DOI: https://doi.org/10.20870/oeno-one.2025.59.2.9309

OPEN ACCESS

SPECIAL ISSUE

Morphological image analysis for estimating grape bunch weight under different irrigation regimes in Cabernet-Sauvignon

Carlos Poblete-Echeverría[1,*], Anke Berry[1], Talitha Venter[1], Sergio Velez[2], Maria Ignacia González Pavez[1,3] and Rubén Iñiguez[4,5]

[1] South African Grape and Wine Research Institute (SAGWRI), Stellenbosch University, Private Bag X1, Matieland 7602, South Africa
[2] JRU Drone Technology, Department of Architectural Constructions and I.C.T., University of Burgos, Burgos, 09001, Spain
[3] Research and Extension Center for Irrigation and Agroclimatology (CITRA), Faculty of Agricultural Sciences, Universidad de Talca, Campus Talca, Chile
[4] Institute of Grapevine and Wine Sciences (University of La Rioja, Consejo Superior de Investigaciones Científicas, Gobierno de La Rioja), 26007 Logroño, Spain
[5] Televitis Research Group, University of La Rioja, 26006 Logroño, Spain

Article number: 9309

*correspondence:
cpe@sun.ac.za

Associate editor:
Laurent Jean-Marie Torregrosa

Received:
15 March 2025

Accepted:
23 May 2025

Published:
16 June 2025

This article is an original research article published in cooperation with the 23rd GiESCO International Conference, July 21-27, 2025, hosted by the Hochschule Geisenheim University in Geisenheim, Germany.

Guest editors: Laurent Torregrosa and Susanne Tittmann.

ABSTRACT

Morphological image analysis has emerged as a powerful tool for assessing physical bunch characteristics in viticulture, particularly for estimating grape bunch weight, a key factor affecting vineyard yield and wine quality. Traditional manual sampling methods are labour-intensive, destructive, and prone to significant errors due to vineyard variability and environmental stresses such as water deficit. To address these challenges, this study investigates the potential of two-dimensional (2D) image analysis for non-destructive grape bunch weight estimation across varying levels of water stress. Images of 359 bunches from Cabernet-Sauvignon vines grown under different irrigation regimes, were analysed to extract 13 morphological features. A stepwise multiple regression model was developed to predict bunch weight based on key image-derived features, demonstrating strong explanatory power (adjusted R2 of the prediction = 0.824). The results indicate that features such as area, perimeter, and circularity are strong predictors of bunch weight. While the model demonstrated high accuracy overall, some deviations were observed in large weight categories indicating opportunities for further refinement. These findings demonstrate that image-based phenotyping can reliably estimate bunch weight across a range of water availability scenarios, supporting more precise and efficient vineyard management practices. Future research should focus on enhancing model robustness by integrating additional morphological descriptors and evaluating broader cultivar variability under field conditions.

KEYWORDS: grape bunch weight, precision viticulture, water stress, morphological image analysis, RGB images, GiESCO 2025

INTRODUCTION

Morphological image analysis is a powerful technique used in various fields, including agriculture, to quantitatively assess the physical characteristics of objects (Herrero-Huerta *et al.,* 2015; Kheiralipour & Kazemi, 2020; Lopes & Cadima, 2021). This approach enables non-destructive, automated, and accurate evaluation of features such as size, shape, texture, and colour, which are critical for monitoring plant growth, detecting diseases, assessing stress, and estimating yield (Aydin *et al.,* 2017). In viticulture, the accurate assessment of grapevine characteristics is essential for optimising crop management and improving wine quality. Among these characteristics, grape bunch weight is a critical factor influencing vine balance, yield potential, and grape quality. Accurate vineyard yield estimation is crucial for the wine industry, as it supports effective harvest planning, winery operations, and marketing strategies (Henry *et al.,* 2019; Victorino *et al.,* 2022a; Moreno & Andújar, 2023). A precise estimation of grape bunch weight not only improves short-term operational efficiency but also facilitates long-term vineyard management decisions, such as adjusting pruning strategies, optimising irrigation schedules, and anticipating winery storage capacity (Nuske *et al.,* 2011; Lopes & Cadima, 2021; Victorino *et al.,* 2022a). Recent advances in image-based morphological analysis have significantly enhanced the accuracy and efficiency of bunch weight estimation, providing non-destructive, rapid, and cultivar-adaptive tools that address the variability inherent in vineyard conditions (Lopes & Cadima, 2021; Victorino *et al.,* 2022a). However, the high level of spatial and temporal variability within vineyards complicates precise predictions of grape bunch weight (Bramley *et al.,* 2011). This variability arises from factors such as differences in vine vigour, microclimate, soil properties, and management practices that change over time and across vineyard blocks (Ferro *et al.,* 2024; Lopes & Cadima, 2021). Moreover, morphological traits influencing bunch weight, such as bunch compactness and berry size, vary among cultivars and are further influenced by environmental conditions including water availability and canopy management (Victorino *et al.,* 2022b; Tello & Ibáñez, 2018). 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, 2004). These errors arise partly because manual sampling often covers only a small proportion of the vineyard, and variability in vine vigour, bunch distribution, and missing vines can bias estimates (Oger *et al.,* 2023).

Morphological berry and bunch characteristics that would impact yield include berry length and diameter translating to berry weight and the number of berries per bunch which could be inferred from bunch size (length, width, and/or volume) (Nuske *et al.,* 2011; Kircherer *et al.,* 2013). Post-harvest bunch characterisation can be time-consuming with traditional measurement methods such as using a ruler (Frege, 1804) or a calliper (Kircherer *et al.,* 2013) for berry length and diameter. 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 *et al.,* 2020). While traditional methods typically rely on sampling 20–30 bunches per vineyard block, image-based approaches can process several hundred bunches within the same timeframe, offering a more representative assessment of vineyard variability and potentially improving the accuracy of yield estimation.

Non-contact measurements based on two-dimensional image processing have been proven to be effective in detecting 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 highlight the potential of these techniques for more complex fruit shapes, such as grape bunches, where the shape and size vary considerably depending on the cultivar, viticulture practices, and environmental conditions. RGB image analysis has been successfully employed in various studies for characterising grape bunches and berries. This technology has been used to evaluate berry number, size, and volume (Kircherer *et al.,* 2013) and berry weight (Tardaguila *et al.,* 2012) as well as bunch shape and compactness (Wycislo *et al.,* 2008). In viticulture, applications of image-based analysis of different spectral bands offer complementary information. RGB bands (visible spectrum) are typically used to extract morphological traits such as area, shape, and colour (Aquino *et al.,* 2018; Diago *et al.,* 2015; Lopes & Cadima, 2021). Near-infrared (NIR) and red-edge (RE) bands, which fall outside the visible range, are more sensitive to physiological traits like water status or canopy vigour and can be used for functional assessments (Liu *et al.,* 2020; Victorino *et al.,* 2022b). Although multispectral imagery can integrate this information to improve phenotypic predictions, RGB images remain the most accessible and cost-effective for morphological analysis. In the present study, emphasis was placed on RGB-based features due to their suitability for describing the physical structure of grape bunches.

Moreover, the use of two-dimensional (2D) 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 convolutional neural network (CNN)-based algorithms, have significantly improved segmentation and counting under field conditions, bringing these technologies closer to practical applications in commercial vineyards (Liu *et al.,* 2020). Multiple linear regression (MLR) has been widely used in agricultural and horticultural image analysis for predictive modelling due to its simplicity, interpretability, and ability to incorporate multiple explanatory variables. In viticulture, Diago *et al.,* (2015) applied MLR to estimate berry weight based on image-derived morphological traits, incorporating grape variety as a categorical variable to account for inter-varietal variability. This study 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 2D analyses, achieving significant correlations across various cultivars. More recently, Victorino *et al.* (2022a) developed predictive MLR models that combined RGB image-based descriptors such as area, berry count, and perimeter, with agronomic factors to accurately estimate grape bunch weight across different cultivars. The strength of MLR lies in its ability to quantify the contribution of each variable, making it particularly useful for identifying relevant predictors from a large set of potentially collinear morphological features, as done in the present study.

Despite the promising results obtained in previous studies, 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.,* 2022b). This highlights the intrinsic variability among grape cultivars, where differences in rachis length, berry size heterogeneity, and bunch compactness can alter the relationship between projected area and actual bunch weight, influencing model performance. A further complicating factor in grape yield estimation is the effect of water stress on bunch characteristics and, consequently, final yield. Irrigation management plays a crucial role in maintaining grape yield and wine quality by mitigating the impacts of water deficits (Wetner *et al.,* 2018). The effects of water stress on grapevine growth and yield are highly dependent on the timing, duration, and intensity of the stress (Munitz *et al.,* 2016; van Leeuwen *et al.,* 2018). Mild to moderate water deficits can enhance berry sugar accumulation and phenolic content, improving grape quality, whereas severe water stress often reduces berry size, yield, and some quality parameters (van Leeuwen *et al.,* 2018; Romero *et al.,* 2017). Water stress influences dry matter partitioning, often favouring root and wood growth at the expense of fruit development (Ojeda *et al.,* 2002; Munitz *et al.,* 2016). The timing of water stress is critical; for example, stress during the post-flowering to veraison period can significantly reduce bunch weight and yield, while mild stress before veraison may be beneficial (Greer & Weston, 2010; van Leeuwen *et al.,* 2018). By analysing morphological characteristics of grape bunches from vines subjected to different levels and timings of water stress, 2D image analysis can help quantify these impacts non-destructively, enabling better irrigation and vineyard management decisions (Victorino *et al.,* 2022a; Lopes *et al.,* 2021). Despite these advances, several open questions persist regarding image-based bunch weight estimation. These include the effect of berry occlusion and variability in image capture conditions on the accuracy of estimation as well as the degree of cultivar dependence, all limiting model generalisation (Diago *et al.,* 2015; Victorino *et al.,* 2022a).

This study aims to evaluate the potential of morphological image analysis, based on RGB images acquired with a compact commercial multispectral camera, commonly used in drone surveys, to estimate grape bunch weight in Cabernet-Sauvignon vines under different water stress conditions. Using a set of 13 morphological descriptors extracted from 2D images captured under controlled laboratory conditions, we examine the relationship between these features and grape bunch weight by applying a stepwise multiple regression model. This case study is focused on the relationship between grape bunch weight and features derived from 2D image analysis in Cabernet-Sauvignon vines growing under different irrigation regimes. The primary goal is to assess how image-derived characteristics can predict grape bunch weight using a simple, and non-destructive method that can contribute to more efficient yield estimation in viticulture. While the present work was conducted under standardised conditions, the approach is designed with future field applications in mind, particularly in the context of high-throughput image acquisition using drone-mounted cameras. By identifying the most relevant image-based variables and testing their performance across a range of bunch morphologies and stress levels, this study lays the groundwork for practical tools to support precision vineyard management. Given the near-linear relationships previously observed between image-based traits (*e.g.*, area, perimeter) and grape bunch weight, a stepwise multiple linear regression (MLR) model was chosen for this study as an interpretable and efficient tool to identify the most relevant predictors from a broad set of morphological features.

MATERIALS AND METHODS

1. Description of experimental sites

The study was conducted 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 18° 55' 12.4" E. The vineyard was planted in 2003 on a standard vertical shoot positioning (VSP) trellis system with a north-south row orientation. The selected block covered 2.42 ha, with a vine spacing of 2 m and an inter-row width of 2.5 m.

2. Data acquisition and image analysis

At harvest (26 and 27 February 2020—days of the year 58 and 59), 359 bunches from 10 vines under two different water stress conditions were randomly collected and transported to the laboratory where bunch images were acquired using a MicaSense RedEdge TM3 Multispectral camera (MicaSence Inc., Seattle, WA, USA). The camera was 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. This controlled setup minimised external variability, ensuring that the extracted morphological features are influenced solely by the inherent properties of each grape bunch rather than by inconsistencies in the image capture environment. In this study from the multispectral bands only the RGB were used for the analysis.

As a reference, the bunches were weighed manually using scales with a precision of ± 1 g. The classification of plant water status was conducted by defining three stress levels based on stem water potential (SWP): Class 1, corresponding to low water stress conditions ($\text{SWP} > -0.9$ MPa); Class 2, associated with moderate water stress ($-0.9 \text{ MPa} \geq \text{SWP} \geq -1.2$ MPa); and Class 3, indicating severe water stress ($\text{SWP} < -1.2$ MPa) as reported in Jasse *et al.* (2021). From this original classification, the vines analysed in this study were later consolidated into two non-overlapping classes: into two water stress levels: (i) low to mild water stress (L-M) and (ii) mild to high water stress (M-H), based on the seasonal average stem water potential during the water stress period. This classification was established prior to harvest and image analysis, ensuring consistency in sampling. The final dataset included 135 bunches in the L-M group and 224 in the M-H group. The monitoring process and water stress characterisation are fully described by Jasse *et al.* (2021).

A script in MATLAB® (v2023b, The MathWorks Inc. (2023), Natick, MA, United States) was written to extract 13 morphological features of the bunch images namely: Area (A), Convex Area (CA), Perimeter (P), EulerNumber (EN), Filled_Area (FA), MinorAxisLength (MiAL), MajorAxisLength (MaAL), Circularity (C), Solidity (S), Eccentricity (Ec), EquivDiameter (ED), Orientation (O) and Extent (E). Pixels on the images were converted into cm^2 using a reference in the image with known dimensions. The process of extracting morphological features is practically automatic and requires only minimal input from the users. Figure 1 presents a summary of the workflow employed for data acquisition and morphological image analysis and Table 1 presents the set of morphological features used in this study to characterise the shape and structure of the grape bunches. Each feature is defined by a specific geometric or topological property derived from image analysis.

3. Data analysis

A stepwise MLR model was selected due to its suitability for identifying key predictive variables among a large set of morphological descriptors. The linear approach provides interpretability, ease of implementation, and effectiveness for initial model development and evaluation. To develop the MLR 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, 2002). The original data set was randomly divided into a training set (60 % of the data comprising 211 observations) and a test set (40 % of the data comprising 148 observations). The training set was used to establish the relationship between the analysed variables (described above) and to train the regression model. In the training and test sets, the water stress variable was classified into two sub-classes, with the following sample sizes: in the training set, 131 samples for the M-H group and 80 for the L-M group; in the test set, 93 samples for the M-H group and 55 for the L-M group.

A simple linear regression analysis evaluated the relationship between actual and estimated bunch weight in the test dataset. The coefficient of determination (R^2_p), and root mean squared error of the prediction (RMSE_p) were the parameters used to evaluate model performance.

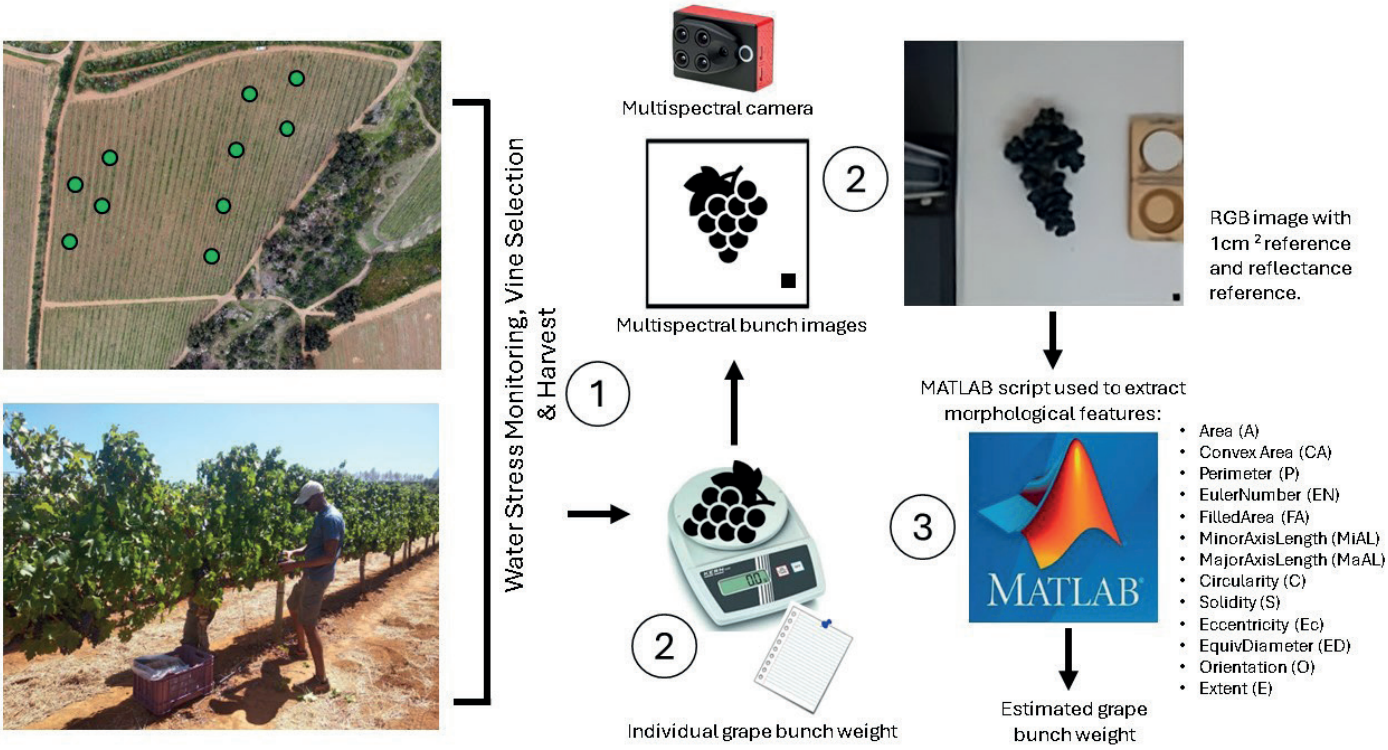

FIGURE 1. Workflow for data acquisition and morphological image analysis.

TABLE 1. Morphological features and their descriptions used for grape bunch shape characterisation.

Morphological feature	Abbreviation	Description in the context of grape bunch analysis
Area	A	Total number of pixels within the bunch region.
Convex Area	CA	Area of the smallest convex polygon that encloses the bunch.
Perimeter	P	Total length of the bunch boundary.
EulerNumber	EN	Topological descriptor: number of objects minus the number of holes.
Filled_Area	FA	Area of the bunch region with internal holes filled.
MinorAxisLength	MiAL	Length of the minor axis of the ellipse that best fits the bunch shape.
MajorAxisLength	MaAL	Length of the major axis of the ellipse that best fits the bunch shape.
Circularity	C	Shape roundness, calculated based on a relationship between area and perimeter. A perfect circle has a circularity of 1. Shapes that deviate from circular (e.g., elongated or irregular shapes) have circularity < 1.
Solidity	S	It is a measurement of compactness calculated as the ratio of Area to Convex Area.
Eccentricity	Ec	It is a measurement of elongation calculated as the ratio of the distance between ellipse foci to its major axis length.
Equivalent Diameter	ED	Diameter of a circle with the same area as the bunch.
Orientation	O	Angle between the horizontal axis and the major axis of the ellipse.
Extent	E	The ratio of area to the area of the bounding box enclosing the bunch.

RESULTS AND DISCUSSION

1. Bunch characterisation

The present study evaluated the relationship between bunch weight and variables derived from the analysis of 2D RGB images. Table 2 presents the descriptive statistics of the reference values (bunch weight) which were divided into training and test datasets.

Although water stress levels were not explicitly considered during the random splitting of the dataset, we verified that both the training and test sets contain comparable proportions of each water stress class. This ensures that the model evaluation is not biased by an uneven representation of water stress conditions. The similarity in averages, standard deviations, and normality between the two sets further supports the representativeness of the analysis. This is an important aspect of maintaining the representativeness of the analysis. In terms of CV, the variability was 37 % and 36 % for the training and testing datasets, respectively. These values indicate a high level of variation, which is also corroborated by the range, as the minimum values were around 40 g, and the maximum values reached 280 g.

The analysis of the 2D images revealed variability in the morphological parameters of grape bunches (Table 3). Morphological features such as Area (A), Convex Area (CA),

TABLE 2. Descriptive statistical analysis of bunch weight data for the training dataset and testing dataset.

Variable	Training Dataset	Testing Dataset
N	211	148
Mean (g)	115.4	116
Median (g)	106.0	106.2
Min (g)	44.3	53.9
Max (g)	283.3	280.7
SD (g)	42.9	42.8
Skew	1.04	1.18
Kurtosis	1.08	1.69
CV (%)	37	36

N is the number of samples, Min is the minimum value, Max is the maximum value, SD is the standard deviation, and CV is the coefficient of variation.

and Filled_Area (FA) show relatively high standard deviations (SDs), indicating substantial dispersion in size-related traits, particularly under both water stress levels. Shape descriptors like Eccentricity (Ec), Circularity (C), and Solidity (S) also display moderate variability, with Eccentricity showing a wider range under M-H stress (1.50) compared to L-M (0.52), indicating more irregular shapes.

MajorAxisLength (MaAL) and MinorAxisLength (MiAL) had mean values of 13.37 cm and 6.03 cm, respectively. The consistently higher values of MaAL compared to MiAL across both stress levels indicate the elongated shape of the bunches. These values are in concordance with those presented by Holzapfel *et al.* (2023) for the same cultivar, where the average length of Cabernet-Sauvignon bunches was 12.86 cm, and the width was 4.46 cm. The Perimeter (P) showed a high mean value of 395,291 cm, suggesting complex bunch structures. Ec and C had mean values of 0.87 and 0.34, respectively, indicating the irregular shape of the bunches.

When water stress level is considered as a factor in the data analysis, we can see a tendency for smaller bunches in vines under high water stress conditions. Specifically, the mean Area under L-M water stress has a mean of 81.38 cm^2 with an SD of 20.77, while under M-H stress, the mean drops to 70.23 cm^2 with a slightly higher SD of 21.42 (Table 3). The differences in Area suggest a morphological response to water availability. The mean bunch weight was 126 g (L-M water stress) versus 109 g (M-H water stress), indicating a notable reduction in size and mass (data not shown). This effect has been widely documented, for example in a meta-analysis conducted by Cameron *et al.* (2024) in which they showed that all yield components (yield, number of berries

TABLE 3. Descriptive statistical analysis for morphological features extracted from the bunch of 2D images.

Morphological feature	Abb.	Units	WSL	Mean	SD	Range	Min	Max
Area	A	cm2	L-M	81.38	20.77	104.47	37.73	142.20
			M-H	70.23	21.42	126.05	29.34	155.39
Convex Area	CA	cm2	L-M	99.69	27.62	147.20	44.26	191.46
			M-H	86.70	28.36	162.44	32.69	195.13
Filled_Area	FA	cm^2	L-M	81.62	20.91	105.10	37.75	142.85
			M-H	70.50	21.55	127.07	29.37	156.44
MajorAxisLength	MaAL	cm	L-M	13.87	2.55	12.07	8.44	20.52
			M-H	13.07	2.44	14.88	7.48	22.36
MinorAxisLength	MiAL	cm	L-M	6.35	1.20	5.62	3.97	9.59
			M-H	5.84	1.47	7.83	3.46	11.29
EquivDiameter	ED	cm	L-M	8.55	1.08	5.51	5.87	11.37
			M-H	7.97	1.23	6.84	5.18	12.03
Perimeter	P	cm	L-M	48.32	9.46	73.14	3.04	76.18
			M-H	47.54	10.58	83.30	3.82	87.12
Orientation	O	degrees	L-M	6.85	21.67	167.79	–86.57	81.21
			M-H	0.53	19.15	139.72	–48.31	91.41
Circularity	C	cm	L-M	0.34	0.07	0.34	0.17	0.50
			M-H	0.34	0.09	0.97	0.16	1.13
EulerNumber	EN	-	L-M	–16.74	10.47	50.00	–50.00	0.00
			M-H	–20.58	16.14	100.00	–99.00	1.00
Extent	E	-	L-M	0.56	0.06	0.30	0.43	0.73
			M-H	0.58	0.11	0.97	0.39	1.35
Eccentricity	Ec	-	L-M	0.85	0.10	0.52	0.43	0.95
			M-H	0.88	0.16	1.50	0.39	1.89
Solidity	S	-	L-M	0.82	0.05	0.22	0.69	0.92
			M-H	0.83	0.12	1.10	0.66	1.76

Abb. Is the abbreviation of the morphological feature name, WSL is the water stress level (Low to Medium (L-M) and Medium to High (M-H), Min is the minimum value, Max is the maximum value, and SD is the standard deviation.

per bunch, bunch size, number of bunches per vine, bunch weights, etc.) were significantly influenced by the reduction in irrigation. Despite the described trend, our dataset also shows a clear effect of intra-vine variability (Figure 2). Figure 2 illustrates the variability of bunch weights for the studied vines under two stress conditions. Most vines exhibit noticeable intra-vine variability in bunch weights among the individual bunches of each vine, which may mask the effects of water stress. Vines such as Vine29 and Vine30 show lower median bunch weights under M-H conditions compared to L-M conditions. This reflects the effect of intra-vine variability on bunch weight distribution, which can influence the accuracy of yield estimations. Another important point is the number of bunches per vine which influences the vine balance and is the main factor in the final yield.

2. Multiple regression model

Table 4 summarises the variable selection process in the stepwise model to predict bunch weight. Variables related to Area, Perimeter, and Circularity were the first to be selected due to their high partial R^2, reinforcing their relevance in predicting Bunch weight. Additionally, shape metrics such as Eccentricity and Solidity also contributed to the final model, suggesting that geometric features play a key role in accurately estimating bunch weight.

Equation 1 shows the final multiple regression equation obtained using a stepwise procedure (BW_{SW}).

$$BW_{SW} = -7.23 + 9.06*A - 1.76*CA + 1.78*P + 213.36*C - 25.19*ED - 4.16*FA - 74.72*S + 36.26*Ec \quad (1)$$

The results of the stepwise regression model to predict bunch weight (Table 3) showed consistent and interpretable patterns in the relationships between the image-derived morphological variables and bunch weight. In particular, Area (A) and Perimeter (P) emerged as the most influential predictors, as expected due to their direct relation to bunch size. This finding aligns with Lopes and Cadima (2021), who also reported a strong correlation between bunch area and bunch weight. Additionally, shape-related metrics such as Circularity (C) and Eccentricity (Ec) provided complementary information about bunch architecture, particularly in capturing the irregularity or elongation of the bunches. In the case of circularity, more circular (compact) bunches tend to have less empty space and higher berry density, which contributes to greater weight. While the reduction in AIC values associated with these variables was relatively small, their inclusion enhanced the interpretability of the model in terms of physical characteristics. Considering the training dataset comprised 211 samples and the final model included eight variables, the variable-to-sample ratio remains within acceptable bounds to

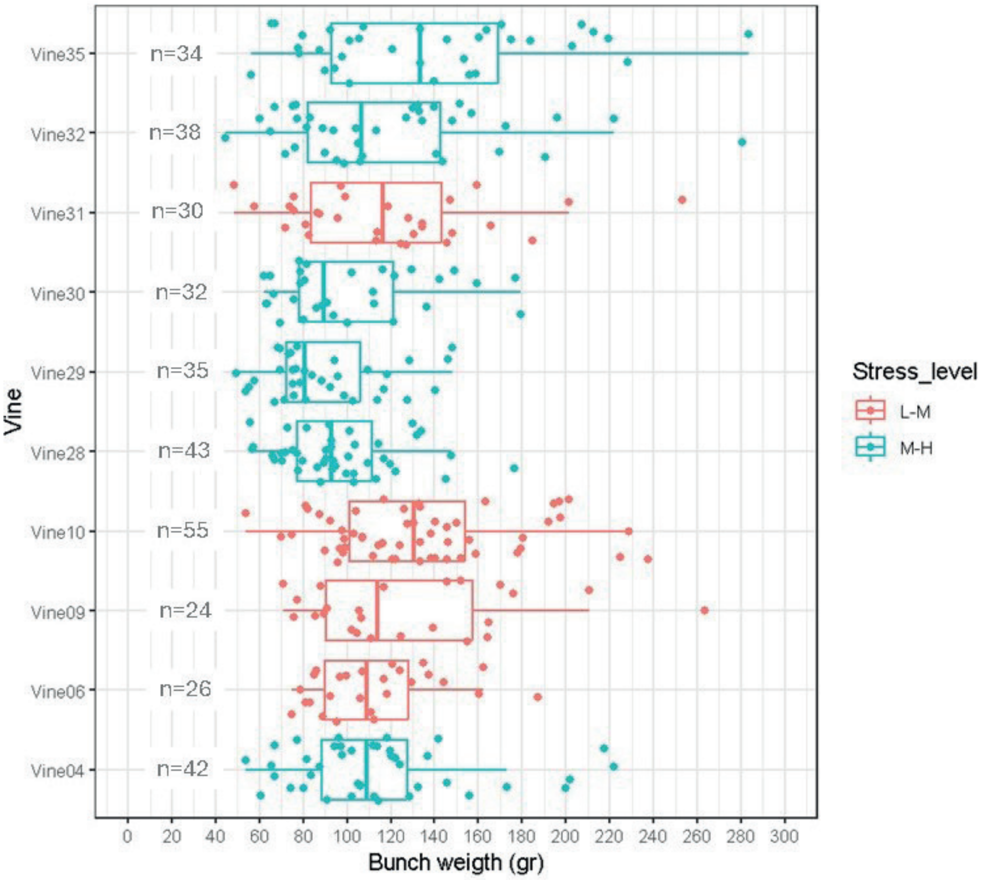

FIGURE 2. Boxplots of bunch weights for selected vines under two water stress conditions: Low to Medium (L-M) and Medium to High (M-H).

TABLE 4. Stepwise variable selection process and associated performance metrics for the regression model.

Step	Variable	Abbreviation	Selection	AIC	R^2	Adj-R^2
1	Area	A	Addition	1994.2	0.749	0.748
2	Convex Area	CA	Addition	1929.7	0.814	0.812
3	Perimeter	P	Addition	1917.9	0.825	0.823
4	Circularity	C	Addition	1898.4	0.841	0.839
5	EquivDiameter	ED	Addition	1880.2	0.857	0.853
6	Filled_Area	FA	Addition	1877.6	0.859	0.855
7	Solidity	S	Addition	1877.4	0.861	0.856
8	Eccentricity	Ec	Addition	1875.9	0.861	0.857
9	MinorAxisLength	MiAL	Removal	-	-	-
10	EulerNumber	EN	Removal	-	-	-
11	MajorAxisLength	MaAL	Removal	-	-	-
12	Orientation	O	Removal	-	-	-
13	Extent	E	Removal	-	-	-

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

avoid overfitting. Orientation and Extent were excluded from the final model due to their low explanatory power.

The relationship between the observed and estimated bunch weights using the multiple regression model is shown in Figure 3. The results obtained from the test set indicated a good fit between the predicted and observed values, particularly for bunches with weights within the average range of approximately 110 g, as evidenced by the R^2_p of 0.824. However, the slope of the regression line was 0.96, indicating that the predicted values slightly deviate from the 1:1 line. The analysis of the distribution of the errors shows that deviations were more noticeable for bunches with large weights, specifically those above 180 g, suggesting that certain morphological characteristics influencing these atypical weights may not be fully captured by the current model.

These findings indicate the potential value of incorporating additional morphological descriptors, such as bunch compactness or internal void distribution, to improve estimation accuracy. While compactness could be derived from metrics like the ratio between filled area and convex area, assessing internal void distribution remains challenging using the current 2D imaging setup. Nonetheless, future work could explore multi-view imaging or structured light scanning to approximate internal density and structural gaps within bunches, as suggested by Lopes and Cadima (2021), who specifically highlighted that bunch morphological characteristics, such as bunch volume and bunch compactness could play important roles in vineyard yield estimation based on their results which showed significant positive correlations between these characteristics and bunch weight.

Overall, the model results indicate that variables derived from 2D image analysis can effectively predict bunch weight. This has been confirmed by other researchers as well (Dunn & Martin, 2004; Font *et al.,* 2015; Hacking *et al.,* 2019; Victorino *et al.,* 2022a). However, challenges were identified with bunches of large weights, unusually elongated or highly compact bunches, suggesting the need to explore further model adjustments that incorporate additional or non-linear features. Notably, the relationship between morphological traits and grape bunch weight may not be strictly linear, partly due to the dimensional mismatch between the descriptors and the target variable. While variables such as Area and Perimeter are 2D, bunch weight is a function of three-dimensional volume and mass. This dimensional discrepancy underlies the nature of allometric relationships, where the exponents in the model depend on the geometric properties being compared. As a result, linear models using 2D traits may systematically under or overestimate weight, especially for bunches with extreme compactness or elongation. Incorporating non-linear transformations (*e.g.*, logarithmic or polynomial terms) or fitting allometric models that account for scaling effects could therefore improve model performance. Future work should examine these approaches in more detail, alongside machine learning techniques that can flexibly capture such complex, non-linear interactions—particularly those related to shape, density, and structural compactness.

A three-dimensional 3D imaging approach may be beneficial in overcoming this issue as it can allow for more complex bunch morphological characteristics, such as bunch volume and bunch density, to be incorporated. Liu *et al.,* (2022) investigated the estimation of bunch characteristics from 3D point-cloud data while Lopes and Cadima (2021) suggested that 3D characteristics could be extracted from 2D images

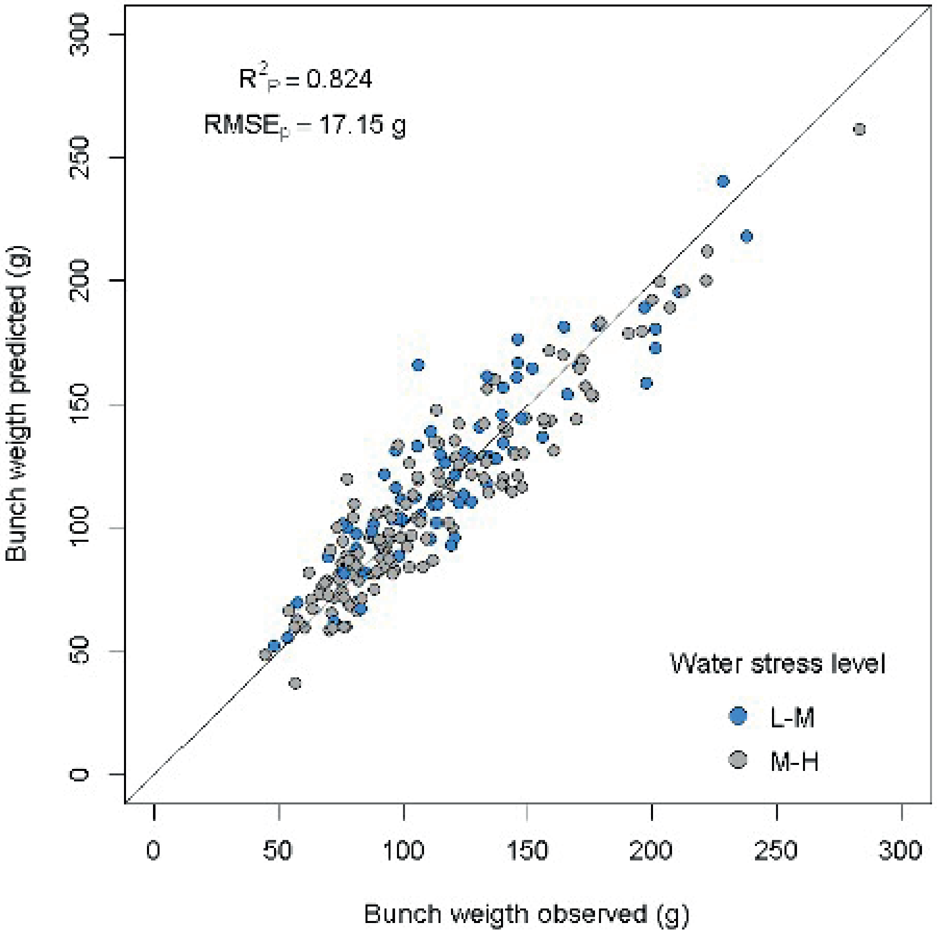

FIGURE 3. Comparison of observed and predicted grape bunch weights from stepwise regression model (Test Set).

using machine vision and modelling techniques. Both of these techniques will require much more advanced data extraction processing and increased computational power, which may limit the ease with which these technologies can be adopted in practice. The current study employed an MLR approach due to its simplicity, interpretability, and effectiveness demonstrated in previous grape bunch weight prediction studies. Several works have successfully used linear regression to predict bunch weight from morphological features extracted via 2D imaging, achieving robust and practical results for precision viticulture (Aquino *et al.,* 2018; Ariza-Sentís *et al.,* 2023). Nonetheless, it is critical to acknowledge that morphological features may exhibit inherently nonlinear, allometric relationships, as documented in plant morphological analyses (Niklas, 2007). Therefore, future research should consider evaluating nonlinear modelling approaches, such as power or exponential models, to potentially enhance predictive accuracy, particularly in datasets with extreme bunch morphology variations.

Benefits to be gained from the successful application of imaging technologies to estimate yield are varied spanning from the vineyard to the cellar. For these imaging technologies to be adopted in practice, it would be ideal if they could be 1) applied in the field and 2) automated, but it is not that simple. While these remain challenging goals, especially under commercial vineyard conditions, the methodology presented in this study provides a foundation for developing high-throughput phenotyping (HTP) tools. In particular, RGB imaging, whether acquired through drone-mounted multispectral cameras or proximal sensors on ground platforms, offers a scalable, non-destructive approach for assessing bunch architecture at the vineyard block level. The morphological descriptors extracted in this work, such as area, perimeter, or circularity, could be computed automatically using real-time image processing pipelines. Combined with GPS and spatial mapping, these estimates could be interpolated to generate yield maps and identify zones of low or high bunch mass for precision harvest planning. Despite these possibilities, difficulties in field application of imaging technologies stem mainly from the influence of the conditions under which the images are captured (specifically viewing angle and ambient light conditions) as noted by other researchers (Lopes & Cadima, 2021). Automation of bunch detection and determination of bunch morphological characteristics is hampered due to the occlusion of bunches (or portions thereof) by the canopy and/or other bunches and particularly due to the occlusion of a large portion of the berries of each bunch. Liu *et al.* (2022) mention that it is difficult to extrapolate and recover missing parts of bunches by hypothetical fitting from available data making it challenging to measure complex fruits (such as a grape bunch) accurately. These aspects remain hurdles for the seamless integration of these technologies into practice, even though they are yielding very promising results under laboratory conditions. Before adopting this methodology for high-throughput phenotyping (HTP) in vineyards, the use of robotic platforms or drones equipped with multispectral cameras could enhance the rapid capture of morphological data across extensive vineyard areas. Advanced machine learning algorithms integrated into vineyard management systems could automate data analysis, enabling real-time assessment of yield and grape and vine health (Vélez *et al.,* 2023). To address the practical challenges, future work should investigate standardised protocols for image capture under varying field conditions, minimising effects like occlusion and variability in lighting. Nevertheless, despite these limitations, the methodology holds considerable promise for application in HTP in vineyards. When integrated with mobile imaging platforms such as ground-based vehicles or unmanned aerial vehicles (UAVs), these technologies could enable rapid, large-scale assessments of traits like bunch number, size, and compactness across entire vineyard blocks. Such capabilities would be valuable for supporting yield estimation, vineyard management decisions, and breeding programs (Rui *et al.,* 2024; Bongomin *et al.,* 2024).

The present methodology, while developed and validated using images collected at harvest, could potentially be applied at earlier stages of grape development. Morphological parameters such as bunch length, area, and compactness are detectable from early bunch formation, although their predictive power may be limited due to ongoing berry growth. Future studies could investigate the temporal stability of these features and the accuracy of early-season predictions. Additionally, improving image acquisition protocols and developing algorithms that are robust to field variability could help bridge the gap between laboratory success and practical vineyard deployment.

The role of water stress in this study is twofold: first, as a condition influencing bunch development and morphology; and second, as a potential source of variability that complicates weight prediction. While the model did not include water stress level as an explicit predictor, exploratory analyses showed clear trends linking higher water stress to reductions in bunch weight and size-related traits, such as Area and Perimeter. Incorporating water stress levels as a categorical or continuous variable in future models may enhance prediction accuracy, particularly in heterogeneous vineyards. The rationale for introducing water stress lies in its proven influence on yield components, as demonstrated by the cited meta-analyses (*e.g.*, Cameron *et al.,* 2024), and our findings are consistent with this broader literature. Importantly, intra-vine and inter-vine variability played a key role in the model's performance. The high variability observed, even within a single stress category, suggests that plant-specific factors, such as bunch number per vine or canopy structure, have a substantial impact. If this model were calibrated in a particularly dry or wet year, both the model parameters and the relative importance of variables would likely shift, as water availability affects bunch architecture and density. Including environmental covariates or stress indices as predictors could help capture this year-to-year plasticity. Compared to previous studies, the model's explanatory power (adjusted R^2 of the prediction 0.824) is competitive. For example, Dunn and Martin (2004) and Hacking *et al.* (2019) reported comparable or slightly lower values when using similar image-based approaches. Our use of only RGB channels limits the depth of spectral information; therefore, future models might benefit from integrating additional wavelengths (*e.g.*, NIR, Red Edge) to capture biochemical or structural traits not visible in the RGB range. Such enhancements could also improve estimation for bunches with atypical shapes or changes in bunch compactness.

CONCLUSION

This study demonstrated the effectiveness of 2D RGB image analysis in predicting grape bunch weight under varying water stress conditions. The integration of morphological descriptors, particularly Area, Perimeter, Circularity, and Eccentricity, into a multiple linear regression model yielded a high predictive performance confirming the relevance of image-derived features in estimating yield components. Circularity, a shape descriptor, provides insight into the compactness and uniformity of the bunch outline. These findings support the integration of image-based methodologies as a reliable tool for vineyard yield estimation, advancing precision viticulture practices, although its limitations in capturing extreme bunch morphologies highlight the need for further refinement. Water stress was shown to influence bunch morphology and weight, with higher stress levels associated with reductions in size-related traits. However, substantial intra-vine variability was observed, underscoring the complexity of yield estimation in heterogeneous vineyard environments. While the current model did not explicitly incorporate water stress as a predictor, its inclusion in future models may enhance robustness and generalisability.

Despite the promising results, challenges remain in translating this methodology to field conditions. Factors such as occlusion, lighting variability, and image acquisition angles can affect the accuracy of morphological measurements. Future research should explore the integration of 3D imaging, nonlinear modelling approaches, and machine learning techniques to better capture the complex relationships between bunch architecture and weight. Additionally, the development of standardised image acquisition protocols and automated processing pipelines will be essential for the practical deployment of high-throughput phenotyping tools in commercial vineyards.

Overall, this work provides a solid foundation for the application of image-based phenotyping in viticulture and highlights the potential of RGB imaging as a scalable, non-destructive approach for yield estimation and vineyard management. Long-term monitoring using this approach could provide valuable insights into yield trends across multiple growing seasons, enabling predictive modelling of vintage quality and optimising resource allocation based on historical data patterns.

ACKNOWLEDGEMENTS

The authors would like to acknowledge South African WINE for funding the project and Thelema Mountain Vineyards for providing the experimental vineyard. The authors also thank the Scholarship programs Internationalisation of Master's Degree Programs (R.U. Nº 136/2019) by the University of Talca, Chile and Research Funding FPI Grant 591/2021 from Universidad de La Rioja, Gobierno de La Rioja, Spain. Dr Sergio Vélez's Distinguished Researcher contract (Beatriz Galindo 573 BG23/00073) is funded by the Spanish Ministry of Science, Innovation and Universities under the 2023 call, within the framework of the State Plan for Scientific, Technical, and Innovation Research (PEICTI) 2021-2023. Special thanks to Pamela Uribe for her contributions to the language editing and grammatical review of the manuscript.

REFERENCES

Aquino, A, Barrio, I, Diago, M. P, Millan, B, & Tardáguila, J. (2018). vitisBerry: An Android-smartphone application to early evaluate the number of grapevine berries by means of image analysis. Computers and Electronics in Agriculture, 148, 19–28. https://doi.org/10.1016/j.compag.2018.03.024

Ariza-Sentís, M, Baja, H, Vélez, S, & Valente, J. (2023). Object detection and tracking on UAV RGB videos for early extraction of grape phenotypic traits. Computers and Electronics in Agriculture, 211, 108051. https://doi.org/10.1016/j.compag.2023.108051

Aydin, A, Çay, A, & Polat, B. (2017). Image analysis applications in plant growth and health assessment. Journal of Agricultural Science and Technology, 19(3), 567–580.

Bongomin, O, Lamo, J, Guina, J. M, Okello, C, Ocen, G. G, Obura, M, Alibu, S, Owino, C. A, Akwero, A, & Ojok, S. (2024). UAV image acquisition and processing for high-throughput phenotyping in agricultural research and breeding programs. Plant Phenome Journal, 7(1), 1–37. https://doi.org/10.1002/ppj2.20096

Bramley, R. G. V, Ouzman, J, & Boss, P. (2011). Variation in vine vigour, grape yield and vineyard soils and topography as indicators of variation in the chemical composition of grapes, wine and wine sensory attributes. Australian Journal of Grape and Wine Research, 17(2), 217–229. https://doi.org/10.1111/j.1755-0238.2011.00136.x

Cameron, W, Petrie, P. R, & Bonada, M. (2024). Effects of vineyard management practices on winegrape yield components. A review using meta-analysis. American Journal of Enology and Viticulture, 75(1), 1–25. https://doi.org/10.5344/ajev.2024.23046

Diago, M. P, Tardáguila, J, Aleixos, N, Millan, B, Prats-Montalban, J. M, Cubero, S, & Blasco, J. (2015). Assessment of cluster yield components by image analysis. Journal of the Science of Food and Agriculture, 95(6), 1274–1282. https://doi.org/10.1002/JSFA.6819

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, 10(3), 196–198. https://doi.org/10.1111/j.1755-0238.2004.tb00022.x

Ferro, G, Oliveira, D, & Ferreira, J. (2024). Assessing grapevine vigor as affected by soil physicochemical and topographic attributes using UAV multispectral imagery. Remote Sensing, 16(3), 789.

Font, D, Tresanchez, M, Martínez, D, Moreno, J, Clotet, E, & Palacín, J. (2015). Vineyard yield estimation based on the analysis of high-resolution images obtained with artificial illumination at night. Sensors, 15, 8284– 8301. https://doi:10.3390/s150408284

Frege, M.C.A. (1804). Versuch einer Classification der Wein-Sorten nach ihre beeren. Meissen. 171.

Greer, D., & Weston, C. (2010). Heat stress affects flowering, berry growth, sugar accumulation and photosynthesis of Vitis vinifera cv. Semillon grapevines in a controlled environment. Functional Plant Biology, 37(3), 206-214. https://doi.org/10.1071/FP09209

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, 19(17), 3652. https://doi.org/10.3390/s19173652

Henry, D, Aubert, H, & Veronese, T. (2019). Proximal radar sensors for precision viticulture. IEEE Transactions on Geoscience and Remote Sensing, 57(7), 4624–4635. https://doi.org/10.1109/TGRS.2019.2891886

Herrero-Huerta, M, González-Aguilera, D, Rodriguez-Gonzalvez, P, & Hernández-López, D. (2015). Vineyard yield estimation by automatic 3D bunch modelling in field conditions. Computers and Electronics in Agriculture, 110, 17–26. https://doi.org/10.1016/j.compag.2014.10.003

Holzapfel, B, Rossouw, G, Bittau, B, Meunier, A, and Dry, I. (2023). Bunchstem and bunch structure of grape cultivars and its implication for abiotic and biotic stress. Acta Horticulturae. 1362, 213-220. https://doi.org/10.17660/ActaHortic.2023.1362.29

Jasse, A, Berry, A, Aleixandre-Tudo, J. L, & Poblete-Echeverría, C. (2021). Intra-block spatial and temporal variability of plant water status and its effect on grape and wine parameters. Agricultural Water Management, 246 (December 2020), 106696. https://doi.org/10.1016/j.agwat.2020.106696

Kheiralipour, K, & Kazemi, A. (2020). A new method to determine morphological properties of fruits and vegetables by image processing technique and nonlinear multivariate modelling. International Journal of Food Properties. 23(1), 368-374. https://doi.org/10.1080/10942912.2020.1729177

Khojastehnazhand, M, Mohammadi, V, & Minaei, S. (2019). Maturity detection and volume estimation of apricot using image processing technique. Scientia Horticulturae. 251, 247–251. https://doi.org/10.1016/j.scienta.2019.03.033

Kircherer, A, Roscher, R, Herzog, K, Simon, S, Förstner, W, & Töpfer, R. (2013). BAT (Berry Analysis Tool): a high-throughput image interpretation tool to acquire the number, diameter, and volume of grapevine berries. Vitis, 52(3): 129–135.

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, 105360. https://doi.org/10.1016/J.COMPAG.2020.105360

Liu, W, Wang, C, Yan, D, Chen, W, & Luo, L. (2022). Estimation of characteristic parameters of grape clusters based on point cloud data. Frontiers in Plant Science, 13, 885167. https://doi.org/10.3389/fpls.2022.885167

Lopes, C, & 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. (2018). In-field high throughput grapevine phenotyping with a consumer-grade depth camera. Computers and Electronics in Agriculture, 156, 293–306. https://doi.org/10.1016/j.compag.2018.11.014

Moreno, H, & Andújar, D. (2023). Proximal sensing for geometric characterization of vines: A review of the latest advances. Computers and Electronics in Agriculture, 210, 107901. https://doi.org/10.1016/J.COMPAG.2023.107901

Munitz, S, Netzer, Y, & Schwartz, A. (2016). Sustained and regulated deficit irrigation of field-grown Merlot grapevines. Australian Journal of Viticulture and Oenology, 23(1):87-94. http://doi.org/10.1111/ajgw.12241

Niklas, K. J. (2007). Plant allometry: Is there a grand unifying theory? Biological Reviews, 79(4), 871–889. https://doi.org/10.1017/S1464793104006499

Nuske, S, Achar, S, Bates, T, Narasimhan, S, & Singh, S. (2011). Yield estimation in vineyards by visual grape detection. International Conference on Intelligent Robots and Systems. San Francisco, CA, USA. https://doi.org/10.1109/IROS.2011.6095069

Oger, B, Laurent, C, Vismara, P, & Tisseyre, B. (2023). How to better estimate bunch number at vineyard level? OENO One, 57(3), 27–39. https://doi.org/10.20870/oeno-one.2023.57.3.7404

Ojeda, H, Andary, C, Kraeva, E, Carbonneau, A, & Deloire, A. (2002). Influence of pre- and post-veraison water deficit on synthesis and concentration of skin phenolic compounds during berry growth of *Vitis vinifera* cv. Shiraz. American Journal of Enology and Viticulture, 53(4), 261-267.

R Core Team. (2024). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

Romero, P., Fernández-Fernández, J. I., & Martínez-Cutillas, A. (2017). Effects of water stress on grapevine physiology and berry composition: A review. Agronomy, 7(1), 18. https://doi.org/10.3390/agronomy7010018

Rui, Z, Zhang, Z, Zhang, M, Azizi, A, Igathinathane, C, Cen, H, Vougioukas, S, Li, H, Zhang, J, Jiang, Y, Jiao, X, Wang, M, Ampatzidis, Y, Oladele, O. I, Gashemi-Vernamkhasti, M, & Radi, R. (2024). High-throughput proximal ground crop phenotyping systems – A comprehensive review. Computers and Electronics in Agriculture, 224, 109108. https://doi.org/10.1016/j.compag.2024.109108

Tardáguila, J., Blanco, J. A., Poni, S., & Diago, M. P. (2012). Mechanical yield regulation in winegrapes: Comparison of early defoliation and crop thinning. Australian Journal of Grape and Wine Research, 18(3), 344 -352. https://doi.org/10.1111/j.1755-0238.2012.00197.x

Tello, J, & Ibáñez, J. (2018). Influence of water stress and canopy management on grape bunch morphology. Journal of Viticulture and Enology, 69(1), 45–54.

Tello, J, Aguirrezábal, R, Hernáiz, S, Larreina, B, Montemayor, M, Vaquero, E, & Ibáñez, J. (2015). Multicultivar and multivariate study of the natural variation for grapevine bunch compactness. Australian Journal of Grape and Wine Research, 21(2), 277–289. https://doi.org/10.1111/ajgw.12140

The MathWorks Inc. (2023). MATLAB. v2023b. Nattick, MA, United States.

van Leeuwen, C, Destrac-Irvine, A, Dubernet, M, Duchêne, E, Gowdy, M, Marguerit, E, Pieri, P., Parker, A, De Rességuier, L, & Ollat, N. (2018). An update on the impact of climate change in viticulture and potential adaptations. Agronomy, 9(9), 514. https://doi.org/10.3390/agronomy9090514

Vélez, S, Ariza-Sentís, M, & Valente, J. (2023). Mapping the spatial variability of Botrytis bunch rot risk in vineyards using UAV multispectral imagery. European Journal of Agronomy, 142, 126691. https://doi.org/10.1016/j.eja.2022.126691

Venables, W. N, & Ripley, B. D. (2002). Modern applied statistics with S. Fourth Edition. Springer, New York. ISBN 0-387-95457-0. https://doi.org/10.1007/978-0-387-21706-2

Victorino, G, Poblete-Echeverría, C, & Lopes, C. M. (2022a). A multicultivar approach for grape bunch weight estimation using image analysis. Horticulturae, 8(3), 233. https://doi.org/10.3390/horticulturae8030233

Victorino, M, Silva, C, & Santos, T. (2022b). Image-based phenotyping for grape bunch weight prediction: Addressing occlusion and cultivar variability. Precision Agriculture, 23(4), 1234–1250. https://doi.org/10.1007/s11119-022-09876-5

Wetner, A, Zanotelli, D, Montagnani, L, Tagliavini, M, & Andreotti, C. (2018). Effect of different timings and intensities of water stress on yield and berry composition of grapevine (cv. Sauvignon blanc) in a mountain environment. Scientia Horticulturae. 236, 137-145. https://doi.org/10.1016/j.scienta.2018.03.037

Wu, M, Yi, X, Luo, H, Li, C, Tang, X, & Chen, K. (2019). On-line measurement method for volume and surface area of red jujube based on multi-contour model. Transactions of the Chinese Society of Agricultural Engineering. 35, 283–290.

Wycislo, A. P, Clark, J. R, & Karcher, D. E. (2008). Fruit shape analysis of Vitis using digital photography. Horticultural Science, 43, 677-680. https://doi.org/10.21273/HORTSCI.43.3.677