress observed during the sampled seasons.

Image-based estimations presented lower absolute errors than the manual method in 5 out of 6 data sets, with only two cultivars presenting values above the |10%| error threshold mentioned for near-harvest estimations by Carrillo et al., 2016. The image-based estimation with the lowest absolute error was obtained on cv. Chardonnay (0.1 %), followed by cvs. Alvarinho (2.8 %) and Syrah (4.4 %), all three cases with values below the strictest thresholds reported in Whitty et al. (2017), |5%|. The highest errors obtained with the image-based method were observed on cvs. Arinto and Encruzado which showed the densest canopies (lowest vBA and POR), being examples of very challenging scenarios for an automatic image-based approach. Overall, with all cultivars combined, the image-based method presented a lower absolute estimation error than the manual approach. As the image-based method is not dependent on historical data, the approach designed in this work seems highly advantageous for the studied cases.

4. Conclusions

Several image-based variables such as visible berry number, bunch perimeter and bunch compactness index, were used as predictors of grapevine yield across different cultivars, after overcoming bunch occlusion by leaves using canopy porosity and visible bunch area. Yield estimation results based on the image-based approach suggested in this work outperformed most manual estimations. Although the manual method is accessible to any winegrower and obtainable at earlier phenological stages, the studied image-based approach presents the advantage of potentially being fully automated and used across whole vineyards, non-invasively.

5. Acknowledgments

This study was supported by the PhD grant SFRH/BD/132305/2017, sponsored by FCT – Fundação para a Ciência e a Tecnologia.

6. Litterature cited

Barriguinha, A., Neto, M. de C., & Gil, A. (2021). Vineyard yield estimation, prediction, and forecasting: A systematic literature review. *Agronomy*, *11*(9). https://doi.org/10.3390/agronomy11091789

Carrillo, E., Matese, A., Rousseau, J., & Tisseyre, B. (2016). Use of multi-spectral airborne imagery to improve yield sampling in viticulture. *Precision Agriculture*, *17*(1), 74–92. https://doi.org/10.1007/s11119-015-9407-8

Dami, I., & Sabbatini, P. (2011). Crop Estimation of Grapes. *Fact Sheet - Agriculture and Natural Resources*, *Stage I*, 1–2.

Dunn, G. M., & Martin, S. R. (2004). Yield prediction from digital image analysis: A technique with potential for vineyard assessments prior to harvest. *Australian Journal of Grape and Wine Research*. https://doi.org/10.1111/j.1755-0238.2004.tb00022.x

Hacking, C., Poona, N., Manzan, N., & Poblete-Echeverría, C. (2019). Investigating 2-D and 3-D proximal remote sensing techniques for vineyard yield estimation. *Sensors (Switzerland)*, *19*(17). https://doi.org/10.3390/s19173652

Liu, S., Zeng, X., & Whitty, M. (2020). A vision-based robust grape berry counting algorithm for fast calibration-free bunch weight estimation in the field. *Computers and Electronics in Agriculture*, *173*(December 2019), 105360. https://doi.org/10.1016/j.compag.2020.105360

Lopes, C. M., & Cadima, J. (2021). Grapevine bunch weight estimation using image-based features: comparing the predictive performance of number of visible berries and bunch area. *Oeno One*, *55*(4), 209–226. https://doi.org/10.20870/OENO-ONE.2021.55.4.4741

Milella, A., Marani, R., Petitti, A., & Reina, G. (2019). In-field high throughput grapevine phenotyping with a consumer-grade depth camera. *Computers and Electronics in Agriculture*, *156*(May 2018), 293–306. https://doi.org/10.1016/j.compag.2018.11.026

Millan, B., Velasco-Forero, S., Aquino, A., Tardaguila, J., & Sazonov, E. (2018). *On-the-Go Grapevine Yield Estimation Using Image Analysis and Boolean Model*. https://doi.org/10.1155/2018/9634752

Pérez-Zavala, R., Torres-Torriti, M., Cheein, F. A., & Troni, G. (2018). A pattern recognition strategy for visual grape bunch detection in vineyards. *Computers and Electronics in Agriculture*, *151*(September 2017), 136–149. https://doi.org/10.1016/j.compag.2018.05.019

Taylor, J. A., Dresser, J. L., Hickey, C. C., Nuske, S. T., & Bates, T. R. (2018). Considerations on spatial crop load mapping. *Australian Journal of Grape and Wine Research*. https://doi.org/10.1111/ajgw.12378

Tello, J., Cubero, S., Blasco, J., Tardaguila, J., Aleixos, N., & Ibáñez, J. (2016). Application of 2D and 3D image technologies to characterise morphological attributes of grapevine clusters. *Journal of the Science of Food and Agriculture*, *96*(13), 4575–4583. https://doi.org/10.1002/jsfa.7675

Victorino, G., Braga, R. P., Santos-Victor, J., & Lopes, C. M. (2022a). Overcoming the challenge of bunch occlusion by leaves for vineyard yield estimation using image analysis. *Oeno One*, *56*(1), 117–131. https://doi.org/10.20870/oeno-one.2022.56.1.4863

Victorino, G., Braga, R., Santos-Victor, J., & Carlos lopes. (2020). *Yield components detection and image-based indicators for non-invasive grapevine yield prediction at different phenological phases ABSTRACT*. *October*, 833–848. https://doi.org/10.20870/oeno-one.2020.54.4.3616

Victorino, G., Poblete-Echeverria, C., & Lopes, C. M. (2022b). *A Multicultivar Approach for Grape Bunch Weight Estimation Using Image Analysis*. 1–15.

Whitty, M., Liu, S., Cossell, S., Jayakody, H., Woods, M., Tang, J., Singh, S., Van Kerk Oerle, P., Wiseham, D., Liu, S., Davidson, A., Stocco, T., Jarrett, J., Jarrett, P., Wotton, C., Shepherd, J., Lim, S., Petrie, P., & Dunn, G. (2017). Improved yield estimation for the Australian wine industry. *Wine Australia. Department of Primary Industries NSW & University of NSW*, *November*, 167.

OIV Organisation Internationale de la Vigne et du Vin. Description of world vine varieties (2nd Edition) 2009. Available online: http://www.oiv.int/en/technicalstandards-and-documents/description-of-grape-varieties/oiv-descriptor-list-for-grape-varieties-and-vitis-species-2ndedition (accessed on 17 june 2022).

Table 1: Summary of stepwise regression between grapevine yield (dependent variable) and visible bunch projected area (vBA), visible bunch projected perimeter (vBP), visible berry number (vBe), estimated total bunch projected area (TBA, Victorino et al. 2022a), compactness index (CI) at veraison, determined using the OIV scale (OIV, 2009). Includes statistical significance for variable selection (p-value), partial R^2 and MSE (mean squared error).

Step	Added Variable	Removed Variable	*p*-Value	Partial R^2	MSE (kg/m)
1	TBA × CI^2	-	0.000	0.837	0.580
2	vBP/vBA × vBe	-	0.051	0.849	0.544
3	vBA/vBP	-	0.125	0.852	0.537
4	vBA/vBP × vBe	-	0.014	0.861	0.511
5	-	vBP/vBA × vBe	0.538	0.860	0.508

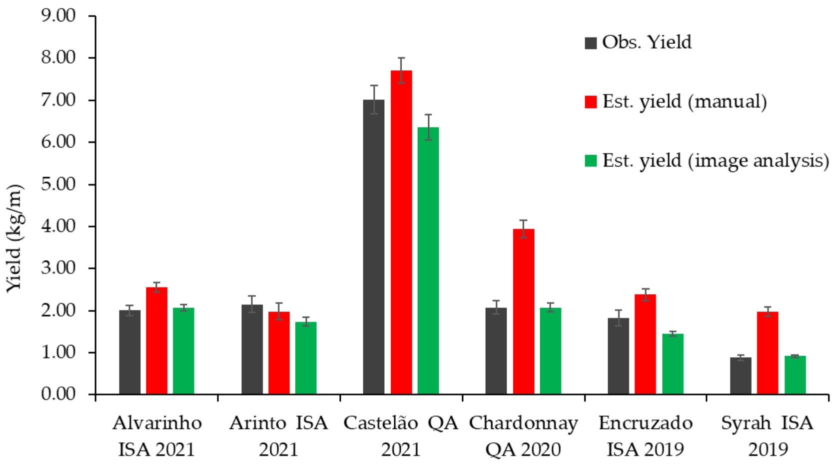

Figure 1: Observed and estimated grapevine yield using manual methods and image analysis for the studied cultivars on the validation set. Average ± std error of yield per vine segment (1 m). ISA: Instituto Superior de Agronomia site, QA: Quinta da Amieira site.