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ORIGINAL PAPER

Forest inventory based on canopy height model derived from airborne laser scanning data

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Abstract
Airborne laser scanning (ALS) has emerged as a remote sensing technology capable of providing data suitable for deriving all types of elevation models. A canopy height model (CHM), which represents absolute height of objects above the ground in metres (e.g., trees), is the one most commonly used within the forest inventory. The aim of this study was to assess the accuracy of forest inventory performed for forest unit covered 17,583 ha (Slovakia, Central Europe) using the CHM derived from ALS data. This objective also included demonstrating the applicability of freely available data and software. Specifically, ALS data acquired during regular airborne survey, QGIS software, and packages for R environment were used for purpose of this study. A total of 180 testing plots (5.6 ha) were used for accuracy assessment. The differences between CHM-predicted and ground-observed forest stand attributes reached a relative root mean square error at 10.9%, 23.1%, and 34.5% for the mean height, mean diameter, and volume, respectively. Moreover, all predictions were unbiased (p-value < 0.05) and the strength of the relationships between CHM-predicted and ground-observed forest stand attributes were relative high ($R^2 = 0.7 – 0.8$).

Key words: airborne LiDAR; natural resources; area-based approach; freeware

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1. Introduction

Remote sensing (RS) has become a reliable source of geospatial data and techniques for forest inventory (Surový & Kuželka 2019). Especially, airborne laser scanning (ALS), as an active RS technology, represents an effective solution to acquire relevant information about forests at tree or stand level (Goodbody et al. 2021). This is primarily because this technology can be used at local or regional level, sensors are not affected by any geometrical distortions, and laser pulses can penetrate through the gaps of the canopy, even in dense forests, to the ground. In this context, related ALS data can achieve high accuracy as well as density and allow automatic classification of terrain, building, and vegetation objects directly from point cloud (Díaz-Varela & González-Ferreiro 2021).

Since ALS can provide data not only from the surface but also from the ground, this technology has been proven to provide data suitable for derivation of all types of elevation models. A canopy height model (CHM), which represents absolute height of objects above the ground in metres (e.g., trees), is the one most commonly used within the forest inventory (Vauhkonen et al. 2014; Zhen et al. 2016). In addition to the sufficient accuracy and resolution (Polidori & El Hage 2020), the main advantages of CHM compared to the point cloud are higher availability and applicability. The reasons are as follows (1) most countries in Central Europe acquire and provide CHM from routine ALS campaigns (Ginzler & Hobi 2015), (2) once a terrain model is available, CHM can also by generated from aerial images acquired by directly/remotely piloted aircraft system (Liu et al. 2020), and (3) commonly available hardware and software, including free available applications, is usable for CHM-based forest inventory (Wang et al. 2021). On the other hand, the CHM (1) is generalized by interpolation or smoothing procedures, (2) may contain unnatural black holes, and (3) does not contain the most of relevant information for forest inventory related to the understory (Jamru 2018; Zhang et al. 2020).

The overall objective of this study was to assess the accuracy of forest inventory performed for forest unit covered 17,583 ha using the CHM derived from ALS data. This objective also included demonstrating the applicability of freely available data and software. Specifically, ALS data from regular airborne survey, QGIS software (QGIS Development Team 2022), and packages for R environment (R Core Team 2021) were used for

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purpose of this study. The CHM-based forest inventory was focused on three characteristics that have a particular importance in forest management and represent the main forest stand attributes, such as mean height, mean diameter, and volume per hectare.

2. Material and methods

2.1. Study Area

The study was conducted in the territory of the forest management unit University Forest Enterprise of the Technical University in Zvolen located in central Slovakia (approx. 48°37´N, 19°05´E). The total area is 17,583 ha and forests occupy 7,483 ha from this area. The elevation reaches interval of 261 – 1,069 meters above sea level. Dominant species include European beech (*Fagus sylvatica* L.), Sessile oak (*Quercus petraea* Matt.), and European silver fir (*Abies alba* Mill.) with 70% coverage (Fig. 1).

2.2. Remote Sensing Data

Aerial survey was conducted as a part of a routine and regular flight campaign in order to create a forest management plan. Since this survey is funded by state resources, related ALS data and derivatives are provided free of charge based on the order addressed to the National Forest Centre.

ALS data acquisition was performed in June 2021 over the entire study area (17,583 ha). This area was scanned using a Leica ALS 70 CM scanner from average altitude of 1,290 m with field of view of 43° and 282 kHz laser pulse repetition rate. The resulting average density of point cloud reached 26 points/m^2. The ALS-derived digital terrain model (DTM) and digital surface model (DSM) were processed in SCOP++ Software environment (Trimble) with vertical accuracy of ±0.2 m. The CHM of 0.5 m resolution was generated as a result of subtraction of these DSM and DTM.

2.3. Ground Data

Ground data were obtained during the leaf-on season in 2021 within 360 circular sample plots with radius of 10 m (11.25 ha). The position of the plot center was located using the Global Navigation Satellite System (GNSS) and a positional error from 1.44 m to 6.25 m was expected for all plots (Murgaš et al. 2018). A total of 12,176 trees with Diameter at Breast Height (DBH) higher than 8 cm were measured for stem position, species, height, and diameter. Tree height was measured using the Vertex IV hypsometer (Haglöf) with total accuracy of ±1.0 m. Measurement of DBH was performed with a tree caliper at the millimeter scale. Tree volume was calculated based on tree height and DBH using allometric model with total accuracy of ±7–12% at tree level (Petráš & Pajtík 1991). Sample plots were classified into nine strata. The main criteria for classification were forest types (B: Beech forests, O: Oak-hornbeam forests, F: Beech-fir forests) and age classes (1: 11 – 40 years, 2: 41 – 80 years, 3: >80 years). In this context, Beech stratum (B1–3), Oak stratum (O1–3), and a Fir stratum (F1–3) was created. Furthermore, sample plots were divided into two groups. The main criteria for dividing was proportionality of these both datasets related to the number of plots, area of plots and stand attributes. In this context, group of 180 training plots (20 plots per stratum) and group of 180 testing plots (20 plots per stratum) was created (Table 1).

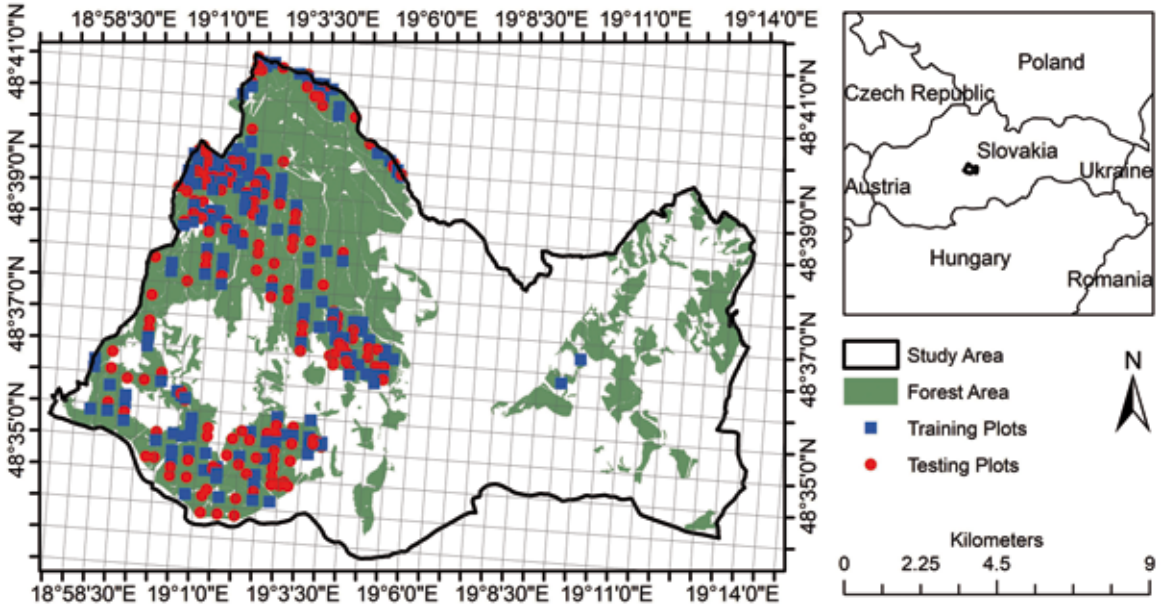

Fig. 1. The study area located in Slovakia, Central Europe.

Table 1. Statistics of ground data from 180 training plots and 180 testing plots (20 plots per stratum).

Stratum	Training Data			Testing Data		
	Height [m]	Diameter [cm]	Volume [m^3 ha^{-1}]	Height [m]	Diameter [cm]	Volume [m^3 ha^{-1}]
All	18.9 ±4.5	23.0 ±6.9	375.9 ±195.2	18.7 ±4.9	22.2 ±7.3	383.5 ±205.0
B1	15.5 ±3.8	15.5 ±2.6	233.2 ±140.2	15.4 ±4.0	15.4 ±2.9	230.8 ±139.8
B2	20.1 ±2.9	22.1 ±3.7	407.2 ±112.6	20.3 ±3.2	22.3 ±3.5	413.4 ±124.5
B3	22.8 ±2.8	31.0 ±6.6	522.5 ±153.0	22.4 ±3.5	30.5 ±7.2	542.8 ±191.4
O1	15.0 ±3.8	15.2 ±2.7	185.8 ±107.5	15.2 ±3.5	15.4 ±2.3	197.6 ±99.2
O2	19.0 ±2.9	21.9 ±2.9	342.1 ±117.3	19.1 ±3.0	22.5 ±2.9	363.5 ±122.9
O3	21.2 ±2.2	30.4 ±6.1	402.0 ±126.5	20.6 ±3.1	28.2 ±6.5	421.8 ±130.2
F1	13.6 ±3.7	14.8 ±2.6	234.3 ±166.1	13.2 ±3.2	14.4 ±2.7	218.3 ±185.0
F2	19.8 ±4.0	23.7 ±3.2	513.7 ±146.6	20.0 ±3.7	23.7 ±3.1	499.5 ±117.9
F3	23.3 ±4.9	34.7 ±7.0	600.0 ±235.8	23.1 ±4.8	34.5 ±7.5	620.7 ±281.8

Note: All: All sample plots; B1–3: Beech stratum; O1–3: Oak stratum; F1–3: Fir stratum; Height: arithmetic mean height; Diameter: arithmetic mean diameter; Volume: volume per hectare.

2.4. CHM-based Forest Inventory

The workflow for CHM-based forest inventory is shown in Fig. 2 and described in detail in the following points:

- The height metrics (i.e., mean, median, standard deviation, minimum, maximum, range, minority, majority) were computed from CHM for specific areas of training plots (n = 180) using zonal statistic tool implemented in the QGIS software (Madry 2021). Specifically, the CHM-based mean height was assessed as most highly correlated height metric to all related forest stand attributes (i.e., mean height, mean diameter, and volume per hectare) using Pearson's correlation analysis (Voght & Johnson 2012).
- The simple nonlinear models for prediction of forest stand attributes were computed from training data using least-squares regression implemented in the R package NLStools (Baty et al. 2015). These models express the relationship between ground-observed forest stand attributes and CHM-based mean height. Here, only statistically significant and best performing models for prediction of specific forest stand attribute (i.e., mean height, mean diameter, and volume per hectare) were selected and used. The statistical significance was assessed using Fisher's test (F-test). The goodness of fit was assessed using error metrics of regression model.
- The mean heights were computed from CHM for specific areas of testing plots (n = 180) using zonal statistic tool function implemented in the QGIS software. Subsequently, the forest stand attributes were predicted for testing plots through the developed regression models. In this way, each of testing plots include observed as well as predicted mean height, mean diameter and volume per hectare. Finally, the accuracy of the CHM-based forest inventory was assessed by comparing the observed and predicted forest stand attributes.
- The regular 20 × 20 m grid covering the forest area was created and the CHM-based mean heights were computed for all grid cells. The size of the grid cells (400 m^2) was set to reflect the size of the ground plots (314 m^2). Subsequently, the forest stand attributes were predicted for all grid cells through the developed regression models. In this way, each grid cell covering the forest area include predicted mean height, mean diameter and volume per hectare.

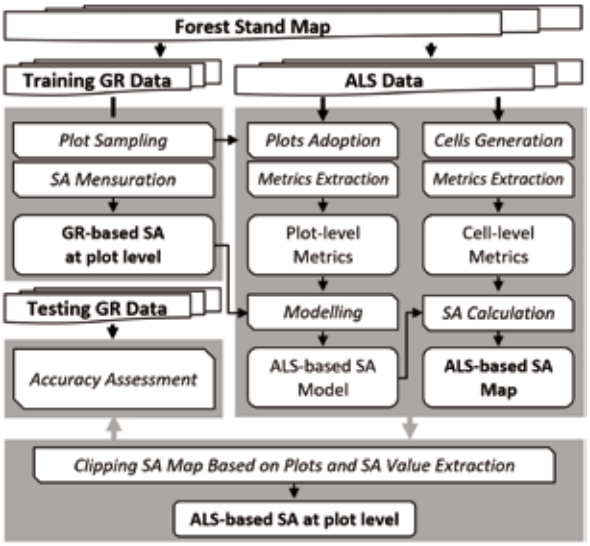

Fig. 2. Flowchart for CHM-based forest inventory. Note: GR: ground; ALS: airborne laser scanning; SA: forest stand attribute.

2.5. Accuracy Assessment

The accuracy of the CHM-based forest inventory was assessed by comparing the observed and predicted forest stand attributes from 180 testing plots. The value of observed forest stand attributes for each sample plot was obtained by ground measurement (Section 2.3). The value of predicted forest stand attributes for each sample plot was obtained by CHM-forest inventory (Section 2.4).

The standard error (Bias, Equation (1)) and root mean square error (RMSE, Equation (2)) were used to assess the model's performance. The relative %Bias and %RMSE were calculated as the ratios of their absolute values and the arithmetic average of the observed data.

The regression function, coefficient of determination (R^2), and F-test of statistical significance of the regression model (p-value) were calculated to assess the strength of the relationship between predicted and observed forest stand attributes (Voght & Johnson 2012).

The t-test, when a normal distribution of mean differences was confirmed, or Wilcoxon test, when a normal distribution of mean differences was not confirmed (Fay & Proschan 2010), were used to assess the significance of differences (p-value < 0.05).

$$Bias = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i) \quad [1]$$

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

where n is the number of plots, y_i is the observed forest stand attribute for plot i, and $\hat{y}_i$ is the predicted forest stand attribute for plot i.

3. Results

The form and performance of regression models for CHM-based forest inventory are presented in Table 2. We found the power function to be most suitable for prediction of height as well as volume and exponential function for prediction of diameter. All predictions were unbiased (p-value < 0.05) and the strength of the relationships between CHM-predicted and ground-observed forest stand attributes were relative high (R^2 = 0.7–0.8).

The CHM-based forest inventory evaluated the mean height at 18.6 ±4.0 m, mean diameter at 21.6 ±5.0 cm and volume at 381.1 ±183.8 m^3 ha^{-1} within the study area (Fig. 3). In this context, the RMSE of CHM-based prediction of forest stand attributes did not exceed 2.0 m (10.9%) for mean height, 5.1 cm (23.1%) for mean diameter and 132.1 m^3 ha^{-1} (34.5%) for volume (Table 3). These predictions were not statistically significantly different relative to the ground-observed data (p-value < 0.05). The relationships (R^2) between CHM-predicted and ground-observed forest stand attributes fluctuated from 0.7 to 0.8 (Fig. 4).

Table 2. Regression models for CHM-based forest inventory.

Attribute	Model Form	N	R^2	SEE	SEE%	p-value
Height	2.57 × (H^0.69) + E	180	0.81	2.05	10.97	<0.001
Diameter	9.84 × EXP(0.04 × H) + E	180	0.74	5.11	22.98	<0.001
Volume	1.99 × (H^1.80) + E	180	0.70	127.80	33.33	<0.001

Note: H: CHM-based mean height; E: error of prediction; N: number of training plots; R^2: coefficient of determination; SEE: standard error of estimates; SEE%: relative standard error of estimates; p-value of F-test, null hypothesis is rejected at $\alpha = 0.05$.

Table 3. Accuracy of CHM-based forest inventory.

Stratum	Height		Diameter		Volume	
	%Bias	%RMSE	%Bias	%RMSE	%Bias	%RMSE
All	−0.60	10.89	−2.72	23.07	−0.62	34.45
B1	3.88	11.67	19.60	26.83	13.44	41.64
B2	0.22	9.62	5.93	16.48	9.80	31.04
B3	−2.68	11.07	−14.44	21.83	0.45	24.42
O1	2.18	11.13	15.76	23.14	22.54	48.33
O2	0.14	12.20	−2.92	15.30	7.37	29.63
O3	−6.47	11.66	−21.33	27.78	−4.54	34.78
F1	1.52	11.75	8.38	14.34	−30.10	55.93
F2	−0.01	9.82	−0.99	17.39	−10.46	31.20
F3	−5.77	10.63	−24.43	30.51	−12.90	34.22

Note: All: All testing plots; B1–3: Beech stratum; O1–3: Oak stratum; F1–3: Fir stratum; %Bias: relative standard error; %RMSE: relative root mean square error; Height: arithmetic mean height; Diameter: arithmetic mean diameter; Volume: volume per hectare.

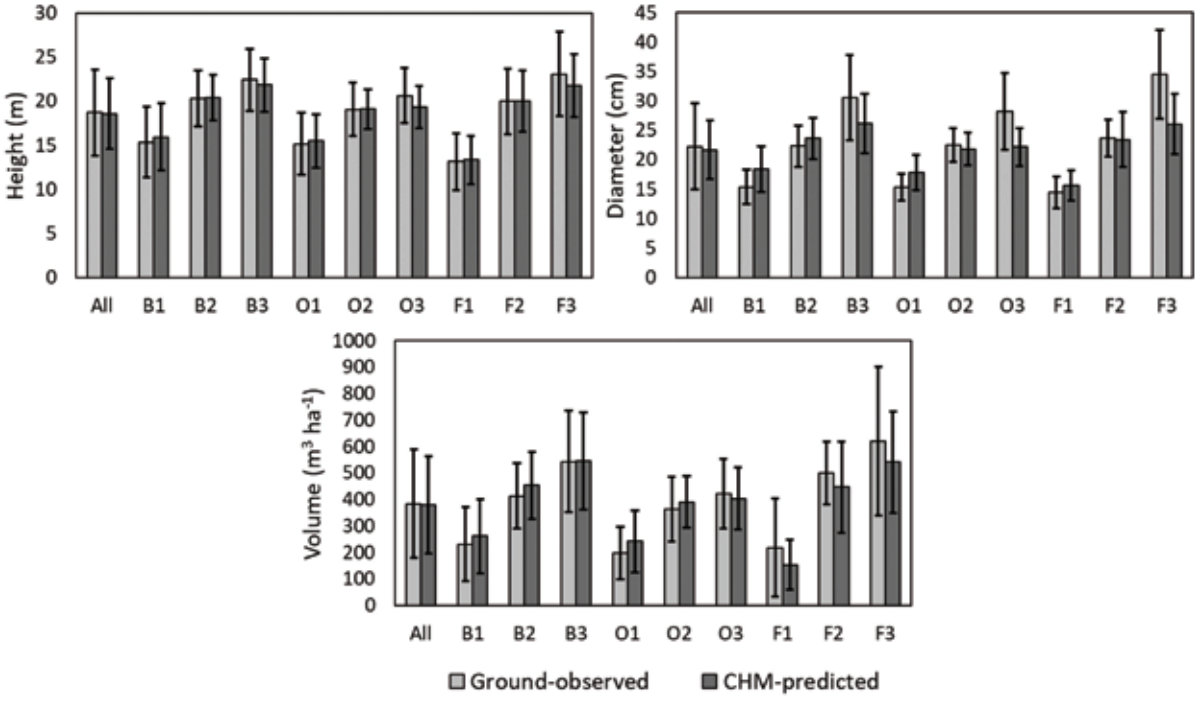

Fig. 3. Ground-observed and CHM-predicted forest stand attributes including standard deviation (whiskers). Note: All: All testing plots; B1–3: Beech stratum; O1–3: Oak stratum; F1–3: Fir stratum.

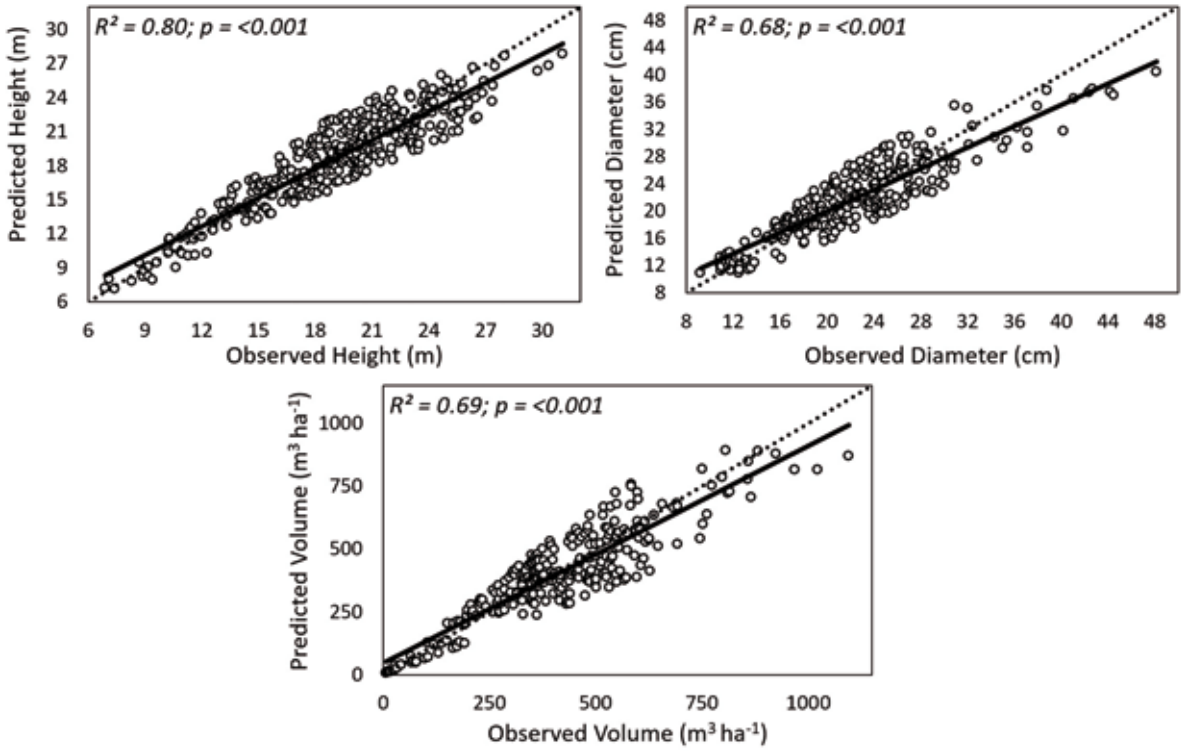

Fig. 4. Relationship between ground-observed and CHM-predicted forest stand attributes from all testing plots. The dashed line represents a 1:1 correspondence.

The final result of CHM-based forest inventory represents a raster layer with resolution of 20 × 20 m consisting values of forest stand attributes (i.e., mean height, mean diameter, and volume per hectare). This result is provided to the stakeholders directly as a product (i.e., raster or vector layer) or indirectly through a web-map service (i.e., website link). The illustrative example of 3D visualization representing CHM-predicted volume for part of study area over grid cell 20 × 20 m is displayed in Fig. 5.

4. Discussion

Forest inventory is strictly required by relevant stakeholders (e.g., forest managers, environmentalist, and policy-makers). However, ground-based measurements are expensive and time consuming. The RS technologies has become a reliable source of geospatial data and techniques for forest inventory. Especially, ALS-based CHM represents an available and usable data source (Kakoulaki et al. 2021) for prediction of forest stand attributes and related techniques provide an opportunity to complement ground-based measurements.

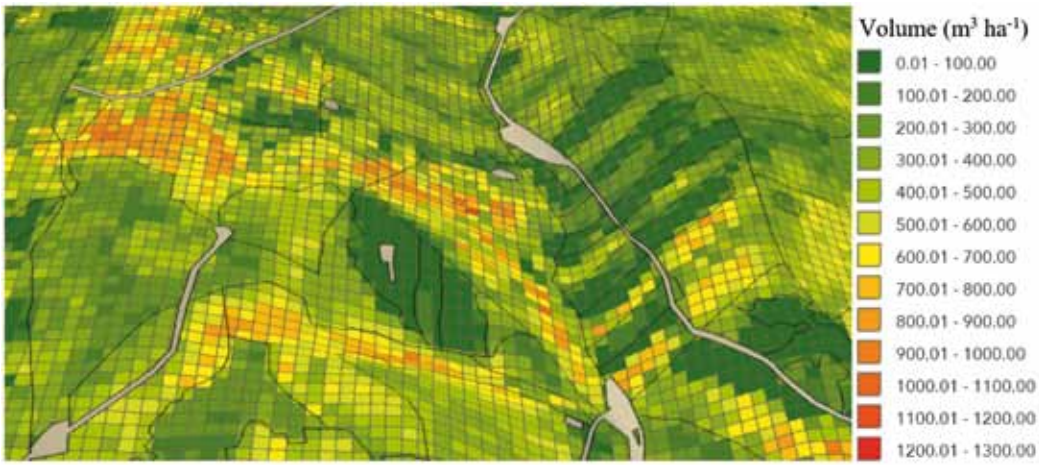

Fig. 5. Visualization of 3D map representing CHM-predicted forest stand attribute for part of study area over grid cell 20 × 20 m (illustrative example for volume per hectare).

The objective of this study was, therefore, to assess the accuracy of forest inventory performed using ALS-based CHM from regular aerial campaign and free available software tools, such as QGIS and packages for R environment. This CHM-based forest inventory was conducted in Central European heterogeneous forests covering 7,483 ha and related accuracy was assessed on 180 testing plots covering 5.6 ha.

In this study, the bias of CHM-based forest inventory for all strata was −0.6% in the case of mean height as well as volume and −2.7% in the case of mean diameter. These results were mainly related to the underestimation of all forest stand attributes within the strata representing old forest (B3, O3, F3) and relative high underestimation of volume in strata representing young fir forest (F1). The prediction of other forest stand attributes within the strata representing young forest were overestimated (B1, O1). The RMSE of CHM-based forest inventory reached the value of 10.9%, 23.1%, and 34.5% for the mean height, mean diameter, and volume, respectively. While the prediction of mean height achieved homogenous accuracy within the strata (10–12%), range of errors related to the prediction of mean diameter and volume was considerable. Specifically, the overall error of mean diameter prediction fluctuated from 14% (F1) to 31% (F3) and overall error of volume prediction fluctuated from 24% (B3) to 56% (F1). Thus, the largest prediction error was found in the youngest (esp., volume) and oldest (esp., diameter) forest stands (Fig. 2). Although this trend has been found also in similar studies (Hill et al. 2014; Cosenza et al. 2018; Mielcarek et al. 2018), statistical significance of increasing or decreasing the development stage on prediction accuracy was not confirmed. However, it is evident that level of RMSE was related to the variability of forest stand characteristics. The overall accuracy of CHM-forest inventory decreased with increasing variability of forest stand characteristics. For example, the variability of volume is significantly higher than variability of mean height (Fig. 6) and consequently the RMSE of CHM-predicted volume is significantly higher than RMSE of CHM-predicted mean height (Table 3).

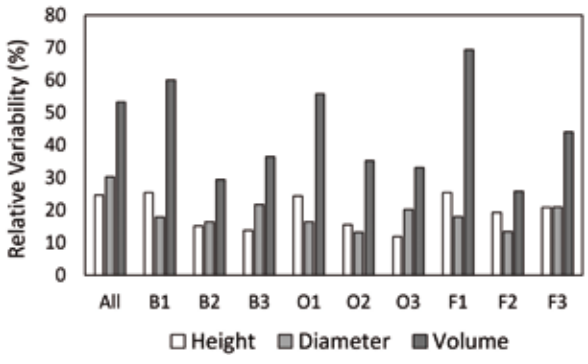

Fig. 6. Relative variability of ground-observed forest stand attributes. Note: All: All sample plots; B1–3: Beech stratum; O1–3: Oak stratum; F1–3: Fir stratum.

Although the CHM-based predictive models are not sufficiently able to describe the full range of variability of forest stand attributes, there are several options to improve the performance of CHM-based forest inventory. For example, (1) higher position accuracy of sample plots (Zhang et al. 2017; Novo-Fernández et al. 2019), (2) higher vertical accuracy and resolution of CHM (Deluzet et al. 2022; Lisiewicz et al. 2022), or (3) application of multiple nonlinear regression or nonparametric machine learning methods (Jiang et al. 2020; Zhao et al. 2022) could contribute to develop predictive models with higher accuracy.

Alternatively, the point cloud-based forest inventory is more suitable solution in heterogeneous forest stands. For example, the point cloud-based forest inventory performed for the same study area achieved the %RMSE which did not exceed 7.2% for mean height, 8.6% for mean diameter, and 21.4% for total volume (Sačkov et al. 2019a; Sačkov et al. 2019b). Moreover, similar or better results have also been provided by other authors, such as study from Brazilian forests (Martins-Neto et al. 2021), Canadian forests (Lamb et al. 2018), or Italian forests (Versace et al. 2020). These and other studies provided %RMSE at 6%–14%, 9%–20%, and 17%–23% for the mean height, mean diameter, and volume, respectively.

5. Conclusions

This study assessed the accuracy of forest inventory performed using ALS-based CHM and free available software tools, such as QGIS and packages for R environment. Our results confirmed that CHM-based forest inventory represents a practical solution that allows make a general overview of natural resources for the whole forest unit. Moreover, this solution can be performed directly and repeatedly by stakeholders without the need for additional investments focused on data, software and hardware. On the other hand, overall accuracy of CHM-based forest inventory in this study did not meet the requirements of forest management from some countries in Central Europe (e.g., Slovakia). Consequently, continuous research and development of CHM-based forest inventory seems to be valid and necessary.

Acknowledgments

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References

Baty, F., Ritz, Ch., Charles, S., Brutsche, M., Flandrois, J. P., Delignette-Muller, M., 2015: A Toolbox for Nonlinear Regression in R – The Package nlstools. Journal of Statistical Software, 66:1–21.

Cosenza, D., Soares, V., Leite, H., Gleriani, J., Amaral, C., Junior, J. et al., 2018: Airborne laser scanning applied to eucalyptus stand inventory at individual tree level. Pesquisa Agropecuaria Brasileira, 53:1373–1382.

Deluzet, M., Erudel, T., Briottet, X., Sheeren, D., Fabre, S., 2022: Individual Tree Crown Delineation Method Based on Multi-Criteria Graph Using Geometric and Spectral Information: Application to Several Temperate Forest Sites. Remote Sensing, 14:1083.

Díaz-Varela, R. A., González-Ferreiro, E., 2021: 3D Point Clouds in Forest Remote Sensing. Remote Sensing, 13:2999.

Fay, M. P., Proschan, M. A., 2010: Wilcoxon-Mann-Whitney or t-test? On assumptions for hypothesis tests and multiple interpretations of decision rules. Statistics Survey, 4:1–39.

Ginzler, C., Hobi, M. L., 2015: Countrywide Stereo-Image Matching for Updating Digital Surface Models in the Framework of the Swiss National Forest Inventory. Remote Sensing, 7:4343–4370.

Goodbody, T. R. H., Coops, N. C., Luther, J. E., Tompalski, P., Mulverhill, C. F., Fournier, R. et al., 2021: Airborne laser scanning for quantifying criteria and indicators of sustainable forest management in Canada. Canadian Journal of Forest Research, 51:14.

Hill, A., Breschan, J., Mandallaz, D., 2014: Accuracy Assessment of Timber Volume Maps Using Forest Inventory Data and LiDAR Canopy Height Models. Forests, 5:2253–2275.

Jamru, L. R., 2018: Correction pit free canopy height model derived from LiDAR data for the broad leaf tropical forest. IOP Conference Series: Earth and Environmental Science, 169:012113.

Jiang, X., Li, G., Lu, D., Chen, E., Wei, X., 2020: Stratification-Based Forest Aboveground Biomass Estimation in a Subtropical Region Using Airborne Lidar Data. Remote Sensing, 12:1101.

Kakoulaki, G., Martinez, A., Florio, P., 2021: Non-commercial Light Detection and Ranging (LiDAR) data in Europe. Luxembourg, Publications Office of the European Union, 35 p.

Lamb, S. M., MacLean, D.A., Hennigar, C.R., Pitt, D.G, 2018: Forecasting Forest Inventory Using Imputed Tree Lists for LiDAR Grid Cells and a Tree-List Growth Model. Forests, 9: 167.

Lisiewicz, M., Kamińska, A., Kraszewski, B., Stereńczak, K., 2022: Correcting the Results of CHM-Based Individual Tree Detection Algorithms to Improve Their Accuracy and Reliability. Remote Sensing, 14: 1822.

Liu, Q., Fu, L., Chen, Q., Wang, G., Luo, P., Sharma, R. P. et al., 2020: Analysis of the Spatial Differences in Canopy Height Models from UAV LiDAR and Photogrammetry. Remote Sensing, 12:2884.

Madry, S., 2021: Introduction to QGIS: Open Source Geographic Information System. USA, Locate Press LLC, 219 p.

Martins-Neto, R. P., Tommaselli, A. M. G., Imai, N. N., David, H. C., Miltiadou, M., Honkavaara, E., 2021: Identification of Significative LiDAR Metrics and Comparison of Machine Learning Approaches for Estimating Stand and Diversity Variables in Heterogeneous Brazilian Atlantic Forest. Remote Sensing, 13:2444.

Mielcarek, M., Stereńczak, K., Khosravipour, A., 2018: Testing and evaluating different LiDAR-derived canopy height model generation methods for tree height estimation. International Journal of Applied Earth Observation and Geoinformation, 71:132–143.

Murgaš, V., Sačkov, I., Sedliak, M., Tunák, D., Chudý F., 2018: Assessing horizontal accuracy of inventory plots in forests with different mix of tree species composition and development stage. Journal of Forest Science, 64:478–485.

Novo-Fernández, A., Barrio-Anta, M., Recondo, C., Cámara-Obregón, A., López-Sánchez, C. A., 2019: Integration of National Forest Inventory and Nationwide Airborne Laser Scanning Data to Improve Forest Yield Predictions in North-Western Spain. Remote Sensing, 11:1693.

Petráš, R., Pajtík, J., 1991: Sústava česko-slovenských objemových tabuliek drevín. Lesnícky časopis, 37:49–56.

Polidori, L., El Hage, M., 2020: Digital Elevation Model Quality Assessment Methods – A Critical Review. Remote Sensing, 12:3522.

Sačkov, I., Kulla, L., Bucha, T., 2019a. A Comparison of Two Tree Detection Methods for Estimation of Forest Stand and Ecological Variables from Airborne LiDAR Data in Central European Forests. Remote Sensing, 11:1431.

Sačkov, I., Scheer, L., Bucha, T., 2019b. Predicting forest stand variables from airborne LiDAR data using a tree detection method in Central European forests. Central European Forestry Journal, 65:191–197.

Surový, P., Kuželka, K., 2019: Acquisition of Forest Attributes for Decision Support at the Forest Enterprise Level Using Remote-Sensing Techniques - A Review. Forests, 10:273.

Vauhkonen, J., Maltamo, M., McRoberts, R. E., Næsset, E., 2014: Introduction to forestry applications of airborne laser scanning. In: Maltamo, M., Næsset, E., Vauhkonen, J. (eds.): Forestry Application of Airborne Laser Scanning: Concept and Case Studies. Springer Netherlands: Dordrecht, The Netherlands, p. 1–16.

Versace, S., Gianelle, D., Frizzera, L., Tognetti, R., Garfì, V., Dalponte, M., 2019: Prediction of Competition Indices in a Norway Spruce and Silver Fir-Dominated Forest Using Lidar Data. Remote Sensing, 11:2734.

Voght, W. P., Johnson, R. B., 2012: Correlation and Regression Analysis. USA, SAGE Publications Ltd, 1632 p.

Wang, H., Seaborn, T., Wang, Z., Caudill, Ch., Link, T., 2021: Modeling tree canopy height using machine learning over mixed vegetation landscapes. International Journal of Applied Earth Observation and Geoinformation, 101:102353.

Zhang, Z., Cao, L., She, G., 2017: Estimating Forest Structural Parameters Using Canopy Metrics Derived from Airborne LiDAR Data in Subtropical Forests. Remote Sensing, 9:940.

Zhang, W., Cai, S., Liang, X., Shao, J., Hu, R., Yu, S. et al., 2020: Cloth simulation-based construction of pit-free canopy height models from airborne LiDAR data. Forest Ecosystems, 7:1–13.

Zhao, J., Zhao, L., Chen, E., Li, Z., Xu, K., Ding, X., 2022: An Improved Generalized Hierarchical Estimation Framework with Geostatistics for Mapping Forest Parameters and Its Uncertainty: A Case Study of Forest Canopy Height. Remote Sensing, 14:568.

Zhen, Z., Quackenbush, L. J., Zhang, L., 2016: Trends in Automatic Individual Tree Crown Detection and Delineation – Evolution of LiDAR Data. Remote Sensing, 8:333.

Other sources

QGIS Development Team, 2022: QGIS Geographic Information System. Open Source Geospatial Foundation Project. http://qgis.osgeo.org.

R Core Team, 2021: R: A language and environment for statistical computing. R Foundation for Statistical Computing. https://www.R-project.org.