

Article

Grapevine Canopy Volume Estimation from UAV Photogrammetric Point Clouds at Different Flight Heights

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Highlights

What are the main findings?

- Envelope methods (convex hull and alpha shape) are generally more sensitive to point density loss than voxel-based grids, which maintain a relative stability, although they were not always the closest to field-based volume estimations.
- Methods parameters (α and voxel size) influence accuracy and should be adapted to point cloud density, canopy structure, and growth stage.

What are the implications of the main findings?

- UAV photogrammetry provides dense, low-cost 3D canopy data suitable for vineyard monitoring at the row or plant level.
- Multi-temporal 3D measurements can support vineyard management and integration with decision support systems.

Abstract

Vegetation volume is a useful indicator for assessing canopy structure and supporting vineyard management tasks such as foliar applications and canopy management. The photogrammetric processing of imagery acquired using unmanned aerial vehicles (UAVs) enables the generation of dense point clouds suitable for estimating canopy volume, although point cloud quality depends on spatial resolution, which is influenced by flight height. This study evaluates the effect of three flight heights (30 m, 60 m, and 100 m) on grapevine canopy volume estimation using convex hull, alpha shape, and voxel-based models. UAV-based RGB imagery and field measurements were collected during three periods at different phenological stages in an experimental vineyard. The strongest agreement with field-measured volume occurred at 30 m, where point density was highest. Envelope-based methods showed reduced performance at higher flight heights, while voxel-based grids remained more stable when voxel size was adapted to point density. Estimator behavior also varied with canopy architecture and development. The results indicate appropriate parameter choices for different flight heights and confirm that UAV-based RGB imagery can provide reliable grapevine canopy volume estimates.



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1. Introduction

The increasing global demand for wine production highlights the importance of ensuring quality and efficient production [1,2]. Achieving these goals is essential for maintaining competitiveness in demanding markets and ensuring the economic suitability of wine production [3]. To support this, systematic vineyard monitoring is required to enable regular collection of structural and physiological grapevine parameters that reflect crop status and support more accurate agronomic decision-making [4,5].

Among these parameters, geometric descriptors have demonstrated to be useful for characterizing canopy structure and vineyard heterogeneity. They provide information relevant to estimating yield potential, vegetative vigor, and overall plant development [6]. Canopy volume, in particular, is important for canopy management strategies [4]. Knowledge of canopy volume allows growers to plan and adjust practices such as pruning, shoot thinning, or leaf removal, helping to maintain an appropriate balance between vegetative growth and grape production [7,8]. Despite its importance, canopy volume is rarely measured in commercial vineyards [7] because ground-based methods are time-consuming and labor-intensive [8,9], with canopy volume being estimated rather than being validated [7]. However, volume information is critical for supporting canopy management, which improves air circulation, reduces disease-favorable microclimates, and improves fruit exposure, contributing to optimized ripening and crop quality.

In this context, remote sensing offers a non-destructive and efficient alternative for monitoring crop structure heterogeneity in different spatial and temporal scales throughout the growing season [6–11]. In particular, unmanned aerial vehicles (UAVs) equipped with high-resolution imaging sensors enable flexible and rapid acquisition of grapevine geometric information [8,12,13]. UAV-based point clouds have been applied in several cropping systems, including orchards [14–16], maize [17], and forest stands [18]. In viticulture, 3D canopy representation supports precision agriculture activities such as spray rate adjustment, pruning assessment, harvester calibration, vigor mapping, and yield estimation [2,4,10,19].

LiDAR sensors, deployed as static systems [20], mounted on tractors [21,22], or integrated into UAVs [23], have been applied to canopy profiling and volume estimation [19]. Recent developments in Structure-from-Motion (SfM) photogrammetry have expanded opportunities for cost-effective 3D characterization using UAV-based RGB imagery [2]. SfM allows the reconstruction of 3D geometry by matching key points across overlapping images acquired from multiple viewpoints [24,25], producing dense point clouds and digital surface models (DSMs) [12,26]. Although photogrammetric models from RGB [25,27] or multispectral imagery [28] tend to be less accurate than LiDAR [29], they remain widely adopted due to their operational simplicity, lower cost, and rapid deployment [8].

In viticulture, UAV-based point clouds have been used to generate crop surface models (CSMs) [25], classify and visualize vegetation structures such as leaves, branches, and fruits [10], estimate leaf area index (LAI) [24,28] with better relationships than vegetation indices [30,31], detect canopy gaps and row alignment [13,26,27], and support in-season yield prediction [10]. UAV-based point clouds have also been effective in characterizing vineyard macro-structures [32], including row spacing, canopy height, and orientation, and in estimating canopy volumes from dense stereo/SfM models [24]. These datasets complement terrestrial LiDAR scans [20], supporting high-throughput monitoring at the

vineyard scale [33]. Improvements in data acquisition strategies, such as low-altitude flights, oblique imagery, and the use of ground control points (GCPs), have been shown to increase spatial accuracy and reduce geometric drift, thereby improving point cloud reliability [24]. However, beyond acquisition, the accuracy and interpretability of canopy metrics depend on the choice of modeling methods and spatial resolution [34]. Therefore, point cloud processing methods are important for extracting canopy characteristics and translating geometric data into agronomic variables [5].

Several geometric approaches are available for estimating canopy volume from point clouds [3,19,34], including convex hulls (CHs) [35,36], voxel-based (VB) grids [3,37], and alpha shapes (α S) [38,39]. These methods differ in how they represent canopy boundaries and handle point density variations. VB methods discretize the canopy fixed-size volumetric cells, making them less sensitive to density fluctuations and suitable for characterizing foliage distribution [5,34]. CH and VH approaches have been applied in orchards and vineyards for volume estimation and gap detection [3,19]. In contrast, α S approaches provide a scale-sensitive surface reconstruction that interpolates between a convex hull ($\alpha \rightarrow \infty$) and more detailed envelopes that allow capture of canopy concavities at smaller α values. The method is based on Delaunay triangulation [38], and the α parameter determines the level of geometric detail. This parameter can be optimized through parameter sweeping and validation against reference measurements, aligning geometric reconstruction with agronomic relevance [5].

Although grapevine geometry has been widely used to estimate canopy volume for predicting LAI [6,7,24,28], chlorophyll concentration, and pruning weight [7], studies directly comparing UAV geometric models with field-measured canopy volumes are limited. A better understanding of how photogrammetric point clouds and different volumetric extraction methods perform relative to field-based volume estimations is therefore needed. In this context, this study evaluates the accuracy and consistency of grapevine canopy volume estimations derived from UAV-based RGB photogrammetric point clouds. The specific goals are to assess how flight height and associated changes in spatial resolution affect point cloud quality for canopy volume estimation, and to compare the performance of multiple geometric estimation methods against volume estimations based on field measurements of vineyard row sections at three phenological stages during the growing season.

2. Materials and Methods

2.1. Study Area

The study was conducted in a 0.56-hectare experimental vineyard (Figure 1) located on the campus of the University of Trás-os-Montes e Alto Douro, Vila Real, Portugal (41°17'08.1" N, 7°44'09.9" W; 467 m altitude). The vineyard plot contains three red grapevine varieties planted in 1996: Tinto Cão (1425 m², 20 rows), Touriga Franca (1600 m², 15 rows), and Tinta Barroca (2575 m², 20 rows). The vines are trained using a double Guyot system [40], with an in-row spacing of approximately 1.20 m and a row spacing of 2.00 m. The 55 rows are oriented in the northeast–southwest direction. This vineyard is rainfed and managed with foliar fertilization and phytosanitary treatments throughout the growing season. The inter-row areas contain spontaneous vegetation, mechanically controlled at least twice per season.

2.2. Data Acquisition

Aerial RGB imagery was acquired using a Phantom 4 (DJI, Shenzhen, China) multi-rotor UAV equipped with its native 12 MP camera mounted on a three-axis gimbal. Flight missions were conducted at 30, 60, and 100 m height above the take-off point, with 90% longitudinal and 80% lateral overlap, and with the camera oriented in a nadir view. Three

flight campaigns were carried out during the 2019 growing season, on 25 July, 22 August, and 23 September, corresponding, respectively, to important phenological stages: veraison (berry coloring and enlargement, BBCH 81), berry ripening (BBCH 85), and harvest maturity (BBCH 89). These stages represent critical periods for canopy management and decision-making, where foliage density and canopy architecture affect volume estimation.



Figure 1. Overview of the studied vineyard plot and the location of the three grapevine varieties within the experimental vineyard.

For each grapevine variety, twenty-four sampling units were established, consisting of eight 5×2 m sections distributed across three rows per variety (Figure 1). Each section contained approximately four to five plants, although some sections had missing plants. To estimate grapevine volume, five measurement points were placed at 1 m intervals along each 5 m row segment, as illustrated in Figure 2. At each measuring point, three variables were recorded: maximum canopy height (h_{max}), defined as the distance from the soil to the top of the canopy; minimum canopy height (h_{min}), the distance from the soil to the lowest leaves; and canopy width (w), the horizontal spread of the foliage measured perpendicular to the row.

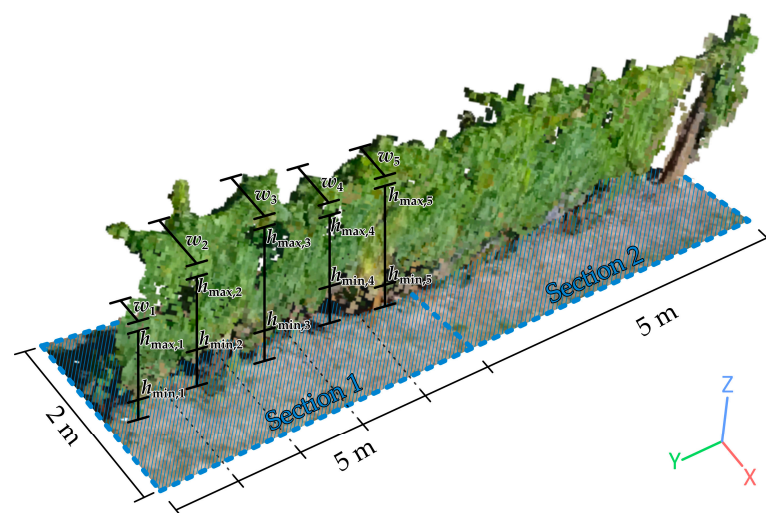


Figure 2. Example of the field measurements performed in a vineyard row section: h_{max} : maximum canopy height; h_{min} : minimum canopy height; w : canopy width.

2.3. Data Processing

The data processing workflow was composed of several steps, from the generation of point clouds through photogrammetric processing to the extraction and analysis of canopy volumes. Figure 3 provides an overview of the complete methodology applied in this study, including photogrammetric reconstruction, point cloud normalization, extraction of vineyard row sections, and the application of geometric models for canopy volume estimation. The following subsections describe each step.

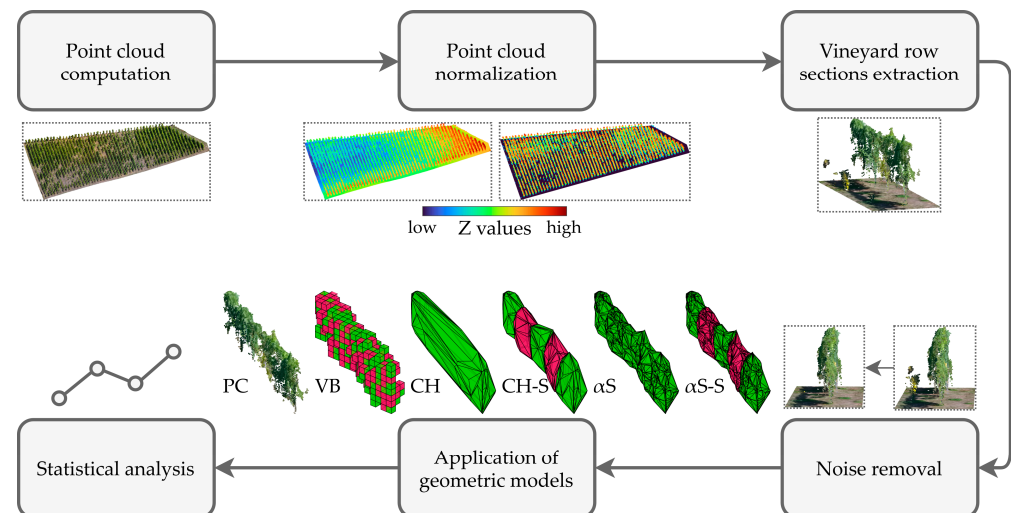


Figure 3. Data processing and canopy volume estimation workflow. PC: point cloud; VB: voxel-based grids; CH: convex hull; CH-S: convex hull using slices; α S: alpha shape, α S-S: alpha shape using slices. Colors indicate visualization purposes: the gradient from blue to red represents point cloud Z values, while green and purple indicate different slices or voxel elements within the geometric models.

2.3.1. Point Cloud Computation

The UAV imagery was processed using Pix4Dmapper (version 4.5.6; Pix4D SA, Lausanne, Switzerland) and SfM techniques to generate dense point clouds and raster products. A project was created for each flight campaign and flight height. Each project was first processed to generate a sparse point cloud, using the full image resolution for key point extraction. For image-pair matching, the “aerial grid or corridor” configuration was selected, and the internal and external camera parameters were calibrated using the standard calibration method. Common landmarks in images from the different flights were used to ensure consistent data alignment. These points were marked in the imagery, and after the identification of all tie points, the internal and external camera parameters were re-optimized. The spatial resolution for the three flight heights was around 0.013 m for 30 m, 0.026 m for 60 m, and 0.042 m for 100 m, as presented in Table 1. Data alignment resulted in root mean square error (RMSE) values below or around the corresponding spatial resolution at all processed UAV flights, indicating that alignment errors did not introduce relevant geometric deviations. All datasets were aligned to the 30 m flight acquired at BBCH 81 using manual tie points identified in common landmarks, serving as a reference for multi-height processing.

A dense point cloud was then generated with high point density. Densification was performed using half of the image size to compute additional 3D points and included processing at multiple image scales (quarter and eighth). Each 3D point had to be correctly re-projected in at least three images to be included in the final dense point cloud. The resulting point clouds were exported as LAS files. The point cloud density decreased with flight height, from more than 4200 points m^{-3} at 30 m to about 500 points m^{-3} at 60 m

and around 100 points m^{-3} at 100 m (Table 1). Figure 4 presents the point clouds from the evaluated rows and grapevine varieties.

Table 1. Photogrammetric processing parameters derived from UAV RGB imagery for the three flight heights and phenological stages (BBCH 81, 85, and 89). Reported values include the ground sampling distance (GSD), alignment error expressed as root mean square error (RMSE), and point cloud density (Pt. Density). Mean values represent the average by phenological stage. The symbol “—” indicates that RMSE was not calculated because the data served as the reference for alignment.

Flight Height	Parameter	BBCH 81	BBCH 85	BBCH 89	Mean
30 m	GSD (m)	0.0128	0.0132	0.0131	0.0130
	RMSE (m)	—	0.005	0.015	0.010
	Pt. Density (m^3)	4356	3985	4340	4227
60 m	GSD (m)	0.0254	0.0258	0.0258	0.0257
	RMSE (m)	0.008	0.002	0.014	0.008
	Pt. Density (m^3)	499	444	592	512
100 m	GSD (m)	0.0419	0.0427	0.0426	0.0424
	RMSE (m)	0.031	0.012	0.015	0.019
	Pt. Density (m^3)	107	93	108	102

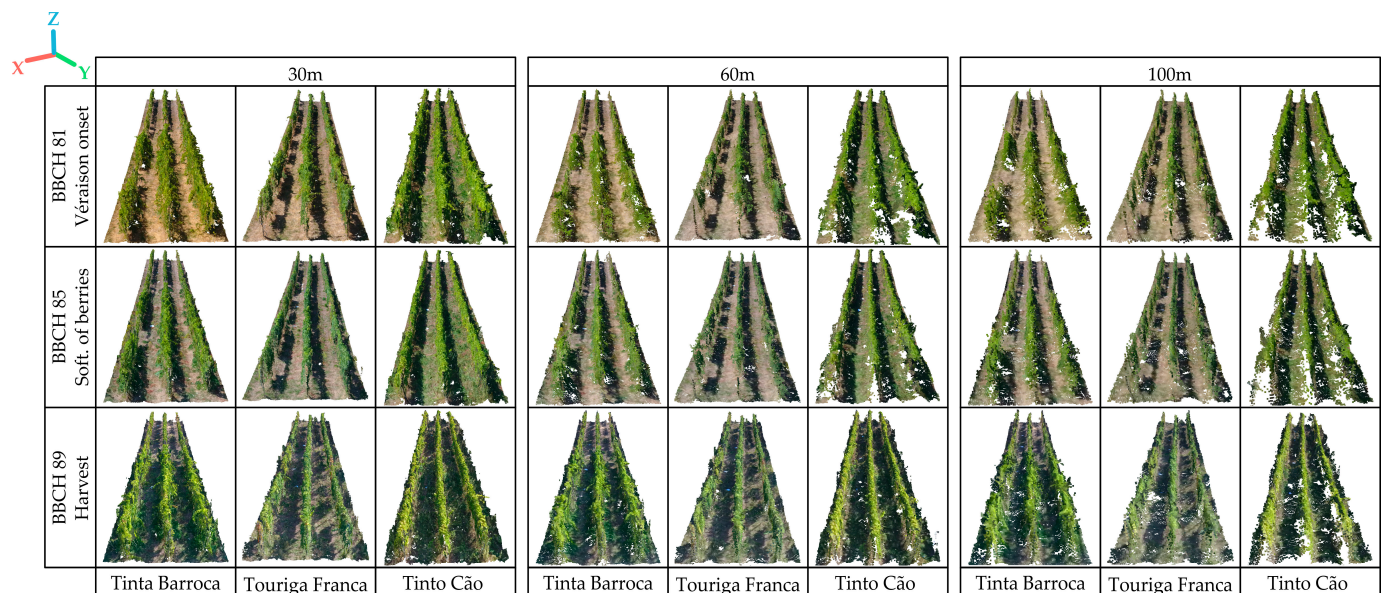


Figure 4. Generated dense point clouds from the evaluated rows in the different varieties and phenological stages.

2.3.2. Point Cloud Preparation

The point clouds from each flight campaign were processed to extract several grapevine-related geometric parameters. Each point cloud was normalized to ground level to remove elevation variability, converting altitude values to relative heights. Ground points were identified using the Simple Morphological Filter (SMRF) algorithm [41], which involved the following: (1) creating a surface map of minimum altitude values; (2) separating ground from non-ground points; and (3) segmenting the original point cloud based on the detected ground layer. Ground elevation was interpolated for all points, and normalization was achieved by subtracting the interpolated ground altitude from the original altitude value. This produced normalized point clouds suitable for comparison among the row sections and flight heights. This step reduces errors caused by elevation differences and provides consistency for comparing canopy structure across different flight heights and campaigns.

The normalized row sections were then extracted from each point cloud using the `lasclip` function from the `LAStools` library (rapidlasso GmbH, Gilching, Germany) within QGIS, based on shapefiles defining the geometry of each sampling section. Each polygon covered a 5 m row segment with a 1 m buffer along the central row line to include all branches and ground. This step generated individual LAS files for each section, which were subsequently used for canopy volume estimation.

A noise removal step was then applied in CloudCompare (version 2.12.1) using the statistical outlier removal (SOR) filter. This filter computes the mean distance from each point and its k nearest neighbors and removes points whose distance exceeds the mean by a specified number of standard deviations. In this study, k was set to six, and the standard deviation multiplier was set to one. The resulting point clouds showed more homogeneous spatial distributions with isolated outliers removed. After automated noise filtering, residual artifacts corresponding to points from inter-row vegetation were removed manually using the interactive segmentation tool in CloudCompare. This step was implemented to mitigate bias caused by tall inter-row vegetation for volume estimation. Manual cleaning was performed following the same consistent procedure, deleting only points clearly outside the canopy envelope and located in the inter-row space. This procedure was applied uniformly to all flight heights and phenological stages.

2.3.3. Data Preprocessing

Before applying the volume estimation methods, all point cloud files were processed using a standardized pipeline developed in MATLAB R2024a (MathWorks, Inc., Natick, MA, USA). Each point cloud was first read using an LAS file reader. Point locations, stored as $[X, Y, Z]$ coordinates, were then translated to a local coordinate system by subtracting the minimum X and Y values, aligning the data with an origin at $(0, 0)$ for reliable data processing and visualization.

To ensure that only canopy points were analyzed, ground points were removed by retaining only those with $Z \geq 0.4$ m, as in other studies [42]. Principal component analysis (PCA) was then applied to the X – Y coordinates of the filtered points to determine the dominant horizontal direction, corresponding to vineyard row orientation. The points were then projected onto this dominant direction, and the projection range was divided into 1 m vertical slices. Slicing enabled local volume computations for methods sensitive to spatial variability along the row.

The slice length was set to 1 m as a balance for comparisons among methods and point density, approximating grapevine spacing and maintaining sufficient point density within each segment. Larger slice lengths would reduce segmentation and approximate results to those obtained without slicing, while smaller slices could improve local detail but could result in a low number of points for volume estimation, particularly in cases with lower point densities.

2.3.4. Convex Hull

Convex hull volumes were computed using the `convhulln` function in MATLAB [43]. For the overall CH method, filtered point cloud was computed by generating a polyhedral envelope that minimally encloses all canopy points. The volume of the polyhedron was calculated and used as an estimate of grapevine canopy volume. Although computationally simple, this approach is hypothesized to overestimate canopy volume by including empty spaces around the actual canopy.

To refine volume estimation, each point cloud was divided into slices along the dominant horizontal direction. For each slice, a convex hull was computed (CH-S), and its volume was determined. The total canopy volume was obtained by summing the volumes

of all slice-specific convex hulls. This slice-based approach method aims to better capture local structural variations that may be lost in a single, global hull computation.

2.3.5. Alpha Shape

Alpha shape volumes were computed using the alphaShape function in MATLAB [38]. For a range of α values (0.1 to 1.0 in increments of 0.1), overall α S were generated for the filtered point cloud, and the enclosed volumes were calculated. The accuracy of this method depends on the choice of α , which controls the level of geometric detail captured.

With the aim to better represent canopy variations, the point cloud was divided into slices along the dominant horizontal orientation. For each slice and α value, an alpha shape was computed and its volume was calculated (α S-S). The total volume was obtained by summing the slice-specific alpha shape volumes.

2.3.6. Voxel-Based Grid

Voxel-based volumes were computed using custom MATLAB routines. The filtered point cloud was discretized into three-dimensional voxels with sizes ranging from 0.10 m to 0.50 m in steps of 0.05 m. Each point was assigned to a voxel based on its coordinates relative to the minimum X, Y, and Z values. Unique voxels occupied by the canopy points were identified, and canopy volume was estimated as the number of occupied voxels multiplied by the cubic volume of a single voxel (voxel size³).

2.3.7. Field Volume Computation

The field measurements collected at each row section were used to reconstruct a continuous three-dimensional canopy representation through a geometric modeling approach in MATLAB. For each section, the five measurement locations were expanded into a point cloud by generating a grid of points between h_{min} and h_{max} (vertical axis) and across the measured canopy width (horizontal axis). This set of points was processed using the alphaShape function in MATLAB, ensuring that all points were included in the reconstruction (Figure 5). The canopy volume for each section was then calculated from the resulting alpha shape object.

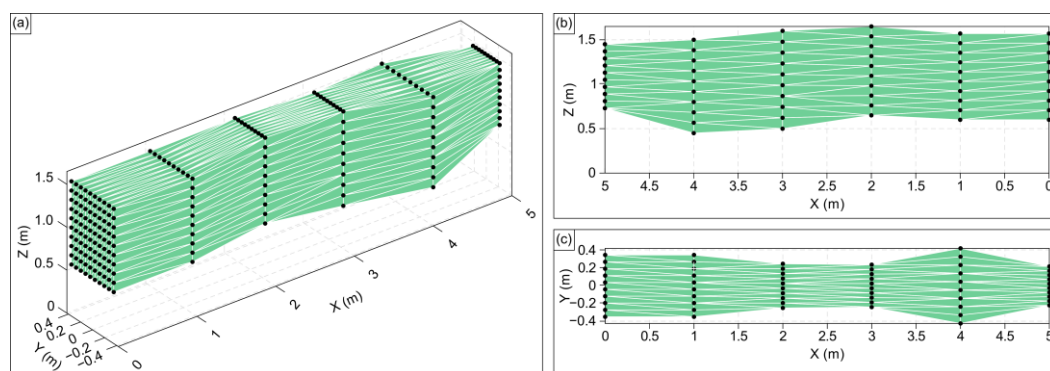


Figure 5. Example of a canopy polygon reconstructed from field measurements (row section 16 during veraison) using the alpha shape approach, shown from three perspectives: (a) three-dimensional view displaying the X, Y, and Z axes; (b) lateral view (X and Z axes); and (c) top view (X and Y axes). Black points represent the measurement-based grid used to generate the canopy model, and white lines indicate the polygon mesh forming the alpha-shape envelope.

This reconstruction method provides a more realistic representation of canopy geometry than a simple rectangular approximation by capturing curvature and transitions between measurement points. Although this approximation does not capture all canopy irregularities, it reduces structural bias and provides a balance between accuracy and field

feasibility. Given that direct measurement of true canopy volume in the field is labor-intensive, this approach was adopted as a baseline rather than an absolute ground truth. It therefore provides a reference for comparison among UAV-based estimation methods.

2.4. Data Analysis

For each processed, filtered, and normalized point cloud, the estimated volumes from CH (overall and slice-based), αS (overall and slice-based), and VB grid methods were compiled into tabular format for subsequent analysis and comparison with field-measured volumes.

All analyses were conducted in R (version 4.3.3) using the packages dplyr [44], ggplot2 [45], car [46], rstatix [47], multcompView [48], Hmisc [49], ggcorrplot [50], and patchwork [51]. Five target variables were analyzed: observed canopy volume and estimated canopy volumes derived from the CH, CH-S, αS , αS -S, and VB methods.

Given that the results produced by some of the methods are parameter-dependent, tuning of these methods (αS , αS -S, and VB) was carried out using a grid search prior to comparisons between flight heights and different methods. Therefore, values of $\alpha \in \{0.1, 0.2, \dots, 1.0\}$ were applied for both αS and αS -S, while voxel sizes in the range $\{0.10, 0.15, \dots, 0.50\}$ m were tested for the VB approach. For each combination of flight height, estimator (αS or VB), and parameter value (α or voxel size), performance was summarized using the median root mean square error (RMSE), computed as in Equation (1). The parameter minimizing the median RMSE [2,52,53] was selected as optimal for a given flight height.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} [m^3] \quad (1)$$

where n is the number of observations, $\hat{y}_i$ is the estimated canopy volume for observation i , and y_i is the corresponding reference volume. When RMSE differences were statistically indistinguishable, a 1-SE rule was applied, favoring simpler and more stable parameter values using the mean bias error (MBE) and mean absolute error (MAE). Remaining ties were resolved sequentially by lower MAE Equation (2), lower $|\text{MBE}|$ Equation (3), a higher portion of estimates within $\pm 10\%$ Equation (4), and a higher Lin's Concordance Correlation Coefficient (CCC).

$$\text{MAE} = \frac{1}{n} \sum_i |\hat{y}_i - y_i| [m^3] \quad (2)$$

$$\text{MBE} = \frac{1}{n} \sum_i (\hat{y}_i - y_i) [m^3] \quad (3)$$

with 95% bootstrap confidence intervals (2000 resamples), together with Spearman correlations, Lin's (CCC), and the proportion of estimates within $\pm 10\%$ of the field volume:

$$\text{within } \pm k\% = \frac{1}{n} \sum_i 1(|\hat{y}_i - y_i| \leq k\% \cdot |y_i|) \quad (4)$$

where n is the number of samples, y_i denotes the observed (reference) value, $\hat{y}_i$ denotes the predicted value and is the relative tolerance (e.g., 0.05, 0.10, and 0.20), and $1(\cdot)$ is the indicator function, which equals 1 when the condition is satisfied and 0 otherwise. The indicator function is evaluated for each sample, and the reported value corresponds to the average of these binary outcomes across all samples, resulting in a proportion between 0 and 1 (e.g., the percentage of predictions within $\pm k\%$ of the observed value).

This analysis included (i) sensitivity curves for data at each flight height (RMSE per α value; RMSE voxel size), (ii) a height-wise summary table of the best parameters, and (iii) complete per-height results, ensuring the reproducibility of the selected

parameters [53,54]. For the best parameters at each flight height, descriptive statistics were computed, including the mean.

Prior to method comparisons, data normality and homogeneity were tested using the Shapiro–Wilk and Levene tests, respectively. When both assumptions were valid ($p > 0.05$), a one-way ANOVA was conducted, followed by Tukey’s HSD test for pairwise comparisons. If assumptions were not met, the Kruskal–Wallis test was applied, followed by Dunn’s multiple comparisons with Bonferroni adjustment.

To compare methods within each flight height under a repeated-measures design (identical samples evaluated using different methods), the Friedman test was used. In these cases, post hoc paired comparisons were performed using the Wilcoxon signed-rank test with Bonferroni adjustment. Post hoc results were summarized using compact letter displays, in which identical letters indicated non-significant differences, with letters codes being placed at the medians in the corresponding boxplots comparing estimation methods across flight heights and phenological stages.

Associations among variables were quantified using Spearman’s rank correlation coefficient (ρ), with corresponding p -values at multiple levels (for methods with multiple parameters). Correlation analyses were performed by flight height and by parameter type (CH, α -S, VB grid), including the observed volume and different phenological stages, to assess the robustness of the associations.

3. Results

The results in this section are presented by flight height at 30, 60, and 100 m and by the method used to estimate grapevine canopy volume. The first part examines how the parameters of each method, the α value and voxel size, respond to changes in flight height and identifies parameter choices that gave the most stable performance. The second part compares the volume estimates from the five approaches with field-based volume estimations. The final part summarizes the behavior of the estimators through descriptive statistics, distributional patterns and correlation structures, allowing a direct view of how each method responded to height, season, and canopy conditions.

3.1. Estimation of Grapevine Canopy Volume

The five methods used to estimate grapevine canopy volume from UAV-based photogrammetric point clouds were compared with field-based volume estimations (Section 2.3.7). These methods were the convex hull applied to the entire section (CH), the convex hull applied to 1 m slices (CH-S), the alpha shape applied to the entire section (α S), the alpha shape applied to 1 m slices (α S-S), and voxel-based grids (VB).

A visual inspection of the reconstructed canopy models showed that slice-based approaches, CH-S and α S-S, produced shapes that followed the canopy structure more closely (Figure 6). These methods captured local depressions and gaps along the grapevines and produced envelopes that reflected observed variability within each row section. In contrast, whole-section approaches, CH and α S, tended to overestimate the canopy volume because the envelopes became smoother and more fully enclosed empty spaces between shoots and leaves. The VB models produced a discrete representation of the canopy. Generally, methods showed better detail at lower flight heights, where higher point density resulted in more complete reconstruction of the canopy surface. Despite these differences, the parameters of the VB and alpha shape approaches could be adjusted to refine representations at each flight height.

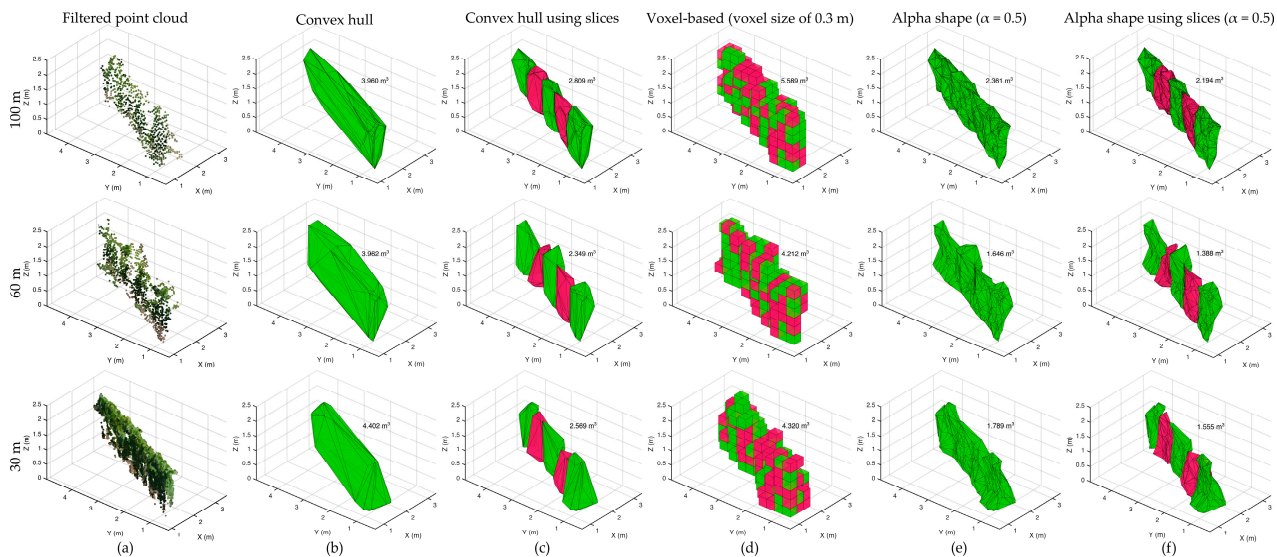


Figure 6. Representative examples of canopy reconstruction methods applied to a grapevine row section (row section 30 during veraison) using point clouds at different flight heights: (a) filtered point cloud ($Z > 0.4$ m); (b) convex hull applied to the entire row section; (c) convex hull applied to 1 m slices; (d) voxel-based grid using a voxel size of 0.3 m; (e) alpha shape applied to the entire section ($\alpha = 0.5$); and (f) alpha shape applied to 1 m slices ($\alpha = 0.5$). Green and purple colors indicate different slices or voxel elements within the geometric models.

3.2. Sensitivity of Methods and Selection of Optimal Parameter Configurations

A sensitivity analysis was carried out by computing the performance of the parameter-dependent methods (α S, α S-S, and VB) across flight height. For each height and method, median error metrics are reported in Table 2. The optimal parameter for each method was selected based on the lowest RMSE, supported by MBE, MAE, and CCC. Using median values helped reduce the influence of local variability and highlight the general pattern around each optimal parameter. Full results for all combinations of methods and parameter values are reported in Tables S1–S4, which provides complementary metrics to Table 2.

Table 2. Sensitivity of model parameters by flight height and method. RMSE and MAE are in m^3 (lower values indicate better performance). Values in bold indicate the parameter configuration selected as optimal, based on the lowest RMSE (tie-breakers: smaller $|\text{MBE}|$, lower MAE, and higher proportion within $\pm 10\%$). MBE is reported with a 95% confidence interval, “within $\pm 10\%$ ” is the proportion of predictions within $\pm 10\%$ of field measurements. * CI 95%: MBE with 95% CI (bootstrap, $R = 2000$). * = significant bias (CI excludes 0); ns = non-significant; CH: convex hull; CH-S: convex hull using 1 m slices; α S: alpha shape; α S-S: alpha shape 1 m slices; and VB: voxel-based grid.

Flight Height (m)	Method	α /Voxel Size (m)	RMSE (m^3)	MAE (m^3)	MBE [CI95%] (m^3)	Within $\pm 10\%$
30	CH	—	2.107	1.791	1.78 [1.62; 1.93] *	0.023
	CH-S	—	0.767	0.543	0.31 [0.22; 0.41] *	0.296
	α S	0.40	0.685	0.497	−0.21 [−0.30; −0.12] *	0.245
		0.50	0.668	0.468	−0.04 [−0.13; 0.05] ns	0.333
		0.60	0.698	0.479	0.09 [0.00; 0.19] *	0.324
		0.70	0.660	0.469	−0.09 [−0.17; 0.00] *	0.315
	α S-S	0.80	0.660	0.464	−0.03 [−0.12; 0.06] ns	0.329
		0.90	0.664	0.462	0.01 [−0.08; 0.10] ns	0.333
		0.10	0.977	0.720	−0.67 [−0.76; −0.58] *	0.144
	VB	0.15	0.699	0.525	0.23 [0.14; 0.31] *	0.296
		0.20	1.260	1.117	1.06 [0.96; 1.15] *	0.088

Table 2. Cont.

Flight Height (m)	Method	α /Voxel Size (m)	RMSE (m ³)	MAE (m ³)	MBE [CI95%] (m ³)	Within $\pm 10\%$
60	CH	—	2.051	1.685	1.58 [1.41; 1.75] *	0.051
	CH-S	—	0.937	0.659	−0.15 [−0.27; −0.02] *	0.213
		0.70	0.956	0.702	−0.25 [−0.37; −0.13] *	0.167
	α S	0.80	0.954	0.691	−0.12 [−0.25; 0.00] ^{ns}	0.194
		0.90	0.965	0.694	−0.01 [−0.14; 0.11] ^{ns}	0.218
	α S-S	0.90	1.007	0.748	−0.5 [−0.62; −0.38] *	0.171
		1.00	0.992	0.731	−0.46 [−0.58; −0.34] *	0.190
		0.15	1.112	0.777	−0.67 [−0.80; −0.56] *	0.176
	VB	0.20	0.921	0.656	0.07 [−0.06; 0.19] ^{ns}	0.264
100		0.25	1.284	1.092	0.83 [0.69; 0.95] *	0.088
	CH	—	2.096	1.712	1.49 [1.30; 1.69] *	0.074
	CH-S	—	1.045	0.753	−0.47 [−0.60; −0.35] *	0.181
		0.80	1.039	0.783	−0.43 [−0.56; −0.30] *	0.162
	α S	0.90	1.025	0.770	−0.30 [−0.45; −0.18] *	0.176
		1.00	1.026	0.764	−0.20 [−0.34; −0.06] *	0.167
	α S-S	0.90	1.209	0.933	−0.86 [−0.98; −0.75] *	0.116
		1.00	1.182	0.902	−0.81 [−0.93; −0.70] *	0.144
		0.20	1.048	0.730	−0.52 [−0.64; −0.40] *	0.199
	VB	0.25	0.997	0.766	0.18 [0.04; 0.31] *	0.190
		0.30	1.416	1.210	0.90 [0.75; 1.04] *	0.074

For point clouds acquired at 30 m, α S-S showed stable performance near α values of 0.7 and 0.9, with RMSE differences below 1% among these settings, making $\alpha = 0.8$ suitable for this flight height. For α S, the best performance was observed at $\alpha = 0.5$ with RMSE = 0.668 m³, while neighboring values (0.40 and 0.60) resulted in slightly higher errors. The VB method was more sensitive to changes in voxel size, with an optimal setting at 0.15 m (RMSE = 0.699 m³). Smaller or larger neighboring voxel sizes (0.10 and 0.20 m) introduced higher errors. The comparison between CH and CH-S demonstrated an improvement when using the slice-based approach (RMSE = 0.767 m³) compared with CH (RMSE = 2.107 m³).

For point cloud data from imagery acquired at 60 m, all methods showed a reduction in accuracy compared with 30 m, except for CH, which showed a slightly lower error rate. For α S, the best performance occurred at $\alpha = 0.8$, with an RMSE of 0.954 m³, while α S-S presented higher errors in the optimal setting (RMSE = 0.992 m³ at $\alpha = 1.0$). The VB grid, with a voxel size of 0.20 m, achieved the lowest RMSE (0.921 m³), whereas neighboring voxel sizes (0.15 and 0.25 m) had higher errors (1.112 and 1.284 m³, respectively). CH-S presented lower errors than CH.

When analyzing volume estimations using point clouds derived from data acquired at 100 m, accuracy decreased for the alpha shape and VB methods. For α S, the optimal parameter was $\alpha = 0.90$, with an RMSE of 1.025 m³. For α S-S, higher errors were obtained (RMSE = 1.182 m³) at $\alpha = 1.00$. The VB grid presented its best performance with a voxel size of 0.25 m (RMSE = 0.997 m³). CH-S presented more accurate estimations (RMSE = 1.045 m³) than CH (to 2.096 m³).

Across data from all flight heights, a trend was observed in the optimal parameters for α S, with α value increasing with flight height, from 0.50 at 30 m to 0.80 at 60 m and 0.90 at 100 m. In contrast, α S-S maintained a stable performance at higher α values = $\alpha = 0.80$ at 30 m and 1.0 at 60 m and 100 m, as presented in Figure 7. RMSE curves for different α values showed greater sensitivity at higher flight heights (60 and 100 m), while at 30 m the error was lower and the plateau of acceptable values

was broader. The largest errors occurred when the lowest evaluated α (0.1) was used, regardless of the dataset. In general, lower errors were associated with point clouds of higher spatial resolution. When comparing the application of the alpha shape method to entire row sections versus its application to one-meter slices, the slice-based approach improved accuracy only at 30 m ($\alpha = 0.8$), while the error of αS ($\alpha = 0.5$) was not statistically significant. For data collected at 60 and 100 m, applying the method to the entire canopy of the row section resulted in lower errors.

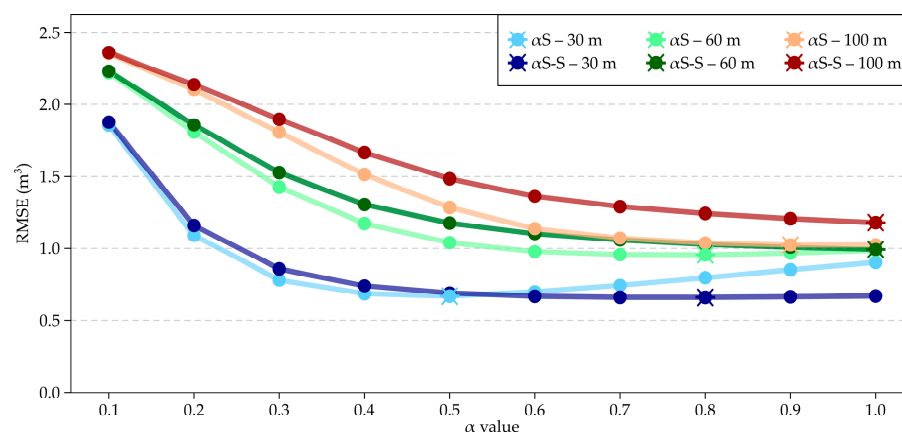


Figure 7. Root mean square error (RMSE) at different α values for the alpha shape methods applied to the overall row section and to one-meter slices across flight heights.

A similar pattern was observed for the VB-based method (Figure 8). The optimal voxel sizes were 0.15, 0.20, and 0.25 m for flight heights of 30, 60, and 100 m, respectively. Errors decreased as voxel size approached these optimal values but increased again when the size exceeded this range. The lowest errors were obtained at 30 m, while the largest errors were associated with voxel sizes beyond the optimal range, typically at higher voxel sizes.

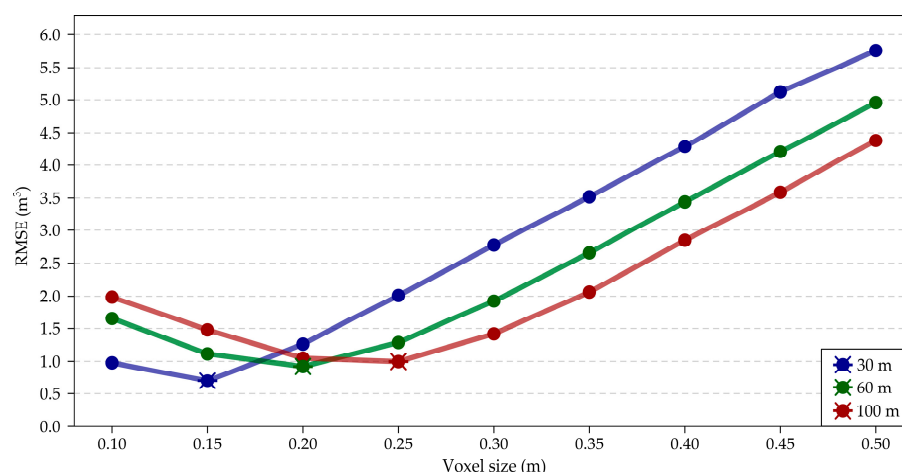


Figure 8. Root mean square error (RMSE) at different VB sizes across flight heights.

For the two convex hull approaches (Figure 9), the slice-based method (CH-S) demonstrated a better performance than the full-row section approach (CH). At 30 and 60 m, errors remained under 1 m^3 , whereas CH produced RMSE values around 2 m^3 . This pattern indicates that slicing reduced the overestimation caused by convex envelopes.

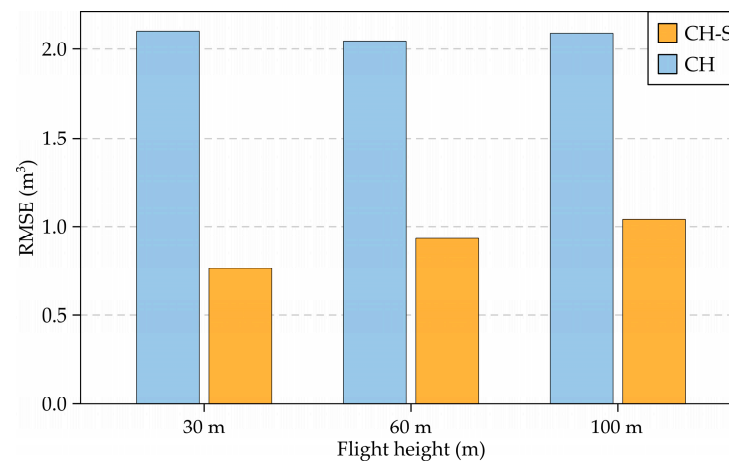


Figure 9. Root mean square error (RMSE) for the convex hull methods applied to the overall row section and to 1 m slices across flight heights.

3.3. Descriptive Statistics, Distributional Patterns, and Between-Group Contrasts

Across all phenological stages and flight height combinations, the mean values of the geometric estimators followed a consistent pattern when compared to the field-measured canopy volume (Table 3), when using the selected α or voxel size for each flight height (Table 2). The mean field volume was $2.22 \pm 0.84 \text{ m}^3$. The mean estimated volumes were $3.84 \pm 1.21 \text{ m}^3$ for CH, $2.12 \pm 0.76 \text{ m}^3$ for CH-S, $1.79 \pm 0.68 \text{ m}^3$ for α S-S, $2.07 \pm 0.78 \text{ m}^3$ for α S, and $2.38 \pm 0.58 \text{ m}^3$ for VB. VB showed the lowest coefficient of variation (25.8%), followed by CH (33.1%) and field-based estimations (36.9%). CH-S, α S, and α S-S showed higher dispersion, with coefficients of variation between about 38.8% and 41.1%. These values indicate that VB produced the most internally consistent estimates, while alpha shape approaches presented greater variability.

Table 3. Flight height-specific descriptive statistics (mean $\pm$ SD; CV%) of geometric estimators at the different flight heights (30 m, 60 m, and 100 m) and when considering them aggregated. CH: convex hull; CH-S: convex hull using 1 m slices; α S: alpha shape; α S-S: alpha shape using 1 m slices; and VB: voxel-based.

Flight Height	30 m		60 m		100 m		All Data	
Estimator	Mean $\pm$ SD	CV%	Mean $\pm$ SD	CV%	Mean $\pm$ SD	CV%	Mean $\pm$ SD	CV%
Field volume	—	—	—	—	—	—	2.22 ± 0.84	36.9
CH	4.00 ± 1.16	29.4	3.81 ± 1.16	32.6	3.71 ± 1.29	37.4	3.84 ± 1.21	33.1
CH-S	2.54 ± 0.80	32.3	2.08 ± 0.74	38.1	1.75 ± 0.75	46.0	2.12 ± 0.76	38.8
α S	2.18 ± 0.73	34.3	2.10 ± 0.78	40.0	1.92 ± 0.83	46.7	2.07 ± 0.78	40.3
α S-S	2.19 ± 0.72	33.7	1.77 ± 0.66	40.3	1.41 ± 0.65	49.3	1.79 ± 0.68	41.1
VB	2.45 ± 0.55	23.2	2.29 ± 0.54	25.0	2.40 ± 0.65	29.2	2.38 ± 0.58	25.8

Flight height, and consequently spatial resolution and point density, influenced the performance of shape-derived metrics, as presented in Table 3. CH decreased from $4.00 \pm 1.16 \text{ m}^3$ at 30 m to $3.81 \pm 1.16 \text{ m}^3$ at 60 m and $3.71 \pm 1.29 \text{ m}^3$ at 100 m, with dispersion increasing from 29.4% to 37.4%. CH-S declined from 2.54 ± 0.80 at 30 m to 2.08 ± 0.74 at 60 m and $1.75 \pm 0.75 \text{ m}^3$ at 100 m, with dispersion rising from 32.3% to 46.0%. The α S and α S-S methods showed similar behavior. α S decreased from 2.18 ± 0.73 at 30 m to $1.92 \pm 0.83 \text{ m}^3$ at 100 m, while α S-S decreased from 2.19 ± 0.72 to 1.41 ± 0.65 , with coefficients of variation increasing from around 33% to nearly 49%. This association between mean volumes from CH and alpha-based models and flight height was strongly negative ($r \approx -0.98$, $p < 0.001$). In contrast, the VB grid remained more stable

in data across different flight heights, with mean values between 2.29 and 2.45 m³ and coefficients of variation between 23% and 29.2%. VB did not show a monotonic relationship with flight height.

To compare dispersion among methods within each flight height, analyses were evaluated using the selected α or voxel size for each height (Table 2). Figure 10 shows the distribution of the estimates and the median-based inferential comparisons among methods. At 30 m, α S and α S-S were not statistically different from the field-based estimations. CH-S, CH, and VB produced higher volume estimations and differed from the field-based estimations and from the alpha shape methods. At 60 m, α S, CH-S, and VB were closest to the field-based estimations; VB differed from α S and CH-S, while α S-S and CH differed from all other approaches. At 100 m, only VB did not differ from the field-based volume estimations. When data from all flight heights were combined and analyzed by phenological stage, separation among methods varied with phenological stage (Figure S1). Across all phenological stages, CH produced the largest values and differed from all other approaches. At BBCH 81, α S, VB, CH-S, and field estimations formed an intermediate group, while α S-S produced lower values. At BBCH 85, field volume estimations, α S, and CH-S were grouped together, VB was also associated with field estimations, and α S-S showed the lowest volumes. At BBCH 89, α S, CH-S, and field estimations formed a mid-range group, while α S-S again showed the smallest volumes.

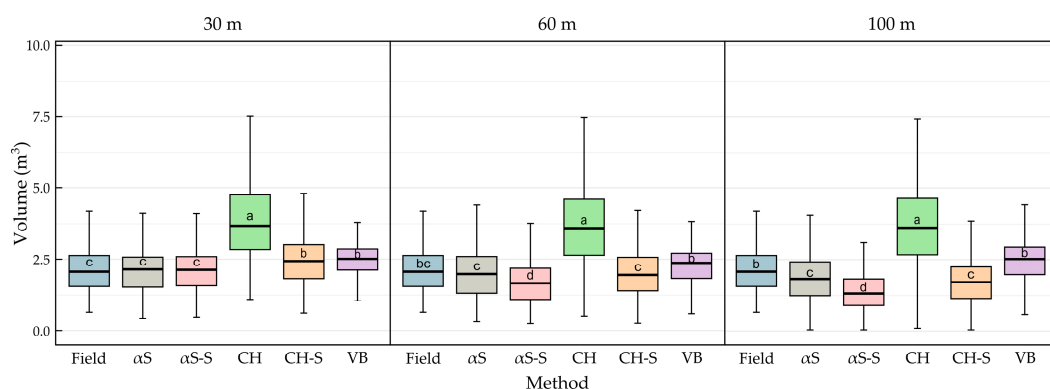


Figure 10. Boxplots of field-based volume and the evaluated methods at 30, 60, and 100 m of flight heights. Different letters show significant differences among methods within each flight height at $p < 0.05$.

Figure 11 summarizes the Spearman correlation coefficients between field-based estimations and UAV-based geometric models. Correlation strength declined as flight height increased. Using point cloud data at 30 m, the overall correlation structure was strong, with a mean off-diagonal ρ of 0.917 and a standard deviation of 0.067. The highest value was among CH-S, α S, and α S-S. The strongest correlation with field-based estimations was $\rho = 0.78$ obtained for α S-S, while all models except CH ($\rho = 0.69$) obtained similar values ($\rho = 0.77$). At 60 m, correlation structure weakened; CH-S, α S, and α S-S again showed the highest value ($\rho = 0.98$ – 0.99) among UAV-based estimation methods. Field-based estimations correlated most strongly with α S and CH ($\rho = 0.63$) and least with VB ($\rho = 0.48$). At 100 m, correlation structure showed the lowest values. CH-S, α S, and α S-S remained the strongest pairings, while field-based estimations correlated most with α S and α S-S ($\rho = 0.58$) and least with VB ($\rho = 0.45$). Across all heights, CH-S, α S, and α S-S were almost collinear, while the weakest pairing was between field-based estimations and VB, more evident in coarser point clouds (60 and 100 m).

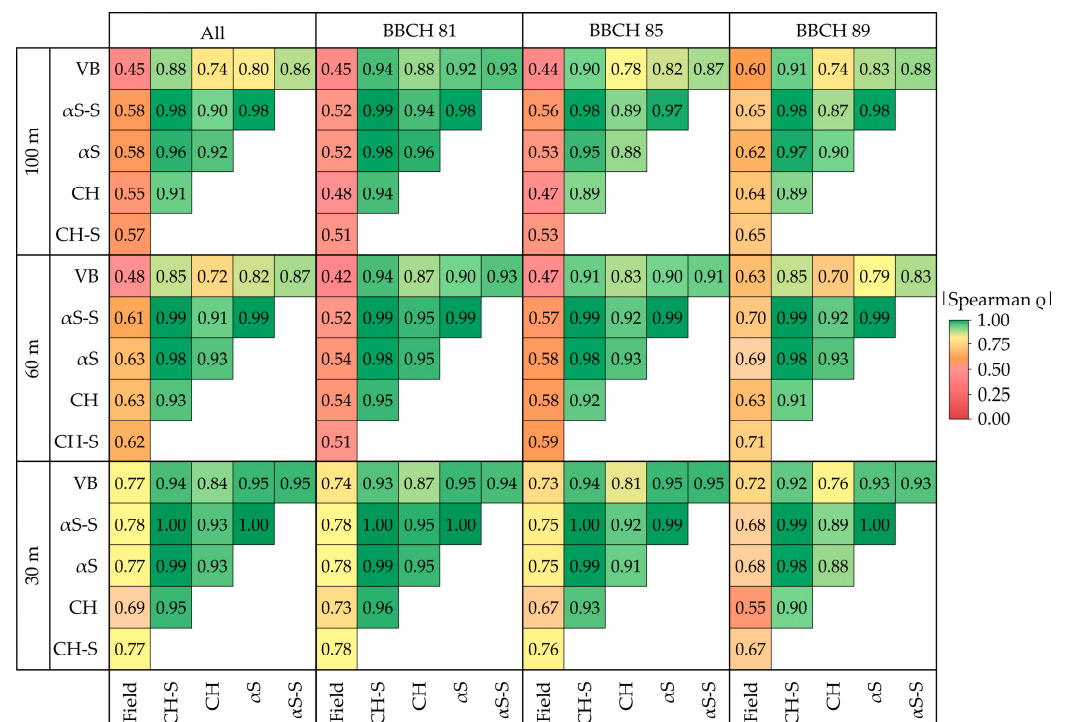


Figure 11. Correlation matrix between field-measured canopy volume and estimates derived from CH-S, αS, αS-S, and VB at the three different flight heights, considering all data and by phenological stage. All coefficients are Spearman's ρ ($p < 0.001$).

Seasonal effects on the correlation structure were analyzed for each BBCH stage within each flight height (Figure 11). During veraison in July (BBCH 81), cohesion was high for data at 30 m. The αS, αS-S, and CH-S methods showed the strongest link ($\rho = 0.78$), while the weakest was CH ($\rho = 0.73$) with field volume estimations. In August, during berry softening (BBCH 85), αS, αS-S, and CH-S showed the strongest pairing ($\rho \approx 0.75$) with field-based volume approximations, while the association between field volume and CH remained the weakest ($\rho = 0.67$). In September, when grapes were harvest-ready (BBCH 89), CH-S, αS, and αS-S again formed the strongest pairing ($\rho \approx 0.98$ – 1.00), while the association between field volume and CH remained the weakest ($\rho = 0.55$). The strongest association with the field-based estimations was for VB ($\rho = 0.72$).

At 60 m, correlation structures were generally stronger than at 100 m. At BBCH 81, internal cohesion was very high for CH-S, αS, and αS-S ($\rho \approx 0.98$ – 0.99). The weakest association with field-based estimations was observed for VB ($\rho = 0.42$), while the strongest was observed for CH and αS ($\rho = 0.54$). At BBCH 85, coherence slightly declined but CH-S, αS, and αS-S remained almost collinear ($\rho \approx 0.98$ – 0.99). The weakest relationship with field estimations was observed for VB ($\rho = 0.47$), while the strongest was observed for CH-S ($\rho = 0.59$). At BBCH 89, cohesion with field-based estimations was moderate. The weakest estimators relative to field volume estimations were observed for VB and CH ($\rho = 0.63$), while the slice-based approaches (αS-S and CH-S) provided the best associations with field data ($\rho \geq 0.70$).

At 100 m, a reduction in association strength from BBCH 81 to BBCH 89 was observed. At BBCH 81, the strongest association occurred among CH-S, αS, and αS-S ($\rho \approx 0.98$), while the weakest field-related pairing was observed for VB ($\rho = 0.45$), and the strongest relationships with field-based estimations were observed for αS and αS-S ($\rho = 0.52$). At BBCH 85, the association among CH-S, αS, and αS-S remained the strongest ($\rho = 0.95$ – 0.98), the weakest field association continued to be observed for VB ($\rho = 0.44$), and the best estimator was αS-S ($\rho = 0.56$). At BBCH 89, the strongest value was again among CH-S, αS,

and α S-S ($\rho \approx 0.97$ – 0.98), while the lowest field-related value was VB ($\rho = 0.60$), and the highest correlation relative to field-based estimations were observed for α S-S and CH-S ($\rho = 0.65$).

4. Discussion

The geometric characteristics of the grapevine canopy influence growth and productivity by affecting light distribution, photosynthesis, water use, and yield potential [55–59]. Several studies have used canopy structure to estimate plant water use and manage irrigation strategies [60,61], prescribe fertilizer application rates [62,63], support disease detection [64], estimate biomass [65], and predict yield [4,66]. Canopy architecture and seasonal changes introduce variability in reconstruction accuracy. Varieties with denser foliage or irregular shoot distribution produced more complex point clouds, which affect boundary-based methods such as CH and α S. Seasonal changes in leaf density during ripening and harvest maturity also influence the performance of these methods, as gaps and concavities became more noticeable. These factors highlight the need for parameter tuning not only by flight height but also by canopy structure and growth stage. Field-based measurements of canopy parameter are difficult to obtain consistently, particularly in grapevines where the canopy forms a continuous and irregular surface with gaps and shoots [5]. Techniques based on contour boxes simplify this structure and may miss internal voids that influence true canopy volume [3,67]. In this study, grapevine canopy volume was derived from UAV photogrammetric point clouds using geometric models with different levels of sensitivity to point density and boundary reconstruction (Figure 6). The field-based volume estimate, improved through a 3D reconstruction approach using alpha shape modeling, remains an approximation. Potential bias may still occur due to unmeasured canopy variability and phenological changes. While this limitation does not compromise the comparative analysis among UAV-based methods, future studies should include uncertainty quantification and repeatability assessments for field measurements or consider other alternatives such as terrestrial LiDAR, which can provide higher accuracy but are less commonly used in vineyards due to cost constraints [68].

The results indicate that flight height influenced the behavior of boundary-based estimators. The reduction in point density at 60 and 100 m decreased the ability of α S and CH methods to reproduce canopy boundaries, leading to a decline in estimated volume (Table 3). This reduction was clear in CH, CH-S, α S, and α S-S, which showed strong negative monotonic associations with height, while VB grids were more stable. These patterns align with previous work showing that coarser imagery reduces reconstruction quality, decreases the fidelity of 3D reconstructions, and accentuates the weaknesses of envelope-based approaches [69]. VB did not show a monotonic trend with flight height because its estimates are less sensitive to reductions in point density. Shape-derived methods (CH, CH-S, α S, α S-S) rely directly on the outer envelope of the point cloud; therefore, decreases in point density shrink the reconstructed canopy boundary. In contrast, VB discretizes space into fixed-size voxels and counts all voxels containing at least one point. As long as the point density remains above the occupancy threshold for most canopy voxels, the estimated volume remains stable. Small fluctuations in point density produce minor, non-monotonic variations in VB estimates, consistent with the weak correlation observed ($r \approx 0.23$, $p \approx 0.85$).

The contrast between CH and CH-S observed in the stratified analysis (Section 3.2.) reflects this effect. CH tended to create artificial volumes by covering empty spaces along the row, whereas slicing reduced this behavior by restricting the convex surface to smaller segments. This improvement is consistent with the reduction in overestimation observed in

the sliced versions and mirrors similar observations in orchard studies where segmentation improves local fidelity [3,70].

At 30 m, point cloud density was sufficient for alpha shape boundaries to follow the canopy outline accurately, which explains why αS and αS -S were closer to the field volume at this height (Figures 10 and 11). However, the decline in accuracy at 60 and 100 m for both αS approaches confirms the sensitivity of the α parameter to sampling density [19], highlighting the importance of selecting parameter values rather than using a fixed value [12]. Since small changes in α change the degree of concavity captured, adjustments become more uncertain when fewer points define the canopy surface [38]. The strong collinearity between αS and αS -S visible in the correlation matrices (Figure 11) reflects their dependence on this parameter.

VB grids were less affected by height-related point density changes, showing stable means and dispersion values (Table 3). This consistency across flight heights and phenological stages makes VB suitable for surveys under variable conditions. Previous studies also report that VB grids tolerate heterogeneous point distributions better than envelope-based surfaces, particularly in sparse vegetation [71]. Furthermore, controlling voxel size improves accuracy, as finer voxel sizes reduce bias and improve correspondence with field data, a pattern observed in biomass estimation studies [39,71].

Variety and phenological stage showed additional variation in data representation accuracy (Tables S5–S10). In August and September, changes in foliage density and spatial distribution influenced point cloud sampling and affected modeled volume. Similar behavior was reported by Torres-Sánchez et al. [72], who observed that phenological variation alters the link between detected points and biomass or yield. Seasonal changes also modified the correlation structure (Figure 11), with links between field-based volume and geometric estimators weakening in August and then recovering in September. Changes in plant volume variability due to plant health should also be considered [73].

The plateaus identified in Figure 7 and the error profiles summarized in Table 2 offer a basis for parameter selection without extensive re-calibration. The best configurations were $\alpha = 0.8$ for αS -S at 30 m, a voxel size of 0.20 m for flights at 60 m, and a voxel size of 0.25 m for flights at 100 m (Table 2). These settings provided lower RMSE, limited bias, and high CCC. Given the gradual rather than abrupt degradation of performance around these values, they offer stable choices for regular use, reinforcing the recommendation of parameter tuning based on the expected level of canopy detail [19]. High-density data at low-altitude allow smaller α values because concavities are well defined, whereas sparse canopies or high-altitude flights may require larger α values. Local tolerance ranges, such as ± 0.05 m for voxel size or ± 0.1 for α at 30 m, reduce the need for height-specific reparameterization and help maintain performance [3].

Boundary-based models are generally more sensitive to density loss than VB, which maintained more stable behavior across flight heights, although it was not always the closest to field measurements (Figure 10). However, VB may over- or underestimate in particular cases. While a linear adjustment could theoretically reduce systematic bias, this approach was not validated on independent data and should be considered exploratory rather than a recommended solution. Future work should evaluate correction strategies using external datasets before implementation.

The slicing strategy applied in this study was adapted to vineyard geometry. Slices were applied along the row direction rather than horizontally, which reduces the effect of missing plants and gaps, an issue observed in the preliminary stratified analysis. The choice of 1 m slices was based on grapevine spacing and point density considerations. Larger slices would diminish the benefits of segmentation by producing envelopes similar to whole-section approaches, while smaller slices could improve local accuracy at lower

fight heights but lead to empty or sparse slices at higher altitudes. This trade-off highlights the need for parameter tuning when adapting slice-based strategies to different canopy structures and flight conditions. Future work could improve this approach by adopting dynamic slicing widths [74] or adapting method parameters per slice [42,75], allowing reconstruction to follow variations within individual row sections.

5. Conclusions

This study evaluated the effect of flight height on UAV-based photogrammetric point clouds and compared several geometric approaches for estimating grapevine canopy volume. Both spatial resolution and the selected volumetric method affected the reconstruction accuracy. Envelope-based approaches (α S, α S-S, CH-S) performed better at 30 m, where point density was highest, but their agreement with field measurements declined at 60 and 100 m as boundary distortion increased. VB grids showed more stable behavior at different flight heights when voxel size was adjusted to point density.

In addition to flight height and method choice, canopy architecture and phenological stage also influenced estimation accuracy. Varieties with dense or irregular foliage can produce more complex point clouds, increasing errors in boundary-based methods. Seasonal changes in leaf density and shoot distribution altered canopy geometry, reducing the effectiveness of single-date calibrations and highlighting the need for seasonal adjustments when reconstruction spans different growth stages.

For operational applications, lower flight heights are preferable for contour-based methods to maintain spatial detail, while voxelization requires tuning voxel size within 0.125–0.50 m depending on canopy structure. Alpha shape methods should avoid fixed α values; systematic parameter scanning is recommended to minimize gaps and smoothing.

Although this study focused on three phenological stages, these periods are relevant for canopy management decisions such as pruning, foliar applications, and harvest planning [42]. Extending data collection to earlier stages, such as leaf development (BBCH 10–19) and inflorescence emergence (BBCH 53–57), would provide a broader assessment of phenological variability and support pruning biomass estimation. Future work should also include point clouds from UAV LiDAR and terrestrial sensors to compare performance across platforms and canopy viewpoints, evaluate steep slope vineyards, and develop optimization procedures that select flight height and method parameters based on cross-validated errors at variety and seasonal levels in vineyards with different architectures and growth conditions.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs18030409/s1>. Figure S1: Boxplots of field volume and the evaluated methods at 30, 60, and 100 m flight height by phenological stage. Different letters show significant differences among methods within each flight height at $p < 0.05$; Table S1: Performance of the different methods using data obtained at 30 m flight height ($n = 216$); Table S2: Performance of the different methods using data obtained at 60 m flight height ($n = 216$); Table S3: Performance of the different methods using data obtained at 100 m flight height ($n = 216$). Table S4: Overall performance of the different methods by flight height for the selected parameters; Table S5: Overall performance of the different methods by phenological stage for data acquired at 30 m flight height ($n = 72$); Table S6: Overall performance of the different methods by phenological stage for data acquired at 60 m flight height ($n = 72$); Table S7: Overall performance of the different methods by phenological stage for data acquired at 100 m flight height ($n = 72$); Table S8: Overall performance of the different methods by grapevine variety for data acquired at 30 m flight height ($n = 72$); Table S9: Overall performance of the different methods by grapevine variety for data acquired at 60 m flight height ($n = 72$); Table S10: Overall performance of the different methods by grapevine variety for data acquired at 100 m flight height ($n = 72$).

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