ESTIMATING RESIDUAL BIOMASS OF OLIVE TREE CROPS USING TERRESTRIAL LASER SCANNING

A. Fernández-Sarría[1], I. López-Cortés[2], J. Estornell[1], B. Velázquez-Martí[3], D. Salazar[2]

[1]Dpto. Ing. Cartográfica, Geodesia y Fotogrametría, Universitat Politècnica de València. Camino de Vera s/n, 46022, Valencia (España).

[2]Dpto. Producción Vegetal, Universitat Politècnica de València. Camino de Vera s/n, 46022, Valencia (España).

[3]Dpto. Ing. Rural y Agroalimentaria, Universitat Politècnica de València. Camino de Vera s/n, 46022, Valencia (España).

Corresponding Author: J. Estornell, email: jaescre@cgf.upv.es

Abstract

Agricultural residues have gained increasing interest as a source of renewable energy. The development of methods and techniques that allow to inventory residual biomass needs to be explored further. In this study, the residual biomass of olive trees was estimated based on parameters derived from using a Terrestrial Laser Scanning System (TLS). To this end, 32 olive trees in 2 orchards in the municipality of Viver, Central Eastern Spain, were selected and measured using a TLS system. The residual biomass of these trees was pruned and weighed. Several algorithms were applied to the TLS data to compute the main parameters of the trees: total height, crown height, crown diameter and crown volume. Regarding the last parameter, 4 methods were tested: the global convex hull volume, the convex hull by slice volume, the section volume, and the volume measured by voxels. In addition, several statistics were computed from the crown points for each tree. Regression models were calculated to predict residual biomass using 3 sets of potential explicative variables: firstly, the height statistics retrieved from 3D cloud data for each crown tree, secondly, the parameters of the trees derived from TLS data and finally, the combination of both sets of variables. Strong relationships between residual biomass and TLS parameters (crown volume parameters) were found (R^2 = 0.86, RMSE = 2.78 kg). The pruning biomass prediction fraction was improved by 6%, in terms of R^2, when the variance of the crown-point elevations was selected (R^2 = 0.92, RMSE = 2.01 kg). The study offers some important insights into the quantification of residual biomass, which is essential information for the production of biofuel.

Keywords: TLS; Residual biomass; Voxel; Convex hull; Cloud metrics

1. Introduction

The agricultural sector represents large potential sources of solid biofuels (Bernetti et al., 2004; Beccali et al, 2009; Scarlat et al., 2011). Biomass sources from agricultural systems can be classified as short rotation coppices and pruning wastage from fruit trees (González-García et al., 2014). Among the agricultural waste types, significant amounts of energy-producing woodchips can be obtained from comminuted pruning residues (Jones et al., 2010). The need to quantify regular wastage, which is generated in agriculture management operations, has led to apply dendrometric techniques to retrieve the main geometric parameters of fruit trees. These data are used to develop tools that allow the potential output of pruning biomass in agricultural crops to be calculated. This has also been encouraged by the requirements as stated by the Intergovernmental Panel on Climate Change (IPCC), which requires that all countries report on all lands and for each to be assigned under one of the following 6 categories: Forest Land, Cropland, Grassland, Water land, Settlements, other land; and requires that reporting should be done according to pre-defined carbon pools and carbon flows. On the other hand, both the management and logistics of energy-pruned wood are based on the quantification of waste (Velázquez-Martí and Annevelink, 2009; Velázquez-Martí and Fernández-González, 2010; Velázquez-Martí et al., 2012a). Furthermore, the commercialization of pruning waste can be an additional income to the commercialization of food products.

Previous studies indicated that the residual biomass of agricultural trees can be estimated using dendrometric parameters measured out in the field such as tree height, crown height and crown diameter (Velázquez-Martí et al., 2011a, b, c; Sajdak et al., 2014; Velázquez-Martí et al., 2016). As an alternative to the classical use of dendrometry, a large list of published studies has been focused on estimating tree parameters by remote sensing techniques such as Airborne Laser Scanning (ALS) and Terrestrial Laser Scanner (TLS), mainly in forestry applications (Solberg et al., 2006; Popescu, 2007; Popescu and Zhao, 2008; Straub and Koch, 2011; Moskal and Zheng, 2012; Srinivasan et al., 2015). These techniques have enabled researchers to obtain highly-detailed geometric properties, even for the tree crowns which were previously unattainable using classical dendrometry.

The modeling of the tree canopy with TLS allows a repeatability of the dendrometric parameters with high detail (millimeter-level). This technique is also capable of determining other parameters no directly measured by traditional techniques such as the biomass components (total, stem and branches) (Liang et al., 2016) and the crown volumes (Fernández-Sarría et al., 2013b; Estornell et al., 2017). Furthermore, TLS systems allows to define irregular crown trees with higher detail compared to traditional techniques (Fernández-Sarría et al., 2013a). In addition, ALS systems allow to improve traditional standwise forest inventory (Holopainen et al., 2010). So, these geographical data could help researchers to model crowns whilst improving the results of earlier studies that had considered the issue of estimating pruning biomass. Modeled volume and statistics derived from LiDAR point clouds can be related to production, necessary inputs (water, fertilizers and pesticides), pruning and energy wood (Palacin et al., 2007; Escolà et al., 2017; Gil et al., 2014; Estornell et al., 2015). ALS techniques demonstrated limited results in extracting 3D crown data since most of the pulses are intercepted by the higher parts of the crown and therefore the data relating to the lower areas are insufficient (Hadás and Estornell, 2016; Hadás et al., 2017). In contrast, good results were reported in olive and walnut trees when TLS data were applied to estimate height, diameter and volume of the crowns (Moorthy et al., 2011; Estornell et al., 2017). In addition, the recording of the data when using laser scanner systems can be optimized by transporting the emitters on board field vehicles what makes this technology more efficient (Rosell et al., 2009).

The aim of this paper was to focus on relating TLS variables retrieved from 3D crown architecture to residual biomass estimation. The key innovation within this study was to analyze if the enhanced detail provided by a TLS system, that allows the generation of a 3D shape of the crown, could in fact improve the earlier studies that had been carried out to estimate pruning biomass, either through data gathered out in the field using traditional techniques or through previously used and tested ALS techniques. The vast majority of these studies are focused on retrieving tree parameters of forest trees such as tree position, trunk and crown diameters, tree height, biomass, and crown volume (Vastaranta et al., 2009; Liang et al., 2012; Kankare et al., 2013; Srinivasan et al., 2014, 2015). In this study, we also analyzed a set of height metrics from TLS point cloud of the crown data which was combined with geometric parameters derived from TLS point cloud (tree and crown height, crown diameter and crown volume) in order to determine whether more accurate results could be obtained for estimating residual biomass.

2. Materials and methods

2.1 Study Area

This study was done in Viver, a municipality located in the inland area of the Castellon province in Spain, (Fig. 1) which has a typical Mediterranean climate: warm with dry summers (22 ºC) and moderate winters (7 ºC). The average annual rainfall is 550 mm. The average elevation is 600 m above sea level. A set of 32 of the *Olea europaea* species were selected in 3 zones, intending to cover the 3 different age ranges observed in the study area: young trees (n=8), medium (n=16) and adult (n=8). In Figure 2, the structure of an olive tree for each class can be observed. The more abundant category found in the study area was the medium-sized one. The olive tree crops that were studied were Arbequina (zone 1) and Picual (zones 2 and 3) (Fig. 1). The characteristics of these varieties are based on The International Union for the Protection of New Varieties of Plants (UPOV, 2011) and are shown in Table 1. UPOV is an intergovernmental organization to provide and to promote an effective system of plant variety characterization and protection with the aim of encouraging the development of new varieties of plants for the benefit of society.

Diameter and height of crown, trunk diameter and total height were measured from each tree in the field at the study site. The stem and crown diameters were measured using a diameter tape. The longest crown diameter and its perpendicular one were measured. The average of these two values was considered as a crown diameter for each tree. The total height was measured using a metric pole. The length of the trunk was also measured with a tape. The height of the crown was calculated as the difference between total height and trunk length. The volume of the crown was calculated using a paraboloid solid as a surface model (Eq. (1)) (Velázquez-Martí et al. 2012b, 2014; Estornell et al., 2017).

$$V_p = \frac{1}{2}\frac{\pi \cdot Dc^2 \cdot Hc}{4} \qquad (1)$$

Being, Vp (m^3) paraboloid volume used to model olive tree crown, Dc crown diameter (m) and Hc crown height (m).

Table 1. Basic pomological characteristics of studied cultivars

UPOV Characteristics		Arbequina cv		Picual cv	
		UPOV Note	UPOV State	UPOV Note	UPOV State
Tree: vigor	1	5	Medium	7	Strong
Tree: growth habit	2	7	Dropping	5	Upright
Tree: canopy density	3	5	Medium	7	Dense
Tree: wood color	4	1	Greyish Green	2	Light grey
Frutiting shoot: number of lateral shoots	6	2	Few presents	4	Many
Fruit: size	21	-	Small	-	Medium
Fruit: weight	-	1.51±0.86		3.67±0.72	

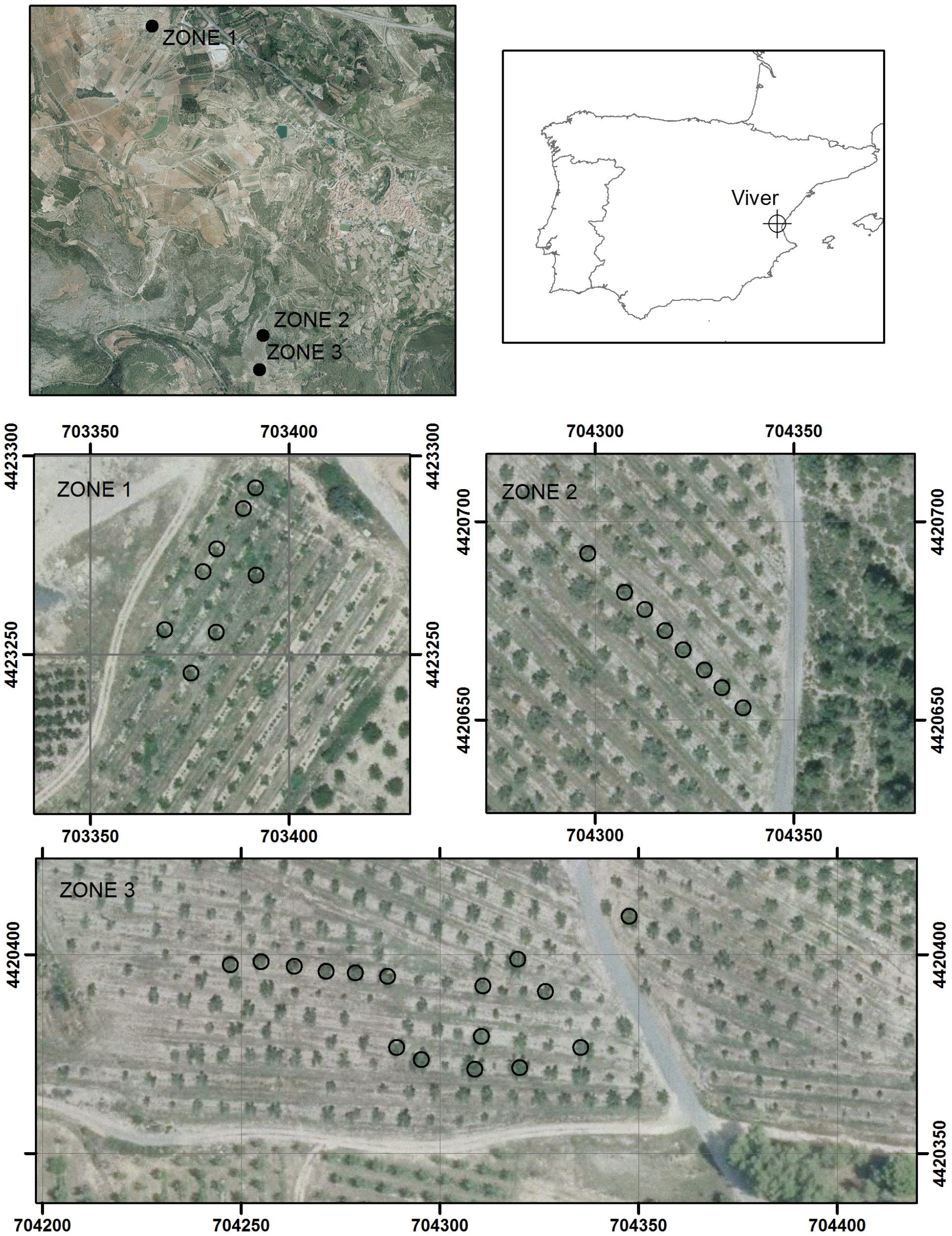

Figure 1. Location map of the olive trees (coordinates in meters, UTM projection, ETRS89 Zone 30 North). Orthophoto courtesy of IGN, Spain.

The main statistics of these parameters are presented in Table 2. In addition, each tree was pruned and its biomass was weighed out in the field. Pruning entailed the use of mechanical harvesting using a trunk vibrator and an inverted umbrella collector. Consequently, the trees only had one trunk and no low branches, in order to achieve a free 60º angle to spread the inverted umbrella structure. Vertical bunds were also removed because they are resiliently strong and are unfruitful.

Table 2. Statistics of the parameters of olive trees measured in field (n=32)

Parameter	mean	standard deviation	minimum	maximum
Stem Diameter (m)	0.25	0.19	0.07	0.81
Crown diameter (m)	3.63	1.05	1.98	6.38
Crown height (m)	2.77	0.33	2.07	3.5
Total height (m)	3.49	0.49	2.47	4.48
Crown parabolic volume, Vp (m^3)	10.45	10.93	3.25	51.23
Residual biomass (kg)	8.24	7.67	2.06	31.4

2.2 Laser scanner data

Olive trees were registered by a LEICA Laser Scanner Scan station C10 (Leica Geosystems, Heerbrugg Switzerland). The main characteristics of this equipment are shown in Table 3. Each tree was scanned on average from 3 positions to assure that the whole tree was registered. For larger trees, an additional scan was carried out. The scanner resolution was set at 7 mm and at 10 m, but since the scanner was placed at a distance lower that this value, the point density was higher. On average, 3 HDS (High Definition System) reference targets, were used to register the different scans and create a unique point cloud for each tree. To do these operations, Cyclone Software v.6 (Leica Geosystems, Heerbrugg Switzerland) was used. Each merged point cloud was filtered manually from shrub and herbaceous vegetation commonly found in olive crops. The existence of points that are registered at a certain distance from the target and present anomalous values of intensity can be a problem in TLS data processing. In this work, 2 routines were developed using MATLAB version R2010b (Mathworks, Inc.): one to eliminate isolated points that showed a specific distance from the rest points, with a threshold of 2.5 cm being set to consider the dimensions of the olive tree leaves. Another routine was implemented to eliminate points that had inconsistently high and low values of intensity. To calculate the total height, the crown height, crown diameter and crown volume, specific routines were developed by MATLAB. 3 entry files were created manually to compute these parameters: one file that contained points of the whole tree, another one that contained the crown points and the last one that used the trunk points.

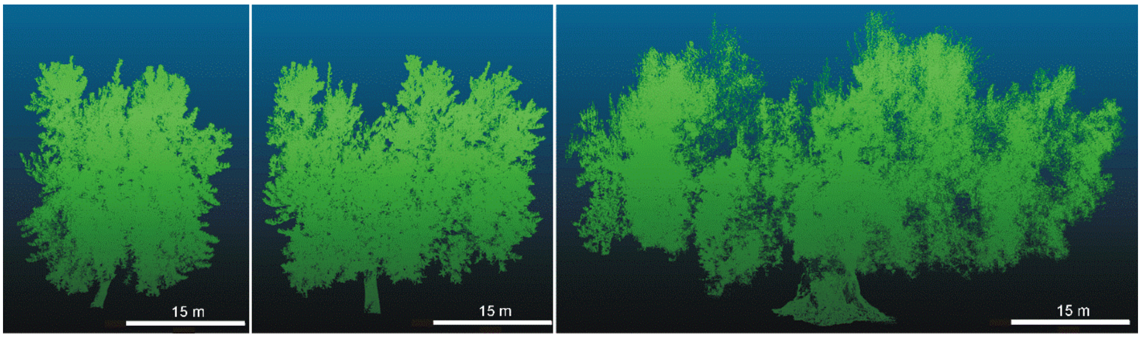

Figure 2. Representation of 3 olive trees registered by the TLS system corresponding to the categories small, medium and large.

Table 3. Basic characteristics of the LEICA C10 TLS (https://hds.leica-geosystems.com).

Technical parameter	Value
Range Leica C10	300 m 90% albedo; 134 m 18% albedo
Scan rate	Up to 50,000 points/second
Field of view	
Horizontal	360º
Vertical	270º
Wavelength	532 nm, visible, green color
Scan resolution (spot size)	From 0-50 m: 4.5 mm
Accuracy of single measurement	
Position	6 mm
Distance	4 mm
Angle (horizontal/vertical)	60 μrad / 60 μrad (12” / 12”)
Modeled surface precision / noise	2 mm
Target acquisition	2 mm
Dual-axis compensator	Selectable on/off, resolution 1”, dynamic range+/- 5’, accuracy 1.5”

2.3 Geometric parameters derived from TLS point clouds

Several routines were developed to calculate the following dendrometric parameters from TLS: total height, crown height, crown diameter and crown volumes using the following methods: global convex hull volume (V_{gch}), convex hull by slice volume (V_{chs}), section volume (V_{sec}) and voxel volume (V_v). These parameters were compared to the parameters measured using traditional techniques. Simple linear regression models were calculated and the values of R^2 and RMSE were obtained.

Total and crown height: the file that contained 3D points of the whole tree was used to calculate the total tree height. This parameter was computed calculating the difference between the points with maximum and minimum heights. For the crown height, the file that contained 3D crown points was used. In this case, this parameter was derived by calculating the difference between the maximum heights and minimum heights of the crown.

Crown diameter: an algorithm was developed in order to obtain this parameter. This method required the calculation of each tree center using 3D crown points. All diameters were obtained by using this point. In relation to all diameters, the maximum diameter and its perpendicular one were selected as crown diameters. Details of this procedure can be found in Fernández-Sarría et al. (2013a). For this parameter, the files that contained trunk and crown points were used; the first one to define the trunk structure (the trunk center was considered the tree center), and the second one to calculate the diameters that pass through the center. The algorithm is described using the following steps: (i) The center of each tree was calculated taking into account all 3D crown points within a section at a height of 5 cm above the trunk to ensure there are enough points in the top part of the trunk to define the shape of its section and then to determine the position of the trunk and the crown center. (ii) The selected points were projected on a XY plane and their Cartesian coordinates were transformed into polar coordinates (measuring the distance and angle with respect to the crown center). (iii) Each tree crown was divided into sections of 5º, to obtain 72 sections. The longest radius of each section was selected. (iv) Each radius selected in each section was added to the opposite one obtaining 36 diameters for each crown. (v) The longest and its perpendicular diameter were selected and the diameter was calculated using the mean of these 2 values.

Crown volumes: 4 approaches to obtain crown volumes were used (Fig. 3). The 4 algorithms were calculated using Matlab (Fernández-Sarría et al., 2013b) and the files with only crown points were used as data entry. The 4 algorithms applied for calculating crown volumes are described below:

• Global convex hull volume (V_{gch}): This is an application to calculate the convex hull surface (quick hull algorithm, Barber et al., 1996) for the crown points of olive trees. In a first step, 6 exterior crown points (maximum and minimum X, Y, Z) were selected to generate an octahedron. Crown points within this volume were discarded and from the remaining points, the furthest crown points of the 4 regions of the octahedron were selected to create a new 3D shape. The same process was repeated until there were no more external points to the 3D shape created in the previous step. The volume of the final 3D shape was calculated as the crown volume for each tree.

• Convex hull by slice volume (V_{chs}): The crown points for each tree were divided into slices that had 10 cm in height. This value was selected to avoid sections without points. The total volume for each tree crown was calculated using the sum of each slice area.

• Section volume (V_{sec}): This method is based on the calculation of a 2D Delaunay triangulation and uses sections at every 10 cm in height. The global volume was obtained by adding the volume of all sections.

• Voxel volume (V_v): This process enables the transformation of a point cloud into small volumetric units (voxels) using 3-dimensional space grid (Hosoi and Omasa, 2006). Due to the small size of olive tree leaves, a voxel size of 3 cm was selected. The volume of each crown was computed adding the volume of each voxel (27 cm^3) with data (points within voxels).

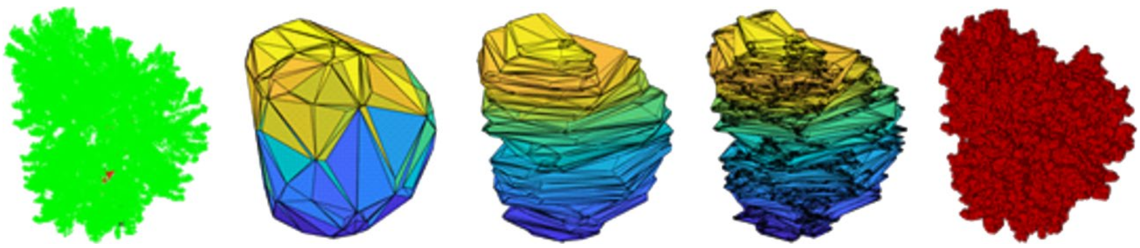

Figure 3. Different ways to define olive crown number 12: TLS point cloud; global convex hull; convex hull by slice volume; section every 10 cm; 3 cm voxels.

The estimation of pruning biomass was also analyzed using a set of height metrics from TLS point cloud for each crown. The elevation of each point was normalized by referring to the minimum elevation of each crown tree. These data were computed using the Cloudmetrics tool of FUSION, version 3.70 (McGaughey, 2014): Total number of returns, Minimum (Elevmin), Maximum (Elevmax), Mean (Elevmean), Mode (Elevmode), Standard deviation (Elevsd), Variance (Elevvar), Coefficient of variation (Elevcv), Interquartile distance (Elevid), Skewness (Elevskew), Kurtosis (Elevkur), AAD (Average Absolute Deviation, ElevAAD), MADMedian (Median of the absolute deviations from the overall median, ElevMADMedian), MADMode (Median of the absolute deviations from the overall mode, ElevMADMode), L-moments (L1, L2, L3, L4), L-moment skewness (Lskew), L-moment kurtosis (Lkur), Percentile values (1st, 5th, 10th , 20th, 25th, 30th, 40th, 50th, 60th, 70th, 75th, 80th, 90th, 95th, 99th percentiles, Pvalue), Canopy relief ratio (CRR) ((mean - min) / (max – min)), Generalized means for the 2nd and 3rd power (Elev quadratic mean, Elevqm and Elev cubic mean, Elevcm).

2.4 Pruning biomass modeling

To estimate the pruning biomass using TLS data, 2 sets of potential independent variables were considered: height metrics from TLS points for each crown, and the tree geometric parameters derived from TLS data (included total height, crown height, crown diameter and crown volume, using the global convex hull volume, convex hull by slice volume, section volume and voxel volume methods). These data were considered to calculate stepwise regression models using the following potential explicative variables: a) height metrics for each TLS crown (model 1); b) geometric parameters derived from TLS point clouds (model 2); and c) combining both sets of data (model3). Multicollinearity using multi regression models was analyzed by means of Variance Inflation Factor (VIF) values. A VIF value lower than 5 indicates that the explicative variables used for calculating the regression models do not show multicollinearity (Rogerson, 2001). Other authors suggested that the maximum value of VIF should be 10 (Marquardt, 1970; Kennedy, 1992; Hair et al., 1995). In our study, we used a more restrictive VIF (value =5) to ensure that the regression models obtained were not affected by multicollinearity.

Shapiro-Wilk tests using a significance level of $\alpha = 0.05$ were applied to analyze whether the residuals followed a normal distribution or not. A cross-validation procedure was used to assess the reliability of these models by leave-one-out technique. A comparison between the Root Mean Squared Prediction Error (RMSEcv) and the Root Mean Square Error of the regression (RMSE) was done. In addition, field data and predicted values obtained from cross-validation techniques were compared, calculating a scatter plot with a regression fit line and the coefficient of determination measurement.

3. Results and discussion

3.1. Crown volume

Figure 4 includes some results relating to the comparisons between field and TLS parameters such as total height, crown diameter and crown volume. Strong relationships were obtained for these tree parameters with R^2 values 0.85, 0.92 and 0.87, respectively. These results are in line with those reported by Moorthy et al., (2011) in olive trees. In addition, similar results were also found for these parameters in walnut trees using TLS data (Estornell et al., 2017). These results confirm the accuracy of the terrestrial laser scanner to retrieve the basic parameters of fruit trees. It is important to highlight the ability of the TLS technique in estimating the crown volumes for olive trees. This variable, as will be seen in the next section, is well correlated with the residual biomass of the crown. The highest correlations between TLS and field crown volumes were obtained for the following methods: global convex hull, convex hull by slice volume, and section volume with same values of determination coefficient ($R^2 = 0.87$). The Kruskal-Wallis test was applied to analyze if there were statistically significant differences among the crown volumes calculated by each of these 3 methods. The statistic was 2.16 and the p value

0.3394 indicating that there were not statistically significant differences among the medians of each group of volumes, with a confidence level of 0.95. These results indicate that any of these tree methods could be used to calculate field crown volumes. In contrast, a significant decrease in terms of R^2 was obtained for V_v (R^2=0.77).

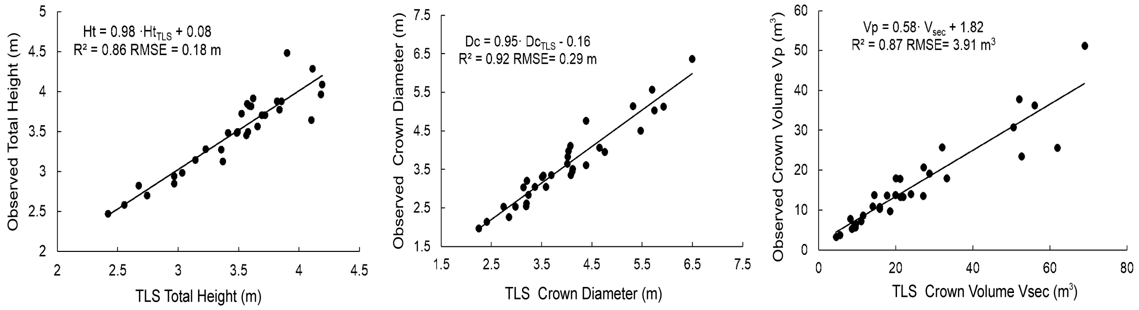

Figure 4. Comparison of field and TLS parameters for Total Height (Ht), Crown Diameter (Dc) and crown volume calculated from field data (V_p) and by the section volume from TLS data (V_{sec}).

3.2. Regression models

The results of the regression models for estimating residual biomass are presented in Table 4 for each group of explanatory variables, namely: height metrics from TLS crown points; geometric parameters computed from TLS data; and combination of both sets of statistics. The model with the lowest R^2 value (0.46) was calculated considering only height metrics derived from the TLS crown points (model 1). For this model, the RMSE and RMSE% were 5.3 kg and 65 %, respectively. In this model, the median of the absolute deviations from the overall median (Elevmad) and the maximum elevation (Elevmax) were selected as explicative variables. However, using these variables that were retrieved from the TLS cloud data to predict the residual biomass of olive trees did not deliver sufficiently good results. In reviewing the literature, no published agricultural studies have yet been found on the retrieval of any statistical parameters relating to tree structures. However, the relevance of these types of variables has been reported in forestry applications for the estimation of tree characteristics (Næsset and Gobakken; 2005, Yu et al., 2011; Kankare et al., 2013) and, mainly, for forest plot attributes (Hevia et al., 2016; Guerra-Hernández et al., 2016; Castaño-Díaz et al., 2017; Domingo et al., 2018). The results improved for models in which the geometric parameters retrieved from TLS data were used (model 2), as evidenced by the explained variance (R^2=0.86). This model included one statistically significant variable: section volume. For this model, the RMSE and RMSE% were 2.78 kg and 33.7 %, respectively. This variable characterizes the tree crown in 3 dimensions and has an obvious relationship with residual biomass. In fact, it was observed that the higher the crown volume, the more pruning biomass that was estimated. Similar results were obtained for crown volumes calculated by the methods: global convex hull and convex hull by slices with values of R^2 of 0.86 and 0.85, respectively. These results are congruous with previous studies indicating that the most accurate correlations were obtained for geometric parameters derived from the TLS data instead of using statistical height parameters retrieved from the crown cloud points (Kankare et al., 2013). In urban forest studies, good results were also found when residual biomass of *Platanus hispanica* was estimated using TLS data (R^2=0.73) (Fernández-Sarría et al., 2013a). In this case, the explanatory variable that was selected was the crown volume calculated by the voxel-based method. In our study, the relevance of this variable to estimate the residual biomass of olive trees was also analyzed, obtaining lower values in terms of R^2 (0.63). A possible explanation for this might be that olive trees especially have a high density of leaves which makes it more difficult for the energy beam to penetrate their crowns and therefore, there is little data within the crown for volume calculation (Fig. 5). Another factor to be considered in this case was the voxel size. Previous studies used larger voxel sizes, 0.25 m – 0.4 m (Hauglin et al., 2013; Fernández-Sarría et al., 2013b) to calculate the crown volumes in forest trees, in comparison with the selective size chosen in our study (0.03 m). This is an important issue for future research. However, larger sizes would be not suitable in the case of estimating canopy gap fraction measurements (Cifuentes et al., 2014; García et al., 2015).

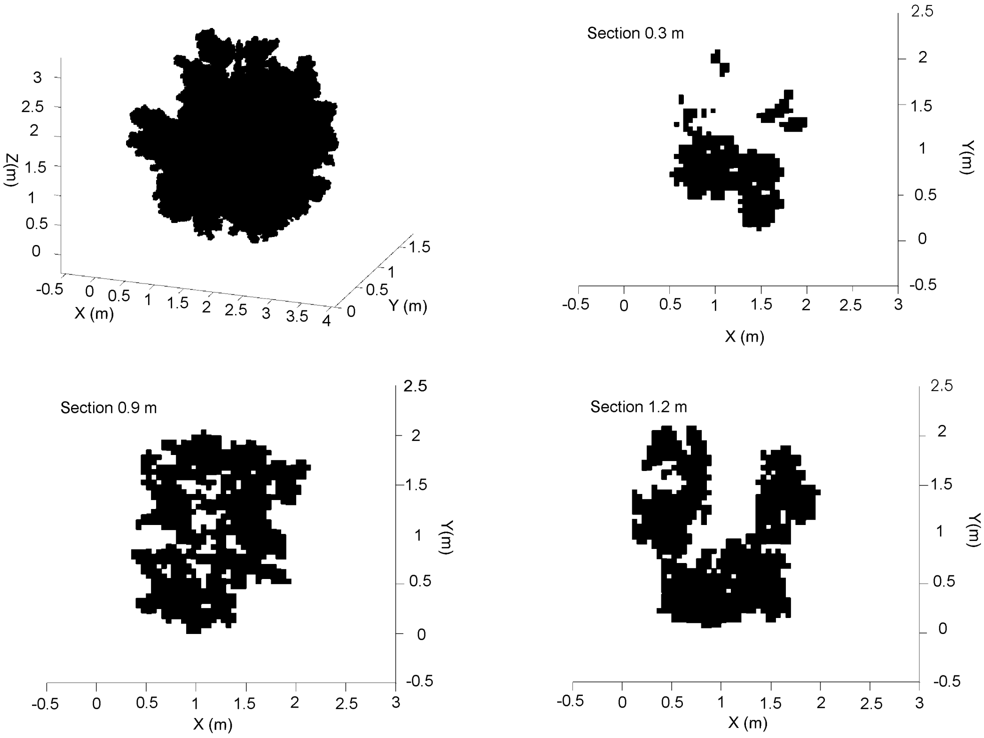

Figure 5. Representation of the 3D crown of a olive tree and 3 horizontal sections at 0.3 m, 0.9 m and 1.2 m.

The most accurate model was obtained when tree parameters and metrics retrieved from the TLS crown data were combined (model 3), which gave R^2, RMSE and RMSE % values of 0.92, 2.01 kg and 24.3%, respectively (Table 4). This stepwise model included 2 significant variables: crown volume calculated by section method (V_{sec}) and height variance of the crown points (Elevvar). In this model, the crown volume explained the large variability in the pruning biomass. This estimation improved by 6% when a metric derived from the TLS cloud data was selected (Elevvar). Similar results were obtained for models that used convex hull by slice volume and Elevar variables (R^2=0.92) and global convex hull volume and Elevar variables (R^2= 0.91). Although these 3 methods to calculate crown volume could be used for residual biomass estimation we selected the V_{sec} since it gave slight improvements in the estimations. Akaike Information Criterion (AIC) was also calculated for each model considering as independent variables Elevvar-section volume, Elevvar- Convex hull slice volume, and Elevvar- Global Convex Hull volume being 1.68, 1.69 and 1.77 selecting the first pair of variables since they gave the lowest AIC value.

TLS predicted versus field-measured biomass showed a good linear relationship close to the 1:1 line (Fig. 6). These outcomes are consistent with earlier research using airborne LiDAR data in olive trees (Estornell et al., 2015). In that study (n=25), the model included 2 significant variables: the area of the crown and maximum intensity. The results in terms of R^2 and RMSE were 0.89 and 2.78 kg (relative RMSE = 30%), respectively. The relative RMSE of the model calculated in our study improved by 6% when compared to the model obtained from ALS data. In addition, we propose a model that does not contain any variable related to intensity values. This type of data may generate some drawbacks relating to atmospheric effects and illumination conditions that need to be normalized.

For the residuals, the results of the Shapiro-Wilk test ($W = 0.955$, p-value > 0.05) indicated that they were normally-distributed (Fig. 6 right). The mean value of the residuals (-0.01) and the near linear pattern of them in the normal probability plot (Fig.6 right) confirmed the normality of the residuals. The validation of estimated pruning biomass was done by the leave-one-out cross-validation technique using the variables selected in the regression model 3, i.e. V_{sec} and Elevvar. As a result, the root mean squared prediction error (RMSEcv) was therefore calculated from the predicted biomass values, applying this validation technique. Similar values were found between RMSEcv and RMSE (2.01 kg vs 2.24 kg), which indicated the capability of the calculated model in estimating the pruning biomass of olive trees. In addition, a strong correlation was found among field data and predicted values that were obtained from using the cross-validation technique (R^2 = 0.91).

Table 4. Residual biomass models using height metrics from TLS of crown points (model 1), geometric parameters derived from TLS (model 2) and the combination of both sets of data (model 3).

Parameter	Estimate	SE	t	P-value	VIF	R^2_{ADJ}	R^2_{cv}	RMSE	$RMSE_{cv}$
Constant	-11.711	9.861	-1.188	0.245					
Elevmax	14.491	2.750	5.239	0.000	1.60	0.46		5.36	
Elevmad	-62.225	24.885	-2.500	0.018	1.60				
Model 1	**B_r = -11.711 + 14.491·Elevmax – 62.225 · Elevmad**								
Constant	-1.795	0.887	-2.023	0.052					
V_{sec}	0.406	0.029	13.812	0.000	1.00	0.86	0.84	2.78	3.03
Model 2	**Br = -1.795 + 0.406·V_{sec}**								
Constant	8.544	2.103	4.063	0.000					
V_{sec}	0.486	0.027	18.309	0.000	1.52	0.92	0.91	2.01	2.23
Elevvar	-29.339	5.674	-5.171	0.000	1.52				
Model 3	**B_r = 8.544 + 0.486·V_{sec} – 29.339·Elevvar**								

B_r: residual biomass (kg); independent variables derived from cloud data for each tree: Elevation maximum (Elevmax); Median of the absolute deviations from the overall median (Elevmad); section volume method (V_{sec}); Elevation variance of each tree point cloud (Elevvar); Standard error of the coefficients (SE); variance inflation factor (VIF); Root Mean Square Error in kg (RMSE); cross validation root mean square error in m ($RMSE_{cv}$); cross validation determination coefficient (R^2_{cv})

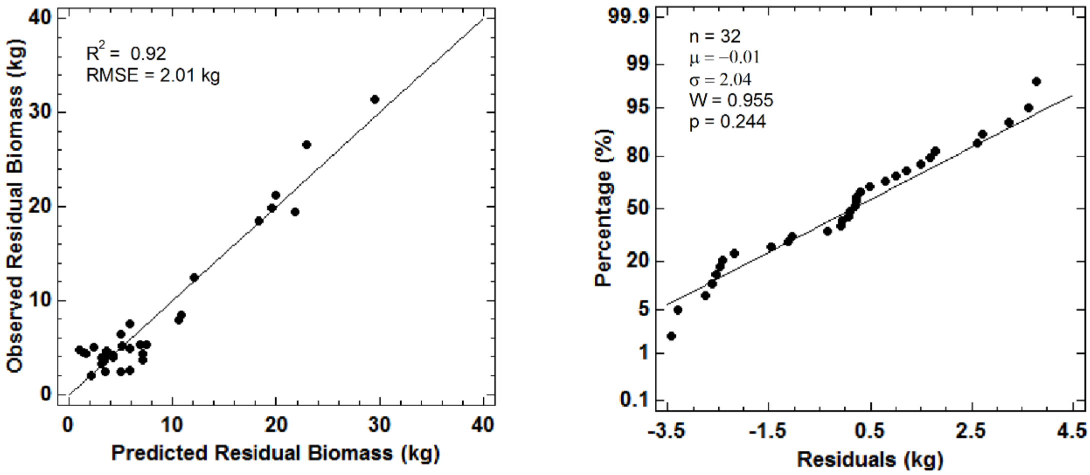

Figure 6. Scatterplots of the predicted versus observed residual biomass (left) and the normal probability plot of the volume residuals (right).

4. Conclusions

In this study, the capability of a TLS system was demonstrated to estimate residual biomass. It was validated that the performance of the models improved when the geometric parameters (crown volume) and height statistics of the TLS crown points (variance of the heights) were combined to estimate residual biomass. The results achieved in this study improved in terms of determination coefficient and RMSE, respectively compared to those obtained in earlier research. In addition, dendrometric parameters such as the total height, crown diameter and crown volume were also obtained with high accuracy, by means of TLS data. These results confirmed that this technology enables the estimation of pruning biomass and other parameters. The methodology applied in this work could be applied to other fruit trees in order to quantify and locate potential pruning biomass in a specific area. Knowledge of the amount of residues available is an important element in the Biofuel Supply Chain, just as much as supplying bio-materials to be processed in biofuel plants.

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