EXTENDED ABSTRACT

Morphological image analysis for determining bunch grape characteristics: A case study on bunch weight in Cabernet-Sauvignon

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INTRODUCTION

Morphological image analysis is a powerful technique used in various fields, including agriculture, to quantitatively assess the physical characteristics of objects. In viticulture, the accurate assessment of grapevine characteristics is essential for optimizing crop management and improving the quality of wine production. Among these characteristics, bunch weight is a critical factor influencing vine health, yield potential, and the quality of grapes harvested. Accurate vineyard yield estimation is crucial for the wine industry as it enables optimization in harvest planning, winery management, and marketing strategies (Victorino et al., 2022). However, the significant spatial and temporal variability within vineyards complicates precise predictions of grape bunch weight (Bramley et al., 2011). Conventional methods, such as manual grape bunch sampling, are destructive, labour-intensive, and prone to significant errors that can exceed 30%, depending on the sampling technique used and vineyard heterogeneity (Dunn & Martin, 2008). To overcome these limitations, sensor-based technologies, particularly image analysis, have shown great potential in addressing these challenges. These tools enable the inspection of a large number of grape bunches within a short time, reducing reliance on extrapolations and errors associated with variability (Liu & Zeng, 2020). Non-contact measurements based on two-dimensional image processing have been proven to be useful in the detection of several key agricultural traits, especially in single fruits with regular and uncomplicated shapes, such as apples and apricots (e.g., Khojastehnazhand et al., 2019; Wu et al., 2019). Other studies also present the potential of these techniques for more complicated fruit shapes, such as grape bunches, where the shape and size are highly dependent of the cultivar, viticulture practices and edaphoclimatic conditions. Diago et al., (2014) demonstrated that features such as the projected area of the bunch, the number of visible berries, and the perimeter are key predictors of bunch weight in two-dimensional analyses, achieving significant correlations across various cultivars. Moreover, the use of two-dimensional imaging has become an effective tool for the automatic segmentation of grape bunches and the counting of visible berries (Aquino et al., 2018; Milella et al., 2018). Advanced methods, such as algorithms based on convolutional neural networks, have significantly improved segmentation and counting under field conditions, bringing these technologies closer to practical applications in commercial vineyards (Liu & Zeng, 2020). However, the dependence of these correlations on the cultivar remains a challenge, as differences in bunch architecture and environmental conditions significantly affect the accuracy of proposed models (Tello et al., 2015; Victorino et al., 2022). Despite these advances, several open questions persist regarding image-based weight estimation. These include berry occlusion, variability in image capture conditions, and cultivar dependence, all which limit model generalization (Diago et al., 2014; Victorino et al., 2022).

RESEARCH OBJECTIVES

This study aims to explore the capabilities of morphological image analysis for determining bunch grape characteristics, as a simple and automatic method based on information derived from a miniaturized multispectral camera, commonly used in drone surveys. From the multispectral camera, RGB, NIR and RE bands will be used as inputs to extract morphological features. Subsequent studies will be performed to extract spectral information and vegetation indexes from the same images, which will be compared with the chemical parameters of the bunches. The case study is focused on the relationship between bunch weight and features derived from 2D image analysis in Cabernet Sauvignon grape bunches. The primary goal is to assess how image-derived characteristics can predict bunch weight. The study seeks to identify the best-performing predictive model for estimating bunch weight using these features, focusing on practical applicability and precision in viticulture.

MATERIAL AND METHODS

Description of experimental sites

The study was carried out at the end of the 2020-2021 growing season in Cabernet Sauvignon vineyard at a commercial farm situated in the Stellenbosch wine region of South Africa at coordinates 33°54′11.8″S and 18°55′12.4″E. The vineyard was planted in the year 2003 on a standard vertical shoot positioning (VSP) trellis system with a North/South row direction. The selected block was a 2.42 ha vineyard planted the vine spacing was 2 m and the inter-row width was 2.5 m. The first season of monitoring in this vineyard is fully described in Jasse et al. (2021).

Data Collection and Image Analysis

Bunch images were collected in laboratory condition using a MicaSense RedEdge TM3 Multispectral camera (MicaSence Inc., Seattle, WA, USA), mounted on a tripod approximately 50 cm above the bunches. A white background was used to prevent noise caused by surrounding objects and to improve thresholding for bunch segmentation. As reference, bunch weight was recorded per individual bunch (359 bunches in total).

Data Analysis

A script in MATLAB® (v.2023b, The MathWorks Inc., Natick, United States) was written to extract a set morphological feature of the bunch images and organize the dataset. Pixels on the images were converted into cm^2 using a reference in the image with known dimensions. To develop the model a stepwise regression procedure was implemented in R Statistical Software (v4.4.1; R Core Team 2024) using the function *stepAIC* from the package *MASS*, which selects the best model based on its Akaike information criterion (AIC) value (Venables & Ripley 2022).The original data set was randomly divided into a training set (with 60% of the data) and test set (with 40% of the data). The training set was used to establish the relationship between the analysed variables (described above) and to train the regression model. A simple linear regression analysis was used to evaluate the relationship between actual bunch weight and estimated bunch weigh from the test dataset. The coefficient of determination (R^2), and root mean squared error (RMSE) were the parameters used to evaluate the model performance.

RESULTS

Bunch Characterization

The present study evaluated the relationship between cluster weight and variables derived from the analysis of two-dimensional images. The variables studied included area (A), convex area (CA), perimeter (P), Euler number (EN), filled area (FA), minor axis length (MiA), major axis length (MaA), circularity (C), solidity (S), and eccentricity (Ec). The results showed consistent and significant patterns in the relationships between the image variables and bunch weight. Table 1 presents the descriptive statistics of the analysed variables for the training and test datasets. The average values of A and P stood out as influential factors in estimating cluster weight, while shape-related metrics, such as circularity (C) and eccentricity (Ec), provided additional insights into bunch architecture.

Multiple Regression Model

Equation 1 show the multiple regression equation was obtained using a stepwise procedure (W_{SW}).

$$W_{SW} = -6.72 + 10.34 * A - 2.19 * CA + 0.00017 * P + 0.17 * EN - 5.4 * FA - 5.86 * MiA - 4.07 * MaA + 152.65 * C - 135.50 * S + 54.92 * Ec \quad (1)$$

The model explained a significant percentage of the variability in bunch weight (adjusted $R^2 = 0.856$) and showed an acceptable root mean square error (RMSE) compared to univariate models (Table 2). Table 2 summarizes the variable selection process in the stepwise model. Variables related to A, P, and C were the first to be selected due to their high partial R^2, reinforcing their relevance in predicting weight. Additionally, shape metrics such as Ec and S also contributed to the final model, suggesting that geometric features play a key role in accurately estimating bunch weight.

Model Validation (Test set)

Figure 1 shows the relationship between the observed and estimated bunch weights using the multiple regression model. The results indicated a good fit between the predicted and observed values, particularly for bunches with weights within the average range. However, greater deviation was observed for bunches with extreme weights, possibly due to specific morphological characteristics that were not adequately represented by the model variables. Overall, the model results indicate that variables derived from two-dimensional image analysis can effectively predict bunch weight. However, challenges were identified with bunches of extreme weights and atypical shapes, suggesting the need to further explore model adjustments that incorporate additional or nonlinear features.

CONCLUSION

This study demonstrated that 2D image-derived variables, such as area, perimeter, and circularity, are effective predictors of grape bunch weight. The stepwise multiple regression model achieved a high explanatory power (adjusted $R^2 = 0.856$), validating its applicability across diverse cluster architectures. However, deviations observed in extreme weights highlight the need for model refinements, including non-linear approaches or additional morphological descriptors. These findings support the integration of image-based methodologies as a reliable tool for vineyard yield estimation, advancing precision viticulture practices. Future research should explore broader cultivar variability and field conditions to enhance model robustness and generalization.

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TABLES AND FIGURE

Table 1. Descriptive statistical analysis for the training dataset and testing dataset.

Variable	Training Dataset	Testing Dataset
N	219	140
Mean	115.4	116
Median	106.0	106.2
Min	44.3	53.9
Max	283.3	280.7
Standard Deviation	42.9	42.8
Skew	1.04	1.18
Kurtosis	1.08	1.69
Coefficient of variation	0.37	0.36

N is the number of samples, Min is the minimum value, and Max is the maximum value.

Table 2. Stepwise variable selection process and associated performance metrics for the regression model.

Step	Variable	Selection	AIC	R^2	Adj-R^2
1	Area	Addition	1981.4	0.735	0.734
2	Convex Area	Addition	1913.4	0.807	0.806
3	Perimeter	Addition	1904.9	0.816	0.814
4	EulerNumber	Addition	1887.8	0.832	0.829
5	FilledArea	Addition	1883.4	0.837	0.833
6	MinorAxisLength	Addition	1880.5	0.840	0.836
7	MajorAxisLength	Addition	1877.1	0.844	0.839
8	Circularity	Addition	1864.7	0.854	0.848
9	Solidity	Addition	1857.7	0.860	0.854
10	Eccentricity	Addition	1855.9	0.862	0.856
11	EquivDiameter	Removed	---	---	---
12	Orientation	Removed	---	---	---
13	Extent	Removed	---	---	---

AIC is the Akaike information criterion; R^2 is the coefficient of determination and Adj-R^2 is the adjusted coefficient of determination.

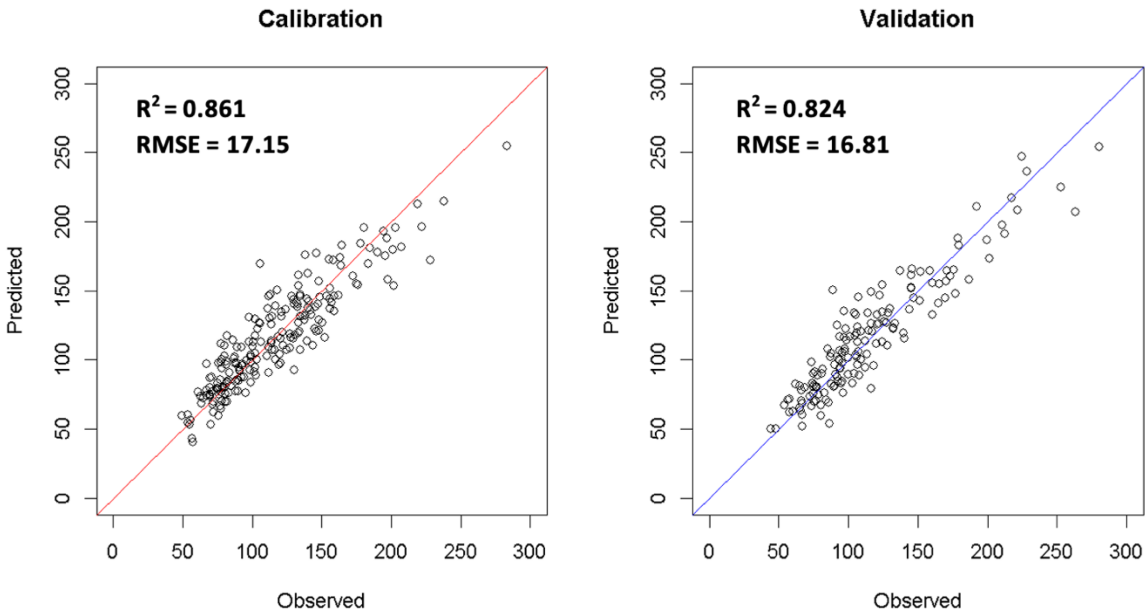

Figure 1. Observed *vs*. predicted grape bunch weights using the stepwise regression model (Calibration and Test set).