Tree Diameter Models from Field and Remote sensing data

Gints Priedītis., Ingus Šmits., Irina Arhipova., Salvis Daģis., and Dagnis Dubrovskis.

Abstract**—**The objective of research is to find DBH prediction models that: use variables derived from remote sensing, field mensuration and previous forest inventory data; can be used in STRS methods; are suitable for Latvian forest conditions. In paper different tree DBH predicting models from field and remote sensing data were researched. The study site is a forest in middle of Latvia at Jelgava district (56º39' N, 23º47' E). The area consists of mixed coniferous and deciduous forest with different age, high density, complex structure, various components, composition and soil conditions. Aerial photography camera (ADS 40) and laser scanner (ALS 50 II) was used to capture the data. LiDAR resolution is 9p/m2 (500 m altitude). The image data is RGB, NIR and PAN spectrum with 20 cm pixel resolution. Image processing was made using Fourier transform, frequency filtering and reverse Fourier transform. LiDAR data processing methods was based on canopy height model, Gaussian mask and local maxima. Field measurements are tree coordinates, species, height, diameter at breast height, crown width. Totally seven different linear models were developed, using data collected. General linear model that predicts DBH includes a tree height, effective crown area, soil type and age factors. It showed strongest relationship between predicted and measured DBH (R^2 = 0,872). Summary results show that the models predict DBH reasonably well and factors included in all models are significant. Using combined LiDAR and optical imagery data is able to detect at least 63 % of all trees and about 85% of the dominant trees. Not identified trees at 82% of cases diameter at breast height was less than 20 cm and 88% of cases height was less than 20 m. Relationship between the Lidar detected height and observed total height shows showed strong relationship (R^2 = 0,986), also between Lidar and aerial photography detected and observed tree crown is strong relationship (R^2 = 0,869).

Keywords**—** DBH prediction models; tree identification, laser scanning, aerial photography, data fusion.

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I. Introduction

DIAMETER at breast height (DBH) and tree height are important tree characteristics used to determine accurate prediction of tree stem volume. Tree volume usually is calculated using volume models or equations, where information of DBH is required.

Today traditional forest inventory often is replaced with remote sensing method, which is usually less time-consuming and less expensive. Optimal forest inventory method often consists of a variety of data sources that are combined with various methods [1], [2]. Airborne laser scanning (ALS) and optical imagery is the most common remote sensing methods used in forest inventory. Single tree remote sensing (STRS) methods are intended to replace field measurements such as position, species, height, DBH and volume. The method's vision is to create it without field visits and measurements [3]. However, data calibration is necessary. Field data collection will need for determination of the diversity, which cannot be measured from the air.

In studies STRS methods, one of the main problems that the authors mentioned is tree species and tree location accurate determination [4], especially in Middle Europe [5], since there is a mixture of different deciduous and coniferous trees. As a result, the indication is much harder. The main conclusion is that the usage of LIDAR method to determine forest inventory parameters will never be one hundred per cent correct [6], [4] especially applying automated tracking methods [7]. However, compared with traditional inventory methods, laser-based method is faster, more cost efficient, and the results are reliable, but with certain restrictions [8].

In Scandinavian countries studies of STRS forest inventory show good results. For example Korpelas research shows that, 10% of all trees were not identified and 12% of the total stock of wood is inaccurate, species identification accuracy - 93.7%, only 4.7% error in the determination of the tree height [9]. Also, Nicholas Coop research results show that there is a close correlation between the STRS data and field measurement data of canopy parameters. As a result, it is possible to successfully obtain quality information on forest indicators [9]. In Peuhkurinena survey traditional forest inventory data and STRS data were compared with harvester data obtained from 22 spruce stands. STRS method showed a 17% higher precision of trees DBH [10]. Practically for all researchers so far it has been difficult to determine the species in mixed forest stands. Automated identification of species with the individual tree method is still problematic, even in cases where access to different types of data [11] is available.

In view of the complexity caused by irregularities and diversity of forest stands STRS methods require necessity to adopt the semi-automatic approach [12],[9] and use auxiliary information [12], [13] to make STRS solvable. Most often, this auxiliary information is obtained through allometry.

Tree allometry establishes quantitative relations between some key characteristic dimensions of trees (usually fairly easy to measure) and other properties (often more difficult to assess).

Allometric relationships for estimating tree-level and stand-level parameters are very important for managing any forest resources [14], [15], [16], [17]. Allometry varies between tree species [18] and within a stand as trees adapt to the intra and interspecific competition [19], also characteristics such as stand density, stand silvicultural history, genetic factors of tree seed, tree position in a stand, site fertility, height above sea level, distance from sea, mineral soil and stand development class [20], [21], [22] affect variables. These variables are usually measured in the field but can also be predicted by regression models [23].

Direct measurements of forest structure are taken on intensively sampled, relatively small field plots, and these data are used to create allometric models that predict forest parameters from easily measured tree attributes. DBH is commonly used as predictors of stem volume and other tree metrics in a wide variety of allometric equations.

There have been numerous studies of this approach. DBH prediction models have been studied by using field measured trees [24] or aerial photographs [25], [26]. More recent efforts have focused on measuring individual tree heights using airborne laser scanning (ALS) data [10], [27], [28] or crown widths from high resolution aerial [29], [30] and satellite imagery [31], then using the modeled DBH to estimate single tree volume, stand volume, total-tree biomass and carbon.

Canopy leaf surface area, tree height, DBH, volume and structural properties are the main tree characteristics that affect each other, but STRS methods can provide direct measurements only for canopy crown and tree height. Tree height using airborne laser scanning can be determined with high precision. Well-known relationship between the DBH and tree height can be used in DBH prediction models. Second parameter is crown size, which has received increasing attention as a means to estimate tree growth [32]. Measurement of tree crown width is difficult and time consuming if they are taken from the ground, but conversely if taken from STRS data. Crown width is used in tree and crown level growth-modeling systems [33], [34]. Equations for predicting the tree dimensions have many applications including estimations of crown surface area and volume in order to asses forest health [35], tree-crown profiles and canopy architecture [33], [36], forest canopy cover [32] and the aboveground biomass. Modeling DBH as a simple linear model between crown width and crown diameter is often adequate [33], [36].

In Latvia, the first attempts to use the STRS methods in forestry started in 2007. Technology comes from the Scandinavian countries. With a large number of research and perseverance they are developed and adapted itself suitable data collection and processing methodology, which is capable of providing high quality data acquisition. Unfortunately, one of the biggest problems is that the data collection and processing methods in Latvian conditions work differently, and those methods cannot provide forest inventory data quality requirements. This is mainly due to the large number of tree species and forest diversity in growing conditions, as well as STRS specifics. Regardless of tree species identification and determination one of the problems is correctly DBH prediction models.

The objective of research is to find DBH prediction models that:

- use variables derived from remote sensing, field mensuration and previous forest inventory data;
- can be used in STRS methods;
- are suitable for Latvian forest conditions.

In paper different tree DBH predicting models from tree height, tree crown dimensions, soil type and age were researched.

II. MATERIALS AND METHODS

A. Site description

The study site was a forest (3 165 ha) in the middle of Latvia in Jelgava District (56º39' N, 23º47' E) and (56.64' N, 24.33' E). The research object consists of two forest complexes. Location of study area in Latvia map is shown in Fig.1.

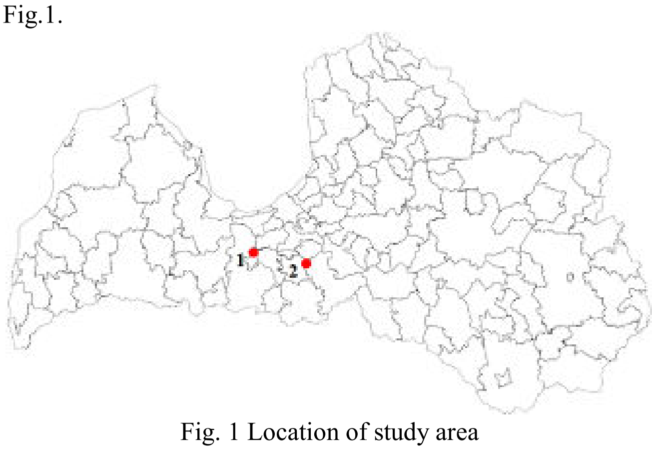

Fig. 1 Location of study area

The area consists of mixed coniferous and deciduous forest with different age, high density, complex structure, various components, composition and soil conditions. Represented species are Scots pine (Pinus sylvestris L.), Norway spruce (Picea abies (L.) H.Karst), silver birch (Betula péndula Roth), black alder (Alnus glutinos L.), and European aspen (Populus trémula L.).

Sample plots were selected in study site using information about previously forest inventory (information about stand age, dominate species and soil conditions were taken from year 2009). Totally 350 stands were selected in order to include all interested species, age groups (five age groups) and growing conditions (five soil type groups). Database processing and plot selection model is presented Fig. 2.

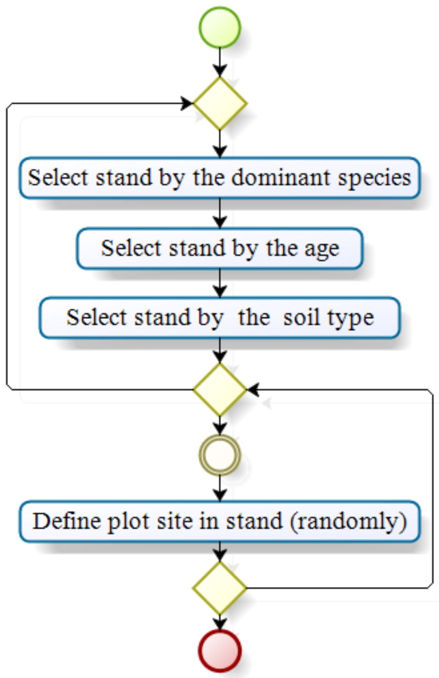

Fig. 2 Database processing and plot selection model

Totally 350 sample plots (0.045 ha) were established during summer 2010. Plot location in the study area shown in Fig. 3.

Fig. 3 Plot location in the study area

Differentially corrected Global Positioning System measurements were used to determine the position of the center of each plot. Accuracy of the positioning was approximately 1 meter.

B. Field measurements

All trees with a diameter at breast height DBH of more than 5 cm were measured and for each tree coordinates, species, height, DBH, age and crown width was recorded. Field data acquisition process model is presented in Fig.3.

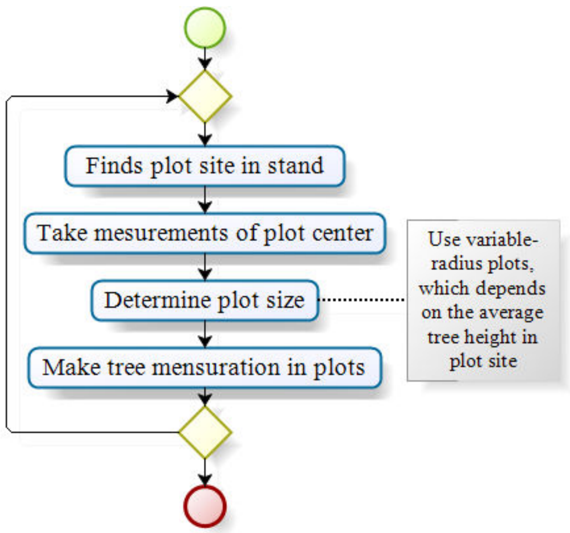

Fig. 3 Field data acquisition process model

Altogether there were measures of 6154 trees in the data. The main characteristics of all trees are presented in Table 1.

Table 1. Characterization of data set. Where DBH is the diameter at breast height (cm), H - tree height (m), VP – crown width (m), A - age (years) and St.ch. – statistical characteristics, N - number of trees.

Specie	St.ch.	DBH	H	VP	A	N
Pine	Mean	26.8	23.3	5.3	76,3	1617
	Min.	5.0	2.5	0.9	6,0	
	Max.	83.8	37.1	12.3	164,0	
Spruce	Mean	17.3	15.4	4.8	70,4	2365
	Min.	5.0	2.2	0.5	7,0	
	Max.	77.8	39.3	13.5	152,0	
Birch	Mean	17.8	19.1	5.4	60,8	1057
	Min.	5.0	4.9	1.1	5,0	
	Max.	54.6	39.9	18.9	114,0	
Alder	Mean	21.9	21.3	6.1	58,0	1016
	Min.	5.4	4.3	1.2	5,0	
	Max.	58.3	36.8	16.4	102,0	
Aspen	Mean	27.35	25.8	6.1	57,0	99
	Min.	6.5	6.7	1.3	13,0	
	Max.	53.5	35.8	13.2	81,0	

The tree crown width was measured by projecting the edges of the crown to the ground and by measuring the length along one axis from edge to edge through the crown center. The diameters of any two axes at 90 degrees to each other were selected and averaged by using arithmetic mean. Tree locations within a plot were measured using center as the origin for determining tree azimuth and distance to the center.

Effective crown area (the area that does not overlap with another tree crown) for each tree (first and second storey trees equally) was calculated using information about its location within a plot and the width of its crown. The foliage was projected on the ground and generally known area calculation formulas were used for calculations of effective crown area. Two more reasons for using effective crown area instead of the simple one are as follows - it acquires more sunlight than the rest of its share and in the process of tree identification by using remote sensing data usually only effective leaf area can be detected. Further data analyzes showed that by using it, instead of simple tree crown, considerable increase of the regression model accuracy can be achieved.

C. Remote sensing data

Data were obtained using a specialized aircraft Pilatus PC-6, which is equipped with a positioning and Geomatics technology company Leica Geosystems equipment - a large format digital aerial photography camera (ADS 40) and laser scanner (ALS 50 II). The study area was flown over by plane and measured. Data were estimated from leaf-on data from May, 2010 having 9 (p/m^2) at 500 m altitude. The image data is RGB (Red, Green, and Blue), NIR (Near Infrared) and PAN (Panchromatic) spectrum with 20 cm pixel resolution.

Individual tree detection from LIDAR data is based on canopy height model. The model was smoothed using a Gaussian mask and the degree of smoothing is defined by the height of pixel. Subsequently, local maxima on the smoothed canopy height model were considered as tree locations. Noisy data was masked (suppressed) using Gaussian mask.

In literature Several methods have been developed to delineate individual trees using LIDAR data processing techniques including the multiple scale segmentation [20], template matching [15], watershed segmentation (Schardt et al., 2002), local maximum filtering [7] and wavelet analysis [12]. In those methods the tree crown must be visually recognizable as a discrete object.

Tree detection from aerial photography data is based on Fourier transform, frequency filtering and reverse Fourier transform. It was performed to each image from the previously prepared data sets. After this process texture of image was obtained (was filtered noise and disturbance that further processing may be falsely considered as local maxima).

To estimate tree crown with we use aerial photography. Every image was performed segmentation process, which aims to find all the pixels that belong to the same tree. Segmentation of the study included a modified region growing algorithm.

Tree height was calculated as the difference between tree highest points of the earth's surface. Highest point of the tree was searched from actual LIDAR data in 3 meter radius from tree center.

Information on tree species in all models was taken from field data.

D. Analytical Work

The analysis of covariance was used to evaluate if certain factors have an effect on the outcome variable. Multiple linear regressions consider more than one independent variable, and it was used to develop models to predict DBH (cm) of individual tree in SPSS for Windows using untransformed data (for age, soil type and species) and transformed data (for DBH, tree height, crown width and effective crown area). Power function was used of the form:

$$\mathrm{Yi} = \beta 0 + \beta 1 \cdot \mathrm{Xi1} + \beta 2 \cdot \mathrm{Xi2} + \ldots + \beta \mathrm{p} \cdot \mathrm{Xip} + \varepsilon \mathrm{i} \tag{1}$$

where Yi is the ith observation of the dependent variable (DBH), Xij is ith observation of the jth independent variable (collected data in sample plots), j = 1, 2, ..., p. The values βj represent parameters to be estimated, and εi is the ith independent identically distributed normal error.

The following seven general linear models were developed, by using data collected in Latvia, Jelgava District:

1. $$\mathrm{Ln(DBH)i} = \beta 0 + \beta 1 \cdot \mathrm{A} + \beta 2 \cdot \mathrm{AAT} + \beta 3 \cdot \mathrm{S} + \varepsilon i \tag{2}$$

2. $$\mathrm{Ln(DBH)i} = \beta 0 + \beta 1 \cdot \mathrm{Ln(H)i} + \beta 2 \cdot \mathrm{S} + \varepsilon i \tag{3}$$

3. $$\mathrm{Ln(DBH)i} = \beta 0 + \beta 1 \cdot \mathrm{Ln(H)i} + \beta 2 \cdot \mathrm{A} + \beta 3 \cdot \mathrm{AAT} + \beta 4 + \mathrm{S} + \varepsilon i \tag{4}$$

4. $$\mathrm{Ln(DBH)i} = \beta 0 + \beta 1 \cdot \mathrm{Ln(H)i} + \beta 2 \cdot \mathrm{Ln(VP)i} + \beta 3 \cdot \mathrm{S} + \varepsilon i \tag{5}$$

5. $$\mathrm{Ln(DBH)i} = \beta 0 + \beta 1 \cdot \mathrm{Ln(H)i} + \beta 2 \cdot \mathrm{Ln(VPE)i} + \beta 3 \cdot \mathrm{S} + \varepsilon i \tag{6}$$

6. $$\mathrm{Ln(DBH)i} = \beta 0 + \beta 1 \cdot \mathrm{Ln(H)i} + \beta 2 \cdot \mathrm{Ln(VP)i} + \beta 3 \cdot \mathrm{A} + \beta 4 \cdot \mathrm{AAT} + \beta 5 \cdot \mathrm{S} + \varepsilon i \tag{7}$$

7. $$\mathrm{Ln(DBH)i} = \beta 0 + \beta 1 \cdot \mathrm{Ln(H)i} + \beta 2 \cdot \mathrm{Ln(VPE)i} + \beta 3 \cdot \mathrm{A} + \beta 4 \cdot \mathrm{AAT} + \beta 5 \cdot \mathrm{S} + \varepsilon i \tag{8}$$

Where DBH is the diameter at breast height (cm), H - tree height (m), VP – crown width (m), VPE - effective crown area (m2), A - age (years) and S - species dummy variable, but AAT - soil type dummy variable for the districts.

All models were extended also to include the factors interaction effects. The intercept was tested to determine if they were statistically different from zero ($P < 0.05$).

Root mean square error of the estimate (RMSE) and the coefficient of determination (R^2) were used to evaluate goodness of fit.

III. Results

A. Tree identification results

The accuracy of tree detection was satisfactorily when we use combined LiDAR and optical imagery data. In Fig. 4 we can see identified tree centers and tree crown area determination results.

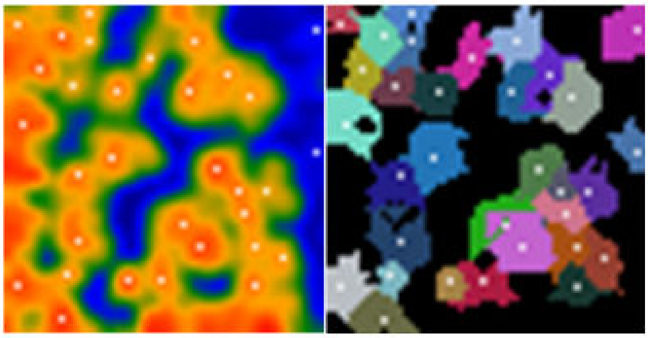

Fig. 4 Tree top recognition and tree crown area determination results.

Results of tree detection using combined LiDAR and aerial photographic method show that 63 % of all trees were unambiguously found, but 37 % of tree were not identified (Table 2.).

Table. 2. Descriptive statistics of tree detection result and tree characterizing parameters (combined LiDAR and optical imagery data)

Result of tree detection		Age	DBH	Tree Height	Crown Width
Trees identified	Mean	68.73	25.85	23.65	5.89
	N	3857	3857	3857	3857
	Std. Dev.	34.30	10.12	6.316	2.02
	Min.	5	2.9	3.5	1.13
	Max.	164	83.8	39.9	18.93
	% of Total	62.7	62.7	62.7	62.7
Trees not identified	Mean	68.74	14.26	13.61	4.39
	N	2297	2297	2297	2297
	Std. Dev.	35.09	7.230	5.68	1.5
	Min.	5	1.6	1.9	0.50
	Max.	164	54.6	37.3	13.31
	% of Total	37.3	37.3	37.3	37.3

If we look at not identified trees, then 82% of cases were trees with diameter at breast height (DBH) less than 20 cm and 88% of cases trees with height less than 20 m. This means that only about 15 % of first storey trees were not identified correctly. Analysis of identified trees shows that 20% of cases Norway spruce, 5% of cases Scots pine, 7% of case Silver birch, 4% of case Black alder and just 1% of cases European aspen were not identified. Identified trees in species level shows that only 45% of cases Norway spruce, 80% of cases Scots pine, 78% of case Silver birch, 77% of case Black alder and 98% of cases European aspen were identified.

B. Tree height estimates results

Figure 5 demonstrates the closeness of fit between the Lidar detected height and ground measured total height of the sample trees. It can be observed that the bias of height estimates ranges from -1.72 m to 0.26 m, and the average and standard deviation of the absolute bias are -0.75 m and 0.51m.

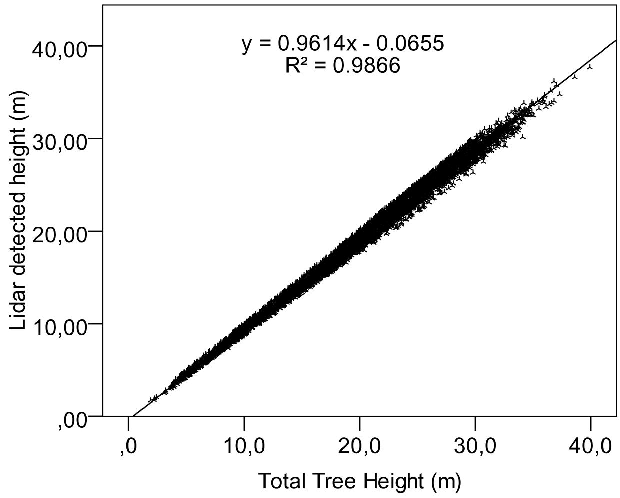

Fig. 5 Relationship between the Lidar detected height and observed total height of the sample trees.

C. Tree crown with estimates results

Figure 6 shows the closeness of fit between the LiDAR and aerial photography.

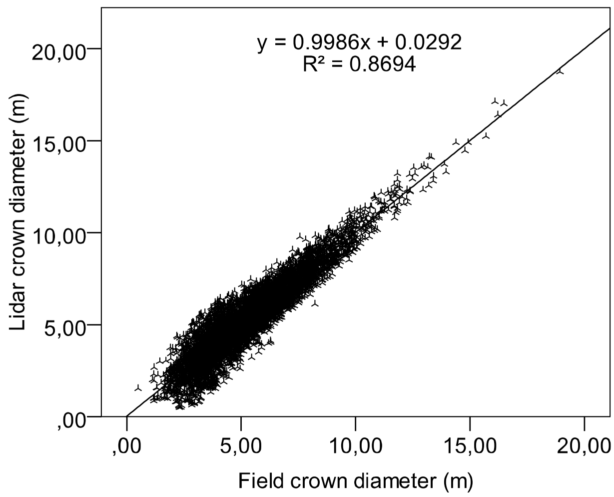

Fig. 6 Relationship between the Lidar and aerial photography detected and observed tree crown of the sample trees.

In this figure, a linear model is fitted with a R^2 value of 0.86 which indicates a strong correlation. In this study, the crown width had a bias ranging from -2.35 m to 1.92 m. The average and standard deviation of crown width estimation bias was -0,15 m and 0,79 m respectively.

D. DBH estimation models results

One of the main tasks was to find out what data is required in order to, as closely as possible, determine DBH. The basis for nearly all models is well-known relationship between the diameter and height of a tree. In Fig.2 are shown relationships between LnDBH and LnH in the study area. There is a linear relationship between LnDBH and LnH, but depending on the species linear regression growth rate is different.

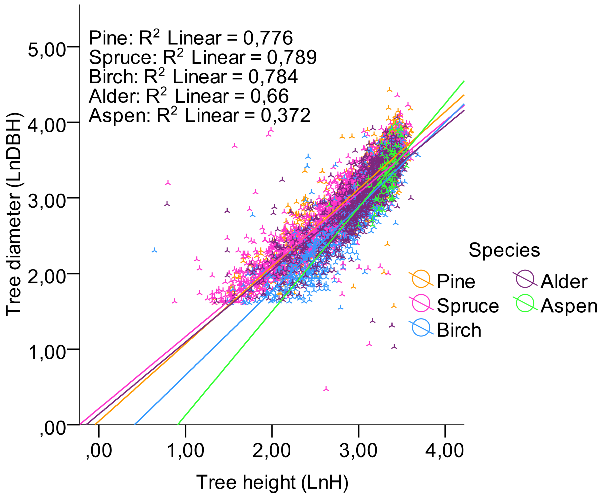

Fig. 5 Relationships between LnDBH and LnH in the study area of main species.

There is a linear relationship between LnDBH and LnH, but depending on the species linear regression growth rate is different.

Model (model no. 2. in Table 3.) that uses measurement of a tree height as a predictor variable can be expected to produce a reasonably accurate estimate of DBH (r2=0,792), but often it is not enough. Model (model no.1. in Table 3.) that includes only information about species, age, soil type and factors interaction effects showed poor results (Table 4). It proved that a tree height is the most important factor in all models.

Models with different combination of factors were tested and the best results were obtained by using one that included 5 factors - tree height, effective crown area, age, tree species and soil type. Using this general linear model, the following results were obtained (Table 5.), where all 5 factors- tree height (p=0,01), effective crown area (p=0,000), age (p=0,068), species (p=0,000) and soil type (p=0,000), as well factors interaction effects, are significant at different level on significance.

Table. 3. Overview of statistical indicators of all models

Model, (Factors)	RMSE	F	Sig.	R^2
1. (A;AAT;S)	9,2	50,6	0,000	0,409
2. (H;S)	165,7	2602,3	0,000	0,792
3. (H;A;AAT;S)	12,1	218,8	0,000	0,822
4. (H;VP;S)	114,2	2471,7	0,000	0,849
5. (H,VPE,S)	114,4	2500,6	0,000	0,851
6. (H,VP,A,AAT,S)	9,6	237,1	0,000	0,871
7. (H,VPE,A,AAT,S)	9,6	239,2	0,000	0,872

Table 4. Overview of model no.1 (A;AAT;S) factor interaction effects.

Model (A;AAT;S)	RMSE	F	Sig.
S	0,4	2,6	0,033
AAT	2,7	14,8	0,000
A	13,2	72,1	0,000
S * A	0,6	3,4	0,007
S * AAT	1,9	10,3	0,000
S * AAT * A	1,8	10,3	0,000
AAT * A	1,3	7,2	0,000

Table 5. Overview of model no.7 (H,VPE,A,AAT, S) factor interaction effects.

Model (H,VPE,A,AAT,S)	RMSE	F	Sig.
S	0,32	7,96	0,000
AAT	0,14	3,51	0,000
A	0,13	3,32	0,068
LnH	0,41	10,35	0,001
LnVPE	0,61	15,27	0,000
S * AAT	0,15	3,74	0,000
S * AAT	0,07	1,84	0,117
S * LnH	0,07	1,79	0,126
S * LnVPE	0,07	1,82	0,120
AAT* A	0,03	0,79	0,647
AAT * LnH	0,16	4,17	0,000
AAT * LnVPE	0,09	2,23	0,006
S* AAT *A	0,08	2,17	0,001
S * AAT * LnH	0,15	3,86	0,000
S * AAT * LnVPE	0,07	1,95	0,003

This model gave the best performance according to values of statistics used to compare models in the fitting phase. Consequently, this model was accepted.

Results of DBH estimation model accuracy show a strong relationship between predicted and measured DBH (shown in Fig. 6).

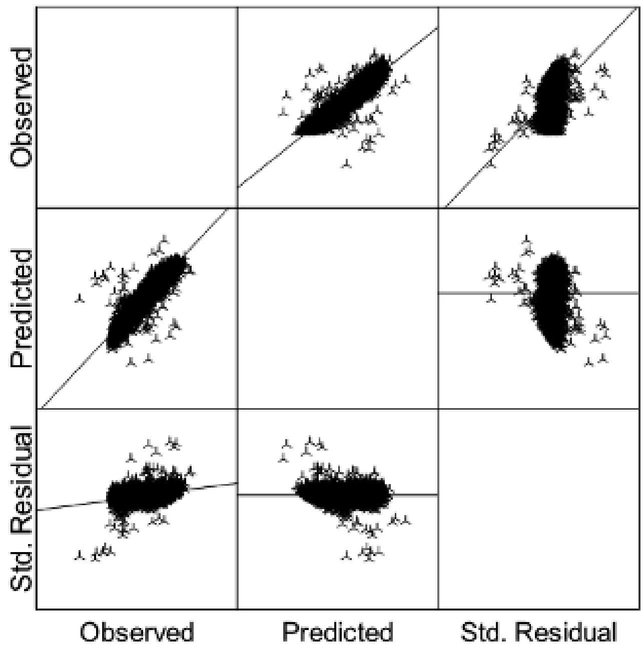

Fig. 6 Predicted and measured DBH

IV. Conclusions

Results of this study show that the developed model can be used in LIDAR-based single tree remote sensing methods to predict DBH if information about soil type and age is available.

Models that use field or remotely-sensed measurement of a tree height as a predictor variable can be expected to produce a reasonably accurate estimate of DBH (R^2=0,792) in Latvian forests, but when the model uses crown dimension measurements and information about age and soil type, the accuracy of DBH increases (R^2=0,872).

Interaction effects between factors included in models must be considered, and statistical analysis shows that they are significant at different level on significance.

A number of studies have also investigated the relationship between DBH and crown dimensions for different tree species and a strong relationship was noted.

Relationship between the Lidar detected height and observed total height shows showed strong relationship (R^2 = 0,986), also between Lidar and aerial photography detected and observed tree crown is strong relationship (R^2 = 0,869).

Simple leaf area calculation must be replaced with one that considers tree concurrency, because it better suits to be used in systems for processing remote sensing data.

It should be possible to improve DBH estimation accuracy if information of tree foliage density, foliage mass or crown length were available. Developed models can be used in LIDAR-based single tree remote sensing methods to predict DBH.

Using combined LiDAR and optical imagery data is able to detect at least 63 % of all trees and about 85% of the dominant trees. This is explained by the fact that trees vary in crown size, shape and optical properties, crowns are often interlaced. These factors affect the treetop positioning and make the identification difficult. The problem is with the small trees and close existing trees identification, as well as high density hardwood stands with homogeneous crown.

Analysis of identified trees shows that 20% of cases Norway spruce were not identified and 55% in species level trees were not identified. This is explained by the fact that the spruce crown geometry is triangular and consequently, the LIDAR transmitted pulses often miss the highest tree point. Pine and birch crown geometry is a little flatter, the measurements are more accurate.

It should be possible to improve DBH estimation accuracy by using more precise measurements of foliage density, foliage mass or crown length. The parameter that could cause most problems when this model is used in practice is tree species, because methods that are capable to determine its value from remote sensing data are still being developed and those that are used in practice usually are able to distinct three or four species.

Latvian forest conditions are difficult for single tree remote sensing methods mainly of mixed deciduous and coniferous spaces with high level of the second storey trees in one stand. Mostly trees are close together with high density and homogeneous crown. It is one of the main reasons for a large number of trees that are omitted.

To improve the recognized number of trees one way is to perform laser scanning in spring when the forest is less dense, the first storey trees are more transparent and the smaller dimension trees can be recognized. Also can use tree crown shape analyze from LIDAR data, and it means that there is a need for LIDAR data with a higher level of point density per square meter.

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