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Estimating forest aboveground biomass by low density lidar data in mixed broad-leaved forests in the Italian Pre-Alps

Antonio Montagnoli[1*], Sara Fusco[1], Mattia Terzaghi[1], Alan Kirschbaum[3], Dirk Pflugmacher[2], Warren B Cohen[4], Gabriella S Scippa[5] and Donato Chiatante[1]

Abstract

Background: Estimation of forest biomass on the regional and global scale is of great importance. Many studies have demonstrated that lidar is an accurate tool for estimating forest aboveground biomass. However, results vary with forest types, terrain conditions and the quality of the lidar data.

Methods: In this study, we investigated the utility of low density lidar data (<2 points·m^{-2}) for estimating forest aboveground biomass in the mountainous forests of northern Italy. As a study site we selected a 4 km^2 area in the Valsassina mountains in Lombardy Region. The site is characterized by mixed and broad-leaved forests with variable stand densities and tree species compositions, being representative for the entire Pre-Alps region in terms of type of forest and geomorphology. We measured and determined tree height, DBH and tree species for 27 randomly located circular plots (radius =10 m) in May 2008. We used allometric equations to calculate total aboveground tree biomass and subsequently plot-level aboveground biomass (mg·ha^{-1}). Lidar data were collected in June 2004.

Results: Our results indicate that low density lidar data can be used to estimate forest aboveground biomass with acceptable accuracies. The best height results show a R^2 = 0.87 from final model and the root mean square error (RMSE) 1.02 m (8.3% of the mean). The best biomass model explained 59% of the variance in the field biomass. Leave-one-out cross validation yielded an RMSE of 30.6 mg·ha^{-1} (20.9% of the mean).

Conclusions: Low-density lidar data can be used to develop a forest aboveground biomass model from plot-level lidar height measurements with acceptable accuracies. In order to monitoring the National Forest Inventory, and respond to Kyoto protocol requirements, this analysis might be applied to a larger area.

Keywords: LiDAR; Allometric equations; Plant height; Mixed forest

Background

Forest biomass is a key biophysical property that describes the carbon content of vegetation. Quantification at various scales, from root system (Montagnoli et al. 2012a, 2014) to above-ground organs, is critical for understanding the stocks and fluxes associated with forest clearance, degradation, and regeneration, particularly given current concerns regarding global climate change (Barrett et al. 2001; Palombo et al. 2014). Knowledge of carbon dynamics (Montagnoli et al. 2012b) is crucial when addressing issues relating to carbon accounting, including quantifying carbon for credit schemes (Patenaude et al. 2004; Kim et al. 2009). National reporting of carbon sources and sinks is also required to fulfill obligations to international agreements such as the United Nations Framework Convention on Climate Change (Rosenqvist et al. 2003). Despite these requirements, there is still much uncertainty in biomass estimation at a range of scales and in particular on how much carbon is cycled through the Earth's forests. Scenario development to assess whether this cycling might change as a result of forest alteration (e.g. degradation induced by climate change) is also needed and is becoming increasingly important as a research field (Brack et al. 2006; Lucas et al. 2008). A better knowledge of forest

* Correspondence: antonio.montagnoli@uninsubria.it
[1]Department of Biotechnology and Life Science, University of Insubria, Via Dunant, 3, 21100 Varese, Italy
Full list of author information is available at the end of the article

ecosystems is critical to greenhouse gas control and biodiversity conservation. In fact, the Kyoto Protocol accounts for sinks of carbon emissions associated to vegetation growth and expansion (UNFCCC 1997; Rosenqvist et al. 2003). This is the reason why sustainable forest management is assuming an increasing importance and represents the second line of action of every governmental institution to be added to their commitment to reduce CO_2 emission. In this context biomass is important to monitor, whether associated with land use change, afforestation, reforestation or deforestation (Schulze et al. 2002). It is not surprising that assessment of vegetated land characteristics by remote sensing is highlighted as a recommended tool in a number of political charters and treaties of different nations (Almeida et al. 2014). A detailed knowledge covering the large areas of variability, which characterize forest biomass and biophysical structure, the properties and the state of evolution of vegetation, is frequently critical given that it requires significant campaign operations in terms of time/operator and cost (Chen et al. 2007; Popescu 2007; Wallerman and Holmgren 2007). Remote sensing in general is an excellent tool for monitoring the environmental state of a vegetation canopy over space and time. It provides spatially continuous and temporally frequent information products over extended areas (Coops et al. 2007; Ota et al. 2014). To date many methods have been used to study the vegetation with remote sensing and different spectral indices have been proposed (e.g. NDVI and EVI) (Glenn et al. 2008; Kouadio et al. 2014; White et al. 2014). Despite recent steady advancements in remote sensing techniques, there still remains an inability to reliably quantify plant diversity and totally eliminate environmental interferences (Wang et al. 2010; Pettorelli et al. 2014). Remote sensing is basically the measurement and interpretation of spatially distributed radiation fluxes reflected or emitted from the Earth surface. The measured radiation fluxes are driven by radiative transfer processes, such as scattering, absorption and emission, intrinsically related to the properties of the observed surface (Campbell 1996;

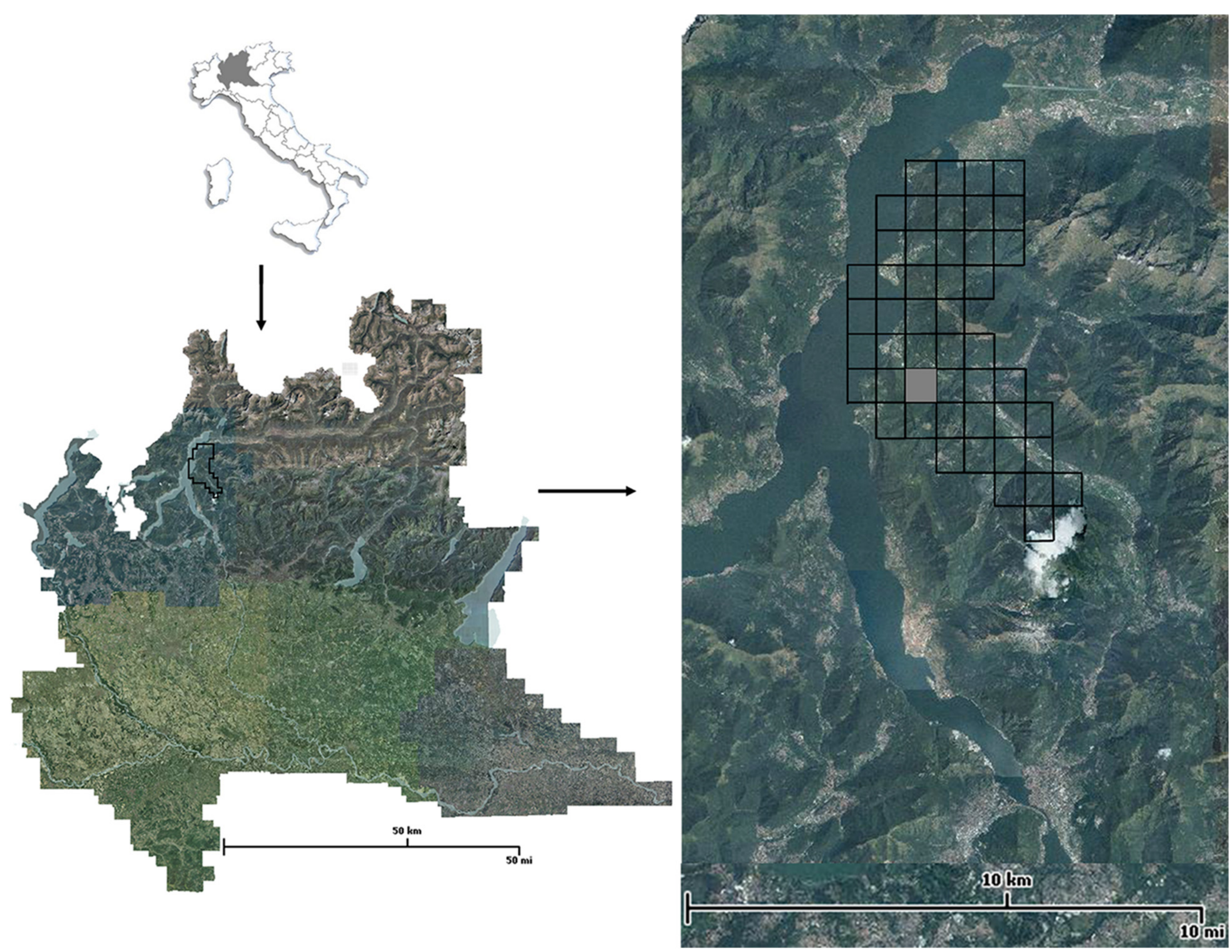

Figure 1 Map of the Lombardia region (larger area, left) and study area location (small black polygon, left). Grid area (right) indicates the LiDAR data survey. Aerial photos from free access Geoportale Lombardia. Gray cell (right) indicate location of field plots.

Jensen 2006). However, the variables controlling the radiative transfer and thus also remotely sensed data are not necessarily directly related to the surface properties of ultimate interest, like vegetation cover or bare soil (Verstraete et al. 1996). Due to the indirect and in the case of vegetation, mostly underdetermined character of this relationship, interpretation of remote sensing data should thus rely on as many independent observations as possible. In addition, the knowledge of the physical and biological processes involved needs to be considered in the interpretation of remote sensing data. Considering the limited amount of measurements generally provided by remote sensing and the high number of open variables, the problem of estimating vegetation properties based on remote sensing data is underdetermined (Wang and Sassen 2001; Combal et al. 2003; Kimes et al. 2006). A reliable retrieval is thus only possible if additional assumptions, constraints or further independent observations (e.g. field data, other sensors) are introduced (Verstraete et al. 1996). Assumptions and constraints are often used to simplify the problem, but are also limiting the retrieval in its transferability since they are generally only applicable for a specific problem (Duggin and Robinove 1990; Kötz et al. 2004). In this context, the aerial territorial survey technique, using laser scanning instruments (lidar) is particularly promising and, in some aspects, represents an alternative to satellite or aerial remote sensing because it makes it possible to directly survey the three-dimensional structure of the vegetation (Lindberg et al. 2012; Korpela and Hovi 2013). Lidar systems are an active remote sensing device that measure the time of travel needed for a pulse of laser energy sent from the airborne system to reach the ground and reflect back to the sensor. The time measured is converted into a distance measurement that is used to derive a precise three-dimensional characterization of the reflecting ground surface (Lim et al. 2003). In fact, the active optical remote sensing system, light detection and ranging (lidar), provides direct measurements on the vertical distribution of canopy elements within a vegetation canopy (Næsset and Bjerknes 2001; Lefsky et al. 2002). The measurement principle of lidar relies on laser pulses propagating vertically through the canopy, while scattering events are recorded as function of time. The remote sensing technique lidar is thus particularly suited to derive vegetation properties such as tree elevation, the vertical profile of foliage and terrain height (Harding et al. 2001). Usually the high resolution of small footprint lidar even allows for the three dimensional geometric reconstruction of single trees within a forest (Hyyppä et al. 2001; Morsdorf et al. 2004; Wang et al. 2008). Furthermore, lidar has also been shown to be an innovative tool for the study of vegetation at large scale, in particular for canopy structure, plant height and biomass (Andersen et al. 2005; Lefsky et al. 2002, 2005, 2010; Hansen et al. 2014). In this study, we investigated the utility of low-density lidar data (<2 points·m^{-2}) whether this type of data are useful for measuring forest attributes, such as height and above ground biomass (AGB) in the mountainous forests of northern Italy. The literature (Bortolot and Wynne 2005; Pilli et al. 2006) shows high correlations between forest AGB and tree height. The objectives of this work were: (i) to develop models of forest AGB from plot-level lidar height metrics and (ii) to understand if low density lidar is accurate enough in such conditions to produce a map of forest AGB for the region.

Methods

Study area

The low density lidar data cover a total area of approximately 80 km^2 located in northern Italy in the Lombardy Pre-Alps (Valsassina; small black box in the larger are,

Table 1 Forest tree density and characteristics for each forest plot of the study area

Plot number	Number of stem	Height (m)	DBH* (cm)
1	40.5	9.3 (0.5)	14.3 (1.4)
2	20	19.4 (0.7)	32.5 (2.4)
3	32	13.5 (0.9)	20.4 (1.8)
4	27	13.8 (1.1)	27.0 (2.7)
5	53	11.6 (0.7)	13.3 (0.7)
6	64	11.9 (0.4)	11.0 (0.5)
7	22	18.4 (1.3)	28.7 (3.1)
8	40	11.0 (0.5)	16.6 (1.1)
9	59	9.4 (0.5)	11.6 (0.9)
10	46	13.3 (0.6)	14.6 (0.9)
11	31	13.8 (0.3)	20.0 (1)
12	80	10.5 (0.4)	12.1 (0.8)
13	56	9.6 (0.5)	13.0 (0.8)
14	36	15.5 (0.9)	19.1 (1.4)
15	47	12.1 (0.6)	14.3 (1.3)
16	32	14.8 (0.8)	19.0 (1.3)
17	38	15.9 (0.6)	25.7 (2)
18	42	11.7 (0.8)	15.8 (1.2)
19	59	12.7 (0.4)	12.0 (0.5)
20	25	11.2 (0.6)	18.8 (1.4)
21	55	15.6 (0.6)	15.3 (0.9)
22	92	9.4 (0.2)	10.9 (0.5)
23	93	10.6 (0.3)	11.0 (0.6)
24	90	9.0 (0.2)	10.4 (0.5)
25	119	8.9 (0.2)	10.4 (0.3)
26	41	9.5 (0.4)	14.4 (1.2)
27	79	10.0 (0.2)	10.2 (0.3)

*DBH (diameter at breast height), height and DBH values are mean of the number of stem (±SE).

Figure 1, left) (46°00′N, 9°23′E centre area coordinates). In the present study, to test if these lidar data are reliable for forest AGB estimation, a sample area of 8 km^2 was analysed (gray cell, Figure 1, right). The study area topography is characterised by a mean elevation of 890 m with minimum elevation of 590 m and maximum of 1293 m. The study area includes mixed and broadleaved forest with variable stand densities and tree species compositions. The site is representative for the entire Pre-Alps region in terms of type of forest and geomorphology. The main forest types are coppice management with plantations of chestnut (*Castanea sativa*) together with beech (*Fagus sylvatica*), birch (*Betula pendula*), linden (*Tilia cordata*), ash (*Fraxinus excelsior*), poplar (*Populus tremula*), field maple (*Acer campestre*), hazel (*Corylus avellana*), European Hop Hornbeam (*Ostrya carpinifolia*), wild cherry (*Prunus avium*) and natural stands of oak (*Quercus* spp.).

Lidar data

Large-footprint discrete first and last returns lidar data were acquired in October 2003 when the canopy first started to change colour in the fall. Acquisition was made by Compagnia Generale Riprese aree SpA, Parma – CGR and property of Regione Lombardia, using an Optech ALTM 3033 scanner Airborne, at flying height of 2000 m with a swath width of 1450 m. Scan angle was 20° with an approximate footprint of 50 cm, and an average pulse spacing of 1.75 m and pulse rate of 33 MHz.

Field measurements

In a selected 2 km × 2 km area (Figure 1, right) 27 circular plots (radius = 10 m) were randomly located. During May 2008 tree number, height and diameter at breast height (DBH) were measured for all tree species within each plot (Table 1). Possible lidar data underestimation of tree height due the 5 years growth discrepancy between lidar data collection (2003) and field measurements was considered minimal. Analysed forests were at the mature stage (20–30 years old) therefore minimal growth was assumed (Brassard et al. 2009; Franceschini and Schneider 2014). Trees with diameters smaller than 5 cm were excluded. A total of 1417 trees were measured on these plots. On each plot the tree heights were measured using a Vertex Laser VL-400 - telemeter/hypsometer (Haglöf), and DBH with a Forestry Suppliers Metric Fabric Diameter Tape. Although it can be difficult to clearly distinguish the treetop in dense forests, the measured forests were not dense enough to completely block the treetops. Moreover, effort was taken in the field to move around in the forest until a spot was found that did not obscure the treetop. Geographic coordinates were recorded at the centre of each plot with a Trimble® GeoXM™ GPS with 1–3 meter accuracy. Specific allometric equations (Leonardi et al. 1996; Hamburg et al. 1997; Gasparini et al. 1998; Zianis et al. 2005; Alberti et al. 2006; Tabacchi et al., 2011) were used to calculate total aboveground tree biomass and subsequently plot-level biomass (mg·ha^{-1}) (see Table 2).

Data analysis

The result of a laser scan is a cloud composed by geographically located points (raw data) corresponding to all the elements composing the scanned surface. The first step in data processing was to identify and exclude (filtering) all outliers due to their distance from the mean surface. The TerraScan™ of Terrasolid software was used for this automated process (Axelsson 1999). Afterwards analysis parameters were manually corrected according to the different geo-morphology characteristics and an additional

Table 2 Biomass equations by tree species

Species name	Equation	Parameters			Reference
		a	*b*	*c*	
Acer campestre (L.)	$a \cdot (DBH)^b$	0.05	2.67		Alberti et al. 2006
Betula pendula (Roth)	$a \cdot [(DBH)^2 \cdot H]^b$	0.5443	0.65270		Hamburg et al. 1997
Castanea sativa (Miller)	$a \cdot (DBH)^b$	0.137	2.247		Leonardi et al. 1996
Corylus avellana (L.)	$a \cdot (H)^b$	0.0768	1.8329		Hamburg et al. 1997
Fagus sylvatica (L.)	$a + b \cdot (DBH)^2 \cdot H$	1.6409	0.030775		Tabacchi et al. 2011
Fraxinus excelsior (L.)	$a \cdot (DBH)^b$	0.11	2.49		Alberti et al. 2006
Populus tremula (L.)	$a \cdot (DBH)^b$	0.0519	2.545		Zianis et al. 2005
Prunus avium (L.)	$a \cdot (DBH)^b$	0.12	2.33		Alberti et al. 2006
Quercus petraea (Matt.) Liebl.	$a \cdot (DBH)^b$	0.2176	2.0513		Alberti et al. 2006
Tilia cordata (Miller)	$\ln(ABW) = a + b \cdot \ln(DBH)$	−2.6788	2.4542		Zianis et al. 2005
Ostrya carpinifolia (Scop.)	$a + b \cdot DBH \cdot H + c \cdot DBH^2$	−4.5877	$5.2638 \cdot 10^{-3}$	$4.09 \cdot 10^{-1}$	Gasparini et al. 1998

DBH = Diameter at breast height; *H* = Plant height; ln = natural logarithm; ABW = Total aboveground woody biomass.
The format of the biomass equation is given in the column labelled Equation, and *a*, *b*, and *c* are parameter values. References to the original papers according to authors.

filtering was applied (Barilotti et al. 2007). Interpolating lidar point elevation to a regular grid with a 5 m resolution created a Digital Surface Model (DSM) and Digital Terrain Model (DTM; 6–9 pulses per 5 m^2). The characterization of the top canopy surface (DSM) included only the highest laser reflection points, while lowest laser reflection points were used to estimate the ground level (DTM) (Lefsky et al. 1999; Holmgren and Persson 2004; Popescu et al. 2004; Popescu 2007).

The low density point clouds may miss the tree tops, because naturally tree tops have fewer hits compared to the tree crowns. The same problem exists in identifying the ground (Suárez et al. 2005), especially in a steep terrain (Estornell et al. 2011) like the Alps. Therefore, the elevation recorded with GPS units was compared with those identified in the lidar point cloud. Lidar returns were extracted for each plot using the geographic coordinates taken in the field. Returns above a threshold of 2 m were considered vegetation returns, and returns below that threshold were considered ground returns. Height threshold was chosen according to plot analysis where all trees below the 2 m cut off were smaller than 3 cm diameter and not considered for measurement. Then data were normalized to height-above-ground using the DTM (spatial resolution 5 meter; Figure 2b) supplied by the lidar vendor. Furthermore, points below two meters were eliminated in the plot to omit returns from understory or falsely classified ground returns (Figure 2c). The software used for these analyses was the free FUSION/LDV developed by Robert J. McGaughey (U.S. Forest Service Pacific Northwest Research Station, Oregon).

Regression analysis

To investigate the relationship of low density returns and AGB, regression models were used to develop equations relating lidar-derived tree height with field inventory tree height and field-based estimates of aboveground biomass for individual plots. In particular, the first relationship analysed was between lidar height metrics and field-measured height. Secondly the relationships between lidar height metrics and AGB from field data was considered at the plot scale (Pflugmacher et al. 2012). Analysis of variances for linear regression was carried out on results of each relationship to test for significance of the slopes at 95% significance level.

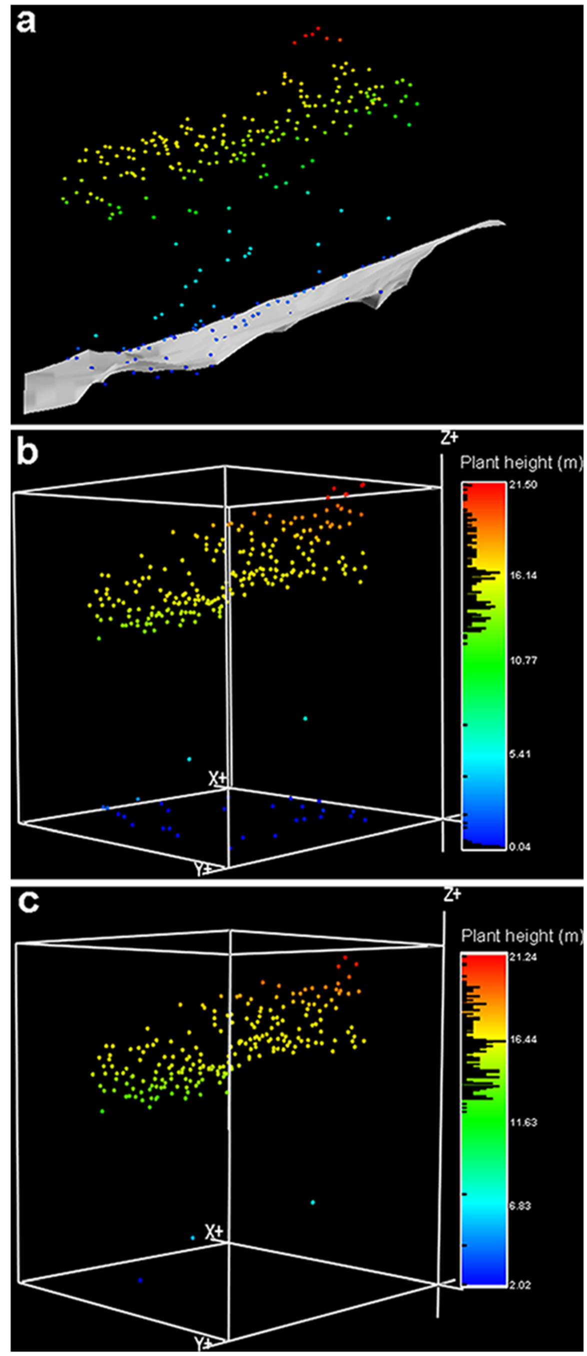

Figure 2 Examples of vertical plot LiDAR return distributions: **(a)** Raw LiDAR data plot; **(b)** data normalized by digital terrain model; **(c)** data points above 2 m from soil surface.

Results and discussion

Plant height

We report the best regression model developed to explain the relationship between lidar height metrics and field-measured height at the plot level. Linear regression indicated a multiple R^2 of 0.87 (Figure 3a; slope test $p < 0.001$) and a root mean square error (RMSE) of 1.02 m (BIAS of 0; Figure 3b), which is approximately 8.3% of the average plant height of all measured trees. Cross validation showed a RMSE of 2.02 m (16.4% of the mean) and a BIAS of 0.02. The final model derived from height distribution data was based on the following multiple percentile of tree height distribution: Height 25%; Height 20%; Height 30%; Height 10%; Height 80%. Our results are in

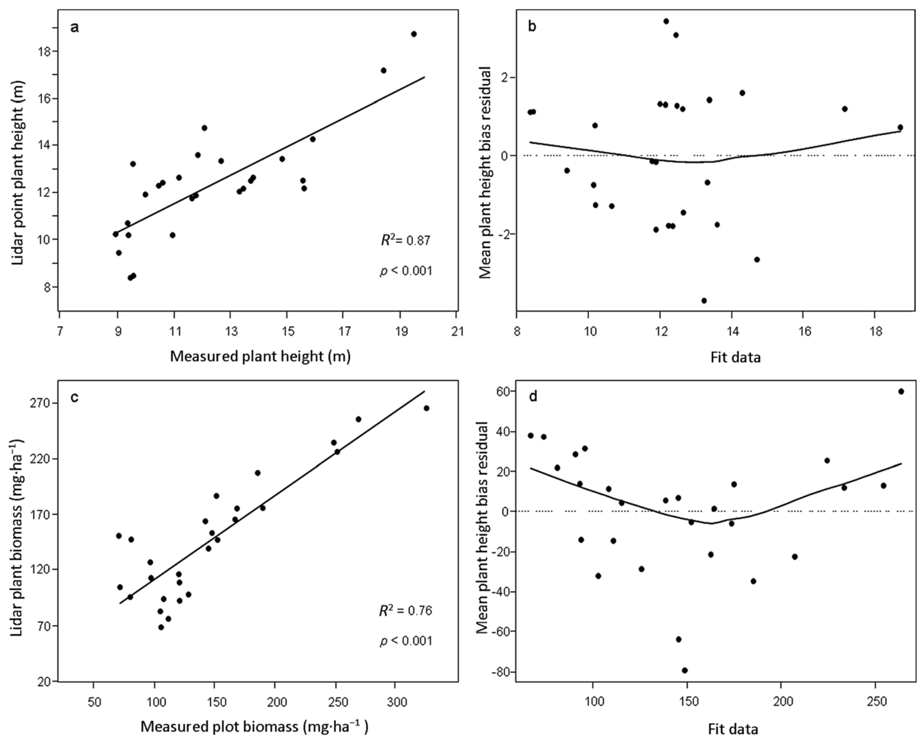

Figure 3 The best regression model developed to explain: **(a)** Relationship between LiDAR data and mean plant height measured in the field; **(b)** plant height BIAS against fitted height data LiDAR derived; **(c)** relationship between LiDAR data and mean biomass measured in the field; **(d)** plant biomass BIAS against fitted height data LiDAR derived.

line with previous studies (Coops et al. 2007; Popescu 2007; Stepper et al. 2014) in which a good correlation between tree height lidar-estimated and field-measured for both needle and broad leaved trees has been reported.

Plant biomass

The best model for the relationship between field AGB and lidar height explained 76% (multiple R^2) of the variance in the field biomass (Figure 3c; slope test $p < 0.001$) with a RMSE of 30.56 mg·ha^{-1} (20.9% of the mean) and a BIAS of 0 (Figure 3d). Leave-one-out cross validation yielded an RMSE of 53.7 mg·ha^{-1} (36.8% of the mean) and a BIAS of 3.7. The final model selected was based on the following multiple percentile of tree height distribution: Height 0; Height 5%; Height 25%; Height 55%; Height 70%; Height 80%; Height 95%; Height 100%.

Potential source of errors can include statistical error associated with estimating coefficients and form of selected equation. Moreover, errors may occur from both field measurement and data processing as well as errors associated with developing wide scale equation by compiling species- and site-specific equation that may be biased in favour of species for which published equations exist (Sileshi 2014). With the present approach, part of the unexplained variance when estimating aboveground biomass is associated with error of estimating biomass with field measurements of DBH and height, error associated with lidar-measured height and GPS misregistration errors. Selected variables for lidar height with measured field AGB (Figure 4a) were applied to the entire sample area of 8 km^2 in order to obtain a biomass map (Figure 4b). Previous studies have successfully estimated AGB or tree volume from lidar-derived vegetation-height statistical metrics in different boreal and temperate forests (Næsset 1997; Magnussen and Boudewyn 1998; Means et al. 2000; Popescu et al. 2004; Hall et al. 2005; Popescu 2007; Alberti et al. 2012). The average AGB and plant height estimated by lidar data of our forests were 146 mg·ha^{-1} and 12.28 m respectively. As demonstrated in previous works (Raber et al. 2002; Clark et al. 2004; Estornell et al. 2011) for relatively dense and structural deciduous forest on steep slope conditions, data characteristics such as scan angle most often causes DTM inaccuracy that effect derived trees canopy height (Raber et al. 2002; Clark et al. 2004). In the present study, plant height normalization performed with a low spatial resolution DTM, might have been another cause of error in lidar metrics calculation. Although these possible effects were not analysed, our results were similar to values of above ground biomass (123.7 mg·ha^{-1}) found in a Pre-alpine beech forest (Montagnoli et al. 2012b). Even though these forests have different species composition, these values

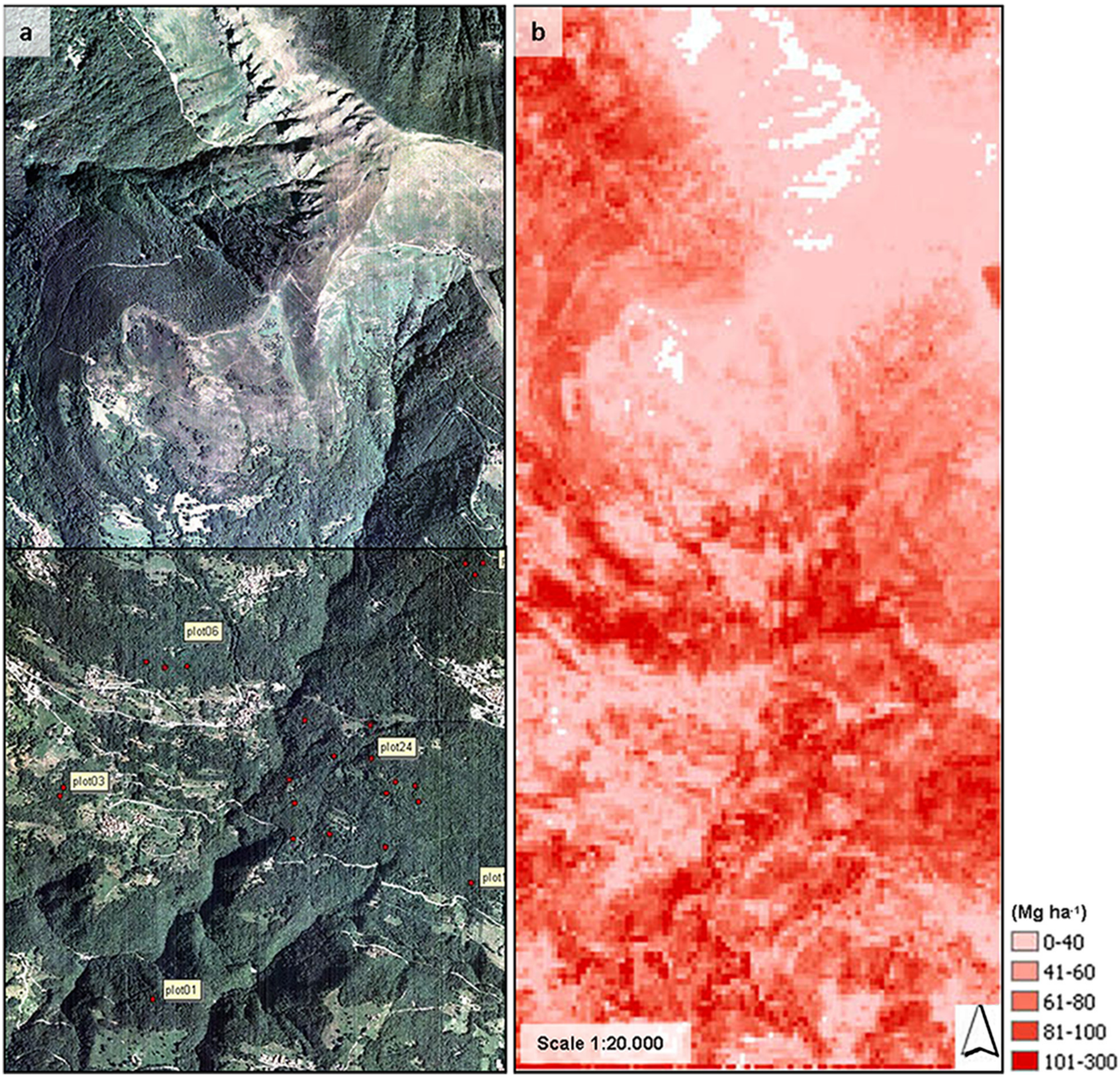

Figure 4 Example of application for plant biomass model by plant height measured by LiDAR data. **(a)** Digital orthophoto, in the lower part showed plots for field plant measurements. **(b)** Example of biomass map of the same area. Plant biomass values, represented by a multiple colours legend, increase from pink (lower value) to red (higher value). Pixel (1 m^2).

are comparable, since our study sites are in the transition zone of lowland and montane forests. Forest estimates (of height, volume and biomass), using laser data, are often based on linear regression models of forest canopy height (Nilsson 1994, 1996) and statistical measures derived from the distribution of laser point data (Lefsky et al. 1999; Næsset and Gobakken 2005). Several studies have noted that measures of canopy characteristics obtained from the laser height distribution, together with selected laser height percentiles, have proven useful for estimating timber volume (Means et al. 1999; Næsset & Økland 2002). Our results also show that mean height was the most reliable estimator of AGB (RMSE = 53.7 mg·ha^{-1}, corresponding to 36.8% of the mean) in single regression analysis. Finally, in our case we also demonstrated a good fitting model even with a difference in time between lidar data collection and field measurements.

Conclusion

Our results, in mixed broad leaved forests growing on patchy slope conditions, indicate that low-density lidar data can be used to develop a forest AGB model from plot-level lidar height measurements in the study area with acceptable accuracies. Moreover, these results highlight the opportunity to apply this analysis to a larger area, with the aim of monitoring the National Forest Inventory, and create a database of the forest carbon content in order to respond to requirements of the Kyoto protocol. The biomass map derived from the selected regression model and the potential for integrating lidar with co-registered multi and hyperspectral digital imagery, make lidar a realistic alternative to traditional forest measurements.

Competing interests
The authors declare that they have no competing interests.

Authors' contributions
Montagnoli make substantial contributions to the study concept and design, to field data collection and relative interpretation. Montagnoli co-writes the draft paper and dealt with manuscript process, improvements and revisions. Fusco leads the research between the Italian and American Labs. She participate to all works aspects such as concept and design, fieldwork, both field and lidar data collection, processing and interpretation. Fusco and Montagnoli were co-writing the draft paper. Terzaghi mainly contributed to the field work. He also partially contributed to the other aspects of the work carried in the Italian lab. Pflugmacher make substantial contribution to the lidar data analysis. Kirschbaum make substantial contribution to the field work concept, design and data collection. Slightly revised the manuscript. Cohen supervised the research and make a substantial contribution to all works aspects. Participate in drafting the article and revising it critically for important intellectual content. Scippa make substantial contribute to experiment and process supervision. Slightly revised the manuscript. Chiatante conceived and supervised the research in all aspects. Contributed to the paper processing. All authors read and approved the final manuscript.

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Author details
[1]Department of Biotechnology and Life Science, University of Insubria, Via Dunant, 3, 21100 Varese, Italy. [2]Department of Forest Ecosystems and Society, Oregon State University, 321 Richardson Hall, Corvallis, OR 97331, USA. [3]National Park Service, Great Lakes Inventory and Monitoring Network, 2800 Lake Shore Drive East, Ashland, WI 54806, USA. [4]USDA Forest Service, Pacific Northwest Research Station, Forestry Sciences Laboratory, 3200 SW Jefferson Way, Corvallis, OR 97331, USA. [5]Department of Biosciences and Territory, University of Molise, 86090 Pesche, Italy.

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