STUDY OF SHRUB COVER AND HEIGHT USING LIDAR DATA IN A MEDITERRANEAN AREA

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ABSTRACT

This work studied the height and coverage of shrub vegetation using LIDAR data. The maximum dominant heights of vegetation were measured in the field in 83 stands of a 0.5 m radius and the data was compared to figures for heights obtained from LIDAR data in concentric areas with different radii. The minimum root mean square error (RMSE) between the field measurements and LIDAR data was found for radii between 1.5 m and 2.25 m, RMSE being 0.26 m. When the slopes are low and an accurate digital terrain model (DTM) is obtained, it was shown that the radius can be reduced. Shrub heights were also studied in plots of 100 m^2. In this case, the 95th percentile of the LIDAR data included in each plot was the best predictor of height with $R^2 = 0.71$ and a RMSE of 0.13 m. For detecting the presence of shrub vegetation, the highest accuracy was obtained when the canopy height model (CHM) and a spectral image were combined – with an overall accuracy of 90%.

Keywords: biomass, LIDAR, canopy height model (CHM), digital terrain models (DTM), shrub height.

Introduction

A high percentage of Mediterranean forest is covered by dense, low shrub. The difficulty involved in shrub management and the lack of information about shrub behavior means that these areas are often left out of spatial planning projects (Velázquez and Anneveling, 2009); nevertheless, these areas are important for the environment and landscape because they represent important CO_2 sinks; prevent soil erosion and desertification; help refill aquifers; and contribute to creating fuel-type maps for better accuracy in fire behavior modeling (Riaño et al., 2007). The development of efficient tools to carry out the shrub conservation is a technical challenge (Velázquez and Fernández, 2009).

To achieve this goal, it is necessary to have updated geographical information to produce an environmental diagnosis and to infer indicators that allow a sustainable – and often protected – development of these areas (Velázquez and Fernández, 2010). New management tools could be based on LIDAR (Light Detection and Ranging) data (Popescu et al., 2002; Yu et al., 2004 ; Reutebuch et al., 2005). LIDAR technology is an active remote sensing system that registers ground elevation measurements and vertical vegetation structures. It is based on the measurement of the time delay from pulse emission by an airborne sensor, to its return after reaching the earth's surface. LIDAR systems can register the return signal of a pulse emitted in different echoes and calculate the coordinates x, y, and z of the point at which the reflection takes place. To achieve this, a differential GPS and an inertial system are used. This information can then be used to provide ground elevations via a *digital terrain model* (DTM); elevations of some objects above the Earth's surface via a *digital surface model* (DSM); and heights of the forest canopy, via a *canopy height model* (CHM). With this information, the terrestrial surface as well as any object above the ground can be studied with great accuracy.

A DTM is the reference surface for calculating dendrometric and dasometric variables of vegetation such as height, biomass, and volume. To compute DTM from LIDAR data it is necessary to apply algorithms to eliminate points belonging to any object above the ground surface, such as vegetation or buildings. Although there are several methods for performing these tasks, complete automation is difficult (Baltsavias, 1999). A comparison and classification of methods can be found in (Sithole and Vosselman, 2004). One of the most commonly used algorithms is based on iterative processes in which minimum elevations of points are selected (Popescu et al., 2002; Clark et al., 2004).

Vegetation height allows detection of growth and shows a high correlation with biomass. This was observed in forests (Hyyppä and Inkinen, 1999; Nelson et al., 2004). However, there are fewer studies in which shrub areas have been studied because of the inherent difficulty: this vegetation is low and occupies a continuous surface in which individuals cannot be defined. In tree studies, two approaches can be followed (Hyyppä et al., 2008): calculation of the dasometric variables in a plot or stand (Nelson et al., 1998; Means et al., 2000; Næsset, 2004; Hudak et al., 2006); or calculation of the dendrometric variables for a tree (Persson et al., 2002; Maltamo et al., 2004; Popescu, 2007), which requires the crown of a tree to be delineated. For shrub areas, only the first approach can be applied because shrubs represent a continuous structure in which individual plants cannot be identified. Moreover, their low height requires great accuracy in the methodology and characteristics of the LIDAR data. For this reason, concentric areas with different radii are used when vegetation heights measured in the field are compared to those calculated from LIDAR data (Streutker and Glenn, 2006). The approach followed in this work was to select LIDAR points within a buffer of an area where the maximum height shrub had also been measured in the field. The radius of the buffer area is defined by factors that affect the accuracy of vegetation height obtained from LIDAR data. According to Hyyppä et al. (2008), these are: the density and coverage of laser pulses; the algorithm used to calculate a DTM; the sensitivity of the laser system; the thresholding algorithms used in processing the signal; the pulse penetration into the canopy; and tree shapes and species. According to Streutker and Glenn (2006), the selection of the radius is related to the horizontal accuracy of the LIDAR data and GPS system. Underestimation of canopy height of shrub vegetation occurs because the pulse does not reflect the upper part of the vegetation (Gaveau and Hill, 2003). Apart from these factors, Su and Bork (2006) reported that errors associated with DTM on high slopes decrease the accuracy of vegetation characterization. Scan angles also affect pulse penetration: if the vegetation is open and not very dense then the pulse penetration will be greater (Hopkinson et al., 2005).

On the other hand, the presence of shrub vegetation can be studied from LIDAR data (Streutker and Glenn, 2006). Most studies combine LIDAR data and spectral images to improve detection (Mundt et al., 2006; Bork and Su, 2007; Mutlu et al, 2008) and produce a classified vegetation map (Hill and Thomson, 2005; Verrelst et al., 2009).

While a number of studies have been carried out on tree areas using LIDAR data, little research into shrub vegetation has been conducted; and most has taken place in areas with low slopes (Su and Bork, 2006; Streutker and Glenn, 2006). For this reason, further work is needed to analyze vegetation in Mediterranean areas – which are characterized by mountains with steep slopes and very irregular variation. The aim of this work was to study the coverage of shrub vegetation and to estimate its height in a steep mountainous area. For height analysis, two approaches were followed: studies of the heights in plots, and in stands. The factors producing better accuracy were also analyzed.

Materials and methods

Study area

The 10 km^2 study area is located in Chiva (Valencia, Spain) and is defined by a rectangle whose UTM coordinates $X_{maximum}$, $Y_{maximum}$, $X_{minimum}$, and $Y_{minimum}$, were 689800, 4376028, 683800, and 4373000, respectively (Figure 1). The area is located in zone 30 in the European Datum 1950 reference system. It is a mountainous area with a predominance of *Quercus coccifera* although other species can be found such as *Rosmarinus officinalis, Ulex parviflorus, Cistus albidus L.* and *Erica multiflora L.* These species are the most abundant in Mediterranean forests. The average percentage occupation is around 55%. The altitude varies between 442 and 1000 meters, and the average slope is 45%.

Data

The LIDAR data was acquired during a flight in December 2007, using an Optech ALTM 2050 system. The technical parameters were: flight height – 700 m; pulse frequency – 50kHz; scan frequency – 47 Hz; and scan angle – ±18º; pulse density – 4 points/m^2. However, given that 10 overlapping flightlines were registered some areas had a higher point density. For this reason, the average point density of the study area considering all the returns was 8 points/m^2. The numbers of echos were 2. More than 99% of the LIDAR data belonged to the first pulse. This could be caused by the low differences between the canopy of vegetation and ground.

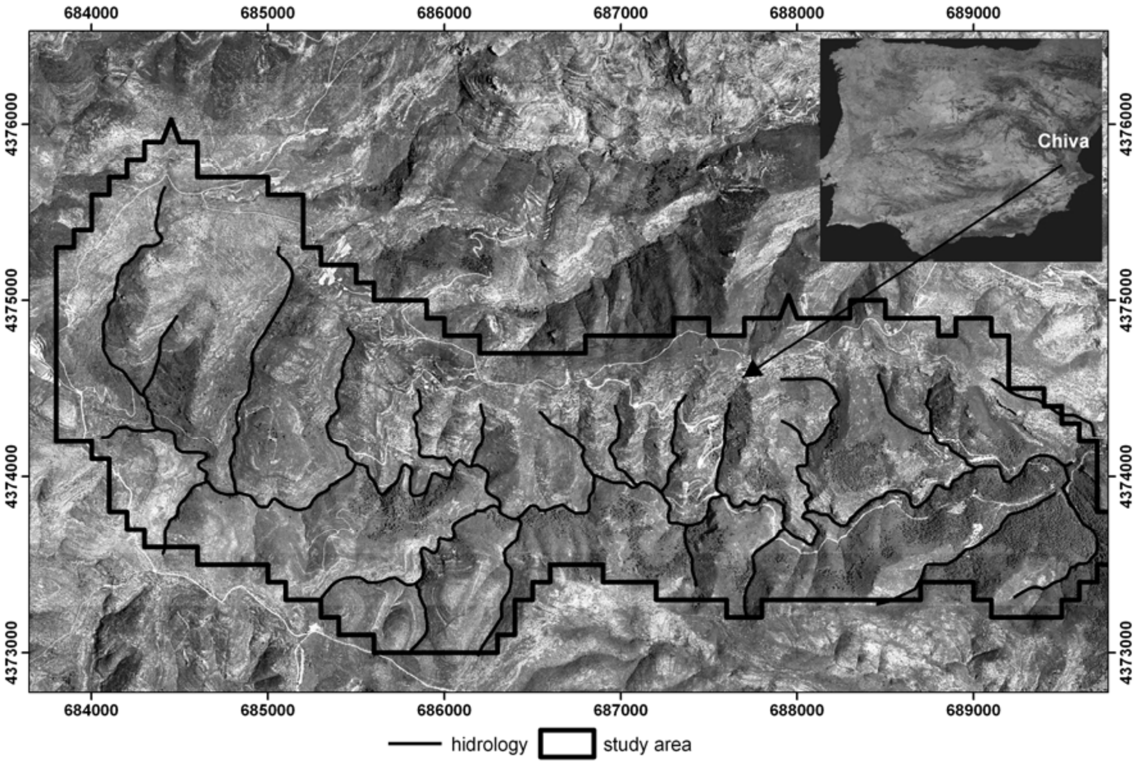

Figure 1. Location of study area in Chiva (Spain). The black polygon represents area surveyed for LIDAR data.

To assess the DTM calculated, 1379 ground-surveyed checkpoints throughout the study area were measured using a RTK-GPS system (Leica System 1200). A transformation between reference systems, ETRS89 to ED50, was carried out with vertical and horizontal accuracy of 1 and 5 centimeters, respectively. Horizontal accuracy of LIDAR points was 0.5 m according to the specifications of the technical report of the flight. For altimetry, 60 checkpoints were selected in flat areas without vegetation (Hopkinson et al., 2005). We compared elevations measured from RTK-GPS and an average elevation of LIDAR points in a buffer of 0.5 m radius with the measured point at the center. The root mean square error (RMSE) was 6 cm. We considered that these results showed that the LIDAR data was accurate enough for this study.

A spectral airborne image registered by the Ultracam D, made by Vexcel Imaging GMBH, was used with a cell size of 0.5 m. This image was collected in July 2006. It contained three spectral bands: infrared, red, and green. The reference system was ETRS89. This image was reprojected to an ED50 reference system with an RMSE of 0.35 m.

DTM and CHM calculation

To compute the DTM from LIDAR data, it is necessary to apply algorithms to eliminate points belonging to any object above the ground surface such as vegetation or buildings. To achieve this, we programmed an application based on iterative processes. As input data type, we used an image with a pixel size of 1 m; and we selected the lowest LIDAR point for each cell.

The DTM iterative algorithm involved five steps:

Step 1: the study area was divided into windows with an initial window size (v1). In each analysis window, the lowest elevation point was selected. With these points, an initial DTM (DTM1) was calculated by applying the Delaunay triangulation method.

Step 2: A smaller analysis window (v2) was selected to find new minimum heights from the input data.

Step 3: We compared the points selected in step 2 with DTM1 (calculated in step 1), and selected those that were lower than a defined height threshold (u1). Points with differences larger than this threshold were rejected. A new DTM (DTM2) was then determined with the selected points.

Step 4: A window size (v3), smaller than v2, was selected. The minimum height in each window was selected.

Step 5: As in step 3, points of minimum height with a difference compared to DTM2 greater than a second threshold (u2) were eliminated. The final DTM was calculated with the remaining points.

The CHM was obtained by selecting the maximum LIDAR data value for each 0.5 x 0.5 m^2 cell. Each cell was then subtracted from the DTM3 value.

Sampling for vegetation height

To analyze the difference between the shrub heights obtained from the LIDAR data and heights measured in the field, two approaches were followed: plots and stands. For vegetation height sampling, a grid with cell sizes of 1 km^2 was defined in the studied area. Then, 29 plots with areas of 100 m^2 were randomly selected and distributed among the cells with at least one plot with vegetation in each cell. The plots were located in different bioclimatic layers (elevation), slopes, and aspects. The maximum dominant height was measured in three different stands included in each plot; these were also randomly selected. The radius of each stand was 0.5 m; the average height was 1.27 m; the standard deviation was 0.29 m; the minimum value was 0.80 m; and the maximum value was 2.5 m. The coordinates of the centre of the stand were also measured using a RTK-GPS system. In all, 86 stands were measured, but only 83 were used for the analysis because no LIDAR data was available for three of the measured points.

Analysis vegetation height by plots

The actual maximum dominant height of the vegetation in each plot was taken as the average of the dominant heights measured in the three stands. To analyze the difference between the shrub heights obtained from the LIDAR data and heights measured, we calculated the mean, the maximum height, and the 80th, 90th, and 95th percentiles of the LIDAR data for each plot. These parameters were used to predict the actual vegetation height using regression models. Values of R^2 and RMSE were also calculated.

Analysis of vegetation height by stands

We analyzed the shrub height in stands by comparing the 83 maximum dominant vegetation heights measured in the field for each stand with the maximum height obtained from the LIDAR data. The three stands in each plot all had different dominant heights; some contained different species or a mixture of several species. For this reason, the heights were treated as independent values. Given that some stands had few LIDAR points, we looked for the concentric area with the minimum RMSE between the vegetation height measured in the field and the LIDAR data. This area was defined by a buffer with the selected radius. The radii used were: 0.50, 0.75, 1, 1.25, 1.5, 1.75, 2, 2.25, 2.5, 2.75, 3, 3.25, and 3.5 m. For each buffer and stand, the maximum height from the LIDAR data was selected (Hopkinson et al., 2005; Streutker and Glenn, 2006). From this data and the vegetation heights measured in the field, the RMSE was calculated**.** The difference between the LIDAR data and the field measurements for each stand and radius was also obtained. The minimum, maximum, mean signed error (MSE), and the standard deviation of these differences were then also calculated.

Next, the influence of the radius on the relationship between the shrub height and LIDAR height was studied according to the sign of the DTM error, slope and density of LIDAR data. To analyze the DTM error, we calculated the difference between coordinate z from 82 RTK-GPS points and coordinate z obtained from the DTM. Using the resulting data, we classified the stands according to the sign of the differences: error>0 m (n=30) and error<0 m (n=52); n being the number of stands. For each stand of the class, the maximum shrub height was selected from the LIDAR data using buffers with radii that varied from 0.5 to 3.5 m. This data was compared with the heights measured in the field. For each radius and class, the RMSE was calculated. One field measurement in this analysis was rejected when the highest radii reached trees making it impossible to study this DTM error in this stand. The accuracy of shrub height was also studied when LIDAR heights were corrected for the DTM error in areas with slopes lower than 20% (n=34). The field shrub heights of these stands were compared to the maximum heights obtained from the LIDAR data for each radius so as to obtain the RMSE.

To analyze the point density factor, the number of LIDAR points was calculated in an area with a radius of 0.5 m for each of the 82 points measured in the field. We used all the returns for this analysis, including the LIDAR data registered from overlapping flightlines. These points were grouped into two classes: density < 8 points/m^2 (n=43); and density > 8 points/m^2 (n=49), with n being the number of points measured in the field. For each class, the field heights of each point were compared to the maximum heights obtained from the LIDAR data included in the buffers with the same radii used in the previous analysis. For each class, the RMSE was calculated.

Analysis of shrub cover

To determine the presence of shrub vegetation, two approaches were applied. Firstly, only CHM obtained from the LIDAR data was used, and its cells were classified using the following intervals: 0-0.3 m – ground; 0.3-2.5 m – shrub vegetation; values greater than 2.5 m – trees. The threshold 0.30 m was obtained by considering the difference between the minimum value for shrub height measured in the field and the RMSE of heights when a radius of 0.5 m was used. The classification was assessed by using 166 points measured in the field and distributed throughout the study area: 83 belonging to the shrub vegetation class, and the remaining 83 to the ground class. The second approach was based on combining the CHM with an airborne spectral image (Figure 2). From this image, the NDVI (normalized difference vegetation index) was calculated and a classification into 4 non-supervised classes was applied. Two overlay layers – the classified image and original image – were then displayed and a reclassification was carried out. The cells with value 1 were classified into non-vegetation and values 2, 3, and 4 into vegetation. This result was combined with the CHM and three new classes were defined: *shrub* if a cell of the CHM was between 0.30 and 2.5 m and belonging to classes 2, 3, or 4 of the previous classified image; *ground* if the cell of the CHM was lower than 0.3 m; and *tree* if the cell of the CHM was greater than 2.5 m.

Results and discussion

DTM calculation

The lowest RMSE occurred with a medium analysis window size: 10, 5 and 2.5 m (v1, v2 and v3), and height thresholds equal to, or greater than, 1.5 m. These parameters produced a DTM (Figure 3) with a mean signed error of 0.02 m, a standard deviation of 0.19 m, and an RMSE of 0.19 m.

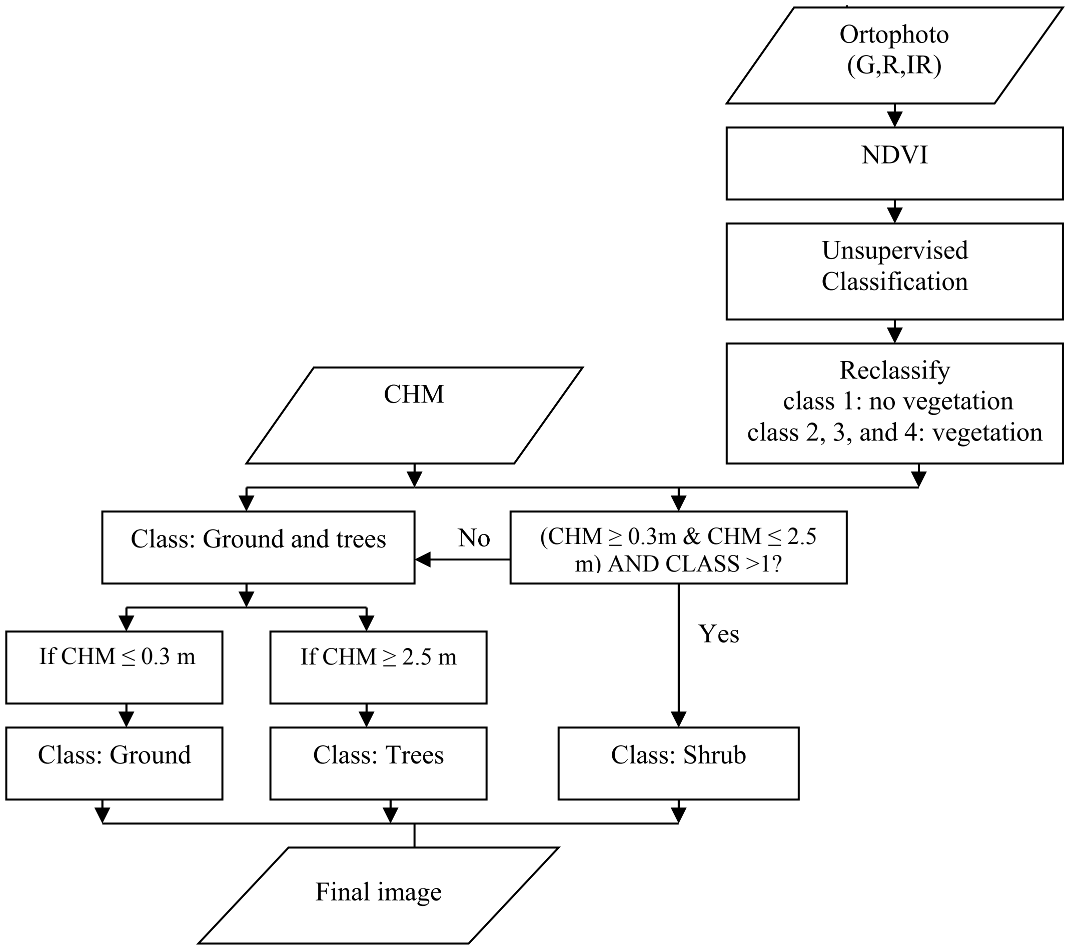

Figure 2. Framework for classifying shrub vegetation

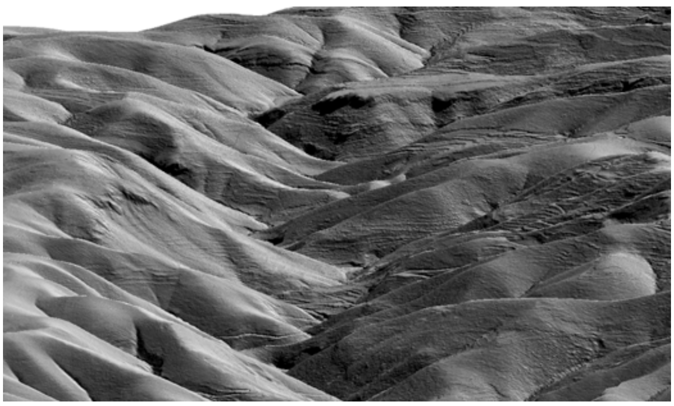

Figure 3. Shaded relief image of a DTM with vector 10, 5, and 2.5 m window; 2.5 m threshold; 1x1m image.

Vegetation height analysis by plots

For the study of vegetation heights in plots, six linear regressions were performed using the following parameters calculated from the LIDAR data within the plots as independent variables: $Height_{mean}$, $Height_{maximum}$, and the 80th, 90th, and 95th percentiles. The average height measured in the field by plot was selected as a dependent variable. As can be observed in Table 1, the maximum correlation was achieved when the 95th percentile was used with an R^2 value of 70.68 %, and an RMSE of 0.13 m, (Table 1). In contrast, the lowest R^2 was found when the maximum height obtained from the LIDAR data by plots was used. This can be explained by considering that there are plants whose maximum height is higher than the maximum dominant height of the vegetation in a plot. These results are in line with the findings of Riaño et al. (2007), who used the 90th percentile to estimate shrub height, obtaining a R^2 of 0.48, and an RMSE of 0.18 m. As well as the algorithm used to calculate the DTM, the differences could be because the point density and the average vegetation height were lower, as it is more difficult to register the shrub height.

Table1. Shrub height estimation from LIDAR data in plots.

Independent variables (LIDAR data)	Symbol	Model	R^2	RMSE (m)
Mean height	H_{mean}	$H = 0.97 + 0.79\ H_{mean}$	47.91	0.18
80th percentile	P_{80}	$H = 0.74 + 0.72\ P_{80}$	57.36	0.16
90th percentile	P_{90}	$H = 0.66 + 0.67\ P_{90}$	64.26	0.15
95th percentile	P_{95}	$H = 0.61 +0.63\ P_{95}$	70.68	0.13
Maximum height	H_{max}	$H = 0.23 + 0.86\ H_{max}$	39.46	0.19

H: maximum dominant real height; P_{80}, P_{90}, P_{95}, are 80th, 90th, and 95th percentiles of the LIDAR data, respectively.

Vegetation height analysis by stands

We analyzed the radius that produced the minimum RMSE between the maximum LIDAR data and the field measurements. Figure 4 shows that the minimum RMSE was found with radii between 1.50 and 2.25 m were used. From these values upwards, the

RMSE increased because points higher than the height measured in the field were selected. This result can be observed in the Table 2: when the radius increases, the sign of the mean error changes, indicating that higher points than the field measurements are being selected. This effect can be appreciated more clearly when a radius of 3.5 m is used. For this value, the mean error is positive, while the maximum error and standard deviation are the highest. The minimum standard deviation occurs with a radius of 1.5 m, indicating that the differences between the heights measured in the field and the heights from the LIDAR data are smaller. These findings support the results reported by Streutker and Glenn (2006), although the conditions of the work were different: their point density was 1.2 points/m^2, and they worked with a flatter relief.

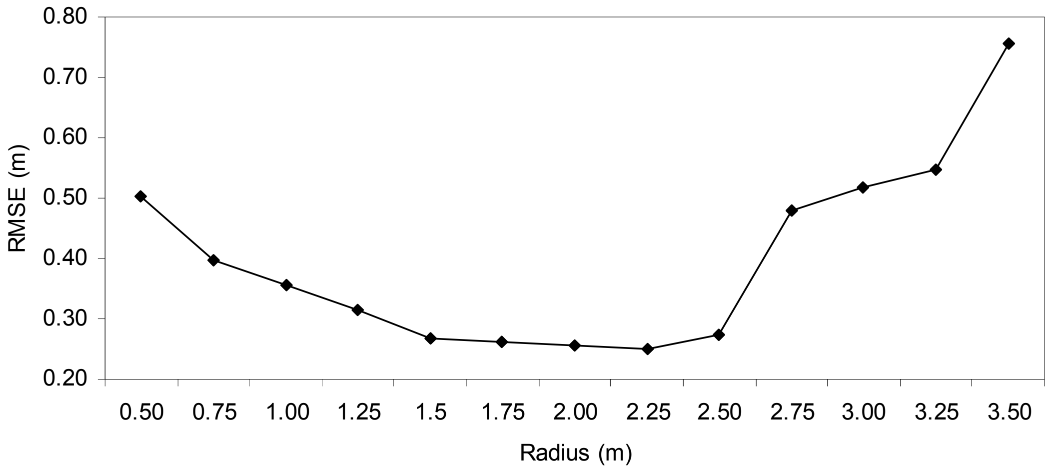

Figure 4. RMSE values from comparison of 83 measured heights and highest LIDAR point for each radius.

Table 2 shows that the mean error for each radius is negative up to a radius of 2.75 m. This finding is in line with other studies which have shown that LIDAR data tends to underestimate shrub heights (Gaveau and Hill, 2003; Hill and Thomson, 2005; Hopkinson et al., 2005; Streutker and Glenn, 2006; Bork and Su, 2007; Riaño et al., 2007).

Table 2. Statistical values for 83 heights calculated by comparing LIDAR data and actual measured height

	Radius of the buffers (m)												
	0.5	0.75	1	1.25	1.5	1.75	2	2.25	2.5	2.75	3	3.25	3.5
Minimum (m)	-1.04	-0.84	-0.82	-0.80	-0.77	-0.77	-0.77	-0.77	-0.77	-0.77	-0.69	-0.55	-0.55
Maximum (m)	0.24	0.24	0.24	0.25	0.36	0.36	0.76	0.76	0.76	3.37	3.71	3.94	6.16
Mean (m)	-0.40	-0.31	-0.25	-0.20	-0.15	-0.12	-0.08	-0.06	-0.03	0.05	0.08	0.12	0.16
Standard Deviation (m)	0.30	0.26	0.25	0.24	0.22	0.23	0.24	0.25	0.27	0.48	0.52	0.54	0.74

The maximum dominant height for stands was estimated by selecting the LIDAR data within an area with a radius of 1.5 m. This radius was chosen because it was included inside the low RMSE range. Moreover, this radius produced the minimum standard deviation between the LIDAR data and field measurements. Consequently, we computed linear regression analyses, and used the following parameters obtained from LIDAR data within an area of a radius of 1.5 m as independent variables: $Height_{mean}$, $Height_{maximum}$, and the 80th, 90th, and 95th percentiles. The maximum dominant height in each stand was estimated by each independent variable. As can be observed in Table 3, the maximum correlation was achieved when the maximum height obtained from the LIDAR data was selected with values of R^2 and an RMSE of 61.49 % and 0.18 m, respectively. Unlike the plots, the 95th percentile was not the parameter that produced the highest correlation. This is because the area for stand analysis was smaller than the area for plots, and so finding heights obtained from LIDAR data that were higher than the field measurement was less likely.

Table 3. Shrub height estimation from LIDAR data in stands.

Independent variables LIDAR data	Symbol	Model	R^2	RMSE (m)
Mean height	H_{mean}	$H = 0.80 + 0.84\ H_{mean}$	41.56	0.23
80th percentile	P_{80}	$H = 0.74 + 0.68\ P_{80}$	47.16	0.21
90th percentile	P_{90}	$H = 0.68 + 0.67\ P_{90}$	51.13	0.21
95th percentile	P_{95}	$H = 0.61 + 0.69\ P_{95}$	57.37	0.19
Maximum height	H_{max}	$H = 0.55 + 0.64\ H_{max}$	61.49	0.18

H: maximum dominant real height; P_{80}, P_{90}, P_{95}, are 80th, 90th, and 95th percentiles of the LIDAR data, respectively

Effect of DTM errors on radius selection

Streuker and Glenn (2006) reported that the selection of the radius is related to the sum of the horizontal accuracy and the GPS system. However, there are other factors, such as DTM errors and point density, which should be analyzed when considering the value of the radius in which the minimum RMSE between LIDAR data and field measurements occurs. Figure 5 shows that the RMSE values are lower when the DTM error is positive (z_{GPS}-z_{DTM} >0) up to a radius of 2.25 m. In contrast, when this error is negative (z_{GPS}-z_{DTM} <0), higher RMSE are found. In the first case, an underestimation of the DTM produces higher vegetation (Figure 6). In the second case, an overestimation of a DTM produces lower vegetation. Thus, DTM error can produce an underestimation or overestimation of canopy height of shrub vegetation. For this reason, it is necessary to select suitable parameters that minimize these errors. The parameters defined for computing the DTM were the result of a previous analysis in which several tests were made in order to select the most suitable parameters in an area with the characteristics of the study area, namely, steep mountains with shrub vegetation. We found that in areas with dense shrub, the mean signed error for the DTM was -0.10 m, which is an acceptable value considering that the average shrub height was 1.27 m.

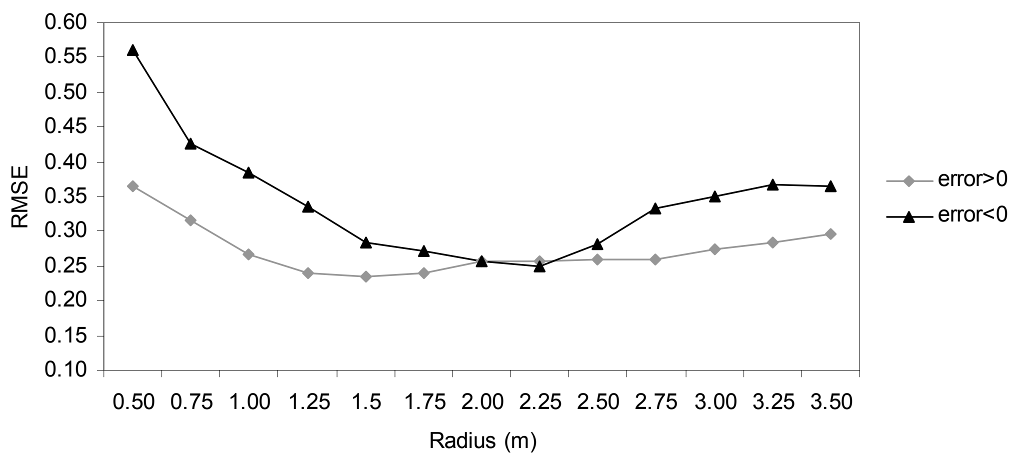

Figure 5.RMSE values for field height and highest LIDAR point for cases of positive (n=32) and negative (n=50) DTM error

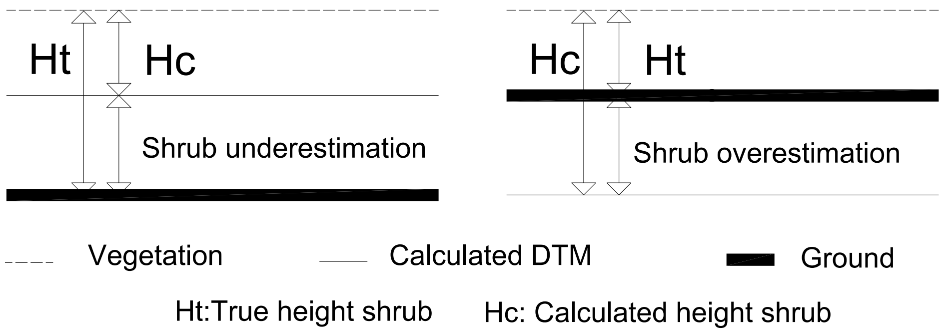

Figure 6. Effects of DTM errors on vegetation height

The MSE was calculated by using points with positive DTM error for each radius. We found that these values were negative up to a radius of 2 m. These results indicate that although the DTM is underestimated, there is an underestimation of canopy height of shrub vegetation. This supports the idea that LIDAR data produces an underestimation of canopy height of shrub vegetation.

Figure 7 shows the variation of the RMSE for points with the DTM corrected by adding the difference between coordinate z from 34 RTK-GPS points and coordinate z obtained from the DTM. A significant decrease in RMSE can be seen when the radius changes from 0.5 to 0.75 m. Unlike what happened when the 83 original points were selected from a radius of 0.75 m upwards, differences between radii in RMSE were small. This finding suggests that if DTM errors are minor and the slopes are low, the minimum error between field measurements and LIDAR data is found with lower radii, in this case for a radius of 0.75 m. This value is close to the horizontal accuracy of LIDAR data.

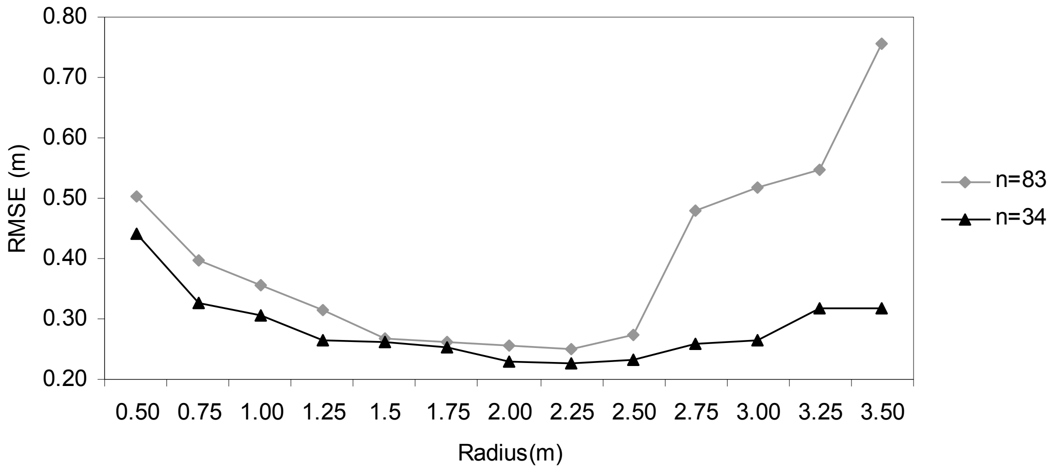

Figure 7. RMSE for all stands (n=83), and stands corrected for DTM error on slopes lower than 20% (n=34).

To explain how the slope can affect the accuracy of shrub height, it is important to consider the cell size used for computing the DTM; in this case it was 1m. When LIDAR data and DTM are overlaid to calculate vegetation height, it is likely that some of these points do not coincide with the true cell because of the processes of interpolation and the creation of an image. This means that the heights of these points are calculated by taking the DTM value from a neighboring cell. When the slopes are steep, as in our study area with an average of 45%, the error could be high considering that average height studied in our work was 1.27 m. This could not happen in areas with low slopes as the adjoining cell value in a DTM would be similar.

Figure 7 illustrates that the values of RMSE are very similar for a radius of 1.5 m, (0.26 m.), but they are lower for corrected DTM error in areas with slopes lower than 20% (n=34). These values of RMSE could explain the errors associated with the LIDAR system. The coincidence in RMSE values for a radius of 1.5 m suggests that when this radius is selected the errors associated with DTM and the slopes are insignificant. This can be explained by the fact that height of vegetation is similar in an area occupied by the value of this radius and there are at least nine values of a DTM to assign to the LIDAR points included in this area, and so the vegetation height can be calculated with more accuracy.

The MSE were calculated from the 34 low slope points corrected for DTM error, and the result was negative up to a radius of 2.75 m. This supports the idea that the LIDAR system tends to underestimate shrub vegetation even when the heights are corrected for DTM error and the slopes are low.

Effect of point density on selection of radius

Figure 8 shows RMSE is lower when a point density is greater than 8 points/m^2 up to a radius of 2.75 m. The differences between RMSE for both densities decrease from 0.14 m when a radius of 0.5 m is used, to 0 m for a radius of 2.5 m.

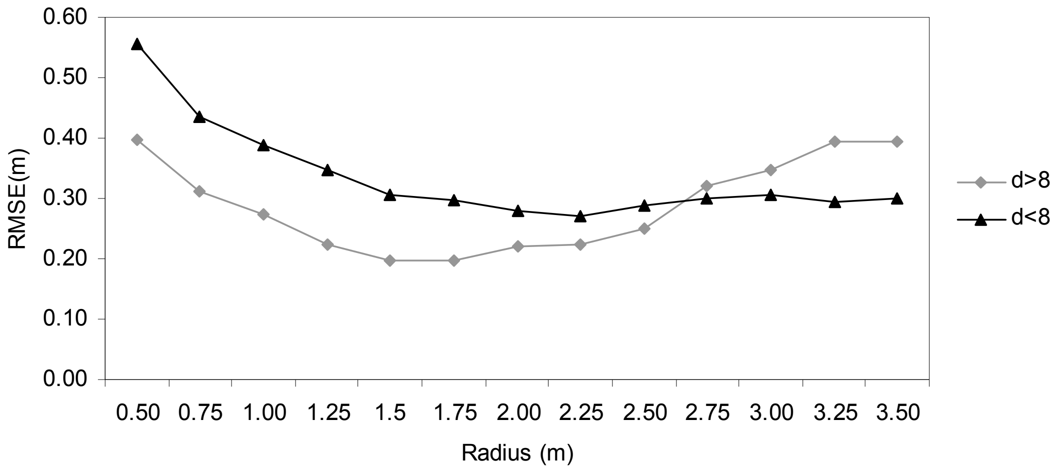

Figure 8. RMSE values for field heights and the highest LIDAR point for point density > 8 points/m^2 (n=43) and point density < 8 points/m^2 (n= 49)

Analysis of shrub coverage

The overall accuracy for the classified CHM was 87%. As can be observed in Table 4b, the user's accuracy for the shrub vegetation class was 84%, which indicates that from 90 points classified as shrub vegetation, 76 were correctly classified and 14 points belonged to the ground class. The producer's accuracy for the shrub vegetation class was 92%, meaning that from 83 points that belonged to this class, 76 were correctly classified. These results can be improved when a spectral image is used (Mundt et al., 2006; Bork and Su, 2007; Mutlu et al., 2008). In our study, the combination of CHM and spectral imagery gave an overall accuracy of 90%. The user's accuracy for shrub vegetation was 94% (Table 4a). This increase was attributed to the following reason. Because an image was used, it was found that some cells with heights between 0.3 and 2.5 m did not belong to the shrub vegetation class; an NDVI image allows cells such as these to be detected . However, the producer's accuracy when combining LIDAR data and the spectral image was lower (87%). This means that when an image was used, some cells belonging to the shrub class were not classified as such. This may be because the image was taken a year and a half earlier, and the vegetation may not have been there at that time. In addition, after geometric correction the RMSE was 0.35 m. This error may mean that when cells belonging to the shrub class were overlaid on the CHM cells, they did not coincide, thus decreasing the producer's accuracy. Nevertheless, the improvement in the user's accuracy for the shrub class was greater than the decrease in the producer's accuracy. The combination of the CHM and a spectral image produced an increase of 3% in overall accuracy.

Table 4. User, producer and overall accuracy with (a) CHM and airborne image combined, and (b) CHM only.

a)

	Reference Data			User's accuracy (%)
	Ground	Shrub	Total	
Ground	78	11	89	87.64
Shrub	5	72	77	93.51
Total	83	83	166	
Producer's accuracy (%)	93.98	86.75		90.36 (Overall)

b)

	Reference Data			User's accuracy (%)
	Ground	Shrub	Total	
Ground	69	7	76	90.79
Shrub	14	76	90	84.44
Total	83	83	166	
Producer's accuracy (%)	83.13	91.57		87.35 (overall)

Conclusion

This work studied shrub height from LIDAR data in plots and stands. The results indicate that LIDAR data can be used to estimate shrub height. This was demonstrated with the acceptable coefficients of determination for the models calculated. For stands, it was shown that the minimum error between LIDAR data and field measurements was found when a buffer between 1.5 m and 2.25 m was used. A lower radius is possible when DTM error and slopes are lower. When a radius of 1.5 m was selected, DTM error and slope value did not affect the accuracy of the shrub height estimation. For this radius, the negative sign of the MSE showed that LIDAR systems tend to underestimate shrub vegetation. Although better results were obtained for shrub presence analysis when a spectral image and LIDAR data area were combined, the improvement was low. In view of the results, it is not worth using it. We used a spectral image to check the results of the classification of the CHM to correct the effects of an underestimation or overestimation of the DTM in those cells of the CHM whose heights were low. We thought it is extremely hard to obtain a more accurate DTM after making several tests to select the most suitable parameters for an area with the characteristics of the study area - steep mountains with a dense cover of shrub vegetation.

These results can be used to estimate the apparent volume of shrub vegetation, which is defined by the area of a stand and the dominant height of vegetation. By means of this data an occupation factor can be applied which relates the apparent volume to the real volume occupied by the plants. Once the dry density of the materials is known, the biomass can be estimated (Velázquez et al., 2010).

This work could be used in change analysis of shrub vegetation. In this analysis two approaches can be performed: detection of new communities or growth of the existent shrub communities. In the first case, we thought that LIDAR data was accurate enough. The results obtained in this paper relating to the shrub cover with an overall accuracy of 87% may confirm this hypothesis. The second case is more difficult. The results obtained for plots could suggest that the shrub growth could be studied for changes higher than 0.13 m. When the study is performed in sub-plots it would be necessary to define the size of the analyzed area. In this work, it was detected that when concentric areas with a radii of 1.5 m are used, the differences between LIDAR data and field measurements are smaller. In this case the RMSE was 0.27 m. Logically, it would be difficult to study changes for values lower than this. However, we detected that LIDAR data produces an underestimation of shrub vegetation, which could affect LIDAR data obtained in different data in the same way. Moreover, we detected that when a high density of LIDAR data is used, the RMSE is 0.20 m. Therefore, it is an important aspect that should be considered when a study of shrub change is carried out.

References

Baltsavias, E.P. 1999. Airborne laser scanning: existing systems and firms and other resources. *ISPRS J. Photogramm. Rem. Sens*. 54:164–198.

Bork, E.W., and J.G. Su. 2007. Integrating lidar data and multispectral imagery for enhanced classification of rangeland vegetation: A meta analysis. *Rem. Sens. Environ.* 111:11-24.

Clark, M.L., D.B. Clark, and D.A. Roberts. 2004. Small-footprint lidar estimation of sub-canopy elevation and tree height in a tropical rain forest landscape. *Rem. Sens. Environ.* 91:68-89.

Gaveau, D.L.A., and R.A. Hill. 2003. Quantifying canopy height underestimation by laser pulse penetration in small-footprint airborne laser scanning data. *Can. J. Rem. Sens.* 29:650-657.

Hill, R.A., and A.G. Thomson. 2005. Mapping woodland species composition and structure using airborne spectral and lidar data. *Int. J. Rem. Sens.* 26:3763-3779.

Hopkinson, C., L.E. Chasmer, G. Sass, I.F. Creed, M. Sitar, W. Kalbfleisch, and P.Treitz. 2005. Vegetation class dependent errors in lidar ground elevation and canopy height estimates in a boreal wetland environment. *Can. J. Rem. Sens.* 31:191-206.

Hudak, A.T., N.L. Crookston, J.S. Evans, M.J. Falkowski, A.M.S. Smith, P.E. Gessler, and P. Morgan. 2006. Regression modeling and mapping of coniferous forest basal area and tree density from discrete-return lidar and multispectral satellite data. *Can. J. Rem. Sens.* 32:126-138.

Hyyppä, J., and M. Inkinen. 1999. Detecting and estimating attributes for single trees using laser scanner. *Photogramm. J. Finl.* 16:27-42.

Hyyppä, J., H. Hyyppä, D. Leckie, F. Gougeon, X. Yu, and M. Maltamo. 2008. Review of methods of small-footprint airborne laser scanning for extracting forest inventory data in boreal forests. *Int. J. Rem. Sens.* 29:1339-1366.

Maltamo, M., K. Eerikäinen, J. Pitkänen, J. Hyyppä, and M. Vehmas. 2004. Estimation of timber volume and stem density based on scanning laser altimetry and expected tree size distribution functions. *Rem. Sens. Environ.* 90:319-330.

Mundt, J.T., D.R. Streutker, and N.F. Glenn. 2006. Mapping sagebrush distribution using fusion of hyperspectral and lidar classifications. *Photogramm. Eng. Rem. Sens.* 72:47-54.

Mutlu, M., S.C. Popescu, C. Stripling, and T. Spencer. 2008. Mapping surface fuel models using lidar and multispectral data fusion for fire behavior. *Rem. Sens. Environ.* 112:274-285.

Means, J.E., S.A. Acker, J.F. Brandon, M. Renslow, L. Emerson, and C.J. Hendrix. 2000. Predicting forest stand characteristics with airborne scanning lidar. Photogramm.

Eng. Rem. Sens. 66:1367-1371.

Næsset, E. 2004. Accuracy of forest inventory using airborne laser scanning: evaluating the first nordic full-scale operational project. *Scand. J. For. Res.* 19:554 – 557.

Nelson, R., W. Krabill, and J. Tonelli. 1998. Estimating forest biomass and volume using airborne laser data. *Rem. Sens. Environ.* 24:247-267.

Nelson, R., A. Short, and M. Valenti. 2004. Measuring biomass and carbon in Delaware using an airborne profiling lidar. *Scand. J. For. Res.* 19:500-511.

Persson, A., J. Holmgren, and U. Söderman. 2002. Detecting and measuring individual trees using an airborne laser scanner. Photogramm. *Eng. Rem. Sens.* 68:925-932.

Popescu, S.C., R.H. Wynne, R.F. Nelson. 2002. Estimating plot-level tree heights with lidar: local filtering with a canopy-height based variable window size. *Comp. Electr. Agric.* 37:71-95.

Popescu, S.C. 2007. Estimating biomass of individual pine trees using airborne lidar. *Biomass & Bioenergy* 31:646-655.

Reutebuch, S.E., H.-E. Andersen, and R.J. McGaughey. 2005. Light detection and ranging (lidar): An emerging tool for multiple resource inventory. *J. For.* 103:286-292.

Riaño D., E. Chuvieco, S.L. Ustin, J. Salas, J.R. Rodríguez-Pérez, L.M. Ribeiro, D.X. Viegas, J.M. Moreno, and H. Fernández. 2007. Estimation of shrub height for fuel-type mapping combining airborne lidar and simultaneous color infrared ortho imaging. *Int. J. Wildland Fire* 16:341-348.

Sithole, G., and G. Vosselman. 2004. Experimental comparison of filter algorithms for bare-Earth extraction from airborne laser scanning point clouds. *ISPRS J. Photogramm. Rem. Sens.* 59:85-101.

Streutker, D.R., and N.F. Glenn. 2006. Lidar measurement of sagebrush steppe vegetation heights. *Rem. Sens. Environ.* 102:135-145.

Su, J.G., and E.W. Bork. 2006. Influence of vegetation, slope, and lidar sampling angle on DEM accuracy. *Photogramm. Eng. Rem. Sens.* 72:1265-1274.

Verrelst J., G.W. Geerling., K.V. Sykora, and J.G.P.W Clevers. 2009. Mapping of aggregated floodplain plant communities using image fusion of CASI and LIDAR data. *Int. J. Appl. Earth Observ. Geoinform.* 11:83-94.

Velazquez-Marti B, Annevelink E. 2009. GIS application to define biomass collection points as sources for linear programming of delivery networks. *T ASABE* 52 (4): 1069-1078

Velazquez-Marti B, Fernandez-Gonzalez E. 2009. Analysis of the process of biomass harvesting with collecting-chippers fed by pick up headers in plantations of olive trees. *Biosyst. Eng.* 104 (2): 184-190

Velazquez-Marti B, Fernandez-Gonzalez E, Estornell J, Ruiz L.A. 2010. Dendrometric and dasometric analysis of the bushy biomass in Mediterranean forests. Source: *For. Ecol. Manag*. 259 (5): 875-882

Velazquez-Marti B, Fernandez-Gonzalez E 2010. Mathematical algorithms to locate factories to transform biomass in bioenergy focused on logistic network construction. *Renew. Energ.* 35 (9): 2136-2142

Yu X., J. Hyyppä, H. Kaartinen, M. Maltamo. 2004. Automatic detection of harvested trees and determination of forest growth using airborne laser scanning. *Rem. Sens. Environ.* 90:451-462.