

Improved Image Acquisition for Accurate Pruning Wood Weight Estimation via Image Analysis in *Vitis vinifera* L.

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Abstract. Pruning wood mass is a key factor in grapevine management, influencing vine growth and yield. Accurate assessment of pruning wood weight helps viticulturists regulate vine balance, optimize shoot production, and improve fruit quality. However, traditional manual methods are time-consuming and labour-intensive, creating a need for more efficient, non-destructive alternatives. While digital imaging technology has advanced in viticulture, enabling non-invasive methods for yield estimation and canopy assessment, research on pruning wood weight estimation is limited due to the need to use artificial backgrounds for background homogenisation. This study evaluates image analysis for estimating pruning wood weight, focusing on the impact of image acquisition conditions rather than segmentation techniques. The goal of this research was to address challenges related to the use of artificial backgrounds during image acquisition examining the relationship between pixel counts in images of pruning wood and actual wood weight under two acquisition modes. Results showed that using an artificial background did not significantly improve estimation accuracy ($R^2=0.70$) compared with no background acquisition mode ($R^2=0.69$). This suggests that a simple camera system could be sufficient for effective pruning wood assessment. Moreover, the possibility to acquire images without the need for an artificial background could enable the use of cameras mounted on vehicles performing routine vineyard operations. This would allow for the collection of data on wood weight from different vineyard areas, providing valuable insights into vine vigour.

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1 Introduction

Pruning wood weight is a key parameter in vineyard management, as it directly influences the balance between vegetative growth and yield and is involved in Ravaz index to calculate vine balance. This metric supports management decisions aimed at improving fruit quality, ensuring production consistency, and achieving desirable oenological outcomes [1, 2, 3, 4]. Its manual determination can be labor-intensive and time-consuming, as it requires separating canes from individual vines and interrupting the normal pruning workflow to collect, weigh, and record the removed biomass [5]. Consequently, there is a clear need for the development of cost-effective methods and procedures [6, 7]. In recent years, image analysis has emerged as a promising tool for non-invasive plant phenotyping and the assessment of yield components [8]. However, only a limited number of studies have applied this approach to the estimation of pruning wood weight [9, 10]. One major limitation of existing approaches is the reliance on artificial backgrounds or artificial illumination to facilitate segmentation. While artificial backgrounds create a controlled acquisition environment, enhancing segmentation accuracy, they require additional equipment and setup time, making them impractical for large-scale or commercial vineyard applications. Similarly, nighttime imaging with artificial lighting improves image quality but restricts operations to specific hours, reducing flexibility and scalability [9, 11, 12]. Additionally, some automated methods rely on depth sensors or LiDAR technology, which, while effective, involve high costs and complex calibration procedures, limiting their widespread adoption in vineyard management. In this study, we propose a more practical and scalable alternative by leveraging natural background conditions. By adjusting the camera angle during image acquisition, the sky itself serves as a uniform background, eliminating the influence of adjacent vine rows and improving segmentation without requiring additional equipment. This approach simplifies implementation and allows for image acquisition during routine vineyard operations, such as pre-pruning or cover crop seeding, without disrupting workflow. By evaluating the relationship between pixel counts and actual pruning wood weight under two acquisition modes, this study aims to enhance the feasibility of image-based assessments for vineyard management, ultimately contributing to precision viticulture practices.

2 Materials and Methods

Image acquisition was carried out in December 2022 before winter pruning, in a commercial vineyard of Catarratto/1103P (*Vitis vinifera* L.) located in Camporeale (37°55'12.82"N, 13°04'28.33"E; 320 m a.s.l.; Palermo, Italy). Vines were trained to a vertical shoot positioning (VSP) trellis system, double cordon pruned and spaced 0.9 m in rows and 2.2 m between rows with northeast-southwest row orientation. Within the vineyard, a total of 36 vines were selected to cover

a wide range of pruning weights. The vines were selected by choosing six groups of six consecutive vines from different areas of the vineyard, characterized by varying NDVI indices (high, medium, and low vigour) and evaluating previous year's yield and pruning wood weight. The images of the vines were manually acquired in the morning between 9:00 AM and 12:00 PM under clear sky conditions using a Canon 1300D digital single-lens reflex camera equipped with an 18–55 mm f/3.5–5.6 DC Canon lens (Canon, Tokyo, Japan). The camera was configured with a sensitivity of ISO 400, an aperture of f/5.6, and a focal length of 24 mm. The exposure time was automatically selected. Vines were photographed under two acquisition modalities: (i) the camera was positioned directly perpendicular to the vine row, 1.5 m from the vines and 1 m above the ground, and a white board was used for background homogenization (WB) as a reference mode already studied in a previous study [10]; (ii) the camera was positioned 1.5 m from the vines with a 35° tilt angle from the ground to obtain images with the sky as homogeneous background (NB) (Figure 1).



Fig. 1. Images of vines manually acquired. Example of the acquisition modes. a, with the presence of artificial background (WB); b, without use of it, the camera was positioned with a 35° tilt angle from the ground (NB).

After image acquisition, vines were pruned, and wood weight was measured using a digital gauge for the ground-truthing process. Acquired images were pre-processed and analysed using the open-source FIJI/ImageJ® software and Trainable Weka Segmentation (TWS) plug-in [14]. The TWS plug-in employs machine learning algorithms to classify red-green-blue or grayscale image pixels into different classes based on similar visual characteristics, such as colour, shape, and texture. The following functions were used for image segmentation in default mode: Gaussian blur, to smooth the image; Sobel filter, to capture the edges in the image; Hessian, to capture the shape of objects; Difference of Gaussians, to highlight edges and other details in the image that vary in size; Membrane projections, to enhance the contrast along

the boundary; FastRandomForest, to build a tree of “if-then” rules to classify image pixels based on the colour, shape, and texture similarities. Prior to segmentation, a supervised classification step was performed by training the algorithm through manually defined traces, or sets of training pixels (STP), within the region of interest (ROI) for each class. For this training phase, one representative image per acquisition modality was selected from the dataset and used as a reference. Four distinct classes were identified within each image—pruning wood (ROI), trunk and cordon, trellis wires, and background—by manually drawing ten freehand lines for each class (approximately 50 pixels in length and 1 pixel in width). The training pixels were randomly selected within the image areas defining each class. This selection process aimed to ensure a representative sampling of the different features present in the dataset. Potential errors in training, such as misclassification of pixels or inconsistent labeling, which could have affected the robustness of the segmentation model, were manually corrected afterward.

The training process yielded a stack of four images (one per class) encompassing all the manually selected lines. Subsequently, the segmentation model was applied to all images. The images obtained were turned into a single image containing only the class “pruning wood”. The image was converted to 8-bit and transformed into the binary format to reduce the amount of information. Next, pruning wood pixels were extracted from the image by automatic thresholding of the b* channel of the CIELAB colour space using Otsu's method [13]. This method calculates the optimal T_{otsu} threshold for a grayscale image by assuming the existence of two classes of pixels, related to the background and foreground, and maximizing their variance to include them in one of the two classes. If I_b represents a grayscale image b* as a two-dimensional function in discrete space whose values fall in the interval $[0, \dots, 255]$:

$$ROI = \begin{cases} 0 & \text{if } I_b(x, y) \leq T_{otsu} \\ 255 & \text{otherwise} \end{cases} \quad (1)$$

This yields a binary image (0 = white and 255 = black) containing only the ROI and background pixels. ROI pixel number was then measured using the Measure tool and turned into a percentage of black pixels in a frame of 1773 x 1182 pixels. The flowchart of the main steps for estimating pruning wood weight is shown in Figure 2.

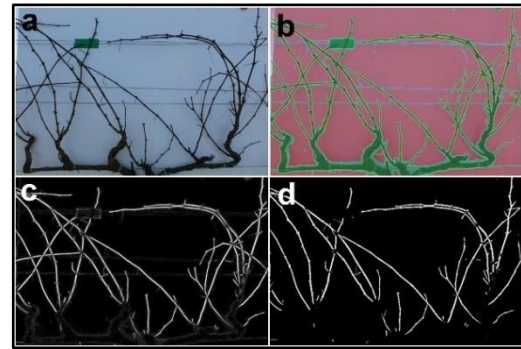


Fig. 2. Flowchart of the main steps in the image analysis process. (a) original image. (b) result of automatic classification. (c) automatic extraction of the Region of Interest (ROI). (d) binary image for pixel counts related to ROI.

The data obtained from the image processing and their relationship to reference ground-truthing values were analysed using the statistical software Minitab® version 17 (Minitab, USA). Regression lines, along with their coefficient of determination (R^2), 95% confidence intervals of the slope coefficients, and p-values were calculated. To quantify the absolute magnitude of the prediction errors, models were evaluated using root-mean-square error (RMSE) according to [15] using the following equation:

$$RMSE = \sqrt{\text{mean}(t - a)^2} \quad (2)$$

Where t (target) is the predicted value and a (actual) the actual value.

3 Results and discussion

The automated segmentation procedure enabled the removal of trunk and cordon components, support wires of the trellis system, and both natural and artificial background elements from the images without the need for manual input; human intervention was required only to eliminate correctly segmented parts belonging to adjacent vines. The segmentation step required approximately twenty seconds per image.

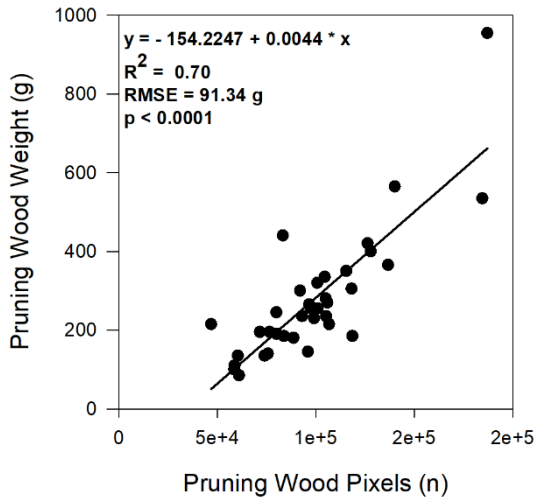


Fig. 3. Correlation between the actual weight of pruning wood (y) and the number of pixels segmented as “pruning wood” (x) with the use of artificial background (WB).

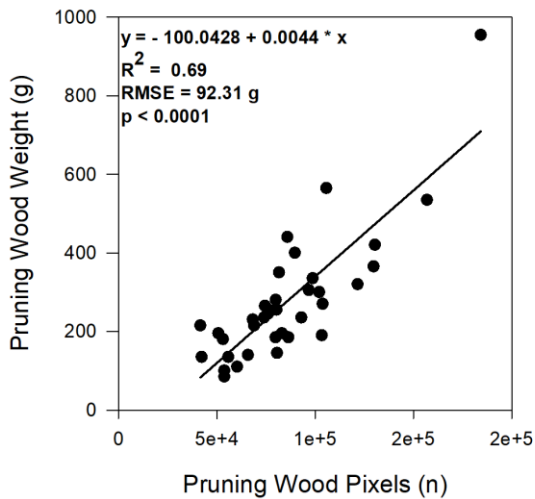


Fig. 4. Correlation between the actual weight of pruning wood (y) and the number of pixels segmented as “pruning wood” (x) without the use of artificial background (NB).

The regression models indicate that estimation performance remained comparable between the two acquisition approaches, irrespective of the presence of an artificial background (Figures 3 and 4). Specifically, the WB mode achieved an R^2 of 0.70, while the NB mode reached 0.69, with corresponding RMSE values of 91.34 g and 92.31 g. These results demonstrate that the use of an artificial background can be avoided without compromising the reliability of pruning wood weight estimation, eliminating the need for specialized equipment beyond a standard camera. This is consistent with the findings of [9], who applied a similar ROI extraction approach under artificial illumination during nighttime conditions. Independently of the background conditions, the segmentation process produced comparable levels of accuracy in estimating wood weight, indicating that this acquisition strategy can be effectively implemented directly in the field without increasing system complexity. This result, in terms of wood weight estimation, enhances the findings of [10], who conducted their study without background but with frontal image acquisition under daylight

conditions. They analysed a set of 39 vines, achieving an R^2 of 0.44 and an RMSE of 230 g using an automated depth segmentation. This outcome was likely due to the algorithm's difficulty in identifying vines with thin shoots, abundant tendrils, and other vines in the background. In our study, this issue was resolved by tilting the camera, which created a uniform background (the sky). Other authors [9] operated on a set of 44 vines obtaining an R^2 of 0.91 and an RMSE of 87.7 g using an artificial background with an R^2 of 0.77 and an RMSE of 148 g on nighttime acquired images without the use of background. Based on this assumption, this new method of acquisition could benefit from any improvement in the segmentation process and underscores the practicality of dispensing with artificial backgrounds, thereby simplifying implementation to only require a camera mounted on routine vineyard vehicles. Indeed, one of the main challenges in applying image analysis techniques is the occlusion. Occlusion occurs when portions of grapevine shoots or canes are partially or fully concealed by overlapping vegetation, making accurate assessment of their size or biomass challenging. This phenomenon arises both from the natural growth habit of the vine—where shoots intersect and overlap—and from increased canopy density associated with higher vigour. Furthermore, in cases where shoots exhibit a procumbent growth habit, mutual superimposition becomes more pronounced, leading to images in which shoot-related pixels are systematically underestimated. As can be seen in our results, when the wood weight and therefore occlusion between shoots increases, the accuracy of the estimate tends to decrease. Other authors [9] pointed out the same issue, evaluating that the coefficient of determination decreased when the lower pruning weight vine values were removed from the model. This suggests that future analyses should consider a larger number of vines, cultivars, and training systems, accounting for factors such as plant vigour and vegetative habitus, which can significantly affect occlusion conditions. Increased shoot overlaps in certain cultivars or pruning systems may lead to an underestimation of wood weight, as it could reduce the accuracy of the segmentation and subsequent weight estimation process. These challenges could be also mitigated by evaluating pruning wood weight not at the individual vine level but per linear meter of row. This approach would reduce the impact of shoot overlapping between adjacent vines, minimizing the risk of over- or underestimation and improving the robustness of the method in real vineyard conditions. By incorporating such improvements, this method could contribute to the development of a powerful, scalable tool for nondestructive vineyard monitoring, contributing significantly to precision viticulture practices. These findings highlight the potential for broader applications of this method beyond the specific conditions tested in this study. In particular, the proposed approach could be adapted to vineyards with different training systems and planting densities, where occlusion and background variability may influence segmentation accuracy. Finally, integrating this method with

automated imaging systems, such as vehicle-mounted cameras, could enhance vineyard monitoring efficiency, supporting precision viticulture practices on a larger scale.

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