Using multi-temporal airborne laser scanner data for predicting change in above ground biomass components in a boreal forest

Prediksjon av endring for biomassekomponenter over bakken ved bruk av data fra flybåren laserskaner i en boreal skog

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Preface

This Master's thesis has been written at the Norwegian University of Life Sciences (UMB), at the Department of Ecology and Natural Resource Management. The thesis constitutes the final project for Master's degree. I use this opportunity to thank a number of people who gave me a full support during my graduation period at UMB.

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Abstract

Boreal forests are the main carbon sink in terrestrial ecosystems, and it account for about 90 % of the annual carbon flux between the atmosphere and the land surface. The amount of carbon that could be stored in the forest ecosystem mainly depends on the tree biomass. In order to estimate a carbon stock, it is necessary to quantify a standing woody biomass in a forest. An accurate estimation of biomass per tree components provides an opportunity for more precise carbon quantification, since the amount of stored carbon differs by the tree components. An estimation of biomass change of tree components in forest ecosystems is accordingly significant for estimation of change in the rate of carbon accumulation and carbon storage. An interest for quantification of tree biomass and its change also increased with respect to augmented use of biomass for energy production.

The aim of present study was to assess the capability of airborne laser scanning (ALS) in the detection of change in aboveground dry biomass (AGB) of different tree components. More specifically, a difference between ALS derived height and density variables observed in 1999 and 2010 has been used to model the change of AGB tree components observed at same time in the field. The height and density variables were derived from the first and last return laser echoes. A Field observed change was obtained as a difference between the AGB of tree components calculated by means of single tree biomass equations for each point in time. The data were collected from 176 sample plots in a boreal forest situated in southeastern Norway. Studied forest was actively managed and various types of changes had taken place during the eleven growth seasons. The change of total AGB during this period was ranged between -275.83 and 216.82 t/ha over sample plots, while the mean total AGB change was 19.31 t/ha. A one single model for prediction of AGB changes was developed for each of the tree component, for both unstratified (first approach) and stratified data (second approach).

The results of the presented study have shown the potential of ALS data in the detection of AGB changes from both approaches. The stratified models were more accurate and some of models explained around 90% of variation in the AGB changes. Obtained results indicated that stratification was important, but the model fit varied quite much between strata for some of the tree components.

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1. Introduction

In regard to forest management and environmental assessments, information about the conditions and changes of forest ecosystems has always been an important issue. About 90 % of the annual carbon flux between the atmosphere and the land surface is done through the those ecosystems (Winjum et al., 1993). This particularly refers to boreal forests, because they are one of the main carbon storages in terrestrial ecosystems. Since the carbon has been accumulated in the forest vegetation, the amount of carbon stored in the forest depends on the quantity of tree biomass. Activities such as deforestation and forest degradation lead to AGB losses in many countries, while the activities like selective wood harvesting, forest fragmentation, forest restoration, ground fires, shifting cultivation, grazing, etc. alter of forest AGB (Houghton 2005). An alteration of the ratio between a different AGB components, as well as reduction of total AGB has a direct influence on carbon cycle (emissions and removes of carbon dioxide) and subsequently on local, regional and even global climate, which is particularly manifested on the air temperature and humidity. Therefore, a monitoring of forests ecosystems which includes reports of forestry activities, biomass quantity, biomass change, carbon stock, carbon flux, etc. is of an essential importance for estimation, control and improving of strategy for the mitigation of climate change. These reports are also mandatory by international conventions, such as Kyoto Protocol, signed and ratified by more than 190 states. Furthermore, the estimation of AGB and its change in forest areas increased since the use of aboveground biomass (AGB) for energy production is in expansion.

An increased need for accurate estimation of forest biomass, also raise the need for advanced methods capable of estimating various properties of tree and forests in the sufficiently short time. During a last two decades, one efficient and accurate method called airborne laser scanning (ALS) have been developed and successfully utilized for those purposes. Based on a remote sensing technology, the ALS system measures the fight time of laser pulses emitted from an aircraft and reflected by objects (e.g. power line, tree canopies, etc) on the ground surface. The collected ALS data in a very short time present a three-dimensional information about those objects. The ALS today offers an opportunity to determine various biophysical properties of trees and forest ecosystems (Næsset, 2002; Lim and Treitz, 2004; Næsset and Gobakken, 2008).

ALS systems were “in the beginning” primary used for topographic purposes, mostly to derive accurate digital terrain models (DTM). Following the development of a laser technology, the ALS was soon used for estimation of forest stand parameters such as determination of tree heights (Nelson et al.,1984; Magnussen and Boudewyn, 1998), stands volume (Nilsson, 1996, Næsset, 1997), diameter and number of stems and basal area (Næsset, 2002). Since those first studies showed a great potential for forestry applications, the use of ALS was continuously extended during last decade. At the local scale, a procedure for stand-level forest inventory were developed and operationally used in Scandinavian countries from the year 2002 (Næsset, 2004b; Næsset, 2007). For this purpose, the scanning system with an ability to collect data from a width of up to several hundred meters in just one overflight is used. An another type of ALS system, so called “the profiling laser” with an ability to collect a vertical profiles of forest canopy from a narrow line was successful utilized in a sampling-based method of forest and biomass inventory at the large area such as regions and countries (Nelson at al., 2003). Particular or general features of the forest such as canopy gaps (Koukoulas and Blackburn, 2004), canopy fractional cover (Hopkinson and Chasmer, 2009), forest maturity (Weber and Boss, 2009) can also be detected by use of the ALS. A high potential of ALS data in the estimation of AGB on individual tree level as well as regional level were confirmed by many studies (e.g. Næsset and Gobakken, 2008; Jochem at al., 2011). The AGB estimation is typically based on a relationship between field observed AGB and various ALS derived values indicating e.g. height and density of canopy. The AGB observed in the field is mostly calculated by means of a single tree equations estimating biomass directly from individual tree measurements, such are diameter at breast height, tree height, crown width, etc. The ALS data represents the three-dimensional structure of the forest canopy which can be utilized as an accurate indirect measure for AGB prediction.

Many studies conducted during the last decade revealed an efficiency of the ALS in detection of change in the forest. Study by Næsset and Gobakken (2005) has shown the capability of the ALS in the estimation of grow of biophysical stand characteristic (Lorey’s mean height, basal area and stand volume) for short growth period. Same study also indicated that growth detection was more predictable by first than by last return echo, and generally had low precision. In addition, Yu at al. (2005) dealt with growth prediction of individual trees showed in particular that the height growth for individual trees can be measured with accuracy better than 0.5 m. The ability for predicting of growth and detecting harvested area and fallen trees using ALS data is reported by Yu at al., (2007). The high potential of ALS data in the detection of AGB change in the Norwegian mountain forest was also reported in study by Bollandsås and Næsset (2010) since model explained 87 % of variation in the AGB change. This study took into consideration only growth of trees as AGB change because the observed period was four seasons and there were no any activities. The prospective of ALS data was then shown in the previous studies dealt with single trees as well as an area based approach, and focused on different forest and trees properties. There is no one study been focused on the estimation of AGB change by tree components before.

With respect to high interest in carbon reporting and further development of methods and testing of the capability of ALS, the objective of present study was to estimate the potential of ALS for detection of change in AGB of tree components and of total AGB inactively managed boreal forest over eleven growth seasons. This study furthermore, assessed whether the estimated ALS-AGB change models differ between AGB of tree components and strata. As a final point, the importance of stratification was assessed by a comparison between the ALS-AGB change models developed in two different approaches.

2. Methods and materials

2.1. Study site

This study was based on data from a forest site in the municipality of Våler (Figure 1) located in Southeastern Norway at approximately 59º 30' 50" N, 10º 54' 4"E, 70 - 120 m a.s.l. (Næsset, 2002). Since Våler is placed in the coastal area of Oslo fjord, there is some climate influence of the Atlantic Ocean, resulting in milder winters and higher annual rainfall in comparison to the inland of Southeastern Norway, with dry climate and colder winters.

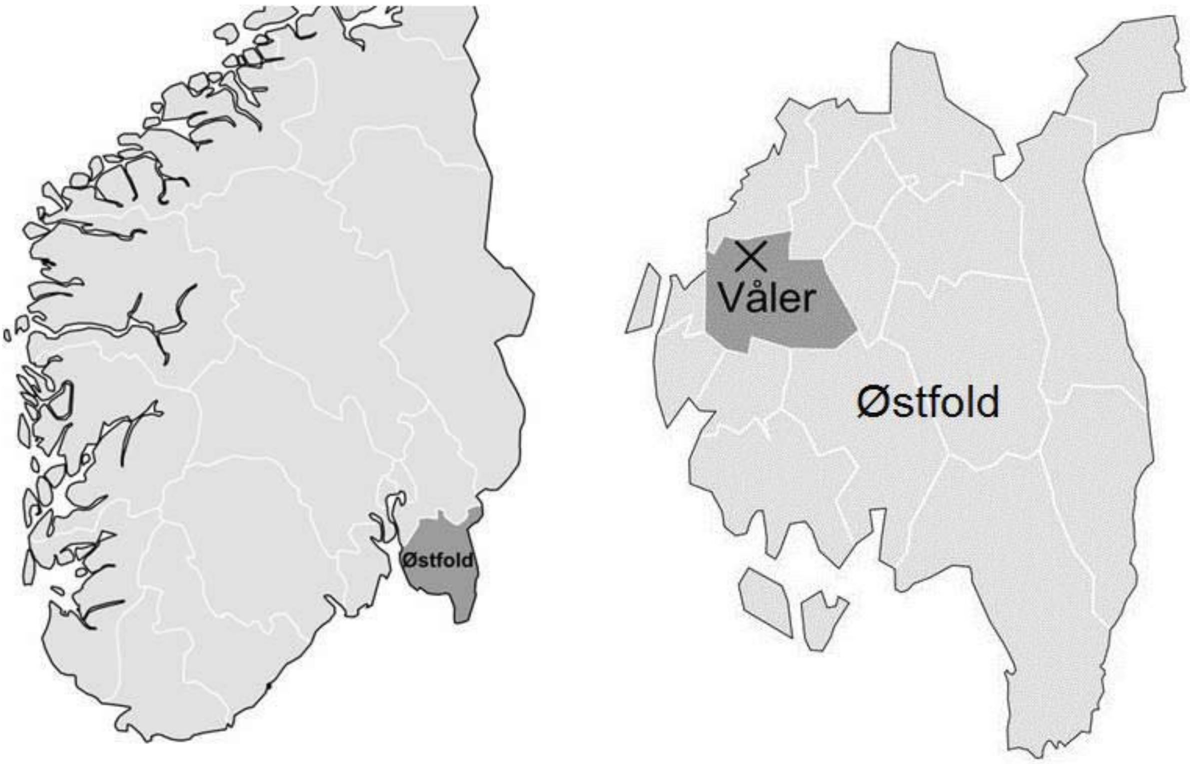


Figure 1.The location of the municipality Våler on the map of Norway

The Nordic boreal forest region has many natural variations. The main tree species are Norway spruce (*Piceaabies* L. Karst.), Scots pine (*Pinussylvestris* L.) and deciduous species (mostly Birch (*Betula sp.* L.) and Poplar (*Populus sp*. L.)). Norway spruce was the dominant species in the current study, representing more than 50%

of the total biomass (Table1). The area in question was approximately 1000 ha and the forest has been actively managed.

The area of Våler has been used for a couple of studies related to forest inventory, various biophysical properties, effects of using different laser instruments etc. (e.g. Bjerknes, 2000; Næsset and Bjerknes, 2001; Næsset, 2002 and Økseter, 2011). Many scientific articles have been published based on ALS and field data collections from this study area. The data for this specific study were collected during two periods, 1999 and 2010.

2.2. Field data

The field data were collected from the 176 circular, 200 m^2 plots. The plots were systematically distributed throughout the entire site (Figure 2).

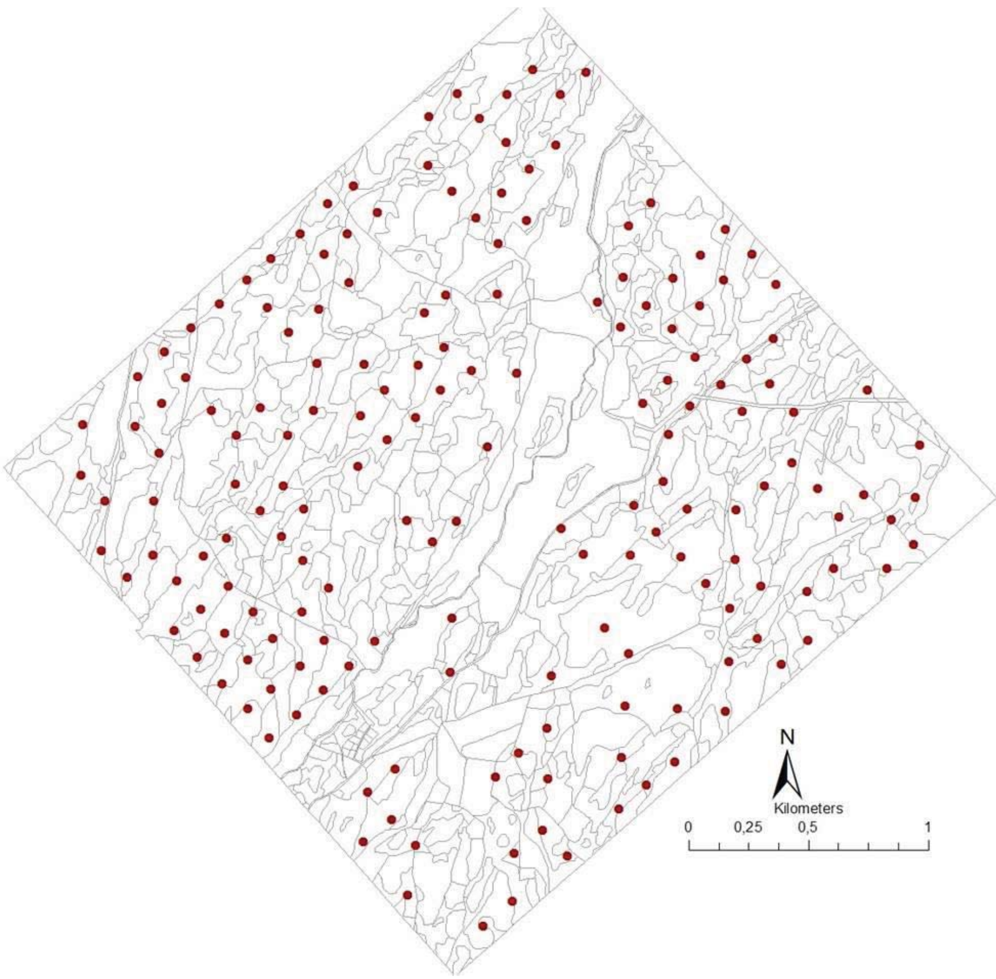


Figure 2 (Made by Roar Økseter) Distribution of the sample plots throughout the study area

The field measurements were carried out for all plots at two points in time. First measurement occasion was during summer of 1999 and the second occasion was during summer and fall of 2010. This means that the data comprised eleven growing seasons.

All plots were classified into mature and young forest. Plots dominated by conifers, were defined as young if total age was below 55, 45, 35, 30, 25, and 20 years for site index values of 6, 8, 11, 14, 17, and ≥20, respectively. The corresponding discriminant ages for birch dominated plots were respectively 30, 25, 25, 25, 20, and 15. The *SI* is defined by the height of the dominant trees at 40 years at breast height (Tveite, 1977). On mature plots, diameters at breast height (d_{bh}) for every tree ($d_{bh} \geq 4$cm) were measured both in 1999 and 2010. Heights were measured only for sample trees. The sample trees were selected randomly amongst the all callipered trees in 1999 (Næsset, 2002) and with probability proportional to the stem basal area at breast height in 2010.

In the young forest, the observations were carried out on a cluster of four circular sub-plots of 20 m^2 (Figure 3) rather than one large plot. Diameters at breast height for all trees with heights down to 1.3 m were measured. In practice this means that

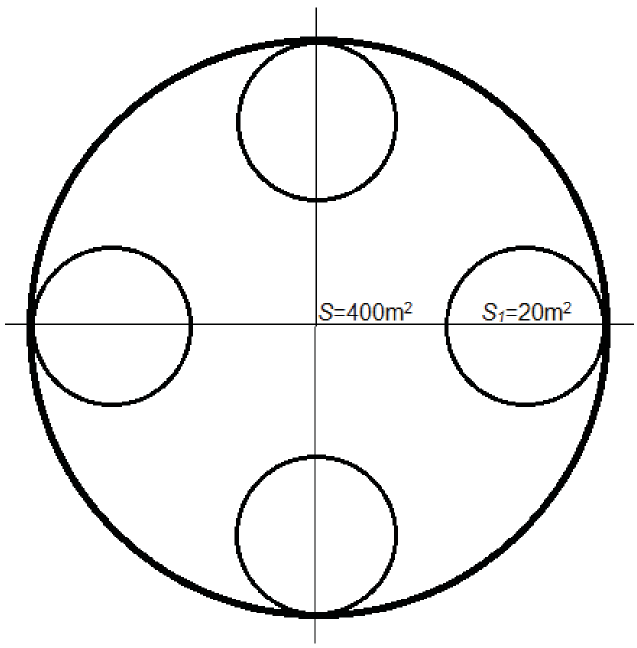


Figure 3 Distribution of sample plots within one, 200 m^2 sample plot in the young forest

diameters were registered down to zero. Heights were measured for four randomly selected trees on each sub-plot.

Differential Global Positioning System (GPS) and Global Navigation Satellite System (GLONASS) were used in order to determine centre point of the each plot. The expected accuracy of planimetric plot coordinates (x and y) was of approximately <0.3 m (Næsset, 2002)

2.3. Calculation of AGB and AGB change from the field data

There exist several models (e.g. Marklund, 1988; Claesson at al., 2001; Zianis, 2005) for prediction of biomass components of standing trees. These models require a minimum of one variable which describe the tree. The main descriptive variables of a tree in this context are diameter and height. Based on those variables, it is possible to calculate more complex variables such as the volume and biomass of the tree. It is not possible to directly measure volume and biomass of the tree on the site. Consequently, the accuracy of biomass estimation depends on relationship between the biomass and descriptive variables. That relationship is also influenced by additional variables such as tree species, diameter ranges, regions, altitudes, etc. In that case, with respect to the additional variables and in order to have accurate estimation, it is necessary to use the appropriate biomass equations.

Since there is no set of AGB equations calibrated for the study area (Våler), the equations developed by Marklund (1988) for the entire Sweden were applied in the current study. Even though being calibrated for Sweden, some studies have indicated that they also are valid for Norwegian conditions (Bollandsås et al., 2009) at least for birch. Because of lack of local equations, the most studies that deal by calculation of AGB and carried out in Norway used the Marklund equations.

Marklund (1988) established several models containing one to eight variables. As explanatory variables, Marklund used a different combination of tree features such as diameter at breast height, height, species, height from ground level to green crown base, crown radius, breast height diameter increment for periods of last five to ten years as well as site characteristics, such as altitude, latitude, site index, etc. Rationally, the Marklund models that contain larger number of explanatory variables are more accurate, but which one can and would be applied directly depends on the availability of data that are collected from the field. The available data in this study were diameters and heights of trees, so the models used relayed on those two explanatory variables. Since those two variables are the most representative tree features, the accuracy of used models is rather satisfactory. On the other hand, the high accuracy and less complexity make used models the most applicable.

2.3.1. The height prediction in the mature forest (2010)

The AGB equations of Marklund rely on both diameter and height as explanatory variables. Since heights were recorded only for sample trees, missing heights had to be estimated. In this study, the missing heights were estimated by first estimating volume of each tree by means of relationships between “true” volumes and so called tariff-volumes. After the estimation of volume, height could be estimated by setting height as the unknown in a volume equation. The procedure is described in detail below.

2.3.1.1. Calculation of mean tariff from the sample dataset

For the sample trees, both diameter and height were measured. Stem volume for each sample tree was then calculated by using volume equations for single trees with diameter and height as independent variables. Different equations were used for spruce (Vestjordet, 1967), pine (Brantseg, 1967), deciduous species (Braastad, 1966). Separate equations were also used within certain diameter ranges. For example, the calculation of volume of spruce is based on three equations established by Vestjordet, (1967) used for trees less than 10 cm, from 10 to 13 and more than 13 cm in diameter at breast height. In addition to true volume, it was also necessary to calculate “tariff volume” for each sample tree. The calculation of tariff volume requires the “tariff height” in addition to diameter.

The “tariff height” assumes a specific diameter - height relationship, and for that reason tariff heights differ from the true heights in most cases. The tariff height in this study was calculated by means of different equations established by Fitje (1977) and Vestjordet (1967) in accordance to diameter and species. Then, the obtained tariff heights were utilized to the calculate tariff volumes of single trees by means of the same equations that were used for calculation of true volume (Vestjordet, 1967; Brantseg, 1967; Braastad, 1966). After the “true” volume and tariff volume were calculated, a tariff was calculated for each sample tree as a ratio between the “true” and tariff volume. Followed by, mean tariffs were calculated for each plot (mean-of-ratios) because the sample trees were selected proportional to stem basal area.

2.3.1.2. Calculation of height of callipered trees

For each plot, each tree with diameter ≥4 cm was callipered. Volume of these callipered trees was estimated by firstly calculating tariff height using the models of Fitje (1977) and Vestjordet (1968), and then calculating the tariff volume using the single tree volume equations. Next, the tariff volume of each tree was multiplied by the mean tariff obtained from the sample tree data.
Since the diameter and volume for each tree was known, the height of each tree was calculated by means of the inverted single tree volume equations (Vestjordet, 1967; Brantseg, 1967; Braastad, 1966). The height then was set as the dependent variable and volume and diameter were independent variables.

A small test was performed for the sample trees in order to check of the accuracy of predicted heights. The test results showed only a 3.36 t (1.13%) difference between the total AGB of sample trees calculated by measured heights and AGB calculated by predicted heights.

2.3.2. The height prediction in the young forest (2010)

All diameters of the trees equal to or higher than 1.3 m were collected on the young forest sample plots. Since the heights were recorded only for four randomly selected sample trees on each sub-plot, it was a necessary to calculate the missing heights for the callipered trees. Most of these trees were outside the range of the volume equations used in this study, so it was needed to select another method than the one used for the mature plots for height prediction. The prediction of heights was therefore carried out by means of a simple linear regression model developed from the sample trees data where diameter and height are known.

In its general form the model is displayed below:

$$Y_{i} = a + bX_i + \varepsilon_i,$$

(equation 1)

where Y_i is tree height, a and b are coefficients to be estimated, X_i is diameter at breast height and ε_i is the error term.

The accuracy of height predictions of young trees were evaluated for the sample trees by a comparison of the total AGB calculated by measured height and the total AGB calculated by predicted heights. The result of this assessment showed that the mean difference was only 0.003 t (1.09%). Afterwards, the heights of callipered trees were predicted by means of the model.

When all heights and diameters were known, the datasets for the young and mature forest were merged into one data set consisting of 176 plots.

The biomass of each of the AGB component (stem, bark, living branches, dead branches and leaves) was calculated using species-specified allometric equations (Marklund, 1988) with breast height diameter and tree height as independent variables.

The total AGB on each plot was calculated as the sum of AGB components (stem, bark, dead and living branches, and foliage). In this study, the biomass of the stump was not included in the AGB. The reasons were practice used in the majority of modern forest management systems where the mature trees are harvested above the root collar, leaving stumps in the forest (Walmsley and Godbold, 2010). Same practice is also eminent in Norway's forest management system.

All plot AGB values were scaled to tons per hectare, with respect that it is more convenient to deal with per hectare values because they are independent of plot size.

2.3.3. Difference between the AGB calculation in 1999 and 2010

The AGB of tree components observed in 1999 was calculated more or less on the same way like the biomass observed in 2010. The mean difference between data collection between 1999 and 2010 was that the sample trees in 1999 were selected randomly. The tariff for each plot was calculated as ratio between the mean volume of each plot and mean tariff volume of the same plot (ratio-of-means). Pointing out that tariffs in 2010 were calculated as ratio between volume and tariff volume for each sample tree and afterwards were calculated the mean tariff for each plot (mean-of-ratios), because the sample trees were selected proportional to stem basal area. Other part of the calculating procedure was the same as for the calculation from 2010.

Table 1 present a data summary with AGB by species, mean volume, mean height and mean basal area values for the study area from both observations (1999 and 2010).

Table 1
Summary of data values for the study area measured in the field in the 1999 and 2010

Variable	1999	2010
AGB of spruce (t/ha)	66.67 (0.51%)	78.97 (0.51%)
AGB of pine (t/ha)	32.59 (0.38%)	36.63 (0.32%)
AGB of deciduous species (t/ha)	13.19 (0.11%)	16.16 (0.17%)
Mean AGB (t/ha)	112.45	131.76
Mean volume (m^3/ha)	175.84	217.38
Mean height (m)	16.31	17.24
Basal area (m^2/ha)	14.44	16.95
Total AGB (t/ha)	112.45	131.76

Finally, the change in the AGB was calculated as the difference between per hectare field observed AGB and its components in 2010 and its corresponding to the value of 1999 (Bollandsås and Næsset, 2010). Summary of the AGB change for the all plots is shown in the Table 2.

Table 2
Summary of AGB change per components

AGB component	Mean change (t/ha)	Standard deviation (SD)	Max negative change (t/ha)	Max positive change(t/ha)
Stem	10.07	56.52	-202.80	147.38
Bark	0.83	5.11	-17.07	11.13
Leaving branches	0.12	16.74	-53.67	34.76
Dead branches	0.10	1.46	-6.22	4.06
Leaves	8.20	7.29	-12.94	31.04
Total AGB	19.31	82.83	-275.83	216.82

2.4. Stratification

Stratification contributes to the process of data classification with respect to relevant characteristics. Depending on a predicted variable, the data could be stratified with respect to one or more characteristics. Previous studies such as Bollandsås and Næsset (2010), Næsset (2002), Næsset (2004a), Naesset and Gobakken (2008) dealing with estimation of biophysical properties of trees and forest ecosystem using ALS data have shown that the relationship between laser derived variables and ground truth values varies between forest stands with different characteristics. Since it is very difficult or even impossible to develop one single good model for the entire forest, it is recommended to classify the forest stands and then develop models for each stratum. The importance of stratification were confirmed in the mentioned studies, where forest stands were classified with respect to some of stand characteristics, such as age class, site index, forest type, biomass change etc. The relationship between laser derived variables and ground truth values in the obtained strata was more linear and consequently the prediction was more accurate.

The data used in this study were collected from the actively managed forest area where the forest stands differ with respect to age, species, site index etc. Beside the natural events, there are many types of changes which occurred during the eleven grow seasons. For that reason, it was also recommendable to classify the forest stands by means of characteristics of the stand and its changes during the observed period. In order to verify a great importance of stratification in the detection of AGB change, models for unstratified and stratified forest stands from two approaches were developed in this study.

The forest stand characteristics for 1999 have been registered for every plot (200 m^2) during forest inventory by digital stereo photogrammetric (based on the airborne photographs). In 2010, the stand characteristics were measured directly on the site.

The plot stands were classified according to developmental class from 1999 and change of developmental class between 1999 and 2010 (Table 3). Each of the four strata comprised stands dominated by forest similar by age (young, advanced, mature forest) and where similar changes in stand characteristics had taken place during the observation period. Then, stands with a different type of AGB change (positive-negative, more-less) were assigned to different strata. Consequently, the stratification enables an easier estimation of AGB change within strata and makes relationship between observed AGB change and ALS-derived variable more stable.

Table 3
Stratification according to developmental class

Stratum	Dev. class in 1999	Change of Dev. class between 1999 and 2010
I	= II	> 0
II	> II	> 0
III	> II	= 0
IV	> II	< 0

There are five different development classes based on site index and stand age, where class I is clear cut area, class II is regenerated area and young forest, III young thinning stand, IV advanced thinning stand, and V mature forest (Gjertsen, 2007).

Based on developmental classes listed above and change of developmental class between 1999 and 2010, the plots were stratified as follows:

- stratum I- young forest stands with positive change in the developmental class,
- stratum II- young and advanced forest stands with positive change in the developmental class,
- stratum III- forest stands without change in the developmental class,

- stratum IV- mature forest stands with negative change in the developmental class.

To be able to implement this type of stratification in real situation, it is necessary to have a photointerpretation of developmental class for each point in time.

The summary of change of AGB components of trees per each stratum is shown in the Table 4.

Table 4
AGB change by components between 1999 and 2010 per stratums

AGB component	Number of sample plots	Mean AGB change	Standard deviation (SD)	Min AGB change	Max AGB change
Stratum I -*Young forest stands with positive change in Dev. Class*	32				
Stem		44.52	19.97	7.10	87.16
Bark		4.78	2.38	0.73	9.79
Living branches		11.91	11.47	-7.67	33.84
Dead branches		1.23	0.70	-0.78	2.51
Leaves		3.38	5.52	-12.94	11.64
Total AGB		65.82	33.35	18.62	134.50
Stratum II-*Young and advanced forest stands with positive change in Dev. Class*	47				
Stem		33.84	1.67	-32.92	131.09
Bark		2.47	3.24	-2.88	10.52
Living branches		4.36	9.33	-17.35	24.22
Dead branches		0.51	1.15	-1.42	4.06
Leaves		12.98	7.03	3.65	30.40
Total AGB		54.17	54.80	-43.76	216.82
Stratum III-*Mature forest stands with no change in Dev. Class*	54				
Stem		15.34	38.83	-185.18	80.10
Bark		1.26	3.549	-17.07	7.48
Living branches		2.62	10.98	-48.42	17.70
Dead branches		0.20	0.93	-4.51	1.39
Leaves		9.83	5.81	1.511	25.67
Total AGB		29.26	56.59	-250.58	131.32
Stratum IV-*Mature forest stands with negative change in Dev. Class*	43				
Stem		-48.18	59.83	-202.80	122.65
Bark		-4.46	5.15	-16.90	8.47
Living branches		-16.41	17.98	-51.59	34.76
Dead branches		-1.33	1.47	-6.22	2.811
Leaves		4.51	5.66	-0.59	25.92
Total AGB		-65.89	88.38	-275.83	194.62

2.5. Laser scanner data

The two laser data acquisitions were carried out on the8th and 9th of June 1999 and 2nd of July 2010, respectively. The flight campaigns were flown as strips with overlap of 50% in 1999 and 55% in 2010. Also, fly strips at a 90 degree angle were done so to correct the systematic errors between the strips. Both acquisitions have used a fixed-wing aircrafts (Piper PA31–310). In 1999 the Optec ALTM-1210 was used and Optech ALTM-Gemini laser scanner was used in 2010. The plane was at an altitude of approximately 700 m above ground (1999) and 900 m (2010). The speed average was 71m s^{-1} (1999) and 80 m s^{-1} (2010). Based on mentioned as well as on other factors such as scan angle, repetition frequency and scan frequency, processing angle, footprint diameter and other parameters, the determined point density on the ground was approximately 1.1 m^{-2} in 1999 and 5.7m^{-2} in 2010. Summary of flight parameter and scanner data for both acquisitions is shown in the Table 5 below.

Table 5
Summary of laser scanner data and flight parameters for the 1999 and 2010 laser data acquisitions

Parameter	1999	2010
System	ALTM-1210	ALTM Gemini
Repetition frequency	10kHz	100kHz
Scan frequency	21Hz	55Hz
Date	8th -9th June	2nd July
Mean speed of aircraft	71 m s^{-1}	80 m s^{-1}
Mean flight altitude	700 m a.g.l.	900 m a.g.l.
Max scan angle	17°	14°
Max processing angle	14°	13.8°
Overlap between strips	50%	55%
Mean footprint diameter	21 cm	22 cm
Mean pulse density	1.1 m^{-2}	5.7 m^{-2}

The ALTM1210 is able to register only two returns for each emitted laser pulse - FIRST and LAST. The ALTM-Gemini, which represents the most advanced models of the previous-generation ALTM series, can register up to four echoes (Ussyshkin and Theriault, 2011). However, in order to estimate the biomass, we did not take advantage of the intermediate echoes from the ALTM-Gemini in this study, only the FIRST and LAST.

Initially, the complete processing of first and last pulse data was done by the contractors Fotonor AS (1999) and BlomGeomatics AS (2010). The planimetric coordinates (x and y) and ellipsoidal height values for all of echoes were calculated. Then, each echo was classified as “ground echo” or “off-ground echo” (vegetation echo). A triangular Irregular Network was created from the planimetric coordinates and ellipsoidal heights of the individual ground laser echoes (Naesset and Gobakken, 2008). The individual vegetation heights of all first and last echoes than were calculated as the difference between the TIN height and height values of each recorded echo (Bollandsås and Næsset, 2010). All echoes outside of the sample plots were excluded from further analyses.
The height distribution created from the first and the last return echoes was used for calculation of percentiles of canopy heights for each sample plot measured in the field. Height distributions were created only for those echoes considered to belong to the tree canopy. It means that the distribution include echoes with height values equal or more than 2 meters. The threshold of 2 meters above ground was used in order to eliminate all the echoes that could be affected by the various factors like bushes, weeds, rocks, debris of fallen trees, etc.

The plot-level percentiles for 0, 10,…, 90 % (h_0, $h_{10}, \ldots, h_{90}$) of the canopy height distribution created from the first and the last echo were calculated. The mean values (h_{mean}), maximum values (h_{max}) and coefficient of variation (h_{cv}) were calculated as well. These variables were labelled “height variables”. The h_{10f} variable denote the height at which the 10% of first laser echoes in the vegetation is accumulated (Bollandsås and Næsset, 2010).
The cumulative proportional canopy densities ($d_0, d_1, \ldots, d_8, d_9$) were calculated for 10 fractions of equal length between the lowest laser height (>2m) and maximum laser height. The canopy densities were calculated as a proportion of laser echoes above the fraction 0(>2m), 1,…9 to total number of echoes (Næsset, 2005). These variables were labelled “density variables”. The d_{1f} variable denote the values of proportion between the first laser echoes that are considered to appear at the 10 % of canopy height observed from the top of the canopy in proportion to the total number of echoes (Bollandsås and Næsset, 2010).

Lastly, the “delta values” in this study signify the difference between laser variables resulting from the first and the last echoes obtained from data from 2010 and corresponding variables from 1999. The delta values were calculated for each of 176 sample plots measured in field.

Example: The δh_{20f} refer to difference in height between the 20th height percentile from the first echoes from data collected in 2010 and the equivalent percentile from data collected in 1999.
The δd_{20l} refer to difference in the canopy densities of the second fraction of canopy height derived from last echo, data from 2010 and corresponding data from 1999. (Bollandsås and Næsset, 2010).
These delta values of heights and densities were used as potential variables in order to explain change in AGB of tree components, which was the main goal of this study.

The mean "delta values" of height and density variables per each stratum derived from first echo are graphical presented in Figures 4 and 5. The most pronounced positive changes in the height variables appeared in stratum I and the most pronounced negative in stratum IV (Figure 4). Furthermore, it is evident that the most pronounced changes for each stratum were found for the high percentiles.

A different situation was evident to some extent in the curve for the AGB change without stratification (labelled "total biomass change" in Figure 4), where the most pronounced changes were in the lower percentiles. The changes in stratum I, II and III and AGB change without stratification were also quite equable in the higher percentiles (h_{30f}, h_{40f}, …, h_{90f}). In the lower percentiles (h_{30f}, h_{20f}, h_{10f}) the changes of height variables were slightly declining for each of stratum. The sharp declining were observed between the first (h_{10f}) and lowest (h_{0f}) percentiles, while the changes in the lowest percentile of height distribution (h_{0f}) for each of stratum and total AGB change were close to zero.

Figure 5 shows that the most pronounced positive changes in the density variables were in stratum I and the most pronounced negative in stratum IV. The magnitude of changes of the density variables shows slightly opposite trend than for height variables. The most changes in the stratum I appear in the middle of canopy (d_{4f}, $d_{5f}d_{6f}$ *and* d_{7f}) with a slight decrease towards higher and lower fractions of canopy. Stratum II and III and AGB change without stratification characterize a minor trend from the small negative density change at the lowest fraction of canopy (d_{0f}) to the most positive change at the higher fraction of canopy (d_{6f}, d_{7f}) and again minor negative trend in direction to the top of canopy (d_{9f}). For the stratum IV, characterized with negative changes, the most changes of density variables was evident at the lowest fraction of canopy (d_{0f}) with very obvious negative trend towards top of canopy.

From another point of view, these figures also manifest various processes (growth, harvesting, mortality rate, natural regeneration, planting, etc.) that were happened in the study area. The effect of mentioned processes is change of AGB. Changes of vertical and horizontal distribution of AGB are recorded in the ALS data presented as height and densities variables derived from ALS data.

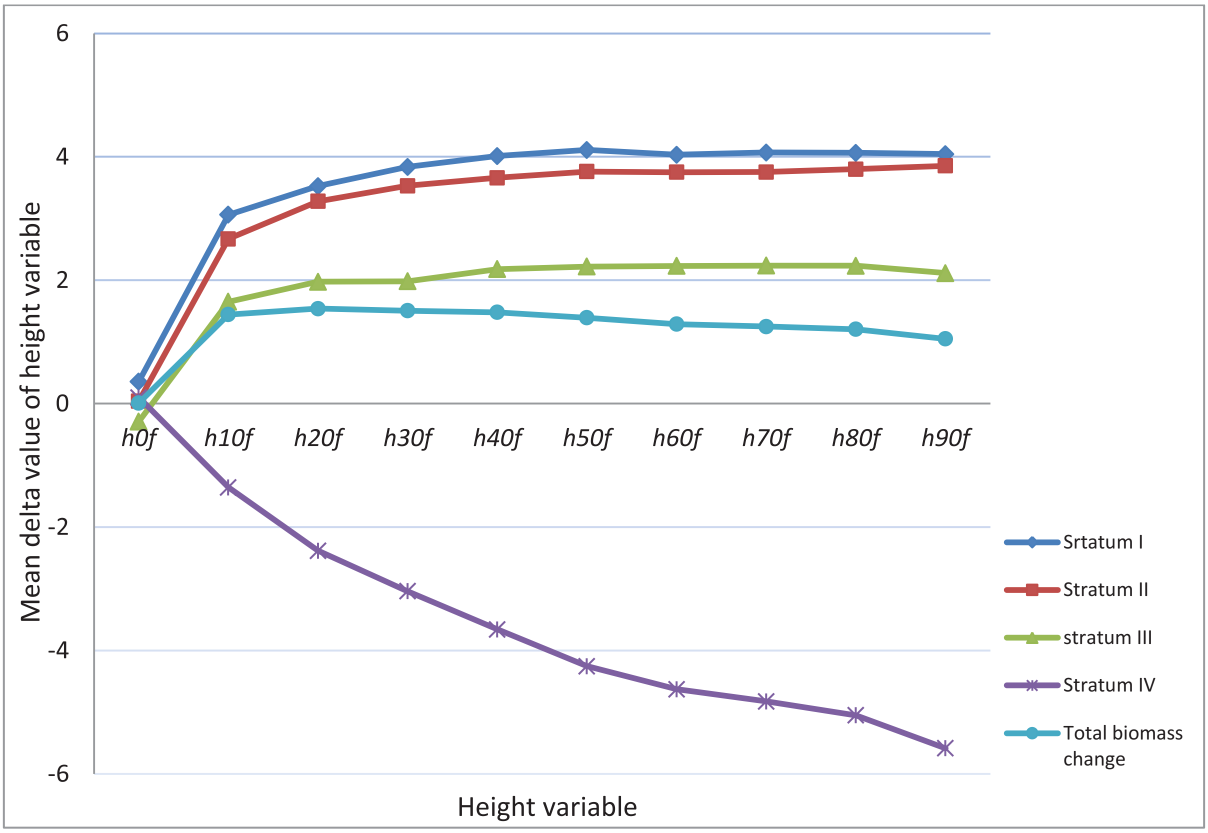


Figure 4. Mean changes for different height variables per stratum between 1999 and 2010, derived from the first echo

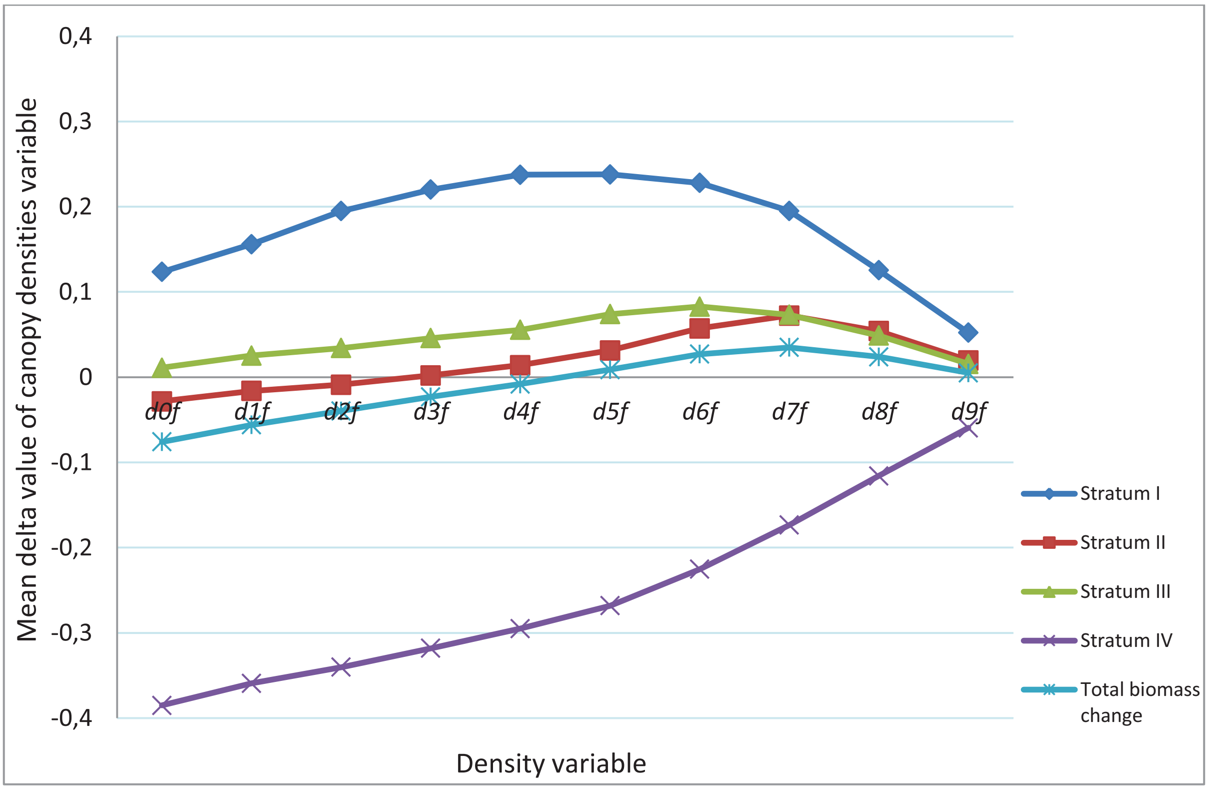


Table 5. Mean changes for different density variables per stratum between 1999 and 2010, derived from the first echo

2.6. Prediction of AGB change

The change of AGB of the tree components (t/ha) over the eleven growing seasons were associated to the ALS-derived delta values by using a multiple regression analysis. The goal of mentioned analysis was to determine a simple model which contains the most contributing variables in order to explain the variation of AGB change.

This study is dealing with two approaches of a prediction.

2.6.1. First approach

The change of AGB of tree components were predicted for the <u>entire forest</u> (176 forest stands without stratification). The height and density variables, mean and maximum height of canopy and both stand characteristics - site index and change in the developmental class between 1999 and 2010 were included in the models as candidate variables. The one single model was developed for each of AGB components and total AGB.

2.6.2. Second approach

The change of AGB of the tree components were predicted for stratified forest stands. The height and densities variables, mean and maximum heights of canopy and only one stand characteristic - site index were included in models as candidate variables. Since the stands were stratified with respect to developmental class, change of developmental class was not included. The one single model was developed for each of AGB components and total AGB for the each single one of the four strata.

2.6.3. Modelling and variables selection

Including all of mentioned variables, the multiple regression models in its complete form contain 46 *(First approach)* or 45 (*Second approach)* independent variables candidates and appear like presented below:

$$\begin{aligned}\delta biomass = \beta_0 + \beta_1\, h_{0f} + \beta_2 h_{10f} + \cdots + \beta_{10} h_{90f} + \beta_{11} h_{meanf} + \beta_{12} h_{maxf} + \ \delta_{13} d_{0f} \\ + \ \beta_{14} d_{1f} + \cdots + \beta_{22} d_{9f} + \beta_{23} h_{0l} + \beta_{24} h_{10l} + \cdots + \beta_{32} h_{\,90l} + \beta_{33} h_{meanl} \\ + \beta_{34} h_{maxl} + \beta_{35} d_{0l} + \beta_{36} d_{1l} + \cdots + \beta_{44} d_{9l} + \beta_{45} SI + \beta_{46} d_{dc} + e\end{aligned}$$

(equation 2)

where $\delta biomass$ = field observed values of AGB change of tree components (t / ha)*;* h_{0f}, h_{10f}, …,h_{90f} = percentiles corresponding to 0, 10,…, 90% of the laser canopy heights (m) derived from the first echo; h_{meanf} = mean of the laser canopy heights (m) derived from the first echo; h_{maxf} = maximum laser canopy heights (m) derived from the first echo; d_{0f}, d_{1f}, …, d_{9f} = canopy densities corresponding to the proportions of first pulse laser echoes above fraction 0, 1, …, 9 to total number of first echoes; h_{0l}, h_{10l}, …,h_{90l} = percentiles corresponding to 0, 10,…, 90% of the laser canopy heights (m) derived from the last echo; h_{meanl} = mean of the laser canopy heights (m) derived from the last echo; h_{maxl} = maximum laser canopy heights (m) derived from the last echo; d_{0l}, d_{1l}, …, d_{9l}= canopy densities corresponding to the proportions last pulse laser echoes above fraction 0, 1, …, 9 to total number of last echoes; *SI* = site index- the height of the dominant trees at 40 years of age; d_{dc}= the difference in the developmental class observed in 1999 and 2010; *e* = a normally distributed error term.

A standard least squares model was fitted with the lm() procedure of the statistical program "R commander" (Fox, 2004).
The R Commander is a free statistical software package that provides a basic-statistics GUI (graphical user interface) for R programming language (Fox, 2004).

Selection of explanatory variables was carried out in two steps. Firstly, a stepwise (forward-backward) variable selection was performed in order to select the most representative ALS-derived variables to be included in the model. Inclusion and removal of variables was based on the partial F statistics with a significance level of 0.05. In some cases, only the one or two variables have been considered as significant ones. In the second step, the additional explanatory variables were manually entered into the model. Manual entering was carried out as regards a significance of each potential variable in the simple linear model where the dependent variable was regressed against to the potential explanatory variable.
In order to linearize relationship, the explanatory variables selected as the most significant were transformed (Montgomery, 2001). Different transformations such as square (x^2), root ($\sqrt{x}$), and reciprocal ($\frac{1}{x}$) were conducted for that purpose. Logarithmic transformation (logx) could not be applied because of the negative value of some of variables. The transformed variables were subsequently put back in the model as potential independent variables. Then, the stepwise (forward-backward) selection was performed once again on the selected the most significant variables and its transformations with a significance level of 0.05. Additional selection was carried out manually and it was based on observation of residual plots and collinearity with the statistically selected variables.
The observation of residual plots is a very effective way to investigate how well the regression model represents the data. A plot of the residuals *(e)* versus any of variable or fitted values (Y_i) could be efficient to explore several model inadequacies.

Only the variables with residual plots shaped as horizontal band do not indicate problem in model. The residual plots shaped in any other form indicate some bias. The variables whose residual indicated some bias were excluded from model (Montgomery, 2001). However, the residual plot gets a different shape if the significant variable is replaced by one of its transformation. Even the residuals of transformed variable were sometimes shaped as horizontal band, the final selection of the transformed variable depends on other criteria of selection that have to be met.

In cases where there are dependencies among variables included in the model, multicollinearity can be a problem. The presence of multicollinearity has potentially strong effect on the estimation of regression coefficients, which implies that model is not first-rate and makes partial prediction (Montgomery, 2001). The multicollinearity in this study was estimated by Variance Inflation Factor (VIF), where the VIF was calculated by running option in the R Commander. However, the estimation was based on the equation:

$$VIF(\beta_{i)} = \frac{1}{1 - R_i^2}$$

(equation 3)

where R_i^2 is the unadjusted R^2 when $X_i$is regressedagainst all the other explanatory variables in the model. If any of VIF is high, then multicollinearity is indicated (Montgomery, 2001). However, there is no the trusty threshold value to judge that VIF is “high”. Montgomery, (2001) says that threshold value of VIF is 10, but in this study it was consider as too high. The threshold values of the VIF in this study were evaluated in the context of deviation observed between the VIFs calculated for all variables included in the model (O’brien, 2007). VIF that was twice deviated from the average of two lowest VIFs was considered as too high and such variables were excluded from the model.

During additional selection a few models similar in evaluation characteristic were developed for some of biomass components. Those models are contained different number of variables or different transformation of the same variables. In these cases, the simplest one was selected as the best one or it was done according to the comparison between models by use Akaike Information Criterion (AIC). The AIC is a criterion for model selection which selects the model that best explains the data with a minimum of free parameters. The best model has the smallest AIC (Yamaoka et al., 1978). In this study the AIC was calculated directly by selecting option in the R Commander. The calculation was based on the equation proposed in Akaike (1974):

$$AIC = 2k - 2\ln(L)$$

(equation 4)

where *k* is the number of parameters in the statistical model, and *L* is the maximum likelihood function for the estimated model (Akaike, 1974).

During the selection of variables and final selection of models, the coefficient of determination (R^2) and standard error of estimate *(SEE)* were observed as the most important criteria.

2.7. Evaluation of models

The accuracy of estimated regression models were assessed by "self validation" because there were not an independent data available. The self validation was based on the coefficient of determination (R^2) and the calculation of Root Mean Square Error (*RMSE*).

The observation of R^2 is used in statistical model analysis to assess how well a fitted model explains total variation in the dependent variable. The value of R^2 indicates whether the model is good or bed and it is also a good a measure to compare the models against each other. The R^2 is defined as the proportion of variation explained in the regression model in relation to the total variation of the dependent variable (Koprivica, 1997). R^2 is ranged between 0 and 1, but higher R^2 indicates that the dependent variable, more explained by the independent variables.R^2 was calculated using equations 5.

$$R^2 = 1 - \frac{SSE}{SS} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

(equation 5)

where R^2 is coefficient of determination, SS (total sum of squares) measures the deviations of the observations from their mean, SSE (sum of squares of errors) measures the deviations of observations from their predicted values, y_i - observed value, $\bar{y}$- mean of observed values and $\hat{y}_i$ - predicted value.

The RMSE is one of the most widely used error measures for the comparison and evaluation of regression models in the climatic and environmental literature (Willmott et al., 1985). RMSE has the same units as the variable being estimated and it is an unbiased estimator of error based on residuals. The residuals represent differences between the observed values and the predicted values. Thus, the RMSE is used as a measure of the spread of the y_i- observed values about the $\hat{y}_i$-predicted values. The calculation of RMSE is based on the equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}$$

(equation 6)

where y_i is observed value, $\hat{y}_i$ is predicted value and n is number of samples (Montgomery, 2001). The non-dimensional (normalized) form of RMSE expressed in percentage was calculated as a ratio of the RMSE and the range of observed values (equation 7). The normalized RMSE (%) enables a comparison of RMSE with different units and better evaluation of RMSE values in relation to the range of observed AGB change.

$$RMSE(\%) = \frac{RMSE}{x_{max} - x_{min}} * 100$$

(equation 7)

The x_{max} is the max value of observed AGB change in the sample plots and x_{min} is the least positive AGB change or the max negative change in the cases where the negative change of AGB were observed.

3. Results

The change of the AGB components of trees (stem, bark, living branches, dead branches and leaves), observed on 176 sample plots were regressed against the height and density variables including mean *(h_{mean})* and maximum *(h_{max})* height of canopy derived from the distribution of first and last return echoes of airborne laser scanner (ALS). The stand characteristics - site index *(Nelson et al.)* and change in developmental class *(d_{dc})* as candidate variables were additionally included in the first approach and in the second approach only site index was included in the models. During the stepwise selection, the multicollinearity problems occurred in many of models. All the variables with multicollinearity were excluded by means of examination of the variance inflation factor (VIF). The best variable combination and simplification of models were carried out by means of observation of coefficient of determination (R^2), standard error of estimate (SEE) and shape of residual plots as the most important criteria.

The total number of finally selected models was 30. Six models were developed in the first approach and six models for the each single one of the four strata in the second approach. All selected models consist of maximum five explanatory variables and models equally represented by height and density variables.

3.1. Results from the first approach

The one single model was developed for each of the AGB components and total AGB change for the entire forest (176 forest stands without stratification, Table 6). Table 6 shows finally selected variables and parameters of estimation of models (coefficient of determination (R^2) and root mean square error $(RMSE)$) for each of AGB component. The most accurate model was developed for the change of biomass of stem, where R^2= 0.78 and $RMSE$= 26.44 *t/ha* as well as the least accurate model for the change of biomass of leaves, where the R^2 =0.48 and $RMSE$=5.22 *t/ha*. The model of the total AGB explicates 77% of the variation in the observed change and $RMSE$ =39.56 *t/ha.* The models were equally represented by height and density variables. In addition, the one of the site characteristic was also selected in the five out of six models as the significant one.

Table 6
Final selected variables and parameters of estimation for the models where the observed change of each biomass components for the whole dataset (176 sample plots) were regressed against the ALS- derived variables.

AGB component	Variables	R^2	$RMSE$ ($RMSE$ %)
Stem	h_{30f}, d_{0l}, d_{dc}	0.78	26.44 (7.55)
Bark	h_{30f}, d_{6l}, d_{dc}	0.76	2.48 (8.79)
Living branches	h_{20f}, d_{1f}, SI^2	0.73	8.62 (9.74)
Dead branches	h_{30f} , d_{6l}	0.72	0.78 (7.58)
Leaves	sqrth_{10l}, d_{0l}^2, sqrtd_{7l}, SI^2, $1/h_{maxf}$	0.48	5.22 (11.86)
Total AGB change	h_{30f}, d_{0f}, SI^2	0.77	39.56 (8.03)

[a] h_{20f} and h_{30f}= The quantiles corresponding to 20 and 30 percentiles of the first pulse laser canopy heights (m); h_{10l}= the quantiles corresponding to the 10 percentiles of the last pulse laser canopy heights (m); h_{maxl}= maxima of first pulse laser canopy heights (m); d_{0f} and d_{1f}= canopy densities corresponding to the proportions of first pulse laser echoes above fractions 0 and 1 to total number of first echoes; d_{0l}, d_{6l}, and d_{7l}= canopy densities corresponding to the proportions of last pulse laser echoes above fractions 0, 6, and 7 to total number of last echoes; *SI*= site index- the height of the dominant trees at 40 years of age and d_{dc}= the difference in the developmental class.

3.2. Results from the second approach

A one single model was developed for each of the AGB components and total AGB change for the each single one of the four strata (Table 7). Table 7 presents final selected variables, coefficient of determination (R^2) and root mean square error ($RMSE$) of the models developed for each single one of four strata. It is obvious by the observation of the parameters of estimation that the best models were developed for the stratum IV, comprised of the mature forest stands characterized with the negative change of the AGB components. Somewhat poorer models were developed in the stratum I and II, comprised of the young and advanced forest stands. There are also a few exceptions, such as change of biomass of leaving branches in stratums I and II and change of biomass of leaves in stratums III where quite inaccurate models were developed.

The stratum I characterize the most positive changes of the AGB components, but a prediction of those changes using ALS-data was not quite accurate.
This is in particular related to the model developed for the prediction of change in the biomass of living branches where R^2=0.40 and $RMSE$ =8.86*t/ha*. At the same time, it was the least accurate model in this study. Enhanced models were developed for the prediction of other AGB components from the stratum I, explicated around 70% of the variation in the observed AGB change. The best model in the stratum I was developed for the change of biomass of bark (R^2= 0.72 and $RMSE$ = 1.25*t/ha*). The

models from this stratum are also characterized by the appearance of the site index as a significant independent variable, beside height and density variables.

A similar situation was also evident in stratum II, which comprise mostly advanced forest stands with a positive change in the developmental class, observed between 1999 and 2010. The least accurate model in this stratum was even developed for the change of biomass of leaving branches where R^2= 0.46 and $RMSE$ = 6.85 *t/ha*. The best one was developed for the prediction of the change of stem biomass - R^2= 0.71 and $RMSE$ = 20.42 *t/ha*. Beside the density variables in the models in stratum II, the mean heights of canopy *(h_{mean})* were mostly appeared as the significant variables unlike of models from the other stratums where that was not the case.

The AGB changes in the stratum III mostly present good models. Exception in this stratum is the model for change of biomass of leaves that is not so promising (R^2= 0.59 and $RMSE$ = 3.72 *t/ha*). Other AGB components from the stratum III characterize quite accurate prediction. The models explicate around 80% of the variations in the observed AGB change. The best one was developed for the change of stem biomass where R^2= 0.86 and $RMSE$ = 14.61 *t/ha.*

The best predictions in this study were in the stratum IV. There are encompassed the mature forest stands characterized with the negative change of AGB tree components. Models of four AGB components explicate between 82% and 93% of the variation in the observed AGB change. This is a quite good result, since the biomass change, for example for stem, was ranged between -202.80 and 122.65 *t/ha* over forest stands, while the developed model explicates 90% of variation in the observed change. The best model in stratum IV was developed for the change of biomass of bark where R^2=0.93 and $RMSE$ =1.51 *t/ha*. At same time, it was the best model in this study. Model for prediction of change of leaves biomass was least accurate in stratum IV characterized with R^2=0.67 and $RMSE$ =3.61 *t/ha*.

Models for prediction of total AGB change were also developed for each single one of four strata. The best one was developed in stratum IV, R^2=0.87 and $RMSE$ = 35.12 *t/ha* and the worst one in stratum I where, R^2= 0.53 and $RMSE$ = 22.74 *t/ha*.

Table 7

Final selected variables and parameter of estimate for the models where the observed change of each biomass components for each of the four strata were regressed against ALS- derived variables.

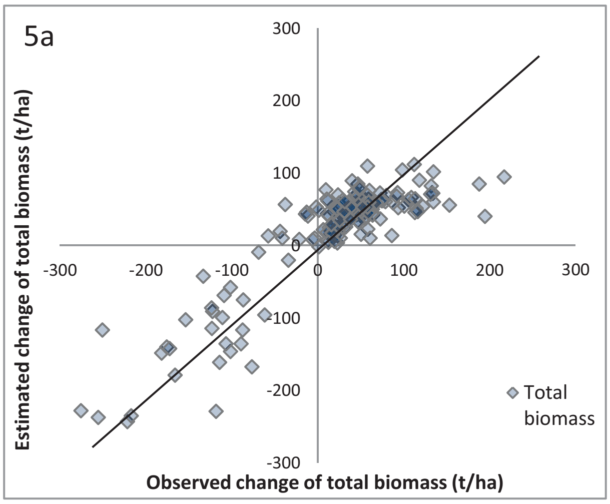
AGB component	Number of sample plots	Independent variables	R^2	$RMSE$ ($RMSE$ %)
Stratum I -*Young forest stands with positive change in Dev. Class*	32			
Stem		h_{20f}, d_{2f}	0.69	11.09 (13.85)
Bark		$1/h_{20f}$, d_{5f}, d_{9l}, SI^2	0.72	1.25 (13.79)
Living branches		$sqrtd_{4f}$, SI^2	0.40	8.86 (21.34)
Dead branches		h_{20l}, $sqrtd_{6l}$, d_{9l}^2	0.69	0.39 (11.85)
Leaves		h_{90f}^2, $sqrtd_{6l}$, $sqrtd_{9l}$, SI^2	0.69	3.08 (12.53)
Total AGB		h_{20f}^2, SI^2	0.53	22.74 (19.62)
Stratum II-*Young and advanced forest stands with positive change in Dev. Class*	47			
Stem		h_{meanf}^2, d_{1l}^2	0.71	20.42 (12.45)
Bark		h_{meanl}^2, d_{0l}^2, d_{9l}	0.66	1.90 (14.17)
Living branches		h_{maxf}, d_{6l}	0.46	6.85 (16.47)
Dead branches		h_{meanf}^2, d_{1l}^2	0.62	0.71 (12.95)
Leaves		h_{meanf}^2, d_{7f}^2, d_{9f}^2	0.63	4.26 (15.92)
Total AGB		d_{7f}^2, d_{1l}^2, h_{meanf}^2	0.74	27.80 (10.66)
Stratum III-*Mature forest stands with no change in Dev. Class*	54			
Stem		h_{30f}^2, h_{10l}^2, d_{7f}, d_{0l}^2	0.86	14.61 (5.51)
Bark		h_{30f}^2, h_{10l}^2, $sqrtd_{6f}$, d_{0l}^2	0.84	1.44 (5.86)
Living branches		h_{30f}^2, h_{10l}^2, d_{0f}^2, $1/d_{6f}$	0.80	4.94 (7.47)
Dead branches		h_{30f}, d_{0f}, d_{8f}	0.79	0.42 (7.11)
Leaves		h_{10l}, d_{2f}^2, $sqrtd_{5f}$, SI^2	0.59	3.72 (15.39)
Total AGB		h_{30f}^2, d_{0f}^2, d_{6f}	0.80	25.16 (6.58)
Stratum IV-*Mature forest stands with negative change in Dev. Class*	43			
Stem		h_{meanl}^2, h_{10l}^2, $1/d_{2f}$, d_{4l}^2	0.90	20.90 (6.42)
Bark		h_{40f}, h_{10l}^2, $1/d_{2f}$, d_{4l}^2	0.93	1.51 (5.95)
Living branches		d_{4l}	0.82	8.39 (9.71)
Dead branches		h_{10f}^2, h_{40f}, d_{6l}^2	0.86	0.61 (6.75)
Leaves		$sqrtd_{4f}$, SI	0.67	3.61 (13.61)
Total AGB		h_{40f}, h_{10l}^2, d_{5l}	0.87	35.12 (7.46)

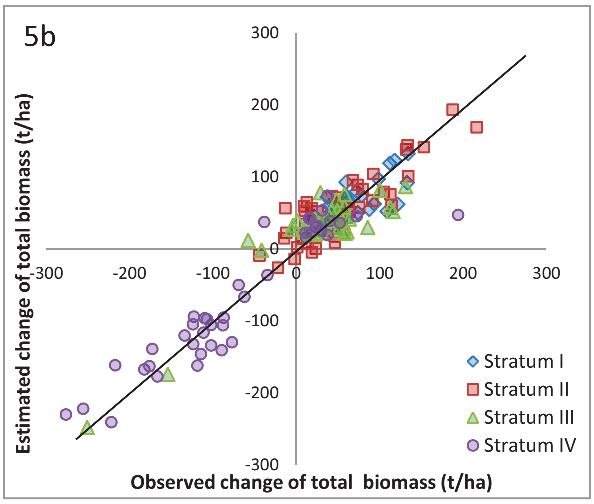
[a] h_{10f}, h_{20f}, h_{30f}, and h_{40f}= the quantiles corresponding to the 10, 20, 30, and 40 percentiles of the first pulse laser canopy heights (m); h_{10l} and h_{20l}= the quantiles corresponding to the 10 and 20 percentiles of the last pulse laser canopy heights (m); h_{maxf}= maxima of first pulse laser canopy heights (m); h_{meanf}= arithmetic mean of first pulse laser canopy heights (m); h_{meanl}= arithmetic mean of last pulse laser canopy heights (m); d_{0f}, d_{2f}, d_{4f} ,d_{5f}, d_{6f}, d_{7f}, d_{8f}, and d_{9f}= canopy densities corresponding to the proportions of first pulse laser echoes above fractions 0, 2, 4, 5, 6, 7, 8, and 9 to total number of first echoes; d_{0l}, d_{1l}, d_{4l}, and d_{5l}= canopy densities corresponding to the proportions of last pulse laser echoes above fractions 0, 1, 4 and 5 to total number of last echoes and *SI*= site index- the height of the dominant trees at 40 years of age.

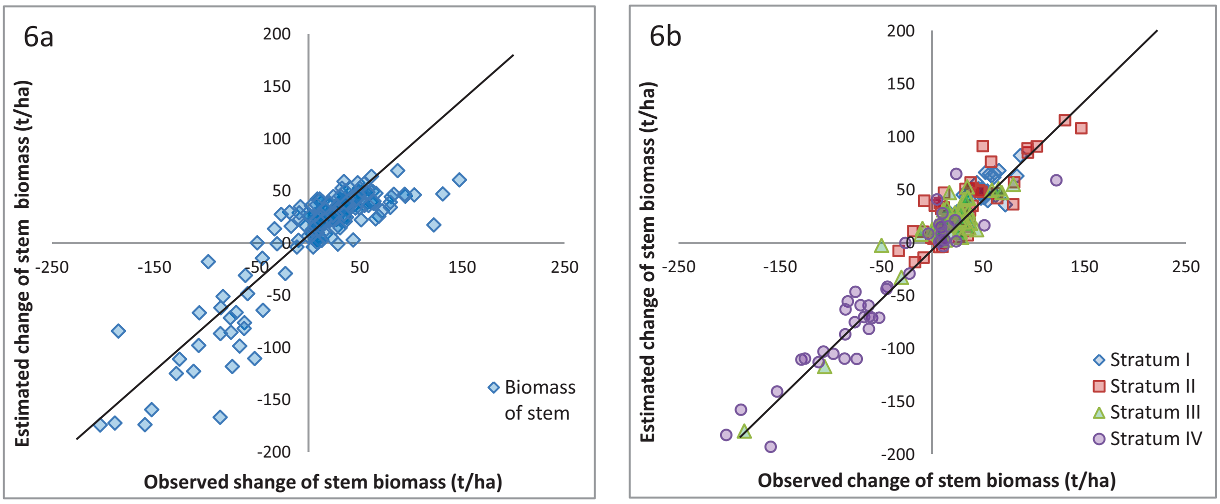
A development of models in two approaches using the same data enabled a comparison of accuracy of those models and deliberation of the effect of stratification. It was discovered that the stratification of forest stands by change in developmental class significantly improved models.

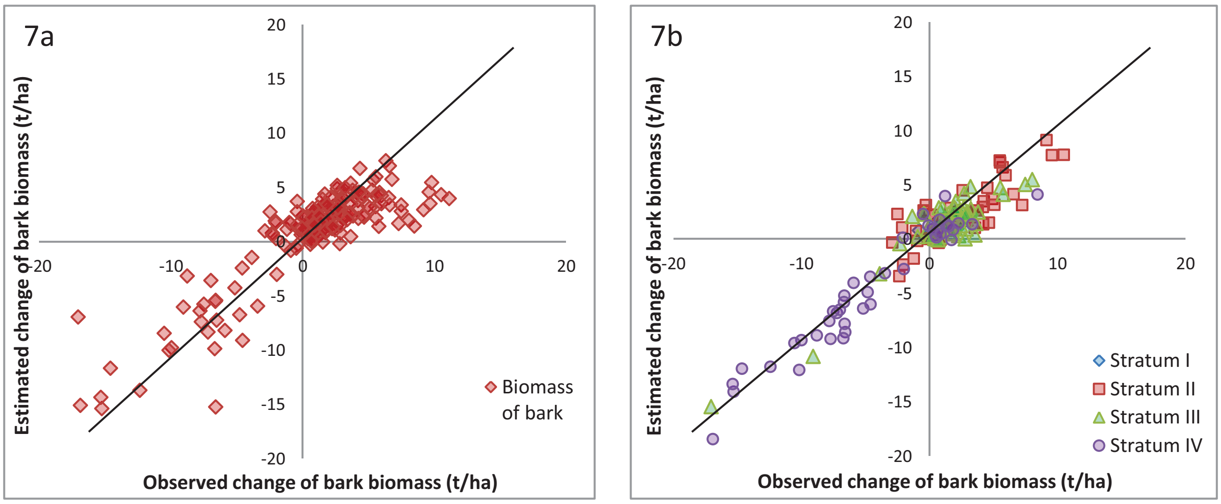
The observed changes of the AGB of tree components were plotted against change predicted by the final regression models and shown on Figures 5, 6, 7, 8, 9, and 10. Figures "5a, 6a, 7a, 8a, 9a, and 10a" on left side show the observed AGB change of each tree component against the corresponding change estimated by use of models developed for entire forest in the first approach. Furthermore, Figures "5b, 6b, 7b, 8b, 9b, and 10b" on the right side shows the observed AGB change of each component against corresponding change estimated by use of models from the second approach developed for each of component within each stratum. The presented graphs provide a visual image of errors in the prediction of biomass change. The prediction is more accurate if errors are smaller or in this case, the prediction is more accurate if points are scattered as close as to a baseline. The prediction by means of an ideal model implies that distribution of the points will appear on graph as a straight line because the errors are equal to zero.

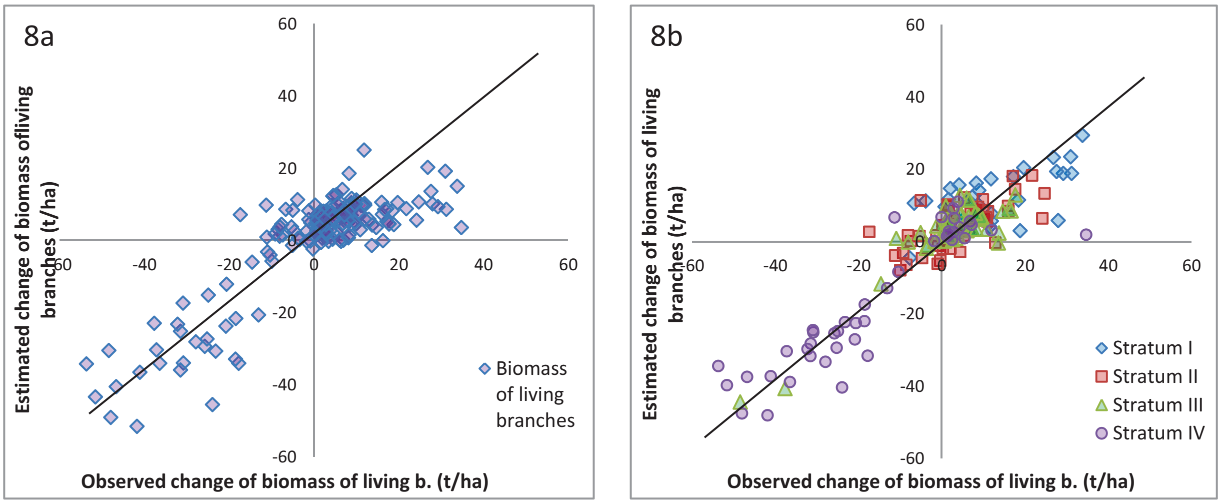
The comparison of graphs from the first and second approach enables a contemplation of accuracy of AGB change predicted by the different models. The higher accuracy of models from the second approach particularly noticeable on the presented graphs is the best illustration of the importance of stratification.

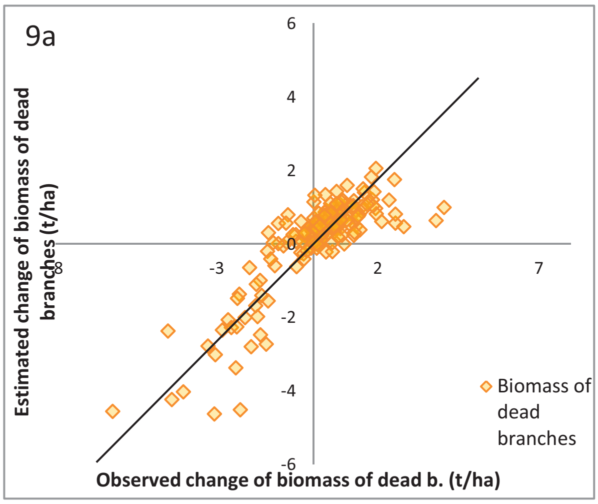


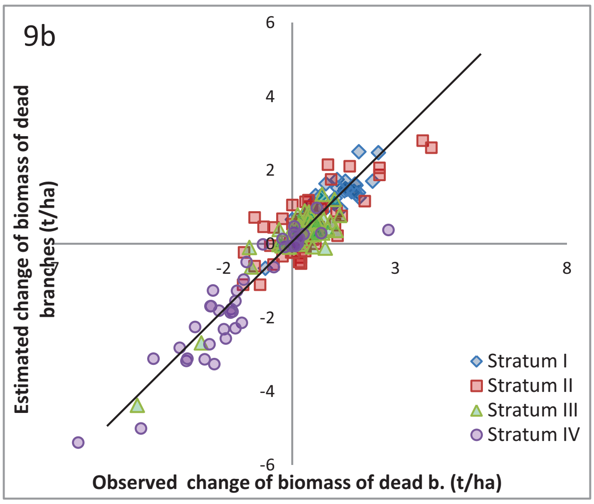


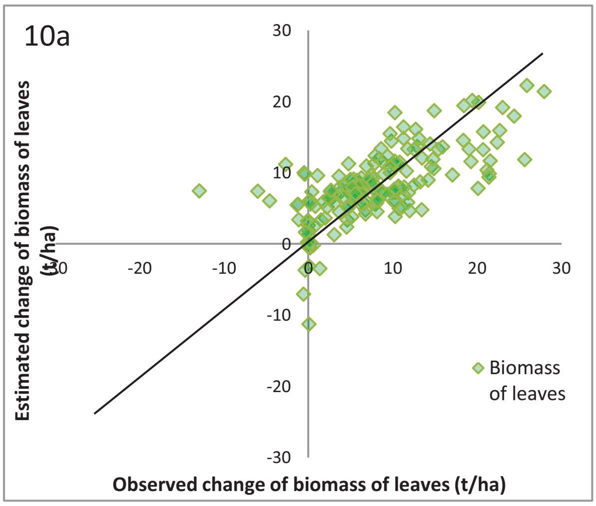

6a
Estimated change of stem biomass (t/ha)
Observed shange of stem biomass (t/ha)
Biomass of stem
6b
Estimated change of stem biomass (t/ha)
Observed change of stem biomass (t/ha)
Stratum I
Stratum II
Stratum III
Stratum IV

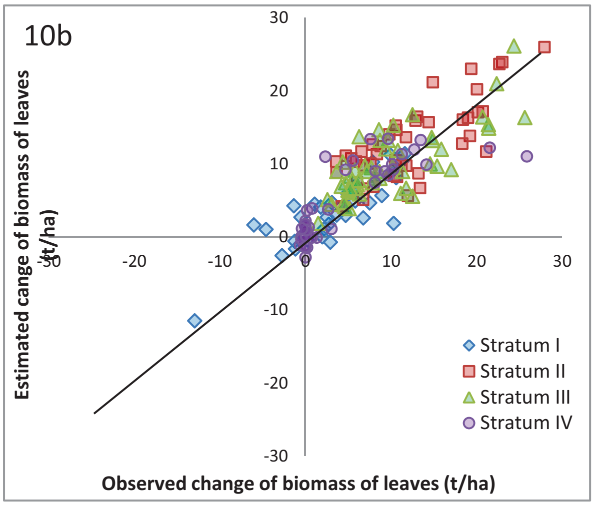

7a
Estimated change of bark biomass (t/ha)
Observed change of bark biomass (t/ha)
Biomass of bark
7b
Estimated change of bark biomass (t/ha)
Observed change of bark biomass (t/ha)
Stratum I
Stratum II
Stratum III
Stratum IV


8a
Estimated change of biomass ofliving branches (t/ha)
Observed change of biomass of living b. (t/ha)
Biomass of living branches
8b
Estimated change of biomass of living branches (t/ha)
Observed change of biomass of living b. (t/ha)
Stratum I
Stratum II
Stratum III
Stratum IV









Some of the presented graphs look rather good and manifests a quite high accuracy of models for some of biomass components. For example, a very good prediction of AGB change is shown on the Figure 6b - biomass of stem and Figure 7b - biomass of bark where the points were equally and closely distributed around the baseline. Figure 8b - biomass of living branches and the Figure 10b - biomass of leaves show somewhat less accuracy of models since wider distribution of points indicate a higher values of error in the estimation of AGB change. Wide distribution of points (high value of errors) spatially characterizes the Figure 10b - biomass of leaves. Since the biomass of leaves contain approximately 2 % of total biomass of stem, that prediction may not strongly affect the prediction of total AGB change. In addition, there are many possible causes that can affect data accuracy and lead to an inaccurate prediction. Some of them suspected/presumed to have an effect of data used in this study were discussed henceforth.

4. Discussion

Use of the Airborne Laser Scanner (ALS) technology for estimating biophysical properties of trees and forests ecosystems rapidly increased in the last decade. The most of previous studies (e.g. Bollandsås and Næsset, 2010; Næsset, 2002; Næsset, 2007; Naesset and Gobakken, 2008) reported that ALS is a very promising technology. Still, the use of the ALS as a advanced regional and national monitoring tool requires a consideration of an additional characteristics such are forest types, forest stand characteristics, instruments, regions etc. For that reason, this study deals with two approaches in the prediction of AGB change. The first approach was an attempt of prediction for the entire forest where some of the stand characteristics were included directly in the models. The second approach was prediction by strata where the forest stands were classified with respect to stand characteristics. The comparison of the results from these two approaches revealed that the appropriate stratification of forest stands create ability for the better predictions of change of AGB of tree components.

The advanced prediction requires accurate values of AGB change observed in the field as well as the ALS data. The observed AGB change in this study was calculated by means of the proved method. The high accuracy of predicted heights was confirmed by small tests that were conducted. The Marklund equations used in this study (callipered for entire Sweden) were commonly used in the similar studies in Norway. A study by Bollandsås et al., (2009) indicated that those are also valid for the conditions in Norway. Since this study is dealing with estimation of change, a systematic error in the AGB equations for estimation of the ground truth will be of minor importance since the error level will be similar for both points in time. Thus, the actual ground truth estimate of change will probably be less influenced by the possible model error compared to the AGB estimates for measurement occasions one and two, respectively. For that reason, the ground truth values of AGB change calculated in this study believed to be very accurate.

The study dealt with data from the 176 forest stands of the various stand characteristics where the forest was actively managed. Beside the growth, there were additional changes such are a different kinds of harvest, wind throws, insects and fungi attacks etc. Those changes on the studied area contributed to very complex relationship between the ALS data and observed AGB change. Having in mind a complexity of such relationship, it was to a certain extent hard to find an appropriate solution for the stratification of the forest stands in order to get the relationship of each particular stratum more linear. Attempts of stratification according to species mixture, positive-negative biomass change and site index were not useful. There were an improvement in a few of strata, but in some of them there was a total absence of observed relationship. Accordingly, those results were not reported. The best solution was the stratification of the forest stands with respect to developmental class and change in the developmental class between 1999 and 2010. Each stratum contained the stands subject of forest similar of age (young, advanced, mature forest) where related changes did happened. This enabled an easy prediction as a key point of the stratification. Logically, the AGB change is more predictable if the prediction encompasses the forest stands where similar AGB change did happened. It is also possible to do this kind of stratifications in a real situation because the developmental class is predictable by use of stereo photogrammetry. Figures 4 and 5 present mean changes of the height and density variables (delta values) between two acquisitions. It was quite visible from those figures that the height and density variables have a potential to explain the total AGB change since an order of curves of the each stratum corresponded to the AGB changes in the same stratum. Followed by, the most positive change of the mean height and density variables in stratum I corresponded to the most positive change in the total observed AGB (65.82 t/ha) from same stratum. In stratum IV, the negative changes were evident in the mean height and density variables as well as ground truth values (-65.89 t/ha). A proper correlation were also evident in the another two strata. Delta values of canopy heights (Figure 4) were decreasing from the top to the lower percentiles of canopy height. This was quite logic for stratum I, since the largest height grow was in the upper part of canopy (Bollandsås and Næsset, 2010) as well as for stratum IV since the negative change were caused by cutting of the largest and highest trees. The stratum II and III are characterized with reasonably equable changes in the height of higher percentiles. This could be explained by same rate of height grow in the advanced forests comprised in those two strata.

The trend for density variables (Figure 5) is slight opposite compared to the height variables but also differ by strata. The most changes in the stratum I appears in the middle of canopy (d_{4f}, $d_{5f}d_{6f}$ *and* d_{7f}). This was expected in the young forest since there was a process of formation of canopy. During the process of formation, the crowns of individual trees get wider and denser in the middle until the forest canopy becomes completely closed. The small negative density changes in the stratum II and III (advanced forest stands) at the lowest fraction of canopy (d_{0f}) were probably caused by natural mortality of the branches in the lower part of canopy, since the canopy became completely closed. Also, some of small trees and bushes were also extinct in the absence of light. The most positive density change at the higher fraction of strata II and III were caused by growth of trees because, the individual tree canopies get denser with growth. Also, an interaction between adjacent tree canopies increases (Bollandsås and Næsset, 2010). At last, minor negative trend of density change in direction to the top of canopy were not expected in strata II and III. The cause of that can lay down in some negative bias, since the very apex of tree top did not have enough mass to trigger an echo (Ørka, 2010) or be caused by an effect of using different sensors. In the stratum IV, the biggest trees were cut or dead during the observed time. That caused the most negative change of density at lowest fraction. After cutting, there was more space for the remaining trees. Subsequently, the crown of remaining trees got wider in the higher fraction since the most of crown of mature trees is placed in the higher parts of tree. The remaining tree crowns then filed up a formed space compensating most of negative change in the higher fraction of canopy.

The successful interpretation of height and density distribution of forest canopy by use of ALS technology requires a consideration of additional factors such as flight parameters and properties of the laser scanner (Table 5). In study like this one, it is particularly important where the delta values of ALS data have derived from the two particular acquisitions. The studies by Næsset (2009) and Ørka (2010) indicates that use of a different sensors, flying altitudes, pulse repetition frequency, leaf (leaf-on, leaf-off) canopy conditions, etc. can have an important effect on the interpretation of ALS data and followed by on the estimation of biophysical properties in the forest ecosystems.

A sensor effect should always be taking into consideration in applications of ALS. The very fast development of the sensor technology imposes use of different devices and can lead to the production of the point clouds more or less different in properties. In that case, the height and density variables derived from ALS- data differ significantly between instruments (Næsset, 2009). The sensor Optech ALTM-Gemini used in this study in 2010 was the most advanced models of the previous ALTMseries such as version ofALTM-1210 used in 1999 (Ussyshkin and Theriault, 2011). Since it is expected that sensors from same - ATLM series producing point clouds of similar properties, the sensors effect was not considered as a significant in this study. Furthermore, in other to achieve minor effect of using different sensors, the models developed for one of sensor combination cannot be applied on data with different combination of sensors.

Beside different sensors, the flight acquisitions in this study were characterized by different flying altitude, pulse repetition frequency, scan frequency, max scan angle, etc. that could also lead to production of the point clouds were slightly different in properties (Næsset, 2009).

In the interpretation of the ALS data, particularly in the height variables of highest percentiles of canopy some bias may be produced, since the very apex of trees top does not have enough mass to trigger an echo (Ørka, 2010). Furthermore, the ASL data could be affected by high trees placed on the board but outside of the sample plots. This usually happened in the young forest stands, when the crowns of high trees placed around sample plots trigger laser echoes. Since the models developed in the stratums I and II (young and advanced forest stands) were less accurate than models from the stratums III and IV (mature forest stands), this appearance probably influenced the ALS data used in this study.

The regression modelling in this study was conducted by the ordinary least-squares regression method (OLS) that is widely used in the studies dealing with remote sensing analyses (e.g. Bollandsås and Næsset, 2010, Næsset, 2002, Næsset and Gobakken, 2008, Nelson et al., 2007). In some cases, during the stepwise selection there was occurred a problem regarding the multicolinearity or “special shapes” of the residual plots. Those problems were usually solved by replacing of variable with its transformation or excluding from the model. It was expected that delta values from both height and density variables would be included in the models as it was case in the other studies that dealt by similar prediction (Næsset and Gobakken, 2008).

The results from the first approach were pointed out at some power of ALS data in the estimation of change of AGB of tree components. Models (Table 6) explained changes of the AGB of four tree components in range between R^2= 0.72 for dead branches and R^2=0.78 for change of stem biomass. Those models were probably improved by the stands characteristics (d_{dc}, SI) since one of characteristic was significant in five out of six models. This seems to be a satisfactory result to a certain extent, but the presented graphs shown some bias of those models. A prediction of change of leaves biomass for the entire forest was quite inaccurate (R^2=0.48). One of the reasons for that can be a different participation of species in the forest stands. Since the spruce, pine and deciduous species differ in crowns shape and in leaves (needles or leaves), it is natural that the biomass change in the forest stands with a domination of different species cannot be accurate predicted by one models. Besides, the leaves and needles trigger laser echo on a different way.
The graphs 6a, 7a, 8a, 9a, and 10a where the observed against predicted AGB changes being plotted indicate some bias of those models since the errors of prediction (point on graphs) for all the components were more or less unequally distributed around baseline. This indicates that models are biased and applying on the independent data would probably give an inaccurate result. The same graphs, excluding 10a (change of biomass of leaves- situation is somewhat different) evident that the bias were the most pronounced for the prediction in the forest stands with the most positive AGB change although the values of errors were smaller than in the prediction for forest stands characterized by the negative AGB change. Since there is no available independent data from the same area, this could be just an assumption based on the observation distribution of errors on the presented graphs. With respect to the complexity of change in the actively managed forest for eleven growth seasons, it was expected that developing of the accurate and unbiased models for entire forest is quite difficult. The main aim of developing a model in first approach was to make a comparison and point out the significance of stratification. For that

reason, this study was more concentrated on the results from the second approach showing more power of ALS data in the detection of biomass change in the boreal forest.

The second approach is something that this study was mostly dealing with. It starts with stratification, through the variables selection, to the end of improvement and validation of the final models. Finally selected models presented in Table 7 showed that the ALS data- ground truth values relationship significantly varies between stratums. Quite accurate and unbiased models were developed for the stratum III and IV explaining more than 80% of variation in the AGB change of tree components. This revealed a high potential of ALS data to explain the variation in AGB change in the stratums where the forest stands were clearly classified. The mature forest stands with small biomass change (positive or negative) were comprised in stratum III and stands with larger negative changes in stratum IV. Somewhat less accurate models in these stratums were developed for the prediction of the change of leaves biomass. It was quite reasonable since both stratums contain forest stands different with species composition. Studies like Næsset and Gobakken (2008) reviled that the effect of tree species compositions beside another was highly significant in the ground truth biomass - ALS data relationship. A different shape of crone and presence of leaves or needles normally results in point clouds formatted in different location of forest canopy (lower or higher up) and in a different form (Næsset and Gobakken, 2008). The prediction of change of leaves biomass was then the most influenced, since a leaves quantity, its shape, volume and biomass quite depends on the tree species composition. An improvement of the prediction of the change of leaves biomass has to be definitely sought in additional stratification within strata, by species composition. Since the change in biomass of leaves is of a quite small value, it is realistic for prediction to be less accurate than for the different AGB components.
The predictions in the strata I and II were to some extent less accurate since the models has explained around 70 % of variation in AGB change. Although this can be accepted as a good prediction, the reason for somewhat less accuracy could be caused by some bias produced through effect of different instruments, flying altitude, scan angle or scan repetition frequency from flight acquisitions (Næsset 2009) or by influence of high trees located around sample plots on the ALS data. The particularly inaccurate models were developed for the prediction of change of biomass of leaving

branches that explained less than 50 % of variation in the biomass change (strata I and II). This also indicates that some of above listed factors maybe had an affect on data. An another possibility is, that the applied stratification in these two strata were not the best solution for separation forest stands by means of similar biomass change. The additional stratification, for example by species composition within these stratums, could probably offer some improvement of models. Unfortunately, it was not possible to perform it in this study since these stratums does not contain a sufficient number of sample plots. The developed models are not representative enough if prediction was based on the small number of sample.

Very good characteristics of models from the second approach are visible as well on the figures 5b, 6b, 7b, and 8b. Presented graphs indicated quite accurate and unbiased prediction for total AGB change, biomass of stem, bark and dead branches, since the errors of prediction have pretty small values and quite uniformly distributed around baseline. Those models are quite reliable and applicable. The lower accuracy of models for the prediction of biomass change of leaving branches (particularly in stratums I and II) and models for the prediction for biomass change of leaves (particularly in stratums III and IV) is quite visible on the Figures 9b and 10b. This indicates wider distribution of errors of prediction around baseline. Although the prediction of biomass change of living branches and leaves are not quite accurate, the presented graphs did not indicate a significant bias of these models, since the errors of prediction (point on graphs) were distributed pretty equable around baseline. Since there is no available study dealing with prediction by components, it was not possible to make a judgement about the prediction of biomass change of living branches and leaves in sense of being good or bad in this study. But, on the basis on the evaluation factors, the models from second approach are quite acceptable and comparable with other studies of prediction of AGB, AGB change or volume in the boreal forests.

The comparison of models from the first and second approach by presented graphs is best indication of a significance of stratification in the process of detection of AGB change using the ALS technology. It is obvious that the prediction for each component from the second approach was more accurate and unbiased. Consequently, controlling the effects of forest stands characteristics and different forest type by implementation of appropriate stratification give more ability for a successful application of ALS technology in detecting of change of AGB tree components in the boreal forest.

5. Conclusion

With respect to results of many studies, the ALS has proved to be the successful method for prediction of biophysical properties of trees and forest ecosystems. The present study confirmed that delta values derived from the multi-temporal ALS datasets have a potential for explaining variation in AGB change of tree components in the boreal forests. The relationship between ALS and observed AGB change significantly varies between AGB tree components based on result of this study. That relationship also varies with forest different of age and different by changes, because developed models for each stratum were significantly different in accuracy. Furthermore, the study confirmed that the forest stand characteristics have strong effect on the prediction of AGB change. The comparison of the first and the second approach revealed that the appropriate stratification is of a high importance in the application of ALS and creates ability for the better predictions. In order to eliminate the effect of using different instrument during flight acquisitions, the developed models are only applicable to data derived from the same combination of instruments. Moreover, the successful prediction also requires a same combination of other parameter of flight acquisitions that can lead to producing data with different properties. The results obtained for prediction of total AGB change in this study were comparable to those from similar study. Unfortunately, there is no available study to compare the models for the prediction of AGB change of tree components. Nonetheless, this study went further in a development of methods and testing of the capability of ALS and confirmed one more possibility of applying ALS technology, the prediction of AGB change of tree components in the boreal forest.

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