VERIFIED TECHNOLOGY

FOREST ABOVEGROUND BIOMASS ASSESSMENT USING AN AREA-BASED APPROACH

Technical documentation of the verified technology,
with description of the technology, and testing method

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Forest aboveground biomass assessment using an area-based approach

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CONTENT

1 Summary

This technical documentation of the verified technology includes an introduction, three thematic chapters, a conclusion, a list of abbreviations, and a list of references.

The introduction explains the need for a verified technology to be used in assessing forest aboveground biomass (AGB) in the forest conditions of the Czech Republic and Central Europe.

Chapter 3 describes the technology for estimating forest AGB using an area-based approach (ABA), specifically including definition of the ABA, as well as description of the data needed from airborne laser scanning, additional field data, and the process of biomass modeling using machine learning methods.

Chapter 4 illustrates the technological approach in developing and applying the biomass model to the Silesian Beskids project study site and verifying the model at the Ždírec nad Doubravou study site.

Chapter 5 estimates and compares the time requirements for forest AGB assessment using conventional field inventory and by the ABA using ALS.

The conclusion reiterates and summarizes the basic knowledge and subcomponents of the technology and provides further recommendations for its use in practice.

2 Introduction. Need for the verified technology

Estimating forest biomass (hereinafter just biomass) is fundamentally important for sustainable forest management and for better understanding the contribution of various forest ecosystems within the global carbon cycle. Spatially continuous forest biomass maps comprise one of the crucial inputs for climate mitigation strategies. Aboveground biomass (AGB) is defined as "the aboveground standing dry mass of live or dead matter from tree or shrub (woody) life forms, expressed as a mass per unit area, typically Mg ha^{-1}" (Duncanson et al. 2021). Specifically, AGB estimates are used to establish the increment or decrement of carbon stored in forest, most often while converting AGB with a factor of 0.5 (i.e., 50% carbon content in dry matter) or more accurately according to woody species categories (Martin et al. 2011, Petersson et al. 2012).

Forest biomass can be estimated using destructive and nondestructive sampling methods. Destructive methods are generally used only for developing so-called allometric equations for specific individual woody species based upon destructively sampled individual trees. These equations then represent empirical relationships for estimating AGB based upon such measurable tree parameters as tree stem diameter and height. Obviously, it would be impractical to destructively sample all standing trees to estimate biomass within a given locality due to the negative environmental impacts and high cost of data collection (Henry et al. 2010). Hence, estimates of biomass within forest ecosystems at local and regional scales are conducted on the basis of selected surveys of forest inventories (national forest inventory, Kucera and Adolt 2019) and generalized allometric equations. In the Czech Republic, merchantable wood volume (measured in m^3) and AGB are estimated for individual regions and individual tree species (Norway spruce, Scots pine, other conifers, and deciduous trees) (Fig. 1). At the operational level of forest management, more robust but less accurate estimates of growing stock at stand level are used for forest management planning. Nevertheless, detailed (stand-level) mapping of forest biomass as a whole has not heretofore been utilized in Czech forest management.

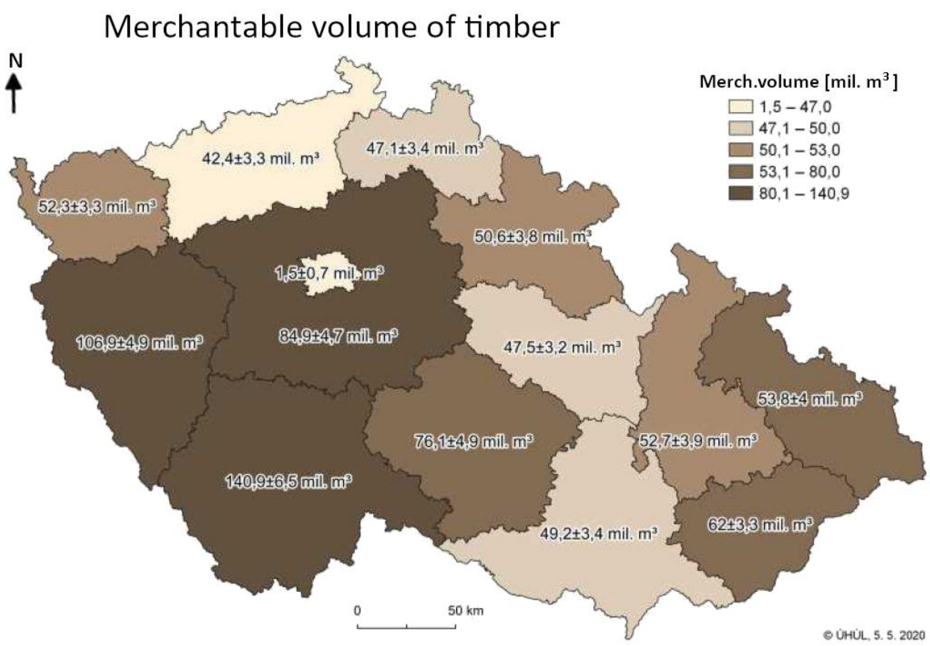


Figure 1. Estimated merchantable tree volume in the Czech Republic in 2019 (source: Forest Management Institute (FMI), http://www.uhul.cz/kdo-jsme/aktuality/974-zasoby-drivi-v-roce-2019).

Experience from abroad shows that airborne laser scanning (ALS) is a remote survey approach increasingly being used for both practical and theoretical forestry applications (Maltamo et al. 2014). In processing ALS data, forest AGB (and other characteristics) can be efficiently assessed and with accuracy and reliability comparable to those achieved by conventional field inventory methods (Melville et al. 2015, Noordermeer et al. 2019, Novotný et al. 2021). A so-called area-based approach (ABA) is most commonly used for modelling AGB using ALS (White et al. 2013, Brubaker et al. 2018, Pears et al. 2019, Davison et al. 2020). Described in the literature are numerous methods for analyzing the relationships between forest AGB and ALS metrics for various data acquisition conditions and scanning parameters, forest structures and types, ALS cloud point densities, and machine learning algorithms (Fig. 2).

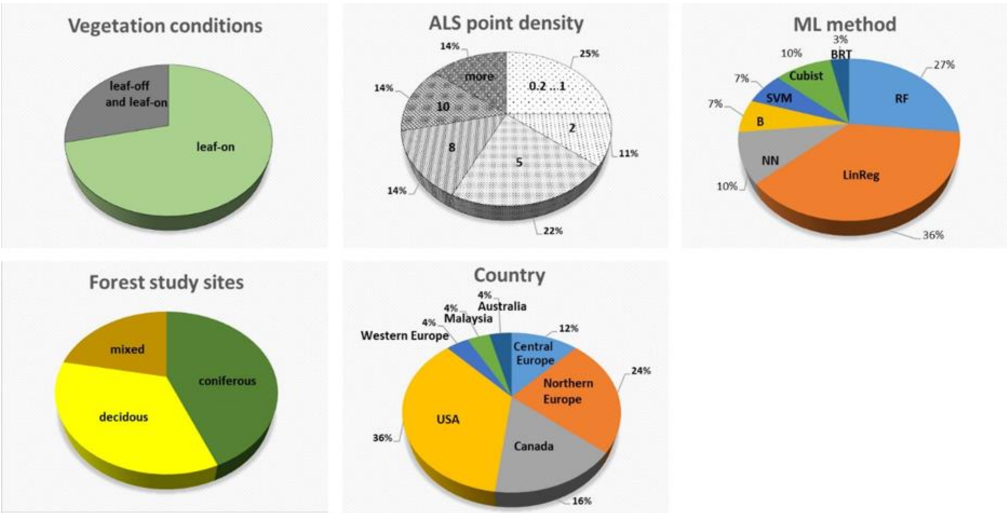


Figure 2. Summary of key characteristics from recent studies on estimating forest aboveground biomass (AGB) from airborne laser scanning (ALS) data using an area-based approach. B = Bayesian model, BRT = boosted regression trees, LinReg = linear regression, ML = machine learning, NN = neural network, RF = random forest, SVR = support vector regression, Cubist® = commercially available rule-based software (Walton 2008).

Although estimating AGB using ABAs and their application to forestry have been the subject of active research for more than three decades (Naesset 2002, Nelson 2013, White et al. 2017), the technology has been little operationalized heretofore within Central Europe’s forest sector compared with the experience in using the technology within forests in Scandinavia (e.g., Naesset 2005, Villika et al. 2012, Kankare et al. 2013, Bouvier 2015), Canada (e.g., White et al. 2015, Tompalski et al. 2019), and the U.S.A. (e.g., Anderson et al. 2013, Blackburn et al. 2021) (Fig. 2). Only a few studies have used ABAs for AGB assessment from ALS data in conditions of Central European forest (Patocka et al. 2016, Hawryto et al. 2017, Parkitna et al. 2021). A study by

Patocka et al. (2016) is the only one known to the authors to describe the application of ALS data for AGB assessment in the Czech Republic. Specific, practical recommendations are needed in order to apply an ABA for forest biomass modelling in the context of Czech Republic forest management, including those for setting ALS data acquisition parameters, season of data acquisition, field methods for collecting data and estimating AGB, as well as algorithms and modelling methods. These technologies are being utilized for purposes of answering the aforementioned questions, and they have been developed and verified for use in conditions of the Czech Republic and its forestry management.

3 Technology for forest aboveground biomass assessment using an area-based approach

The technology for forest AGB estimation consists in three fundamental stages: acquisition and preprocessing of airborne and field data, modelling of the biomass by the ABA, and validation of the resulting maps. Key subcomponents of a successful implementation are in particular to meet certain requirements from the viewpoints of input data quality, careful preparation of the training data set for modeling, and evaluating the plausibility of the model (Fig. 3).

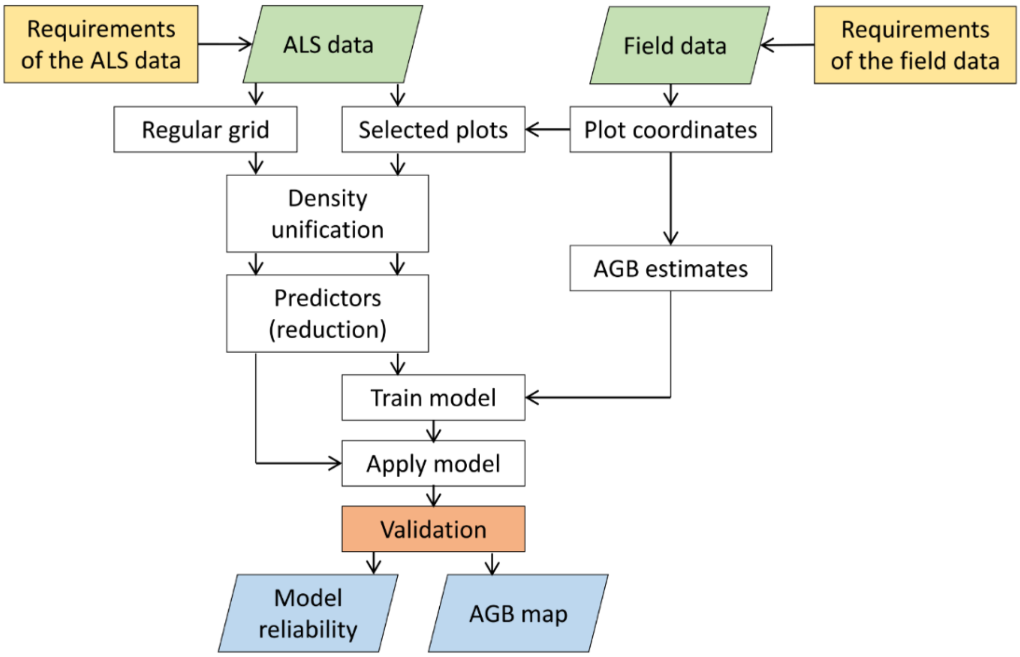


Figure 3. Scheme of technology for forest aboveground biomass (AGB) assessment.

3.1 Definition of the area-based approach

The basic principle behind the area-based approach (ABA) is that the 3D point cloud acquired by laser scanning contains information to characterize the ground surface and vegetation layers above that surface. The points representing vegetation and their heights are utilized to quantify specific metrics, among which include values for descriptive statistics (mean, percentile, and others) and values depending upon the density of the cloud with respect to crown-layer permeability. All of this information, in combination with field survey data concerning the explained variable (AGB), provides the basis for building prediction models (Naesset 2002, Vastaranta et al. 2013, Maltamo et al. 2014) (Fig. 4). The main benefit of this modelling from aerial data consists in large-area prediction that on the level of an entire forest stand is of greater quality than can be obtained by extrapolation from individual inventory plots measured by conventional stand-level sampling.

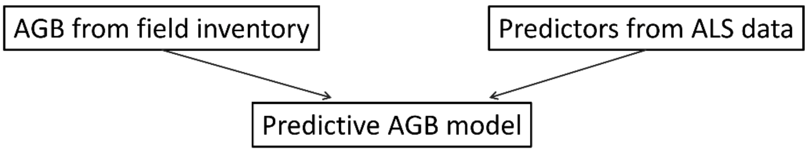


Figure 4. Main components of the area-based approach. AGB is forest aboveground biomass.

3.2 Airborne laser scanning data for the area-based approach

In this subsection, the usual parameters of point cloud data are discussed. The parameters are needed for the technological process and the individual steps of data preparation.

3.2.1 Point cloud parameters

A basic precondition for AGB estimation using the ABA is coverage of the area of interest by ALS. In accordance with the conclusions reached by Brovkina et al. (2022, under review) and other studies, an ideal ALS point density for this technology is approximately 7.5 points/m^2. Nevertheless, a sparser point density (2.5 or 5 points/m^2) does not much impair the model's quality and also can be used (Fig. 5).

Canopy conditions (leaf-on and leaf-off) have been shown to have no statistically significant impact on the strength of AGB models (Brovkina et al. 2022). Depending upon the species composition in the area of interest and the target quantity (i.e., merchantable wood volume vs. total aboveground biomass), however, it may be more appropriate to acquire data with or without leaves.

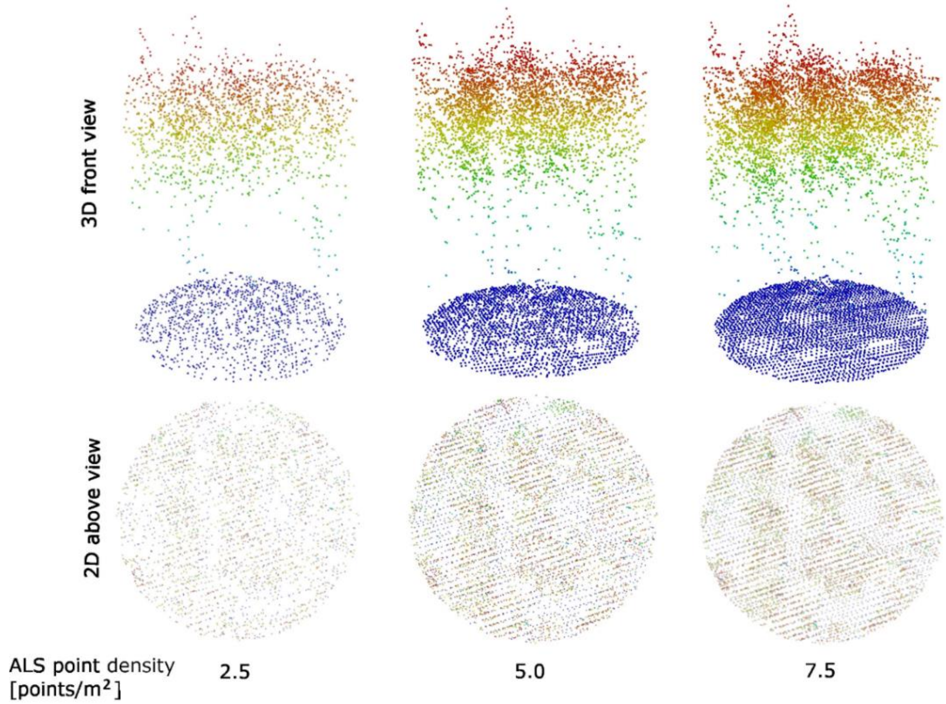


Figure 5. Cutout of a point cloud from airborne laser scanning data showing various point densities.

3.2.2 Preparation of airborne data for modeling

The first step in data processing is wave decomposition and geometric correction based upon the trajectory of the aircraft. This stage is specific to the type of device, and it is performed in software from the manufacturer of the laser scanner. The basic input for this technology is a point cloud of the entire area of interest in LAS format.

In the second step, the noise points (if any) are removed from the cloud, cloud points are classified as terrain, buildings, higher vegetation and others (or minimally as terrain and others) and the Z coordinate is recalculated from altitude above sea level to height above terrain. A number of algorithms and software solutions are available for use in this step, such as the LAStools (http://lastools.org/) script package. An example illustrating this part of the procedure is shown in Fig. 6.

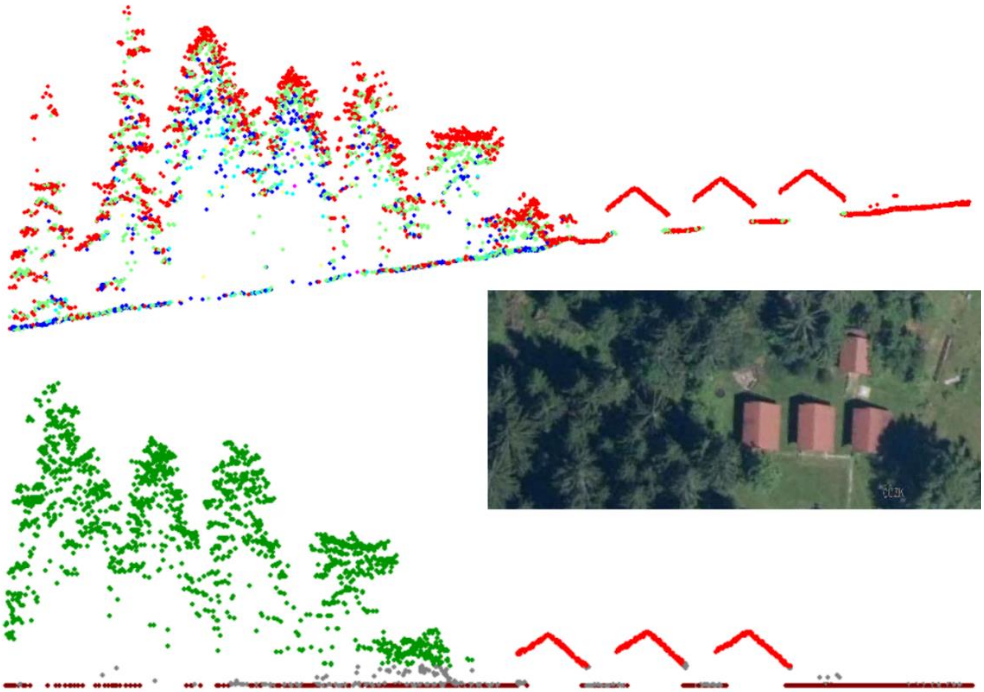


Figure 6. Illustration of point cloud classification and point cloud conversion to elevation. Shown at top is a section of the cloud in its original form, where the Z coordinate corresponds to altitude above sea level, and so we see that the forest and cottages stand on a slight slope. The points of the cloud are colored according to the order of reflection within one laser pulse. This emphasizes the fact that where the laser beam is reflected from solid surfaces (roof, meadow), it is reflected once; and in the forest stand, multiple reflections occur within one beam. In the lower part, the same section of the cloud is displayed after processing such that the Z coordinate corresponds to the height aboveground. Individual points are colored according to the classification into classes: brown = terrain, green = higher vegetation, red = buildings, gray = aboveground points unclassified.

The theoretical basis of the area-based approach is the relationship that exists between the value of the inventory quantity (AGB) and statistical quantities describing the structure of the forest by means of a point cloud. In the following text, we refer to these quantities as predictors.

Crucial for the model-training stage are the ground- (*in situ*-) determined biomass values that are tied to a particular place (according to X and Y coordinates) and its specific surroundings. In the following step, we assume that the basic unit of the field measurements and area-based approach is a circular area of 500 m^2. From a methodological point of view, however, the procedure can be easily be adapted to different but analogous unit sizes.

In applying the model, a regular point network of the selected spatial step (for example, 20 m) is most often used, where the coordinates of individual points play the same role as do the coordinates of the field plots in the training stage. In the steps described below, we do not distinguish between these two situations.

We draw a circular buffer with 12.61 m radius around the X-Y coordinates and select from the point cloud a subset of points that lie inside. An example of the sub-cloud thus obtained is shown in Fig. 5.

Usually, density of the point cloud is not homogeneous in the coverage of a larger area of interest by a mosaic of individual flight lines. To avoid introducing inhomogeneity also into the calculated predictors, it is recommended to unify the density on the sub-cloud sections. This can be done by randomly dropping a suitable number of points from the cloud so that the number of so-called first reflections (which correspond to the number of transmitted laser pulses) is the same for all sub-clouds. (For example, 2500, which corresponds to a density of 5 pulses/m^2 for a circle of 500 m^2.) The sub-cloud points (with or without density unification) comprise the input for calculating the predictors. An example illustrating this part of the procedure is shown in Fig. 7.

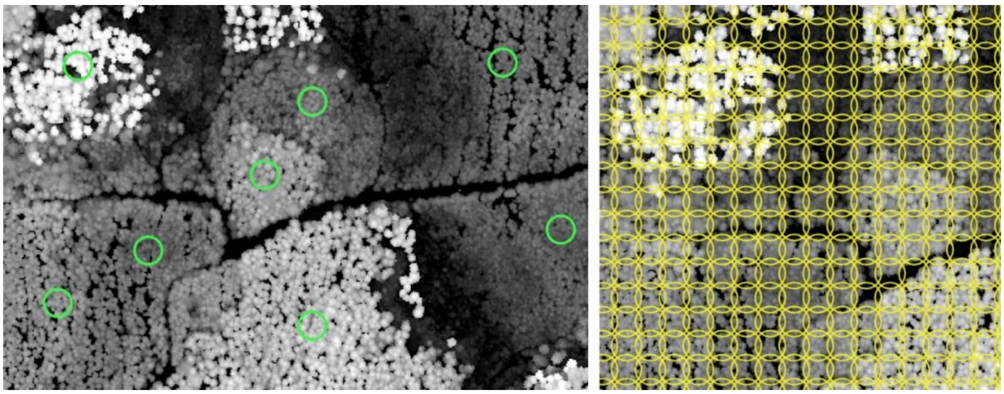


Figure 7. Illustration of the arrangement of the sub-clouds within the point cloud for the training stage (left) and for the application stage (right). The marked circles have an area of 500 m^2. They are distributed in a regular network with a step of 20 m in the application stage.

The available literature about ABAs recommends a number of statistical quantities characterizing the point (sub-) cloud and its structure and which are related to AGB. The point cloud is perceived as a set of statistical values representing height of individual points above the terrain. Above this are calculated the position's characteristics (mean, median, quantiles) and variability characteristics (standard deviation and higher statistical moments). The specifics of laser scanning of forest are then the permeability characteristics most often calculated as the ratio of the number of points under a certain height versus the total number of all points.

The part of the point cloud corresponding to the target quantity (AGB) usually enters the calculation described above. This can be, for example, all points classified as aboveground or all points whose Z coordinates (heights) exceed a specified minimum threshold (for example 1.3 m).

All calculated predictors are paired with the ground value of the target quantity for the training stage. They enter the machine learning process described in subsection 3.4. The specific issue of reducing the number of predictors is addressed in paragraph 3.4.1. For the model application stage, the relevant predictors are the input from which the target quantity for each node of the regular network is calculated.

Classification of the point cloud into individual classes was mentioned at the beginning of this subsection. (See also Fig. 6) Terrain class points are a prerequisite for calculating height aboveground. The classification of other classes (higher vegetation and buildings) can (but need not) be used as ancillary information, when, for example, only higher vegetation class points are taken into calculating predictors or, on the contrary, when nodes of the regular network in the vicinity classified as buildings occur in numbers exceeding a set limit are excluded from the modeling because they do not represent forest.

3.3 Type of field data for the area-based approach

The measured field data serve as calibration and validation material for estimates of AGB using Earth remote sensing products. For the quantification of AGB, conventional statistical forest inventory procedures are used that are based upon area extrapolation of data from a network of inventory plots (Tomppo et al. 2010). Inventory plots can have different shapes and arrangements, the most common being circular concentric plots (see below). Such plots are used in national forest ecosystem inventories in countries within the boreal, temperate, and tropical vegetation zones (Tomppo et al. 2010). AGB cannot be measured directly. It is quantified based upon measurable data for forest stands that are entered into empirical models for quantifying volume of merchantable wood or AGB directly and their individual components. The target product is the AGB value expressed per unit area, most typically in tons of dry matter per hectare. Somogyi et al. (2007) discuss in detail the alternative methods for quantifying aboveground biomass according to the type of input data.

The actual data collection in the field is by common forestry methods using modern measurement technology. Field-Map technology is a suitable tool for comprehensive collection and evaluation of forest inventory data (e.g., Cienciala et al. 2017, www.field-map.com). The circular plots should be distributed across the area of interest so that the result is a statistically representative random sample. The area can be stratified according to age classes or forest type and thus achieve a more even coverage of the range of stand types. Existing permanent inventory plots may be used or temporary plots may be established.

3.3.1 Shape and size of inventory plots

All inventory plots have a circular shape with radius r = 12.62 m (500 m^2). To optimize the field survey, a concentric circle with radius 7 m is used to measure smaller trees with diameter at breast height (DBH) of 7 cm and more. Trees with DBH of 12 cm and more are then measured over the entire area.

To measure tree regeneration (trees from height of 0.1 m and DBH up to 6.9 cm), a circle with radius of 2 m is used, located 7 m north of the center of the area (Fig. 8). Due to its negligible quantitative contribution, forest regeneration is often neglected for verification and validation of AGB data using remote sensing products, but it is important information regarding ecosystem dynamics and for forestry practice.

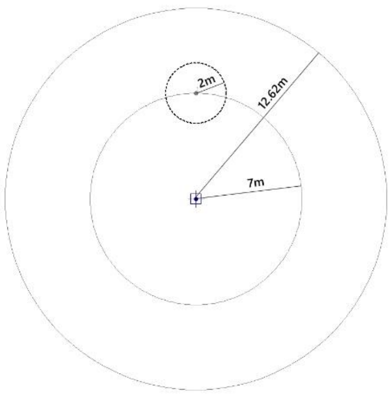


Figure 8. Scheme of an inventory plot with concentric circles.

The practical procedure for establishing and measuring the inventory plot consists of several consecutive steps (Table 1). The first step is to find and secure the center of the inventory plot. This is followed by description of the area, measurement, and description of individual objects. All measured and descriptive data are sent and written to the Field-Map Data Collector. To increase the quality of data, an essential activity before leaving the inventory plot is carefully to check the data for completeness of the database and, graphically, the tree heights.

Table 1. Steps for establishing and measuring an inventory plot.

Activity
Identifying inventory plot center
Securing inventory plot center
Tree measurement and description
Description of tree regeneration
Checking the database

<u>Identifying the center of an inventory plot</u>

GNSS (Global Navigation Satellite System) satellite navigation is used when searching for the center of the inventory plot. Under the canopy, where the accuracy GNSS is lower, it is possible to use laser rangefinder navigation, which utilizes in addition an electronic compass. Existing maps and aerial photographs will be used to navigate close to the inventory plot.

<u>Securing the center of an inventory plot</u>

The center of each inventory plot must be secured in the field so that it can be traced back (in repeated or control surveys). To do this, so-called marked points are used. These points lie outside the inventory plot, and are precisely established from the center of the plot. By measuring back from the marked point, it is possible to trace the original center of the plot quickly and accurately. Trees that are significant in the stand (e.g., under-represented tree species and dominant trees) are most often used as marked points. The marked point is highlighted in the field in ecological color (in the case of a tree, at eye level and on any elevated tree roots).

<u>Describing basic characteristics of the inventory plot</u>

The basic characteristics of an inventory plot are included in the layer “Plot” (Table 2).

Table 2. Attributes of the "Plot" layer.

Attribute	Field type	Unit
Identification number	number	-
Coordinates of the plot center	number	m
Magnetic declination	number	degrees
Date of measurements	date	-
Responsible worker	text	-
Note	text	-

3.3.2 Tree measurement and description

All measurements and descriptions will be made only on those trees having the centers of their trunks at breast height within the inventory plot at the time of the survey and whose DBH values exceed the limit set for measurements within the individual inventory circles (Table 3).

Table 3. Parameters of inventory plots.

Radius of inventory plot circle (m)	Area of inventory plot circle (m^2)	Tree DBH measured within individual inventory circles
2.00	12.6	Trees from height 0.1 m up to DBH 6.9 cm over bark (tree regeneration)
7.00	153.9	Trees with DBH $\geq$ 7.0 cm over bark
12.62	500.0	Trees with DBH $\geq$ 12.0 cm over bark

Following the principle of using inventory circles contributes to significant time savings during field survey. This arrangement ensures that the features from trees of all sizes identified in the plot are examined, but, at the same time, the laborious effort of measuring small trees and regeneration is significantly reduced. The size of concentric circles can be adjusted and applied accordingly for conversions to the total plot size.

The parameters included in Table 4 are measured and/or recorded for all trees with DBH at least 7 cm.

Table 4. Attributes of the “Tree” layer.

Attribute	Field type	Unit	Assessed yes or no	
			Living tree	Standing dead tree
ID number of tree	number	-	yes	yes
Tree coordinates (X, Y, (Z) or polar coordinate)	number	m	yes	yes
DBH – diameter at breast height	number	mm	yes	yes
Tree height*	number	m	yes	no
Tree species	look-up list	-	yes	yes
Tree age	number	years	yes	yes
Double-stemmed tree	look-up list	-	yes	no
Standing dead tree	look-up list	-	yes	yes
Tree break	look-up list	-	yes	no

**Only for selected sample trees.*

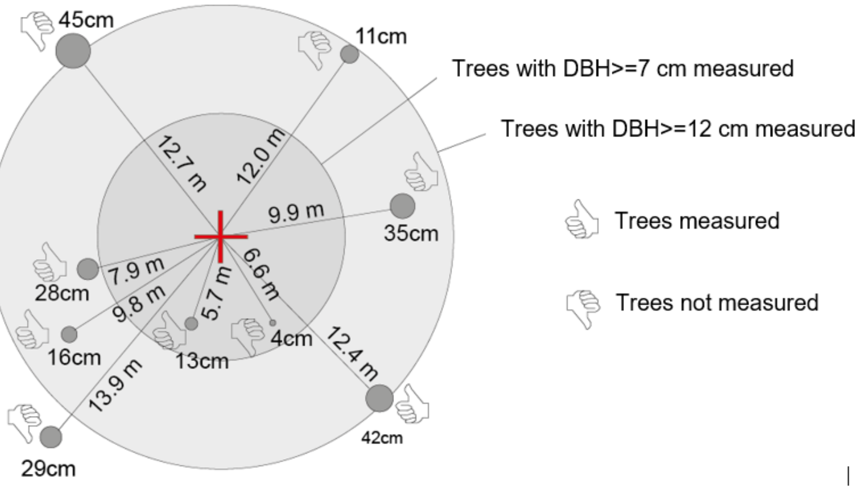


Figure 9. Measurement of tree positions within an inventory plot, with an example of rules for including trees according to their positions in the plot and DBH

Technologies and technical procedures for measuring the attributes of surveyed trees in the inventory plots are based upon methodological standards for measuring forest inventory (Černý et al. 2010).

3.3.3 Description of tree regeneration (if included in the methodology requirements)

Tree regeneration within the so-called regeneration circle (r = 2.0 m with an area of 12.57 m^2) is evaluated on each plot. Because in mapping and measuring large trees the workers are moving about more in the center of the inventory plot, the regeneration circle is situated 7 m north of the plot center. Regeneration assessment applies to all individuals of tree vegetation from a height of 0.1 m to trees with DBH up to 6.9 cm over bark.

If there is no tree individual from the height of 0.1 m up to DBH of 6.9 cm within the regeneration circle, then regeneration is not evaluated in the area, even if individuals of these dimensions are in the immediate vicinity of the regeneration circle.

The basis for evaluating tree regeneration is classification of the individuals into so-called regeneration height classes, which are defined by the height of the trees and tree species. The number of individuals in the class, tree species, age, average DBH, and average height are then determined for individual restoration classes.

Table 5. Attributes of the "Regeneration" layer.

Attribute	Field type	Unit
Regeneration height class	look-up list	-
Tree species	look-up list	-
Number of trees	number	n
Average tree age	number	years
Mean DBH	number	cm
Mean tree height	number	m

The regeneration individuals of each tree species that are within the regeneration circle are included into the following height classes according to their heights to monitor the regeneration parameters:

1. Tree height from 0.1 m to 0.5 m
2. Tree height from 0.5 m to 1.3 m
3. Tree height from 1.3 m to DBH of 6.9 cm over bark

3.3.4 Measurement evaluation and biomass estimation

Data collection in the field is followed by data evaluation for individual inventory plots. Inventory Analyst, which is a part of the Field-Map technology (www.field-map.com), can be a suitable tool for evaluating the collected data.

For biomass calculations, it is necessary to know DBH and height for all included trees. Because height measurement is limited to sample trees only, it is necessary to calculate the model height applicable for all trees. An example is the parameterization of the exponential model in the elevation chart (Fig. 10). The most accurate result is achieved by parameterizing the height model at the level of a tree species group and individual inventory plots.

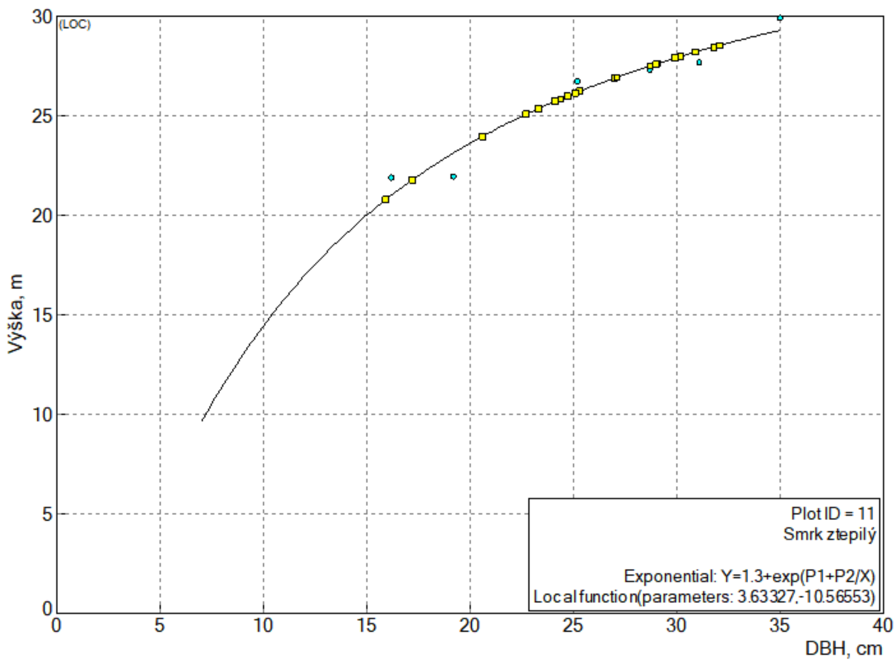


Figure 10. Example of tree height model and parameters of exponential curve. Blue points: heights measured in the field, yellow points: estimated model heights. Y-axis: tree height (Výška).

The next step is to calculate AGB according to published allometric equations (Table 6) using the measured DBH and the calculated model height. For the recorded trees with DBH of 7–12 cm from a partial plot area (concentric circle, Fig. 2) it is necessary to use an expansion factor, which converts to the entire area of the inventory plot according to the ratio of the area of concentric circles. Specifically, 153.94 m^2/500 m^2 = 3.25.

Table 6. Reference allometric equation for biomass estimation by tree species groups.

Tree species (group)	Reference
Spruce (all species)	Vonderach et al. 2018
Silver Fir	Vonderach et al. 2018
Douglas Fir	Vonderach et al. 2018
Pine (all species)	Cienciala et al. 2006
Larch	Wirth et al. 2004
Oak (all species)	Cienciala et al. 2008
English maple	Vonderach et al. 2018

Tree species (group)	Reference
Ash	Vonderach et al. 2018
Birch	Bronisz et al. 2016
Linden	Čihák et al. 2014
Alder	Johansson 2000
Beech and other broadleaves	Wutzler et al. 2008

Aboveground biomass of trees with stem and crown breaks must be reduced by an appropriate coefficient according to their heights. By summing the biomass values of all tree species in the inventory plot, it is thus possible to obtain a total AGB for the entire circular plot of 500 m^2. For subsequent calibration and verification with remote sensing products, and according to the focus of the study and statistical requirements of calibration and/or verification, specific selection of a set of measured data for AGB of individual inventory areas is used.

3.4 Biomass modeling with machine learning

Spatial information from the point cloud enters the modeling process by means of calculated statistical quantities, known as predictors, the combination of which always corresponds to the biomass value determined according to the field survey.

3.4.1 Reducing the number of predictors

The modeling process itself is preceded by a stage that should reduce the number of predictors that enter into the modeling. This is done to preserve or strengthen the predictive power of the model by removing redundant or less useful information with respect to the explained quantity. Thresholding can be performed on the basis of mutual correlation to maintain the maximum possible independence of the predictors from one another. Methods based upon recursive selection also can be used, as can be ordering of individual predictors according to their common F-values. The selection of input predictors should be independent of which machine learning algorithm is used in the training.

3.4.2 Data set stratification

Generally, a train-and-test approach is advantageously used for such modeling. The data set is split into a training subset and a testing subset. This splitting intentionally narrows the data set to train the model and provides for independently assessing the model's success on data that is completely outside the training process.

A random stratified distribution with respect to the explained variable is carried out in order to have the most representative data set in both training and testing subsets. It is appropriate to consider species composition as a possible predictor to ensure that no training includes only one type of forest. This is done at both the level of basic classification (for example, deciduous / coniferous / mixed) and level of the predominant species (for example, spruce). Another forest inventory parameter that is used for stratification is stand age. It is recommended to adjust stratification to local forest characteristics, such as to reflect into it factors that we can expect might have influence upon the explained variable.

It is important to split the data set into modeling sets several times to assess the influence of specific distribution on the resulting prediction and, if necessary, to remove a model that has not been able to capture and appropriately predict its given set.

3.4.3 Machine learning process

A parametric or nonparametric approach can be used for the modeling. The parametric approach is more appropriate from the viewpoint of interpretating and understanding the basic relationship between the explained variable and the given predictors, but it is more demanding in relation to input data. The use of nonparametric methods, which usually achieve greater prediction accuracy, is less demanding in its input needs but provides poorer interpretability. In this case, there is also the possibility to enter combinations of both continuous and categorical variables into the learning process.

When using machine learning methods in the training process, one can rely on the default internal settings of the method parameters, select some specific settings, or determine a set of permissible values for individual so-called hyperparameters of the model and to allow the model itself to choose the optimal settings of these parameters with respect to the training set.

3.4.4 Best model selection and its application

A set of potential predictions was obtained from one method. The set size was determined by the number of considered divisions per train-and-test subset. To select the best prediction from the set, some criterion or point evaluation of the model is needed. Recent literature suggests the most commonly used evaluations are based upon R^2, root mean square error (RMSE), bias, or possibly their relative form. Our findings suggest to use a more complex evaluation of model suitability, which is determined by the sum of partial point-rated characteristics. The limits for the point evaluation of individual characteristics or threshold values should be defined as objectively as possible using, for example, quantiles of point-rated characteristics. The mean of several so-called “best” models (we usually use 10 models) is assigned as the resulting prediction. Individual models can be similar in terms of point evaluation, and their predictive ability can vary depending on the forest stand type. This multi-model prediction approach allows an overview as to within which areas the deviation between models may be greater when comparing the map of differences between individual model predictions and the resulting map.

By “applying the model” we understand the biomass values calculation based upon predictors in a regular point network that essentially could have any spatial resolution. See also interpretation and examples in the final paragraph of subsection 3.2.2. One selected model or several models can be applied. In the second case, it is possible also to generate a standard deviation map of the submodels, which approximates the uncertainty. Concrete examples are presented in Section 4.

4 Testing the technology

The models for estimating biomass were developed primarily within forest plots in the Silesian Beskids, where work was ongoing for project QK1910150. The technology was subsequently verified on forest plots in the vicinity of the town of Ždírec nad Doubravou managed by the company Stora Enso (https://www.storaenso.com/cs-cz/).

4.1 Silesian Beskids forest site

The study site is situated within the Czech Republic part of the Silesian Beskids (49.6°N, 18.8°E) along the eastern border of the Czech Republic at altitudes between 500 and 900 m a.s.l. (Fig. 11). The studied temperate mixed forest stands spread across ca 4,000 ha were dominated by Norway spruce

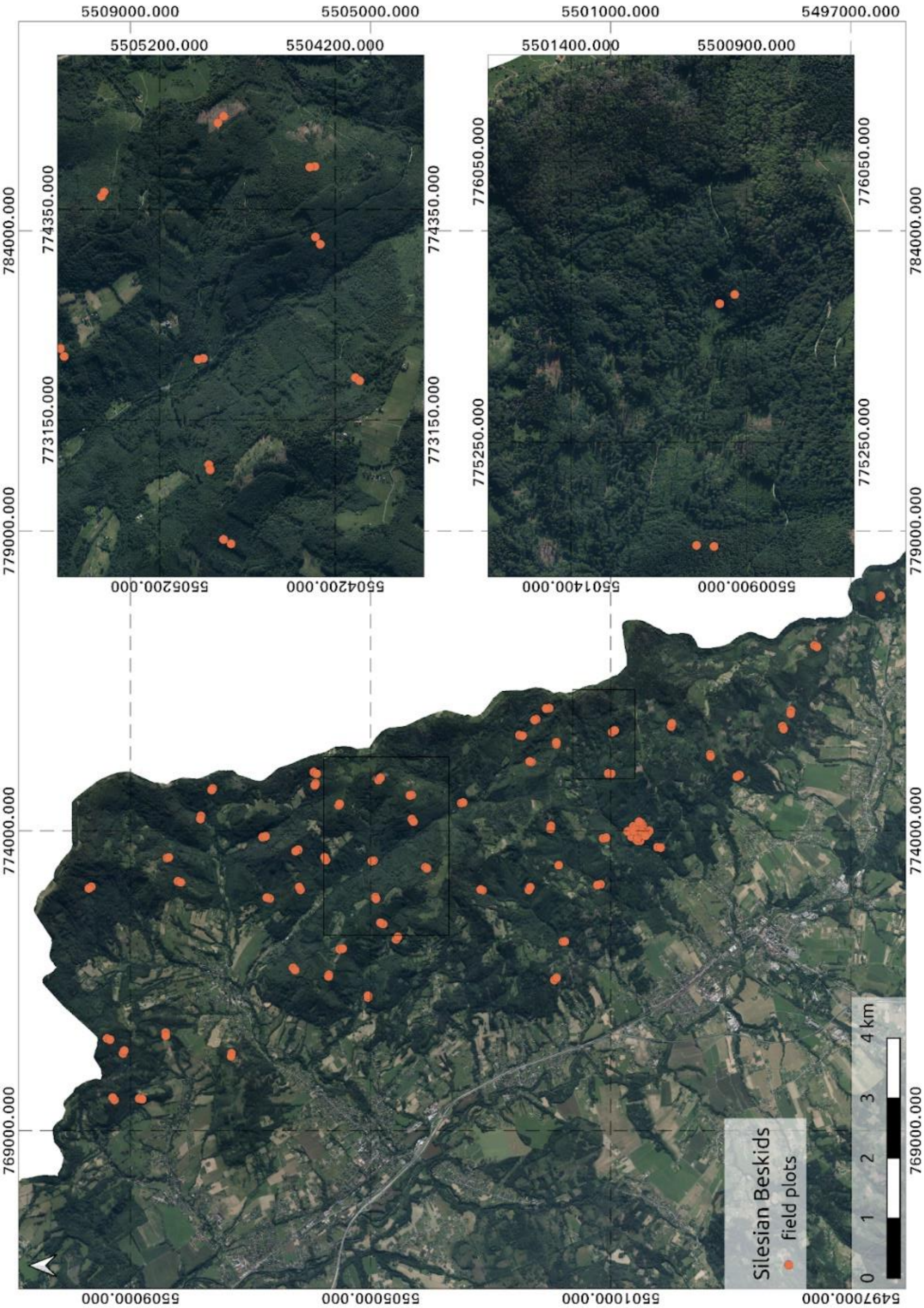


Figure 11. Field survey plots in Silesian Beskids (Map background: Orthophoto TopGIS).

(*Picea abies* (L.) H. Karst) and European beech (*Fagus sylvatica* L.) accompanied sparsely by silver fir (*Abies* alba Mill.), sycamore (*Acer pseudoplatanus* L.), Scots pine (*Pinus sylvestris* L.), European ash (*Fraxinus excelsior* L.), and silver birch (*Betula pendula* Roth). Interspersed were also less common forest species.

Field data on trees and their biomass were collected during the vegetation season in July 2019 on 109 sample plots using Field-Map technology (www.fieldmap.cz) as described in subsection 3.3. Model tree height was calculated for all trees based upon measured sample heights fitting an exponential function. AGB was estimated at tree level based upon DBH and model tree height using published allometry equations (Wirth et al. 2004, Cienciala et al. 2006, 2008, Wutzler et al. 2008, Vonderach et al. 2018).

The ALS data were acquired on 26 July in 2019 using the airborne RIEGL LMS-Q780 scanning system. The average flying altitude was 410 m above ground level. Together with a pulse repetition of 400 kHz, these acquisition parameters yielded a point density of up to 15 points/m^2. Preprocessing of the raw ALS data included the steps described in 3.2.2.

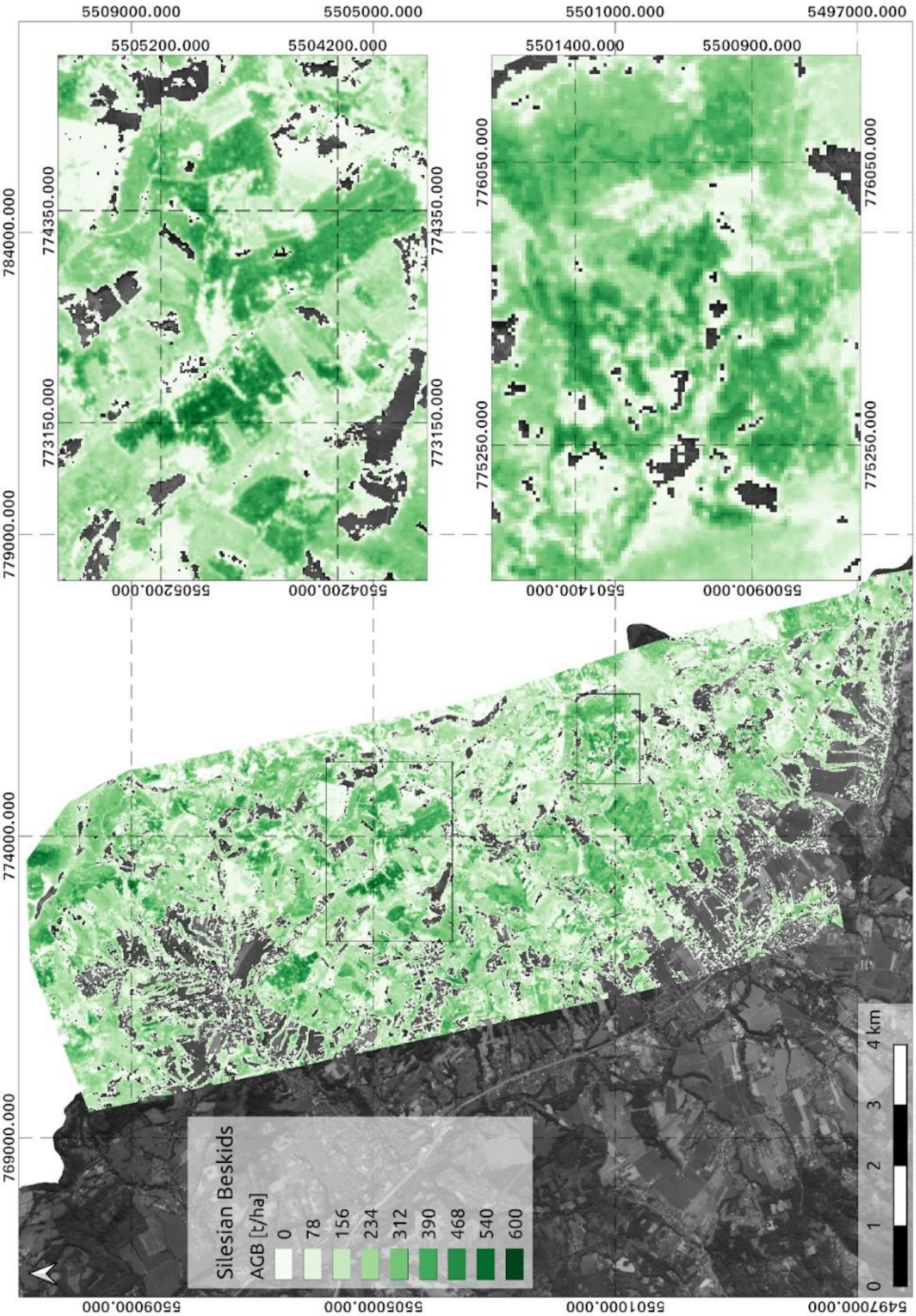
Three methods were chosen for eliminating predictors. The first of the methods arranged the individual predictors according to their common F-values. A fixed number of predictors with the best ratings were selected. The second method used recursive selection with cross-validation, where assessment was based upon the support vector machine method with a linear core. The minimum number of predictors was four. The third method used correlation with the explained variable. Seven predictors were obtained: mean tree height and quantiles Q30 and Q70 for points aboveground; for points with a threshold of 2 m standard deviation of height, slope, permeability P40, and crown coverage area. The selection of input predictors was independent of the machine learning algorithm used in the training.

The train-and-test approach was used for modeling. The data set was stratified into a training set (75%) and a testing part (25%). Stratification considered the type and distribution of forest. According to the relative proportion of conifers in the measured area, we distinguished three types of forest stand: ≥0.65 coniferous, ≤0.35 deciduous, the remainder was considered a mixed area.

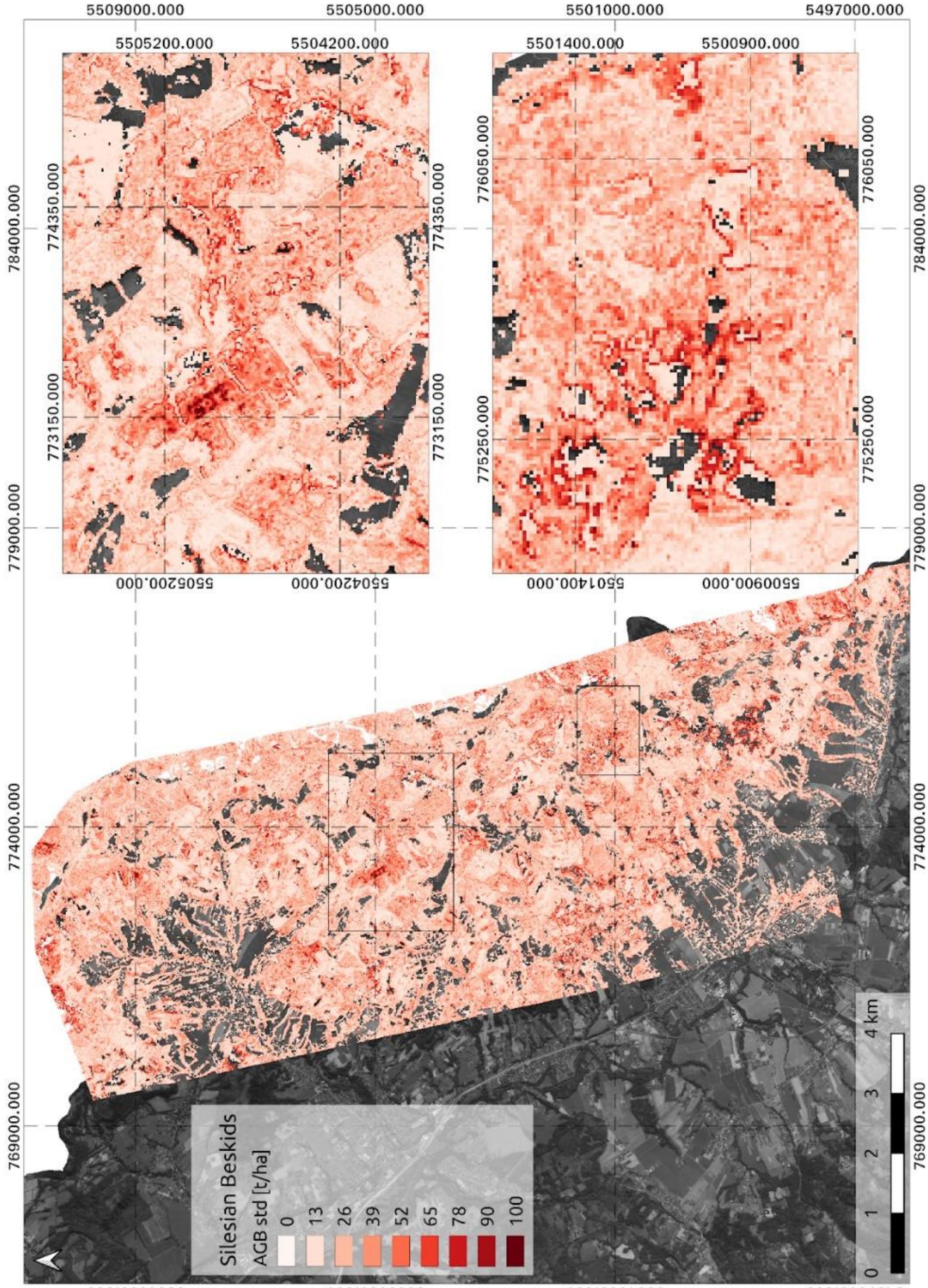
The modeling was performed in a Python environment using the scikit-learn library (cite: Scikit-learn: Machine Learning in Python, Pedregosa et al., JMLR 12, pp. 2825-2830, 2011.). Optimal setting of the hyperparameters of the methods used was done with the GridSearchCV function. The Random Forest and Multi-layer Perceptron methods showed good predictive power.

Best models were selected on the basis of several characteristics: R^2, RMSE, and the so-called Class score and Regression score. The Class score evaluated deviation from the field survey data. If the deviation was less than 25 t/ha, the estimate was graded with a score of three points. The score was one point less with each additional 25 t/ha. The resulting Class score was the mean of the individual evaluations. The Regression score evaluated susceptibility of the model to values discretization and linked the number of unique predictors and field data. To avoid overtraining of the model, $R^2 = 1$ of the training set was not allowed. The minimum (maximum) value of individual characteristics was determined on the basis of Q75 of each quantity. The resulting set of models was in descending order with respect to the Class score, then to R^2, and ascending to RMSE. The first 10 models were declared to be the best ones. The model was characterized by $R^2 = 0.87$ at the level of the training set, $R^2 = 0.85$ at the level of the test set, and was considered as a balanced model capable to predict the given area with a given accuracy. Also, the final model was characterized by RMSE = 53.95 t/ha and Class score = 1.94. Based upon the Regression score, the model could be declared not prone to discretization of the prediction.

For the Silesian Beskids site, a set of predictors was calculated in a regular grid with a spatial resolution of 10 m. The best 10 models were applied. In case of negative prediction value, that value was set to zero. The resulting map was a mean prediction from all those models applied. The standard deviation of the resulting product illustrated which parts were more prone to greater inaccuracy and where, on the contrary, the selected models almost matched. From Fig. 12b it is apparent that in our case, the model weakness was in the transitional parts of the forest – from the lower forest stands to the higher or perhaps marginal forest. The deviation for higher vegetation was within the RMSE of the model.

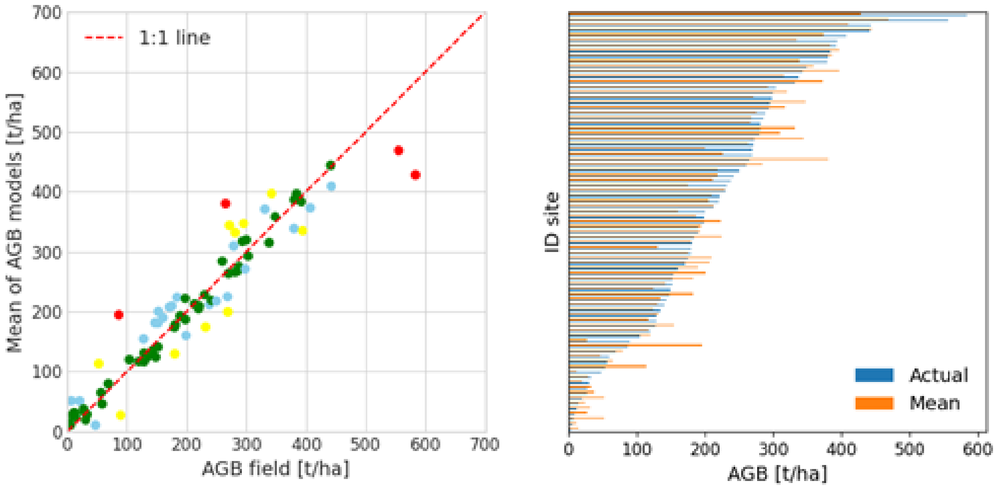

Silesian Beskids
AGB [t/ha]
0
78
156
234
312
390
468
540
600
0
1
2
3
4 km
5509000.000
5505000.000
5501000.000
5497000.000
769000.000
774000.000
779000.000
784000.000
5505200.000
5504200.000
5501400.000
5500900.000
773150.000
774350.000
775250.000
776050.000

a)



Silesian Beskids
AGB std [t/ha]
0
13
26
39
52
65
78
90
100
0 1 2 3 4 km
5509000.000
5505000.000
5501000.000
5497000.000
769000.000
774000.000
779000.000
784000.000
5505200.000
5504200.000
774350.000
773150.000
5501400.000
5500900.000
776050.000
775250.000

b)



c)

Figure 12. Aboveground biomass (AGB) map (a), map showing standard deviation of the submodels (b), and visualization of biomass model performance (c) at the Silesian Beskids study site. Scatter plot scale is colorized according to differences in AGB estimates between field survey AGB and modeled AGB: green is difference ≤25 t/ha, blue is difference of 25–50 t/ha, yellow is difference of 50–75 t/ha, and red is difference >75 t/ha.

4.2 Ždírec nad Doubravou forest site

To verify the model built in 4.1 and the technology as a whole (Fig. 3) a private forest property at Ždírec nad Doubravou was chosen. The forest site has an area of 168 ha and is situated where the Bohemian–Moravian Highlands meet the Iron Mountains (Fig. 13).

Field data were collected during the vegetation season in October 2021 using Field-Map technology (www.fieldmap.cz) as described in 3.3. Fifteen subplots were visited, where 454 trees and 137 heights were measured. These were mainly coniferous stands in which spruce predominated and the merchantable volume on the plots ranged from 0 to 628 t.

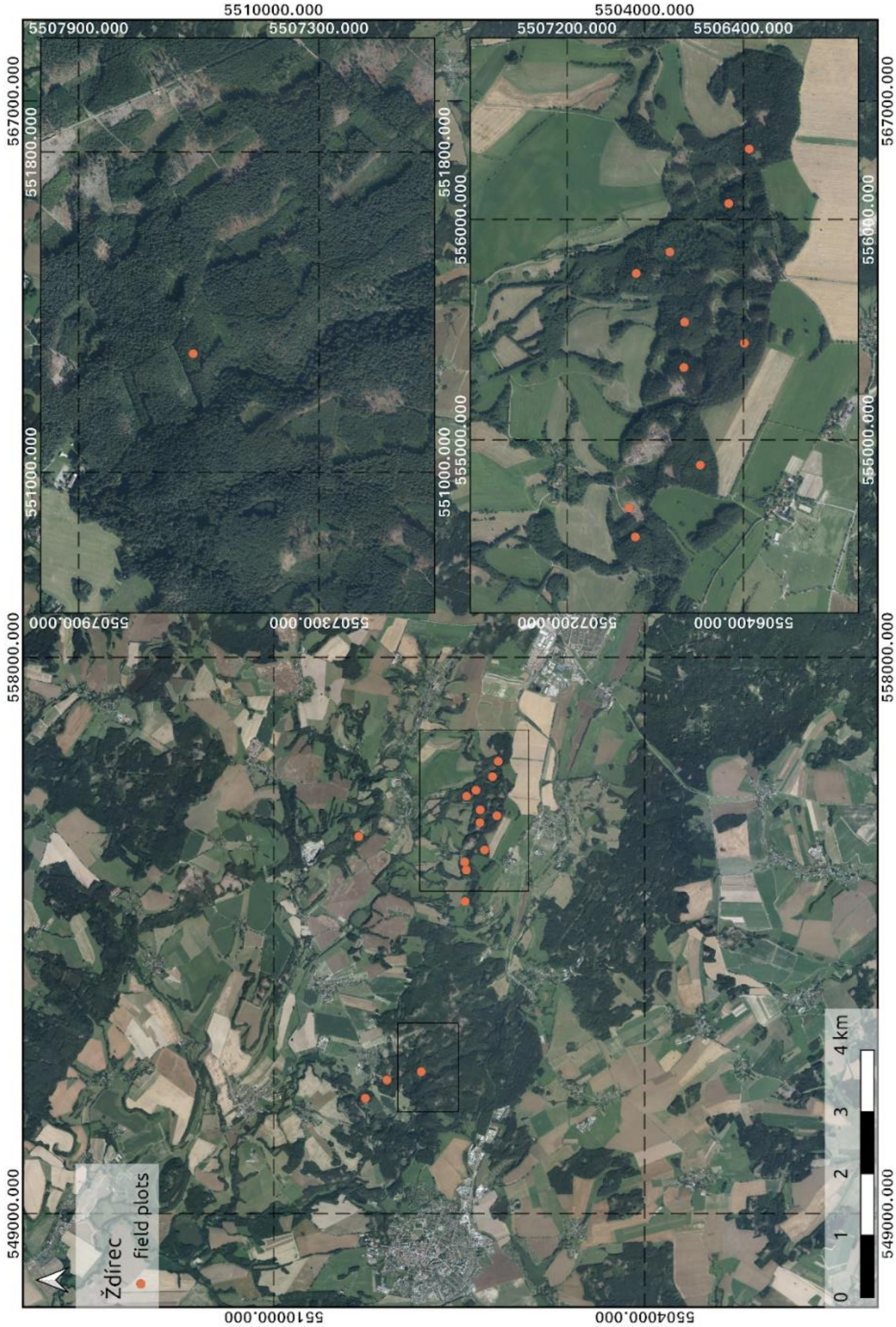
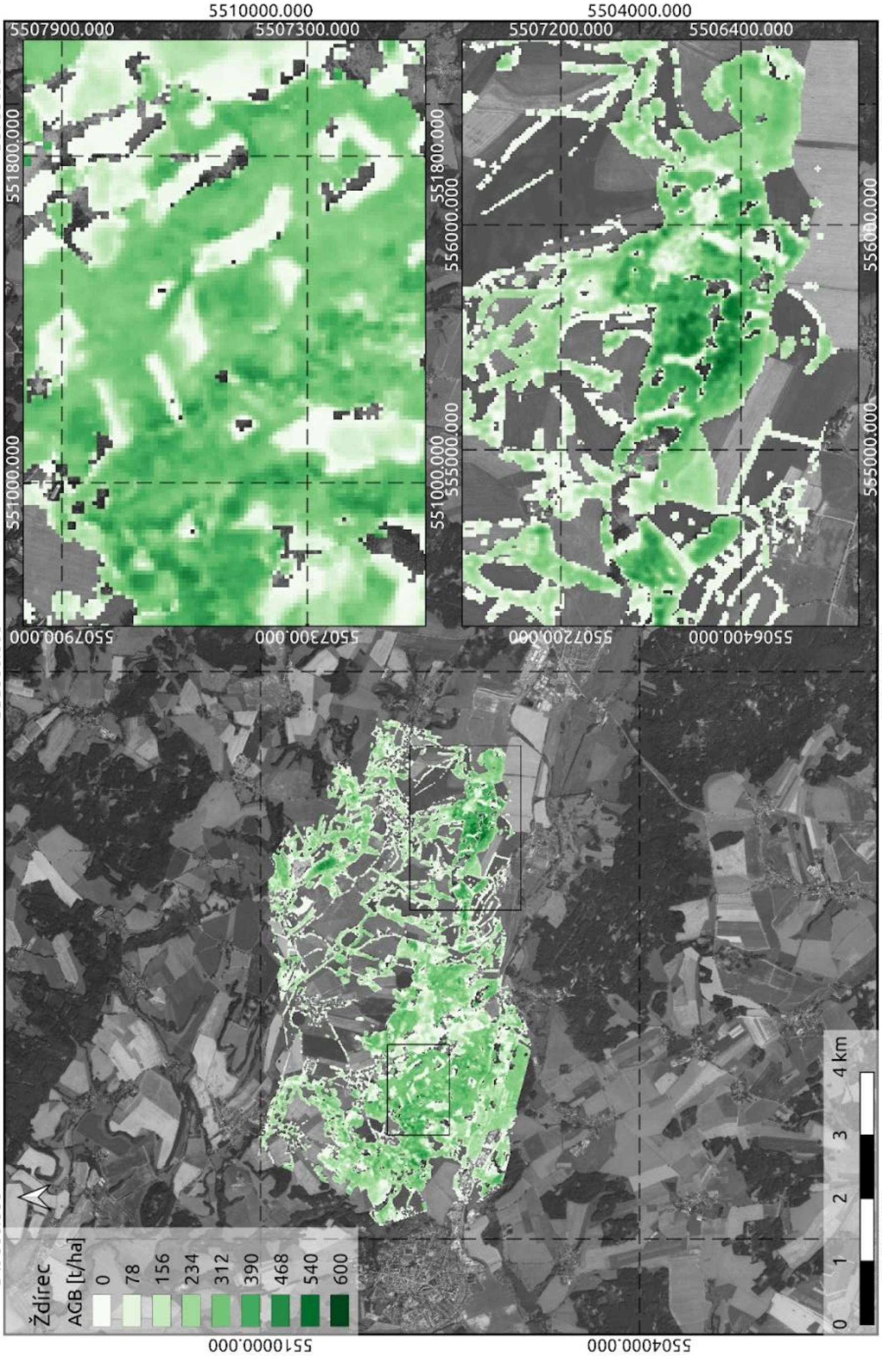


Figure 13. Field survey plots near Ždírec nad Doubravou (Map background: Orthophoto TopGIS).

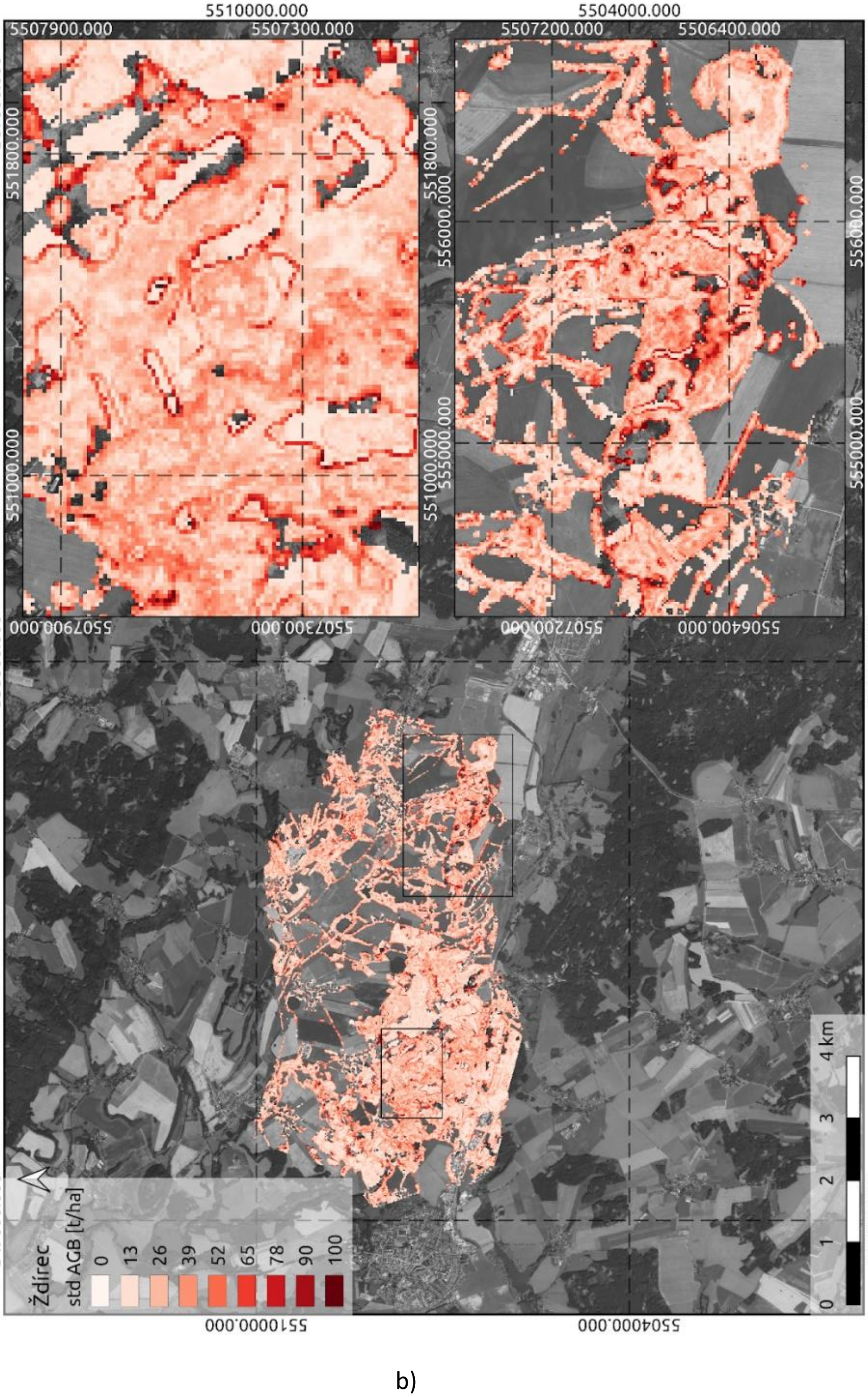
The ALS data were acquired on 1 October in 2021 (Fig. 14), using the airborne RIEGL LMS-Q780 scanning system. The average flying altitude was 500 m above ground level. Together with a pulse repetition of 400 kHz, these acquisition parameters yielded a point density of up to 15 points/m^2. Preprocessing of the raw ALS data included the steps described in 3.2.2.

Figure 14. Layout of airborne flight lines for laser scanning data collection at the Ždírec nad Doubravou forest site (Map background: Mapy.cz, ©Seznam.cz, ©TopGis).

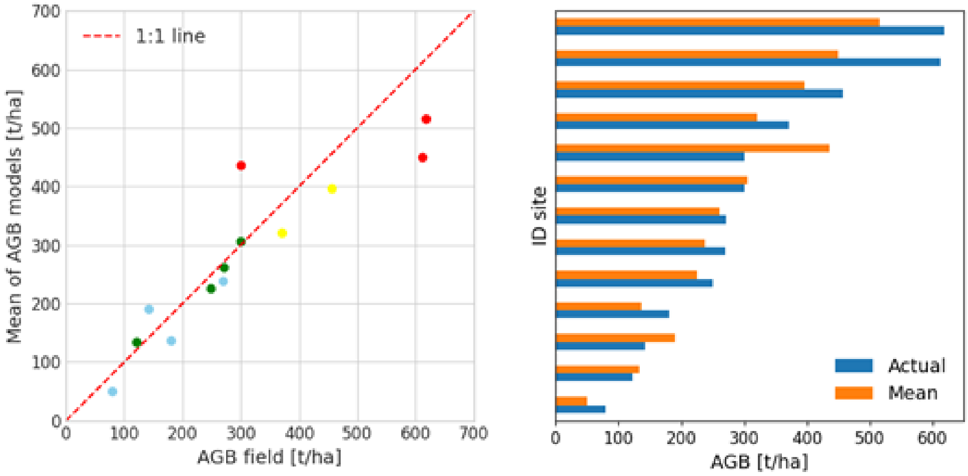
The model developed for the Silesian Beskids forest site (4.1) was applied to produce the biomass map for the Ždírec nad Doubravou forest site. The final AGB map was characterized with RMSE = 165 [t/ha] and R^2 = 0.7 (Fig. 15).



a)


Ždírec
std AGB [t/ha]
0
13
26
39
52
65
78
90
100
0
1
2
3
4 km
5510000.000
5504000.000
5507900.000
5507300.000
5507200.000
5506400.000
567000.000
558000.000
549000.000
551800.000
551000.000
556000.000
555000.000

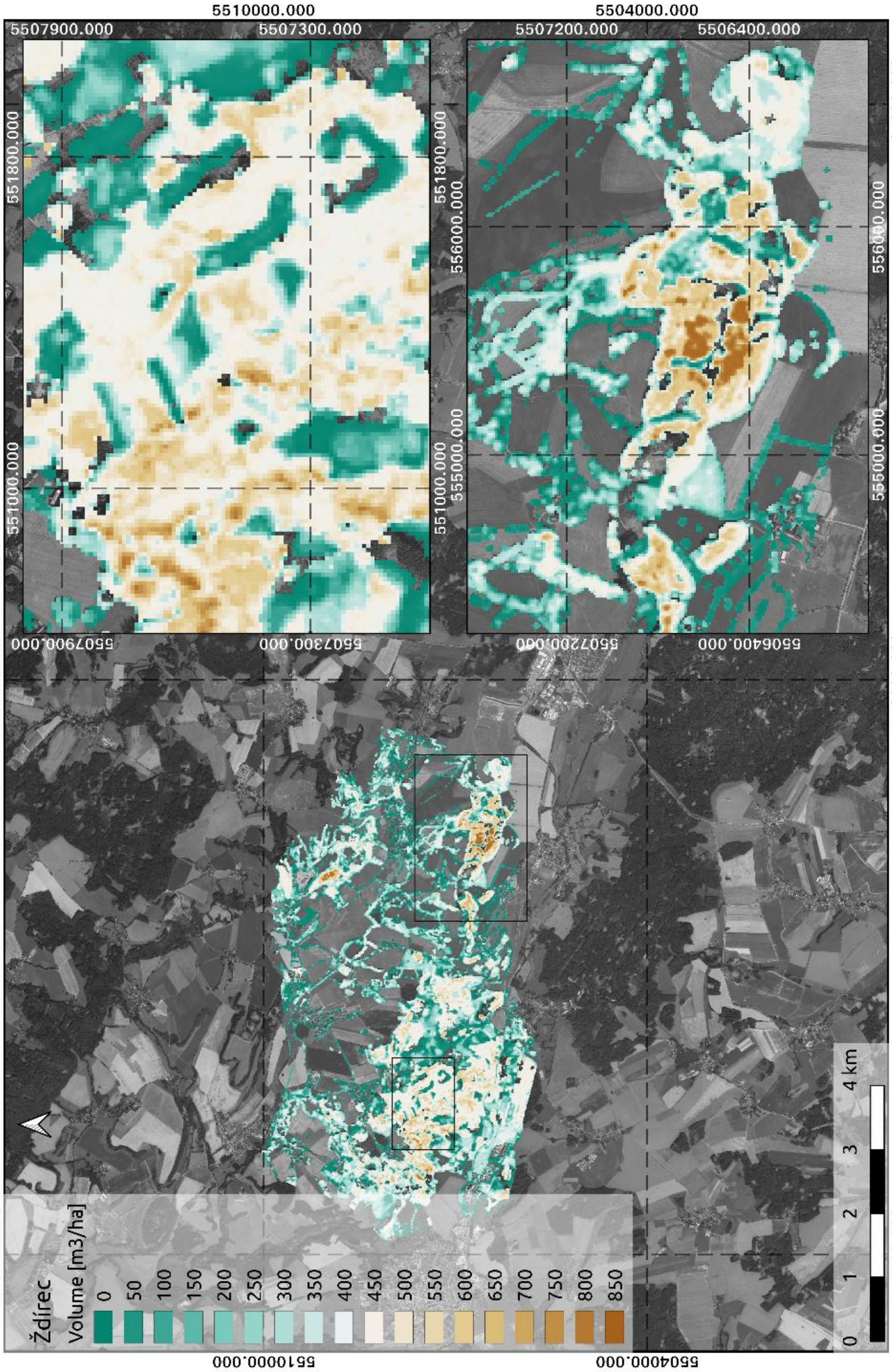
b)



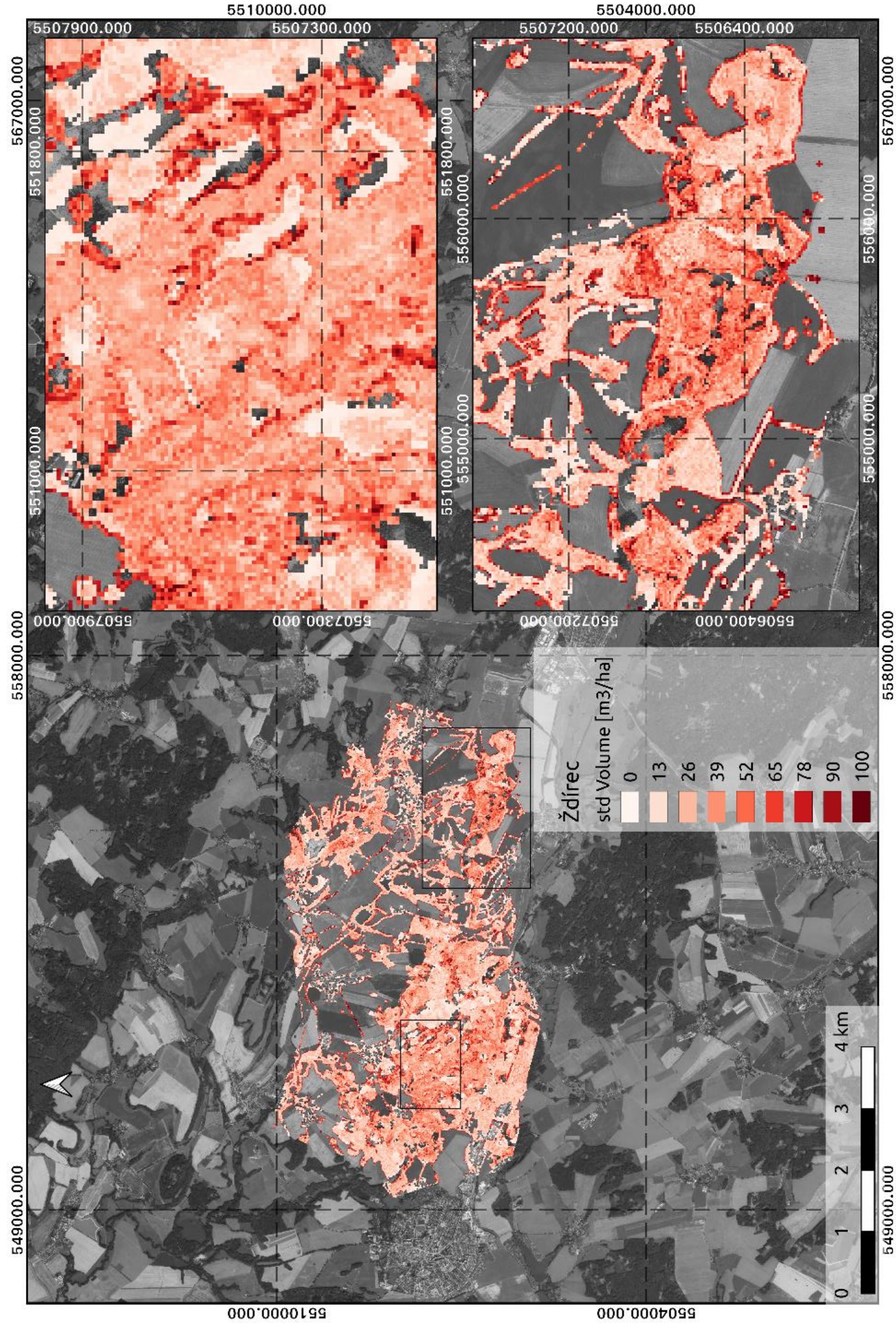
c)

Figure 15. Aboveground biomass (AGB) map (a), map showing standard deviation of the submodels, and visualization of biomass model performance (c) at Ždírec nad Doubravou study site. Scatter plot scale is colorized according to differences in AGB estimates between field survey AGB and modeled AGB: green is difference ≤25 t/ha, blue is difference of 25–50 t/ha, yellow is difference of 50–75 t/ha, and red is difference >75 t/ha.

A map of merchantable tree volume was produced for the Ždírec nad Doubravou study site using the described technology and modeling approach (Fig. 16), where reference AGB values for modeling were converted to tree volume units using tree allometry. Merchantable tree volume estimates on stand level are more often used in forest practice by forest owners in the Czech Republic while AGB is used for assessing changes of carbon stock. These two quantities (tree volume and AGB) allow quantification of the analogous processes and have a strong correlation (Fig. 17, Table 7).


Ždírec
Volume [m3/ha]
0
50
100
150
200
250
300
350
400
450
500
550
600
650
700
750
800
850
0
1
2
3
4 km
5510000.000
5504000.000
549000.000
558000.000
567000.000
5507900.000
5507300.000
5507200.000
5506400.000
551800.000
551000.000
556000.000
555000.000

a)



b)

Figure 16. Merchantable tree volume map (a), and its standard deviation between submodels (b).

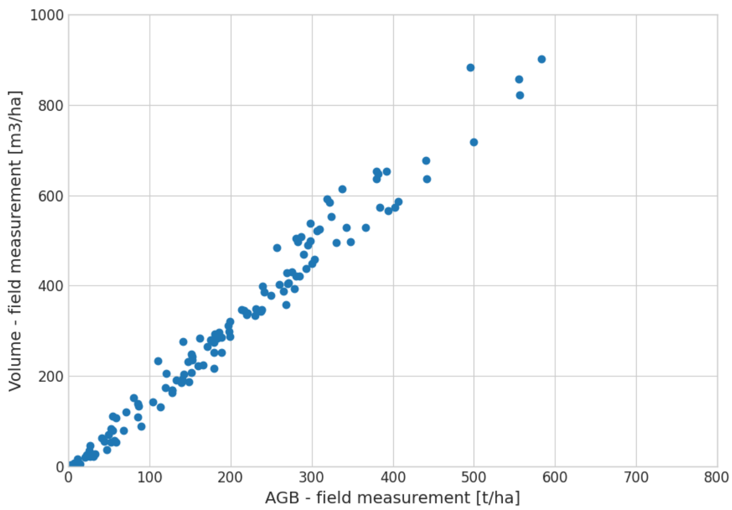


Figure 17. Relationship between volume and aboveground biomass (AGB) calculated from field measurements.

Table 7. Aboveground biomass and merchantable tree volume for selected individual trees measured at the Ždírec nad Doubravou forest site.

Species	Volume [m^3/ha]	Aboveground biomass [t/ha]
Norway spruce	448	271.6
Pedunculate oak	22.8	17.4
Silver fir	198.8	94.8
Norway spruce	4.4	2.8
European beech	59.8	63.2
Silver fir	7.4	4.2
Norway spruce	127.4	75.2
Scots pine	35.6	17.4
European beech	31.4	33.8

5 Economic aspects of the technology's use

Efficiency (in economic terms) is a value determined as the ratio between the results of an activity consisting in the production of goods or services and the cost of labor and other resources necessary for realizing that production (Samuelson and Nordhaus, 2009). The time requirements for forest AGB assessment (time required to complete processing of the estimation) were quantified using two approaches: 1) conventional field inventory, and 2) ABA using ALS. We then analyzed those time demands in comparison with the accuracy achieved from using these approaches (as a measure of the results of the activity) while disregarding the costs of labor.

Time requirements were estimated independently and summarized for the stages campaign preparation, data acquisition, and data processing for both approaches and then for the two cases described herein above: 1) for 15 forest plots from the Ždírec nad Doubravou forest site, and 2) for 101 forest plots from the Silesian Beskids forest site (Table 8). Time requirements needed for terrain data acquisition were based upon the authors' experience in mountainous forest: 60 min per plot in the case of field measurements using Field-Map technology (Novotný et al. 2021). The uncertainty of having weather and other conditions suitable for flight and for ALS campaigns was considered in calculating time demands.

Table 8. Time spent for field inventory and ALS approaches. *A* is a variant for 15 forest plots from Ždírec nad Doubravou forest site. *B* is a variant for 101 forest plots from Silesian Beskids forest site.

Stage	Aspect	**ALS**		**Field**	
		A (entire forest area)	**B** *(entire forest area)*	*A (200 trees)*	*B (1400 trees)*
Campaign preparation	Setup time	4	4	5	7
	Minimum number of personnel	1	1	1	1
	Required total time [work hours]	4	4	5	7
Data acquisition	Setup time and data acquisition	2	2.5	9	100
	Minimum number of personnel	2	2	2	2
	Required total time [work hours]	4	5	18	200
Data processing	Preprocessing	5	6	-	-
	AGB modelling / AGB calculating	2	2	8	8
	Required total time [work hours]	7	8	8	8
	Totals [work hours]	**15**	**16**	**31**	**215**

ALS workload increased by ca 7% (from 15 work hours to 16 work hours) when the number of analyzed forest plots increased by almost 7 times (from 15 plots to 101) (Table 8). By comparison, the field measurements workload increased by roughly 7 times (from 31 work hours to 215 work hours) under the same conditions. The laser scanning technologies acquire information about all trees at forest sites, thereby allowing to produce wall-to-wall AGB maps. Meanwhile the field measurements cover only individual forest plots.

The technology of forest AGB assessment based upon ALS data was shown to be less time demanding in comparison with field AGB assessment, and it demonstrated reasonably accurate biomass estimates. On this basis, we can see that the technology could play an important role in stand-level forest inventory over large areas and can be recommended to aid forest management practice in the Czech Republic.

6 Conclusion

The technology for Forest Aboveground Biomass Assessment Using an Area-Based Approach was developed and tested for the conditions of Czech forestry. Testing of the technology at the Ždírec nad Doubravou experimental forest locality confirmed applicability of the procedures for estimating quantities and area distribution of aboveground biomass in forest stands.

The technical documentation for the technology describes the procedures and practical recommendations for its use in the context of Czech forestry. Specifically, this concerns the setting of data acquisition parameters, the season for airborne data acquisition, field survey data collection, and the selection of modeling algorithms.

These procedures show a promising way of applying modern methods of airborne laser scanning in forestry that will allow repeated data acquisition and obtaining the current spatial distribution of aboveground biomass. Quantitative assessment of biomass changes can thus supplement critical information on the state of development of forest resources in relation to the carbon cycle and the changing conditions of the growth environment.

List of abbreviations

ABA – area-based approach
AGB – aboveground biomass
ALS – airborne laser scanning
DBH – diameter at breast height
RMSE – root mean squared error

References

Anderson, R.S. 2012. Estimating Aboveground Biomass and Average Annual Wood Biomass Increment with Airborne Leaf-on and Leaf-off LiDAR in Great Lakes Forest Types. NORTH. J. APPL. FOR. 30(1).

Blackburn, R.C., Buscaglia, R., Sanchez Meador, A.J. 2021. Mixtures of airborne lidar-based approaches improve predictions of forest structure. Canadian Journal of Forest Research, 51 (8), 1106-1116.

Bouvier, M., Durrieu, S., Fournier, R.A., Renaud, J.-P. 2015. Generalizing predictive models of forest inventory attributes using an area-based approach with airborne lidar data. Remote Sensing of Environment, 156: 322-334.

Bronisz, K., Strub, M., Cieszewski, C. J., Bijak, S., Bronisz, A., Tomusiak, R., Wojtan, R., & Zasada, M. 2016. Empirical equations for estimating aboveground biomass of Betula pendula growing on former farmland in central Poland. Silva Fennica, 50. https://doi.org/10.14214/sf.1559

Brubaker, K., Johnson, Q., Kaye, M. 2018. Spatial patterns of tree and shrub biomass in a deciduous forest using leaf-off and leaf-on lidar. Canadian Journal of Forest Research, 48 (9). https://doi.org/10.1139/cjfr-2018-0033.

Cienciala, E., Apltauer, J., Exnerová, Z., Tatarinov, F. 2008. Biomass functions applicable to oak trees grown in Central-European forestry. Journal of Forest Science 54(3):109–20.

Cienciala, E., Černý, M., Apltauer, J., Exnerová, Z., Tatarinov, F. 2006. Biomass Functions Applicable to Scots Pine. Trees 20(4):483–95. doi: 10.1007/s00468-006-0064-4.

Cienciala, E., Tumajer, J., Zatloukal, V., Beranová, J., Holá, Š., Hůnová, I., & Russ, R. 2017. Recent spruce decline with biotic pathogen infestation as a result of interacting climate, deposition and soil variables. European Journal of Forest Research, 136(2), 307–317. https://doi.org/10.1007/s10342-017-1032-9

Černý, M., Kučera, M., Cienciala, E., Beranová, J. 2010. Czech Republic –Chapter 8 of Tomppo et al. (eds) National Forest Inventories: Pathways for Common Reporting. https://doi.org/10.1007/978-90-481-3233-1

Čihak, T., Hlásny, T., Stolariková, R., Vejpustková, M., Marušák, R. 2014. Functions for the aboveground woody biomass in Small-leaved lime (Tilia cordata Mill.). Lesnícky časopis – Forestry Journal. 60. 150-158.

Davison, S., Donoghue, D.N.M., Galiatsatos, N. 2020. The effect of leaf-on and leaf-off forest canopy conditions on LiDAR derived estimations of forest structural diversity. Int J Appl Earth Obs Geoinformation, 92.

Duncanson, L., Armston, J., Disney, M., Avitabile, V., Barbier, N. 2021. LPV Protocols. Aboveground Biomass. Good Practices for Satellite-Derived Land Product Validation: Land Product Validation Subgroup (WGCV/CEOS), doi:10.5067/doc/ceoswgcv/lpv/agb.001.

Hawryło, P., Tompalski, P., Wezyk, P. 2017. Area-based estimation of growing stock volume in Scots pine stands using ALS and airborne image-based point clouds. Forestry. 90. 686–696. 10.1093/forestry/cpx026.

Henry, M., Besnard, A., Asante, W.A., Eshun, J., Adu-Bredu, S., Valentini, R. et al. 2010. Wood density, phytomass variations within and among trees, and allometric equations in a tropical rainforest of Africa. Forest Ecology and Management 260: 1375–1388.

Johansson, T. 2000. Biomass equations for determining fractions of common and grey alders growing on abandoned farmland and some practical implications. Biomass and Bioenergy, 18, 147–159. https://doi.org/10.1016/S0961-9534(99)00078-1.

Kankare, V., Vastaranta, M., Holopainen, M., Räty, M., Yu, X., Hyyppä, J., Hyyppä, H., Alho, P., Viitala, R. 2013. Retrieval of Forest Aboveground Biomass and Stem Volume with Airborne Scanning LiDAR. Remote Sens., 5, 2257-2274. https://doi.org/10.3390/rs5052257

Maltamo M., Naesset, E., Vauhkonen, J. 2014. Forestry applications of airborne laser scanning. Publisher Springer Netherlands, ISBN 978-94-017-8662-1.

Martin, A.R., Thomas, S.C.2011. A reassessment of carbon content in tropical trees. PLoS One, 6:e23533.

Melville, G., Stone, C. & Turner, R. 2015. Application of LiDAR data to maximize the efficiency of inventory plots in softwood plantations. *N.Z. j. of For. Sci.* 45, 9. https://doi.org/10.1186/s40490-015-0038-7.

Naesset, E. 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. Remote Sensing of Environment 80, 88-99.

Naesset E. 2005. Assessing sensor effects and effects of leaf-off and leaf-on canopy conditions on biophysical stand properties derived from small-footprint airborne laser data. Remote Sensing of Environment 98(2):356-370.

Nelson, R. 2013. How did we get here? An early history of forestry LiDAR. Canadian Journal of Remote Sensing, 39: S1-S12.

Noordermeer, L., Bollandsås, O.M., Ørka, H.O., Næsset, E., Gobakken, T. 2019. Comparing the accuracies of forest attributes predicted from airborne laser scanning and digital aerial photogrammetry in operational forest inventories. Remote Sensing of Environment, 226: 26-37.

Novotny, J., Navratilova, B., Albert, J., Cienciala, E., Fajmon, L., Brovkina, O. 2021. Comparison of spruce and beech tree attributes from field data, airborne and terrestrial laser scanning using manual and automatic methods. Remote Sensing Applications: Society and Environment, 23.

Parkitna, K., Krok, G., Miścicki, S., Ukalski, K., Lisańczuk, M., Mitelsztedt, K., Magnussen, S., Markiewicz, A., Stereńczak, K. 2021. Modelling growing stock volume of forest stands with various ALS area-based approaches. Forestry: An International Journal of Forest Research. 10.1093/forestry/cpab011.

Patocka, Z., Mikita, T. 2016. Use of area-based approach to process the airborne laser scanning data in forest inventory. Zpravy Lesnickeho Vyzkumu. 61. 115-124.

Pearse, G., Watt, M., Dash, J., Stone, C., Caccamo, G. 2019. Comparison of models describing forest inventory attributes using standard and voxel-based lidar predictors across a range of pulse densities. International Journal of Applied Earth Observation and Geoinformation. 78. 10.1016/j.jag.2018.10.008.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P. et al. 2011. Scikit-learn: Machine Learning in Python. J. Mach. Learn. Res. 12, null (2/1/2011), 2825–2830.

Petersson, H., Holm, S., Stahl, G., Alger, D., Fridman, J., Lehtonen, A., Lundstrom, A., Makipaa, R. 2012. Individual tree biomass equations or biomass expansion factors for assessment of carbon stock changes in living biomass - A comparative study. Forest Ecology and Management, 270: 78-84.

Samuelson P., Nordhaus W. 2009. Economics. - M.: Williams, 19th ed. 1360p.ISBN-13: 978-0-07-351129-0.

Somogyi, Z., Cienciala, E., Mäkipää, R., Muukkonen, P., Lehtonen, a., & Weiss, P. 2007. Indirect methods of large-scale forest biomass estimation. European Journal of Forest Research, 126(2), 197–207. https://doi.org/10.1007/s10342-006-0125-7.

Tompalski, P., White, J.C., Coops, N.C., Wulder, M.A. 2019. Demonstrating the transferability of forest inventory attribute models derived using airborne laser scanning data. Remote Sensing of Environment, 227: 110-124.

Tomppo, E., Gschwantner, T., Lawrence, M., & McRoberts, R. E. 2010. National forest inventories: Pathways for common reporting. In National Forest Inventories: Pathways for Common Reporting. https://doi.org/10.1007/978-90-481-3233-1

Vastaranta, M., Wulder, M.A., White, J.C., Pekkarinen, A., Tuominen, S., Ginzler, C. et al. 2013. Airborne laser scanning and digital stereo imagery measures of forest structure: comparative results and implications to forest mapping and inventory update. Can.J.Remote Sens. 39, 382-395.

Villikka, M., Packalen, P., Maltamo, M. 2012. The Suitability of Leaf-off Airborne Laser Scanning Data in an Area-based Forest Inventory of Coniferous and Deciduous Trees. Silva Fennica. 46. 10.14214/sf.68.

Vonderach, C., Kändler, G., Dormann, C.F. 2018. Consistent Set of Additive Biomass Functions for Eight Tree Species in Germany Fit by Nonlinear Seemingly Unrelated Regression. *Annals of Forest Science* 75(2):49. doi: 10.1007/s13595-018-0728-4.

Walton, J. T. 2008. Subpixel urban land cover estimation: Comparing cubist, random forests, and support vector regression. Photogrammetric Engineering and Remote Sensing, 74, 1213–1222.

White, J.C., Wulder, M.A., Varhola, A., Vastaranta, M., Coops, N.C., Cook, B.D., Pitt, D., Woods, M. 2013. A best practices guide for generating forest inventory attributes from airborne laser scanning data using an area-based approach. Natural Resources Canada, Canadian Forest Service, Canadian Wood Fibre Centre, Victoria, BC. Information Report FI-X-010.

White, J.C., Tompalski, P., Vastaranta, M., Wulder, M.A., Saarinen, S., Stepper, C., Coops, N.C. 2017. A model development and application guide for generating an enhanced forest inventory using airborne laser scanning data and an area-based approach. CWFC Information Report FI-X-018, 38 pp.

Wirth, C., Schumacher, J., Detlef, S.E. 2004. Generic biomass functions for Norway spruce in Central Europe - A meta-analysis approach toward prediction and uncertainty estimation. Tree physiology 24:121–39. doi: 10.1093/treephys/24.2.121.

Wutzler, T., Wirth, C., Schumacher, J. 2008. Generic Biomass Functions for Common Beech (Fagus Sylvatica) in Central Europe: Predictions and Components of Uncertainty. Canadian Journal of Forest Research. doi: 10.1139/X07-194.