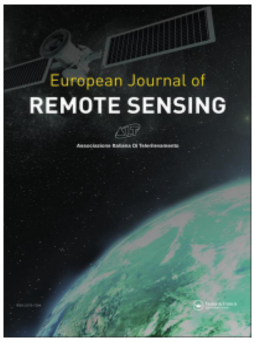

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The transferability and cross-use of airborne laser scanning-based leaf-off and leaf-on biomass models

M. Maltamo[a], P. Packalen[b], L. Laukkanen[a] and L. Korhonen[a]

[a]School of Forest Sciences, University of Eastern Finland, Joensuu, Finland; [b]Bioeconomy and Environment, Natural Resource Institute of Finland, Helsinki, Finland

ABSTRACT

Airborne laser scanning data (ALS) can be acquired during leaf-on or leaf-off conditions. Thus, the relationship between ALS metrics and vegetation is different, especially in forests dominated by deciduous tree species. We studied the application of leaf-off and leaf-on ALS data in two boreal forest inventory areas in Finland and modelled above ground biomass (AGB). The relative RMSE was typically approximately 20%. In both study areas, we also cross-used the models, i.e. leaf-off model was applied with leaf-on data and vice versa. This increased RMSE% and caused over- and underestimates, especially in plots dominated by deciduous species. However, calibration by empirical ratio estimator (mean between cross-used and correct estimates) removed the over- and underestimates and decreased the RMSE%. When the models were transferred to other study areas and applied with their intended ALS data type, the RMSE% values increased, but only slightly. When the models were transferred to other study areas and cross-used with the wrong ALS data type, the increase in RMSE and over- or underestimation was the largest. However, also the empirical ratio estimator from the other inventory areas could be transferred, and the calibration improved the correctly transferred and cross-used AGB estimates in most cases.

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Aboveground biomass; LiDAR; leaf conditions; model transfer; boreal forest; forest inventory

Introduction

Three-dimensional (3D) description of vegetation by airborne laser scanning (ALS) has proven to be an accurate source of information for forestry (Fassnacht et al., 2024; Maltamo et al., 2021). Several forest applications that employ ALS data have proceeded to practical use. One example is the ALS-based forest management inventory, which is applied to large areas in Nordic countries and Canada (Maltamo et al., 2021; Næsset, 2007; White et al., 2025). However, ALS is also utilized in sampling-based national forest inventories, pre-harvest inventories and inventories focusing on non-wood forest products (Bohlin et al., 2021; Grafström et al., 2017; Hauglin et al., 2018) to mention a few. Ecological and biodiversity applications employing ALS data have also emerged. Due to its capability to accurately measure 3D forest structure, ALS data are highly suitable for the estimation of e.g. leaf area index, canopy cover and vertical forest structure (Holt-Hanssen & Solberg, 2007; Korhonen et al., 2011; Penner et al., 2023).

Forestry applications are, however, not the primary use of ALS data. Instead, national-level land surveys and the construction of digital terrain models (DTMs) have long been the most important way to utilize ALS data (National Land Survey of Finland, 2024). Leaf-off ALS data, collected in the spring before the budburst, are commonly preferred in land surveys to avoid a bias caused by vegetation in DTM construction. On the other hand, in forest inventories, midsummer leaf-on conditions are usually preferred, although leaf-off data can also be used (White et al., 2015). Since the joint use of the same leaf-off data in both land surveys and forestry applications can provide significant cost savings, in practice the data acquisitions are often combined (Nord-Larsen & Schumacher, 2012). The main effect that the use of leaf-off data has on vegetation surveys is that the laser pulses penetrate considerably deeper into deciduous tree crowns (Wasser et al., 2013). Also, the proportion of pulses that reflect only from the ground or the lower vegetation layer is larger (Hill & Broughton, 2009). In principle, the relationship between ALS metrics and

CONTACT M. Maltamo matti.maltamo@uef.fi School of Forest Sciences, University of Eastern Finland, Yliopistokatu 7, P.O. Box 111, Joensuu 80101, Finland

pure coniferous stands should be similar to both leaf-off and leaf-on data, although more abundant ground vegetation in leaf-on conditions may slightly affect the normalized heights.

The use of leaf-off data has provided promising results in applications related to structural diversity, such as mapping the understory or canopy closure (Davison et al., 2020; Hill & Broughton, 2009; Parent & Volin, 2014). The use of leaf-off data also has benefits in forestry, since it discriminates the species of individual trees better than leaf-on data (Brandtberg, 2007; Kim et al., 2009; Ørka et al., 2009; Reitberger et al., 2008). The use of leaf-off data can also improve the ability to separate species in inventories that employ the area-based-approach (ABA) (Bouvier et al., 2015; Hawbaker et al., 2010; Villikka et al., 2012; White et al., 2015), which is currently more commonly used in forestry.

Næsset (2005) was the first one to construct separate stand attribute models with data collected in both leaf-on and leaf-off conditions. His models had a similar accuracy in both conditions, but the last echoes were more affected by canopy conditions than the first echoes. Villikka et al. (2012) also constructed stand attribute models with leaf-off and leaf-on data. Their main observation was that the cross-use of data sets, i.e. applying a model constructed with leaf-off data with leaf-on data or vice versa, increased root mean square error (RMSE) values and caused serious bias. Thus, the combined use of leaf-on and leaf-off models was not recommended. White et al. (2015) constructed stand attribute models (including above-ground biomass (AGB)) using separated and pooled leaf-off and leaf-on data. They also constructed models for the whole data and separately by forest types. According to their results, pooling the ALS data only had a minor effect, but generic models with those combined forest types resulted in larger RMSE values. Similarly, as in Villikka et al. (2012), they recommended avoiding the cross-use of different data types.

Yet another aspect to consider is the transferability of ALS-based stand attribute models between different ALS inventory areas. Forest management inventory campaigns always include wall-to-wall ALS data, which is often supplemented by optical aerial photographs and local field data. However, for example in large-scale biomass mapping applications, it may not be possible to have local field data due to the extensive costs or difficult reachability of the inventory area. Under such conditions, there is an alternative to use existing field plots and models. During the last 10 years, the use of earlier ground truth data from geographically neighboring areas has been examined in many studies (Fekety et al., 2018; Gopalakrishnan et al., 2015; Kotivuori et al., 2018; Tompalski et al., 2019). The results are generally promising, but transferring models requires that transferability is already considered in the model construction phase. There may be situations where the constructed models need to be both transferred between areas and cross-used under different leaf conditions. This case is especially common with spaceborne lidar sensors such as GEDI (Global Ecosystem Dynamics Investigation) and ICESat-2, which collect data throughout the year in different leaf conditions (Cushman et al., 2023; Varvia et al., 2022).

Our aim in this study was to evaluate the accuracy and transferability of ALS-based AGB models constructed using ABA in both leaf-on and leaf-off conditions. We constructed the models for the whole study data (AGB_{tot}) and separately for coniferous (AGB_{con}) and deciduous (AGB_{dec}) species groups in two separate inventory areas, both of which were covered by independent acquisitions of leaf-off and leaf-on ALS data. Models were then cross-used in different leaf conditions both within their respective inventory areas and when transferred to the other inventory areas. Finally, we tested the use of an empirical ratio estimator (Snowdon, 1991) to decrease the bias resulting from the cross-use of models under different leaf conditions.

Materials and methods

Study areas

Our study areas, Suonenjoki and Liperi, are managed boreal forests located in Eastern Finland (Figure 1). The approximate distance between these areas is 80 km. Both areas are dominated by coniferous species Scots pine (*Pinus sylvestris* L.) and Norway spruce (*Picea abies* (L.) H. Karst.), but deciduous birch species such as downy (Betula *pubescens* Ehrh.) or silver birch (Betula pendula Roth) also occur as a minority species. Operational inventories were implemented in both study areas, and the same areas have also been used in previous research and development projects, where the comparisons of simultaneous use of leaf-off and leaf-on ALS data sets were one of the objectives.

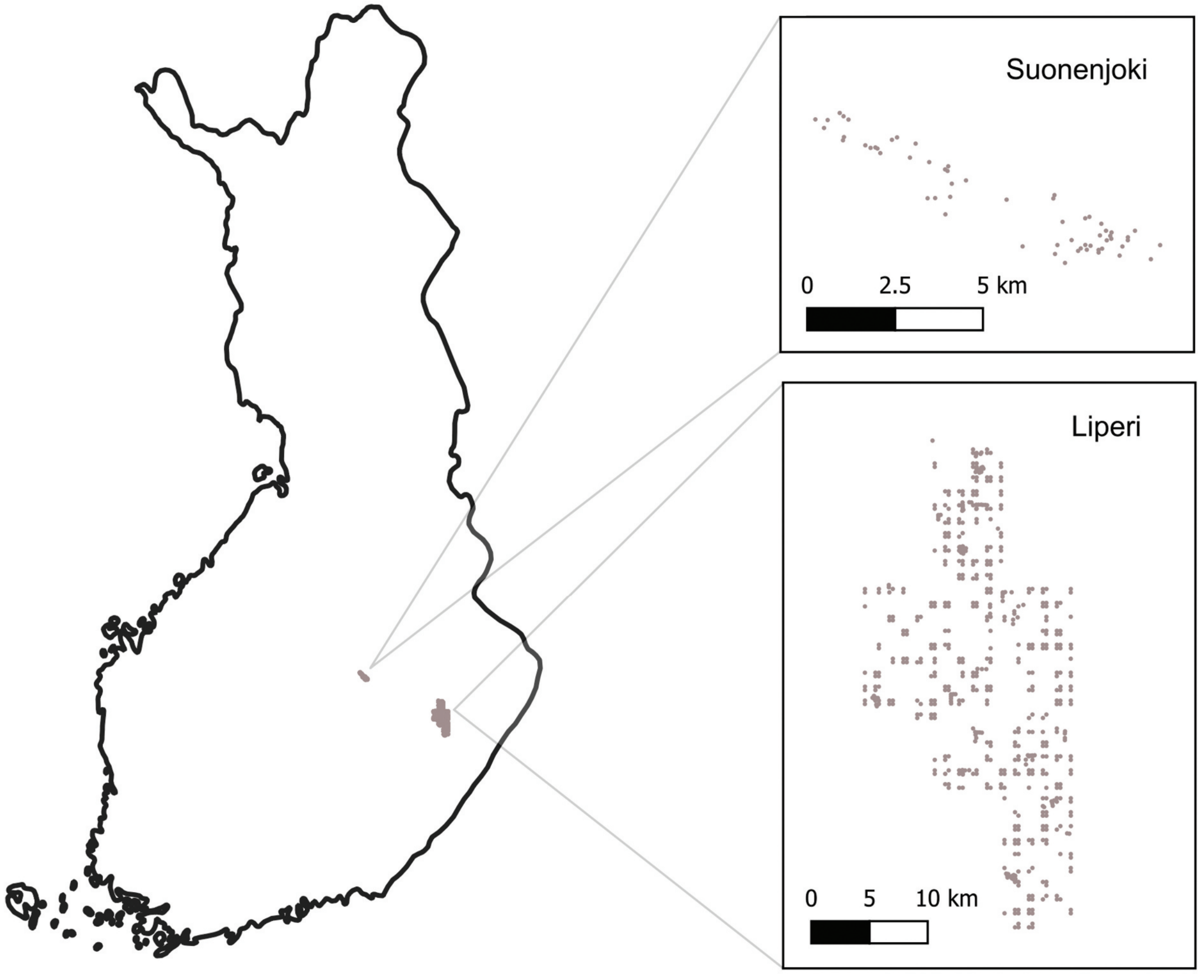

Figure 1. Map of the AGB study areas and plots in Finland.

Field data

Both study areas were covered by field plots with a radius of 9 m (12.52 m in sparse stands). There were a total of 192 plots in Suonenjoki, 60 of which were dominated by deciduous species. Correspondingly, in Liperi, there were altogether 695 plots, 70 of which were dominated by deciduous species. In Suonenjoki, the field data was collected using purposive sampling, which aimed at having about 1/3 of the plots in forests dominated by deciduous species. In Liperi, the plot locations represented a systematic sample.

All trees within the plots with diameter at breast height (DBH) ≥ 5 cm were measured. The tree level measurements included DBH, tree species, and tree class (living or dead). In Suonenjoki, the heights were measured only for a set of sample trees, and the heights of the remaining trees were predicted by a height model constructed with the sample tree data. In Liperi, all tree heights were measured. Although we only considered AGB in this study, other main forest attributes are also presented in Table 1. Plot-level AGB values per hectare were estimated using the tree-level models by Repola (2008, 2009). His models applied species, DBH and height as predictor variables. Correspondingly, the volume was estimated using the tree level equations of Laasasenaho (1982).

ALS data and its processing

In Suonenjoki, both ALS data sets were collected in 2008 with an Optech ALTM Gemini instrument. The same scanning configuration was applied in both leaf-on and leaf-off acquisitions (Villikka et al., 2012). The leaf-off data were collected on 16–17 May 2008, and the leaf-on data on 31 August and 1 September 2008. The test site was scanned from an altitude of 2,000 m above ground level (a.g.l.) using a field of view of 28

Table 1. Chosen stand attributes in the study areas of Suonenjoki and Liperi in Finland. DGM and HFM refer to basal median diameter and height, respectively.

	Suonenjoki						Liperi					
	All plots		Coniferous plots		Deciduous plots		All plots		Coniferous plots		Deciduous plots	
	Mean	Range	Mean	Range	Mean	Range	Mean	Range	Mean	Range	Mean	Range
AGB, Mkgha^{-1}	108.1	13.2–319.3	117.2	18.0–319.3	88.2	13.2–280.8	90.1	5.4–410.0	93.1	5.4–410.0	68.3	7.3–195.4
Volume, m^{3}ha^{-1}	204.7	24.5–752.7	223.7	28.2–752.7	162.9	24.5–564.6	174.4	10.1–1012.6	182.3	10.2–1012.6	117.5	12.3–369.3
DGM, cm	21.5	7.8–60.3	22.5	9.2–46.3	19.5	7.8–60.3	20.7	5.8–53.2	21.0	5.8–42.7	18.6	7.6–53.2
HGM, m	18.1	5.6–32.9	17.9	5.6–31.4	18.4	6.3–32.9	17.8	4.6–32.7	18.0	4.6–32.7	16.8	7.6–31.6
Basal area, m^{2}ha^{-1}	23.6	4.5–61.7	25.3	8.9–61.7	18.8	4.5–45.5	20.2	1.6–70.9	20.8	1.6–70.1	15.4	1.8–38.3
Proportion (%) of coniferous species	66.4	0–100	89.5	54.2–100	15.5	0–49.7	82.4	0–100	90.9	51.8–100	20.5	0–49.4

degrees and a side overlap of 20%. The flight speed was 75 ms^{-1}, and the pulse frequency was 50 kHz. This resulted in a swath width of approximately 1000 m and a nominal sampling density of about 0.6 pulses per square meter (Villikka et al., 2012).

In Liperi, Multispectral ALS data were collected at an altitude of 850 m above ground level with a Teledyne Optech Titan scanner (Maltamo et al., 2020). The data were collected in June 2016 under leaf-on conditions. The Titan scanner measured up to four ranges and intensity measurements per pulse using 1550 nm, 1064 nm, and 532 nm wavelengths for the first, second and third channels, respectively. On average, the pulse density per flight line was 4.8 pulses per square meter for channels 1 and 2, and 3.7 for channel 3 (Maltamo et al., 2020). We only used data from the second channel in our analysis for better comparability with the leaf-off data set.

The Liperi leaf-off ALS data set was collected on 30 April – May 2016 with a Leica ALS60 device (Maltamo et al., 2020). The flying altitude was 2,400 m above ground level, and the strip overlap was 20%. This configuration provided a pulse density of 0.8 pulses per square meter. The ALS60 ALS system used the 1064 nm wavelength, which was similar to the channel 2 of the Titan sensor mentioned above (Maltamo et al., 2020).

The ALS echoes were classified into ground and vegetation hits using the approach presented by Axelsson (2000). The orthometric echo heights were normalized into heights above the ground level using the LAStools software. The ABA metrics were computed for each plot without a height threshold by using only the first of many and only echoes (f). Last or intermediate echoes were not used at all, as they were expected to be more sensitive to effects caused by different scanners and leaf conditions. The metrics included average (avg) and maximum (max) heights, standard deviations (std) of the heights, averages of squared heights (qav), height percentiles p5, p10, p20, … , p90, p95, canopy density percentiles b30, b40, … b90, b95, and a canopy cover index calculated from the first echoes (cov) (Maltamo et al., 2023).

Modelling and the accuracy

We constructed linear regression models for the aboveground biomass separately for both areas and for both leaf-off and leaf-on conditions. In addition to AGB_{tot} of the whole data, we also modelled AGB separately for plots dominated by coniferous (AGB_{con}) and deciduous (AGB_{dec}) species. This resulted in altogether 12 different AGB models. We tested different variable transformations but finally decided to use a square root (√) transformation of the dependent variable AGB in all models. Square root (√) and natural logarithm (ln) transformations were also computed for each independent variable obtained from ALS data. The independent variables were selected from a list of all model candidates with two predictors according to the lowest root mean square error (RMSE) value.

The models were cross-used in all other datasets. For example, the model constructed in Suonenjoki leaf-off conditions was tested with Suonenjoki leaf-on data and transferred to Liperi for tests in both leaf-off and leaf-on conditions. A bias correction was made in the prediction phase by adding the second power of model residual error (s_e^2) to all predictions. When cross-using models in the same study area, an empirical ratio estimator for bias correction (Snowdon, 1991) was estimated from the ratio of the mean of the predictions of the correct leaf condition model and the mean of the predictions of the cross-used model. Therefore, for example, the following ratio was used to calibrate leaf-on data to leaf-off conditions:

$$\boldsymbol{AGB_{calibrated}} = \frac{\widehat{\bar{AGB}}_{leafoff}}{\widehat{\bar{AGB}}_{leafon}} \tag{1}$$

From here on, we refer to this bias correction when we use the term calibrate. The cross-predicted estimates were calibrated by multiplying them by the ratio estimator. When transferring the model to other study areas and cross-using it, the ratio estimator was also transferred. The performance of AGB_{con} and AGB_{dec} models combined to cover the whole data was also tested except in the case of cross-use.

The accuracy of the constructed models was evaluated in terms of the RMSE:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{\left(AGB_i - \widehat{AGB}_i\right)^2}{n}} \quad (2)$$

where n is the number of plots, AGB_i is the observed AGB for plot i and $\widehat{AGB}_i$ is the predicted AGB for plot i.

The mean deviation (MD) was also calculated as follows:

$$\boldsymbol{MD} = \sum_{i=1}^{n} \frac{\left(AGB_i - \widehat{AGB}_i\right)}{n} \quad (3)$$

Subsequently, RMSE% was calculated by dividing the RMSE by the observed attribute mean and then multiplying the result by 100.

Results

The constructed AGB models are presented in Table 2. The models have two independent variables. Usually, one was a height metric, and the other was a density metric (Table 2). The most often **used** metrics were squared average height (qav) and lower density metric b20, and also an ALS-based estimate of canopy cover (cov) and another density metric b30 were often selected for the model. There was no conformity in which metric was used in deciduous or coniferous dominated plots or in leaf-off or leaf-on data as a predictor variable.

The empirical ratio estimators used to calibrate the cross-used models are presented in Table 3. The coefficients are close to each other, except for the estimator for deciduous tree species dominated plots in Liperi. Otherwise, the estimators were rather moderate, i.e. close to value 1.

The reliability figures of the constructed models, including cross-use and calibration in the same study area where they were constructed, are presented in Table 4. In the table, the first column indicates the validation data. This is followed by the different modelling data sets according to leaf conditions. The first modelling data are always the same as the validation data, thus the first RMSE% and md values indicate model accuracy. This is followed by the cross-used alternatives. In the case of cross-use also the calibrated values using empirical ratio estimators are shown. In addition to the case of cross-use, the reliability figures are also given for the alternative in which predictions of coniferous and deciduous models are summed.

The model accuracies for the whole data (AGBtot) and for coniferous tree species dominated plots only (AGB_{con}) in the training data were approximately 20%, with the exception of leaf-on data in Suonenjoki (AGB_{tot}) (Table 4). The RMSE% values were higher for deciduous-dominated plots than for coniferous-dominated plots. When predictions of models constructed according to dominant species were combined to cover the whole data, the results were better than those in the case of the whole data models. As expected, the mean deviation was close to zero in the modelling data despite back-transformation.

When the models were cross-used in the same inventory area, both RMSE% (range for the AGB_{tot} was 26–34%) and especially MD-values increased (Table 4). Additionally, the behavior of MD-values in relation to leaf conditions was logical. The increase in both reliability figures was greatest in the case of models of deciduous dominated plots. When each of these model estimates was calibrated by multiplying the estimates with the calculated empirical ratio estimators, the MD-values approached zero, and also RMSE% (range for the AGB_{tot} was 22–30%) values decreased.

In the next step, the models were transferred to the other study area and applied using both similar and dissimilar leaf conditions (Table 5). In the case of the transfer, the RMSE% values increased again (the range for the AGB_{tot} was 24–32%), with the increase being largest for the models constructed using deciduous dominated plots. Also, the mean deviations increased, but there were no clear trends showing under- or overestimations.

In the final phase, the models were both transferred to other inventory areas and cross-used (Table 5). Again, the RMSE% values increased % (range for the AGB_{tot} was 27–34%), but surprisingly little, except for the models constructed using deciduous dominated plots. Also, here, the changes in the MD-values were logical, i.e. the leaf-off model yielded an overestimate in leaf-on data and vice versa. Finally, these estimates were calibrated using

Table 2. Models constructed for the aboveground biomass: AGB_{tot} = biomass of the whole data, AGB_{con} = biomass of the coniferous dominated plots and AGB_{dec} = biomass of the deciduous dominated plots. The selected ALS metrics, their coefficients and model reliability figures are also presented. For ALS metric abbreviations, see the ALS data processing section.

Study area	Data	De-pen-dent vari-able	Model																	
			Intercept	b30	max	p90	avg	sqrt (cov)	b20	p60	qav	cov	b70	sqrt (avg)	sqrt (qav)	sqrt (b20)	sqrt (std)	ln (max)	R^2	Residual standard error
Suonenjoki	Leaf-off	AGB_{tot}	6.936	−0.103	0.314														0.81	1.15
		AGB_{con}	7.21	−0.084		0.35													0.83	1.04
		$AGB_{\mathbf{dec}}$	−0.097				0.491	0.532											0.84	1.03
	Leaf-on	AGB_{tot}	5.49			0.36			−0.073										0.70	1.45
		AGB_{con}	6.152						−0.0526	0.433									0.81	1.09
		AGB_{dec}	−2.56					0.935			0.0173								0.81	1.12
Liperi	Leaf-off	AGB_{tot}	−2.93										0.0207	4.029					0.86	1.04
		AGB_{con}	0.981									0.0464			0.524				0.88	0.96
		AGB_{dec}	1.955													−0.781	5.001		0.77	1.27
	Leaf-on	AGB_{tot}	3.971	−0.0323											0.598				0.86	1.02
		AGB_{con}	0.212												0.597	−0.411			0.89	0.89
		AGB_{dec}	−7.626											2.898				2.53	0.79	1.20

Table 3. Empirical ratio estimators between leaf-off and leaf-on, and vice versa, AGB estimates in the study areas.

	AGB $_{tot}$ off/on	AGB $_{con}$ off/on	AGB $_{dec}$ off/on	AGB $_{tot}$ on/off	AGB $_{con}$ on/off	AGB $_{dec}$ on/off
Suonenjoki	1.130	1.069	1.290	0.862	0.923	0.776
Liperi	1.133	1.084	1.727	0.882	0.917	0.770

Table 4. Reliability figures of the constructed AGB models in the same study area. All models are tested in their model data, cross-used and calibrated in the same study area. Con+dec refer to AGB_{con} and AGB_{dec} model results combined to cover the whole data.

Validation data	Modelling data		Modelling data		Modelling data	
Liperi leaf-off	Liperi leaf-off		Liperi leaf-on		Liperi leaf-on calibrated	
	RMSE%	MD	RMSE%	MD	RMSE%	MD
Whole data	23.26	0.00	26.43	10.60	24.48	0.28
Coniferous	21.14	0.61	22.94	7.81	21.78	0.62
Deciduous	32.94	−0.03	56.49	28.74	36.82	0.25
Con +dec	22.25	0.53			23.22	0.57
Liperi leaf-on	Liperi leaf-on		Liperi leaf-off		Liperi leaf-off calibrated	
Whole data	22.32	0.04	26.33	−11.97	23.93	0.04
Coniferous	19.52	−0.10	21.72	−8.50	20.24	−0.10
Deciduous	29.66	−0.04	47.43	−20.47	37.94	−0.04
Con +dec	20.47	−0.09			22.01	−0.10
Suonenjoki leaf-off	Suonenjoki leaf-off		Suonenjoki leaf-on		Suonenjoki leaf-on calibrated	
Whole data	22.86	−0.26	26.50	12.17	23.46	−0.26
Coniferous	19.90	−0.13	21.59	7.41	20.85	−0.13
Deciduous	21.01	0.09	31.11	19.87	23.60	0.09
Con +dec	20.29	−0.06			21.61	−0.05
Suonenjoki leaf-on	Suonenjoki leaf-on		Suonenjoki leaf-off		Suonenjoki leaf-off calibrated	
Whole data	28.43	0.08	34.03	−17.22	29.92	0.08
Coniferous	20.75	0.03	22.69	−9.76	21.72	0.00
Deciduous	24.78	0.07	39.71	−25.37	28.04	0.07
Con +dec	21.80	0.04			23.33	0.03

Table 5. Reliability figures of the AGB models when applied to the other test areas. All models were transferred to other study areas, cross-used and calibrated in the other areas.

Validation data	Modelling data		Modelling data		Modelling data	
Liperi leaf-off	Suonenjoki leaf-off		Suonenjoki leaf-on		Suonen joki leaf-on calibrated	
	RMSE %	MD	RMSE%	MD	RMSE%	MD
Whole data	26.87	8.08	30.31	15.75	24.53	6.09
Coniferous	21.56	−0.03	26.94	7.17	26.76	1.28
Deciduous	58.89	27.32	73.14	38.57	62.12	29.96
Con +dec	26.03	3.28			30.67	4.75
Liperi leaf-on	Suonenjoki leaf-on		Suonen joki leaf-off		Suonenjoki leaf-off calibrated	
Whole data	25.62	5.80	28.27	−10.07	26.87	4.39
Coniferous	23.90	−1.51	22.73	−9.32	21.01	−1.13
Deciduous	36.04	8.01	37.35	−11.39	35.25	6.49
Con +dec	25.02	−0.36			22.38	−0.21
Suonenjoki leaf-off	Liperi leaf-off		Liperi leaf-on		Liperi leaf-on calibrated	
Whole data	25.19	−4.95	26.86	5.62	29.55	−8.01
Coniferous	20.85	2.48	23.44	11.48	22.62	4.40
Deciduous	40.13	−22.1	25.21	8.09	31.67	−14.94
Con +dec	26.19	−5.28			24.88	−1.77
Suonenjoki leaf-on	Liperi leaf-on		Liperi leaf-off		Liperi leaf-off calibrated	
Whole data	32.40	−6.93	33.82	−17.48	29.32	−2.40
Coniferous	22.32	1.73	22.76	−6.66	21.91	3.03
Deciduous	29.07	−8.28	44.66	−24.85	35.79	0.34
Con +dec	23.96	−1.50			25.54	2.19

empirical ratio estimators calculated from the other (same as for modelling data) inventory areas. In most cases, this calibration succeeded and both RMSE% (range for the AGB_{tot} was 22–30%) and MD-values decreased.

An example of the AGB estimation alternatives of this study is shown in Figure 2. The Suonenjoki leaf-off ALS data is used and the scatterplot illustrates AGB model prediction, cross-use, calibration and transfer.

Discussion

This study compared AGB predictions obtained using ALS data sets acquired in leaf-off and leaf-on conditions in two separate study areas. The accuracies of the different AGB prediction alternatives were

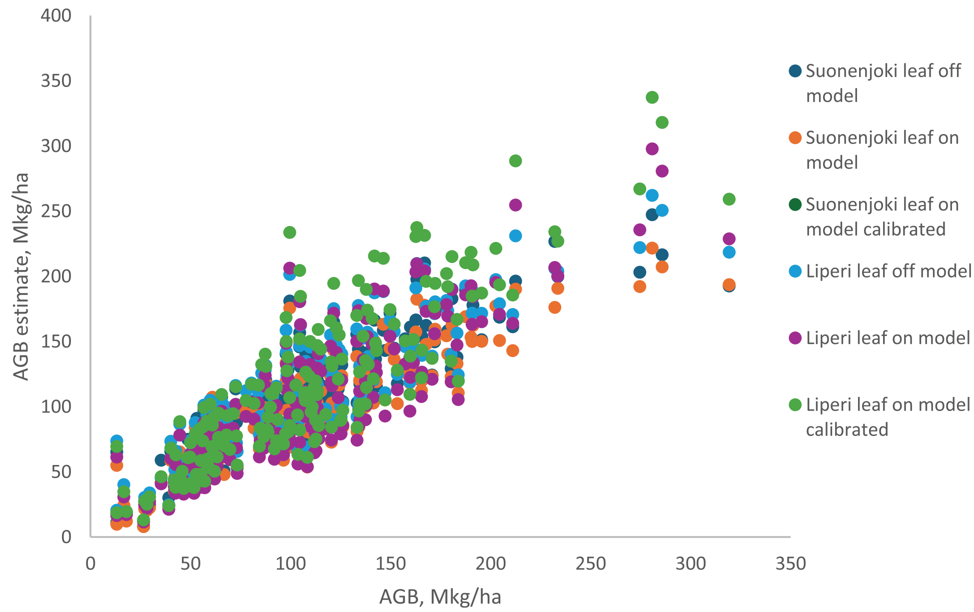

Figure 2. An illustration of AGB predictions in the Suonenjoki study area, Finland, using leaf off ALS data and different AGB models.

close to each other, except for the Suonenjoki leaf-on data, where the RMSE values were higher. The model accuracy values were also in line with the previous studies (Næsset, 2005; Villikka et al., 2012). The RMSE values of species-group specific models were usually smaller for AGB_{con} and larger for AGB_{dec} than for AGB_{tot}. However, when the plots dominated by different species groups were combined to present the whole data, the results were usually more accurate than the AGB_{tot} estimates, since the proportion of deciduous dominated plots was small. Still, one must remember that the use of species-group specific models requires pre-classification of the inventory area according to the main species of inventory units, which is not error-free. An example of such a classification is the Multisource National Forest Inventory of Finland (Tomppo et al., 2008).

When models were transferred to the other inventory areas, the RMSE values somewhat increased, most notably in the case of AGB_{dec}. Species-group specific models were no longer more accurate than AGB_{tot} in every case. The amount of mean deviation increased as well, and there were no clear over- or under-estimations. Most probably, the increases in the RMSE and mean deviation were influenced by the laser scanning sensor effects. Also, in this regard, the results seen in the model transfer were comparable to an earlier study (Kotivuori et al., 2018).

Concerning the cross-use of the models, the mean deviation values increased as expected (Villikka et al., 2012; White et al., 2015). The behavior was logical in all cases, i.e. overestimations were observed when the leaf-off-models were applied to leaf-on-data and vice versa. The RMSE values also increased, but the increase was smallest for conifer dominated plots. The results concerning cross-use were better here than in the study of Villikka et al. (2012), although the Suonenjoki study material was the same. The reason could be that the ALS metrics were calculated differently, and the models of Villikka et al. (2012) had a larger number of independent variables, which also included the last echo metrics.

The most interesting results were obtained when models were cross-used and their estimates calibrated. The calibration was done by the empirical ratio estimator, which was calculated as a relationship between the average predictions of the correctly applied model, and the average predictions of the cross-used model. Within the same inventory area, calibration removed the bias and also decreased RMSE values in all cases. The results were almost the same when the models were first transferred and then had their estimates calibrated. In only one case (Liperi leaf-on condition models applied in Suonenjoki leaf-off-data), the calibration was too strong (underestimates turned to overestimates) and the results got worse when compared to the uncalibrated case. At its best, the accuracy of the model transfer was close to the accuracy of the original model (Suonenjoki leaf-off-AGB_{tot} model in Liperi leaf-on-data).

The largest RMSE and bias values were obtained for models that were constructed for deciduous species. This was expected from the previous studies, where it was stated that the canopy heights derived from ALS data had a higher variability under leaf-off conditions (Næsset, 2005). Our study areas have been acquired using different sampling schemes (purposive sampling vs. objective sampling). Thus, the proportions of deciduous-dominated plots were therefore different, the proportion of coniferous trees was larger in Liperi than in Suonenjoki (Table 1). This had an effect on the accuracy of AGB_{dec} models, but not on the transfer or calibration. In fact, the applied ratio estimators were rather similar in both inventory areas, except for the leaf-off/leaf-on case in Liperi. One must also remember that our deciduous-dominated plots also had coniferous trees and vice versa. So, most of the plots were not pure monocultures but typically managed stands in Southern Finland. Thus, the ratio estimators obtained for total AGB reflected the average relationship between leaf-on and leaf-off ALS metrics in the Finnish forests and thus improved the model transferability.

This study showed that the ALS-based biomass models constructed under leaf-off and leaf-on conditions can be transferred and cross-used at different inventory areas, provided that their predictions are calibrated by a ratio estimator. It is even possible that model transfer with cross-use and calibration leads to a better accuracy than a transfer under the same leaf conditions, or at least, the results are comparable. However, care must be taken when constructing models. Our models were rather simple with just two predictors, which may be a benefit in transfer and cross-use scenarios. Tests with more complex models (more than two independent variables and also last echo predictors) showed that the cross-use and calibration especially became more difficult (results not shown). A requirement for calibrating model estimates is that there must be an inventory area available where both leaf-off and leaf-on data have been acquired during the same year. Empirical ratio estimators can be calculated after the leaf-off and leaf-on models have been constructed. An obvious application of this information is in a new inventory area, where ALS data are available, but there is no possibility to acquire local field data. Such situations are common in studies involving spaceborne lidar data. For example, regression models applied with GEDI waveforms (e.g., Duncanson et al., 2022) could be calibrated for leaf-on and leaf-off conditions using a ratio estimator.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The raw data were obtained from the following open sources: field plots by the Finnish Forest Centre at https://avoin.metsakeskus.fi/aineistot/Inventointikoealat/Kunta/, ALS areas by the National Land Survey of Finland at https://www.maanmittauslaitos.fi/laserkeilaus-ja-ilmakuvaus. 5p ALS data from the National Land Survey of Finland at https://asiointi.maanmittauslaitos.fi/karttapaikka/tiedostopalvelu/laserkeilausaineisto_5p, access to 5p laser data is limited outside of Finland and the European Union.

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