Airborne remote sensing for forest inventory attributes assessment: experience of Flying Laboratory of Imaging Systems (FLIS) in the Czech Republic

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Abstract. The paper contributes to the recent studies for forest inventory attributes assessment from airborne data using experience of Flying Laboratory of Imaging Systems (FLIS). The advanced methods of airborne hyperspectral and laser scanning data processing are summarized to demonstrate the applicability of FLIS in assessment of forest inventory attributes for tree and plot levels in selected forest areas in the Czech Republic. Specifically, assessments of tree height, tree position, crown base, crown width, aboveground biomass, species composition, dead trees, and health status are presented.

1. Introduction

The primary objective of forest inventory is to produce and report timely and accurate estimates of forest resources. The uses and applications for inventory data and estimates increase, so do the number of variables requiring measurements or observation. The highest ratio of studies relevant for forest enterprise rely on airborne data; which can be attributed to the typical extent of forest enterprise and level of detail of data required for decision making in practical forestry [1, 2]. Potentially, airborne remote sensing in forest inventory can increase the speed, cost efficiency and timeliness associated with inventories.

Airborne data has been shown to be an appropriate tool to assess selective forest inventory attributes [2-5]. National forest inventory in the Czech Republic (Národní Inventarizace Lesů, NIL) use airborne visible and near infrared (VNIR) images to classify inventory plots to land cover category: forest, other wooded land, other land with tree cover and other land [6]. Height of trees and percentage of tree cover is estimated for forest inventory plots based on visual stereo-interpretation and object-oriented classification of VNIR images [7]. CzechTerra statistical inventory of landscape of the Czech Republic (www.czechterra.cz) combines the analysis of airborne images and field surveys.

The paper contributes to the recent studies for forest inventory attributes assessment from airborne data using experience of Flying Laboratory of Imaging Systems (FLIS) [8-11]. More specifically, the advanced methods of airborne HS and ALS data processing are summarized to demonstrate the
applicability of FLIS in assessment of forest inventory attributes for tree and plot levels in selected forest areas in the Czech Republic.

2. Methods and Materials

2.1. Study sites
Forest inventory attributes have been estimated in three study sites located in different forest ecosystems: Bílý Kříž, Těšínské Beskydy and Lanžhot. Bílý Kříž site (BK; 18° 54′ E, 49° 50′ N, at an altitude of 750 to 950 m ASL), is characterized by managed forest stands of monoculture Norway spruce (Picea abies L.) of ages ~30 to 95 years, along with an admixture of broadleaved trees (22.7%) with a mean age of 75 years, represented mostly by European beech (Fagus sylvatica L.). Těšínské Beskydy (TB; 18° 47′ E, 49° 37′ N, at an altitude of 500 to 900 m ASL), is also covered by managed forest stands of ages ~30 to 75 years, with Norway spruce (Picea abies L.) and European beech (Fagus sylvatica L.) as the dominant tree species and scattered admixture of Scots pine (Pinus sylvestris L.), silver fir (Abies alba L.), European larch (Larix decidua L.), and ash (Fraxinus excelsior L.). Lanžhot site (LH, 48° 40.09′ N, 16°56.78′ E, at an altitude of about 200 m ASL) is a floodplain forest of typical hardwood species of age ~110 years, represented mostly by English oak (Quercus robur L.), Narrow-leaved ash (Fraxinus angustifolia Vahl), hornbeam (Carpinus betulus L.) and linden (Tilia cordata Mill.).

2.2. Airborne data
Airborne data have been acquired with the Flying Laboratory of Imaging Systems (FLIS) (figure 1). FLIS consists of an airborne carrier, imaging spectroradiometers and a laser scanner. Photogrammetric airplane Cessna 208B Grand Caravan with two hatches serves as an airborne carrier. The basic sensor equipment consists of hyperspectral sensors CASI-1500, SASI-600 and TASI-600, produced by company Itres. These sensors are push broom scanners that scan the area of interest by individual rows. All hyperspectral sensors are equipped with custom-made sensing chips to ensure higher the so-called "full well capacity" of the detector allowing a higher range of measured signal without saturation. Greater dynamic range allows easier detection of the objects scanned.

![Figure 1](image-url). Flying Laboratory of Imaging System – FLIS. (a) - airplane Cessna 208B Grand Caravan, (b) - data acquisition equipment.

The LMS Q780 airborne full-waveform laser scanner positioned on the board of the plane is a product of the company Riegl. All four scanners acquire data simultaneously. The aircraft is equipped with other devices and systems to improve the quality of the scanned data and to acquire auxiliary data for the final processing (the navigation system, gyroscopic platform, etc.). The current position and location of the aircraft (in three axes) is monitored using the GNSS/IMU POS AV inertial navigation...
unit. The data acquired by the sensors are synchronized with the signal from the GNSS/IMU unit and recorded into the acquisition computer.

Airborne data presented in the study, have been acquired during several airborne campaigns related to various purposes/projects and have been used to demonstrate their suitability to assess selected forest inventory attributes (table 1).

| Site | Airborne data | Date of acquisition | Parameters | Estimated inventory attribute |
|------|---------------|---------------------|------------|-------------------------------|
| BK*  | ALS<sup>d</sup> | Summer 2017         | 10 point/m<sup>2</sup> | AGB<sup>f</sup> tree level   |
|      | HS            | Summer 2015         | 0.4-1 μm, 72 bands, 0.4 m | CW tree level, Tree position |
| TB<sup>b</sup> | ALS<sup>d</sup> | Summer 2013        | 1 point/m<sup>2</sup> | AGB<sup>f</sup> plot level   |
|      |               | Summer 2019        | 20 points/m<sup>2</sup> | Height plot level, Health status |
|      | HS<sup>e</sup> | Summer 2015        | 0.4-1 μm, 72 bands, 1 m | CW<sup>h</sup> plot level, Dead trees |
|      |               | Summer 2019        | 0.4-1 μm, 72 bands, 0.4 m | Health status, Crown base |
| LH<sup>c</sup> | HS<sup>e</sup> | Summer 2015        | 0.4-1 μm, 72 bands, 1 m | Species |
|      |               | Summer 2016        |                        |                               |
|      |               | Spring 2019        |                        |                               |
|      |               | Autumn 2019        |                        |                               |

* BK is Bílý Kříž.
* TB is Těšínské Beskydy.
* LH is Lanžhot sites.
* ALS is airborne laser scanning.
* HS is hyperspectral.
* HS data parameters (column Parameters) are provided in the next order: spectral range, number of spectral bands, spatial resolution.
* AGB is aboveground biomass.
* CW is crown width.

2.3. Airborne data pre-processing

Corrections of the hyperspectral images are performed according to a processing chain established at CzechGlobe [8]. The radiometric correction procedure consists in subtracting dark current and converting raw values scanned by the sensor (DN – digital numbers) into physically defined units of radiance. Radiometric corrections of measured data are carried out in RadCorr (Itres Ltd) using laboratory-determined calibration parameters for each pixel of the sensor matrix. The values of the final image data are given in radiometric units [μW cm<sup>-2</sup> sr<sup>-1</sup> nm<sup>-1</sup>]. Georeferencing is performed by means of parametric geocoding using data acquired by the GNSS/IMU unit and digital terrain model in GeoCor (Itres Ltd.) program. In one single step, geometric corrections, orthorectification and georeferencing of data is performed. For the resampling of data to the coordinate system, the nearest neighbor method is used. Hyperspectral data are usually georeferenced into the UTM coordinate system (zone 33N, ETRS-89). Data are mosaicked, if necessary, using the “Min. nadir” method, i.e. if two lines overlap, a pixel that is nearer the nadir is placed in the mosaic. This mosaicking method reliably eliminates marginal pixels more affected by the BRDF effect. Atmospheric corrections of scanned data are performed in the ATCOR-4 (ReSeAplicationSchlapfler/DLR) program using the
MODRAN radiation transfer model of the atmosphere. The resulting atmospherically corrected data are expressed in reflectance values at surface level.

Airborne laser scanner data pre-processing is carried out particularly using programs provided by the scanner manufacturer and included trajectory calculation, georeferencing, relative orientation of individual flight lines and exporting.

2.4. Field data
The field data were collected accordingly to the date of airborne data acquisition (table 1).

The field data at BK and TB study sites were collected using the Field-Map technology (www.fieldmap.cz), including an electronic caliper for breast height measurements and laser rangefinder for tree height and tree crown attributes by IFER-Institute of Forest Ecosystem Research (www.ifer.cz). The sampling plots were circular with an area of 500 m² (a radius of 12.62 m). At each plot, two concentric circles were used to conduct measurements of all trees with diameter at breast height (DBH) from 7 cm (inner plot circle with a radius of 3 m) and from 12 cm (across entire plot) of all trees above 7 cm. The BK site consisted of 23 spruce sampling plots altogether. The TB site contained 39 spruce, 14 beech, and 15 mixed (spruce and beech) sampling plots. Tree height was measured for all trees unless there were more than 10 trees species per plot. In those instances, the height of the remaining trees was estimated using locally derived species-specific height functions with DBH as an independent variable based on the measured tree samples. Position, crown base (CB) and crown width (CW) of selected trees were measured. CB were measured at the point where the main primary crown begins, which means where there were at least two living branches in case of conifers and the first bifurcation of tree trunk in the case of broadleaves. CW (projections) were represented by at least five points measured on the ground under crown circumference as visually assessed by field workers. The commonly used spruce stand decline indicators were collected and analyzed for spruce plots at TB site: dead trees, crown break, resin exudation, discoloration, dry tree tops, reduced increments of tree top shoots, decreased vitality by IUFRO (International Union of Forest Research Organizations) classification [12].

The field data at LH site included measurement of individual tree positions (75 trees) and identification of tree species (9 tree species). Allometric equations were used to calculate selected inventory attributes from field measurements:

\[
CW = a \cdot DBH^b \cdot H^c
\]

where, a and b are empirical parameters [13]

\[
AGB_{\text{spruce}} = AGB_{\text{needles}} + AGB_{\text{branches}} + AGB_{\text{dry.branches}} + AGB_{\text{stem}} [14]
\]

\[
AGB_{\text{beech}} = 0.0551 \cdot DBH^{2.11} \cdot H^{0.589} [15]
\]

2.5. Assessment of selected forest inventory attributes using airborne data
The next forest inventory attributes were estimated with the use of FLIS (figure 2): tree position, tree height (tree and plot level), crown width (tree and plot level), crown base, aboveground biomass (tree and plot level), species composition, dead trees, and health status.

![Figure 2. Scheme of selected forest inventory attributes estimated with the use of FLIS (Flying Laboratory of Imaging System). AGB is aboveground biomass.](image)

2.5.1. Tree height and tree position. A height of trees can be estimated from ALS data for individual tree level and for plot (canopy) level. For individual tree height, ALS point cloud (20 points/m²) was
transformed into a canopy height model (CHM), which is a subtraction of a digital terrain model (DTM) from a digital surface model (DSM). Ground points in the cloud were classified using lastools scripts (http://www.cs.unc.edu/~isenburg/lastools/). Positions and heights of individual trees were detected in the CHM as local maxima of height. The CHM was smoothed with a Gaussian low pass filter and then local maxima was searched with a sliding window of a size that varied adaptively (see [16] for details).

For plot (canopy) level tree height, the first return ALS points (1 point/m²) and bare earth points were generated and the difference between these two-point datasets was determined. The difference results represented, over forest, the canopy height. The accuracy of ALS canopy height was estimated by comparison with field measurements of tree height at each plot.

2.5.2. Crown width. A tree crown width can be estimated from HS data for individual tree level and for plot (canopy) level. For individual tree crown width, a segmentation procedure was applied for the derivation of individual tree crowns. We used a local maxima approach for tree detection and seeded region growing for the delineation phase of the segmentation procedure. Positions of trees were searched as local maxima of brightness, using a sliding window of a size that varied adaptively. Crown segments were then grown, using stopping conditions based on an expected crown size and a brightness difference (see [17] for details). We used data from the near infrared spectral region (20 spectral bands from 0.791 nm to 0.971 nm) as an input layer in the segmentation procedure because it has the maximum vegetation reflectance and a principal relationship to the structural properties of the canopy [18]. There suliting crown segments were saved as a shape file and tree crown widths (diameters) were calculated with a geographic information system (GIS).

For plot level, crown width was estimated using a methodology consisted of the combination of a window binarization procedure and a granulometric algorithm. The result of this automatic processing was represented in an image comprising the crown width values in pixels. For each forest plot from the field measurements, the crown width was assessed as a mean value of all widths of the respective plot (see [13] for details).

2.5.3. Crown base. Crown base was estimated from ALS data in automatic mode. The estimation was based on analysis of the relationship between cloud density and height. A threshold was calculated based upon the maximum number of points in one height bin. Crown base estimate was defined with the first significant increase in point count that was higher than a preset threshold.

2.5.4. Aboveground biomass. Aboveground biomass can be estimated from airborne data for individual tree level and for plot (canopy) level. The method for AGB estimation at tree level used the fusion of HS and ALS data and included: development of a map of species composition from HS data, individual tree crown detection from LiDAR data, tree height estimation from LiDAR data, and AGB estimation using allometric equations (2-3) [11, 19].

For plot level, area-based approach (ABA) [20] was applied to estimate aboveground biomass. The aim of ABA was the development of a predictive model and its application to the entire study site. Metrics describing the three-dimensional distribution of the ALS point cloud derived for each section were used as predictors of the model. These were variables related to stand height and density: height quantiles, mean and standard deviation, statistical moments (skewness, kurtosis) and transmittance indices. The estimated tree level and ABA biomass was compared with field-measured tree- and plot level biomass, correspondently.

2.5.5. Species composition. Tree species were mapped using classification methods of HS data. BK site included species classes (“spruce”, “beech”, “birch”, “silver fir”), “shadows” and “artificial objects” (roads and buildings). TB site included species classes (“spruce”, “beech”, “pine”, “silver fir”), “shadows” and “artificial objects”. LH site included 9 species classes (“oak”, “wild apple”, “conker tree”, “hornbeam”, “ash”, “maple”, “elm”, “linden” and “willow”). Maximum Likelihood,
Mahalanobis Distance, Artificial neural network (ANN) and Support vector machine (SVM) methods were applied to classify tree species. The accuracy of the classification result was estimated by calculation of a confusion matrix, overall accuracy and Kappa coefficient.

2.5.6. Dead trees. Dead (dry) trees were identified from HS data. The principal component analysis (PCA) was applied as a preprocessing step for the classification of hyperspectral images. The first 4 principal component images contained significant information about dead tree spectral features. The thresholds were assigned for the “dead tree” class using the second PCA image. This class was identified and extracted from the image. To exclude falls pixels of other objects (such as roads or sand), “dead tree” class was clipped with ALS mask containing objects higher than 5 m.

2.5.7. Health status. Health status of spruce stand was analyzed using HS data. A composite spruce decline indicator was formed from field indicators that most affected spectral reflectance of spruce plots: dead tree, discoloration, dry tree top and IUFRO vitality. The canopy-level spectral reflectance properties of spruce stands were investigated to identify categories of spruce stand decline: healthy, initial decline, and initial to moderate decline. It was revealed, that specific values of the composite indicator corresponded to the categories of spruce stand decline (see [9] for details).

2.6. Statistical methods
A confusion matrix was calculated to compare the species classification result with ground truth information. The overall accuracy was calculated by summing the number of pixels classified correctly and dividing it by the total number of pixels. The Kappa coefficient was used to compare the specific class differences between the classifications. We used the coefficient of determination, R², to indicate how well the tree level and the plot level estimates from HS and ALS data fit the respective results from field data. Root mean squared error (RMSE) was calculated for the quantitative assessment of inventory attributes from the study methods. The coefficient of variation of the RMSE, CVRMSE, was useful for the non-dimensional comparison of RMSE normalized to the mean of the observed data.

3. Results and Discussion
Statistical variables to estimate accuracy of forest inventory attributes from FLIS airborne data are presented in table 2. More detailed analysis of the results can be found in published studies related to the assessment of each forest inventory attribute [9 – 11, 13, 16, 17, 19].

The findings of the methods presented in our paper are comparable with the recent studies that estimate forest inventory attributes from airborne remote sensing.

Tree height from our study was estimated with R² of 0.99 for tree level, and R² of 0.86 for plot level. Popescu and Wynne [21] found a similar agreement between ALS and field measurements in a pine (Pinus sylvestric L.) forest (R²= 0.99) for individual trees. Luther et al [22] predicted the average height of black spruce (Picea mariana L.) with R²= 0.86 from ALS data. Tree-based estimation of tree height and volume was demonstrated by Sačkov et al [23]; they achieved relative RMSE of 8% and 46%, respectively. Huang et al [24] compared field-measured crown width and crown width determined from object-oriented segmentation at high resolution airborne imagery (0.5 m) with R² of 0.61 and RMSE of 2.10 m for uneven-aged mixed hardwood and conifer trees, which is slightly lower than our crown width estimates for tree level (R² of 0.61, RMSE of 0.46 m).

Our tree level AGB estimates demonstrated R² of 0.85 (CVRMSE of 28%) in mixed forest. Findings of Laurin et al [25] showed R² of 0.70 for AGB assessment with integration of HS and ALS data in a tropical forest. Plot level AGB estimates using ABA showed nRMSE of 18% in our study, which is comparable with nRMSE for AGB estimates from 12% to 23% reported in White et al [26].

Richter et al [27] classified 10 deciduous tree species in foodplant forest from airborne HS data. Up to 78.4% overall accuracy was achieved using Partial Least Squares classification algorithm for the stacked HS dataset acquired in August and September. Our findings showed overall accuracy of
89.4% to classify 9 deciduous tree species using SVM algorithm for HS data acquired in the beginning of August. Shen and Cao [28] combined metrics from both ALS data and hyperspectral imagery to classify five tree species using Random Forest classifier. The overall classification accuracy was 85% and the combination of ALS and HS data showed improved accuracy in comparison to only HS data based classification.

Table 2. Accuracy of forest inventory attributes estimates from airborne data.

| Forest inventory attribute | Accuracy of estimates |
|----------------------------|-----------------------|
| Tree position              | Mean positional errors of 0.5 m to the reference field positions |
| Tree height                | Tree level R² of 0.99 (BKᵇ site), plot level R² of 0.86 (TBᶜ site) |
| Crown width                | Tree level R² of 0.61 (RMSE of 0.46 m) (BKᵇ site), plot level R² of 0.79 (RMSE of 0.37 m) (TBᶜ site). |
| AGBᵃ                      | Tree level R² of 0.85 (CVRMSE of 28%) (BKᵇ site), plot level R² of 0.87 (nRMSE of 18%) (TBᶜ site). |
| Species composition        | OAᵈ of 86% and Kappa of 0.78 (BKᵇ site), OAᵈ of 87% and Kappa of 0.82 (TBᶜ site), OAᵈ of 89.4% and Kappa of 0.78 (LBᵉ site, HS data from beginning of August) |
| Dead trees                 | OAᵈ of 91% and Kappa of 84 (TBᶜ site) |
| Health status              | Accuracy of 81% (TBᶜ site, for composite indicator to estimate spruce decline categories) |

ᵃAGB is aboveground biomass.
ᵇBK is Bílí Klíž.
ᶜTB is Těšínské Beskydy.
ᵈOA is overall accuracy.
ᵉLH is Lanžhot sites.

Identification of dead trees from HS data and PCA achieved the accuracy of 91% in our study. Parsher and King [29] mapped dead wood in forest canopies irrespective on the cause of mortality. They utilized high resolution color infrared airborne imagery and with the direct detection approach they achieved 94% accuracy in validation site. The proposed in our study methodology of spruce health status identification is potentially timely and economically expedient, since foliar spectral measurements, canopy chemistry, and laboratory analysis are not required. Lausch et al [30] reported also the capability of airborne hyperspectral data to distinguish between healthy and green-attacked trees in the spectral range of 450–890 nm. However, their classification result gained only 64% accuracy compared to our method accuracy of 81%.

The selection of airborne data type is mainly dependent on the forest attributes which shall be derived from the remote sensing data. In the case of using FLIS, data from hyperspectral and laser sensors can be acquired simultaneously during an airborne campaign. The use of FLIS can potentially be a benefit because only one airborne campaign with FLIS is needed to estimate the full set of forest inventory attributes described in the study (figure 2). Although airborne remote sensing data cannot completely replace ground sample data, they have now been incorporated into forest inventory and increasingly used to enhance it. The airborne remote sensing technologies have created possibilities for efficient production of accurate forest data sets on local and regional level, which also changed traditional forest inventories way. The proposed methods can also find application in the practice of international projects implementation devoted to the analysis of the state of forests (https://innoforestview.site/, etc.).

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