Analysis on the Use of Multiple Returns LiDAR Data for the Estimation of Tree Stems Volume

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***Abstract*—Small footprint Light Detection and Ranging (LiDAR) data have been shown to be a very accurate technology to predict stem volume. In particular, most recent sensors are able to acquire multiple return (more than 2) data at very high hit density, allowing one to have detailed characterization of the canopy. In this paper, we utilize very high density (>8 hits per m^2) LiDAR data acquired over a forest stand in Italy. Our approach was as follows: Individual trees were first extracted from the LiDAR data and a series of attributes from both the first, and non-first (multiple), hits associated with each crown were then extracted. These variables were then correlated with ground truth individual estimates of stem volume. Our results indicate that: i) non-first returns are informative for the estimation of stem volume (in particular the second return); ii) some attributes (e.g., *maximum at the power of n*) better emphasize the information content of returns different from the first respect to other metrics (e.g., *minimum*, *mean*); and iii) the combined use of variables belonging to different returns slightly increases the overall model accuracy. Moreover, we found that the best model for stem volume estimation ($\mathrm{adj}-R^2 = 0.77, P < 0.0001, SE = 0.06$) comprised four variables belonging to three returns (first, second, and third). The results of this analysis are important as they underline the effectiveness of the use of multiple return LiDAR data, underling the connection between LiDAR hits different from the first and tree structure and characteristics.**

***Index Terms*—Forestry, laser scanning, multiple returns Light Detection And Ranging (LiDAR), stem volume estimation, variable extraction.**

I. Introduction

PREDICTION of stem volume is an important goal of sustainable forestry, with estimates critical for both forest inventories as well as for assessing terrestrial carbon stocks as a key component of carbon accounting (i.e., [1] and [2]). Although tree stem volume is generally estimated using ground based measurements, a large number of studies have demonstrated the capacity of using remotely sensed data for this purpose (e.g., [2]–[13]). There are a number of advantages of using remote sensing for the estimation of forest stem volume including the possibility to have measurements from every location in the forest, or the ability to collect data in areas difficultly accessible on the ground.

One remote sensing technology which has been widely investigated over the past decade to estimate forestry attributes is Light Detection And Ranging (LiDAR) (e.g., [2]–[13]). These investigations can be divided into studies at stand level (e.g., [3]–[6]) and studies at single tree level (e.g., [2], and [7]–[12]), with stand approaches consisting of estimating the stem volume of groups of trees usually starting from circular plot of a given radius, while single tree approaches estimate individual stem volume of each tree.

Among these two scales of application, the majority of the studies have focused on the stand level, principally due to the ready availability of plot level data from forest inventory. Moreover, in the past the majority of the LiDAR sensors did not acquire data with a sufficiently high posting density to allow multiple hits per tree crown, thus making single tree level prediction of volume difficult. Naesset [3] analyzed the effects of different sensors (Optech ALTM1233 and ALTM3100), flying altitudes (1100, 1200, and 2000 m), and pulse repetition frequencies (PRF) (33, 50, and 100 kHz) on the estimation of stem volume and mean height at stand level using first and last return LiDAR data. The study concluded that: i) different sensors produce point clouds with different properties; ii) low PRFs tend to produce upward shifted canopy height distributions compared to higher PRFs; iii) all the datasets acquired in different conditions appear to be suitable for the estimation of volume (the "best" model developed has a R^2 of 0.92) and mean height, with a mean error of up to 10.7% for stem volume and 2.5% for mean height [3]. In [4], Coops *et al.* estimated the canopy structure of a Douglas-fir forest with first return LiDAR data and found high correlations between field data and LiDAR derived data ($R^2 = 0.85$ ($P < 0.001$, $SE = 1.8$ m) for the mean height, and $R^2 = 0.65$ ($P < 0.05$, $SE = 14.1\ m^2ha^{-1}$) for basal area). Patenaude *et al.* in [5] estimated the aboveground carbon content in a number of plots using first and last return LiDAR data and also found strong correlations ($R = 0.74$, $P < 0.01$, $SE = 4.06\ t\ ha^{-1}$).

At the single tree scale Popescu *et al.* in [7] estimated forest volume and biomass at the individual tree level using LiDAR first return and a crown extraction algorithm with encouraging

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TABLE I
SUMMARY OF THE FIELD MEASUREMENTS (N = NUMBER OF TREES; DB = DIAMETER AT BREAST HEIGHT (1.30 m); CB = CROWN BASE HEIGHT)

Characteristic		Species					
		All	*Abies alba*	*Picea abies*	*Fagus sylvatica*	*Larix decidua*	*Pinus sylvestris*
N		243	111	106	14	10	2
%		100	45.68	43.62	5.76	4.12	0.82
Tree Height (m)	Range	11.1 - 37.1	13.9 - 36.6	15.4 - 37.1	11.1 - 28.7	15.5 - 29.2	14.1 - 16.2
	Mean	26.27	25.81	27.73	21.87	24.15	15.15
	S.D	4.88	4.45	4.76	4.2	4.21	1.48
DBH (cm)	Range	16 - 74	16 - 74	22 - 72	18 - 47	35 - 63	26 - 34
	Mean	44.68	43.71	47.56	29.71	48.8	30
	S.D	11.09	9.53	11.23	8.72	9.33	5.66
CBH (m)	Range	1.4 – 23.3	2.1 – 20.8	1.4 – 23.3	2 – 15.4	1.5 – 16.5	6.8 – 10.1
	Mean	11.33	12.22	10.86	8.46	11.13	8.45
	S.D	4.57	3.80	5.23	3.70	4.33	2.33
Volume (m^3)	Range	0.16 - 6.50	0.19 - 6.50	0.29 - 5.69	0.16 - 2.24	0.63 - 2.90	0.33 - 0.66
	Mean	2.01	1.95	2.3	0.8	1.7	0.5
	S.D	1.12	0.99	1.2	0.61	0.76	0.23

results (83% of the variance explained for the estimation of volume). Similarly, Hyyppa *et al.* in [8] proposed a method for the estimation of stem volume using first return at single tree level, based on the segmentation of the individual tree crowns. Bortolot *et al.* [2] used an individual tree-based approach to estimate forest biomass using first return LiDAR data, obtaining good results with R ranging between 0.59 and 0.82. In [10], Wang *et al.* proposed a procedure for the analysis of the vertical canopy structure and the 3-D modeling of forest. From their analysis, they derived parameters from first return LiDAR data characterizing crown volume tree diameter and height. Likewise, Falkowski *et al.* in [11] proposed an automated technique for the estimation of tree crowns based on spatial wavelet analysis and accurately predicted crown diameters $(\mathrm{R} = 0.86)$.

In the majority of these single stem volume analyses, first return LiDAR data have been used with little investigation into the information content and applicability of returns different from the first or the last. This lack of investigation is principally due to the fact that, until recently, most sensors only recorded dual returns (first and last hit); however, more recently multiple return, discrete small footprint LiDAR systems have become available allowing multiple returns (more than 2) to be recorded and subsequently analyzed. However, while the multiple return system may have the capacity to record more than two returns per LiDAR pulse, numerous factors influence the number of returns [4], including the amount of energy needed to trigger a return, the minimum time differences between two echoes, and the specific method used to detect an echo. All these factors affect the minimum distance between returns. For example, in the Optech ALTM3100 (the sensor used in this study) the minimum distance detected between the first and the second return is 2.1 m, which increases to 3.8 m for any subsequent returns [3]. Despite these potential limitations, multiple LiDAR returns potentially provide an increase in the information provided by these sensors, in particular in applications such as predicting crown and stem attributes where multiple returns are expected. The goal of this paper, therefore, is to examine the differences in the capacity of LiDAR pulse returns to predict individual stem volume based on their relative return. Our analysis is focalized on: i) single variables; ii) group of variables according to their characteristics (e.g., standard metrics, percentiles, etc) and returns (first, second, third, and fourth); and iii) all the variables. Moreover, we analyze the generalization ability of the best model developed with a cross-validation analysis.

This paper is organized as follows. In Section II, we describe the study area and data used; in Section III, we present our approach with a particular focus on the phase of variables extraction. Section IV illustrates the experimental results, with important discussions on the outcomes of the experiments, and, finally, in Section V, we draw some conclusions.

II. DATA SET DESCRIPTION

The focus area for this study is a 500 ha forest stand located in the Trento Province in the north of Italy in the Italian Alps. It has a variable topography with Norway spruce (*Picea abies*) and Silver Fir (*Abies alba*), the dominant species and subdominant species including *Fagus sylvatica*, *Larix decidua* and *Pinus sylvestris*.

The field data for this study were collected in 2007 with the relascopic technique. Fifty plots were randomly distributed over the study area. Within each sampling point, a standard cluster of five angle count sampling (ACS) was used to estimate mean basal area around the point, while the diameter at breast height (DBH) (1.30 m) was measured for all trees with $\mathrm{DBH} > 17.5\ \mathrm{cm}$. For each sample plot, some tree heights (about 4–6 of tallest trees for species that were present in the central ACS) were measured with a Vertex hypsometer, in order to select an acceptable height-diameter function for the estimation of tree volume. For trees for which only the diameter was measured, the height was estimated using a local height-diameter function selected using the information provided by the heights measured. The height-diameter relationships were provided by the Forest Service of the Province of Trento (Italy).

The LiDAR data were acquired on September 4, 2007, using an Optech ALTM 3100 laser scanner, with a mean density of 8.6 points per square meter. The laser pulse wavelength and the PRFs were 1064 nm and 100 kHz, respectively, with the system recording up to four returns per pulse.

In order eliminate the effect of the topography on the elevation of the LiDAR hits and to retrieve the exact height of each tree, it was necessary to subtract from each LiDAR return the height of the underlying terrain. To this end, a Digital Terrain

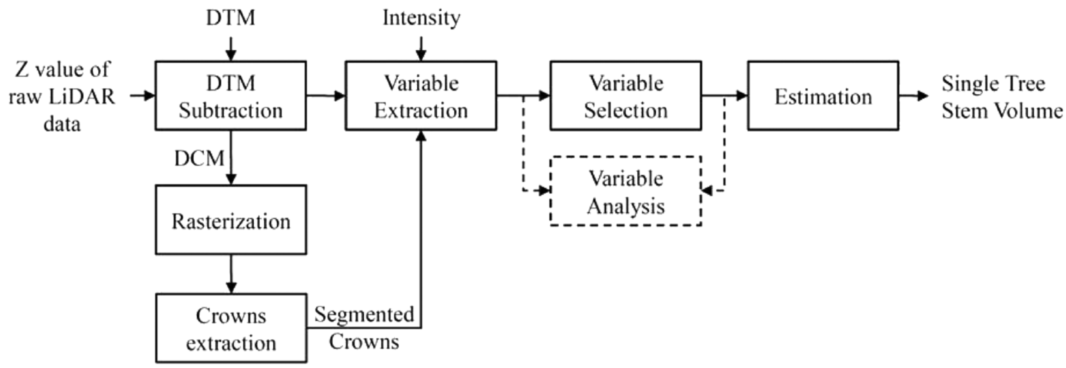

Fig. 1. Architecture of the system adopted.

Model (DTM) with a spatial resolution of 1 m was generated starting from the data acquired. The DTM was provided by the company. that acquired the LiDAR data. This surface was then subtracted from all returns points.

III. Methods

The approach followed in this paper is shown in Fig. 1.

In order to derive individual crowns we first derived a Digital Canopy Model (DCM), which was calculated as the mean height of all first return hits within a 1×1 m grid.

To retrieve the individual tree crowns from the DCM, we applied the algorithm described in [7], implemented in the software TreeVaW.[1] This algorithm assumes a circular shape for the tree crowns and it is based on two main steps: i) the individual trees are located using a moving window; ii) starting from the individual tree positions, the diameter of each crown is estimated.

As described in Popescu *et al.* [7], [8], in the first step, the local maximum (LM) technique is used to locate the tree tops. In particular, this algorithm operates with a square window of $n \times n$ pixels and a circular window of variable sizes. After this step, the crown diameter is identified. In this phase, at first, the algorithm applies a median 3×3 filter in order to reduce the outliers, preserving the edges. The crown diameter is computed as the average between two values measured along two perpendicular directions from the tree top location. In order to describe the crown profile along these two perpendicular directions the algorithm fits them with a fourth degrees polynomial using the singular value decomposition (SVD). The lengths of these profiles are determined by the window size, and they are usually double of the window size. The use of a fourth degree polynomial allows one to exploit a concave shape with three extreme values. These values could be both local maxima and minima, and the values of the independent variable at extreme functional are called critical points. The algorithm finds these points and analyzes them with a derivative analysis (first and second derivative). In particular, the sign of the second derivative allows one to know if the concavity has changed. If it happens we have a point of inflection that usually occurs on the edges of a crown profile. The distance between these points is used to compute the tree crowns. The final value of the crown diameter is the average between the diameters measured on the two directions.

All tree locations were overlaid onto both a 20 cm orthophoto and the derived TreeVaW crown polygons. The size of the tree crown and tree species from the field data were used to ensure the individual tree data matched the extracted crown information to avoid errors connected with tree positions in the final model (see Table I for a detailed description of the final ground truth available). Only tree crowns which were positively matched to the LiDAR data were used in the analysis. Once the tree position and the diameter of the crown were extracted, a cylinder is defined representing the individual tree within the dataset, and all LiDAR hits were extracted.

[1]http://www-ssl.tamu.edu/personnel/s_popescu/TreeVaW/

TABLE II
Correlation Between the Maximum of the First Return Inside the Crown and the Tree Height

Characteristic	N	RMSE	adj-R^2
All trees	243	1.44	0.91
Abies alba	111	1.38	0.90
Picea abies	106	1.54	0.90
Fagus sylvatica	14	1.26	0.91
Larix decidua	10	1.21	0.92
Pinus sylvestris	2	-	-

From each identified crown, we extracted a series of variables from both the elevation and the intensity information of each pulse. We divided the variables extracted into five different groups: i) "standard metrics": *minimum*, *maximum*, *mean*, and *range* value of the elevation of each return (e.g., [4], [7], and [13]); ii) "distributional metrics": *standard deviation*, *kurtosis*, *skewness*, *coefficient of variation* of the elevation of each return (i.e., [13]), crown *radius*, crown *area* and crown *volume* (calculated as a cylinder having as area the crown area and as height the difference between the DCM and the average height of the second, third or fourth return according to which is the last return available after the first); iii) "intensity metrics": the *mean* value of the intensity for each return; iv) "percentiles": the percentiles of the elevation from the fifth to the 95th for each return (e.g., [13]); and v) "$\mathrm{maximum}^{\mathrm{n}}$": the maximum of each return elevation at the power of n (with $n = 0.1, \ldots, 5$) (e.g., [6]).

In order to assess the relationships between the LiDAR extracted variables and the volume we utilized a stepwise selection procedure. This approach has widely been used in previous research (e.g., [1] and [13]), and it is an enhancement of the forward stepwise selection. In this technique, variables are added and deleted from the model according to their significance (see [14] for a more detailed description).

No predictor variable was left in the model with a significance value of the F statistic greater than 0.01. This value was applied instead of the most common 0.05 as a model with a reduced

TABLE III
VARIABLES EXTRACTED FROM EACH CROWN AND THEIR $\mathrm{adj}-\mathrm{R}^2$ RELATIVE TO THE VOLUME ESTIMATION CONSIDERING ALL THE REFERENCE POINTS AND THE POINTS DIVIDED BY SPECIES

	Return	Variable	adj-R^2		
			All	*Abies alba*	*Picea abies*
Standard metrics	1st	maximum	0.70	0.62	0.75
		minimum	0.10	0.06	0.13
		Mean	0.47	0.37	0.55
		range	0.46	0.36	0.51
	2nd	maximum	0.69	0.62	0.74
		minimum	0.02	0.01	0.03
		mean	0.41	0.34	0.50
		range	0.50	0.38	0.56
	3rd	maximum	0.49	0.44	0.51
		minimum	0.00	0.00	0.01
		mean	0.32	0.29	0.35
		range	0.45	0.40	0.45
	4th	maximum	0.31	0.28	0.31
		minimum	0.04	0.06	0.03
		mean	0.22	0.22	0.20
		range	0.28	0.26	0.27
Maximum^n	1st	n=0.1, …, 5	0.65 - 0.74	0.58 – 0.67	0.72 – 0.77
	2nd	n=0.1, …, 5	0.61 - 0.74	0.55 – 0.68	0.69 – 0.77
	3rd	n=0.1, …, 5	0.12 - 0.63	0.12 – 0.58	0.10 – 0.67
	4th	n=0.1, …, 5	0.19 - 0.32	0.18 – 0.33	0.18 – 0.32
Percentiles	1st	5th to 95th	0.00 - 0.70	0.00 – 0.61	0.01 – 0.75
	2nd	5th to 95th	0.00 - 0.66	0.00 – 0.60	0.00 – 0.72
	3rd	5th to 95th	0.00 - 0.46	0.01 – 0.41	0.00 – 0.49
	4th	5th to 95th	0.04 - 0.31	0.05 – 0.28	0.03 – 0.31
Distributional Metrics	1st	standard deviation	0.47	0.38	0.44
		kurtosis	0.00	0.00	0.01
		skewness	0.01	0.00	0.06
		coefficient of variation	0.22	0.20	0.14
	2nd	standard deviation	0.25	0.15	0.29
		kurtosis	0.00	0.00	0.00
		skewness	0.04	0.02	0.06
		coefficient of variation	0.03	0.02	0.03
	3rd	standard deviation	0.30	0.28	0.27
		kurtosis	0.01	0.03	0.01
		skewness	0.01	0.02	0.02
		coefficient of variation	0.17	0.21	0.11
	4th	standard deviation	0.25	0.22	0.24
		kurtosis	0.12	0.13	0.10
		skewness	0.02	0.03	0.01
		coefficient of variation	0.20	0.21	0.16
		area	0.50	0.38	0.53
		radius	0.52	0.41	0.56
		cylinder volume	0.38	0.25	0.44
Intensity metrics	1st	mean	0.10	0.09	0.03
	2nd	mean	0.00	0.03	0.00
	3rd	mean	0.04	0.06	0.01
	4th	mean	0.08	0.14	0.07

number of variables allow us to obtain a more stable model with a higher generalization ability.

In the estimation phase, we utilized multivariate linear regression. In the analysis we used all the ground truth points for the creation of the model. Subsequently with the best model we applied a ten-fold cross-validation analysis using 90% of the data (about 219 trees) for the training and 10% for the test (about 24) in order to analyze the generalization ability of the model.

IV. RESULTS

Four sets of analysis were undertaken. First, we analyzed the relationship between the LiDAR data and the tree heights (Section IV-A). Second, we focused on the stem volume estimation by analyzing its relationship with the extracted variables, considering each variable separately (Section IV-B), groups of variables (Section IV-C), and all the variables together (Section IV-D).

A. *Correlation Between First Return LiDAR Data and Tree Heights*

The relationship between individual tree height and the *maximum of the first return* is shown in Table II. The overall relationship across all species is highly significant ($\mathrm{adj}-\mathrm{R}^2 = 0.91$, $\mathrm{P} < 0.0001$, $\mathrm{SE} = 0.3$). When stratified by species, the relationship remains highly significant ($\mathrm{adj}-\mathrm{R}^2 = 0.90$ to 0.92).

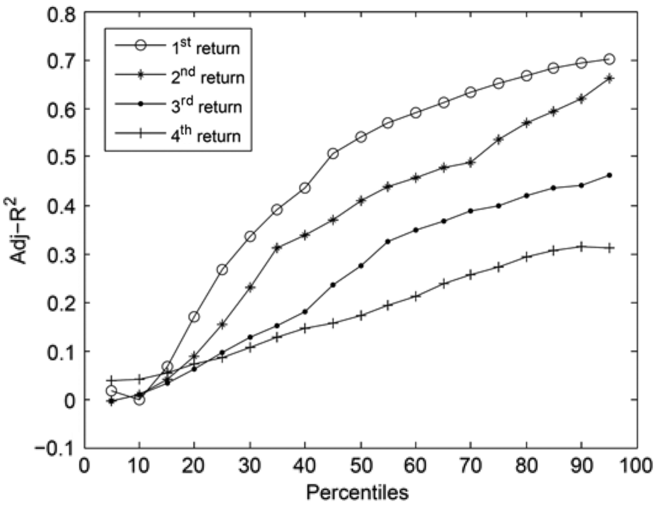

Fig. 2. $\mathrm{Adj}-\mathrm{R}^2$ of the percentiles of the elevation of the different returns.

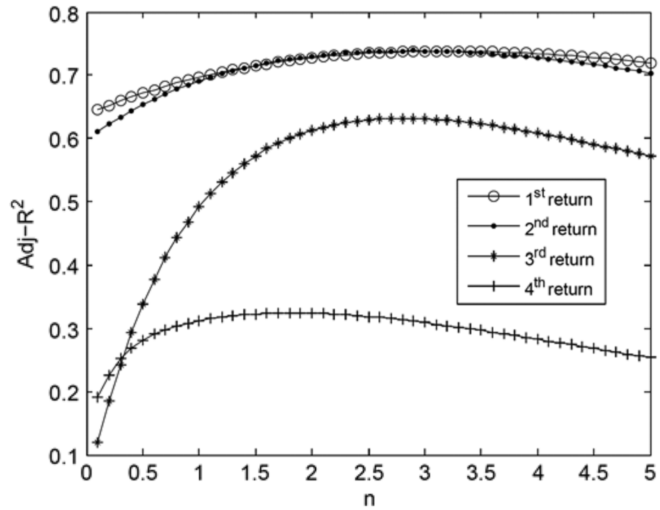

Fig. 3. $\mathrm{Adj}-\mathrm{R}^2$ of the maximum of the different returns at the power of n.

B. Regression Analysis of Each Variable Extracted in the Estimation of Stem Volume

The relationship between individual stem volume and the extracted LiDAR variables presented in Section III is shown in Table III. Results are shown for all the reference points and for the two main species present in the investigated area.

Among the "Standard metrics" the variable which emerges to be the most highly correlated with the stem volume is the *maximum of the first return* ($\mathrm{adj}-\mathrm{R}^2 = 0.7$, $\mathrm{P} < 0.0001$, $\mathrm{SE} = 0.06$). This result was anticipated as the ground truth tree stem volume was computed as a function of both height and the DBH of the stem. The second highest correlation occurs with the *maximum of the second return* ($\mathrm{adj}-\mathrm{R}^2$ of 0.69, $\mathrm{P} < 0.0001$, $\mathrm{SE} = 0.06$).

Among the "Distributional metrics" the variables most highly correlated with volume are the *radius* and the *area*; however, in both cases, the correlation is quite low ($\mathrm{adj}-\mathrm{R}^2$ of 0.52 and 0.5, respectively).

Fig. 2 shows a correllogram of the relationship between the stem volume and the "percentiles", based on the four returns. Results indicate the most significant percentile is the 95th for all the returns, with the first return the most informative ($\mathrm{adj}-\mathrm{R}^2 = 0.70$, $\mathrm{P} < 0.0001$, $\mathrm{SE} = 0.06$), followed by the second return ($\mathrm{adj}-\mathrm{R}^2 = 0.66$, $\mathrm{P} < 0.0001$, $\mathrm{SE} = 0.06$).

The behavior of the "$\mathrm{maximum}^{\mathrm{n}}$" metric is shown in Fig. 3. It is worth nothing that these are the variables that provide the highest levels of correlation, with a maximum of $\mathrm{adj}-\mathrm{R}^2$ of 0.74 ($\mathrm{P} < 0.0001$, $\mathrm{SE} = 0.06$). In particular, for these variables there is no difference between the first and the second return. Moreover, in this case also the third return has quite high correlations, exhibiting a maximum adjusted R^2 of 0.63 ($\mathrm{P} < 0.0001$, $\mathrm{SE} = 0.06$). This underlines the potential of returns different from the first.

Regarding the variables extracted from the intensity information, they resulted in a very low level of information ($\mathrm{adj}-\mathrm{R}^2 = 0.1$, $\mathrm{P} < 0.0001$, $\mathrm{SE} = 0.02$).

From Table III, it is also possible to see the behavior of $\mathrm{adj}-\mathrm{R}^2$ for the two main species present in the area. As these species belong to the same family, the values of $\mathrm{adj}-\mathrm{R}^2$ are quite similar for all of them, with slightly higher values for the *Picea abies* with respect to the *Abies alba*. Moreover, the values obtained for these species are quite similar to the ones obtained considering all the reference points.

C. Regression Analysis Considering Groups of Variables for the Estimation of Tree Stem Volume

Once individual correlations were assessed, we performed regression analysis based on the groups of variables. Table IV shows the results of the stepwise selection applied to different groups of variables. Interestingly the best model incorporates all classes of variables. This is important, as it underlines that the combined use of these variables increases the predictive capacity of the model. Indeed the model created with all the returns provides always higher values of $\mathrm{adj}-\mathrm{R}^2$ with respect to the ones generated with only variables belonging to one return.

Concerning the "standard metrics", the variable that was always selected is the *maximum*. In two cases, other variables were also selected, like the *range of the fourth return* and the *mean of the first one*.

The model created using the "distribution metrics" has the largest number of variables (6) ($\mathrm{adj}-\mathrm{R}^2 = 0.75$, $\mathrm{P} < 0.0001$, $\mathrm{SE} = 0.06$). These variables belong to different sources (first and fourth return), and they are connected also to the geometry of the tree (*area* and *cylinder volume*).

Among the "percentiles", the variables derived from the first return provides the regression model with the highest accuracy ($\mathrm{adj}-\mathrm{R}^2 = 0.75$, $\mathrm{P} < 0.0001$, $\mathrm{SE} = 0.06$); however, in most cases, the second return does equally well ($\mathrm{adj}-\mathrm{R}^2 = 0.66$, $\mathrm{P} < 0.0001$, $\mathrm{SE} = 0.06$). The model extracted with all the variables ($\mathrm{adj}-\mathrm{R}^2 = 0.75, \mathrm{P} < 0.0001, \mathrm{SE} = 0.06$) is made up by three variables belonging to the first return and one variable from the fourth, even if this variable is the last one selected.

Concerning the "intensity metrics", also in this case, they do not provide good results, with an adjusted R^2 of only 0.13 ($\mathrm{P} < 0.0001$, $\mathrm{SE} = 0.02$).

The set "$\mathrm{maximum}^{\mathrm{n}}$" included the variables that provide the highest correlations ($\mathrm{adj}-\mathrm{R}^2 = 0.75$, $\mathrm{P} < 0.0001$, $\mathrm{SE} =$

TABLE IV
SELECTED MODELS FOR THE DIFFERENT SETS OF VARIABLES FOR THE ESTIMATION OF TREE STEM VOLUME

Initial variables set	Returns	RMSE	adj-R^2	N° var.	Variables selected
Standard metrics	All	0.60	0.72	2	maximum of the 1st return range of the 4th return
	1st	0.61	0.71	2	maximum mean
	2nd	0.62	0.69	1	maximum
	3rd	0.80	0.49	1	maximum
	4th	0.93	0.32	1	maximum
Other metrics	All	0.57	0.75	6	skewness of the 1st return area cylinder volume standard deviation of the 1st return standard deviation of the 4th return coefficient of variation of the 1st return
	1st	0.60	0.72	4	standard deviation coefficient of variation kurtosis skewness
	2nd	0.78	0.52	2	standard deviation coefficient of variation
	3rd	0.83	0.45	2	standard deviation coefficient of variation
	4th	0.93	0.32	2	standard deviation coefficient of variation
Intensity metrics	All	1.04	0.13	2	mean of the 1st return mean of the 4th return
Percentiles	All	0.57	0.75	4	10th percentile of the 1st return 55th percentile of the 1st return 85th percentile of the 1st return 90th percentile of the 4th return
	1st	0.58	0.74	3	10th percentile 55th percentile 85th percentile
	2nd	0.65	0.66	1	95th percentile
	3rd	0.82	0.46	1	95th percentile
	4th	0.90	0.37	3	5th percentile 15th percentile 90th percentile
Maximum^n	All	0.56	0.75	3	maximum of the 1st at the power of 2 maximum of the 2nd at the power of 3.5 maximum of the 4th at the power of 4.2
	1st	0.57	0.74	1	maximum at the power of 3.2
	2nd	0.57	0.74	1	maximum at the power of 2.9
	3rd	0.69	0.63	2	maximum at the power of 1.1 maximum at the power of 1.4
	4th	0.91	0.35	2	maximum at the power of 0.3 maximum at the power of 3.8

0.06). In this case, it is worth noting that the model developed with the variables belonging to the first ($\mathrm{adj} - \mathrm{R}^2 = 0.74$, $\mathrm{P} < 0.0001, \mathrm{SE} = 0.06$) and the second ($\mathrm{adj}-\mathrm{R}^2 = 0.74, \mathrm{P} < 0.0001$, $\mathrm{SE} = 0.06$) return provide the same results, underling the effectiveness of these variables, as well as also the amount of information contained in the second return. Moreover, also the variables extracted from the third return provide quite good correlations ($\mathrm{adj} - \mathrm{R}^2 = 0.63, \mathrm{P} < 0.0001, \mathrm{SE} = 0.06$).

D. Regression Analysis Using All the Variables Extracted for the Estimation of Tree Stem Volume

In this final analysis, we considered all the variables extracted from all the four returns. Table V shows that the model developed using all the variables has the highest correlation ($\mathrm{adj} - \mathrm{R}^2 = 0.77, \mathrm{P} < 0.0001, \mathrm{SE} = 0.06$). In this case, the model is made up of four variables belonging to the first, the second and the third return. This is important as the selected variables represent different sources of information. However, the *maximum* variable is always selected in all the five selections, and also the variables of the group "$\mathrm{maximum}^n$" are always present. It is worth noting that another important source of information for the estimation of volume is that associated with the "percentiles". Fig. 4 shows the relationship between the predicted versus observed stem volume.

As the model derived from the variables of all returns is the one that provides the highest accuracy, we decided to use it in the cross-validation analysis. The results are shown in Table VI.

Concerning the results on the training set, they are quite similar to the ones presented in Table V, whereas for the test set,

TABLE V
SELECTED MODELS FOR THE ESTIMATION OF TREE STEM VOLUME CONSIDERING ALL THE VARIABLES EXTRACTED

Initial variables set	Returns	RMSE	adj-R^2	N° var.	Variables in the final model
All the variables extracted	All	0.55	0.77	4	maximum of the 1st return maximum of the 2nd return at the power of 4.8 10th percentile of the 1st return 10th percentile of the 3rd return
	1st	0.56	0.75	3	maximum standard deviation maximum at the power of 5
	2nd	0.58	0.74	1	maximum at the power of 3.4
	3rd	0.68	0.63	3	maximum maximum at the power of 1.1 maximum at the power of 5
	4th	0.91	0.34	2	maximum maximum at the power of 5

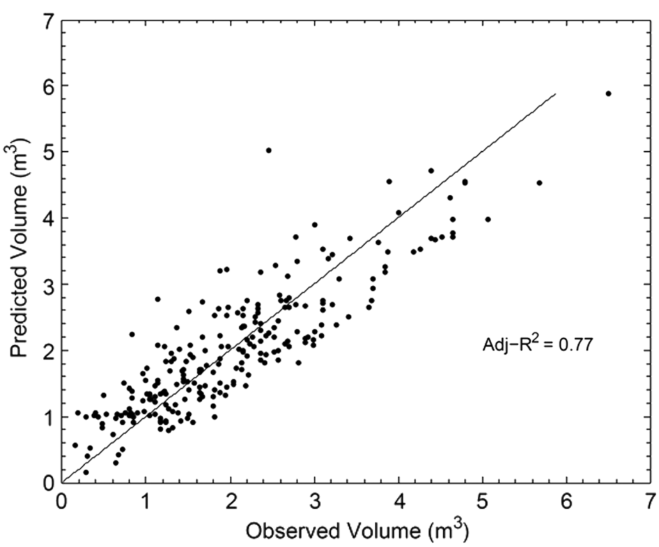

Fig. 4. Observed volume versus predicted volume for all the 243 trees of the ground truth.

there is a slight decrease of the $\mathrm{adj}-\mathrm{R}^2$ (while the RMSE remains unchanged).

E. Analysis on the Relationship Between the Number of Hits per Return and the Crown Depth

In this final analysis, we examined if a relationship exists between the number of hits per return and the depth of the tree crowns. Fig. 5 shows crown depth versus the percentage of hits on the total for all the four returns considered. Twelve groups of crown depth were defined from 6 to 28 m. Only trees with a height between 20 and 40 m were considered. From a theoretical viewpoint, we expect that as much the crown is depth as high the possibility to have hits over the first return is. In greater detail, analyzing the specification of the sensor considered in this study we know that the minimum distance between the first and the second pulse is 2.1 m, and 3.8 m for any subsequent return [3]. This is confirmed from our analysis. In Fig. 5, it is possible to see that there is a slight trend for which we have a reduction of the percentage of first return hits, in favor to the hits belonging to the other returns. In particular we move from an 81.5% of the first returns for the range between 6 and 8 m to 51.1% for the range from 26 to 28 m. Meanwhile we have an increase of the second return (from 15.8% to 34%), of the third (from 2.6% to 13%) and of the fourth one (from 0.1% to 1.9%).

F. Discussion

From these results, it is possible to draw a number of conclusions on the use of LiDAR variables to predict individual stem volume and on the exploitation of information contained in the non-first returns.

In this study, ground truth individual stem volume was estimated using an equation of the form $V = \beta D^{\gamma} H^{\delta}$ where V is the stem volume, D is the diameter at breast height (DBH), H is the height of the tree, and β, γ, δ are parameters dependent on the species, the geographical area, and the terrain characteristics.

This equation explains the reason for which throughout the analysis the *maximum of the first return* is considered to be informative in the stem volume estimation. This variable is highly correlated with tree height, likewise other variables such as the percentiles over the 80th. The variables "$\mathrm{maximum}^{\mathrm{n}}$" in particular emerge to be highly correlated with the stem volume. This comes from the fact that in the computation of the volume the height of the tree at a certain power is used. This could be also a reason for the efficiency on how this kind of variable emphasizes the information content of the second and third return. In particular, the maximum of the second return at the power of 2.9 provides an adjusted R^2 of 0.74, while the maximum of the third return moved from a correlation of 0.49 to 0.63 at the power of 2.7.

Concerning the percentiles, many studies in the literature used this kind of variables in the estimation phase (e.g, [13]). This is mainly due to the fact that high percentage percentiles usually represent better the tree height with respect to the "maximum" (the *maximum* could be an outlier), and that the percentiles around the 50th could be used as a measure of crowns density. We can expect a connection between the density of the crown and the tree stem volume, and in particular trees with a higher crown density have a higher stem volume.

Moreover, from our analysis, it is clear that the returns different from the first are informative in the estimation of the tree stem volume. In greater detail, the second return provides good results comparable to those obtained with the first return. Also in this case the information contained in the second return can

TABLE VI
RESULTS OBTAINED WITH A TEN-FOLD CROSS VALIDATION

Variables in the final model	Training		Test	
	RMSE	adj-R^2	RMSE	adj-R^2
maximum of the 1st return maximum of the 2nd return at the power of 4.8 10th percentile of the 1st return 10th percentile of the 3rd return	0.55	0.76	0.55	0.71

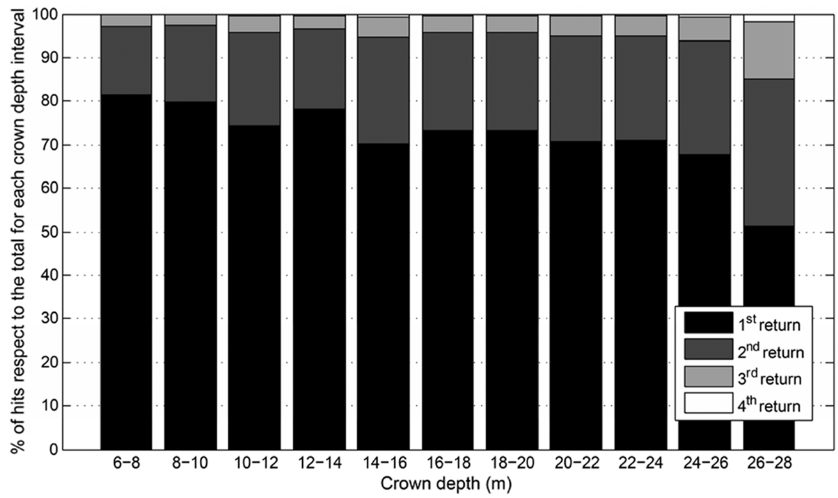

Fig. 5. Crown depth versus percentage of hits per return.

be related to the crown density and, thus, to the volume. The same consideration holds for the variables of the third return.

Concerning the variables descriptive of the tree crown (e.g., the *radius* and the *area* of the crown), they are correlated with the stem volume, as confirmed from some literature studies (e.g., [7]).

It is worth noting that the combined use of variables belonging to different returns allows one to increase the estimation accuracy. In all the models developed starting from ensembles of variables belonging to different returns, the stepwise selection included variables extracted from almost all the returns. In particular, in the final model used, we have variables belonging to the first, the second, and the third return.

V. CONCLUSIONS

In this paper, we have presented an analysis on the effectiveness of the use of multireturn LiDAR data in the estimation of tree stem volume at individual tree level. We have studied a multireturn LiDAR data set characterized by four returns. We have also analyzed different kinds of variables extracted from the different returns, deriving some interesting conclusions.

1) The use of variables belonging to all the returns allows one to obtain an increase of the estimation accuracy. In our particular case, the final best model is based on variables extracted from the first, the second, and the third returns.
2) The variables "$\mathrm{maximum}^{\mathrm{n}}$" allow one to emphasize the information contained in all the returns and, in particular, to obtain good correlations only using the second or the third returns.
3) There exists a correlation between the crown depth and the number of hits per return; in greater detail, increasing the crown depth, the probability to have returns different from the first increases.

As future developments of this work we plan to: i) analyze the effectiveness of different kinds of variable-selection techniques; ii) study other kinds of nonlinear estimators (e.g., Support Vector Regression); iii) investigate the interaction of LiDAR data with other sources of information (e.g., multispectral and hyperspectral remote sensing images); iv) analyze the effects of the undetected crowns (e.g., in multilayer forests) on the estimation of the of stem volume in forest inventories; v) study the possibility to identify information on the dominated layers from the analysis of different LiDAR returns in multilayer forests.

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