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Tree extraction and estimation of walnut structure parameters using airborne LiDAR data

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ABSTRACT

The development of new tools based on remote sensing data in agriculture contributes to cost reduction, increased production, and greater profitability. Airborne LiDAR (Light Detection and Ranging) data show a significant potential for geometrically characterizing tree plantations. This study aims to develop a methodology to extract walnut (*Juglans regia* L.) crowns under leafless conditions using airborne LiDAR data. An original approach based on the alpha-shape algorithm, identification of local maxima, and k-means algorithms is developed to extract the crowns of walnut trees in a plot located in Viver (Eastern Spain) with 192 trees. In addition, stem diameter and volume, crown diameter, total height, and crown height were estimated from cloud metrics and other 2D parameters such as crown area, and diameter derived from LiDAR data. A correct identification was made of 178 trees (92.7%). For structure parameters, the most accurate results were obtained for crown diameter, stem diameter, and stem volume with coefficient of determination values (R^2) equal to 0.95, 0.87 and 0.83; and RMSE values of 0.43 m (5.70%), 0.02 m (9.35%) and 0.016 m^3 (21.55%), respectively. The models that gave the lowest R^2 values were 0.69 for total height and 0.70 for crown height, with RMSE values of 0.84 m (12.4%) and 0.83 m (14.5%), respectively. A suitable definition of the central and lower parts of tree canopies was observed. Results of this study generate valuable information, which can be applied for improving the management of walnut plantations.

1. Introduction

The development of advanced technological tools can help maximize efficiency and profitability in agriculture. The protection of the environment is a key element for guaranteeing the sustainability of this productive sector. Precision agriculture has emerged as a discipline that involves a management strategy based on collecting and analyzing data (nutrients, topography, water status, climate, growth, and production) at individual and local levels to study the inter and intra-field variability of crops (Joint Research Centre of the European Commission, 2014). This information supports management decisions that enable improved agricultural production. Extensive research has shown the potential of remote sensing in precision agriculture. Satellite images were used to estimate crop biomass (Marshall and Thenkabail, 2015; Zeng and Chen, 2018); crop biophysical parameters (Xie et al., 2019); fertilization (Sripada et al., 2006; Tilling et al., 2007; Miao et al., 2009); water status (Moller et al., 2007; Bellvert et al., 2016; Gutiérrez et al., 2018); and weed management (Peña-Barragán et al., 2010; Sa et al., 2018). Most of these studies aimed to find relationships among agricultural parameters measured in field and vegetation reflectance using specific spectral bands collected in the optical-reflective and thermal domains. The strong contrast in reflectance for some spectral bands motivated the development of spectral indices for these applications (Sripada et al., 2006). However, there is a limited understanding of how the different geometric parameters of fruit trees can improve management of fruit tree plantations. LiDAR technology has significant potential for estimating structure parameters (Moorthy et al., 2011; Hadas et al., 2017; Colaço et al., 2017), fruit detection (Gené-Mola et al., 2020) and pruning biomass (Estornell et al., 2015).

LiDAR data can be collected by terrestrial and airborne sensors. Terrestrial laser scanners are usually stationed at specific positions, or can be mounted in ground-based vehicles. Airborne sensors can be

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installed in planes, helicopters, drones, and even satellites such as in the ICESat-2 mission. When comparing these technologies, it is significant that terrestrial systems enable registering data in millimeter detail (Liang et al, 2016). However, commonly reported problems include the large amounts of data registered by these systems and canopy gaps (Hilker et al., 2012). Canopy gaps can be partially solved by using a larger number of positions, but this makes the technique less efficient (Trochta et al., 2013). Another option is to apply mobile systems (Gil et al., 2014), but these systems cannot always be used in irregular and reduced plantation spacing and in small agricultural plots. Airborne sensors can cover large areas and collect data on all the trees in plots and including trees that are very close together and therefore difficult to measure using other LIDAR systems. It is hypothesized that for leafless trees it is possible to register with more detail the interior parts of the canopies, and consequently, parameters such as crown height and crown volume could be estimated more accurately. This last parameter has a relevant potential for adjusting spray volume (Miranda-Fuentes et al., 2016) and leaf area index (Arnó et al., 2013). Previous studies also reported the importance of canopy height for estimating crown and pruning biomass (Velázquez-Martí et al., 2014; Estornell et al., 2015). Given the above, it is worthwhile exploring the performance of airborne LiDAR systems for defining the central and lower canopy parts of leafless fruit trees.

Allometric equations to estimate aboveground biomass and stem volumes from deondrometric parameters measured in the field can be frequently found in forestry science (Schlaegel, 1984; Clark et al., 1986; Jenkins et al., 2004). However, little attention has been paid in agriculture to developing models which quantify the total biomass of fruit trees and the fraction that can be extracted from pruning (Velázquez-Martí et al., 2011a and 2013). This is relevant for understanding the role of agricultural plantations in $C0^2$ sequestration and the significance of these agricultural wastes for biofuel production. To develop these studies with airborne LiDAR data it is crucial to develop the crown extraction algorithms commonly used in forestry, so that they can also be used successfully for deciduous trees (Hadas, 2015). A tree spatial database can be generated from these data that can be updated with field and remote sensing information. In addition, the location, size, and distribution of trees can be mapped to enable the optimal use of farm equipment and distribute resources such as fertilizers and herbicides. Some studies reported the use of LiDAR data in variable rate techniques for pesticide application (Walklate et al., 2002, Gil et al., 2014).

This study aims to develop and adapt a methodology to extract crown trees of *Juglans regia* L. using airborne LiDAR data. This species was selected due the significant increase of this crop in Spain, expanding from 10,212 ha in 2010 to 15,204 ha in 2019 (Ministerio de Agricultura y Pesca, Alimentación y Medio Ambiente 2010 and 2019). In addition, this species can be planted for fruit production and also for obtaining crown and stem wood. The performance of airborne LiDAR data to estimate structure parameters, i.e. total and crown heights, stem and crown diameters, and stem volume, under leafless conditions was analyzed, as well as the capability of this technology to register intermediate and low strata of the crowns.

2. Materials and methods

2.1. Study area

The study was located in Viver, a municipality in an inland area of Castellon province (Eastern Spain) with a Mediterranean climate characterized by hot and dry summers (average temperature 22° C and 62 mm of average total rainfall), and moderate winters (average temperature 7° C and 120 mm of rainfall). Annual rainfall is 556 mm and it mainly falls in spring and autumn. The species under investigation was *Juglans regia* L. (Fig. 1) which is grown for nut production. The walnuts were located in a plot with an average elevation of 660 m a.s.l. and a slope of around 3%. The age of the trees was 28 years. The soil was calcareous and had a loamy-sand texture with an isopropyl-n-phenyl carbamate (IPC) of 35. It was a deep soil with little organic matter. The irrigation method was based on controlled deficit irrigation. The growth of walnut trees was considered very suitable for the age of the plantation considering that pruning was carefully eliminating unnecessary wood to produce good aeration and a high photosynthetic efficiency.

2.2. Materials

This research was carried out in a plot with 192 walnut trees. LiDAR data used in this study belongs to the Aerial Orthophoto National Plan in Spain (PNOA; ceded by © IGN), with the following characteristics: flight date January 24 to 27, 2018; sensor: LM7800; average height: 3000 m a.

Fig. 1. Representative walnut tree selected for this study with structure parameters close to the mean values.

s.l.; pulse rate: 266667 Hz; field of view (FOV) of LiDAR point collection: 50°; scanning frequency: 100 LxS; plane speed: 160 knots; data density in the study area 4 points·m-2 on average.

For a sample of n = 21 walnut tree structure parameters, i.e. total, crown and stem height, crown and stem diameter, and stem volume were obtained from direct field measurements (Table 1). Total height was measured with a pole measuring the maximum height of each tree from three observer points. To obtain stem height, the distance between ground and the first stem bifurcation was measured by tape. Crown height was obtained by calculating the difference between total and stem height. Stem diameter was measured with a diameter tape at a distance of 0.6 m from the ground, which was representative for a whole stem. Field measurements were performed during the same period as LiDAR campaigns.

Moreover, an orthophotomap (Orthophoto 2017 CC BY 4.0 © Institut Cartogràfic Valencià, Generalitat) dated on July 5, 2020, with the pixel size of 0.25 m was used to measure four crown diameters from the north–south, east–west, northwest-southeast and northeast-southwest directions for each tree. An average of these four values was calculated to obtain a crown diameter parameter for each walnut tree. In the orthophotomap, walnut trees were leafy, and crown shapes and corresponding diameters could be identified more accurately than when leafless. Crown growing differences between these two periods can be considered insignificant, since annual pruning was applied after the LiDAR flight. To determine stem volume, diameters were measured every 20 cm starting from the stem base until its top. Stem volumes for each tree were calculated as a sum of the volumes of conical frustums limited by measurement intervals.

2.3. Methods

2.3.1. Crown extraction

An original approach for walnut tree identification and crown delineation from a point cloud was developed. The approach consists of several steps: i.e. point-cloud normalization and split; identification of local maxima on surface models; crown segmentation; and delineation. Open-source CloudCompare software was used for the first step only, and multiple Matlab scripts for the remaining processing were implemented.

In the pre-processing step, point cloud was classified to ground and non-ground points using the CSF algorithm (Zhang et al., 2016). Ground points were used to create a digital terrain model (DTM) with a resolution of 1x1 m. Non-ground points were used to generate a normalized point cloud, by replacing absolute point heights with normalized heights H_{norm}, i.e. normal distances from the generated DTM.

In the next step, an alpha-shape algorithm (Edelsbrunner et al., 1983) was applied to split the normalized point cloud into smaller areas. Alpha-shape is a generalization of the convex hull concept and uses Delaunay triangulation associated with a characteristic radius r. In this study, r was set to 0.7; points below a threshold height of 1.5 m were discarded; and areas smaller than 1 m^2 were rejected. This step significantly improved the processing performance and computational times. Moreover, the alpha-shape already produced crown contours for trees with non-overlapping crowns (Hadas et al., 2019). However, overlapping trees were aggregated into groups, which required further separation.

Table 1
Statistics of walnut parameters: total height (Ht); crown diameter (Dc); crown height (Hc); stem diameter (Ds); stem height (Hs); and stem volume (Vs); standard deviation (SD), minimum value (Min), maximum value (Max).

Statistic	Ht (m)	Dc (m)	Hc (m)	Ds (m)	Hs (m)	Vs (m^3)
Mean	6.76	7.54	5.71	0.25	1.05	0.075
SD	1.51	1.98	1.52	0.06	0.17	0.039
Min	4.60	4.24	3.53	0.14	0.73	0.025
Max	9.25	10.63	8.33	0.34	1.38	0.160

To separate trees with overlapping crowns, a widely used method of treetop identification for conifers was adopted, which is based on an analysis of a smoothened raster. First, the normalized point cloud was clipped using areas identified in the previous step, and normalized heights were used to generate a digital surface model (DSM) of each area as a raster with a resolution of 3x3 m. The built-in Matlab function imregionalmax was used to identify local maxima on each DSM, which approximately represented treetops. It was assumed that a DSM smaller than 4x4 cells may contain a single local maximum, but there was no assumption on a local maxima number for a larger DSM. Treetops were further used as seed points for a k-means algorithm, which segmented the point cloud into clusters, which were considered as points reflected from individual trees. Each cluster was then delineated using alpha-shape algorithm again, to obtain preliminary crown contours for all trees.

Height thresholding and alpha-shape algorithm itself left out points reflected from low and protruding branches. To correct such issues, crown contour polygons were iteratively enlarged by the nearest point. This procedure ended, when all non-aggregated points were further from the closest polygon than twice the r. The new polygons were considered as final crown contours determined for the entire study area and were visually compared with the orthophotomap. This layer was used to compute the area (A_{CLiDAR}) and diameter (D_{CLiDAR}) of the crowns.

2.3.2. Structure parameters

A sample of 21 walnut trees was selected in the study plot. A set of statistical parameters based on LiDAR point elevations within each extracted crown was calculated using the Cloudmetrics tool in FUSION software version 3.80 (McGaughey, 2014). The potential variables used for this study were: minimum, maximum, mean, median, standard deviation, variance, coefficient of variation, interquartile distance, skewness, kurtosis, AAD (average absolute deviation), MADMedian (median of the absolute deviations from the overall median), L-moments (L1, L2, L3, L4), L-moment skewness, L-moment kurtosis, percentile values (1st, 5th, 10th, 20th, 25th, 30th, 40th, 50th, 60th, 70th, 75th, 80th, 90th, 95th, 99th percentiles), canopy relief ratio ((mean - min) / (max – min)), generalized means for the 2nd and 3rd power (elev quadratic mean and elev cubic mean). Points with heights lower than 0.25 m were discarded so as to only consider vegetation points. In addition, the area and diameter of each crown were computed from a crown polygon layer extracted in the previous step from LiDAR data. This set of metrics was used to estimate total height (Ht), crown height (Hc), stem diameter (Ds), crown diameter (Dc) and stem volume (Vs) by applying stepwise regression ($\alpha = 0.05$). A leave-one-out-cross-validation method was applied to analyze the performance of regression models.

This method is appropriate for small datasets according to the scientific literature (Brovelli et al., 2008; Cheng et al., 2017) and it provides an unbiased estimate of the true error expected for independent data (Moore et al., 2001; Hastie et al., 2001; Varma and Simon, 2006). The determination coefficient R^2, absolute root mean square error (RMSE), and relative RMSE (RMSE%), calculated by dividing the absolute RMSE with the mean value for each parameter calculated from field data, were computed for the regression models and compared to the parameters obtained from the cross-validation technique. Scatter plots with a regression fit line were obtained for each parameter.

3. Results

3.1. Crown extraction

After applying the alpha-shape algorithm, multiple trees merged together, especially in the central part of the test area (Fig. 2a). This was expected due to the overlapping crowns of walnut trees. In the next step, 204 local maxima were found (Fig. 2b) on the generated 3x3 m DSM,

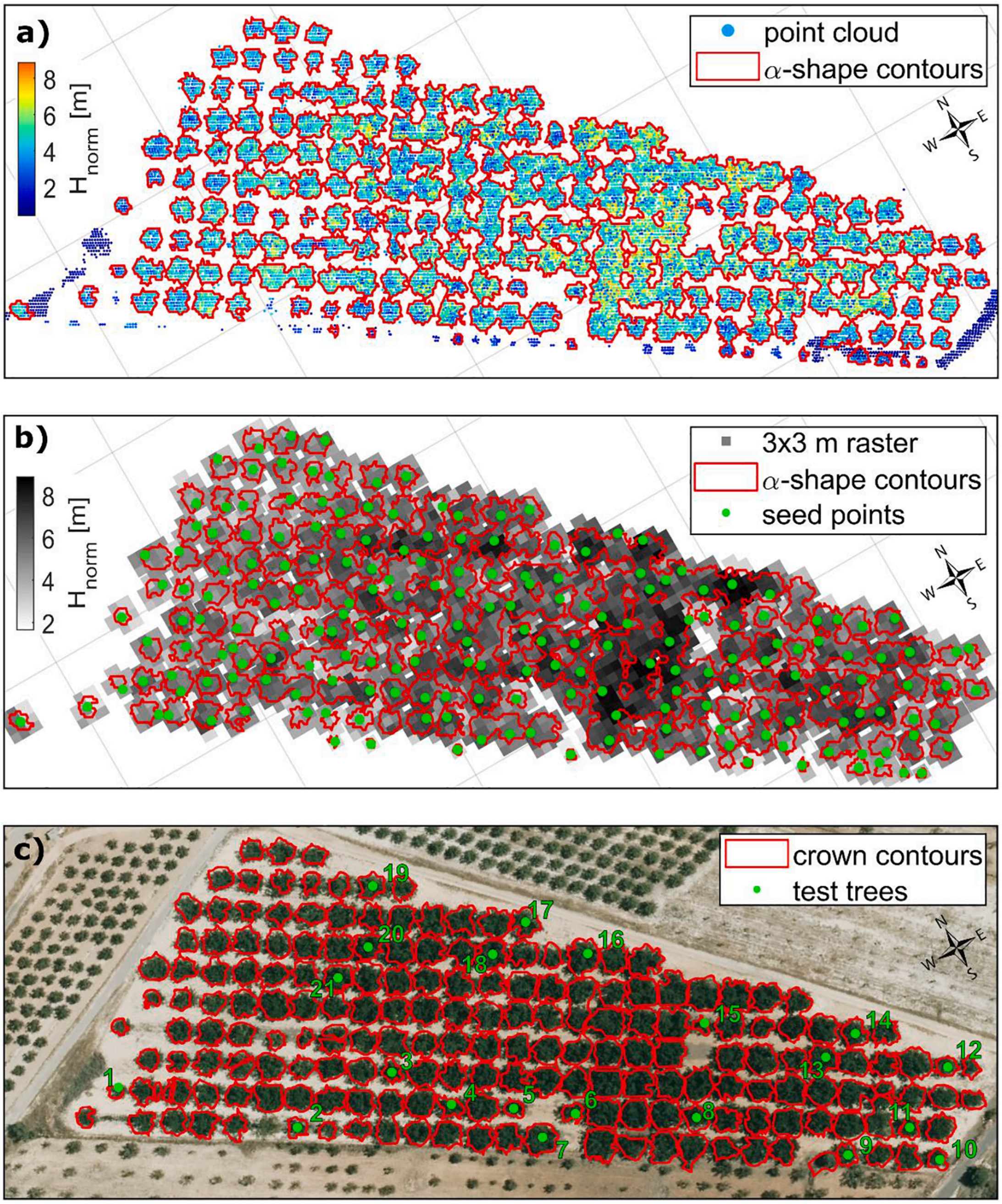

Fig. 2. Results of tree crown delineation approach at various stages: (a) normalized point cloud split with alpha-shape algorithm; (b) seed points for k-means algorithm detected on DSM rasters; (c) final crown contours and test trees with a orthophotomap in the background.

and the corresponding clusters were obtained with a k-means algorithm. Ten clusters at the south-eastern edges of the test region and one cluster on the far west were disregarded from further analysis, as they did not represent walnut trees. Among 193 final crown contours (Fig. 2c) there were 178 correctly delineated crowns. There were three crown contours which still aggregated to two trees each, constituting omission errors. Another four trees were divided into two contours each, thus generating commission errors. Finally, there was a single tree, whose contour was far too large at the cost of reduced crown contours for the three neighboring trees. All 21 test trees were in the group of correctly determined trees.

3.2. Structure parameters

The most accurate fit was obtained for crown diameter (Dc) with values of R^2, RMSE, and RMSE% equal to 0.95, 0.43 m, 5.70%, respectively (Table 2). This stepwise model included only one variable, crown diameter (D_{CLiDAR}), that was calculated from crown polygons. Appropriate models were also obtained for stem parameters, i.e. volume and diameter, with R^2 equal to 0.83 and 0.87, respectively. In these models, one variable was also selected: crown area derived from LiDAR data (A_{CLiDAR}) and crown diameter (D_{CLiDAR}), respectively. For total (Ht) and crown height (Hc) less accurate results were found. R^2, RMSE and RMSE% for Ht were 0.69 m, 0.84 m, and 12.43%, respectively. For Hc, these values were 0.70 m, 0.83 m and 14.54%, respectively. Underestimation of total height for each walnut tree was detected for most of the test trees (Fig. 3). Mean difference among total height measured in the field and maximum elevation derived from LiDAR data for each tree was 0.41 m. This result indicated that airborne LiDAR system underestimated tree heights. In this figure, an overestimation of the minimum

Table 2
Regression models developed for each parameter using LiDAR data variables.

Parameter	Model	R^2	RMSE	RMSE (%)	R^2_{cv}	$RMSE_{cv}$
Ds [m]	$Ds = -0.0136 + 0.034 \cdot D_{CLiDAR}$	0.87	0.02 m	9.35	0.86	0.02 m
Dc [m]	$Dc = -0.93 + 1.12 \cdot D_{CLiDAR}$	0.95	0.43 m	5.70	0.95	0.44 m
Ht [m]	$Ht = -1.01 + 1.22 \cdot Elev_{Max}$	0.69	0.84 m	12.43	0.67	0.85 m
Hc [m]	$Hc = -2.10 + 1.23 \cdot Elev_{Max}$	0.70	0.83 m	14.54	0.67	0.85 m
Vs [m^3]	$Vs = -0.0015 + 0.0017 \cdot A_{CLiDAR}$	0.83	0.016 m^3	21.55	0.81	0.017 m^3

The estimated walnut parameters were: stem diameter (Ds); crown diameter (Dc); total height (Ht); crown height (Hc); stem volume (Vs). Independent variables derived from LiDAR data within each tree were: crown diameter derived from LiDAR data (D_{CLiDAR}); maximum elevation ($Elev_{max}$); crown area derived from tree extraction algorithm applied using LiDAR data (A_{CLiDAR}); determination coefficient for each model (R^2); root mean square error (RMSE); RMSE percentage compared to average field values for each parameter (RMSE %); cross validation determination coefficient (R^2_{cv}); cross validation root mean square error ($RMSE_{cv}$).

height registered by LiDAR data was also observed (a mean difference of −0.51 m compared to field measurements).

Validation of the results was based on the comparison of RMSE and R^2 values of regression models and cross validation techniques. Similar values of RMSE - $RMSE_{cv}$ and R^2 - R^2_{cv} were found for each parameter (Table 2). In addition, a linear relationship close to the 1:1 line was observed among field data and cross validation predicted values for each parameter (Fig. 4).

4. Discussion

4.1. Crown extraction

Crowns were delineated with a high success rate of 92.7%, although the average density of the point cloud was relatively low when compared with other recent studies (Wan Mohd Jaafar et al. 2018; Hadas et al. 2019). This was achieved for deciduous trees, for which the task is more challenging due to the non-conical shape of the crowns (Hadas 2015). The high success rate can be explained by the fact that walnut crowns were artificially shaped by regular pruning, so that the top parts of crowns were separated from each other. Some delineation errors occurred for the highest trees with overlapping crowns. We attribute this to the inability of the local maxima search algorithm to identify treetops correctly in such a challenging condition. Because it is critical for k-means algorithms to provide either the number of expected clusters (trees) or seed point (tree top locations), the identification of treetops is a critical step. Although definition of DTM resolution, or its smoothing window, directly affects treetop identification (Morsdorf et al. 2003; Zhao and Popescu 2007), k-means remains a popular approach (Gupta et al. 2010; Dalponte et al., 2015). Recently, a density-based spatial clustering of applications with noise (DBSCAN) algorithm is receiving more attention in LiDAR data segmentation (Ferrara et al. 2018, Wang et al, 2019). This non-parametric algorithm could be considered as an alternative for k-means and eliminates the DTM analysis, producing a segmentation accuracy of 87% (Wang et al. 2020).

4.2. Structure parameters

The results indicate that walnut parameters were estimated accurately from airborne LiDAR data acquired during leafless conditions. For stem parameters, it is important to note that accurate models were obtained for estimating stem volume and diameter. Although LiDAR technology cannot register stem parameters directly, 2D crown variables (crown diameter and crown area) derived from LiDAR data showed a high explanatory power for predicting stem parameters. For stem diameter, the reported results are in line with previous studies on agricultural tree species, e.g. *Olea europaea* L. and *Prunus dulcis* Miller (López-Cortés et al., 2019; Gandia-Ventura, 2020). For these studies, R^2 values were 0.84 and 0.82, respectively, being crown area and crown diameter derived from LiDAR data the most significant variables. For forest species, strong relationships were also found for stem parameters considering crown area and crown perimeter (Popescu, 2007; Shrestha and Wynne, 2012). The results obtained in the present study confirm the capability of airborne LiDAR data to estimate stem parameters for fruit trees. Previous research reported the importance of these variables to predict pruning biomass (Velázquez-Martí et al., 2011a; Sajdak et al., 2014). To our knowledge, no studies estimating the stem volume of fruit trees by airborne LiDAR data have been made. However, results obtained in this study reveal the significance of crown area parameters when estimating this parameter for the *Juglans regia* L. species. A biophysical and proportional relationship between crown area and stem volume was found.

Other studies reported the relevance of stem volume for estimating crown biomass in almond, olive, and orange trees (Fernández-Puritach

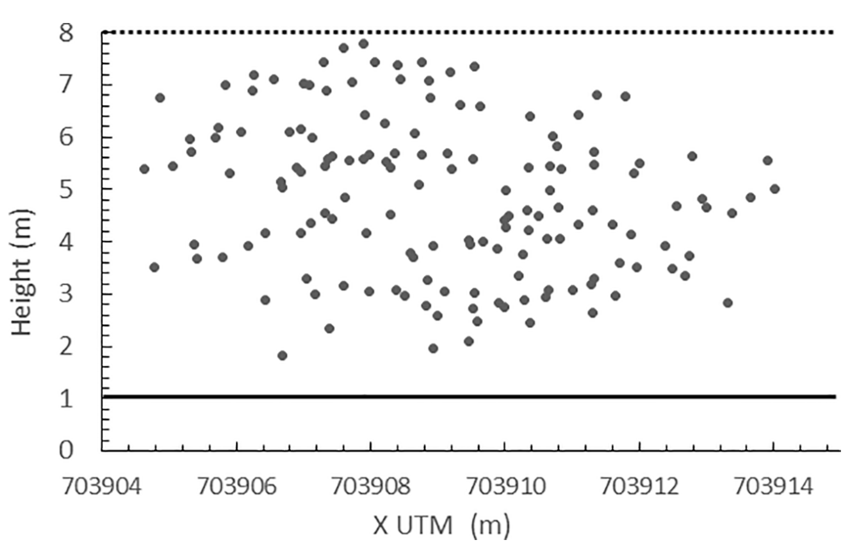

Fig. 3. Scatterplot of crown LiDAR data of a representative tree that is close the average difference in total height and crown height between field and LiDAR data. Bold line represents distance from ground to the first stem bifurcation measured in the field. Dotted line represents the maximum height measured in the field.

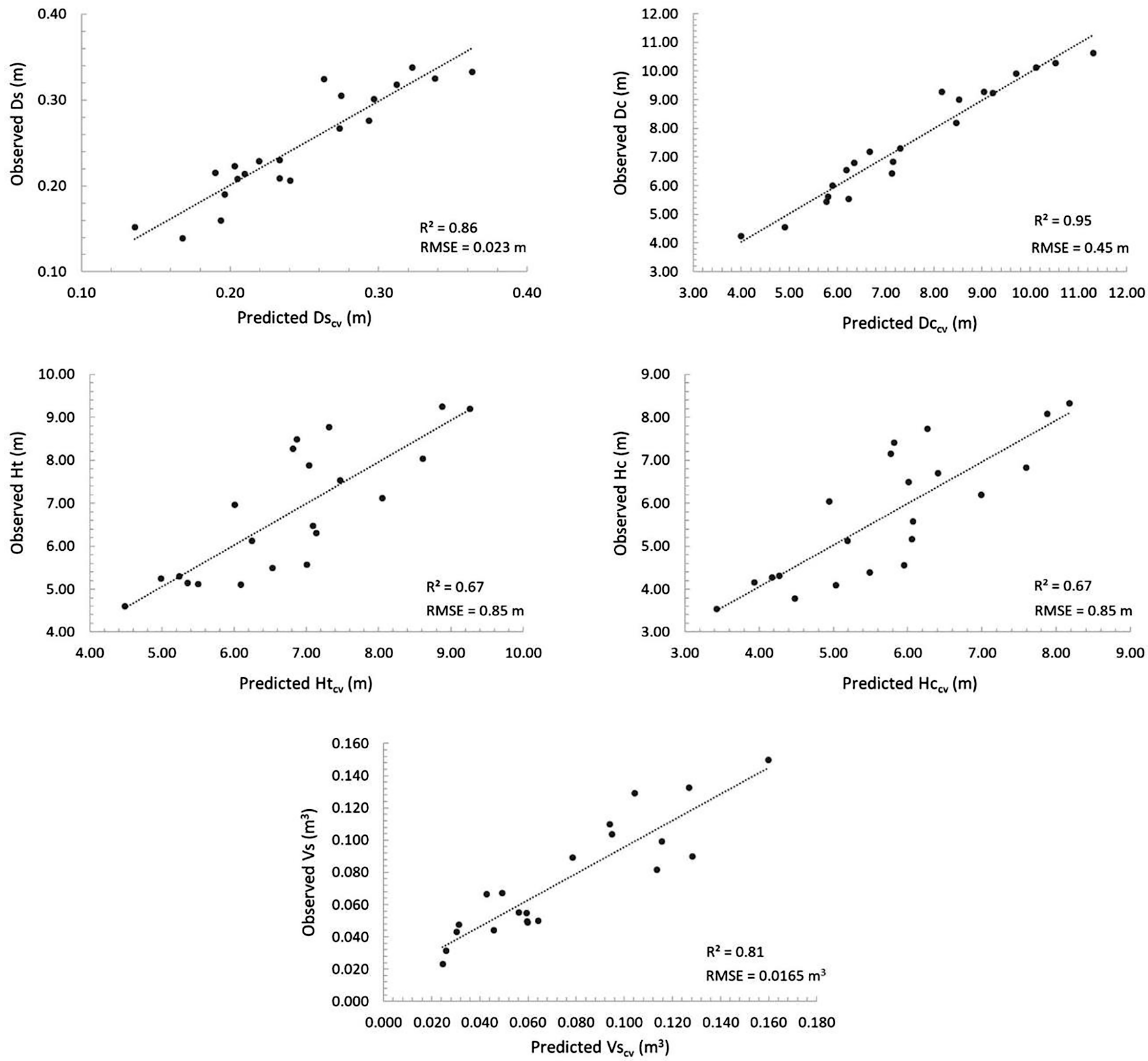

Fig. 4. Scatterplot for each field and cross-validation predicted parameter.

et al., 2013; Velázquez-Martí et al., 2014). Unlike forestry, fruit tree biomass is concentrated mainly in the crowns (Velázquez-Martí et al., 2014). Allometric equations to estimate timber volume or above ground biomass from simple field measurements are defined in forestry (Schlaegel, 1984; Clark et al., 1986; Jenkins et al., 2004). In reviewing the literature, several studies estimated these parameters from LiDAR data (Shrestha and Wynne, 2012; Kankare et al., 2014; Hauglin et al., 2014). However, further research is required in agriculture to obtain regression models that enable quantifying tree biomass and the fraction that can be removed in management tasks such as pruning. The results reported in this study encourage further research in this topic to compute the total biomass of fruit trees.

A strong correlation was found for crown diameter measured in field and derived from LiDAR data. For its computation, it was needed, firstly, to develop and adapt an algorithm to extract crown trees from LiDAR data. An aspect worth considering is that the density of points classified as vegetation (height >0.25 m) was approximately 2.5 points$\cdot$m^{-2}. This result showed that approximately 60% of the original 3D point cloud within each crown tree corresponded to hits on branches. The rest of the LiDAR points were classified as ground points. These findings suggest that crown architecture of walnut trees can be defined accurately by airborne LiDAR data in leafless conditions. In addition, a better performance for this technique is expected for representing the central and lower parts of canopies – as will be discussed for tree height analysis. Previous studies reported that olive trees with a mean crown diameter of 4.01 m were defined accurately using a density of 4 points$\cdot$m^{-2} (Hadas et al., 2017). For Platanus hispanica, a crown layer was also extracted using 0.7$\cdot$points m^{-2} in urban environments, with crown diameter values ranged from 4.1 m to 11 m in leafy conditions (Estornell et al., 2018). However, no literature was found on how point density can affect the structure parameters of leafless fruit trees. Several studies reported the relevance of crown diameter for estimating crown biomass in olive trees (Velázquez-Martí et al., 2014) and pruning biomass in olive and almond trees (Velázquez-Martí et al., 2011a; Velázquez-Martí et al., 2011b). Crown area, which was also computed in this study from LiDAR data, showed a significant relevance for estimating pruning biomass in olive trees (Estornell et al., 2015) and the biomass of conifers and broadleaf trees (Shrestha and Wynne, 2012).

Out of the analyzed parameters, total and crown height were estimated with less accuracy. A general underestimation for total height was detected. These results were in line with previous studies on fruit trees and confirm that airborne LiDAR systems underestimate the top canopy of olive and almond trees (Estornell et al., 2015; Gandia-Ventura, 2020). This underestimation was widely proven in forestry studies (Lefsky et al., 2002; Gaveau and Hill, 2003; Yu et al., 2004; Hill and Thomson, 2005; Hopkinson et al., 2005; Streutker and Glenn, 2006; Bork and Su, 2007). This effect could be explained by considering that to obtain a return, it is necessary to exceed a threshold in the backscattered laser energy in the discretization process of the signal. In other words, a deeper area of canopy is needed for the energy beam to be reflected, and as a consequence, the return is generated in a lower part of the tree. However, underestimations could vary when considering several factors. Hirata (2004) reported that differences in tree height estimation were affected by point density. This result was also in line with another study in which olive tree heights were compared using two sets of LiDAR data (0.5 points/m^2, and greater than 3.5 points/m^2) obtaining a bias of -1.48 m, and -0.72 m, respectively ($n = 25$) (Hadas and Estornell, 2016). Other studies reported that small footprint sizes generate more accurate results than large footprints (Hirata, 2004; Andersen et al., 2006). In the latter case, although the beam of energy is distributed over a larger area, a lower signal-to-noise ratio can be produced in small terminal features of some canopies, and this generates an insufficient returning signal. Another disadvantage of large footprints is that a mixture of reflections from the targets within the path of the laser beam can be generated (Andersen et al., 2006).

Underestimation of tree height is also dependent on tree species due to differences in crown forms (Yu et al., 2004; Andersen et al. 2006). Narrow crowns are more likely to be missed (Andersen et al., 2006). In this study, Douglas fir heights were estimated with less accuracy than ponderosa pines. In this context, a lower probability of registering the treetop locations of leafless trees is expected, although this also depends on other factors such as the tree size. DTM accuracy is another factor to be considered when evaluating tree height estimations (Leckie et al., 2003; Gatziolis et al., 2010). Nevertheless, this factor is not considered relevant in agricultural environments as the terrain slope is gentle and gaps among trees can be observed due the applied plantation framework. Values of RMSE of around 1 m were found for height forest trees with average heights around 15–20 m (Kwak et al., 2007; Popescu and Zhao, 2008). In contrast, fruit trees are shorter than forest trees as their heights are managed to facilitate agricultural practices (harvesting and the application of pesticides). In our study the average height of the trees was 6.8 m and the RMSE value was 0.84 m. In relative terms, the underestimation of fruit trees from LiDAR data was more significant than for forest trees. For canopy height, an expected overestimation (-0.51) of this height was detected. However, these differences were lower than those reported for olive trees, i.e. -1.18 m (Estornell et al., 2015). Previous studies reported that little information is registered for the central and lowest parts of canopies for olive trees (Estornell et al., 2015), beech (Van der Zande et al., 2006), and leafy Platanus hispanica (Estornell et al., 2018), and this generates poor results for the canopy height parameter. In contrast, as can be observed in Fig. 3, that there is a regular distribution of points throughout the canopy with some points close to the lowest strata of the canopy.

These results suggest that a leafless 3D canopy can be defined properly using airborne LiDAR data. A good estimation of crown height is needed since this parameter was significant for estimating crown and pruning biomass (Velázquez-Martí et al., 2014; Estornell et al., 2015). Nevertheless, according to the main statistics in Table 1, the walnut trees in our study can be considered medium-large in size (28 years). Although the set of trees sampled can be appropriate for estimating the structural parameters of the plot, the results should be interpreted with caution as the trees in our study did not include small-medium trees.

5. Conclusions

Leafless tree crowns of *Juglans regia* L. were extracted successfully from airborne LiDAR data. This was achieved using an original approach which combines alpha-shape algorithm, identification of local maxima on DSM and k-means algorithm. Moreover, structural parameters such as diameter, volume stem, and crown diameter were estimated accurately from these data. A higher density of points distributed in the intermediate and lower stratums of walnut trees was observed when compared to other evergreen agriculture species such as olive trees. Collecting LiDAR data under leafless conditions, far from being a drawback, enabled a more accurate determination of the crown minimum height and therefore crown height. The results of this study could be applied to improve monitoring and management of agriculture plantations such as walnut trees. A spatial database of trees for a plot can be generated including structure parameter information and other management data (pesticides and pruning) that could be estimated from LiDAR structure parameters and this would enable the monitoring and analysis of changes. In addition, the results of this study could be applied to estimate total biomass of this species. To do this, it is crucial to develop models that enable estimations to be made from structure parameters, which can be accurately derived from airborne LiDAR data.

CRediT authorship contribution statement

J. Estornell: Conceptualization, Methodology, Investigation, Writing - original draft, Writing - review & editing, Visualization, Supervision. **E. Hadas:** Conceptualization, Methodology, Investigation, Writing - original draft, Data curation, Visualization, Supervision. **J. Martí:** Software, Formal analysis, Writing - review & editing, Writing - review & editing, Visualization, Supervision. **I. López-Cortés:** Software, Formal analysis, Visualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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