Folia Forestalia Polonica, series A, 2012, Vol. 54 (2), 84–93

ORIGINAL ARTICLE

Forest biomass estimation by the use of airborne laser scanning data and in situ FieldMap measurements in a spruce forest stand

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Abstract

The main purpose of this study is to analyze the possibility of stand biomass evaluation based on biometric measurements from airborne laser scanning data in a spruce forest test area. Data fusion of airborne laser scanning, and aerial orthoimagery (0.5 m spatial resolution), as well as the use of FieldMap equipment in the measurement of reference data in sampling plots makes it possible to estimate different stand parameters. An important stage of height evaluation in the spruce test area is the DTM extraction based on LiDAR data. The traditional forest management plans of the study area and DTM based on topographic maps (1 : 5.000) were used for accuracy assessments.

Key words

airborne laser scanning, biometric field measurements, data fusion, forest biomass estimation, remote sensing

Introduction

Concerns about global climate change have highlighted the importance of finding efficient ways of quantifying terrestrial carbon stocks at regional, continental, and global scales (Boudreau et al. 2008). In this context, remote sensing technologies have gained large importance over the last decades in addressing these issues, and have been utilized as a reliable support for ground field inventories. At present, the trend is to minimize field data collection procedures by automatic extraction of parameters from remote sensing data. For forestry purposes, LiDAR technology is being used increasingly due to its ability to provide accurate 3D representations of forest structure throughout a geolocated points "cloud" which penetrates the forest canopy.

Airborne LiDAR has been confirmed as the ideal technology for obtaining accurate canopy height models over large forested areas because of its high precision and its ability to receive ground returns over vegetated areas (Vazirabad et al. 2011). LiDAR has been shown to accurately estimate LAI and above ground biomass even in high-biomass ecosystems where passive optical and active radar sensors typically fail to do so (Levsky et al. 2002). A significant advantage of LiDAR is that it can measure not only tree height but also crown dimensions, thus improving estimates of forest

Received 1 August 2011 / Accepted 26 April 2012

volume and biomass, from individual trees to regional areas (Popescu et al. 2003; Popescu 2007).

Since the mid to late 1980s, the use of LiDAR for forestry applications has advanced with technology to include a number of functions, such as forest inventory surveys, estimation of stand heights, crown cover density, and ground elevation beneath the forest canopy (Tiede et al. 2005).

Previous studies using LiDAR were conducted to determine forest structural characteristics over small areas. In this paper, we contribute to the growing evidence that LiDAR can be exploited over large scales to provide results that are transferrable into practical applications. One such previous example is from New Zealand, where LiDAR data was used to estimate forest biomass and fulfill the requirements made by the United Nations Framework Convention on Climate Change, and New Zealand's submission under Article 7.1 of the Kyoto Protocol (New Zealand Government 2011).

There are two main approaches for estimating LiDAR-based biomass and volume (Bartolot and Wynne 2005): one is using distributional metrics in conjunction with regression equations to predict forest properties, and the other is to use computer vision techniques to locate and measure the properties of individual trees using CHMs (canopy height models). Zhao et al. (2009) proposed a scale-invariant prediction model of above ground biomass using LiDAR data.

A comprehensive review concerning the use of LiDAR for biomass estimation can be found in Vazirabad et al. 2011.

In Romania, LiDAR is an emerging technology with only limited research conducted to test its vast potential. This article represents the first results concerning LiDAR applications in forestry in Romania, and is focused on assessing the feasibility of stand biomass evaluation based on biometric measurements from airborne laser scanning data in a spruce forest test area.

Material and methods

Test site. The test site is in Romania, Vâlcea county, in the area of Voineasa Forest District, within the Lotru river valley. The prevailing species are spruce [*Picea abies* (L.) H. Karst.] and beech (*Fagus sylvatica* L.), which are found in both pure and mixed stands. The area is in a mountainous region, covered mostly with pasture and forest, water bodies and different types of constructions.

ALS data

We used airborne LiDAR data collected in 2008–2009 by an airborne Riegl LMS-Q560 device connected to a precision GPS/IMU system, which allows laser measurements to be corrected in real-time. The data were provided in "las" LiDAR data format, using the UTM coordinate system, elevation High Above Ellipsoid (HAE). The density was 1.6 points (hits) per square meter for each strip. To manage, visualize, process, and analyze airborne LiDAR data and imagery, two software packages were used:

- MARS Explorer – function-limited 30-day trial license – a commercial application developed by the Merrick Company;
- Fusion – forestry oriented free software for managing geospatial data, developed and maintained by the USDA (United States Department of Agriculture) Forest Service.

GPS Measured Data

The coordinates of the plot centers were measured using a Trimble Pro XH GPS receiver, working in double frequency L1/L2 with a Zephyr external antenna and a Trimble Recon PDA dataloger, with Trimble Terrasync Professional software installed.

The plot centers coordinates collected by GPS using geographic coordinates (Lon/Lat) on the WGS 1984 ellipsoid were transferred, corrected, and reprojected in the UTM coordinate system (the elevation reference HAE – High Above Ellipsoid) and exported in GIS format with Trimble GPS Pathfinder Office software (Fig. 1). For improved accuracy, a differential correction was performed using data from the nearest GPS permanent EUREF stations DEVA, BUCU and BACA, provided online via the Internet.

FieldMap reference data

We used FieldMap (forestry professional software and equipment for field measurements) to determine reference data by measuring individual tree parameters. Tree position, height, stem diameter and tree crown projection were measured (Fig. 2). Tree heights were measured using a Haglöf Vertex IV Hypsometer**.** To process and analyze biometric data we used SPSS software.

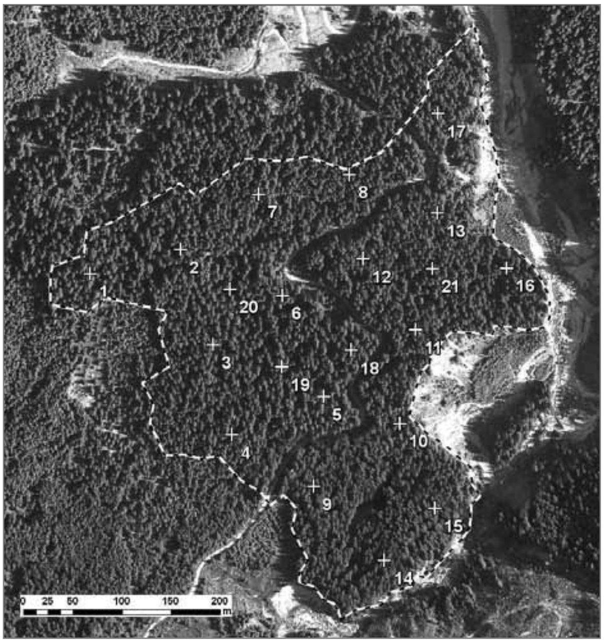

Fig. 1. GPS measured center plots (56A parcel) and the forest stand limit

Our main goal was to determine biomass using heights obtained via LiDAR data. For this, we had to measure field reference data in 21 plots in order to obtain 90% accuracy in volume and biomass estimation. All individual trees measured in these plots were spruce (*P. abies*).

The classification of LiDAR point clouds, DSM (which in forest areas is identical to the canopy height model – CHM), and DTM extraction were processed in MARS software. The raw LiDAR data was provided as a collection of unclassified points. For DTM extraction we classified the last and single returns by applying an automatic filter based on a ground distance algorithm. Four classes were created: Ground, Small Vegetation, Medium Vegetation and High Vegetation. For the DTM extraction only the Ground class was considered. For the CHM extraction, we considered the first returns, both single and multiple echoes.

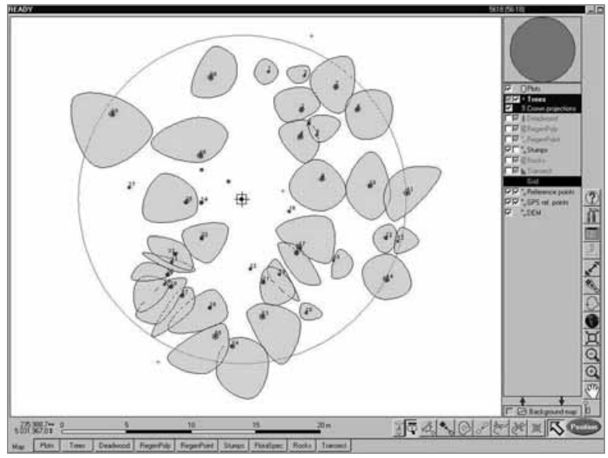

Fig. 2. FieldMap measured crown projections in plot no 18

Fusion software was used in conjunction with the DTM and a subset of LiDAR points to measure the height of individual trees inside the plot area. To estimate height

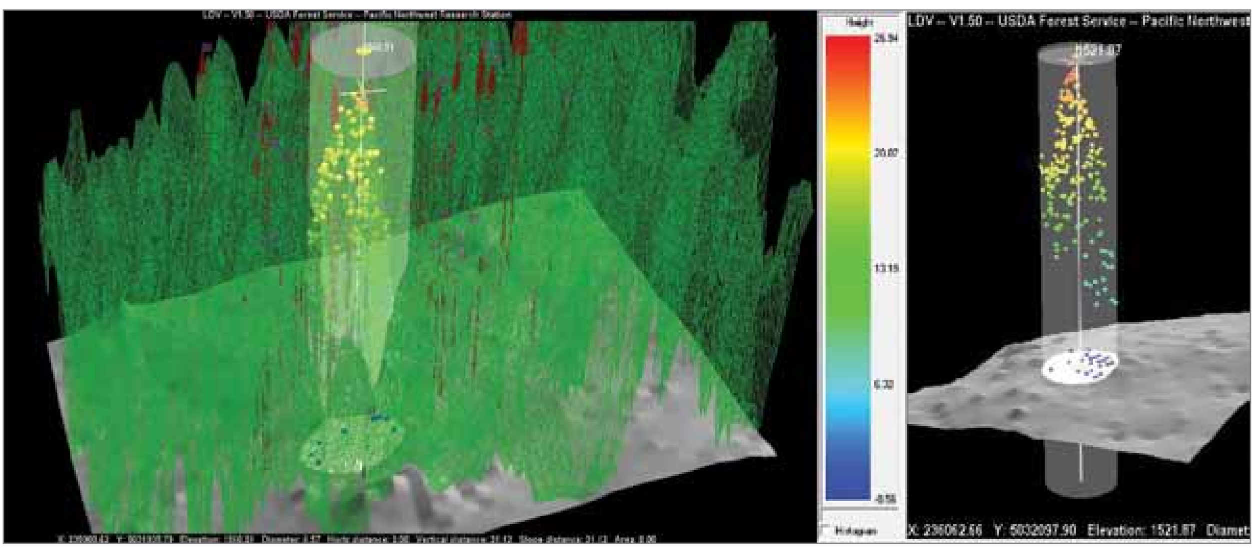

Fig. 3. Semi automatic tree height measurement in Fusion software

with Fusion software, an area including only one tree was selected and the height was computed as the difference between the Z-value of the highest point (local maxima), and the Z-value of the ground level (local minima). The estimation of tree height is actually the difference between CHM and DTM for that tree (Fig. 3).

It was particularly important to ensure that the trees measured in the field corresponded accurately with those identified in the LiDAR point cloud. This ambiguity was resolved via the following operations:

– clipping the LiDAR data corresponding to the measured field plots (Fig. 4);

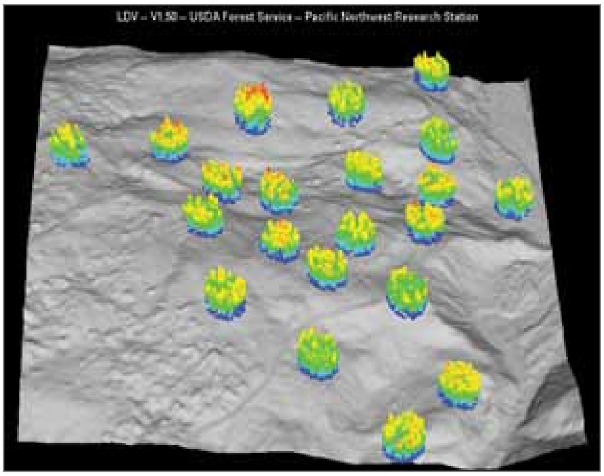

Fig. 4. Digital terrain model and LiDAR data clipped for the 21 plot areas (FUSION)

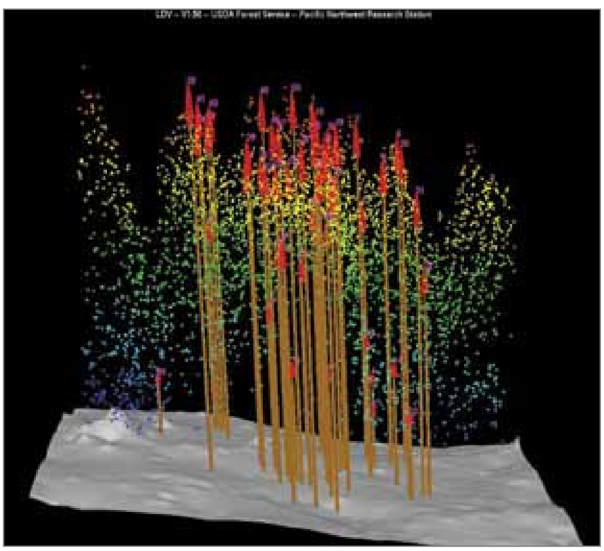

Fig. 5. LDV FUSION window: field measured trees, LiDAR point cloud, DTM for plot 5619

– import and visualization of tree field measurements with FUSION software (Fig. 5);
– import and display of the CHM in FUSION software. This was done by running the *CanopyModel* command line process from the FUSION LiDAR Toolkit (Fig. 6).

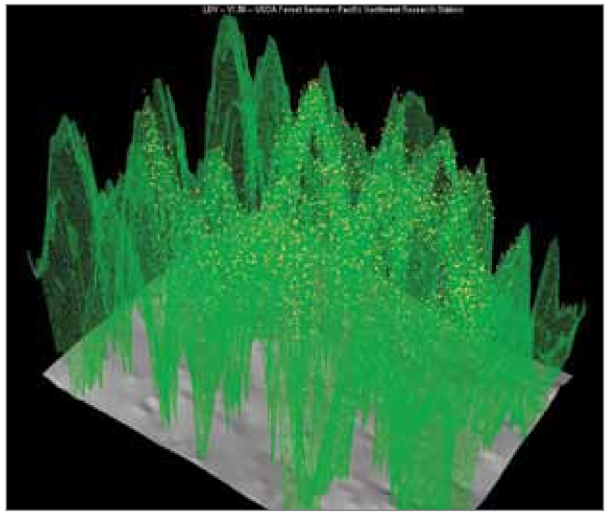

Fig. 6. FUSION 3D canopy height model for the plot 5619

Stem volume per plot and per hectare were determined from the field data, using individual tree stem volume calculated by a formula according to Giurgiu (Tab. 1).

$$\log v = a_0 + a_1 \log d + a_2 \log^2 d + \\ + a_3 \log h + a_4 \log^2 h \quad (1)$$

were:
d – diameter at breast height in cm,
h – tree height in m,
v – tree stem volume in m^3.

Tab. 1. Coefficients a_0, a_1, a_2, a_3, a_4 established for spruce (Giurgiu et al. 2004)

Species/ Coefficient	a_0	a_1	a_2	a_3	a_4
Spruce	–4.18161	2.08131	–0.11819	0.70119	0.148181

Biomass was calculated using three methods: two of which calculate biomass for each plot, and a third which uses LiDAR-measured heights. All three methods took into account only trees with DBH > 13 cm.

Tab. 2. Coefficients established for spruce (Wirth et al. 2004)

Compartment	β_0	ln$D$	(ln$D$)^2	ln$H$	(ln$H$)^2	ln$A$	(ln$A$ × ln$D$)
Branches	–0,64565	2.85424	–	–2.98493	0.41798	–	–
Dry branches	–1.21969	1.49138	–	–1.25928	–	–	0.18222
Stem	–2.83958	2.55203	–0.14991	–0.19172	0.25739	–0.08278	–
Roots	–8.35049	4.56828	–0.33006	–	–	0.28074	–

A. Biomass using a series of formulas for spruce according to Wirth (based on diameter, height and age) for branches, dry branches, stem and roots (Tab. 2)

– Branches:

$$\ln W_b = \beta_0 + \beta_1 \ln D + \beta_2 \ln H + \beta_3 (\ln H)^2$$

– Dry branches:

$$\ln W_d = \beta_0 + \beta_1 \ln D + \beta_2 \ln H + \beta_3 (\ln A \text{ x } \ln D)$$

– Stem:

$$\ln W_s = \beta_0 + \beta_1 \ln D + \beta_2 (\ln D)^2 + \beta_3 \ln H + \\ + \beta_4 (\ln H)^2 + \beta_5 \ln A$$

– Roots:

$$\ln W_r = \beta_0 + \beta_1 \ln D + \beta_2 (\ln D)^2 + \beta_3 \ln A$$

where:
W_b – branches biomass (kg dry mass tree^{-1}),
W_d – dry branches biomass (kg dry mass tree^{-1}),
W_s – stem biomass (kg dry mass tree^{-1}),
W_r – roots biomass (kg dry mass tree^{-1}),
D – diameter at breast height (cm),
H – height of tree (m),
A – age of tree (years).

B. Giurgiu method for estimating total tree biomass for spruce using the following equation:

$$y = 44.855 - 9.8498x + 0{,}7929x^2$$

where:
y – total biomass in kg ha^{-1},
x – diameter at breast height in cm.

C. Biomass estimation using LiDAR determined heights. This method implies a series of preparatory steps:

a. Computation of missing LiDAR heights using the regression equation based on all trees for which both LiDAR and field heights were measured:

$$h_{LiDAR} = 0.9393\ h_{field} + 0.5182$$

b. Computation of mean h_{LiDAR}.

c. Computation of corrected mean height h_{cor} using the following regression equation based on field and LiDAR data:

$$h_{cor} = 1.0067\ h_{LiDAR} + 0.8278$$

d. Computation of normal basal area and volume for the corrected mean height $h_{cor} = h_{mean}$, according to Giurgiu (Tab. 3):

– $h_{mean} \leq 22$ m

$$G_n = a_1 h_{mean} + a_2 h_{mean}{}^2 + a_3 h_{mean}{}^3 + a_4 h_{mean}{}^4$$

– $h_{mean} > 22$m

$$G_n = F + b_1(h_{mean} - 22) + b_2(h_{mean} - 22)^2 + \\ + b_3(h_{mean} - 22)^3 + b_4(h_{mean} - 22)^4$$

– $h_{mean} \leq 22$ m

$$V_n = a_1 h_{mean} + a_2 h_{mean}{}^2 + a_3 h_{mean}{}^3 + a_4 h_{mean}{}^4$$

– $h_{mean} > 22$ m

$$V_n = C + b_1(h_{mean} - 22) + b_2(h_{mean} - 22)^2 + \\ + b_3(h_{mean} - 22)^3 + b_4(h_{mean} - 22)^4$$

where:
G_n – normal basal area for the mean height,
V_n – normal volume for the mean height.

e. Computation of total volume and biomass for the determined h_{mean}

$$\text{Density index} = G_n / G_{tfield}$$

V_t – V_n x density index,
V_t – total volume (m^3),
Stem biomass – V_t x wood volumetric density (kg m^{-3}),
Total biomass – stem biomass / 65% (65% represent the percent of the stem biomass from total biomass (Giurgiu et al.)).

Tab. 3. Coefficients a_1, a_2, a_3, a_4 and b_1, b_2, b_3, b_4, F, C established for spruce (Giurgiu, Drăghiciu 2004)

h_{mean}	V_n				
	a_1	a_2	a_3	a_4	
≤ 22 m	1.1147	1.7463	–0.0252	–0.0003	
	b_1	b_2	b_3	b_4	C
> 22 m	31.331	–0.1794	–0.0023	0.00005	531
G_n					
	a_1	a_2	a_3	a_4	
≤ 22 m	3.768738	–0.08049	0.00316	–0.000094	
	b_1	b_2	b_3	b_4	F
> 22 m	1.483433	–0.06672	0.002892	–0.000051	55.6

Results

Checking the statistical coverage probability

Field measurements were summarized and were statistical indicators such as sample mean, standard deviation, and coefficient of variation were calculated for all 21 plots (Tab. 4).

Tab. 4. Statistical indicators of the field data

No of plots	Characteristic considered	Sample mean	Standard deviation	Coefficient of variation
21	Total basal area (m^2)	3.30	0.67	20
	Volume (m^3)	36.35	9.15	25

The low value of the volume coefficient of variation (25%) signifies that all 21 plots were relatively similar in volume and spread uniformly across the test site, each being highly representative of the stand as a whole.

The aim tolerance was ±10% at a statistical coverage probability of 90%. The percentage of inventory was less than 10% (21 circular plots areas of 500 m^2 each), and the error of representativeness (p) was calculated with the following simplified formula:

$$p = \frac{t \times s\%}{\sqrt{n}}$$

where:

t – Student coefficient at 20 degrees of freedom (t = 1.725),

$s\%$ – coefficient of volume variation (25%),

n – number of plots (21).

The representativeness error calculated with the above formula was 9.4% (within the 10% tolerance), which means the number of plots areas chosen for parcel 56A was sufficiently adequate to obtain 90% accuracy in volume and biomass estimation.

Computing biomass from field data

Firstly, we compared the two terrestrial methods using a paired samples t-test. The significance of the t-test showed that there were no significant differences between them ($t(20) = 0.652$, $p = 0.522$) (Tab. 5).

Correlation between heights measured in the field and those measured by LiDAR

Heights determined via LiDAR data were compared with those measured in the field and interpreted statistically to determine the correlation coefficient between the two sets of values and the significance of the coefficient of variation was tested (Tab. 6). The results show a strong linear correlation between the two sets of height measurements across each of the sample areas (Fig. 7).

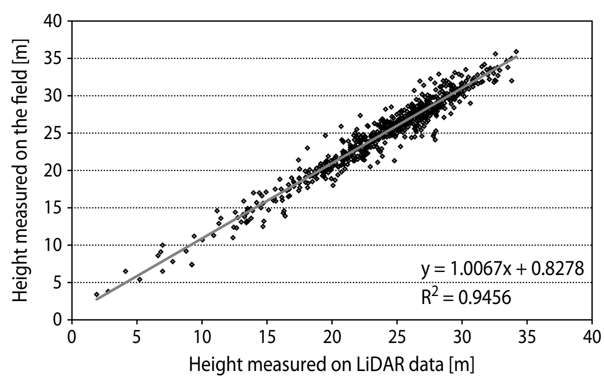

Fig. 7. Correlation between height measured in the field and by LiDAR

From the table with fusioned field-LiDAR biometric measurements we derived the correlation between height measured by LiDAR (h_{iLiDAR}) and real heights (h_i):

$$h_i = 1.0067\, h_{iLiDAR} + 0.8278$$

Tab. 5. Comparison between two terrestrial methods (Giurgiu–Wirth) that estimate biomass

Plot ID	Method I - Giurgiu			Method II – Wirth – Biomass kg ha^{-1}				
	Basal area (*G*) m^2ha^{-1}	Volume (*v*) m^3ha^{-1}	Biomass (kg ha^{-1})	Branches (kg ha^{-1})	Dry branches (kg ha^{-1})	Stem (kg ha^{-1})	Roots (kg ha^{-1})	Total (kg ha^{-1})
561	72.82	738.13	500,271.58	56,726.11	14,207.71	285,980.21	101,900.09	458,814.11
562	60.62	713.21	435,199.57	50,359.17	10,488.35	287,237.29	87,126.62	435,211.42
563	68.42	703.69	462,403.13	52,442.04	13,602.13	273,663.47	94,070.93	433,778.56
564	80.96	844.16	528,953.91	56,585.06	15,154.75	336,084.40	110,130.71	517,954.91
565	68.59	740.81	478,685.53	54,184.91	13,361.77	291,393.28	97,827.52	456,767.47
566	53.05	574.92	353,544.06	38,274.01	9,195.39	229,622.50	72,575.11	349,667.01
567	107.86	1,311.03	751,396.42	82,119.94	17,124.86	535,292.07	152,496.01	787,032.89
568	72.17	752.03	457,633.87	46,852.13	14,664.72	303,333.21	97,731.47	462,581.54
569	50.60	451.37	317,838.42	68,053.65	19,637.10	178,537.26	65,926.49	332,154.50
5610	57.88	503.95	343,639.03	36,139.62	12,286.95	194,922.67	73,167.86	316,517.09
5611	70.05	818.07	507,026.18	59,476.83	12,592.39	324,050.48	101,227.56	497,347.26
5612	67.37	757.95	450,293.27	47,552.46	12,001.84	306,146.30	93,478.55	459,179.14
5613	62.60	597.86	392,990.60	40,620.28	12,488.05	234,338.36	83,344.41	370,791.10
5614	73.62	819.44	484,476.60	51,446.28	13,192.24	332,061.67	100,953.26	497,653.46
5615	76.20	861.10	505,095.70	54,047.03	14,094.27	349,839.60	105,305.08	523,285.97
5616	48.42	530.75	337,508.53	36,480.15	8,760.02	209,445.27	69,358.35	324,043.78
5617	54.44	621.76	359,301.36	36,451.51	9,397.78	253,619.46	75,519.02	374,987.76
5618	56.67	609.34	386,290.98	40,575.92	10,440.65	241,493.82	80,473.44	372,983.83
5619	73.50	871.11	504,345.99	53,374.50	12,661.51	354,797.74	104,386.74	525,220.49
5620	50.85	578.00	378,525.84	45,698.29	9,315.14	223,454.74	74,177.85	352,646.02
5621	60.64	689.71	397,494.86	42,961.96	11,699.25	284,198.75	83,134.05	421,994.01
MEAN	66.06	718.49	444,424.54	50,020.09	12,684.14	287,119.64	91,633.86	441,457.73
%		–	–	11.30	2.90	65.00	20.80	100.00

Tab. 6. Table with values of correlation coefficients, transformed correlation coefficients (z), and u statistics for each of the 21 plots

IDPlot	Number of trees measured	Correlation coefficient (r)	Z	U
1	2	3	4	5
561	24	0.812	1.133	5.191
562	22	0.987	2.523	10.999
563	41	0.976	2.203	13.582
564	34	0.973	2.152	11.983
565	29	0.990	2.656	13.545
566	20	0.984	2.411	9.943
567	35	0.975	2.180	12.335
568	40	0.913	1.544	9.390
569	32	0.968	2.063	11.110

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1	2	3	4	5
5610	47	0.932	1.677	11.122
5611	24	0.976	2.207	10.116
5612	29	0.953	1.866	9.514
5613	45	0.957	1.909	12.371
5614	37	0.956	1.899	11.075
5615	32	0.904	1.496	8.057
5616	23	0.984	2.419	10.818
5617	27	0.986	2.467	12.086
5618	27	0.943	1.762	8.633
5619	32	0.966	2.035	10.958
5620	12	0.978	2.246	6.737
5621	29	0.949	1.818	9.270

Frequency by diameter class

In order to calculate the mean diameter, the distribution of field-measured diameters was determined and compared to the normal distribution. Small diameters were overrepresented compared to the normal, and so diameters lower than 13 cm were excluded from volume and biomass determination (Fig. 8). These trees represented about 1% of total biomass.

Computing mean height

The first step was to compute the missing adjusted LiDAR heights according to the inverse function:

$$h_{LiDAR} = 0.9393\ h_{field} + 0.5182$$

The second step was to determine the mean adjusted LiDAR height corresponding to the mean diameter class. The mean diameter of 29.5 cm belongs to the 28–30 diameter class and the mean adjusted LiDAR height is 22.81 m.

Finally, the mean height was calculated from the mean adjusted LiDAR height by the direct function:

$$h_{mean} = 1.0067\ h_{LiDAR} + 0.8278 = 23.79\ \text{m}$$

Computing normal basal area, total volume and biomass for the determined mean height

For the third method, the total biomass was derived from stem biomass, which was assumed to be 65% of total biomass (Giurgiu et al. 2004), which is consistent with the tree stem biomass computed by the Wirth equation (Tab. 7).

To compare the results of the third biomass estimating method with the first two classic ones, a one-sample t-test was used. If, when calculating the biomass, we

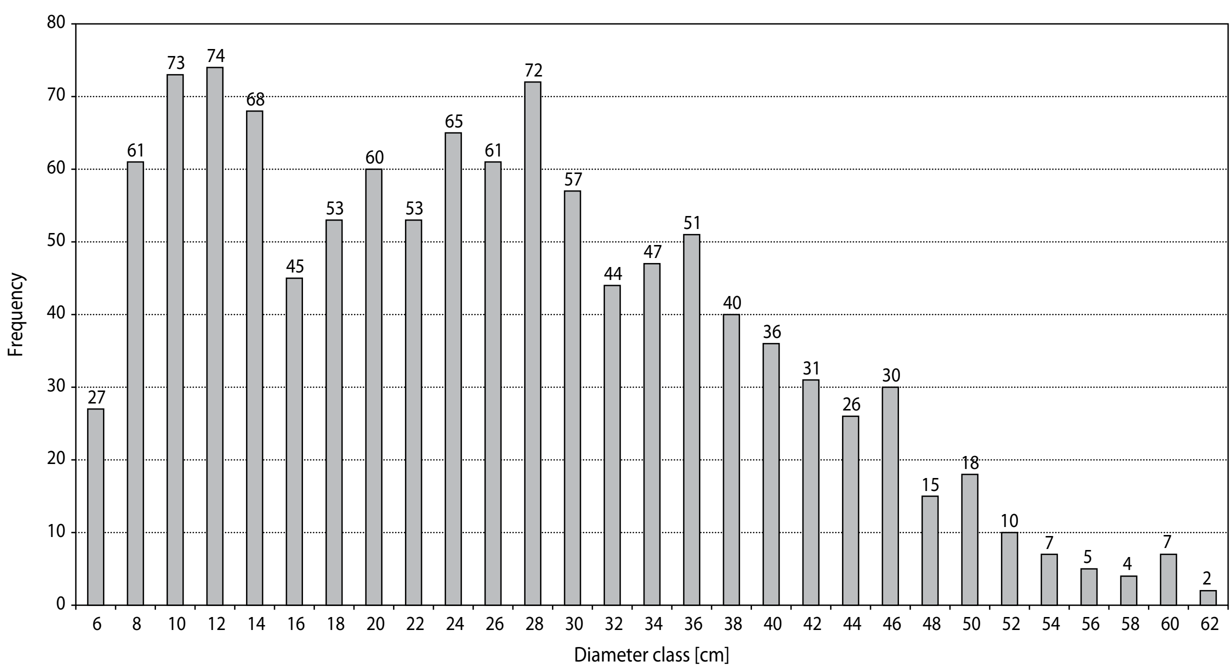

Fig. 8. Frequency by diameter class

Tab. 7. Biomass determination using mean height from LiDAR data

V_n (m^3 ha^{-1})	G_n (m^2 ha^{-1})	G (m^2 ha^{-1})	Density index G/G_n	V_t (m^3 ha^{-1})	Volumetric density for 366 kg m^{-3}		Volumetric density for 399 kg m^{-3}	
					Stem biomass (kg ha^{-1})	Total biomass (kg ha^{-1})	Stem biomass (kg ha^{-1})	Total biomass (kg ha^{-1})
586.65	58.06	66.06	1.14	667.47	244,293.80	375,836.62	266,320.29	409,723.53

use the general density of 372 kg m^{-3} (Giurgiu et al. 2004), between the first two calculated biomasses and the third, there are significant differences ($t(20) = 2.976$, $p = 0.007$; $t(20) = 2.605$, $p = 0.017$). This result seemed odd, because when comparing the volumes calculated based on field data reported in ha with the total volume determined by the third method, no significant differences were recorded ($t(20) = 1.283$, $p = 0.214$). Based on the stem biomass computed using the Wirth formula (b_{st}) and the volumes of each tree (v_{st}), we determined a local regression equation for estimating stem biomass as a function of volume:

$$b_{St}=392.797\ v_{st}+5.883$$

When applying this equation to the calculation of stem biomass in the third method, the resulting total biomass is not significantly different from the biomasses obtained using the first two methods ($t(20) = 1.958$, $p = 0.06$; $t(20) = 1.669$, $p = 0.111$).

Discussion

The plots were typical of high density spruce stands from mountainous areas, which are not straightforward to analyze. From the total of 1142 trees across 21 sample areas, height could be measured for 641 individuals (56% of total). However, the trees represented in the LiDAR data accounted for 90% of the biomass. Therefore it can be concluded that preliminary LiDAR data provides a good estimate of biomass. Although a little over 50% of the total number of trees were identifiable via LiDAR, these were the dominant and co-dominant individuals, representing most of the stand biomass. In fact, the 10% of the biomass not identifiable on LiDAR data represents under-developped and dominated trees from the lower ceiling. These results are comparable to those obtained in other research centers.

The method of estimating biomass using only height measurements obtained via LiDAR compares favorably with the widely accepted existing biomass equations used in Europe and Romania. Good correlations between LiDAR measured heights and field measured heights were obtained from existing data, and biomass estimation was also accurate. Additionally it was possible to derive a correlation between mean height and dominant height (measured on LiDAR), or between the biomass of visible trees and total biomass. Usually the tree and stand heights measured via LiDAR are underestimates, so good field data are important in obtaining good correlation equations.

The analysis presented above was applied to point clouds of low density, and so the LiDAR data parameters are another factor affecting the accuracy of results. In this respect, a larger number of LiDAR crossings over the same area, or the use of high frequency scanners could provide higher accuracy.

This method still requires field data to obtain a good estimation of the mean height, as only dominant trees are visible in LiDAR data. Using LiDAR we are able to measure only the top stand layer, so the method described is applicable only to the one-layer stands. Additionally, an adequate number of LiDAR observations in different stand situations (age, density, productivity) are required. Local biomass equations and wood volumetric density should be developed in order to use this method.

Conclusions

This paper represents an individual tree-based approach, developed as a method to evaluate the dry biomass of spruce forests by combining airborne LiDAR sampling and ground plots. The preliminary results confirmed previous research results from other countries that LiDAR data has a strong potential to provide precise information on biomass, and can offer a good estimation using only LiDAR measured heights. Further studies will aim to further develop the method, in order to use less field data for biomass estimation and to include a crown diameter/DBH correlation. Another topic of interest is the automatic identification of trees, and the extraction of tree heights extending across all of the forest stand area.

Acknowledgements

We are grateful to Mr. Cristian Glonţ, the manager of SC Primul Meridian SRL Company, who offered us without charge the LiDAR data for the test area.

References

Bortolot Z., Wynne R. 2005. Estimating forest biomass using small footprint LiDAR data: An individual tree-based approach that incorporates training data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 59, 342–360.

Giurgiu V., Decei I., Drăghiciu D. 2004. Forest mensuration methods and tabels. Editura CERES, Bucureşti, 33–36, 53.

Giurgiu V., Drăghiciu D. 2004. Mathemathical – growths models and yield tables for stands Dendrometric methods and tables. Editura CERES, Bucureşti, 51–53, 61–63, 571.

Lefsky M., Warren C., Geoffrey P., Harding D. 2002. LiDAR remote sensing for ecosystem studies. *Bioscience*, 52 (1), 19–30.

Mcgaughey R.J. 2010. FUSION/LDV: Software for LiDAR Data Analysis and Visualization

Merrick & Company 2009. MARS Explorer 6 Help Manual.

New Zealand Government – Ministry for the Environment. 2011. New Zealand's Greenhouse Gas Inventory 1990–2009, 9.

Popescu S., Wynne R., Nelson R. 2003. Measuring individual tree crown diameter with LiDAR and assessing its influence on estimating forest volume and biomass. Canadian Journal of Remote Sensing, 29 (5), 564–577.

Popescu S. 2007. Estimating biomass of individual pine trees using airborne LiDAR. Biomass and Bioenergy, 31, 646–655 .

Tiede D., Hochleitner G., Blaschke T. A full gis-based workflow for tree identification and tree crown delineation using laser scanning. In: CMRT05. IAPRS (eds.: U. Stilla, F. Rottensteiner, S. Hinz). Vol. XXXVI, Part 3/W24, 29–30 August 2005, Vienna, Austria, 9–14.

Wirth C., Schumacher J., Schulze E-D. 2004. Generic biomass functions for Norway spruce in Central Europe – a meta-analysis approach toward prediction and uncertainty estimation. Tree Physiology, 24, 121–139.

Vazirabad Y.F., Karslioglu M.O. 2011. LiDAR for Biomass Estimation. In: Biomass – Detection, Production and Usage (ed.: D. Matovic). InTech, DOI: 10.5772/973.

Zhao K., Popescu S., Nelson R. 2009. LiDAR remote sensing of forest biomass: A scale-invariant estimation approach using airborne lasers. *Remote Sensing of Environment*, 113, 182–196.