ИССЛЕДОВАТЕЛЬСКИЕ СТАТЬИ

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ESTIMATION OF MEAN TREE STAND VOLUME USING HIGH-RESOLUTION AERIAL RGB IMAGERY AND DIGITAL SURFACE MODEL, OBTAINED FROM SUAV, AND TRESTIMA MOBILE APPLICATION

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This study considers a remote sensing technique for mean volume estimation based on a very high-resolution (VHR) aerial RGB imagery obtained using a small-sized unmanned aerial vehicle (sUAV) and a high-resolution photogrammetric digital surface model (DSM) as well as an innovative technology for field measurements (Trestima). The study area covers approx. 220 ha of forestland in Finland. The work concerns the entire process from remote sensing and field data acquisition to statistical analysis and forest volume wall-to-wall mapping. The study showed that the VHR aerial imagery and the high-resolution DSM produced based on the application of the sUAV have good prospects for forest inventory. For the sUAV based estimation of forest variables such as Height, Basal Area and mean Volume, Root Mean Square Error constituted 6.6 %, 22.6 and 26.7 %, respectively. Application of Trestima for estimation of the mean volume of the standing forest showed minor difference over the existing Forest Management Plan at all the selected forest compartments. Simultaneously, the results of the study confirmed that the technologies and the tools applied at this work could be a reliable and potentially cost-effective means of forest data acquisition with high potential of operational use.

Keywords: *remote sensing, UAV, Trestima, forest inventory, digital surface model, mean volume.*

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INTRODUCTION

Accurate enough data about forest resources is a crucial element of decision making for different stakeholders involved in forestry. The data gives significant benefits for forest policy development and management, i.e. area planning, forest growth planning, harvesting methods and equipment planning, final products planning and reforestation strategy. Typically, forests cover large areas and it is hard to survey them entirely at least in a reasonable time frame. In that respect, forest inventory based on remote sensing has been quite well established around the globe, which helps solving the problem.

The most recent development of the new generation of forest inventory tools refers to an airborne laser scanning (ALS). ALS has been extensively used in Finland for many different purposes including forest management, volumetric applications and terrain modeling (Maltamo et al., 2014). The major advantage of ALS in forestry is a three-dimensional (3D) product, which allows accurate estimation of 3D forest features as e.g. canopy height above ground level (AGL) and terrain estimation. ALS requires an application of heavy-duty conventional aerial vehicles/platforms and complex light detection and ranging (LiDAR) equipment, which also makes the technology rather expensive, for example, for a property level, small-sized areas or specific tasks, where application of ALS is impossible or not feasible.

There is yet one more tool, which is based on aerial imagery and known as photogrammetry. The results of the photogrammetric modeling are capable of deriving almost the same 3D features similar to those produced by ALS (Järnstedt et al., 2012; Tuominen et al., 2015). However, the photogrammetry, to be applied at forestry applications, requires accurate terrain data as, in general case, it does not allow any data below canopy.

Nevertheless, it is believed that photogrammetry could be less expensive (Tuominen et al., 2015, p. 3–4) as it does not require both complex laser equipment and manned aerial platforms and delivers a very high-resolution aerial imagery (VHR) as a default product, whereas ALS in general case requires optical imagery (Järnstedt et al., 2012), which means, at least, some extra equipment. Finally, over time, accurate enough terrain data becomes available (as, for example, in Finland), which makes using historical data about ground level possible. In that regard, the method of forest inventory based on photogrammetry sounds quite promising for operational purposes in the future. It is also worth mentioning that both methods require equal field data (ground truth) acquisition efforts, which makes them equal from that point of view.

Previously, the problem of a digital surface model (DSM) application for forest variable estimation purposes has been studied e.g. by Järnstedt et al. (2012) and Tuominen et al. (2015). They obtained positive results regarding a potential use of high-resolution DSM for forest inventory purposes.

The objective of this particular study is to estimate the forest volume based on a high-resolution DSM and VHR aerial RGB (red, green and blue) imagery derived by application of a small unmanned aerial vehicle (sUAV) with a regular RGB digital camera. The work also includes an unique part related to an application of an innovative tool for field data acquisition known as Trestima (Mobiilisovellukset, 2013; Rouvinen, 2014*a*), which employs smartphones for data collection via regular terrestrial photographing of a forest. Data acquired using Trestima has been used to compare with the results obtained from statistical modeling and the existing forest management plan.

RESEARCH AREA AND INITIAL MATERIALS

For the purpose of the study the forest area Falkgölen (approx. 60°00′50.78″ N, 23°24′35.29″ E) was selected (Fig. 1), which is located in the municipality of Raseborg of South-Western Finland.

In total, the study area covers approximately 220 ha and is represented by pine and spruce dominated forest of different age classes as well as few compartments with dominance of birch and/or larch.

The available Forest Management Plan (FMP) for the period of 2014–2023 (in Swedish: Skogsbruksplan) (updated in 2014) has been used as an initial material of the project work as well as a reference at data comparison. The FMP, in general case, corresponds to the state of the forest at the moment of field work and data acquisition.

Additionally, the following datasets produced by National Land Survey of Finland (NLS) were also applied at different stages of the work:

– basic topographic map raster 1:10 000 (NLS block K3444R);

– vector database, containing roads, wetlands, bedrock and other relevant vector data about natural objects (NLS block K3444R); and

– laser scanning data (point cloud) (NLS block K3444E4), which was used to derive digital terrain model (DTM) of 0.15 m Z value accuracy (Laser scanning data, 2015).

TOOLS AND METHODS

Data acquisition using sUAV. Aerial data acquisition was performed using sUAV, model Quest UAV Q200. The vehicle is featured by fully autonomous performance. Tested flight endurance

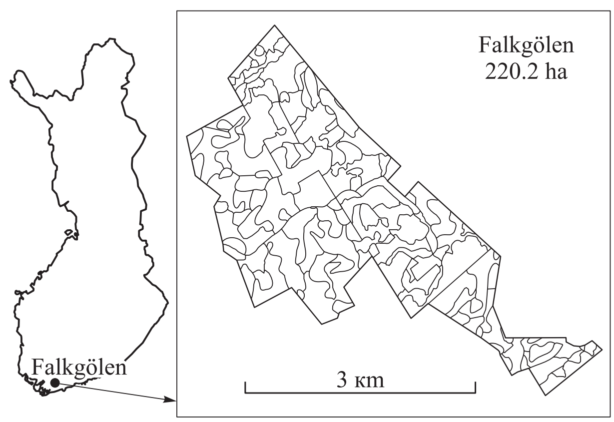


Fig. 1. Area of interest (AOI) location (left) and area boundaries (incl. forest compartments) (right).

of the sUAV constitutes approximately 20–25 min depending on local weather conditions (Rybakov, 2015). Wingspan of the sUAV is approximately 2.3 m. At normal weather conditions the sUAV cruises at ground speed of approx. 55 km/h. This particular sUAV was tailored to be used along with a payload – Panasonic Lumix LX-5 digital RGB camera, which was employed as a sensor to collect aerial images. The camera had been modified by the sUAV producer to be triggered by sUAV autopilot. At this mission, the trigger was programmed to produce images with a speed of one shot per 2.5 second.

All in all, six flights covering the entire area were performed (Fig. 2, see p. 6).

The flight altitude varied from approximately 150 to 180 m above ground level.

Flight operations were carried out during daytime between 12.00 and 16.00 EET on 21 August, 2013.

Prior to the flight occasion a network of twelve ground control points (GCP) was established, which were evenly distributed throughout the AOI (Fig. 3, see p. 6).

Coordinates of GCPs were measured with GNSS/RTK Topcon equipment with an accuracy of 1–2 cm XY (plane) and 2–3 cm Z (vertical). The GCPs were later used as a georeferenced at photogrammetric modelling.

All in all, during flight mission 2539 images were captured with an average estimated overlap exceeding 60 % along and 80 % across.

Production of remote sensing data – data processing: high resolution digital surface model and VHR aerial imagery. The aerial images acquired were processed using a photogrammetric software Agisoft Photoscan Professional Edition version 1.0.0 build 1768 (64 bit), an educational license (developer – Agisoft LLC, Russia). As a result of photogrammetric modeling, two basic products were produced:

– the VHR aerial image-orthophoto with the resolution of 0.061 m/pix (Fig. 4, see p. 6);

– dense point cloud with point density of 9 points per square meter (Fig. 5, see p. 6), containing the following point classes: 1 (unclassified), 2 (ground), 3 (low vegetation) and 7 (noise) (Agisoft, 2014).

For the purpose of further post-processing the VHR orthophoto was resampled to 0.25 m/pix using ESRI™ ArcMap standard tools (see Fig. 4).

Such a resolution of the aerial image raster was selected as according to Tuominen et al. (2015, p. 5) as it is normally used for forest surveys in Finland.

Next, the dense point cloud dataset was rendered into a digital surface model (DSM) also of a pixel size of 0.25 m. At this stage, points classified as noise were filtered out and respectively their elevations were not included into the resulting DSM. As all elevation values of the DSM by default are given above sea level (ASL), which makes impossible to detect true height of a surface judging by DSM along, the DSM was transformed into DSM above ground level (AGL) (also could be referred to as a canopy height model (CHM)) by normalization procedure applying mathematical extraction of the ground level from DSM via raster calculation using ESRI™ ArcMap (Equation 1) (Fig. 6, see p. 7).

Where DSM_{AGL} is a digital surface model above ground level, DSM_{ASL} is a digital surface model above sea level based on sUAV point cloud and DTM is a digital terrain model based on LiDAR point cloud. Prior to the calculations, DTM was also resampled into raster resolution of 0.25 m/pix.

$$DSM_{AGL} = DSM_{ASL} - DTM. \quad (1)$$

As the photogrammetric dense point cloud represents DSM, i.e. does not contain terrain data under the canopy, it was amended by points of class 2 (ground) from the NLS laser scanning dataset. The modified point cloud was further applied at 3D feature extraction (Fig. 7, see p. 7).

All data were georeferenced to EUREF–TM-35FIN (EPSG code: 3067) – the projected coordinate system.

Organization of forest inventory (field campaign) and forest data gathering. Two-phase sampling was selected a major field sampling technique. This technique also known as double sampling was offered in 1938 by Neyman and since then turns to stay one of the best choices for forest inventories (Tuominen et al., 2006).

The AOI has been covered by a first-phase plots grid (fishnet) of approx. 299.98 m^2 (17.32 m × 17.32 m) cell. This solution bases on the decision to employ fixed radius of 9.77 m plots as second-phase sampling, which corresponds the area of approx. 299.87 m^2.

Stratification (Tuominen et al., 2006) was conducted based on the following auxiliary data. First of all, existing forest management plan (FMP) information, including forest compartment borders and dominant species over compartments, as well as data about stages of the forest development at each compartment. Secondly, soil types were in-

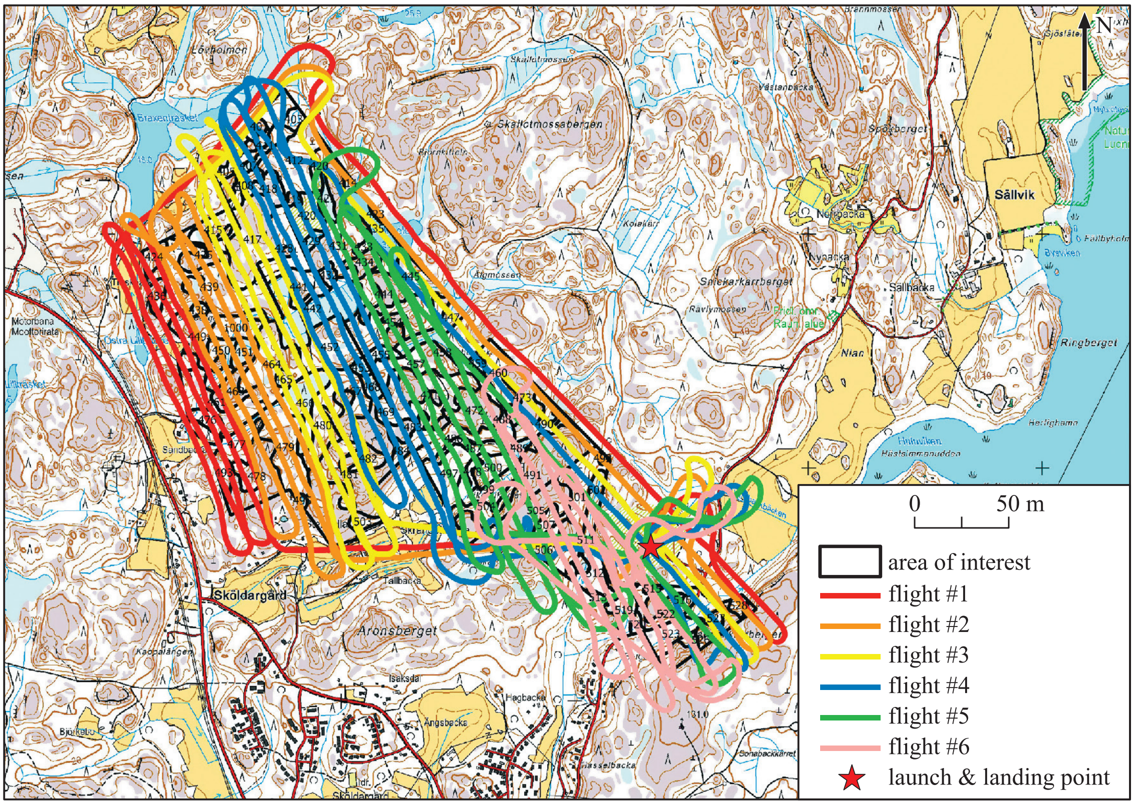


Fig. 2. Flights realized (flightlogs N. 1–6) over AOI and launch/landing point.

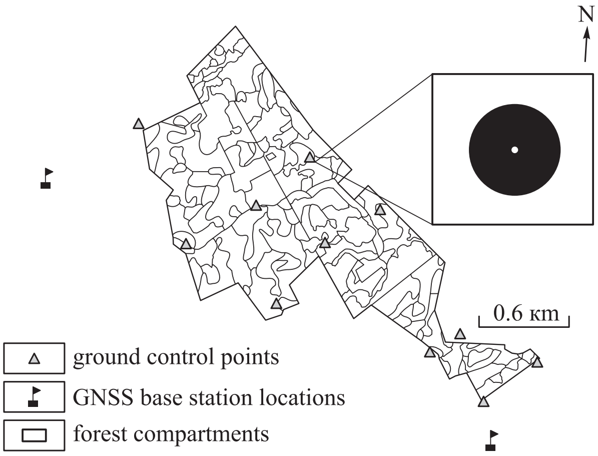


Fig. 3. AOI boarders and GCPs arrangement.

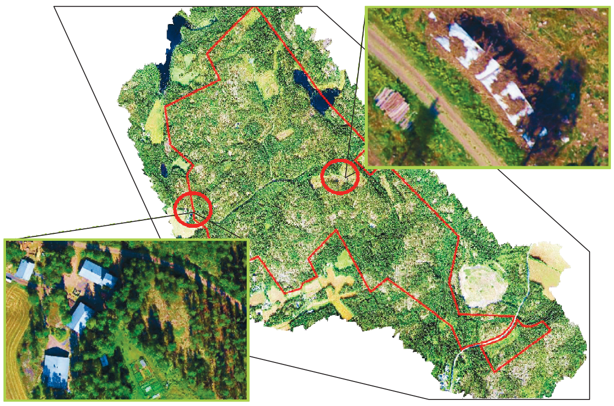


Fig. 4. Orthophoto (0.25 m/pix) and two patches of original resolution 0.06 m/pix.

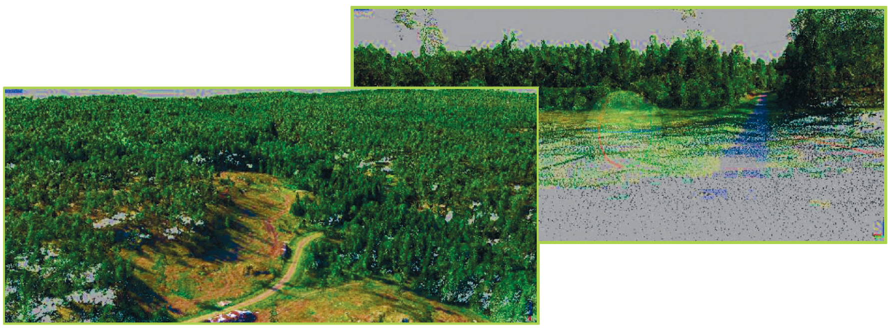


Fig. 5. Photogrammetric dense point cloud (from left to right: view from above, view from ground level) (visualization at Agisoft Photoscan screen).

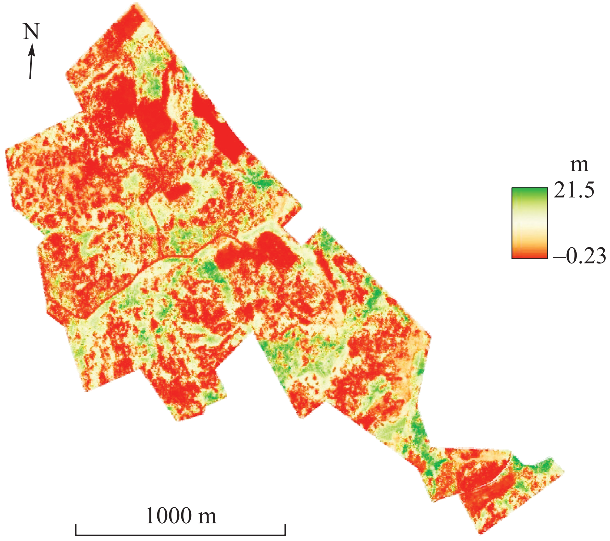


Fig. 6. Normalized DSM–DSM_{AGL}.

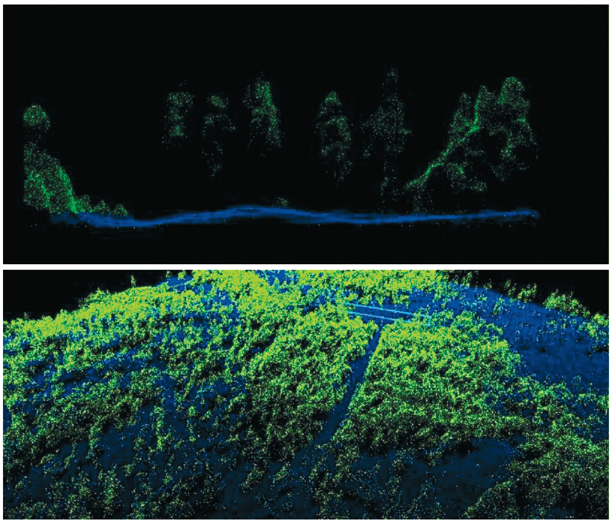


Fig. 7. Dense point cloud (merge of photogrammetric and LiDAR data), profile section (top) and 3D view (bottom) (canopy – green, ground – blue).

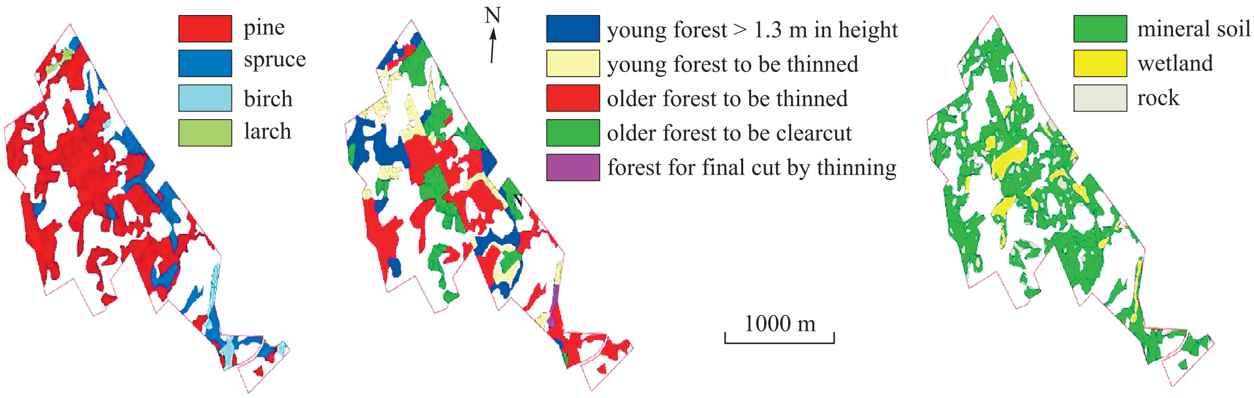


Fig. 8. Stratification of the AOI (from left to right: species, development stages and soils).

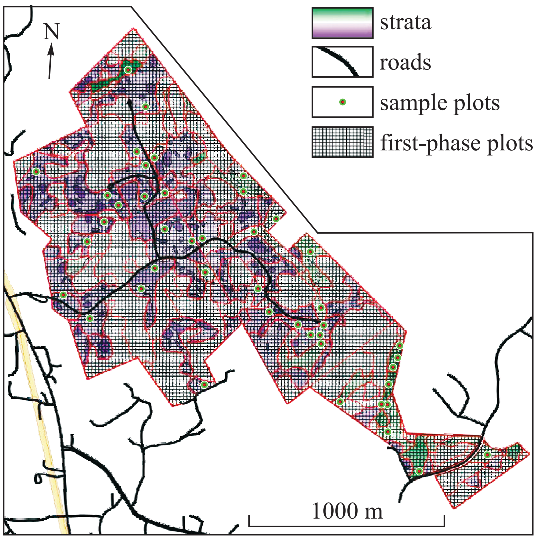


Fig. 9. Sample plots and strata.

cluded into stratification based on available NLS data, i. e. based on basic map raster and topographic database. The resulting number of strata turned to be 43 (Fig. 8).

Next, second-phase sample plots were as signed. Due to the relatively large size of the area and limited resources, it was decided to assign one sample plot per stratum. All in all, 44 plots were allocated (Fig. 9).

This approach of allocating the field measurements resembles the grouping method (Tuominen et al., 2006). The number of field plots employed at this study was small and thus, the sUAV based estimation of forest variables was not carried out stratum-wise. Instead, the forest variables were estimated by regression modeling using all 44 field plots.

Table 1. Field plots statistics

Forest attribute / values	Average	Min	Max	Standard deviation
Volume, m^3/ha	177.2	10.2	472.2	112.2
Volume of pine, m^3/ha	80.1	0.0	248.8	71.4
Volume of spruce, m^3/ha	61.2	0.0	307.9	83.2
Volume of broad-leaved trees, m^3/ha	35.9	0.0	215.1	43.2
Weighted mean diameter, cm	24.3	8.9	37.2	6.1
Weighted mean height, m	17.2	7.9	26.0	4.0
BA, m^2/ha	21.0	1.6	49.5	10.9

At each second-phase sample plot a standard number of attributes were measured: a diameter breast height (DBH) of each tally tree > 5 cm DBH and a height (H) for a basal median tree per species. All in all, at 44 field sample plots individual metrics of 944 trees of different species were measured, including DBH of each tally tree as well as H for 109basal median trees.

At the next stage, forest variables were calculated: the tree height (H) was estimated based on the model of Eerikäinen (2009) as well as volume per each tree (and volume for field plot, respectively) was calculated based on model of Laasasenaho (1982) using the tree heights measured. The resulting statistics of the field plots is presented in Table 1.

Statistical analysis and forest volumes wall-to-wall mapping. *Theoretical background for sUAV based estimation of forest variables.* Auxiliary data/features derived from such auxiliary sources as DSM or an aerial imagery may well correlate to different forest variables (Tuominen et al., 2006), e. g. mean volume, basal area (BA), average height or DBH.

There are several techniques for estimation of the variables based on the remote sensing data. In case of this study, a linear regression was chosen for sUAV-based estimation of forest variables, which has been justified by the lack of field measurements over strata.

Regression is based on the idea that a variable *Y* (dependent variable) could be explained by variable (s) *X* (independent variable(s)) (Sykes, 1992) assuming that their relationship is linear. In case of just one independent variable *X* the regression is called simple linear regression. When *Y* can be explained by more than one independent variable the regression is called multiple linear regression (Sykes, 1992).

Linear regression can be expressed by the following equation (Equation 2).

$$Y = \beta X + \varepsilon, \tag{2}$$

where, Y is a dependent variable y_1, y_2 ... y_n (n = 1, ...), which in our case refers to a forest variable (either basal area (BA) or height (H));

X is an independent variable matrix, which in our case refers to a number of selected features extracted from remote sensing data such as VHR aerial imagery, high-resolution DSM normalized to the ground level as well as the dense point cloud;

β – regression coefficients β_1, β_2 ... β_m (m = 1, ...);

ε – a constant for regression line.

As estimations cannot be 100 % accurate there are several means to study their accuracy (Equations 3, 4 and 5).

$$Bias = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)}{n}, \tag{3}$$

which describes the an average bias of an estimation ($\hat{y}_i$) from observed values (y_i),

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}, \tag{4}$$

RMSE (root mean square error) is the major measure of the estimation accuracy, which shows the probability of an estimate to deviate from its true value, and

$$RMSE_{\%} = 100\frac{RMSE}{\overline{y}}, \tag{5}$$

$RMSE_{\%}$ – the same as *RMSE* but expressed in percent, where $\overline{y}$ is an average of observed values.

Remote sensing feature extraction, selection of features, regression modeling and accuracy testing. The two basic types of the features, which are Haralick textural features (Haralick et al., 1973) and 3D features (Nasset, 1997*a*, *b*, 2002, 2004), were extracted from the remote sensing datasets, which were the VHR aerial imagery, the high-resolution

Table 2. Haralick and 3D features

Haralick features	
First-order statistics in the spatial domain	
SA	Sum Average
ENT	Entropy
DE	Difference Entropy
SE	Sum Entropy
VAR	Variance
DV	Difference Variance
SV	Sum Variance
Second-order statistics in the spatial domain	
ASM	Angular Second Moment
IDM	Inverse Difference Moment
Contr	Contrast
Corr	Correlation
MOC	Information Measures of Correlation
3D features	
havg	Average value of H above ground level of vegetation pulses, first returns, meters
hstd	Standard deviation of H above ground level of vegetation pulses, first returns
h0, h5, h10, h20, h30, h40, h50, h60, h70, h80, h85, h90, h95, h100	H above ground level, where percentages of vegetation pulses, %: 0, 5, 10, 20…95, 100 were accumulated, m
hcv	Coefficient of variation of H above ground level of vegetation pulses, first returns, %
veg	Proportion of vegetation pulses, first returns, %
d0, d1, d2, d3, d4, d5, d6, d7, d8, d9	Proportion of vegetation pulses having H above ground level above fraction 0, 1 … 9 from all points, first returns, %
p20, p40, p60, p80, p95	Proportion of vegetation pulses having H above ground level greater or equal to corresponding percentile of H, first returns, %
pcg	Ratio of number of vegetation pulses to the number of ground points, first returns, %
pgh	Proportion of ground pulses, first returns, %

DSM and the dense point cloud. The features were extracted by execution of programming scripts at GRASS 7.0svn – the free GIS software and at R – the free statistical software package. The Haralick features were extracted from the respective rasters of R, G, B channels of RGB orthophoto and a raster of high-resolution DSM raster (for the purpose of shortening also later referred to as «h»). The 3D features were extracted from the dense point cloud. The list of the features is given in Table 2.

In order to select a proper set of features, which is the best way to explain each forest variable, A Sequential Forward Feature Selection (SFFS) procedure was applied (Senin, 2015), employing Microsoft Excel, which possesses an embedded functionality for multiple linear regression analysis. Briefly, the SFFS works in the following way. First, the best correlating feature should be found and its significance (with the selected level of significance of 0.05) is tested based on *F*-test explained by Senin (2015). In case the significance is proved, a new feature is added to the model and tested the same way. The procedure continues until at the next stage the best calculated *F*-criteria for a feature becomes lower than *F*-criteria derived from a table (Table of critical values for the *F* distribution (for use with ANOVA), 2015).

Wall-to-wall mapping. Based on the solution found for multiple linear regression the sUAV based estimation of the variables was performed for the entire area of interest. Consequently, a wall-to-wall mapping was performed per respective forest compartment. Wall-to-wall mapping of BA and V was executed by averaging their estimates obtained per each first-phase sample plot within a particular compartment over its area. H mapping was performed by weighing H of each first-phase sample plot by BA, which is independent of H as well as represents the size of the trees within the sample plot, with further averaging over the area of a compartment.

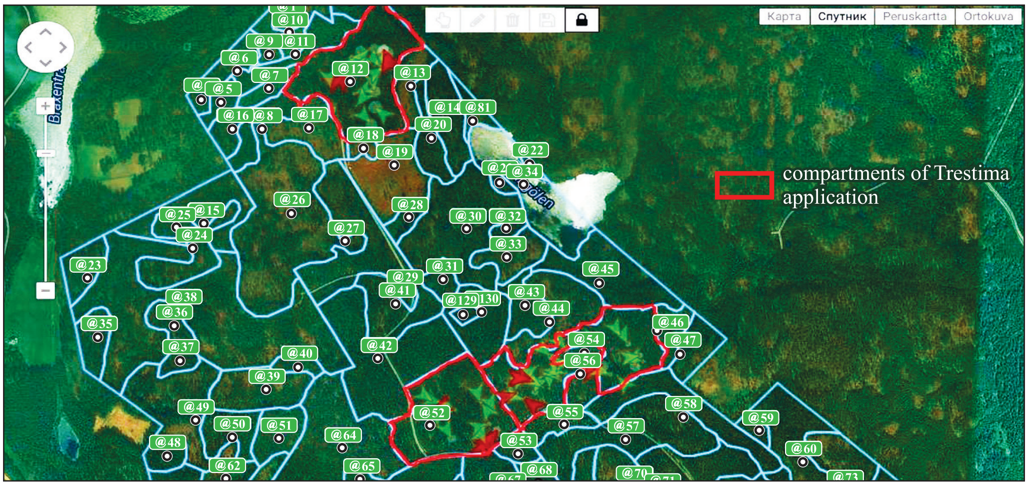
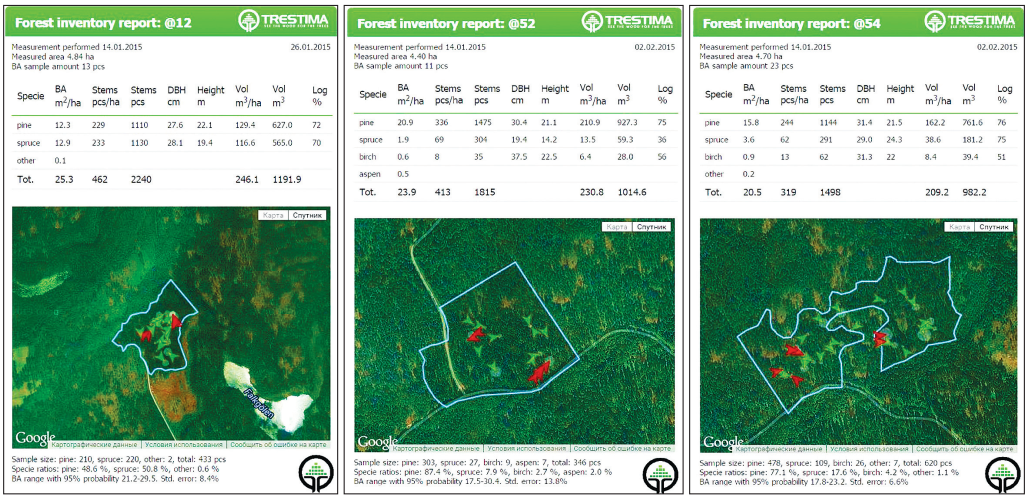


Fig. 10. Compartments, where Trestima was applied.

Fig. 11. Trestima measurements (examples for BA, DBH and H).



Forest inventory report: @12 TRESTIMA

Measurement performed 14.01.2015 26.01.2015
Measured area 4.84 ha
BA sample amount 13 pcs

Specie	BA m^2/ha	Stems pcs/ha	Stems pcs	DBH cm	Height m	Vol m^3/ha	Vol m^3	Log %
pine	12.3	229	1110	27.6	22.1	129.4	627.0	72
spruce	12.9	233	1130	28.1	19.4	116.6	565.0	70
other	0.1							
Tot.	25.3	462	2240			246.1	1191.9	

Sample size: pine: 210, spruce: 220, other: 2, total: 433 pcs
Specie ratios: pine: 48.6 %, spruce: 50.8 %, other: 0.6 %
BA range with 95% probability 21.2-29.5. Std. error: 8.4%

Forest inventory report: @52 TRESTIMA

Measurement performed 14.01.2015 02.02.2015
Measured area 4.40 ha
BA sample amount 11 pcs

Specie	BA m^2/ha	Stems pcs/ha	Stems pcs	DBH cm	Height m	Vol m^3/ha	Vol m^3	Log %
pine	20.9	336	1475	30.4	21.1	210.9	927.3	75
spruce	1.9	69	304	19.4	14.2	13.5	59.3	36
birch	0.6	8	35	37.5	22.5	6.4	28.0	56
aspen	0.5							
Tot.	23.9	413	1815			230.8	1014.6	

Sample size: pine: 303, spruce: 27, birch: 9, aspen: 7, total: 346 pcs
Specie ratios: pine: 87.4 %, spruce: 7.9 %, birch: 2.7 %, aspen: 2.0 %
BA range with 95% probability 17.5-30.4. Std. error: 13.8%

Forest inventory report: @54 TRESTIMA

Measurement performed 14.01.2015 02.02.2015
Measured area 4.70 ha
BA sample amount 23 pcs

Specie	BA m^2/ha	Stems pcs/ha	Stems pcs	DBH cm	Height m	Vol m^3/ha	Vol m^3	Log %
pine	15.8	244	1144	31.4	21.5	162.2	761.6	76
spruce	3.6	62	291	29.0	24.3	38.6	181.2	75
birch	0.9	13	62	31.3	22	8.4	39.4	51
other	0.2							
Tot.	20.5	319	1498			209.2	982.2	

Sample size: pine: 478, spruce: 109, birch: 26, other: 7, total: 620 pcs
Specie ratios: pine: 77.1 %, spruce: 17.6 %, birch: 4.2 %, other: 1.1 %
BA range with 95% probability 17.8-23.2. Std. error: 6.6%

Fig. 12. Variables and compartment geometry visualization at Trestima web-interface (reports by Trestima).

Estimation of local variables based on application of Trestima, comparison to FMP. As the final step of the forest variables estimation yet another technique called Trestima was used. Trestima is a system, which bases on an application of smartphones for estimation of local forest variables via simple terrestrial photographing of a forest and exploits a principle of the relascope as it has been in detail explained by Rouvinen (2014*a*, *b*).

In the framework of the project Trestima was applied at three forest compartments/figures of the study area totaling to 65 samples (images/measurements) of BA, H and DBH (Fig. 10).

The measurements were performed in less than one hour of net time at the area of approx. 13.9 ha. The weather and forest conditions are shown/visible in the images (Fig. 11).

The same standard set of forest variables was delivered after application of Trestima at each selected compartment i. e. mean V, BA, DBH, H as well a variable responsible for a number of stems per hectare, per tree species (Fig. 11, 12).

Later, data by Trestima were compared to an information stated in the forest management plan (FMP) and sUAV based estimations.

RESULTS AND DISCUSSION

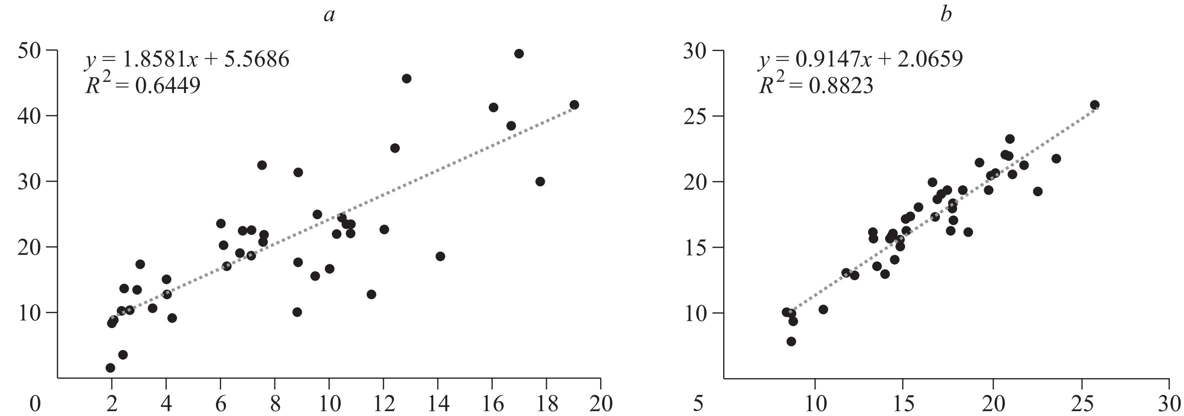
sUAV based estimation of forest variables over area of interest. At the first stage of sUAV based estimation single best correlating remote sensing features were found for variables basal area (BA), height (H) and mean volume (V) (Fig. 13).

These features were later used at the sequential forward feature selection (SFFS) procedure as a starting point of further iterations.

Fig. 13 shows that H has the best correlations with one of the 3D features (h_80) extracted from high-resolution DSM, whereas BA's and V's best correlation is at quite a low level and bases on a Haralick feature (h_SA) extracted from high-resolution DSM raster.

At the next stage, SFFS procedure was applied and as a result of multiple linear regression modeling appropriate sets of the features, which the best way explain BA, H and V, were selected (Table 3).

Where, for example, for a Haralick feature h_SA first letter «h» relates to the respective raster (red (*r*), green (*g*), blue (*b*) or DSM (*h*)) and «SA» relates to the name of a Haralick feature; the 3D features possess their own unique names. Consequently, a solu-



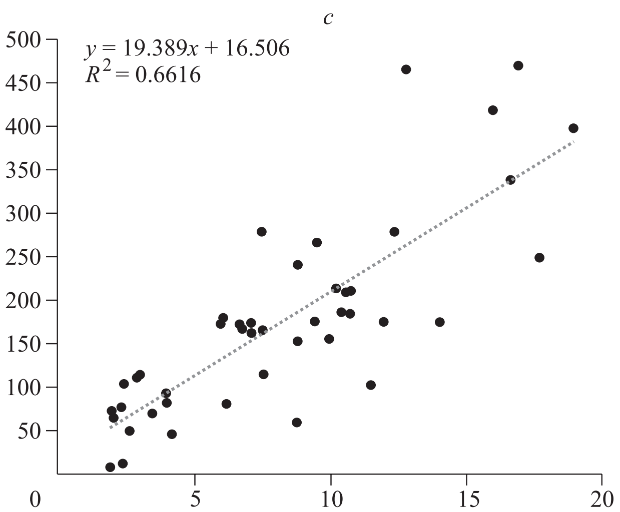


Fig. 13. *a* – BA (axis *Y*) vsh_SA (axis *X*); *b* – H (axis *Y*) vs h_80 (axis *X*); *c* – V (axis *Y*) vs h_SA (axis *X*).

Table 3. Selected features

Variable	Selected features
BA, m^2/ha	(1) h_SA (Haralick), (2) h0 (3D), (3) pcg (3D), (4) r_MOC-1 (Haralick), (5) d9 (3D)
H, m	(1) h80 (3D), (2) h_Contr (Haralick), (3) h95 (3D)
V, m^3/ha	(1) h_SA (Haralick), (2) h0 (3D), (3) d1 (3D), (4) h_DV (Haralick), (5) pcg (3D)

Table 4. Correlation analysis statistics

Variable	ε	β_1	β_2	β_3	β_4	β_5	R^2
BA, m^2/ha	18.61760	1.64636	1.09478	0.00412	130.2300	–0.5411	0.81
H, m	4.311	1.274	0.106	–0.487	–	–	0.92
V, m^3/ha	71.7576	20.8621	18.8554	–1.4868	10 982.72	0.0387	0.82

Table 5. sUAV based estimation accuracy assessment

Variable	RMSE	*RMSE*, %	Average
BA, m^2/ha	4.74	22.60	20.97
H, m	1.14	6.60	17.19
V, m^3/ha	47.24	26.75	177.19

tion for regression coefficients (β) and a constant (ε) was found applying the SFFS procedure (Table 4).

As it has been shown in Table 4 the resulting correlation, explained by coefficient of determination R^2, equals 0.81 for BA, 0.92 for H and 0.82 for V, whereas R^2 for the single best correlating features found for the very same variables (see Fig. 13) equals 0.64, 0.88 and 0.66, respectively. This result shows significant improvement of the estimation accuracy at transition from a simple linear regression to a multiple linear regression. The improvement is especially considerable for the BA and V estimation. Both sets of the features equally include Haralick and 3D features. However, it is remarkable that most of the features for the all the variables (BA, H and V) are related to the 3D model of the forest and only one feature in the set concerned with BA is related to the VHR aerial imagery.

Next, RMSE was calculated for each variable – BA, H and V, respectively. The sUAV based estimation accuracy assessment results are presented in Table 5.

From Table 5 it is visible that the best estimation concerns H, which may be explained by high initial correlation with the remote sensing data (see Fig. 13, *b*) and its further improvement (see Table 4). Accuracy of BA and V estimation is lower due to the similar reason explained above for H.

Wall-to-wall mapping. Wall-to-wall mapping results are presented as relevant rasters in Fig. 14, as well as a classified raster of sUAV based volume estimation per compartment is given in Fig. 15.

Comparison of sUAV based estimates, FMP and Trestima. At the final step, all the estimates obtained within the framework of the remote sensing statistical analysis and Trestima survey were directly compared over the data available from the existing Forest management plan (FMP). The following comparisons were performed:

– sUAV based estimation of BA and H were compared over respective FMP variables for all relevant compartments of the AOI (Fig. 16, 17, see p. 14).

– sUAV based estimation of BA and V (m^3/ha) were compared for three reference compartments (number 412, 454 and 456 according to their ordinal numeration given in the FMP) over respective variables of Trestima survey and of the FMP (Fig. 18, 19, see p. 15);

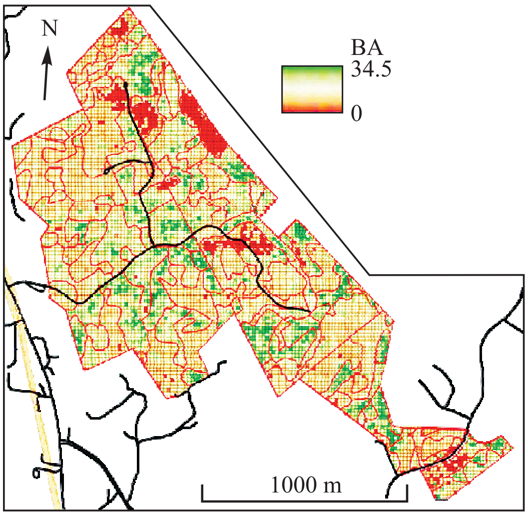
– sUAV based estimation of mean weighted H was compared versus respective H given inthe FMP for the three reference compartments (number 412, 454 and 456 according to their ordinal numeration given in the FMP) (Fig. 20, see p. 15);

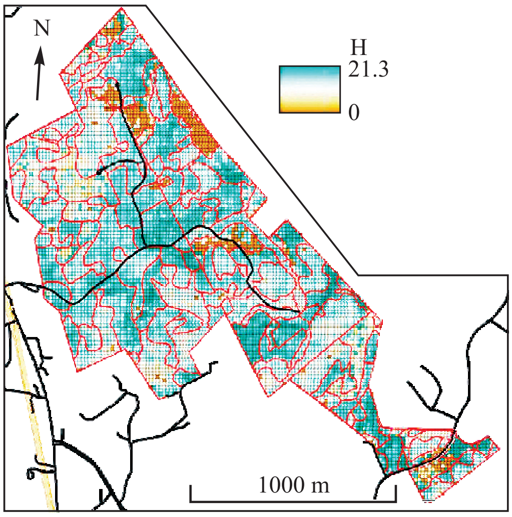
– comparison of stem quantity given provided by the FMP and Trestima (Fig. 21, see p. 15).

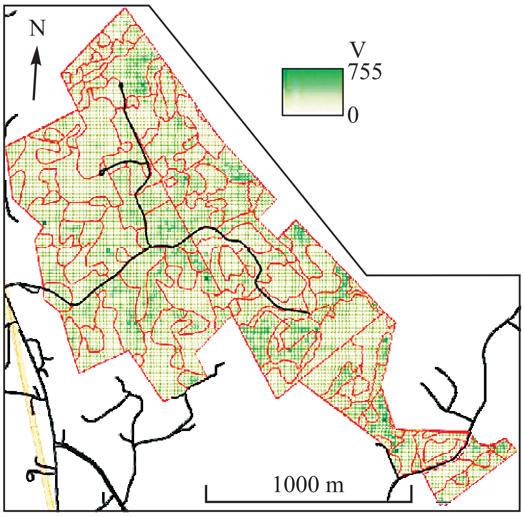
The comparison presented on Fig. 16 shows that the difference between BA stated in the FMP and sUAV based estimation of BA is inconsiderable at a limited number of compartments only, whereas at the most compartments BA deviates significantly – exceeding (+/–) 1 m^2.

The comparison of H stated in the FMP and sUAV based estimation of H (see Fig. 17) shows that the difference ranges in the corridor of ±5 meters at the most compartments with a trend of H by the FMP to surpass the H estimated.

The performed comparisons, which are illustrated in Fig. 18, 19 and 20, show that Trestima demonstrates the best fit with the FMP data at all the compared variables with an average difference ranging from ±1–16 %.







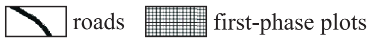


Fig. 14. sUAV based estimation rasters (from left to right: basal area (BA, m^2/ha), height (H, m), volume (V, m^3/ha).

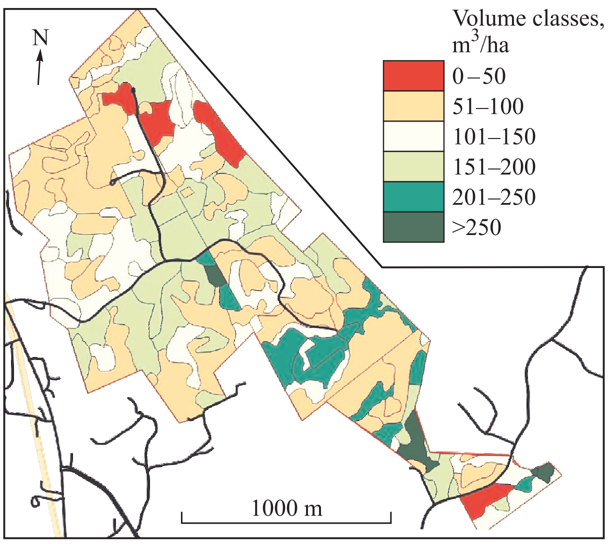


Fig. 15. Volume (V) classification of compartments.

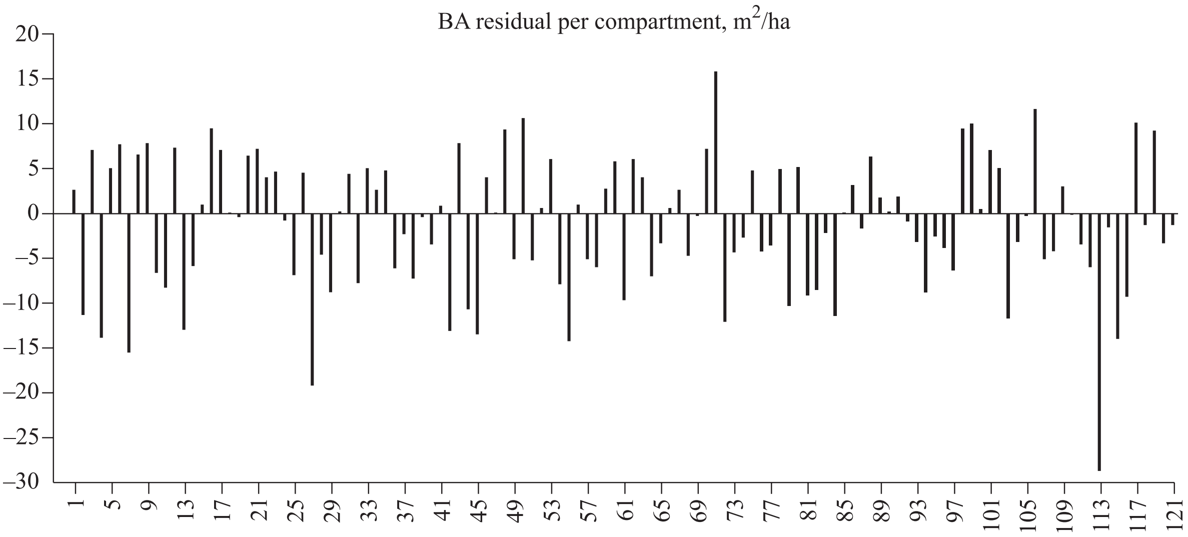


Fig. 16. Difference between BA by FMP and BA estimated per compartment.

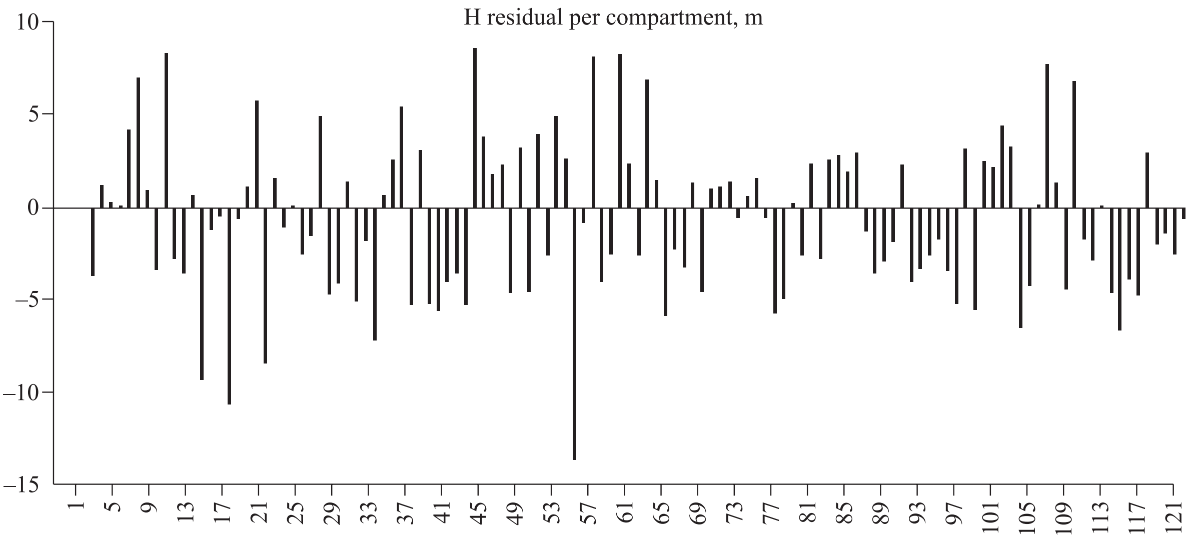


Fig. 17. Difference between H by FMP and H estimated per compartment.

The sUAV based estimation results however show slightly lower values of variables BA and H (Fig. 18 and 20) versus FMP data, which leads to the respective underestimation of the volume (V, m^3/ha) (Fig. 19).

Since Trestima does not represent the H variable comparable with the sUAV based estimation and the FMP, it was decided to exclude the data given by Trestima at the comparison illustrated in Fig. 20. It is due to the fact that at this study Trestima rendered the height of a tree per species, which was subjectively chosen in the field to be a basal median, whereas the FMP operates weighted mean H per tree species for entire compartment. sUAV based estimates operate weighted mean H irrespective of the tree species.

The final comparison was concerned stem quantity estimation (Fig. 21).

It shows some difference between the FMP and Trestima data. This comparison is given as it is as at this part further analysis was impossible without clear understanding of estimation approach used at both FMP and Trestima.

Notably, the speed of sampling using Trestima, which constituted 13.9 ha in less than one hour net time, was equal to a normal speed of walk in the forest.

In some part, this project work is a repetition of what had been done so far (Järnstedt et al., 2012 or Tuominen et al., 2015). On the other hand, some new ideas were realized among which, for example, was the application of the sUAV with the RGB digi-

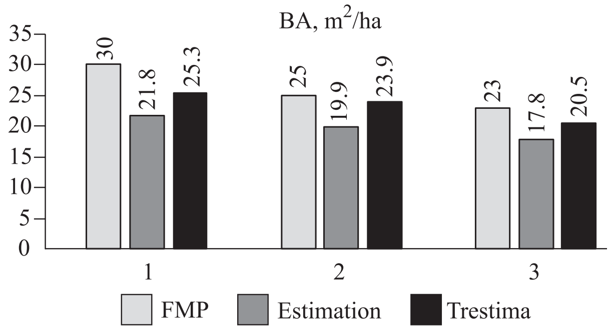


Fig. 18. Comparison of BA.

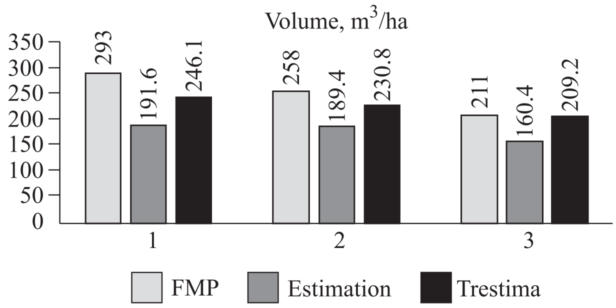


Fig. 19. Comparison of volume.

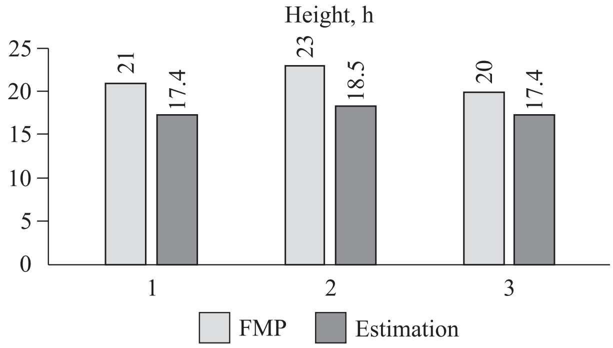


Fig. 20. Comparison of height, m.

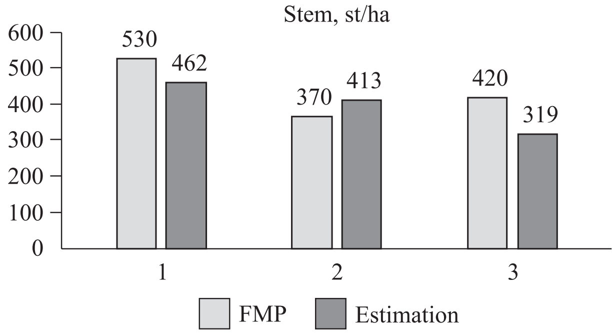


Fig. 21. Comparison of number of stems (units).

tal camera for forest inventory and application of the Trestima system as a tool for field measurements (although, at the project the mean forest volume of a limited number of compartments was measured by Trestima).

The study showed that remote sensing data i. e. RGB aerial imagery and digital surface model obtained with sUAV with respective ground truth data were able to deliver features suitable for mean forest volume estimation.

When it comes to the sUAV based estimation of H, the achieved RMSE of 6–7 % turned out to be better compared to the results of the study by Tuominen et al. (2015), where RMSE of 8–9 % was obtained using airborne laser scanning (ALS) dataset, which (the ALS data) is considered the most accurate, and little worse or almost similar, respectively, compared to the results of the study by Yu et al. (2015), where RMSE for H was 4.61–5.30 % for ALS and 6.90 % for a 3D model extracted from an aerial imagery.

sUAV based estimation of BA (RMSE of 22–23 %) also turned to be slightly better at this study versus, for example, the recent studies by Tuominen, Haapanen (2011), where results indicate RMSE of 25–26 % for ALS based estimation, and by Järnstedt (2012) where results indicate RMSE of 27–28 % for ALS based estimation and 36–37 % for photo based estimation, respectively. However, BA estimation of this study is worse compared to the results by Yu et al. (2015), which showed RMSE of 14.75–15.91 % for ALS and 18.24 % for the 3D model extracted from the aerial imagery.

Respective sUAV based estimation of V resulted in RMSE of 26–27 %. This result is almost the same as the one reported by Tuominen et al. (2015), where more advanced estimation techniques were applied, and, respectively, worse compared to Yu et al. (2015) with RMSE of 15.91–16.72 % for ALS and 19.37 % for the aerial imagery based 3D model.

However, despite promising RMSEs, a direct comparison of variables on the local (compartment) level versus available reference data of the FMP introduces some questions to the sUAV based estimation results that show quite some deviation (see Fig. 16 and 17). For example, the sUAV based estimation of H (see Fig. 17) at more than 50 % of the forest compartments shows a systematic difference at the level of approx. 5 meters (see Fig. 20). This requires special attention. A possible answer may be the lack of clear knowledge about forest management activities that may have been performed in some forest compartments since the date of remote sensing and field data acquisition and might have an effect on the local relevance of the FMP data. Simultaneously, quality of the high-resolution DSM and/or the niceties of the 3D/Haralick features extraction algorithms could be studied more in detail.

An application of more advanced estimation techniques such as the *k-nn* method (Tuominen et al., 2006) might also have given results that are more accurate. However, that requires more field data. The combination of the *k-nn* estimation and more extensive field measurements, for example, with several sample plots per stratum, could have played a positive role for the accuracy.

Here it should be however noted that the inaccuracies revealed at comparison of the sUAV based estimations versus FMP (see Fig. 16, 17 and 18–20), could also be explained by inaccuracy of the FMP estimations themselves. The study by Haara, Korhonen (2004) showed that forest variables estimation techniques that used to be employed at forest management planning have the following accuracy constraints: mean forest compartment volume RMSE ranges from 10.6 to 33.9 %, basal area RMSE from 6.6 to 24.5 % and basal area weighted average height from 10.9 to 19.2 %. In that regard, factually FMP data cannot be used as a solid reference as, in general case, may possess rather high level of inaccuracy.

When it comes to Trestima as a sampling tool, if compared to, for example, the relascope or the fixed radius sample plot method, which require more complex arrangements such as marking of a sample plot center, making written notes for each single measurement etc., it, along with the accuracy indication achieved at this study, demonstrates good prospects to be either a forest inventory tool and/or as a forest data validation tool, which could be used by forest engineers or forest owners at their regular measurements. As this study at Trestima application has been limited to just three forest compartments, the results concerned with Trestima can be considered just as a preliminarily assessment of the technology in comparison to sUAV based and FMP estimations. Meanwhile, Siipilehto et. al (2016) at their study, where several inventory methods (ALS, Trestima and EMO (Uusitalo and Kivinen, 2000)) were compared over data of a harvester's measurement system, have shown that Trestima gives the following accuracy (RMSE) at predicting forest variables: 14.6–16.5 % for H, 30.9–31.3 % for BA, 38.0–43.2 % for V and 34.2–43 % for a number of stems. However, that is the only study exists at the moment, where Trestima has been scrutinized. There is no other relevant studies on the matter. In that regard, there is a need to continue further research on Trestima method.

Overall, the results of the study confirmed that the technologies and the tools applied at this work could be reliable and potentially cost-effective means of data acquisition for forest inventories with high potential of operational usage as well as leave a room for further development.

For example, the results indicate good prospects for the application of sUAVs (or any other cheap aerial platform) for forest inventory, which may deliver high quality data (VHR aerial imagery and high-resolution elevation model) of a quality close or even similar to ALS. The mentioned above data of photogrammetric modeling carry some necessary features for further estimation of forest variables with potential accuracy close to performance of ALS data, provided that the terrain is well defined from other sources. In that respect, one of the possible directions for further development may lie in the field of improvement of forest variables estimation accuracy by application of other more advanced estimation techniques.

Yet another interesting field could be to study if a photogrammetric high-resolution surface model may be used to render an accurate and/or sufficient enough terrain model. This particular application may be of extreme interest in forestry for the areas where terrain data is missing or of low quality. For example, this is the case at the entire territory of Russia, Africa and Asia, to name a few. The solution for the problem of lacking reliable terrain data, if found based on photogrammetry, can significantly ease further data processing and may also let avoiding complex arrangements at remote sensing data georeferencing.

Simultaneously, as most of the features of the selected sets belong to the 3D canopy model, it would have been very useful to test Haralick features only, similar to the work performed by Tuominen, Pekkarinen (2005), to check if the same accuracy is achievable. The problem originates from the fact that, as it has been stated above, accurate enough DTM is not available widely. In practice that means that in such circumstances most of the 3D features considered at this study would be impossible to derive, as the DSM could not be normalized to the ground level.

Trestima, however, can already be used as it is. This technique looks prospective for ground truthing. However, existing forest inventory practices employ conventional methods and tools based on the application of relascope or fixed radius based sampling, which imply manual or semi-automated measurements. In that respect, Trestima will require new developments to be integrated into approved forest inventory systems.

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ОЦЕНКА СРЕДНЕГО ОБЪЕМА ДРЕВОСТОЯ С ИСПОЛЬЗОВАНИЕМ RGB АЭРОФОТОСНИМКОВ И ЦИФРОВОЙ МОДЕЛИ ПОВЕРХНОСТИ ВЫСОКОГО РАЗРЕШЕНИЯ, ПОЛУЧЕННЫХ С БЕСПИЛОТНОГО ЛЕТАТЕЛЬНОГО АППАРАТА, И МОБИЛЬНОГО ПРИЛОЖЕНИЯ ТРЕСТИМА

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Приводятся результаты изучения способа дистанционного зондирования для оценки среднего объема, основанного на RGB аэрофотоснимках и цифровой модели поверхности высокого разрешения, полученных при помощи беспилотного летательного аппарата (БПЛА), а также инновационной технологии Трестима как средства для полевых измерений. Территория исследования составляет 220 га лесных земель в Финляндии. Работа затрагивает весь процесс – от дистанционного зондирования и сбора полевых данных до статистического анализа и составления карт объемов леса. Исследование показало, что аэрофотоснимки и цифровая модель поверхности высокого разрешения, полученные путем применения БПЛА, имеют хорошую перспективу для инвентаризации лесов. При оценке лесных переменных, таких как высота, площадь поперечных сечений стволов и средний объем, среднеквадратическая ошибка составила 6.6, 22.6 и 28.5 % соответственно. Применение технологии Трестима для оценки среднего объема древостоя продемонстрировало незначительные отличия от Плана освоения лесов на всех выбранных лесотаксационных выделах. Одновременно результаты исследования подтвердили, что примененные в данной работе технологии могут быть надежными и потенциально экономически эффективными средствами сбора лесных данных с перспективой операционного применения.

Ключевые слова: *дистанционное зондирование, БПЛА, Трестима, инвентаризация лесов, цифровая модель поверхности, средний объем.*