Journal of
Applied Remote Sensing

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Abstract. Shrub vegetation is a key element of Mediterranean forest areas and it is necessary to develop tools that allow a precise knowledge of this vegetation. This study aims to predict shrub volume and analyze the factors affecting the accuracy of these estimations in small stands using airborne discrete-return LiDAR data. The study was performed over 83 circular stands with 0.5 m radius located in Chiva (Spain) mainly occupied by *Quercus coccifera.* The vegetation inside each area was clear cut, and the height and the diameter of each plant was measured to compute the volume of shrub vegetation per stand. Volume values were related with maximum height values derived from LiDAR data reaching a coefficient of determination value $R^2 = 0.26$. Afterwards, factors affecting the quality of volume estimations were analyzed, i.e., vegetation type, LiDAR density, and accuracy of the digital terrain model (DTM). Significant accuracy improvements ($R^2 = 0.71$) were detected for stands with 0.5 m, LiDAR data density greater than 8 points/m^2, vegetation *Q. coccifera*, and error associated to the DTM less than 0.20 m. These results show the feasibility of using LiDAR data to predict shrub volume under certain conditions, which can contribute to improved forest management and characterization. *© 2012 Society of Photo-Optical Instrumentation Engineers (SPIE).* [DOI: 10.1117/1.JRS.6.063544]

Keywords: shrub; volume; LiDAR data; digital terrain model.

Paper 11265 received Dec. 12, 2011; revised manuscript received Apr. 26, 2012; accepted for publication May 2, 2012; published online Jun. 21, 2012.

1 Introduction

The presence of shrub vegetation is widely spread in Mediterranean ecosystems. From an environmental point of view these areas play a significant role as they prevent soil erosion and desertification, which can help refill aquifers[1] or contribute to wildlife habitat preservation.[2] In addition, an accurate knowledge of these areas enables the creation of fuel-type maps to improve the fire behavior modeling accuracy.[3] Therefore, defining and developing tools that allow a better understanding of these areas is necessary in order to improve their management and maintenance. LiDAR data have been widely used in forestry for estimating forest canopy fuels;[4–6] estimating forest parameters;[7–9] creation of inventories;[10,11] estimation of forest carbon stocks;[12,13] analysis of forest dynamics.[14–16] According to,[17] forest studies based on LiDAR data are usually developed following two approaches: by estimating dendrometric variables such as stem diameter, volume, biomass, height,[18–20] which requires a preceding identification of individuals; and by estimating dasometric variables at plot or stand level. A common denominator of these studies is the requirement of the computation of a digital terrain model (DTM), which constitutes the reference surface to which all the LiDAR data are normalized.

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Despite the large number of studies developed in forestry based on LiDAR data, few studies have been focused on shrub vegetation, yet less conducted in the estimation of variables, such as biomass and volume. Most studies aim to perform classifications and mapping shrub areas,[2,21,22] and to estimate shrub heights.[3,23,24] In order to study the areas occupied by shrub, from the two approaches foreseen for forestry applications, dendrometric characterization of individual shrubs is very complex, as shrubs often occupy a continuous area in which the crown definition is quite difficult. Therefore, the approach based on estimation of dasometric parameters seems more plausible. However, some studies have shown the potential to estimate the height and biomass in small stands (radius $= 0.5$ m).[25] Streutker and Glenn[23] compared the field height of shrub vegetation and the maximum height derived from LiDAR data, obtaining the maximum correlation value when the maximum LiDAR height was calculated considering an area with radius 1.5 m around the point measured at field. These results agreed with those obtained by[26] that pointed out that the radius value depends on several factors, such as accuracy of LiDAR system, GPS unit employed, DTM error, slope, or density of LiDAR data. All of them affect the accuracy of the statistics derived from LiDAR data.

The objective of this study is to attain an estimation of shrub volume in small stands (radius $= 0.5$ m) using LiDAR data. The influence of vegetation species, error associated to DTM, and density of LiDAR data on the accuracy of the models obtained is also analyzed. Additionally, the effect on volume estimations when statistics derived from LiDAR data are calculated using greater radii is tested, as well as the relationships between the values of these radii and the above-mentioned factors.

2 Materials and Methods

2.1 *Study Area*

The study area is located in the municipality of Chiva (Spain), covering an area of 10 km^2, included in a rectangle defined by UTM coordinates X_{maximum}, Y_{maximum}, X_{minimum}, and Y_{minimum} (689800, 4376028, 683800, 4373000), zone 30N, in the reference system European Datum 1950 (Fig. 1). The area is mountainous and predominantly covered by shrub vegetation, in which the height varies between 442 and 1000 m with an average slope of 45%. The most abundant species is *Quercus coccifera* (Fig. 2), widely spread in the Mediterranean region.[27,28]

2.2 *LiDAR Data*

The airborne discrete-return LiDAR data were acquired during a flight in December 2007, using an Optech ALTM 2050 system. The technical parameters can be found in Table 1. The altimetry accuracy of LiDAR data was assessed by means of 60 checkpoints located in flat areas without

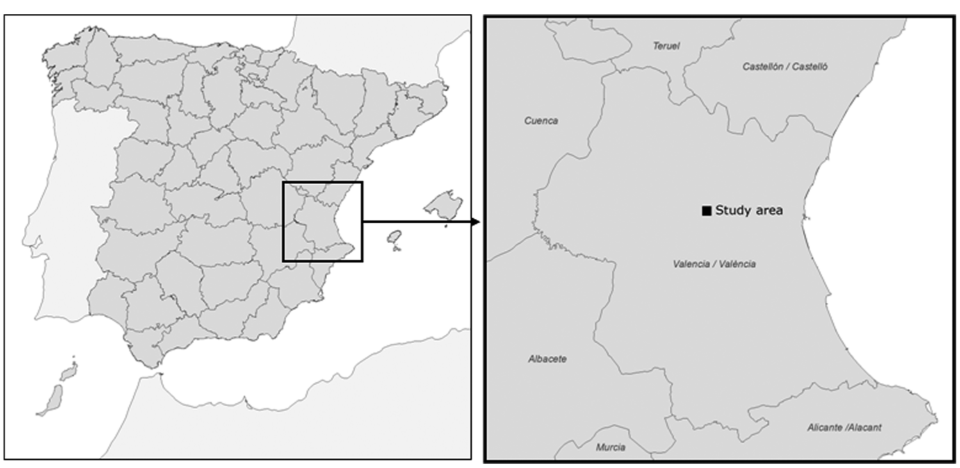


Fig. 1 Location of study area in Chiva (Spain).

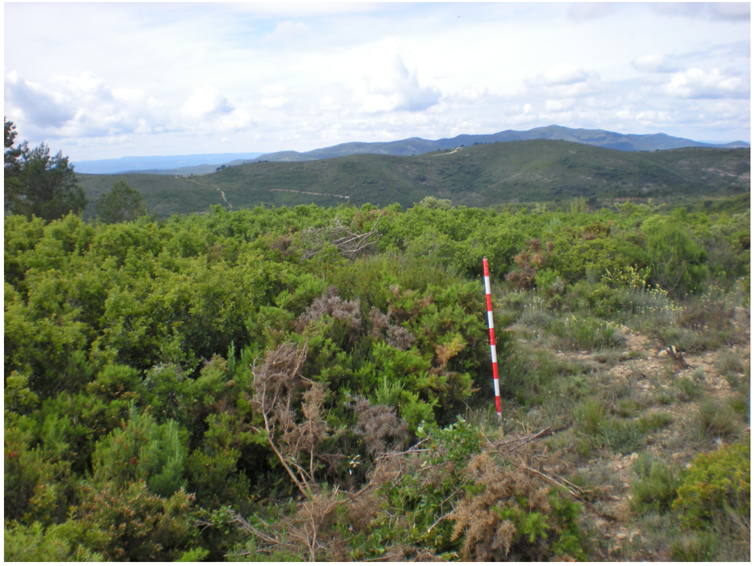


Fig. 2 Image of the study area showing a dense presence of kermes oak (*Quercus coccifera*).

Table 1 ALTM 2050 laser scanner performance parameters.

Parameter	
Flight height	700 m above ground
Pulse frequency	50 kHz
Scan frequency	47 Hz
Scan angle	±18°
Speed flight	70 m/s
Swath width	400 m
Distance between a scanning trajectory flight	300 m
Number of strips	10
Total points obtained for the test area	78,919,301
Pulse density	8 points/m^2
Number of echoes	2

vegetation and measured using a real time kinematic (RTK) GPS system (Leica System 1200). The root mean square error (RMSE) of the set of measurements was 6 cm. The horizontal accuracy of LiDAR points was 0.5 m according to the specifications of the technical report of the vendor company.

In order to calculate statistics derived from LiDAR data that are used as explanatory variables in the regression models, it is necessary to previously compute a DTM. Then, raw LiDAR data and the DTM are combined to convert point elevations into heights above ground. This DTM was done using iterative processes for selecting minimum elevations in decreasing analysis windows and height thresholds for removing vegetation points. Several tests were carried out to set the optimal parameters (further information can be found in Ref. 29). A set of 1397 checkpoints randomly located across the study area were measured with a RTK-GPS system. The DTM with the minimum root mean square error ($\text{RMSE} = 0.19$ m) was achieved using the following parameters: analysis window sizes of 10, 5 and 2.5 m, and height thresholds equal or greater than 1.5 m.

2.3 *Volume Field Data*

To obtain field data volume, 83 circular stands of 0.5 m radius were randomly located throughout the study area in different bioclimatic layers (elevation), slopes and aspects. Field work was timed to practically coincide with the acquisition of LiDAR data. It was performed within a period of three months after the LIDAR data acquisition, remaining the structure of vegetation invariable for this period of time. In each stand, a clearing was performed and the length and base diameter of each plant was measured. In addition, the species of each plant were also identified. It should be pointed that stands larger than 0.5 m radius could not be clear cut because of environmental reasons. To determine field volume it was necessary to characterize the dendrometry of the plants, following the next steps:[1]

Step 1 Determination of a global form factor, f. This factor is calculated as quotient of the actual volume of the plant and the volume of a geometric model taken as reference [Eq. (1)]. The actual volume of each plant was obtained by submerging it in water and determining the volume displaced. The volume model was calculated as a solid of revolution from the diameter of the main stem and the plant height. In this study, a cylinder was used as a solid of revolution, as it was the best adapted to the species studied.[1]

$$f = \frac{\text{Real volume of the plant}}{\text{Model volume of the plant}}. \tag{1}$$

Step 2 Estimation of the actual volume of each plant from variables such as height and stem diameter, the values of form factor calculated in the previous step and using Eq. (2).

$$V_i = \frac{\pi \cdot d^2}{4} \cdot h \cdot f, \tag{2}$$

where V_i is the real volume of the whole plant, d is the base diameter of the main stem, h the height of the individual plant measured for each plant in the sample group, and f the form factor.

Step 3 Estimation of the actual volume of each stand adding the actual volume of each individual from the diameter and length measurements in the field and applying Eq. 2. In Table 2 the statistics of dominant heights and volume of stands are presented.

2.4 *Analysis of the Factors that Affect the Accuracy of Volume Estimation*

To estimate the volume of shrub vegetation from LiDAR data, the maximum height from the LiDAR point cloud within each stand was calculated. This statistic was used as the only explanatory variable in the regression model. Previously, the bare-earth surface elevation was first subtracted from each LiDAR point by using the DTM.

Then, the affection of the vegetation type, error associated to the DTM, and the density of LiDAR data on the accuracy of volume estimations in small stands was analyzed. In order to analyze the vegetation factor in the prediction models the stands were grouped into two classes: stands with *Q. coccifera* ($n = 47$) and stands with others species, i.e., *Rosmarinus officinalis, Ulex parviflorus, Cistus albidus L.* and *Erica multiflora L.* ($n = 36$) The number of LiDAR

Table 2 Statistics of height and volume derived from field data.

Statistic	Height (m)	Volume (dm^3)
Mean	1.27	4568.86
Minimum	0.80	1130.76
Maximum	2.50	11095.16
Standard deviation	0.29	2201.84

points per stand was calculated to study the density factor, then the stands were classified into two classes: density > 8 points/m^2 ($n = 47$) and density < 8 points/m^2 ($n = 36$). The mean density and standard deviation of the stands belonging to the first group were 12 points/m^2 and 4 points/m^2, respectively. For the second group, the mean and the standard deviation were 4.36 points/m^2 and 1.79 points/m^2, respectively. In order to study how the error associated to DTM affects the estimation of volume, the differences between the coordinate z of each stand center measured with GPS-RTK and the coordinate z of the DTM were calculated. Then, the stands were grouped into two classes. Stands with differences lower than 0.20 m in absolute value belonged to the first group ($n = 52$) and stands with differences greater than 0.20 m in absolute value belonged to the second group ($n = 31$). This threshold value was the RMSE of DTM computed. The volume for each group of stands classified by vegetation type, density and DTM error was estimated, then the values of R^2 and RMSE compared. All possible combinations considering two factors were also analyzed (Table 3). Finally, shrub volume was predicted considering the best conditions i.e., stands with *Q. coccifera*, density > 8 points/m^2, and DTM error lower than 0.20 m.

One of the main restrictions to analyze the capability of the LiDAR technology to study shrub vegetation in small areas is the low number of points available per stand. In addition, the above factors can affect the performance of the estimations. To overcome this difficulty, statistics for areas with homogenous vegetation type and density were calculated by extracting LiDAR points in larger radii. The following concentric radii were analyzed (in meters): 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2, 2.25, 2.5, 2.75, 3, 3.25, and 3.5. Linear regressions were computed to estimate the volume of the plants, and the R^2 of the models obtained were compared.

To study the relationships between the factors (point density, error associated to DTM, vegetation type) and the radius value, the variation of R^2 for different radii was calculated considering the following cases: all the stands ($n = 83$); stands with density greater than 8 points/m^2 ($n = 47$); stands with DTM error lower than 0.20 m ($n = 52$); stands with *Q. coccifera* ($n = 47$); stands with density greater than 8 points/m^2 and DTM error lower than 0.20 m ($n = 39$); stands with *Q. coccifera* and DTM error lower than 0.20 m ($n = 30$); stands with *Q. coccifera* and density greater than 8 points/m^2($n = 32$); and finally by combining the above three factors ($n = 26$).

3 Results and Discussion

As observed in Table 3, a low coefficient of determination value was obtained when shrub volume was estimated considering all the stands ($R^2 = 0.26$). The models with the lowest R^2 value were found when shrub volume was estimated in stands having DTM error greater than 0.20 m, other species (*R. officinalis, U. parviflorus, C. albidus L. and E. multiflora L.*)

Table 3 Shrub volume estimation in each stand of 0.5 m radius considering all the stands and the factors vegetation, DTM error, and LiDAR density. The column *n* indicates the number of stands considered in each case.

Case	n	Models	R^2	RMSE (dm^3)
All stands	83	$V = 1803.3 + 3062.7 \cdot H_{max}$	0.26	1929
Quercus coccifera	47	$V = 704.9 + 3951.7 \cdot H_{max}$	0.38	1971
Other species	36	$V = 3033.4 + 1966.5 \cdot H_{max}$	0.14	1790
Density > 8 points/m^2	47	$V = 489.4 + 4073.1 \cdot H_{max}$	0.36	1922
Density < 8 points/m^2	36	$V = 2597.7 + 2553.2 \cdot H_{max}$	0.19	1859
Error DTM < 0.20 m	52	$V = 755.4 + 3803.6 \cdot H_{max}$	0.38	1877
Error DTM > 0.20 m	31	$V = 2871.1 + 2401.5 \cdot H_{max}$	0.14	1895

as vegetation type, and density data less than 8 points/m^2 ($R^2 = 0.14$ to 0.19). These results can be explained taking into account that in the selection of points within each stand of 0.5 m radius, it was found that several stands had very few points, making it unlikely that some of them belonged to the canopy. Besides, unlike forests composed by old growth trees, our study area is mainly occupied by shrub vegetation with average height of 1.27 m. It is also characterized by rough terrain with high slopes, which requires high accuracy in the computation of the DTM. Consequently, these facts may explain the low R^2 in stands with DTM error greater than 0.20 m. Regarding the low results in the prediction of volume in stands with other vegetation types, some of them were occupied by *C. albidus L.*, characterized by an open canopy, which makes more difficult LiDAR pulse to be intercepted by the top of the canopy. This effect can be more significant in small area stands where the number of LiDAR points is low. In addition to these factors, the recent development of small footprint full-waveform LiDAR systems is expected to improve the performance of discrete-return LiDAR systems based on first/last pulse registration, by increasing the number of points or values registered per footprint. Some authors report a higher effective point density (factor of two to three) achieved using these LiDAR systems compared to first/last pulse data in forestry areas composed by trees.[30] These technical advantages may improve the characterization of tree shape and structure, but further research is required to test if full-waveform LiDAR systems improve the estimation of shrub vegetation volume, especially in small stands.

Better results were obtained for predicting volume when the stands were grouped combining the above factors (Table 4). For stands with vegetation *Q. coccifera* and density greater than 8 points/m^2, the R^2 value was 0.62. For stands with vegetation *Q. coccifera* and error associated to DTM lower than 0.20 m the R^2 value was 0.60. The best model was obtained when shrub volume was estimated combining these three factors ($R^2 = 0.71$). These results show the feasibility of predicting shrub volume in small areas (radius = 0.5 m) occupied by *Q. coccifera* using accurate DTM and high-density LiDAR data. Stratification of shrub vegetation type should be considered for the selective application of models to different strata. This may be done by combining LiDAR data and high-resolution imagery (spectral and spatial). Good results in shrub species have been obtained using these data and applying object-based vegetation classification

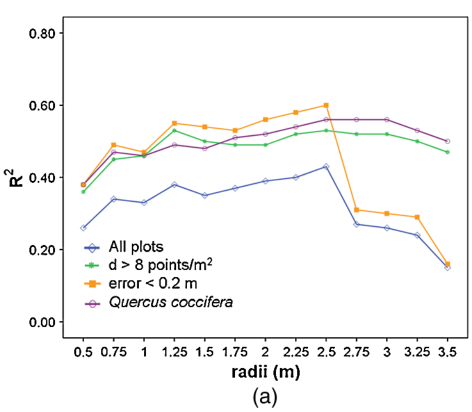
Table 4 Shrub volume estimation in a stand of 0.5 m combining the factors vegetation, DTM error, and LiDAR density.

Case		n	Models	R^2	RMSE (dm^3)
Quercus coccifera	Density < 8 points/m^2	15	$V = 2396.0 + 2843.6 \cdot H_{\max}$	0.14	2386
	Density > 8 points/m^2	32	$V = -1126.0 + 5313.5 \cdot H_{\max}$	0.62	1573
	Error DTM > 0.20 m	17	$V = 2571.7 + 2378 \cdot H_{\max}$	0.09	2268
	Error DTM < 0.20 m	30	$V = -757.9 + 5008.6 \cdot H_{\max}$	0.60	1672
Other species	Density < 8 points/m^2	21	$V = 2710.3 + 2396.2 \cdot H_{\max}$	0.27	1509
	Density > 8 points/m^2	14	$V = 2525.6 + 2054.4 \cdot H_{\max}$	0.14	1534
	Error DTM > 0.20 m	14	$V = 3171.3 + 2516.0 \cdot H_{\max}$	0.31	1390
	Error DTM < 0.20 m	21	$V = 1954.9 + 2468.4 \cdot H_{\max}$	0.26	1403
Density > 8 points/m^2	Error DTM > 0.20 m	8	$V = 5321.0 - 1603.5 \cdot H_{\max}$	0.04	1565
	Error DTM < 0.20 m	39	$V = 144.899 + 4369.5 \cdot H_{\max}$	0.40	1973
Density < 8 points/m^2	Error DTM > 0.20 m	23	$V = 2803.6 + 2874.3 \cdot H_{\max}$	0.23	1931
	Error DTM < 0.20 m	13	$V = 2115.4 + 2157.3 \cdot H_{\max}$	0.22	1538
Quercus coccifera	Density > 8 points/m^2 Error DTM < 0.20 m	26	$V = -1957.1 + 5952.6 \cdot H_{\max}$	0.71	1477

techniques.[31] Thus, the previous detection of areas with *Q. coccifera* may allow the efficient application of the obtained models for volume estimation. Nevertheless, some areas are covered by vegetation associations, making the classification processes difficult. Other factors, such as LiDAR density and DTM accuracy, are being improved by the progressive development of more accurate systems. In addition, to obtain an accurate DTM in areas densely covered by shrub vegetation it would be necessary to use filters allowing the selection of appropriate parameters to remove LiDAR points belonging to vegetation.

As reported above, using greater radii to extract LiDAR data in homogenous areas to derive explanatory variables can produce better results in biomass and height estimation.[23,26] The influence of the radius size in the estimation of the volume considering statistics derived from LiDAR data was analyzed. Using all stands, the maximum R^2 is found between the radii 1.25 and 2.5 m (R^2 0.38 to 0.43). A significant increase in terms of R^2 can be observed between the radii 0.5 m and 1.25 m for all the cases [Fig. 3(a)]. Those radii (1.25 to 2.5 m) also produced better results for stands with LiDAR density higher than 8 points/m^2 (R^2 0.53), type vegetation *Q. coccifera* (R^2 0.49 to 0.56), and DTM error lower than 0.2 m (R^2 0.55 to 0.60). It is remarkable that when using a density greater than 8 points/m^2, the maximum R^2 value is obtained for a lower radius size ($r = 1.25$ m). In contrast, for the stands with DTM error lower than 0.20 m the optimal radius was 2.5 m. This fact can be explained considering that 13 of the 52 stands with DTM error lower than 0.20 m have a density lower than 8 points/m^2. Hence, greater radii are required for obtaining the best model ($R^2 = 0.60$). In this case, an important decrease from radii 2.75 upwards is also observed. From this radius value the homogeneity of the areas seems to decrease and vegetation height tends to be different to that with a 0.5-m radius.

As observed in Fig. 3(b) sharp increases of R^2 are obtained when the stands are grouped considering more than one factor. In addition, these results are obtained for smaller radii. Practically for all cases in which factors are combined the optimal radii are found between 0.5 and 1.25 m. The highest R^2 values are found when the shrub volume is estimated in stands with *Q. coccifera*, density greater than 8 points/m^2, and DTM error 0.20 m (R^2 0.71 to 0.75). This result indicates that the radius may not be a relevant factor given these conditions. This conclusion can also be drawn for the stands with *Q. coccifera* and density greater than 8 points/m^2. The model obtained considering these factors shows lower R^2 values, varying from 0.61 to 0.62 for the radii 0.5 to 1.25 m. Comparing the results obtained in both cases, there is a noticeable increase of the R^2 value, remarking the importance of the accurate computation of DTM to study shrub vegetation. For stands with DTM error lower than 0.2 m and density greater than 8 points/m^2, the maximum R^2 was obtained for a radius of 1.25 m ($R^2 = 0.62$).



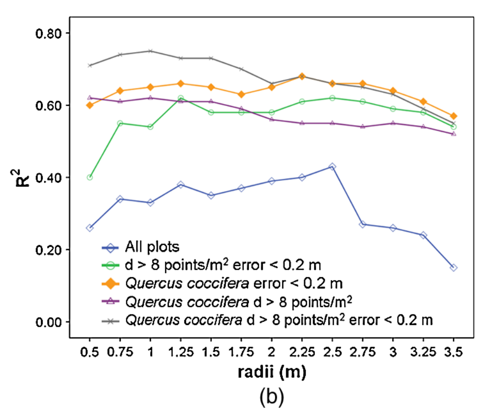


Fig. 3 (a) Coefficients of determination (R^2) of linear regression models for estimating volume considering the maximum height of LiDAR data in concentric areas of radius ranging from 0.5 to 3.5 m from the stand centre in stands with: DTM error lower than 0.20 m ($n = 52$); data density higher than 8 points/m^2 ($n = 47$); vegetation type *Q. coccifera* ($n = 47$); for all the stands ($n = 83$). (b) Combining the following factors: DTM error lower than 0.20 m and density higher than 8 points/m^2 ($n = 39$); *Q. coccifera* and DTM error lower than 0.20 m ($n = 30$); *Q. coccifera* and density higher than 8 points/m^2 ($n = 32$); *Q. coccifera*, density higher than 8 points/m^2, and DTM error lower than 0.20 m ($n = 26$).

4 Conclusions

The restrictions of LiDAR data to estimate shrub volume in small stands has been proved. However, significant improvements in the estimations can be obtained on *Q. coccifera* shrub areas under certain conditions (use of accurate DTM with error lower than 0.20 m, and use LiDAR density data greater than 8 points/m^2). The results of this study reveal that using greater radii for deriving statistics of LiDAR data in homogenous areas can be useful to estimate the volume in stands with DTM error lower than 0.20 m and combining stands with this DTM accuracy and presence of *Q. coccifera*. Nevertheless, for stands with the tree factors mentioned above, radii greater than 0.50 m do not produce a noticeable increase in the accuracy of the predicted models. The results of this study could be applied to improve the knowledge of shrub vegetation, characteristic of Mediterranean forests. Moreover, the volume estimated can be used to determine the biomass of the area, multiplying by the density of the vegetation.

Acknowledgments

The authors appreciate the financial support provided by the Spanish Ministerio de Ciencia e Innovación in the framework of the project CGL2010-19591.

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