COMPARISON OF LIDAR-BASED MODELS FOR TRUE LEAF AREA INDEX AND EFFECTIVE LEAF AREA INDEX ESTIMATION IN YOUNG BEECH FORESTS

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Abstract

The leaf area index (LAI) is one of the most common leaf area and canopy structure quantifiers. Direct LAI measurement and determination of canopy characteristics in larger areas is unrealistic due to the large number of measurements required to create the distribution model. This study compares the regression models for the ALS-based calculation of LAI, where the effective leaf area index (eLAI) determined by optical methods and the LAI determined by the direct destructive method and developed by allometric equations were used as response variables. LiDAR metrics and the laser penetration index (LPI) were used as predictor variables. The regression models of LPI and eLAI dependency and the LiDAR metrics and eLAI dependency showed coefficients of determination (R^2) of 0.75 and 0.92, respectively; the advantage of using LiDAR metrics for more accurate modelling is demonstrated. The model for true LAI estimation reached a R^2 of 0.88.

Keywords: airborne laser scanning, LiDAR, leaf area index, effective leaf area index, LAI, eLAI, allometric models, destructive method, indirect methods

INTRODUCTION

The most used environmental indicator characterizing the canopy structure is leaf area index (LAI). LAI is a key feature of the forest structure that serves as the primary indicator for the exchange of matter and energy within forest ecosystems. LAI is a dimensionless variable characterized as the maximum area of photosynthetic tissue per unit of ground area (Myneni *et al.,* 1997). The amount of LAI depends on the species composition of the stand, the development stage, the prevailing site factors,

the season, and the type of forest management. It is a dynamic parameter that changes from day to day (especially in spring and autumn), and over time, the physical and biological forces that form and change the forest environment affect it. LAI is likewise one way to evaluate the health status of trees unfolding from these factors. Methods for LAI detection can be divided into three categories: direct, semidirect, and indirect. The direct methods generally use destructive procedures to estimate the total number of leaves on the tree and their areas, whereas the indirect methods use some

aspect of the radiation regime within the stand and derive LAI from light distribution under the canopy (Jonckheere *et al.,* 2004).

The direct methods are most accurate for sample trees but very time-consuming; therefore, they are not used for the determination of spatial and temporal LAI distribution. However, they may be considered the most important for validation of indirect methods. These include the destructive method of collecting leaves from standing trees and collecting falling leaves to litter-traps (Jonckheere *et al.,* 2004). The direct destructive method damages trees irreversibly, so it is not used in larger and more valuable trees. The semi-direct methods include allometric models based on simple physical dimensions (diameter at breast height (DBH), tree height, base crown, crown projection, etc.) as predictor variables and LAI as a response variable determined by the direct method (Asner *et al.,* 2003). Allometric relations are accurate, but they are stand-specific or species-specific (Mencuccini and Grace, 1995; Le Dantec *et al.,* 2000).

Currently, indirect methods based on non-contact transmittance measurements are used in forest stands. These methods use the Beer–Lambert law (Monsi and Saeki, 2005).

The leaf area index can be determined on the basis of gap fraction information or based on the combination of gap fraction and gap size distribution using tracing radiation and architecture of canopies (TRAC) or hemispheric photo analysis (Chen and Cihlar, 1995).

The indirect optical methods are characterized by nonseparation of the leaves from different parts of the crown layer, such as branches or parts of the stem. The indirect methods determine so-called effective leaf area index (eLAI), which can be used for recalculation into true LAI by the correction factor, which is stand-specific and species-specific. The factor reflects the mutual overlapping of the needles within the annual shoot, the branches, and the whorls, thus the proportion of wood in the sensor field of view (Chen *et al.,* 1991). In the case of beech, this factor is not used, because leaves are mostly randomly distributed. Therefore, to determine true LAI, it is sufficient to repeat the measurement out of the vegetation period; the woody area index (WAI) is determined and subtracted from eLAI (Caldwell *et al.,* 1983a; 1983b).

The indirect techniques using remote sensing are the most suitable for estimating LAI on a wider spatial scale. We can divide them into techniques using passive optical sensors and LiDAR. The basis of LAI estimation using passive optical sensors is the correlation between LAI and some of the vegetation indices, e.g., Normalized Difference Vegetation Index (NDVI) (Lüdeke *et al.,* 1991; Gower *et al.,* 1999). The disadvantage is seen especially in case of high LAI value occurrences when the NDVI is so saturated that it is unable to distinguish these high LAI values, which means the NDVI and LAI will not increase linearly (Zheng and Moskal, 1991). The other technology is airborne laser scanning (ALS), which has been used in most studies to estimate an effective leaf index, but is not correct in case of non-random distribution of foliage and does not distinguish nonfoliage elements (e.g., branches, bark) in the canopy. Corrections must be made for calculation of true LAI (Chen *et al.,* 1997; Leblanc *et al.,* 2005).

Airborne laser scanning uses a laser scanner carried mainly by satellite, aircraft, helicopter or unmanned aerial vehicle. The entire system is able to capture accurate three-dimensional data thanks to the inertial navigation system (INS) and Global Navigation Satellite System. Most studies have used small-footprint, discrete return scanners, and LAI estimation using some penetration indices (semi-empirical approach) or LiDAR metrics (empirical approach). The created models are valid only for the trees and stands for which they were derived and calibrated (Riaño *et al.,* 2004; Solberg *et al.,* 2010). ALS-based models for eLAI estimation can be calibrated using terrestrial laser scanning (Musselman *et al.,* 2013).

In this paper, we compare different regression models based on the laser penetration index and LiDAR metrics as predictor variables and models based on effective leaf area index and true leaf area index as response variables. We focused only on modelling of young beech forest stands, because in situ measurements, especially by the direct destructive method, are time-consuming. There are not many studies using true LAI as the response variable in ALS-based modelling, e.g., (Beets *et al.,* 2011; Qu *et al.,* 2018). eLAI as response variable is commonly used for LAI estimation based on remote sensing resulting in underestimation of true LAI.

MATERIALS AND METHODS

Study Area

The field measurements were carried out during August and September 2015 at the University Forest Enterprise Křtiny (UFE), an organizational part of Mendel University in Brno, Czech Republic. The sample plots were placed in young beech forest stands (21 years old) with a tree species composition of 91% beech (*Fagus sylvatica* L.), 8% larch (*Larix decidua* Mill.), and 1% oak (*Quercus petraea* Matt.). The average tree height of the forest stand was 9 m and the average DBH was 9 cm. In total, 6 sample plots were surveyed tacheometrically using total station.

ALS Data Acquisition and Initial Processing

The airborne laser scanning data used in this study was scanned on September 17 and 18, 2014, in the ETRS-89 UTM 33N coordinate system and the GRS-80 geodetic reference system. The parameters of airborne laser scanning acquisition are shown in Tab. I.

I: *Area laser scanning (ALS) acquisition parameters*

Sensor	Leica ALS70
Date	Sept. 2014
Flight speed (ms^{-1})	70
Flying altitude (m a.g.l.)	700
Pulse repetition frequency (kHz)	301.8
Pulse density	7.8
Half scan angle (deg.)	24

The data classification was performed in TerraScan software. Ground points were classified by automatic methods as Class 2, Ground, and first return points as Class 5, High Vegetation.

Destructive Methods and Allometric Equations

All tree girths at breast height were measured in the forest stands, and 9 sample trees were chosen on the basis of the girth distribution frequency. Each sample tree was cut into 1 m sections, from which sample leaves were collected for calculation of SLA, and then LAI.

The sample leaves were scanned immediately after harvesting, and their exact area was determined using ImageJ image analysis software (National Institutes of Health, Bethesda, MD, USA). These leaves were dried for 48 h at 105 °C and then weighed with milligram precision. The specific leaf area of the leaves was calculated from the known dry mass by the following formula:

$$SLA = S_f \times m_d^{-1}, \tag{1}$$

where:
S_f........leaf fresh mass area and
m_d.....dry mass weight.

All leaves of individual sections were also harvested and dried for 48 h at 105 °C. After being weighed, the ratio of SLA to tree segment was applied and the segment leaf area was calculated. Based on a regression analysis, allometric equations were created where tree girth was used as an independent variable. Leaf areas on the plots were estimated based on these dependencies.

Indirect Methods

LAI-2200 Plant Canopy Analyzer (Li-cor Inc.), hemispherical photographs, and PSI LaiPen LP 100 (Photon Systems Instruments, s. r. o.) were used to measure effective leaf area. The use of these tools requires the absence of direct sunlight; thus, all measurements were performed strictly in diffuse radiation (homogeneously overcast sky or short time before sunrise or short time after sunset).

Two sensors of the LI-COR LAI-2200 PCA were used to determine LAI. One sensor was set up on a tripod at a height of 180 cm in an unshaded area, where it was set to automatically measure radiation at half-minute intervals. eLAI was determined based on comparing radiation in the forest stand and in the area with a clear view of the sky.

The LaiPen LP 100 works on a similar principle as the LI-COR LAI 2200 PCA. The instrument measures the transmittance value as the irradiance ratio obtained under and over the canopy. Two instruments were used, one on a reference area with a clear view of the sky and the other to measure in the plots. Horizontal levelling of the instrument was achieved using the gyroscope integrated within it.

Effective leaf index was also determined by image analysis of hemispherical photographs. For this purpose, a set consisting of a Sony NEX-7 camera with an FC-E8 fish-eye lens served to capture images with a field of view of 180°. The entire system was installed into the auto-levelling platform to keep the camera in the horizontal position. Effective leaf area index was estimated in WinScanopy software (Regent Instruments Inc.).

LAI Estimation Using ALS Data

In ArcMap (ESRI Inc.) software, the laser penetration index for each sample plot 5.5 m in diameter was calculated by using the following formula (Musselman *et al.,* 2013):

$$LPI = \frac{mG}{mG + mV}, \tag{2}$$

where:
m_G.....the number of returns belonging to the ground per unit area and
m_V.....the number of first returns per unit area.

The area size for the LPI calculation was determined by correlation matrices. LPI was calculated for different area sizes, and the highest correlation with the eLAI measurement results was sought. Area size depends on instrument field of view and tree heights (or crown projection for the destructive method) (Mikita *et al.,* 2011). The size of the plots cut out from the point cloud has a significant effect on the success of regression models.

Another method of LAI calculation by laser scanning was the use of LiDAR metrics, which were calculated in FUSION software (US Department of Agriculture, Forest Service, Pacific Northwest Research Station). In the beginning, the sample plots (square shape, diameter 5.5 m) were clipped from the point cloud by the *clipdata* command, then the LiDAR metrics of the individual plots were calculated using the *cloudmetrics* command. The *cloudmetrics* command computes a variety of metrics describing a point cloud. This metrics are based on point elevation attributes and return intensity (for more details, see the FUSION manual (McGaughey *et al.,* 2018)). Most significant metrics are percentile values for point elevations and various ratios of returns above specific height

breaks. The LiDAR metrics were selected using the sequential replacement technique in the leaps package for *R*. These selected metrics served as predictors for the linear regression model. A regression triplet was tested in the final models.

RESULTS

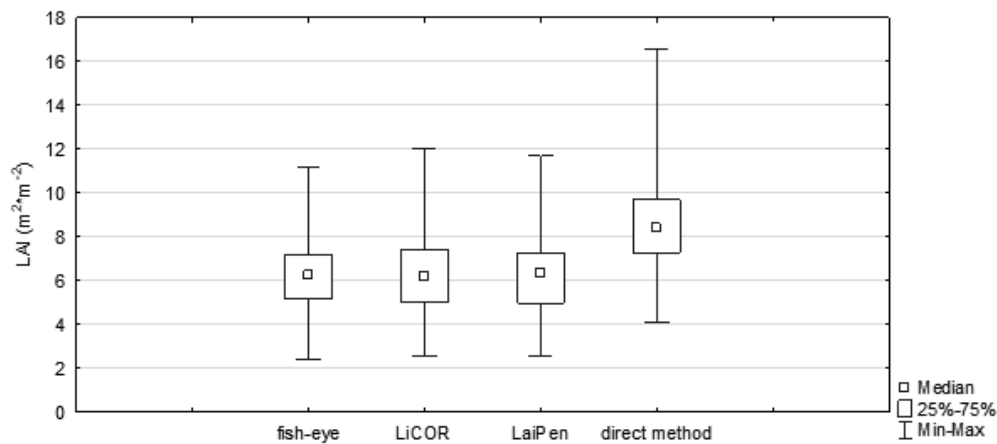### Linear Regression Model Based on LPI (Predictor) and eLAI (Response)

Using the *PMCMR* package for *R*, the Friedman test and the Neményi test of multiple comparison was used. Optical methods were found to provide similar results (Tab. II, Fig. 1).

Therefore, a mean of eLAI values per sample plot measured by the LI-COR LAI-2200 PLA were used as response variables. An important part of the regression analysis is examination of the regression triplet, i.e., procedures for identifying the model quality for a given set of data, the data quality of a proposed model, and fulfilment of all least-squares assumptions. The following tests were performed: Fisher–Snedecor overall test, Scott's multicollinearity criterion, Cook–Weisberg test for heteroscedasticity, Jarque–Berra test for normality, Wald test for autocorrelation, Durbin–Watson test for autocorrelation, and sign test. Based on these tests, no negative conclusions that would affect the credibility of the regression model were drawn. The resulting linear regression model is described in Tabs. III and IV. Tab. IV shows the estimates and significances of regression model parameters. All parameters are significant.

II: *Friedman and Neményi post-hoc test. The significant differences are highlighted in bold.*

	Fish-eye	Li-COR	LaiPen
	Friedman Chi-Squared = 230.57, *df* = 3, *p-value* < 2.2*10^{-16}		
Li-COR	0.98	–	–
LaiPen	0.97	1.00	–
Direct	$< 2 \times 10^{-16}$	$< 2 \times 10^{-16}$	$< 2 \times 10^{-16}$

1: *Box plot of LAI values determined by individual methods*

III: *Statistical characteristics of regression model based on LPI and eLAI*

Coefficient of Determination R^2	0.7450
Mean squared prediction error (*MSPE*)	1.4426
Akaike information criterion (*AIC*)	-0.1598
Cross-validated R^2	0.398
Cross-validated *RMSE*	1.2

IV: *Estimation of regression model parameters*

Variable	Estimate	Std. Error	Conclusion	p-Value	Lower Limit	Upper Limit
Intercept	10.6855	1.3520	Significant	0.0014	6.9317	14.4393
LPI	-29.0258	8.4901	Significant	0.0268	-52.5981	-5.4535

V: *Statistical characteristics of regression model based on LiDAR metric and eLAI*

Coefficient of Determination R^2	0.9212
Mean squared prediction error (*MSPE*)	0.4189
Akaike information criterion (*AIC*)	-7.209
Cross-validated R^2	0.791
Cross-validated *RMSE*	0.65

VI: *Estimation of regression model parameters*

Variable	Estimate	Std. Error	Conclusion	p-value	Lower Limit	Upper Limit
Abs	-8.2859	2.1303	Significant	0.0177	-14.2007	-2.3713
Percentage of all returns above 2.00	0.2073	0.0303	Significant	0.0024	0.1232	0.2915

VII: *Allometric model parameters and statistical characteristics*

Formula	a	R^2	*MSPE*	*AIC*
$y = e^{ax}$	0.0893	0.83	81.62	32.29

VIII: *Statistical parameters of the resulting regression model for LAI estimation based on LiDAR metrics*

Parameter	Predictor	R^2	*RMSE*	*AIC*	cvR^2	*cvRMSE*	Indirect Method Correlation
0.1984	Percentage of all returns above mean	0.8665	0.4758	-4.6020	0.875	0.69	0.51

Another model uses the most correlated LiDAR metric as a predictor. Based on these tests, no negative conclusions that would affect the credibility of the regression model were drawn. The resulting linear regression model is described in Tabs. V and VI. Tab. VI shows the estimates and significances of the regression model parameters. All parameters are significant.

Allometric Equations for LAI Determination at Plot Level

Several allometric models (tree girth as predictor and leaf area as response) using nonlinear regression analysis (power, exponential, and polynomial functions) were created on the basis of girths and leaf areas of nine sample trees, where girth is predictor variable and leaf area is response variable. The Gauss–Newton derivative method of numerical nonlinear optimization was used for model fitting in most of the cases. In case of method divergence, derivative-free method simplex was used. Most models contain errors in the regression triplet. The power and polynomial model contain a residual dependency. The exponential model in the form $y = ae^{bx}$ contains heteroscedasticity and residual dependency; therefore, the model was refitted to the form $y = e^{ax}$. The regression triplet test of the second exponential model showed no negative conclusions that would affect the credibility of the regression model. Allometric model parameters and statistical characteristics are described in Tab. VII.

LAI Modelling-Based LiDAR Metrics (Predictors)

LAI was determined on plots by using the above-mentioned allometric equations. Linear regression model–based LiDAR metrics for LAI estimation were fitted. The best predictors were selected using sequential replacement techniques in the leaps package for R. These models were validated using leave-one-out cross-validation (LOOCV). Tab. VIII shows the parameter estimate and predictor variable for regression model, including statistical parameters and results of cross-validation and correlation with indirect method.

DISCUSSION

The range of LAI values depends on the method of estimation used. The eLAI values detected by the optical methods were similar and the differences between them were statistically insignificant. Based on analysis of variance, we can say that the optical methods (more precisely, the devices used) underestimated the true leaf area; LAI determined by the direct destructive method was more accurate by 29%, on average.

Bréda (2013) compared the LAI values measured using the LI-COR LAI 2000 PCA instrument with measurement by litter-traps. The LAI values of other plots of our study are higher (max. 11.80 m^2.m^{-2}), because Bréda (2013) used another direct method, determination by litter-traps. Morrison (1991) reported a bias of 10% with respect to the average.

The results of Bréda (2013) obtained by LAI 2000 PCA ranged from 4.2 up to 5.2 $m^2.m^{-2}$, similar to our results. The deviation of direct and indirect methods is also similar.

Mussche *et al.* (2001) determined eLAI (LAI) values by LAI 2200 PCA, hemispherical photos, and litter-traps ranging from 3.68 to 5.08 $m^2.m^{-2}$ for stands with 50% beech composition; the highest values were reached by the litter-traps. In comparison with LAI directly measured by litter-trap, the underestimation of LAI calculated by hemispheric photo analysis was 27.55% and by the LAI 2200 PCA was 21.65%. The underestimation is comparable to our study despite the different approach to the direct method. The average underestimation of the LAI 2200 PCA in comparison with litter-traps was determined by Cutini *et al.* (1998) to be 29.57%, and that again corresponds to our study despite the use of the different direct method.

In case of LiDAR utilization for LAI modelling, it very much depends on the method of obtaining a response variable, whether it is eLAI computed by optical methods or LAI obtained by direct measurement. Airborne laser scanning generally correlates well with hemispherical photos, which can be extended to all optical methods (Alonzo *et al.*, 2015). ALS is a suitable. technology for aerial mapping of LAI distribution, and this is confirmed by many earlier studies, e.g., (Riaño *et al.*, 2004; Solberg, 2010; Musselman *et al.*, 2013; Alonzo *et al.*, 2015; Kwak *et al.*, 2007; Barilotti *et al.*, 2006; Peduzzi *et al.*, 2012; Pirotti, 2011).

Several regression models were created with coefficients of determination ranging from 0.75 to 0.92, whereas models containing LiDAR metrics as predictor variables achieved higher coefficients. It was not possible to create an LPI model to estimate LAI with the destructive method as response variable. The higher success using LiDAR metrics is mainly due to preservation of the total amount of points in the point cloud; in the case of LPI, the first return points and points on the ground were used. Therefore, LiDAR metrics had better describe the vertical structure of the stand. Kwak *et al.* (2007) made similar claims; they reached higher coefficients of determination than in the case of LPI by using the Laser Interception Index (LII), which they explain by preservation of the total amount of points.

Riaño *et al.* (2004) stated that LAI estimation is generally better for deciduous than coniferous stands. Barilotti *et al.* (2006) created a regression model for eLAI calculation with a R^2 of 0.89; field measurements were carried out using the LI-COR LAI-2000 PCA. Musselman *et al.* (2013) created a regression model with a R^2 of 0.64; they performed 24 measurements using hemispherical photo analysis. Kwak *et al.* (2007) created equations of eLAI and LPI dependence for three tree species. They reached R^2 of 0.73 for *Larix leptolepis* Sieb. et Zucc. and R^2 of 0.81 for *Quercus* spp. and Pinus koraiensis Sieb. et Zucc. They also used a different index than the LPI (the laser interception index), thus they achieved higher coefficients of determination (0.85–0.88). Peduzzi *et al.* (2012) created a regression model for mixed forests in Virginia, which explained 69% variability of eLAI. In combination with radar interferometry data, they created a model with a R^2 of 0.77. Solberg (2010) estimated eLAI from ALS data in pine stands affected by defoliation; the created models had very high coefficients of determination (from 0.92 to 0.94). Higher coefficients of determination may be related to a smaller overlay of the leaves and better laser beam penetration.

CONCLUSION

The created models are valid only at the regional level or at the level of the forest-like structure, i.e., stands with similar species composition and age. Pirotti (2011) mentioned the same; the regression models published here are similar to the regression rebate as models of other authors. Most authors developed ALS-based models for calculation of effective LAI. However, the destruction methods are the most accurate. This work has revealed a significant benefit of using LiDAR metrics compared to the laser penetration index, also for modelling of effective leaf area index. Qu *et al.* (2018) confirm it, but they recommend using the height metrics. In our research, the density metric *Percentage of all returns above mean* was used. In the empirical approach to modelling, both height and density metrics are calculated, and the best ones are selected. Qu *et al.* (2018) also points out the risk of multicollinearity between similar height metrics. Using height and density metrics together will avoid multicollinearity.

However, an effective LAI usually underestimates the actual LAI. This paper of showed the possibilities of upscaling the actual LAI using airborne laser scanning. The LiDAR metrics-based model reach the R^2 of 0.87, the highest coefficient of determination during the cross-validation (0.88), and the lowest cross validated root mean square error (0.69).

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