# Accurate estimation of grapevine bunch weight using image analysis: a case study with two Portuguese cultivars

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***Abstract***

**Vineyard yield estimation can bring several benefits to all the grape and wine production chain. Among several methods the ones based on estimation of yield components are the most used at farm level. However, as they are manual, destructive and very time-consuming, there is a strong demand to replace them with low-cost and reliable automated methods. Recent advances in machine vision have provided accurate tools for bunch and/or berry recognition. However, converting the visible bunch area on the images into bunch mass is still a big challenge. In the frame of the EU VINBOT research project (www.vinbot.eu), an experiment was set up using the cultivars Viosinho (white; 100 bunches) and 'Trincadeira' (red, 48 bunches) to study the relationships between the projected bunch area (Ba) on the 2D images and the corresponding bunch weight (Bw) measured at harvest. In the laboratory, bunches were submitted to image acquisition using a compact RGB camera. Then each bunch was assessed to obtain the following morphological attributes: Bw, bunch volume (Bv), berry number (BE#) and weight (BEw) and rachis length (Rl). Bunch compactness (Bc) was calculated as the ratio between BE# and Rl, while the Ba was computed using ImageJ® software. Correlation analysis shows that most part of these variables are significantly and positively correlated with Bw. However, as not all variables are easy to obtain by automated image analysis, some were excluded and a forward stepwise regression between Bw (dependent variable) and the variables BE#, Ba, Bv and Bc (independent variables) was performed. The final models obtained explained a very high proportion of bunch weight variability ($R^2$=0.98 and 0.99 for 'Viosinho' and 'Trincadeira', respectively) with a very small error. These results indicate that grapevine bunch weight can be estimated with high accuracy from 2D images using explanatory variables derived from bunch morphological attributes.**

**Keywords:** bunch compactness, bunch volume, precision viticulture, vineyard yield estimation

## INTRODUCTION

Vineyard yield estimation can bring several benefits to all the grape and wine production chain as evidenced in the following examples: planning cluster thinning (in order to prevent excessive production and consequent poor wine quality); planning and organizing harvest operations (hand labor, equipment, etc.); planning cellar needs (scheduling grape intake; allocating tank space, purchasing tanks, barrels, oenological products, bottles and others); planning purchases and/or grape sales; establishing grape prices and managing wine stocks; managing grape and wine market; programming investments and development of marketing strategies. All these potential benefits make yield estimation one of the major current research topics in viticulture.

Vineyard yield estimation can be obtained by several methods, being the methods based on manual sampling of yield components (number and/or weight) the most used at farm level (Clingeleffer et al., 2001). These methods are based on manual counting and/or

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weighing of samples of yield components (e.g., inflorescences, berries and bunches) combined with historical data. These procedures, besides being destructive, are very labor intensive and could provide inaccurate results as they are extrapolated for the entire vineyard based only on the assessment of a small sample.

Recently, several attempts have been made to apply image analysis and other machine vision technologies for bunch and/or berry automatic recognition from 2D images and processing methods for grape yield estimation (see review by Seng et al., 2018). These studies showed that bunch detection in images and the estimation of the corresponding bunch area using image analysis technologies is feasible and is becoming more and more accurate (e.g., Diago et al., 2012; Reis et al., 2012; Nuske et al., 2013, 2014; Font et al., 2015; Aquino et al., 2018, Di Gennaro et al., 2019). The detection and counting of grape berries using computer vision and machine learning techniques has also been successfully tested in several studies (e.g., Battany, 2008; Nuske et al., 2013, 2014; Diago et al., 2015; Liu et al., 2015; Aquino et al., 2017; Pérez-Zavala et al., 2018). The automatic evaluation of bunch dimensions (length, width and volume) was also successfully achieved by the analysis of 2D images as reported by Herrero-Huerta et al. (2015) who were able to reconstruct bunches in 3D from images and develop algorithms and techniques to estimate bunch volume. Also, Tello et al. (2016) showed that the geometric reconstruction of the bunch morphological volume from 2D features can be obtained with high accuracy based on dimensional analysis of bunches. Concerning bunch compactness (density of berry distribution within the bunch) several imaging methods have also been developed to automate the assessment of this important bunch feature (e.g., Cubero et al., 2015; Tello et al., 2016; Chen et al., 2018).

All the above-mentioned technologies, when combined with on-the-go image acquisition, can provide continuous and massive data on yield and yield components from an entire vineyard. The recent EU research project VINBOT (www.vinbot.eu) is an example where it was used an all-terrain autonomous mobile robot with a set of sensors for capturing vineyard images and obtain yield maps (Lopes et al., 2017). In this project, the approach of "Convolutional Neural Networks inside of Deep Learning Field", based on a structure of stacked multi-layer neural networks (Krizhevsky et al., 2012), was used for image segmentation and grape recognition. Once the bunches were recognized, the total area occupied by the bunches or bunch fractions in the image was computed in pixels, converted into actual area and then converted into mass of grapes, using empirical relationships between bunch projected area and weight. The first results indicate that the algorithms underestimated yield, being bunch occlusions the major explanation (Lopes et al., 2017). However, the empirical models used to convert the projected area into kilograms of grapes could have also amplified the errors, contributing to reduce the prediction ability of the Vinbot algorithms. Indeed, this conversion was done using only a linear relationship between the projected bunch area and the corresponding weight. As this relationship depends on several factors related to bunch traits (length, width, form, volume, compactness, etc.), adding other bunch attributes as explanatory variables will contribute to improve the accuracy of the algorithms used to convert the projected bunch area into weight. The aim of this work was to explore the relationships between bunch morphological attributes and weight on two Portuguese grapevine cultivars, in order to improve the accuracy of the algorithms used for the estimation of bunch weigh from 2D images.

## MATERIAL AND METHODS

### Plant material

The bunches used in this work were picked during the 2014 vintage from two plots of the "Instituto Superior de Agronomia" experimental vineyard, located in Lisbon (lat. 38.71°N; long. 9.18°W). The grapevines of the white cultivar 'Viosinho' (9 years old) were grafted on 1103 Paulsen rootstock and spaced 1.0 m within and 2.5 m between rows, while the grapevines of the red cultivar 'Trincadeira' (16 years old) were grafted on 140 Ru rootstock and spaced 1.2 m within and 2.5 m between rows. Both cultivars were trained to a vertical shoot positioning with two pairs of movable wires and spur-pruned to a Royat

Cordon system (unilateral for 'Viosinho' and bilateral for 'Trincadeira'). Similar standard cultural practices were applied to both vineyard plots, except for defoliation, carried out at pre-bloom in the 'Trincadeira' plot to reduce the potential detrimental effects of bunch rot. In order to encompass the maximum bunch weight variability, all bunches from five vines (a total of 100 for 'Viosinho' and 48 for 'Trincadeira') were harvested at commercial maturity (~23 °Brix), labeled and then transported to the laboratory for detailed assessments.

### Bunch assessments

In the laboratory, each bunch was photographed in front of a white background with a compact RGB digital camera (Figure 1). Using ImageJ® software, the total area of the bunch was computed as the number of pixels in the segmented image and converted into square centimeters. Then each bunch was assessed to obtain the following attributes: weight (Bw), morphological volume (Bv), projected area (Ba), berry number (BE#), total weight of the berries (TBEw), average weight per berry (BEw) and rachis length (Rl). Bunch compactness (Bc) was calculated as the ratio between BE# and Rl, while Bv was assessed by the water displacement method (Tello and Ibáñez, 2014).

Figure 1. Three selected bunch images of the white cultivar 'Viosinho' (left) and of the red cultivar 'Trincadeira' (right) showing a big variability in size and shape.

### Data analysis

Correlation and regression analysis were performed to evaluate the relationships between all variables. The selection of explanatory variables to estimate Bw was done using a forward stepwise regression with 0.05 critical F statistic. All the statistical analyses were performed using SAS® statistical software.

## RESULTS AND DISCUSSION

### Bunch attribute variability

The bunches of both cultivars are described in the Portuguese grapevine catalog (www.ivv.gov.pt/np4/home.html) (Instituto da Vinha e do Vinho, 2011) as having a small ('Viosinho') and medium ('Trincadeira') size and medium compactness but, as shown in Table 1 and Figure 1, when considering all bunches present in a vine, a high variability was observed in all the assessed attributes, due to the natural variability of bunch morphology. As compared to 'Viosinho', the bunches of 'Trincadeira' presented a lower average weight and a higher variability of all attributes, differences that can be explained, in addition to the genetic effect, by the effects of the early defoliation that was performed at pre-bloom to reduce cluster compactness (Palliotti et al., 2012).

### Relationships between variables

Table 2 shows the Pearson correlation coefficients (r) of the relationships between Bw and all the variables measured and calculated on the bunches of the two cultivars. For 'Viosinho', all variables were significantly and positively correlated with Bw being the highest r-value shown by the variables TBEw, BE# and Bv, while the lowest r-value was obtained with the variable BEw. The variables Ba and Bc also presented very high and significant correlation with Bw (r=0.93 and 0.89, respectively). 'Trincadeira' showed a similar pattern to that reported for 'Viosinho', except for the variable BEw, which showed a non-significant correlation with Bw.

Table 1. Summary statistics of measured and calculated variables for each bunch of the cultivars 'Viosinho' ($n$=100) and 'Trincadeira' ($n$=48): number of berries per bunch (BE#); total weight of berries per bunch (TBEw); average weight per berry (BEw); bunch volume (Bv); rachis length (Rl), bunch compactness (Bc) and bunch projected area in the 2D image (Ba). Avg: average; Max: maximum value; Min: minimum value; C.V.: coefficient of variation.

| Bunch attributes | Viosinho | | | | Trincadeira | | | |
|---|---|---|---|---|---|---|---|---|
| | Min | Avg | Max | C.V. | Min | Avg | Max | C.V. |
| BW (g) | 19.2 | 175.8 | 512.0 | 55.6 | 6.9 | 85.6 | 290.8 | 85.4 |
| BE# | 14.0 | 101.1 | 276.0 | 53.0 | 4.0 | 54.1 | 174.0 | 86.7 |
| TBEw (g) | 18.3 | 168.6 | 493.1 | 55.9 | 6.4 | 81.8 | 280.6 | 86.3 |
| BEw (g) | 1.1 | 1.6 | 2.1 | 11.9 | 0.7 | 1.7 | 3.3 | 32.6 |
| Bv (mL) | 18.0 | 157.8 | 460.0 | 55.2 | 8.0 | 78.5 | 260.0 | 84.4 |
| Rl (cm) | 6.3 | 13.0 | 17.3 | 17.7 | 4.0 | 9.2 | 15.0 | 29.7 |
| Bc (berries $cm^{-1}$) | 1.9 | 7.5 | 17.6 | 43.6 | 0.5 | 5.1 | 13.8 | 69.2 |
| Ba ($cm^2$) | 21.9 | 101.0 | 210.4 | 39.0 | 9.9 | 52.0 | 119.6 | 58.4 |

Table 2. Pearson correlation coefficients (r) obtained from the correlations between Bw and all the variables measured and calculated on the bunches of 'Viosinho' ($n$=100) and 'Trincadeira' ($n$=48). BE#: number of berries per bunch; TBEw: total weight of berries per bunch; BEw: average weight per berry; Bv: bunch morphological volume; Rl: rachis length, Bc: bunch compactness; Ba: bunch projected area in the image.

| Cultivar | BE# | TBEw | BEw | Bv | Rl | Bc | Ba |
|---|---|---|---|---|---|---|---|
| Viosinho | 0.98 | 0.99 | 0.40 | 0.98 | 0.71 | 0.93 | 0.89 |
| Trincadeira | 0.95 | 0.99 | -0.25 | 0.99 | 0.76 | 0.92 | 0.92 |

The high and significant correlation coefficients obtained indicate that many of the studied variables can be used as predictors of bunch weight. In order to find the best explanatory variables to estimate Bw, a stepwise regression analysis between Bw (dependent variable) and a subset of the above variables that can be easily extracted by automated image analysis (Ba, Bv, BE# and Bc) was performed.

For 'Viosinho', the first variable selected was Bv (partial $R^2$=0.978). In the second and third steps of the regression, the variables BE# and Ba were chosen respectively, but with a very low contribution to the explanation of Bw variance (partial $R^2$<0.01). The variable Bc did not meet the significance level to be included in the model. The final model obtained for 'Viosinho' is reported in Equation 1.

$$Bw = -9.37240 + 0.71166Bv + 0.56362B\# + 0.15765Ba \quad (1)$$

Adj. $R^2$=0.985 ($p$<0.001); $n$=100; RMSE=11.9 g

For 'Trincadeira', the variable Bv was also the first one to enter the model, explaining almost all the Bw variance (partial $R^2$=0.999). In the second step the variable Ba was chosen but with a very low contribution (partial $R^2$<0.001). No other variable met the significance level to be included in the model (Equation 2).

$$Bw = -0.13914 + 1.12519Bv - 0.04853Ba \quad (2)$$

Adj. $R^2$=0.999 (p<0.001); $n$=48; RMSE=2.2 g

In order to check the possibility of using a single model for both cultivars the stepwise regression was repeated for the pooled data ($n$=148 bunches). The results mirrored those obtained for 'Viosinho' (Table 3). The final model is reported in Equation 3 and, as shown in Figure 2, the estimated values fit very well with the actual Bw.

$$Bw = -5.85999 + 0.85301Bv + 0.33324BE\# + 0.13123Ba \quad (3)$$

Adj. $R^2$=0.989 (p<0.001); $n$=148; RMSE=10.7 g

Table 3. Summary of stepwise regression analysis between bunch weight (Bw) (dependent variable) and the independent variables bunch volume (Bv), number of berries per bunch (BE#) and bunch projected area (Ba). Pooled data of 'Viosinho' ($n$=100) and 'Trincadeira' ($n$=48) grapevine cultivars.

| Step | Var. entered | Partial $R^2$ | Model $R^2$ | Cp[a] | F value | Prob. F | RMSE[a] (g) |
|---|---|---|---|---|---|---|---|
| 1 | Bv | 0.9856 | 0.9856 | 44.2 | 9978.7 | <0.0001 | 12.1 |
| 2 | B# | 0.0027 | 0.9883 | 11.3 | 33.0 | <0.0001 | 10.9 |
| 3 | Ba | 0.0006 | 0.9888 | 6.1 | 7.1 | 0.0085 | 10.7 |

[a]Cp Mallows; RMSE – root mean square error.

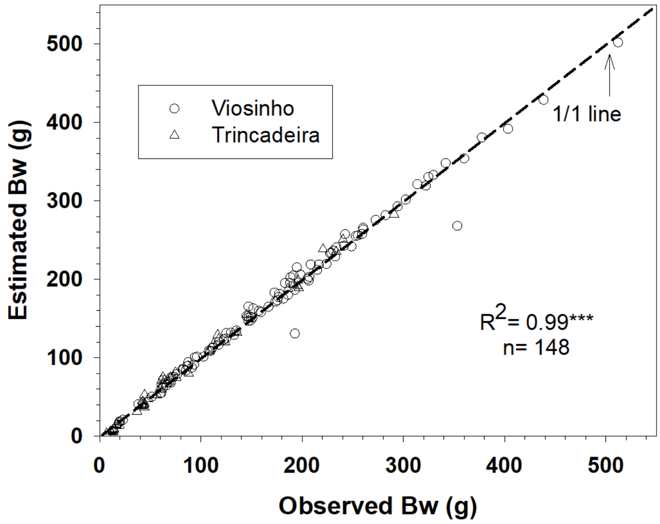


Figure 2. Relationship between observed and estimated bunch weight values (BW) using the model reported in Equation 3 and based on pooled data of the cultivars 'Viosinho' ($n$=100) and 'Trincadeira' ($n$=48). The dotted line represents the 1:1 line. *** indicates significance at $P$<0.001.

In all models, the variable Bv was the first variable selected with a very high partial $R^2$ showing that this bunch attribute is a very important predictor of Bw, as also reported by other authors for other grapevine cultivars (Nuske et al., 2014; Font et al., 2015). These results reinforce the need to use automated image analysis methods for extracting Bv as described in previous reports (e.g., Nuske et al., 2014; Font et al., 2015; Herrero-Huerta et al., 2015; Liu et al., 2015; Tello et al., 2016), and/or to develop new ones.

BE# was the second variable selected (except for 'Trincadeira') confirming its importance as a yield predictor (Clingeleffer et al., 2001). However, in the multiple regression model, after the selection of the variable Bv, the contribution of BE# to explain Bw variance was almost negligible.

As reported in several publications (Diago et al., 2012; Reis et al., 2012; Nuske et al., 2013, 2014; Font et al., 2015; Aquino et al., 2018; Di Gennaro et al., 2019) bunch projected area in the image is an easy feature to extract with image analysis and machine vision technologies. However, despite having a very high and significant correlation coefficient with BW, in the multiple regression model, Ba showed a very low contribution to explain Bw variance when the variable Bv was present.

In all models, the variable Bc, an indicator of bunch density (Tello and Ibáñez, 2018), never met the 0.05 significance level to be included in the model indicating that, despite being a variable that combines two bunch traits (BE# and Rl), in presence of other variables like Bv, its contribution to explain Bw becomes negligible.

**CONCLUSIONS**

In order to improve the accuracy of the algorithms for the estimation of bunch weight from 2D images and find the best yield predictors, in this work, the relationships between bunch attributes and corresponding weight were explored in two Portuguese grapevine cultivars. In both cultivars, most of the assessed bunch attributes (volume, projected area, berry number and weight, rachis length and bunch compactness) were significantly and positively correlated with bunch weight, indicating that they can be used as explanatory variables to predict bunch weight. Using a multiple stepwise regression approach, bunch volume resulted a very powerful estimator of bunch weight. After the selection of bunch volume, the other variables included in the model were the number of berries and bunch area but with a very low contribution to explain bunch weight variance. The obtained models (per cultivar or combined) presented a very good fit with actual bunch weight and a very low error, indicating that grapevine bunch weight can be estimated with high accuracy from 2D images using explanatory variables derived from automated non-intrusive assessment of bunch morphological attributes. Further research is needed to validate these models on other cultivars, sites and seasons. Moreover, additional research effort should be done to improve the methodologies for automated image-based technologies to determine bunch volume.

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