Remote Sensing of Environment 115 (2011) 2486–2498

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Fusion of airborne LiDAR and satellite multispectral data for the estimation of timber volume in the Southern Alps

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ARTICLE INFO

Article history:
Received 5 November 2010
Received in revised form 17 May 2011
Accepted 18 May 2011

Keywords:
LiDAR
Multispectral
Stem volume estimation
Forest
Mountain region

ABSTRACT

Remote sensing can be considered a key instrument for studies related to forests and their dynamics. At present, the increasing availability of multisensor acquisitions over the same areas, offers the possibility to combine data from different sensors (e.g., optical, RADAR, LiDAR). This paper presents an analysis on the fusion of airborne LiDAR and satellite multispectral data (IRS 1C LISS III), for the prediction of forest stem volume at plot level in a complex mountain area (Province of Trento, Southern Italian Alps), characterized by different tree species, complex morphology (i.e. altitude ranges from 65 m to 3700 m above sea level), and a range of different climates (from the sub-Mediterranean to Alpine type). 799 sample plots were randomly distributed over the 3000 km^2 of the forested areas of the Trento Province. From each plot, a set of variables were extracted from both LiDAR and multispectral data. A regression analysis was carried out considering two data sources (LiDAR and multispectral) and their combination, and dividing the plot areas into groups according to their species composition, altitude and slope. Experimental results show that the combination of LiDAR and IRS 1C LISS III data, for the estimation of stem volume, is effective in all the experiments considered. The best developed models comprise variables extracted from both of these data sources. The RMSE% on an independent validation set for the stem volume estimation models ranges between 17.2% and 26.5%, considering macro sets of tree species (deciduous, evergreen and mixed), between 17.5% and 29.0%, considering dominant species plots, and between 15.5% and 21.3% considering altitude and slope sets.

1. Introduction

Remote sensing of biophysical variables is a key component for the quantification of forest structure, volume, physiology and carbon fluxes in forests. At present, there are many studies that use remote sensing data for the estimation of forest parameters. This study is focused on Light Detection And Ranging (LiDAR) and multispectral data. These two data sources can be considered complementary, as one provides structural information and the other spectral information. LiDAR represents one of the best sources of information for investigating forest structural parameters (e.g., stem volume, basal area, or height), as it provides detailed data on the vertical structure of the canopy. Satellite multispectral data, like IRS 1C LISS III, provide spectral information of the ground cover, allowing the detection of forest composition and estimation of some species-related attributes.

Many studies in the literature use LiDAR data to analyze forest environments and their biophysical parameters. The first countries to extensively apply LiDAR data in forestry were Scandinavian ones and it is here that we can find the majority of studies in the literature (e.g., Næsset, 2005, 2009; Næsset & Gobakken, 2008). At present, studies also exist in many other countries, from North America to Southern Europe (e.g., Dorigo et al., 2010; Garcia et al., 2010; Ioki et al., 2010). In the following we provide some examples with different study area characteristics. Næsset (2005) carried out a study on the estimation differences between leaf-off and leaf-on conditions during LiDAR acquisition. The author analyzed an area of about 30 km^2 dominated by Norway Spruce and Scots Pine, and limited presence of Birch. In general the mean height, basal area, and volume, estimated by the models in both conditions were quite similar. The author concluded that in mixed forest the accuracy of estimated biophysical properties is almost unaffected by leaf-off conditions. Hollaus et al. (2007) estimated stem volume over a 128 km^2 forested area in Austria. The area is mainly covered by Norway Spruce and has an altitude range between 800 and 2900 m. They verified different sampling plot sizes and obtained an Adjusted-R^2 of 0.84 using a plot size of diameter 24. Ioki et al. (2010) analyzed 20 field plots in Japan characterized by broadleaved deciduous species. They considered LiDAR metrics related to tree heights (percentiles) and forest canopy structure. For the estimation of the stand volume they found that the best model comprised a height and a canopy structure variable. The best result in

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0034-4257/$ – see front matter
doi:10.1016/j.rse.2011.05.009

terms of Adjusted-R^2 was 0.75 with an RMSE% of 16.4%. Lim et al. (2003) analyzed 49 plots in a broadleaves forest in Canada dominated by Sugar Maple and Yellow Birch. They estimated ten forest parameters and obtained an R^2 of 0.87 for the total wood volume estimation.

Satellite multispectral data have since long been widely used in the estimation of forest attributes (e.g., Hall et al., 2006; Kajisa et al., 2008). These data are much less expensive than LiDAR, they cover large areas, and in some cases they allow one to obtain convincing results. For example, Hall et al. (2006) estimated the above ground biomass and the stand volume with a model that generates empirical relationships between continuous estimates of forest structure attributes and spectral variables derived from Landsat ETM + data. The analyzed area covered 2600 km^2, an altitude range between 1070 and 1725 m, and the main species were coniferous. In the volume estimation, they obtained a R^2 close to 0.70. Kajisa et al. (2008) made a study in a mixed forest of coniferous and evergreen broadleaved species in Japan. They estimated stand volume of 622 field sample plots using Landsat-ETM + bands and a k-NN estimator. They obtained a RMSE% of 66.2%.

A promising field of remote sensing data analysis is data fusion. Theoretically, the combination of sensors that measure different types of information can improve the estimation results. In particular, if the information is complementary, each sensor can explain a part of the target variability. Considering the fusion of LiDAR and satellite multispectral data in the literature one can find some studies (e.g., Fransson et al., 2004; Hudak et al., 2006; Latifi et al., 2010). Hudak et al. (2006) compared estimations of basal area and tree density obtained using a combination of LiDAR and ALI satellite data. They analyzed a forest area in Idaho, USA characterized by a large extension (880 km^2) and the presence of mainly coniferous trees. From the experimental results it emerged that the most informative variables were shown to be LiDAR-derived, even if the combination of the two information sources allowed a slight increase in the accuracy of estimations. Latifi et al. (2010) estimated, using non-parametric methods, the timber volume and biomass in a temperate forest combining LiDAR and Landsat TM data. The analyzed area was located in Southwestern Germany, with an extension of 9 km^2 and the presence of both coniferous and broadleaves species. They tested several variable selection systems, concluding that the majority of the selected variables in all the methods considered were LiDAR derived. The best models for volume estimation with LiDAR, multispectral, and LiDAR and multispectral obtained RMSE% values of 23.9%, 44.5%, and 23.2%, respectively.

The literature review presented above illustrates that many studies and different types of analyses have been carried out using LiDAR and multispectral data for the estimation of forest attributes. It is possible to find studies on many kinds of biophysical parameters, different LiDAR acquisitions (e.g., Næsset, 2005, 2009) and in study areas with different characteristics (e.g., large extension: Næsset & Gobakken, 2008; high altitudinal range: Dorigo et al., 2010; large species variability: Breidenbach et al., 2010). In this paper we focus on the fusion of LiDAR and IRS 1C LISS III multispectral data in a mountainous environment. The goal of this paper is to present an analysis on the combined use of these sensors in an area that comprises three characteristics: i) large extension; ii) high altitudinal range; and iii) large species variability. In particular, these data are analyzed both separately and combined, considering different levels of species aggregations (all the sample areas together, divided by macro classes and divided by single species) and different altitude and slope ranges. The effectiveness of the models for each permutation is verified using a validation data set. This analysis is potentially useful as it includes the application of some standard techniques (like the prediction of stem volume through LiDAR-derived variables), with promising advances in data managing (like data fusion), in a large mountain area in the Alps.

2. Methods

2.1. Study area

The study area is the territory of the Autonomous Province of Trento (see Fig. 1), in the Southern Italian Alps. The total area of the province is 6212 km², of which 54.7% is forested (Rodeghiero et al., 2010). The morphology of this area is quite complex as the altitude ranges from 65 m to 3764 m a.s.l., with almost half (49.9%) of the territory ranging between 1000 and 2000 m a.s.l. From a climatic point of view, the province can be divided into four ecological regions: i) sub-Mediterranean; ii) sub-continental; iii) continental; and iv) alpine.

About 80% of the forested area can be classified as high stand forests used for timber production, whereas the remaining 20% are managed as coppices for wood production. In 67% of the forested area, conifers are the dominant species, (i.e. Silver Fir (*Abies alba*), Norway Spruce (*Picea abies*), European Larch (*Larix decidua*), Austrian Pine (*Pinus nigra*) and Scots Pine (*Pinus sylvestris*)), whereas the remaining 33% of forests are dominated by broadleaves (i.e. European Beech (*Fagus sylvatica*), Hop hornbeam (*Ostrya carpinifolia*), Oaks (*Quercus* ss.pp.) and Maples (*Acer* ss.pp.)). For more details see Rodeghiero et al. (2010).

2.2. Field data

The field data for this study were collected in the growing seasons of 2004 and 2005. For the definition of the ground reference data, a random sampling based approach was adopted in order to obtain a statistically significant representation of the study area. Sample points were randomly distributed across the analyzed forested area using a GIS software according to an unaligned systematic sampling design (see EPA, 2002). A square grid with cells of 1 km × 1 km was laid over an orthophoto of the study area, and in each square a sample point was randomly inserted and classified as being inside or outside the forest study area. Approximately 4000 points were classified as forest within the boundaries of the study area, of which 799 points were randomly selected.

For each sampling point, trees were selected according to the Bitterlich method, in which the probability of a tree selection is proportional to the square of its Diameter at Breast Height (DBH)

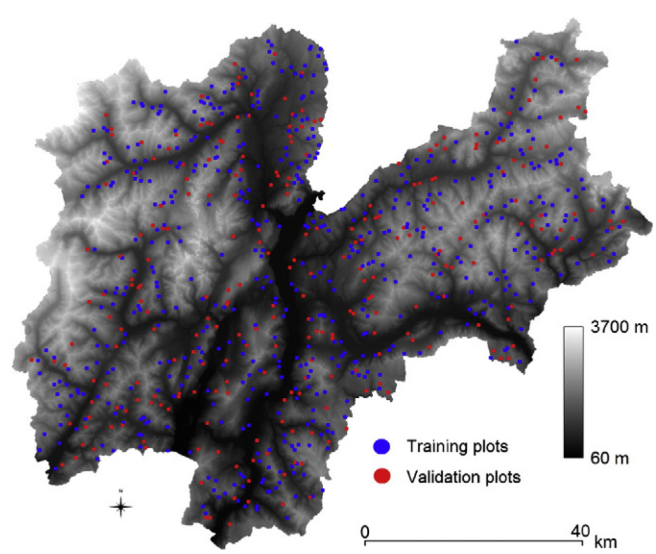

Fig. 1. The digital terrain model of the Province of Trento. The blue circles indicate training areas and the red circles indicate validation areas.

measured at 1.30 m (Shiver & Borders, 1996). For each sampling point, we chose a standard cluster of five Angle Count Sampling (ACS): one in the position of the sampling point and four at a distance of 14 m along the cardinal directions. The basal area of the plot was calculated as the mean value of the five ACS. The stem volume of each tree was calculated using species-specific equations based on height and diameter published in Salvadori and Ambrosi (2005). The tree heights were determined according to specific tables provided by the Forest Service of the Province of Trento for each area. The DBH was measured for all trees with DBH > 2.5 cm. More details can be found in Tonolli et al. (2011).

The position of field plots on the ground was assessed with a Trimble Geo-CE XT GPS receiver with the help of an external antenna. The final position of each point is the average of more than 180 GPS acquisitions.

Plots were divided into training and validation sets (see Table 1). Two thirds of the plots (training set) were used for the model definition and the remaining third of the samples were used for independent validation. For both data sets, the sample plots were divided according to the species composition, altitude and slope. Regarding species composition, firstly, some macro classes were considered: i) deciduous; ii) evergreen; and iii) mixed. These classes were defined considering a composition threshold of 80%; when neither evergreen nor deciduous species covered more than 80% of the area, the plot was classified as mixed. Secondly, the dominant species were considered: i) Silver Fir and Norway Spruce; ii) Pine (i.e. Austrian Pine and Scots Pine); iii) Larch; iv) European Beech; and v) other broadleaves (e.g., Hop Hornbeam, Oaks and Maples). In this case a plot was defined belonging to one of these classes considering a composition threshold of 50%. Regarding altitude ranges, we considered plots below 750 m, between 750 and 1250 m, 1250 and 1750 m, and above 1750 m. Regarding slope, we considered plots below 15°, between 15 and 25°, 25 and 35°, and above 35°. See Table 1 for a detailed description of these data sets. It is worth noting that the statistics of training and validation data sets are almost the same. Some differences remain, especially for the species for which a limited number of sample plots are available.

Fig. 2 shows the frequency distribution of the altitude, and slope of the sample areas divided into training and validation data sets. The figure illustrates that the distribution of these attributes is similar for both the training and the validation data sets.

Table 1
Descriptive statistics for the stem volume of the sample points collected in the Province of Trento used in the experiments. The sample plots are divided according to species composition, and altitude and slope ranges.

	N	Mean ($m^3\ ha^{-1}$)	SD	Range ($m^3\ ha^{-1}$)
Training Set				
All	534	241.9	148.8	6.9–874.9
Deciduous	169	157.3	118.8	6.9–630.9
Evergreen	199	317.3	157.6	20.2–874.9
Mixed	166	237.6	114.7	19.7–698.3
Silver Fir and Norway Spruce	247	320.6	149.0	19.7–874.9
Pine	54	183.5	81.6	49.9–372.2
Larch	71	166.1	117.9	11.8–491.7
European Beech	68	208.8	107.0	6.9–630.9
Other Broadleaves	94	149.6	116.3	9.3–560.9
≤750 m	67	153.2	95.7	9.3–369.7
>750–≤1250 m	163	234.5	131.2	6.9–698.3
>1250–≤1750 m	226	290.2	152.5	20.2–794.5
>1750 m	78	193.3	158.3	11.8–874.9
≤15°	76	251.5	149.8	6.9–775.7
>15–≤25°	126	279.1	166.3	10.2–874.9
>25–≤35°	194	235.3	140.5	17.6–742.1
>35°	138	211.7	135.9	9.3–698.3
Validation Set				
All	265	240.6	150.0	9.3–749.6
Deciduous	83	137.7	77.8	18.4–383.5
Evergreen	99	326.7	158.3	9.3–749.6
Mixed	83	240.9	129.6	10.2–508.9
Silver Fir and Norway Spruce	117	321.5	154.5	9.3–749.6
Pine	31	201.8	113.6	10.2–421.3
Larch	39	201.4	141.9	15.2–508.8
European Beech	35	183.4	87.2	38.8–414.1
Other Broadleaves	43	130.8	77.7	18.4–323.2
≤750 m	39	135.2	88.5	10.2–365.5
> 750–≤1250 m	99	250.8	135.4	33.1–672.5
>1250–≤1750 m	89	295.4	149.3	10.5–749.6
>1750 m	38	194.1	171.8	9.3–723.3
≤15°	34	245.5	148.6	26.7–705.2
>15–≤25°	73	250.2	153.5	18.4–723.3
>25–≤35°	99	238.6	144.1	10.2–541.0
>35°	59	229.5	159.0	9.3–749.6

2.3. LiDAR and multispectral data

LiDAR data were acquired to generate a digital terrain model (DTM) of the entire Autonomous Province of Trento between October 2006 and December 2007. The acquisitions started in October 2006 in the areas with the highest altitude. During the months from November to March, areas below 2000 m were acquired. Snowfalls in the winter of 2006/2007 were very low in this area and thus all the acquisitions were carried out in the absence of snow. Between April and October 2007 acquisitions in high mountain areas (over 2000 m with very low vegetation coverage) were completed, and in the final months of 2007 the areas at lowest altitude were covered. This allows us to have a dataset over the vegetated areas in leaf-off conditions. The sensor used was an Optech ALTM 3100C system with a pulse repetition frequency of 100 kHz and a laser wavelength between 400 and 800 nm. The maximum scan angle adopted was 25°. For the acquisition, a PARTENAVIA P68 airplane was flown at a height between 1000 m and 1800 m above ground with a flight speed of 250 km h^{-1}. The mean point density was about 0.48 m^2. For each emitted pulse, both first and last pulses were recorded.

IRS 1C LISS III multispectral data were acquired on the 18th July, 2003. This multispectral data comprised four bands: green (520–590 nm), red (620–680 nm), near-infrared (NIR; 770–860 nm), and shortwave infrared (SWIR; 1550–1700 nm). The ground spatial resolution was 23.5 m per pixel for the first three bands and 70.8 m for the SWIR band. Cloud cover was 10% for the upper left quadrant of the image, 0% for the upper right, 20% for the lower left and 10% for the lower right.

2.4. Data processing

Fig. 3 shows a flowchart of the processing steps carried out in this paper. In the following subsections all the steps are detailed.

2.4.1. Remote sensing data preprocessing

The preprocessing applied to the LiDAR data consisted of subtracting of the Digital Terrain Model (DTM) from the absolute height a.s.l. of each LiDAR pulse. The DTM had been independently derived from these acquired LiDAR data beforehand at a ground resolution of 1 m (x and y axis) and of 60 cm on the z axis (public provincial data set). The process of DTM extraction was carried out by the company that acquired the data with the software TerraScan.

Multispectral data were atmospherically corrected with the 6S model (Second Simulation of Satellite Signal in the Solar Spectrum) implemented as a module in GRASS GIS V6.4 (Neteler & Mitasova, 2008). For this purpose, the sensor specifications of IRS 1C LISS III had to be implemented first. The correction was performed with the midlatitude summer atmospheric model, the continental aerosols model, and an estimated visibility of 60 km. In absence of site specific observations, the 6S model was parameterized with generic data. A verification was done using the dark object approach since large water bodies exist within the study area.

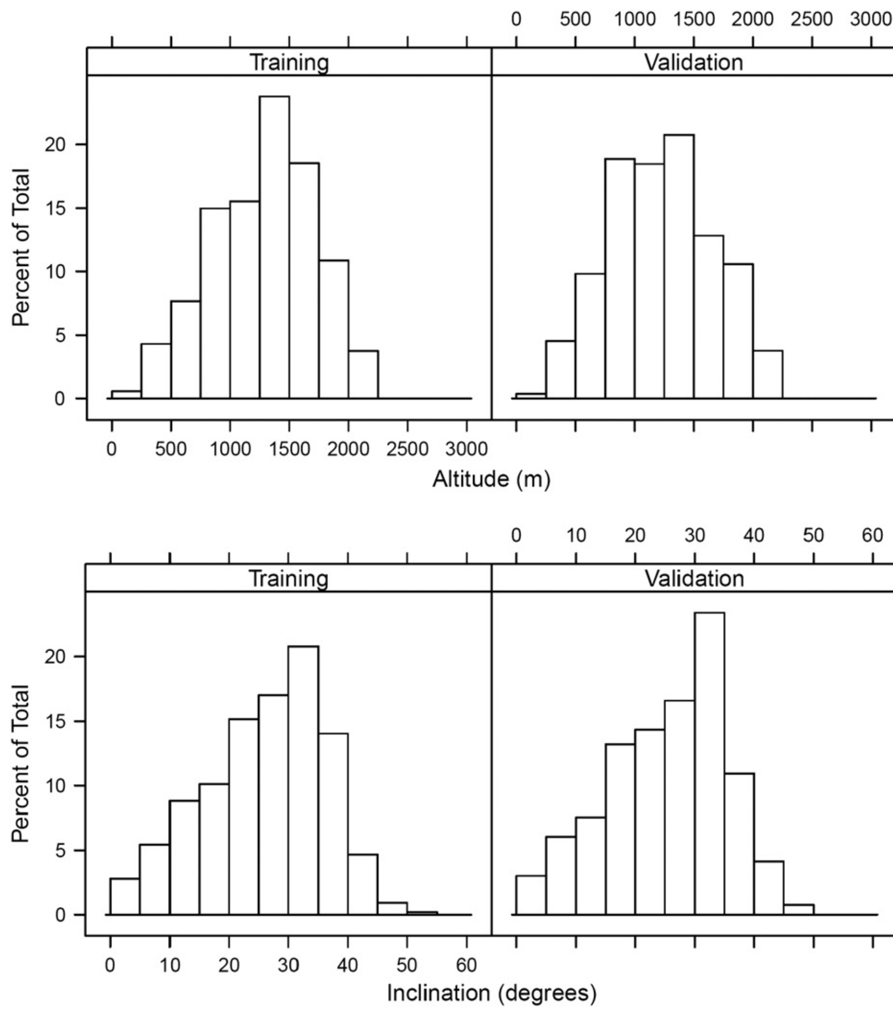

Fig. 2. Frequency distribution of the sample areas of training and validation data sets according to the altitude and ground slope.

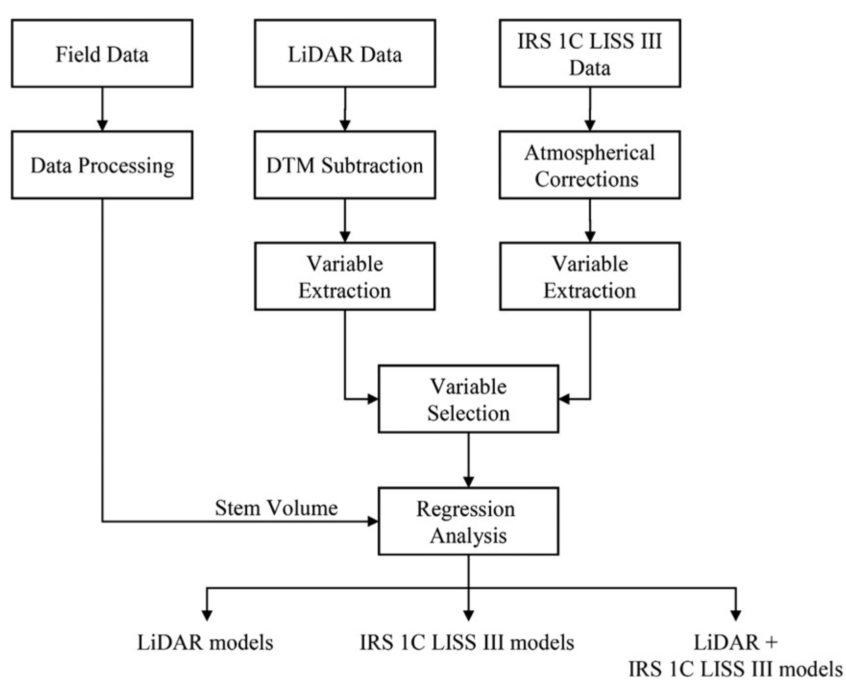

Fig. 3. Flowchart for model building methods.

2.4.2. LiDAR variables

According to the results of a previous study (Tonolli et al., in press), and considering the ACS scheme adopted for the extraction of the LiDAR variables, we considered a circle with a radius of 28 m. For each sample point the LiDAR pulses falling inside the circle were selected. From these pulses, a series of variables were extracted from each plot. In particular, variables belonging to three categories have been extracted: i) height; ii) coverage; and iii) other variables. Table 2 shows a summary of this data set. For the calculation of these variables, only LiDAR pulses with a height of more than 1.3 m ($I_{1.3m}$) above ground were considered.

Height variables have been widely used previously (e.g., Andersen et al., 2005; Næsset & Gobakken, 2008; Næsset & Økland, 2002) and they have been shown to be effective for tree height characterization. Coverage variables are related to the description of the canopy density and coverage (e.g., Næsset et al., 2005). The variable "*N_LiDAR*" represents the number of dominant trees in the considered plot. It was extracted according to a tree top identification algorithm (for more details see Hyyppä et al., 2001).

2.4.3. IRS 1C LISS III variables

Starting from the central point of each plot, a circle with a 28 m radius was delimited and the pixels of the multispectral image falling inside this circle were considered. The average value of these pixels was used for the extraction of some variables from each plot (see Table 3). In particular, variables belonging to three categories were extracted: i) normalized bands; ii) simple band ratios; and iii) normalized band ratios. We chose these variables as they have been used in previous studies (e.g., Erdody & Moskal, 2010; Packalen & Maltamo, 2007; Powell et al., 2010). These variables included, first of all, the IRS normalized bands (green, red, Infrared and SWIR). Both vegetation indices which use simple ratios between the NIR and SWIR bands, and normalized indices were used.

A particular attention was paid to the SWIR band and to the vegetation indices which make use of the SWIR band. The use of the SWIR region of the spectrum for predicting biophysical vegetation attributes, in fact, is one of the most promising approaches to deal with the saturation problem (Vescovo & Gianelle, 2008).

2.4.4. Analysis

A regression analysis was carried out in order to define some predictive models for the stem volume estimation based on LiDAR, IRS 1C LISS III predictor variables, and a combination of both. For each of the three data sources, 17 models were developed according to species composition, and altitude and slope ranges.

Statistical analyses were performed using the R software package (version 2.12.0).[1] In order to select the most suitable set of variables we applied the protocol proposed in Hudak et al. (2006). We used the *lm* linear model function of R to create the full models and then a stepwise selection was applied (*stepAIC* function). Once the stepwise model was identified, an exhaustive method was applied for a variable count that ranged from 1 to the number of variables selected by the stepwise model. The function used to determine the best subsets was *regsubsets* of the *leaps* R package. The model statistic used for the selection of the best model was Mallows Cp statistic (Mallows, 1973). Among these models, we selected the one with the lowest number of variables that had no significant differences (tested with an ANOVA test) with the model with the lowest AIC (Akaike, 1974).

The values of stem volume were Box-Cox transformed (i.e., Box & Cox, 1964) in order to improve the subsequent estimation results. This transformation is used to stabilize the variances of the sample volumes, and to reduce or eliminate the correlation between the means and standard deviations.

All the developed models were tested on an independent validation data set representative of the forest areas of the Province of Trento.

Table 2
Variables extracted from LiDAR pulses in each plot area.

Variable ID	Variable description
Height	
H_{mean}	Mean value of $I_{1.3m}$
H_{max}	Max value of $I_{1.3m}$
H_{CV}	Coefficient of variation of $I_{1.3m}$
H_{q20}	20th quintile of $I_{1.3m}$
H_{q50}	50th quintile of $I_{1.3m}$
H_{q90}	90th quintile of $I_{1.3m}$
$H_{q90}^{2.5}$	90th quintile of $I_{1.3m}$ at the power of 2.5
H_{q95}	95th quintile of $I_{1.3m}$
Coverage	
$C_{1.3m}$	Canopy density as c_{Ihc}/c_{Ih} where c_{Ihc} is the number of $I_{1.3m}$ values and c_{Ih} is the total number of pulses
C_{mean}	Ratio c_{Ihm}/c_{Ih} where c_{Ihm} is the number of canopy pulses with *Ihc* values majors of h_{mean}
C_{q20}	Ratio c_{Ih20}/c_{Ih} where c_{Ih20} is the number of canopy pulses with *Ihc* values majors of h_{q90}
C_{q50}	Ratio c_{Ih50}/c_{Ih} where c_{Ih50} is the number of canopy pulses with *Ihc* values majors of h_{q90}
C_{q90}	Ratio c_{Ih90}/c_{Ih} where c_{Ih90} is the number of canopy pulses with *Ihc* values majors of h_{q90}
Other variables	
N_LiDAR	Number of trees extracted from LiDAR data

Table 3
Variables extracted from ISR 1C LISS III data in each sample plot.

Variable ID	Variable description
Normalized bands	
B1N	Green band normalized between 0 and 1
B2N	Red band normalized between 0 and 1
B3N	NIR band normalized between 0 and 1
B4N	SWIR band normalized between 0 and 1
Simple band ratios	
RR	SWIR/Red reflectance ratio
SR	Simple ratio: NIR/Red reflectance ratio (Jordan, 1969)
SRc	Corrected Simple Ratio (Brown et al. 2000)
MSR	Modified Simple Ratio (Chen, 1996)
CI	Canopy Index (Vescovo & Gianelle, 2008)
Normalized band ratios	
NDVI	Normalized Difference Vegetation Index (Rouse et al., 1974)
NDVIc	Corrected NDVI (Nemani et al., 1993)
GNDVIgreen	Green Normalized Difference Vegetation Index (Gitelson et al., 1996)
NDWI	Normalized Difference Water Index (Lymburner et al., 2000)
NCI	Normalized Canopy Index (Vescovo & Gianelle, 2008)

3. Results

In the models obtained using LiDAR data and the nine species compositions (Table 4), a height variable is always one of the most significant. H_{mean} and H_{max} are the most significant for the "Evergreen" and the "Silver Fir and Norway Spruce" sets. For the "Deciduous" set, the most significant variables are the percentiles and coefficient of variations of the LiDAR pulses (H_{CV}). In addition, coverage variables emerged to be important as they were always selected and they were among the most significant in four sets out of nine. The number of trees extracted from the LiDAR data (N_LiDAR) emerged to be particularly significant for coniferous species, even if it was also selected in "Mixed" and "Other Broadleaves" sets. All the LiDAR variables were present in at least one model.

In the models comprising only IRS 1C LISS III variables, the most selected ones were related to infrared bands. In six out of nine models the B3N and RR variable was selected, in four models the NDVIc, and NDWI. In particular in four models ("All","Deciduous", "Evergreen", "Silver Fir and Norway Spruce") we found the combination of B3N, RR

[1] http://www.r-project.org/

Table 4
Best subsets regression models obtained with the three variable data sets (L, LiDAR; M, IRS 1C LISS III; L + M, LiDAR + IRS 1C LISS III) and the nine species data sets considered. Significance levels are as follows: ***, $p<0.001$; **, $p<0.01$; *, $p<0.05$; ., $p<0.1$; ns, not significant.

		Selected variables	(Intercept)	H_{max}	H_{mean}	H_{cv}	H_{q20}	H_{q50}	H_{q90}	$H_{q90}^{2.5}$	H_{q95}	$C_{1.3m}$	C_{med}	C_{q20}	C_{q50}	C_{q90}	N_LiDAR	B1norm	B2norm	B3norm	B4norm	SR	NDVI	MSR	RR	GNDVIgreen	SRc	NDVIc	NDWI	CI	NCI
All	L	6	**	***		**	*		***	**					***																
	M	5	**																	***		**	**		***				***		
	L + M	9	***	**		***			***	*					***					***					**			*	**		
Deciduous	L	5	ns					***	.		ns				*	*															
	M	4	***																	***					***			**	***		
	L + M	6	**					***		*				**		**					***				**						
Evergreen	L	6	ns	***	***		**	***								**	**														
	M	5	***																	***	*		.		*				***		
	L + M	14	**	***	***			*	**	ns		.			.		*		***				**		**		**		***		ns
Mixed	L	4	***			***					***					***	.														
	M	4	***															***	*						***						***
	L + M	4	***			***					***					***	.														
Silver Fir	L	6	ns	***	***			**	**				***				**														
Norway	M	4	***																	***					***			**	***		
Spruce	L + M	10	**	***	***			**	*				***				*			**			*					*	**		
Pine	L	5	***	*		*				***		*		*																	
	M	2	.																									**			.
	L + M	10	*	***			**		*	***		***							**	***				*	***				***		
Larch	L	5	ns			***					***	.				.	**														
	M	4	.																*	**					.			***			
	L + M	9	***		***			**							.	.	**				***	***						***	*		
European	L	3	**			**					***					.															
Beech	M	2	ns																				**							***	
	L + M	5	ns					***								**						ns		ns							*
Other	L	7	ns						***	.		**	***	ns	**		*														
Broadleaves	M	3	ns																***	***							***				
	L + M	11	**						**	*	.	**	***	*	*		**								***			***		***	

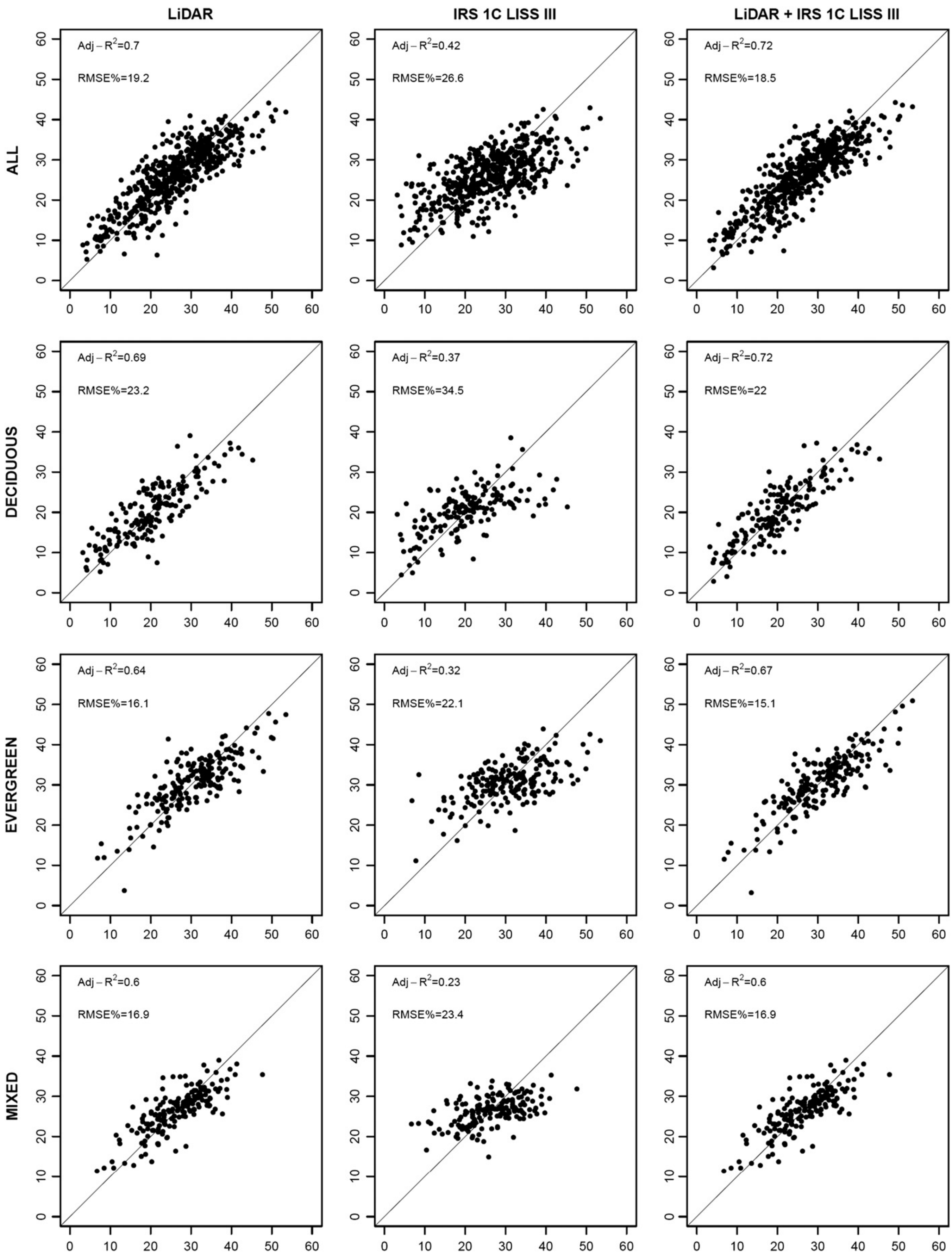

Fig. 4. Observed (x axis) versus predicted (y axis) volumes (Box-Cox transformed) for the group models considered. The solid lines represent the 1:1 relationship.

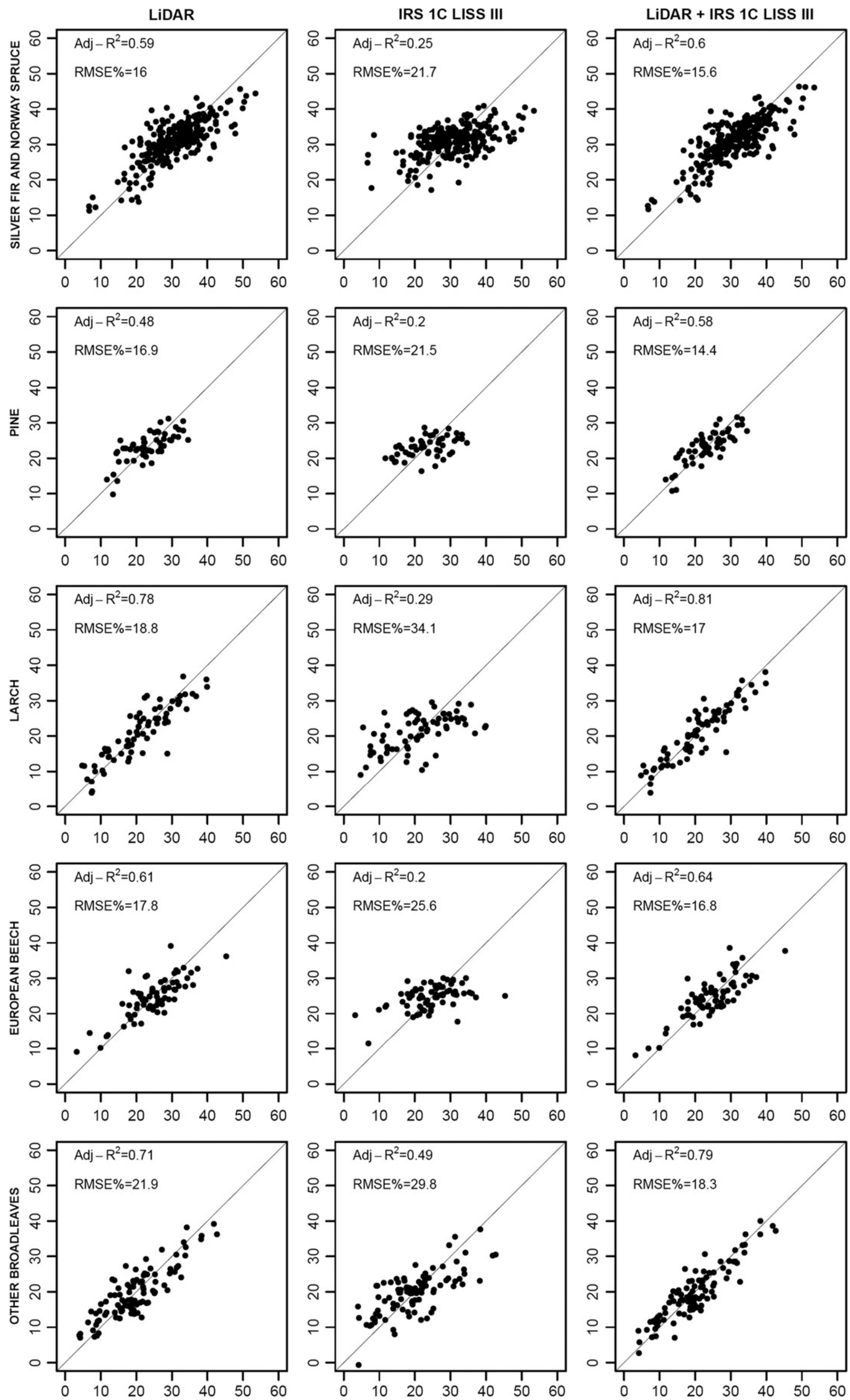

Fig. 5. Observed (x axis) versus predicted (y axis) volumes (Box-Cox transformed) for the models based on single species division. The solid lines represent 1:1 relationship.

and NDWI. The set that diverges most from the others was the “European Beech”, where the most significant variable was CI, even if this variable was also related to infrared (CI = B4N-B1N). Only two variables were never selected: MSR and GNDVIgreen.

Concerning LiDAR + IRS 1 C LISS III variable models, only the “Mixed” set comprised variables from only one sensor source. In all the other models we found a combination of both sensors. Six models out of nine had a multispectral variable among the most significant (“All”, “Deciduous”, “Evergreen”, “Pine”, “Larch”, “Other Broadleaves”). These models, with respect to the LiDAR and IRS 1C LISS III ones, combine a higher number of variables.

Figs. 4 and 5 show the observed versus the predicted volumes (Box-Cox transformed) and the results in terms of Adjusted-R^2 and RMSE% obtained for the training data sets considering the models defined according to species composition and data source. The RMSE% is computed as the ratio between the RMSE and the mean value of the observations expressed as a percentage. For the LiDAR models, the best and worst results are obtained for the data sets with the prevalence of one specific species. “Larch” model reached an Adjusted-R^2 of 0.78, while “Pine” model recorded a value of just 0.48. The division into macro classes (Evergreen, Deciduous and Mixed) does not seem to provide an increase in accuracy in terms of Adjusted-R^2 (we noticed a decrease from 0.05 to 0.12 of its value), respect the “All” model while the RMSE% decreases. In particular the data set “All” has an RMSE% of 19.2, while “Evergreen” is around 16.0.

IRS 1C LISS III variables alone allow one to obtain reasonable results in terms of Adjusted-R^2 only on the “Other Broadleaves” data set (Adjusted-R^2 = 0.49), while for the other data sets the results were not as good (Adjusted-R^2 between 0.20 and 0.42). In particular, for some prevalent species sets (“Silver Fir and Norway Spruce”, “Pine”, “Larch” and “European Beech”), results are particularly poor. Also in terms of RMSE%, the results obtained with the multispectral information worsens compared to those obtained with LiDAR, with values ranging from 21.5 to 34.5.

The models that always provide the best results are those obtained with the combination of the two information sources (LiDAR + IRS 1C LISS III). Improvements in both Adjusted-R^2 and RMSE% were registered.

Table 5 shows the RMSE% results obtained for the validation data set with the models defined according to the species composition and the data sources. The performance is comparable to that obtained for the training data set (e.g., 18.5% on the training and 19.9% on the validation for the “All” data set using both data sources). Models comprising LiDAR variables provide the best results, while models comprising only IRS 1C LISS III variables are less effective. It is worth noting that in the validation data set the differences between LiDAR and LiDAR + IRS 1C LISS III models are less marked compared to differences in the training data set and, in some cases, LiDAR variables alone provide better results.

Table 5
RMSE% results obtained for the validation data set using three sets of variables (LiDAR, IRS 1C LISS III and LiDAR + IRS 1C LISS III) and the nine species data sets (All, Deciduous, Evergreen, Mixed, Silver Fir and Norway Spruce, Pine, Larch, European Beech and Other broadleaves).

	LiDAR	IRS 1C LISS III	LiDAR + IRS 1C LISS III
	RMSE(%)	RMSE(%)	RMSE(%)
All	20.1	28.8	19.9
Deciduous	26.0	35.6	26.5
Evergreen	18.5	23.0	17.2
Mixed	18.9	28.9	18.9
Silver Fir and Norway Spruce	17.9	24.5	17.5
Pine	28.0	31.1	27.9
Larch	21.4	37.9	26.5
European Beech	21.6	26.9	23.0
Other Broadleaves	28.6	40.7	29.0

Table 6
Best subsets regression models obtained with the three variable data sets (L, LiDAR; M, IRS 1C LISS III; L + M, LiDAR + IRS 1C LISS III) and the altitude and slope subdivisions. Significance levels are as follows: ***, p<0.001; **, p<0.01; *, p<0.05; ., p<0.1; ns, not significant.

		Selected variables	(Intercept)	H_{max}	H_{mean}	H_{cv}	H_{q20}	H_{q50}	H_{q90}	$H_{q90}^{2.5}$	H_{q95}	$C_{1.3m}$	C_{med}	C_{q20}	C_{q50}	C_{q90}	N_LiDAR	B1norm	B2norm	B3norm	B4norm	SR	NDVI	MSR	RR	GNDVIgreen	SRc	NDVIc	NDWI	CI	NCI
≤750 m	L	4	ns			.			***	**				**																	
	M	3	***															***		**											***
	L + M	5	*			.			***	*				**				.													
>750–≤1250 m	L	4	***	***		***					***					***															
	M	2	***																***												***
	L + M	7	ns	**		***			***							***			*						**					**	
>1250–≤1750 m	L	4	*		***					.						***	.														
	M	4	***																	***					***			**	***		
	L + M	8	***			***			***			*			.	ns	**				***					*					
>1750 m	L	4	ns	.	***										*		**														
	M	8	**															***	**	.		**	**	**	**						***
	L + M	8	*				***					***										*	*	*				**		*	*
≤15°	L	6	ns	ns					***		**		**	***			.														
	M	2	***																			***					***				
	L + M	8	.	*					**	.	*		**	**			*				ns										
>15–≤25°	L	5	ns	**			***		***	**						***															
	M	4	***															***	*						*						*
	L + M	8	ns	**			***	**	***	***			***					*	ns												
>25–≤35°	L	5	***	*		***				*	***		***																		
	M	6	***															ns				***	***		***			***	***		
	L + M	9	***	**		***				.	***			ns	*	.									**					***	
>35°	L	3	**		**		*								***																
	M	4	***																	***					**			*	***		
	L + M	4	*				***									***									*					***	

In Fig. 6, the box-plots of the residuals distributions are shown. The residuals are divided according to species groups, and for each group, a subdivision according to the variables source is adopted. Residuals for both the training and validation data sets are shown. It is apparent that the distribution of the residuals is much larger for the models based only on IRS 1 C LISS III variables compared to the other models. In particular, LiDAR and LiDAR + IRS 1C LISS III models provide very similar results. For the training data set, the median value is around zero for almost all the models considered. This is important as it shows that the models do not have significant underestimation or overestimation problems. For the validation data set the distribution is generally broader even if it is quite similar to that obtained for the training data set showing a good generalization ability of the models.

In Table 6 it is possible to see the models obtained considering four altitude and slope ranges of the sample plots. In LiDAR-based models it is possible to find both height and coverage variables. As in Table 4, it is not possible to find a variable that is the most significant in all the models. It is worth noting that the variable N_LiDAR is present only in the models for plots above 1250 m. Above this threshold we have much more coniferous species compared to broadleaves. This also confirms the comments of Table 4. Concerning the slope in this case, both height and coverage variables are present in the models, even if by increasing the slope, the weight of height variables increases.

IRS 1C LISS III models for both altitude and slope subsets, comprises variables from all the three categories considered. Among the normalized bands B4N was never selected, and among the vegetation indexes, GNDVIgreen and CI were never used. The model for altitudes over 1750 m is the most complex with eight variables selected belonging to all the categories (normalized bands, vegetation indexes and normalized vegetation indexes). The simplest model is that for altitudes between 750 and 1250 m. Regarding the slope, the simplest model was defined for almost flats terrains (slope < 15°).

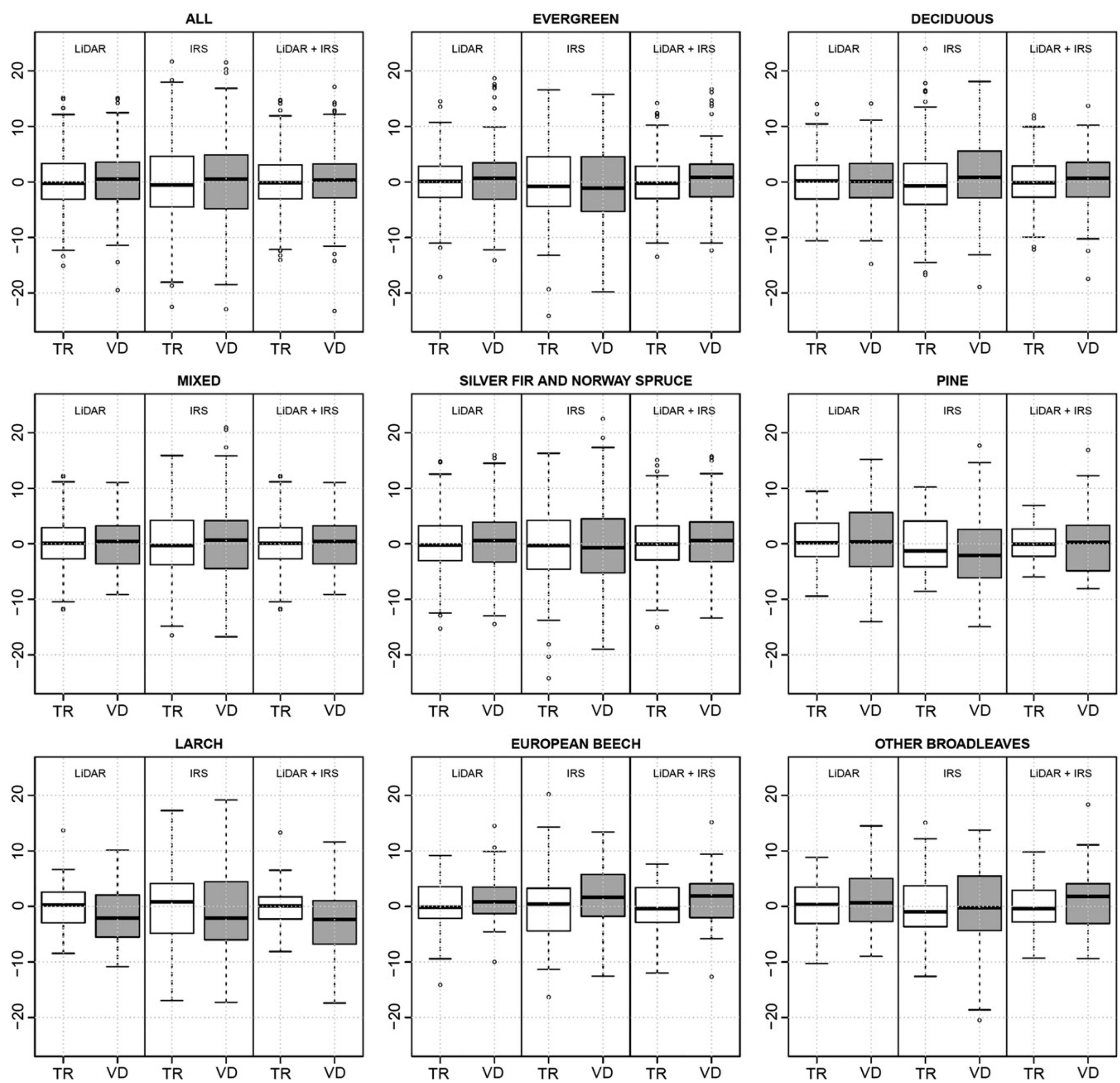

Fig. 6. Box plot distributions of the model residuals, considering the training (TR) and validation (VD) data sets. The midpoint of the box plot represents the median, the hinges (end of the boxes) represent the 25th and 75th quartiles, the lines are drawn from each hinge to 1.5 times the spread (75th–25th quartile) or to the most extreme value (if smaller). Any point outside these values is represented as a circular point.

Table 7
Results obtained for the training (TR) and validation (VD) data sets using three sets of variables (LiDAR, IRS 1C LISS III and LiDAR + IRS 1C LISS III) and the altitude and slope subdivisions.

	LiDAR			IRS 1C LISS III			LiDAR + IRS 1C LISS III		
	Adj-R^2	RMSE% TR	RMSE% VD	Adj-R^2	RMSE% TR	RMSE% VD	Adj-R^2	RMSE% TR	RMSE% VD
≤750 m	0.68	20.4	21.9	0.43	27.4	29.5	0.69	19.8	21.3
>750–≤1250 m	0.61	19.6	18.8	0.27	27.0	25.9	0.63	18.9	18.2
>1250–≤1750 m	0.68	16.4	16.3	0.34	23.6	23.4	0.71	15.7	15.5
>1750 m	0.76	21.3	21.6	0.63	25.5	25.8	0.81	18.6	18.8
≤15°	0.71	17.4	17.5	0.41	25.4	25.5	0.72	16.7	16.8
>15–≤25°	0.69	18.3	19.4	0.42	25.1	26.6	0.71	17.6	18.7
>25–≤35°	0.75	17.2	17.2	0.46	25.1	25.1	0.77	16.3	16.3
>35°	0.68	20.0	19.4	0.37	28.3	27.3	0.70	19.6	19.0

Models comprising both LiDAR and multispectral variables are simpler compared to those with species distinction. All the models for all altitudes and slope subsets combine variables extracted from both data sources.

Table 7 reports the accuracy results on training and validation sets. For all the models it is worth noting that the results on the training and validation sets are quite similar, showing a good generalization ability of the models. Regarding the altitude models the best results were obtained for sample plots located above 1750 m. In this case, the model comprising both LiDAR and IRS 1C LISS III variables have an Adjusted-R^2 of 0.81. For the slope subdivisions the best model obtained an Adjusted-R^2 of 0.77 with inclination of the plots between 25 and 35°. It is worth noting that the results for the different slope ranges are all quite similar. As for the species sets, we noticed an improvement in the estimation performance by combining LiDAR and multispectral data. IRS 1C LISS III models do not provide good results, with the exclusion of the set for altitudes over 1750 m where we have an Adjusted-R^2 of 0.63.

4. Discussion

The most important and informative variables for the estimation of stem volume are those derived from LiDAR. This confirms the expectations and the results previously presented in the literature (e.g., Erdody & Moskal, 2010; Fransson et al., 2004; Hudak et al., 2006). In almost all the models comprising LiDAR data, height and coverage variables were selected in first and second place. It is possible to find similar results, for example in Næsset et al. (2005), Næsset (2009), and in the Austrian Alps in Hollaus et al. (2007).

Height is a key parameter in the estimation of stem volume, as the volume is computed with height–diameter relationships. A variable relevant in LiDAR-based models is the number of trees per hectare (N_LiDAR). It is worth noting that this variable is significant in coniferous sets, like “Silver Fir and Norway Spruce”, and “Larch”, and in coniferous dominated sets (e.g., plots above 1750 m in elevation). The same occurs when the inclination is below 15°. The combination of plot variables with single tree information, like N_LiDAR, was studied in the literature, and it was demonstrated that this combination allows one to improve the estimation results (e.g., Lindberg et al., 2010).

Among the multispectral variables, the red, NIR and SWIR bands play a key role. This result confirms other findings reported in the literature for red and NIR bands (i.e., Muukkonen & Heiskanen, 2005, 2007). Hall et al. (2006) showed that visible and SWIR bands of Landsat ETM + data are correlated with the physical structure of the forest canopy, such as height, basal area and volume. Regarding the NIR band, Lu et al. (2004) conducted a detailed analysis of the Landsat TM5 reflectance data and they noticed that the presence of emergent trees with high DBH and tall canopy have a negative impact on the reflectance due to canopy shadowing. In another study using IKONOS data, Asner and Warner (2003) demonstrated that a 10% increase in the shadow fraction resulted in a 3% and 10% decrease in red and NIR response, respectively. In our study among the models based on the slope data sets, the NIR band is present only when the slope is higher than 35°. At this slope the possibility to have shadows is much higher.

In models based on both LiDAR and IRS 1C LISS III data the variables of these sensors are almost equally distributed with a dominance of those derived from LiDAR. Only in the “Mixed” case just LiDAR variables were selected. This result has been partially confirmed by other studies in the literature (e.g., Hudak et al., 2006; Latifi et al., 2010).

Regarding the Adjusted-R^2, it is evident that the contribution of IRS 1C LISS III variables to the predictive capacity of the final model is limited (the increase ranges between 0.01 and 0.1). In previous works in the literature it is possible to register similar behaviors (e.g., Hudak et al., 2006). In Latifi et al. (2010) the authors did not register a significant increase in the estimation performances with the combination of LiDAR and Landsat TM data, and in some cases they registered a deterioration in the performances.

Among the species datasets the one that performs best with only multispectral variables is “Other broadleaves”. Importantly, unlike the “Mixed” data set, the “Other broadleaves” data set comprises sample plots of mono specific species. This means that there is variability between the plot species, but low intra plot variability (in the “Mixed” data set the variability is intra plot). Thus, multispectral data are able to discriminate species variability, which is not possible with LiDAR data alone.

The results obtained using only multispectral data are also confirmed by other findings in the literature (e.g., Fransson et al., 2004; Latifi et al., 2010). Latifi et al. (2010) obtained an RMSE% for stem volume estimation of about 23% with LiDAR-derived variables, which increased to 44% using Landsat TM variables.

As explained in the data set description, the LiDAR data were acquired during leaf-off periods. A study of Næsset (2005) demonstrated that in a coniferous dominated area the use of data acquired in leaf-on or leaf-off conditions did not provide significantly different results.

It is also necessary to consider in this analysis that the LiDAR data were not all acquired at the same period (the acquisition span over one year) and at the same conditions (e.g., different flight altitudes). Moreover, the large scan angle of the flights can create problems in the points at the edges of each scan, making the LiDAR measure less accurate. All of these factors make the dataset “non optimal”, but it is necessary to consider that over an area of more than 6000 km^2 with a high altitudinal range it is quite difficult to make flights at the same time, and always under the same flight conditions.

Many studies exist (e.g., Næsset & Gobakken, 2008) which underline the importance of dividing the sample areas by species type, soil productivity, age, etc., and in fact we have noticed that some species division allowed us to obtain very good results (i.e., Adj-$R^2 = 0.81$ for “Larch” and Adj-$R^2 = 0.79$ for “Other Broadleaves”). In general the same happened with the altitude and slope datasets. These data sets, in an area like the one analyzed, also influenced the species distribution (e.g., above 1750 m almost only coniferous species are present). This behavior is not univocal. In the Southern

Alps it is possible to find multiple situations with the same altitude or slope. As an example, with a slope higher than 35° and altitude below 750 m, mainly broadleaves species are present (e.g., Hop Hornbeam), while with the same slope but altitude over 1250 mainly Norway Spruce is present.

Comparing our results with others obtained from datasets located in the Alps (e.g., Hollaus et al., 2009, 2007) we can see that the results are quite similar. Hollaus et al. (2007) obtained an Adjusted-R^2 of 0.85 for the estimation of stem volume in the Austrian federal state of Vorarlberg. Their dataset is characterized by high altitude variability, but low species variability (96% Norway Spruce).

In this study we used the angle count sampling (ACS) method for the collection of the ground truth data. The ACS method is widely used for forest inventory purposes and many studies exist that combine ACS ground truth with LiDAR data (e.g., Hollaus et al., 2009, 2007; Jochem et al., 2011; Tonolli et al., in press). Piqué et al. (in press) verified that for forest inventory purposes ACS provides results that are not significantly different to those for fixed radius plots. The advantage of this method is that it is much faster than the fixed radius plot, and thus less expensive. Regarding the combination of ACS ground truth with LiDAR data Maltamo et al. (2007) compared the estimation results for stem volume using both fixed and truncated-ACS methods, finding that fixed plots provide better results, even if the differences with truncated-ACS are negligible.

In a future practical application of this study in the Alps, and in mountain areas in general, we can consider all the three divisions analyzed in this paper (species, altitude and slope) as realistic approaches. Species division can be achieved with a classification map obtained using remote sensing images, while altitude and inclination can be achieved with the help of a detailed Digital Terrain Model of the area. Other divisions (e.g. age, soil fertility), are more difficult to achieve with remotely sensed data. Thus, the results obtained can be considered important as they produced a spatially distributed map of stem volume over a large area (more than 3000 km^2), characterized by complex geomorphology and the presence of many tree species.

Finally, we focus on costs. LiDAR acquisition, over an area like the one analyzed in this study, is extremely expensive (in the order of some hundreds of thousands of Euro), and it becomes more expensive if the acquisition is carried out only in leaf-on season with a high points density. In contrast, an IRS 1C LISS III image is much cheaper (about one thousand Euros), and one image provides coverage of the entire Province of Trento (6200 km^2). The presented analysis shows that merely using IRS 1C LISS III data, only limited results can be obtained and that LiDAR data are necessary in order to achieve accurate estimates of stem volume. An option could be to use these data for a raw estimation of stem volume, and then to acquire LiDAR data only over areas where the value of the wood can justify an expensive acquisition.

5. Conclusions

In this paper, an analysis on the fusion of LiDAR and IRS 1C LISS III data for the estimation of forest stem volume has been presented. The analysis indicates that: i) the combination of LiDAR and multispectral data can be useful as it provides a slight increase in estimation accuracy (an increase of Adjusted-R^2 between 1 and 4%), especially for some species groups; ii) models derived using only multispectral data do not provide high level results for the estimation of stem volumes in an area like the Province of Trento; iii) LiDAR variables alone provide the majority of the explanative contribution; iv) stratification according to species, altitude and slope allow in some cases to improve the estimation results; and v) the models presented can be effectively used for the estimation of stem volume over the entire Province of Trento, even if the LiDAR data considered were acquired in the leaf-off season.

Possible future developments of this work are: i) to consider other target variables (such as LAI, basal area); ii) to analyze the optimal number of sample plots in order to maintain a good generalization ability of the model over the entire Province of Trento; and iii) to analyze the combination of LiDAR data with other multispectral data.

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