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Prediction of forest attributes using airborne laser scanning-based models without new in-situ field measurements

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Academic dissertation

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ABSTRACT

The era of airborne laser scanning (ALS) and the development of new forest inventory methods has reduced the need for field visits and overall inventory costs over the last two decades. Although the development of inventory methods has been considerable, some systematic field visits are usually always required. For example, the most common ALS inventory method, the area-based approach (ABA), leans on field sample plot measurements. Likewise in the ALS inventory, the ABA method can also be used in drone-based inventories with image point cloud (IPC) data. Due to the small areal coverage of the drones, local sample plot measurements in drone image point cloud (DIPC) inventories are not usually profitable. The objective of this thesis was to examine the performance of ALS-based forest attribute models in ALS- and DIPC-based ABA inventories without new in-situ field measurements.

In this study, nationwide ALS models for three forest attributes (stem volume, above ground biomass and dominant height) were fitted for the whole of Finland, and regional-level error rates of the nationwide model predictions were assessed. As the nationwide models tended to exhibit systematic region-wise under- and over-predictions, different calibration methods were examined. First, calibration of nationwide models with a small number of new field measurements from the target area was simulated. Second, the nationwide stem volume model or its regional predictions was calibrated without new in-situ field measurements by three test scenarios: a) using additional calibration variables in the models to account for geographical and environmental conditions throughout the country, b) refitting of the models by using existing sample plots from nearby regions, and c) matching the regional-level predictions with national forest inventory data. The DICP-based forest inventory without new in-situ field measurements was evaluated by replacing the ALS metrics from the ALS-based models with DIPC metrics when the models were applied. In the DIPC inventory, the metrics used in the ALS models were selected carefully so that they would be similar to the corresponding DIPC metrics.

The results showed that forest attributes can be predicted without new in-situ field measurements using nationwide ALS-based models with moderate error rates. The systematic errors associated with the nationwide models decreased when the models were fitted with additional calibration variables, such as degree days, precipitation, and tree species proportions. However, the measurement of a carefully selected set of sample plots (e.g., 20 plots) from the target area for the calibration of the nationwide model is recommended, in instances where it is economically feasible. Prediction of forest attributes using ALS-based models with DIPC metrics is possible provided the predictor variables describe the upper canopy layer. The lowest error rates in DIPC-based inventories were obtained when the ALS-based model was fitted in a nearby region and the inventory units were disaggregated to coniferous and deciduous dominated areas before the prediction.

Keywords: remote sensing, airborne laser scanning, area-based approach, nationwide model, regional model, drone, image point cloud

Kotivuori E (2022) Puustotunnusten ennustaminen laserkeilauspohjaisten mallien avulla ilman uusia paikallisia maastomittauksia. Dissertationes Forestales 328. 54 s.
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TIIVISTELMÄ

Laserkeilauksen aikakausi ja uusien inventointimenetelmien kehitys on vähentänyt maastomittausten tarvetta ja inventointien kokonaiskustannuksia viimeisen kahden vuosikymmenen aikana. Vaikka menetelmäkehitys onkin ollut merkittävää, systemaattisia maastomittauksia tarvitaan käytännössä yhä edelleen. Esimerkiksi yleisesti käytössä oleva aluepohjainen inventointimenetelmä tukeutuu maastossa tehtäviin koealamittauksiin. Laserkeilausperusteisten inventointien lisäksi aluepohjaista menetelmää voidaan käyttää myös lennokeilla tehtävissä inventoinneissa ilmakuvapistepilviä hyödyntäen. Maastossa tehtävät koealamittaukset eivät ole yleensä lennokki-ilmakuvapistepilviä käytettäessä kannattavia lennokkien pienen toiminta-alueen takia. Tämän väitöskirjan tavoitteena oli tutkia laserkeilauspohjaisten mallien toimivuutta laserkeilaukseen ja lennokki-ilmakuvapistepilviin perustuvissa inventoinneissa ilman uusia paikallisia maastomittauksia.

Tässä tutkimuksessa valtakunnalliset laserkeilauspohjaiset mallit sovitettiin koko Suomen alueelle kolmelle puustotunnukselle (runkotilavuus, maan yläpuolinen biomassa ja valtapituus) ja niiden virheitä tarkasteltiin aluetasolla. Valtakunnallisten mallien aluetason ennusteet olivat usein systemaattisia yli- tai aliarvioita, minkä takia tutkittiin erilaisia kalibrointimenetelmiä. Ensimmäisenä testattiin valtakunnallisten mallien kalibrointia pienellä määrällä uusia maastomittauksia. Tämän jälkeen valtakunnallinen tilavuusmalli tai sen ennusteet kalibroitiin ilman uusia paikallisia maastomittauksia kolmen skenaarion avulla: a) käyttämällä malleissa ympäristöä ja maantieteellisiä olosuhteita kuvaavia lisäselittäjiä, b) uudelleen sovittamalla mallit käyttäen opetuskoealoja lähimmiltä inventointialueilta ja c) sovittamalla ennusteet alueittain valtakunnan metsien inventoinnin tietoihin. Lennokki-inventointia ilman uusia paikallisia maastomittauksia tutkittiin korvaamalla laserkeilauspohjaisten mallien selittäjät ilmakuvapistepilvistä johdetuilla tunnuksilla malleja käytettäessä. Laserkeilauspohjaisten mallien selittäjinä käytettiin niitä tunnuksia, jotka olivat mahdollisimman samankaltaisia laserkeilaus- ja lennokkiaineistojen välillä.

Tulokset osoittivat, että puustotunnusten ennustaminen ilman uusia paikallisia maastomittauksia on mahdollista kohtalaisella tarkkuudella laserkeilauspohjaisten mallien avulla. Systemaattiset virheet minimoituivat, kun yleiset mallit kalibroitiin lisäselittäjien, kuten lämpösumma-, sadanta- ja puulajisuhdetietojen avulla. Huolellisesti valittujen lisäkoealojen käyttö valtakunnallisten mallien kalibrointiin on kuitenkin suositeltavaa, jos uusien koealojen hankinta on taloudellisesti mahdollista. Laserkeilauspohjaisia malleja on mahdollista käyttää puustotunnusten ennustamiseen lennokki-ilmakuvapistepilvistä johdettujen selittäjien avulla erityisesti silloin, kun mallien selittäjät kuvaavat ylintä latvuskerrosta. Pienimmät virheet lennokki-inventoinnissa saavutettiin käyttämällä laserkeilausperusteista mallia lähimmältä samankaltaiselta alueelta luokittelemalla ennustusyksiköt havu- ja lehtipuuvaltaisuuden mukaan ennen ennustamista.

Avainsanat: kaukokartoitus, laserkeilaus, aluepohjainen inventointi, yleinen malli, aluetason malli, lennokki, ilmakuvapistepilvi

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This thesis was pre-examined by Dr. Hans Ole Ørka and Dr. Markus Hollaus. I am grateful to my pre-examiners for their critical feedback and suggestions, which improved the quality of this work. I would also like to thank Dr. Jussi Peuhkurinen who will be my opponent in public examination.

I would like to thank my late dad, Osmo Kotivuori, and my mom, Raija Piirainen, who always encouraged me to study and work hard in life. I will forever remember all the care and love that you have given me. I would also like to thank my brother, Jukka Piirainen, for inspiring me in science when I was only a little boy. Finally, I would like to express my deepest gratitude to my wife, Ilona Mustonen, who has closely watched this project, has always listened to my problems, and has showed me endless unconditional love. I love you more than there are stars in the universe!

Joensuu, June 2022
Eetu Kotivuori

LIST OF ORIGINAL ARTICLES

This dissertation is based on following three articles, which are referred in text by their Roman numerals (study **I**, **II**, and **III**):

I Kotivuori E, Korhonen L, Packalen P (2016) Nationwide airborne laser scanning based models for volume, biomass and dominant height in Finland. Silva Fennica 50(4), article id 1567. 28 p. https://doi.org/10.14214/sf.1567.

II Kotivuori E, Maltamo M, Korhonen L, Packalen P (2018) Calibration of nationwide airborne laser scanning based stem volume models. Remote Sensing of Environment 210: 179–192. https://doi.org/10.1016/j.rse.2018.02.069.

III Kotivuori E, Kukkonen M, Mehtätalo L, Maltamo M, Korhonen L, Packalen P (2020) Forest inventories for small areas using drone imagery without in-situ field measurements. Remote Sensing of Environment 237, 111404. 13 p. https://doi.org/10.1016/j.rse.2019.111404.

Eetu Kotivuori was the corresponding author in all three articles. The corresponding author had overall responsibility for the studies, i.e., responsibility for data processing, modelling, analysis, writing and editing. Petteri Packalen and Lauri Korhonen offered the original research ideas and planned the study design with the corresponding author for study **I**. The research ideas in study **II** were based on the findings of study **I**, which were further processed into a study design by the corresponding author together with Matti Maltamo, Lauri Korhonen and Petteri Packalen. It should be noted that Matti Maltamo and Lauri Korhonen offered considerable phytogeographical knowledge for study **II** and that Petteri Packalen assisted the corresponding author in the collection of the research data for studies **I** and **II**. Mikko Kukkonen contributed with fresh research ideas, drone data collection and data processing in study **III**. The design of study **III** was mostly developed by Mikko Kukkonen and the corresponding author. Lauri Mehtätalo and Petteri Packalen planned the further statistical analyses (e.g., variance estimation) in study **III** and supported the corresponding author in the construction of nonlinear models. Lauri Mehtätalo was also consulted in study **I** with regard to nationwide model calibration. All co-authors participated by commenting on and editing the manuscripts.

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LIST OF ABBREVIATIONS

ABA	Area-based approach
AGB	Above-ground biomass at hectare level (t ha^{-1})
ALS	Airborne laser scanning
AV1	Calibration of nationwide model with one additional calibration variable
AV2	Calibration of nationwide model with two additional calibration variables
AV3	Calibration of nationwide model with three additional calibration variables
BLUP	Best linear unbiased predictor
CHM	Canopy height model
DBH	Diameter at breast height
DIPC	Drone image point cloud
DTM	Digital terrain model
GSD	Ground sampling distance
H	Tree height (m)
Hdom	Dominant height (m)
IPC	Image point cloud
ITD	Individual tree detection
LiDAR	Light detection and ranging
LocALS	Alternative scenario for drone inventory using local ALS and field data
$LocALS_D$	Alternative scenario for drone inventory using local ALS and field data and disaggregation of inventory units to coniferous and deciduous dominated
MD	Mean difference
MS-NFI	Multi-source national forest inventory
N	Nationwide model
NatDIPC	Drone inventory scenario using the nationwide ALS model
$NatDIPC_D$	Drone inventory scenario using the nationwide ALS model and disaggregation of inventory units to coniferous and deciduous dominated
NFI	National forest inventory
NFI1	Calibration of nationwide models with multi-source national forest inventory data
NFI2	Calibration of nationwide models with multi-source national forest inventory data by removing inconsistencies between the used datasets
NGLS	Nonlinear generalized least squares
NN1	Calibration of nationwide models by refitting the models with training data form nearby regions
NN2	Calibration of nationwide models by refitting the models with training data form nearby regions with similar vegetation sub-zone
OLS	Ordinary least squares
PRF	Pulse repetition frequency
R	Regional model
RegDIPC	Drone inventory scenario using the regional ALS model
$RegDIPC_D$	Drone inventory scenario using the regional ALS model and disaggregation of inventory units to coniferous and deciduous dominated
RMSE	Root mean square error
SN	Calibration of nationwide model with minor new field measurements
V	Stem volume at hectare level (m^3 ha^{-1})

1 INTRODUCTION

1.1 Modern stand-level forest management inventories in Finland

Traditionally, stand-level forest management inventories in Finland were conducted using time-consuming fieldwork and manual stand delineation by visual interpretation of aerial images. The field measurements were based on angle count sampling plots and basal area median tree assessments (Haara and Korhonen 2004; Koivuniemi and Korhonen 2006; Maltamo et al. 2021). Each stand was measured separately. However, since the beginning of 21st century, the use of Light Detection and Ranging (LiDAR) technology has been widely studied and applied in forestry (Maltamo et al. 2014; Maltamo et al. 2021). One the most important LiDAR applications in forest inventories has been the introduction of airborne laser scanning (ALS). When combined with an area-based approach (ABA), ALS has attained an important role in modern stand-level inventories (e.g., Næsset 2002; Næsset 2004b; Holmgren 2004; Maltamo et al. 2006). The ABA inventory has reduced the need for field visits; from stand-specific field measurements to inventory area-wise field sample plot collections. Aside from ABA, individual tree detection-based (ITD) forest inventories have gained considerable research interest (e.g., Pitkänen et al. 2004, Vauhkonen 2010, Dalponte et al. 2018b, Kotivuori et al. 2021). Although the research efforts have described various ITD-based inventory procedures, the traditional ABA has remained as the primary inventory method in operational use. The main reasons to favor ABA are its more straightforward implementation and typically lower error rates (Kotivuori et al. 2021). However, it should be noted that ABA and ITD can be used to meet different forest inventory needs and can also support each other (Peuhkurinen et al. 2011; Kotivuori et al. 2021).

In ALS-based ABA inventories, ALS data are used to describe the three-dimensional (3D) structure of the forest area. In other words, the metrics derived from the ALS point cloud are used for the prediction of different growing stock characteristics, such as stem volume, above-ground biomass and dominant tree height (Vauhkonen et al. 2014). Models are fitted at the sample plot-level and applied to larger areas using grid cells that are of similar size to the sample plots (Maltamo and Packalen 2014). Grid cell-level predictions are then aggregated to predict forest attributes at the forest stand-level and over larger areas (e.g., estates, municipalities, region, country). Compared to the traditional field work-based approach, ALS-based ABA has decreased the error rates associated with forest attribute predictions (e.g., root mean square error of stem volume has decreased from 20% to 10%) (Haara and Korhonen 2004; Packalén and Maltamo 2007).

Currently, ALS datasets cover entire countries (Chapter 8 in Melin et al. 2017). In Finland, low-density ALS data are available for the entire country and the second round of data collection has already started. Until the 2020s, low-density ALS datasets (< 1 points m^{-2}) were mostly used in practical applications (Maltamo et al. 2021). Since then, however, dense ALS datasets have become increasingly common (> 5 points m^{-2}). An ALS-based ABA inventory is a cost-efficient inventory routine for relatively large areas (> 100,000 ha). Operational applications usually require species-specific predictions of forest attributes for forest management and planning (Maltamo and Packalen 2014). However, tree species was not considered in this thesis.

1.2 Prediction of forest attributes without new in-situ field measurements

As outlined above, field work for sample plot measurements is still needed for ALS-based ABA inventories. A number of strategies to minimize the number of sample plots have been studied to date (e.g., Junttila et al. 2013). One approach is to use ALS data to improve the efficiency of plot selection (Maltamo et al. 2011; Gobakken et al. 2013; Grafström and Ringvall 2013). Also, other a-priori information, such as the geographical location and site type can be used for sample plot selection (Maltamo et al. 2011). However, it has also been shown that if the number of sample plots is too small, the prediction accuracy is reduced, which will lead to suboptimal decisions in forest planning (Ruotsalainen et al. 2019). The most cost-efficient method in an ALS-based inventory is to use ALS and field training data from former inventory projects for model fitting. The fitted ALS models would then be used in the new inventory area and applied with the new ALS data. In addition to regional stand management inventory projects, cost-efficient forest attribute maps for the whole country would also be useful in many applications (Nilsson et al. 2017; Mäkisara et al. 2019; Hollaus et al. 2021). Options for predictions without local field training data are 1) to build models that cover large areas (i.e., nationwide models), 2) to use the existing training data from a nearby inventory area (transfer the models), or 3) combine options 1 and 2.

Næsset et al. (2005) were the first to utilize datasets from two separate ALS-based inventory projects for the prediction of forest attributes. They fitted so called "common models" for various forest attributes using ordinary least squares (OLS), seemingly unrelated (SUR) and partial least squares (PLS) regression methods. Næsset et al. (2005) highlighted the possibility to combine data from separate inventory areas. They also underlined the importance of careful comparison of the forests and the properties of the applied ALS sensors. They proposed the OLS method as a straightforward prediction method for practical ALS inventories. Uuttera et al. (2006) used the ALS-based ABA models presented by Suvanto et al. (2005) in two geographically separate inventory areas in Finland. The first target area was located about 300 km to the north and the second area about 150 km to the east from the fitting area (Suvanto et al. 2005). They also tested the use of the ABA models constructed by Næsset (2002) from Norway in these target areas. The results were compared to the traditional approach where forest stands were first pre-delineated with aerial images and then inventoried with stand-level sample plots. Overall, the results reported by Uuttera et al. (2006) indicate that transferred ABA models exhibit better performance than the traditional field inventory approach. However, systematic prediction errors were reported with both methods.

Following these pioneers, Breidenbach et al. (2008) illustrated the usability of mixed effect models by combining datasets from USA and Germany. They pointed out that mixed-effect models can be calibrated with a smaller number of sample plots than would be needed to construct completely new models. In the same year, Næsset and Gobakken (2008) tested nationwide models for the first time in Norway. They successfully predicted above-ground and below-ground biomass across ten inventory areas. The best model performance in their study was obtained by including the variables that represent the inventory area, age classes and tree species proportions in the ALS-based models. They observed strong local relationships between ALS-derived metrics and biomass, and suggested collection of continuous nationwide field samples for better nationwide biomass monitoring. Two years later, Suvanto and Maltamo (2010) compared basic and weighted OLS estimations for the prediction of forest attributes by combining sample plots from the target area and the former inventory area (120 km apart). They tested different sample sizes from the target area (10–

212 plots), including sample plots from the former inventory area as auxiliary data (472 plots). Predictions were compared with locally fitted regression models. According to their results, 40–50 sample plots for the local basal area and stem volume models was sufficient to obtain similar error rates than using former inventory plots as auxiliary data.

Fekety et al. (2018) examined the transferability of ABA-based forest attribute models in USA. They used the data from six ALS acquisitions from separate areas. The ALS-based models were fitted for basal area and stem number using the random forest method. Their results indicated that basal area models were more transferable between the inventory areas than stem number models. Similar research was conducted by Tompalski et al. (2019) and van Ewijk et al. (2020) in Canada. Tompalski et al. (2019) studied how the existing random forest method, k most similar neighbor and OLS models for Lorey's height, quadratic mean diameter and (gross) volume were transferable to other areas in British Columbia. Transferability of the models was more dependent on the modelled forest attribute and the modelling technique than the point cloud characteristics (Tompalski et al. 2019). For example, Lorey's height models fitted by OLS were the most transferable between the areas. In turn, van Ewijk et al. (2020) studied the transferability of Lorey's height, quadratic mean diameter, (gross) volume and basal area models using the random forest method and OLS. Their study areas were located about 2,200 km apart on an east-west axis. They reported that model transfer to the target area performed best when the models were calibrated with a small number of sample plots from the target area. Use of calibration plots in the context of model transferability was also studied by de Lera Garrido et al. (2022) in Norway. They calibrated temporally and spatially transferred models for volume, stem number and dominant height with a different number of local sample plots and concluded that calibration reduces the systematic errors.

The above-mentioned studies (Næsset et al. 2005; Uuttera et al. 2006; Næsset and Gobakken 2008; etc.) relied on plots measured in operational, regional-level forest management inventories. One possible option is to also create nationwide or regional ABA models by using sample plots from the national forest inventory (NFI) in conjunction with ALS data. For example, Hollaus et al. (2009) used ALS and NFI data to predict stem volume in Austria by using an existing volume model built for a smaller area (Hollaus 2006), which was calibrated for the whole target area. Hollaus et al. (2009) posited that the stratification of the data based on coniferous and deciduous domination would improve the predictive models. Gopalakrishnan et al. (2015), in turn, predicted dominant tree heights for large areas in USA using NFI sample plots. They fitted the OLS model for dominant height using ALS data from 76 separate areas; with such an extensive dataset, the r-squared (R^2) value of the nationwide height model was 0.74. They emphasized the effects of vegetation heterogeneity on the prediction errors. Similarly, Monnet et al. (2016) combined NFI sample plots and nationwide ALS data to predict various forest attributes (e.g., mean height and diameter, stem volume, basal area) wall-to-wall in one of the 26 cantons of Switzerland (Valais). Their models were calibrated for six strata using flight year, flight altitude and geographical location and observed that the low positioning accuracy of NFI plots increased the error rates.

Maltamo et al. (2016), Nilsson et al. (2017) and Rahlf et al. (2021) examined the use of NFI data in large area ALS-based predictions in Sweden and Norway. Maltamo et al. (2016) utilized NFI sample plots to predict above-ground biomass across a long (1500 km) transect in Norway. In particular, they noted the importance of species information in large area predictions. Nilsson et al. (2017) refitted the pre-selected regression model forms for ALS blocks with 350 geographically close NFI sample plots, and predicted stem volume, mean height, mean diameter, basal area and biomass for the whole of Sweden. Nilsson et al. (2017)

validated the prediction at the stand-level and noted that the predictions were suitable for forest management planning in Sweden. Rahlf et al. (2021) refitted the NFI-based mixed-effect model used in Norwegian forest resource mapping (Astrup et al. 2019) using NFI sample plots and ALS data from the study area located in southern Norway. The study area consisted of three ALS-based forest management inventory projects. The aim was to predict the volume of mature spruce stands. They compared performance to traditional ALS-based forest management inventories and to scenarios where NFI sample plots and plots from forest management inventory were combined. Rahlf et al. (2021) noted that NFI-based models using ALS data and NFI sample plots resulted in good or even better performance than traditional ALS-based inventories. However, the combination of NFI and forest management inventory sample plots did not clearly improve the stem volume predictions.

1.3 Effects of ALS data acquisition parameters and environmental conditions

The use of multiple ALS sensors in data acquisition cannot be avoided if the objective is to utilize ALS data from large areas and former inventories. The time frame for data collection depends on the size of the scanned areas and the available resources. For example, in Finland, low-density country-level ALS data were collected within 10 years (between 2010 and 2020). From the beginning of the 2020s, the time interval between ALS acquisitions in the same area will be about six years. In this kind of time frame, multiple sensor models and individual sensor units are inevitably used. The data acquisition settings, e.g., flight altitude, scan angle and pulse repetition frequency (PRF), also vary between projects. In addition, sensor software and hardware updates may change the properties of the ALS datasets, even if the same unit is used. Technology is constantly developing, which makes harmonization of ALS data difficult. Nowadays, ALS systems offer point clouds even from multiple wavelengths, which could produce differing sets of ALS metrics in the prediction process (Dalponte et al. 2018a; Kukkonen et al. 2019b). However, it should also be noted that mixing data from spring and summer acquisitions is not recommended because the height distribution of ALS echoes in deciduous dominated forests is dissimilar between leaf-off and leaf-on data (Næsset 2005; Villikka et al. 2012).

The differences between ALS sensors and acquisition settings can be observed from ALS-derived height and density metrics (Næsset 2005; Næsset 2009). For example, increasing pulse penetration into the canopy may be caused by larger pulse energy and peak power (Næsset 2005; Hopkinson 2007). Increasing flight altitude, in turn, leads to reduced pulse penetration and a reduced proportion of pulses with multiple echoes (Hopkinson 2007; Næsset 2009). However, it has been noted that the different error rates associated with the prediction of forest attributes are more related to differences in height distributions than proportions of echo categories (Keränen et al. 2016). The first return data is considered more stable for different flying altitudes and canopy conditions than the last return data (Næsset 2004a; Næsset 2005). The large scan angles (up to 30°) seem to have only minimal effects on ALS metrics and on ALS-based forest attribute predictions (van Lier et al. 2022) but conversely has clear effects on foliage profile estimation (Qin et al. 2017).

Likewise, growing conditions may also vary within large geographical areas. Given the size of Finland, growing conditions differ in both north-south and east-west directions. The thermal growing season in northern Finland may start up to one month later and end one month earlier than in southern Finland (Ilmatieteen laitos 2020). In addition, the influence of Baltic Sea in the west and increasing elevation along a southwest-northeast axis affect the growing conditions between the regions. There are also two large watershed areas in southern Finland, Maanselkä and Suomenselkä, where elevations are higher than in the surrounding areas (Tapana and WSOY 1999). Regional variations in annual precipitation and wetland proportions similarly affect the vegetation (Chapter III in Kalliola 1973). These changes in vegetation can be addressed geographically in many ways. For example, vegetation in Finland can be divided into hemi-, south-, mid-, and north-boreal zones on the basis of similar soil, topographic and climatic conditions (Chapter V in Kalliola 1973). These vegetation zones are further divided into sub-zones by the vegetation changes in microclimates. There are also herb-rich centers (e.g., Triangle of Lapland and Sortavala's herb-rich center in Tohmajärvi) around Finland, where the vegetation clearly differs from the surroundings (Figure 2 in Hotanen et al. 2018).

The use of land and forest resources has also modified regional species distributions and age class proportions throughout history. In Finland, forests were partly used in slash-and-burn silviculture and for tar burning activities between the 16th and 20th centuries, especially in eastern Finland, which has impacted the soil and the forest structure in these areas (Heikinheimo 1915). Nowadays, official recommendations offer guidelines for regional forest management (Äijälä et al. 2019). For example, thinning intensities greatly depend on degree-days and local site fertility, together with dominant height and basal area (Appendix 5 in Äijälä et al. 2019). As described above (Section 1.2), these environmental and geographical properties can be taken into account in ALS inventories. Information that includes main tree species, geographical location, elevation, climate, age class and vegetation heterogeneity as predictor variables can improve the model performance (e.g. Næsset and Gobakken 2008; Gopalakrishnan et al. 2015; Maltamo et al. 2016). Næsset and Gobakken (2008) suggested that environmental properties may influence the predictions more than the observed differences between ALS sensors.

1.4 Drone-based forest inventory

In contrast to the ALS-based ABA inventories, drone-based (i.e., UAV, unmanned aerial system) inventory applications have shown promise over small areas (< 100 ha). Due to the high costs of drone-sized LiDAR sensors, most of drone applications currently rely on image point clouds (IPC). These are created using automated photogrammetric processes where a 3D structure is derived using overlapping images (Lisein et al. 2013). Drone-based IPC (DIPC) can then be used in the same manner as ALS data in ABA inventories (Puliti et al. 2015, Tuominen et al. 2015, Ota et al. 2017). However, sample plot measurements for DIPC-based ABA inventories are not usually economically feasible as the inventory cost per hectare is very high for small areas. Moreover, if real-time kinematic (RTK) or other accurate positioning for the drone is not available, ground control points (GCP) for the georeferencing of DIPC are required. The use of the GCP will further increase the costs of small area inventories.

One option to decrease the costs of the DIPC inventory is to use existing ALS-based nationwide or regional ABA models in conjunction with DIPC data. In other words, ALS metrics from ALS-based forest attribute models are replaced with DIPC metrics when the models are applied in the target area. Before the prediction, it should be confirmed that the DIPC metrics are comparable to the corresponding ALS metrics. Analogous point cloud metrics describe forest attributes similarly and ensure logical predictions (Navarro et al. 2020). Another option to decrease the costs is to use existing ALS data for the georeferencing of DIPC. It should also be noted that in some applications, such as the monitoring of forest wind and snow damage (Manninen 2019), separate field data may not be needed at all. Likewise, some drone-based ITD applications do not require any local field measurements (e.g., Panagiotidis et al. 2017, Mohan et al. 2017). In particular, when drone-sized LiDAR sensors become more common and affordable, ITD with the crown and trunk detection from the point clouds will offer new possibilities for small area inventories (Puliti et al. 2020, Kukkonen et al. 2021b).

1.5 Objectives

The main objective of this thesis was to examine the performance and transferability of ALS-based forest attribute models without new in-situ field measurements in ALS- and DIPC-based forest management inventories. The objectives of the three original articles were:

I To examine the error rates of nationwide ALS-based stem volume, above-ground biomass and dominant height models in Finland. An additional objective was to study the calibration of nationwide models using a small number of sample plots from the target region.

II To compare options for calibration of a nationwide ALS-based stem volume model without new field measurements by using the geographical and environmental predictor variables, calibration plots from nearby inventory areas, or multi-source NFI data.

III To identify the metrics that are analogous between ALS and DIPC datasets and assess the usability of nationwide and regional ALS-based models in cost-efficient DIPC-based small area forest inventories.

2 MATERIALS

2.1 Nationwide data for ALS-based forest attribute models (I, II, III)

2.1.1 Field data

The main field data in this thesis consisted of field sample plot measurements from 22 ALS-based stand-level forest management inventory projects. The inventory areas were selected subjectively so that the areas represented the full variation in environmental and geographical conditions throughout Finland (Figures 1 and 2). Field datasets were collected between 2011 and 2015 by three contractors: Finnish Forest Centre, TerraTec Oy and Blom Kartta Oy. Each contractor used slightly different field measurement protocols. In study **I**, sample plots from nine areas were used (Table 1), while in studies **II** and **III**, sample plots from all 22 areas were used.

Field measurements were conducted by measuring diameter at breast height (DBH) and recording the tree species for all trees that were counted inside the circular sample plots within a certain DBH limit. Sample plot radii were either 5.64, 9, 12.62 or 12.65 m depending on the inventory project, maturity of the forest, and stem number of the forest stand. Sample plots were distributed using either systematic sampling with L-shape clusters, systematic stratified cluster sampling, or random sampling. The field data were harmonized by omitting all trees with DBH < 5 cm and sample plots with total stem volume < 3 m^3 ha^{-1}. In addition, trees identified as dead, and sample plots located in young seedling stands were omitted.

Tree heights (H) were measured for all trees in the inventory areas, which were measured by TerraTec Oy and Blom Kartta Oy (see study **I** for details). In other areas, tree heights were only measured for a sample number of trees. For remainder of the trees, height was predicted using height models calibrated for each plot (Eerikäinen 2009). In one of the areas (Ilomantsi), field data were measured 1–2 years after the ALS data collection and, therefore, the NFI-based growth model service was used to account for the growth in a backward manner. The growth model service was provided by Luke (Natural Resources Institute Finland).

Forest attributes considered in this thesis are stem volume (V), above-ground biomass (AGB) and dominant height (Hdom). For each sample plot, V was estimated by 1) calculating V by tree species (pine, spruce and birch) using the two parameter (DBH and H) models described in Laasasenaho (1982), 2) aggregating tree-level estimates to the plot-level, and 3) scaling the estimates to the hectare level (m^3 ha^{-1}) (**I**, **II**, **III**). The most common pine, spruce and birch trees in Finland are Scots pine (*Pinus sylvestris* (L.)), Norway spruce (*Picea abies* (L.) Karst.), silver birch (*Betula pendula* Roth) and downy birch (*Betula Pubescens* Ehrh.). The AGB of each sample plot was estimated similarly to V using the tree-level models described in Repola (2008 and 2009) (**I**). Dominant height (m) was estimated as the mean height of the 100 trees with the largest DBH values per hectare (Chapter 4.2.1 in Kangas et al. 2011) (**I**). The basic statistics of the nationwide field data are presented in Table 1, where inventory areas are listed from north to south. Table 1 clearly shows the geographical variation of forest attributes along the north-south axis.

Table 1. Inventory year, number of sample plots, average stem volume (V), average above-ground biomass (AGB) and average dominant height (Hdom) in the inventory areas in the nationwide field data. Roman numerals indicate the inventory areas used and the forest attributes of interest examined in studies **I**, **II** and **III**.

Inventory area	Inventory year	Number of sample plots		V (m^3 ha^{-1})		AGB (t ha^{-1})	Hdom (m)	Study
		I	**II, III**	**I**	**II, III**	**I**	**I**	
Savukoski	2015		233		71.1			**II, III**
Sodankylä	2015		301		86.4			**II, III**
Kolari	2013	534	301	100.9	101.8	56.3	13.9	**I, II, III**
Kuusamo	2014		301		92.0			**II, III**
Ranua	2012	613	301	98.3	98.1	55.9	12.9	**I, II, III**
Tornio	2013	596	301	97.2	98.0	57.3	12.7	**I, II, III**
Pudasjärvi	2015		301		109.4			**II, III**
Kuhmo	2014		301		127.5			**II, III**
Siikalatva	2013	657	301	118.0	114.5	64.4	15.6	**I, II, III**
Toholampi	2012	587	301	102.8	108.3	55.8	14.7	**I, II, III**
Maaninka	2015		301		157.4			**II, III**
Kaavi	2014		301		148.4			**II, III**
Ilomantsi	2014–2015		149		213.8			**II, III**
Ähtäri	2013	1233	301	139.7	137.6	73.9	16.8	**I, II, III**
Kristiinankaupunki	2015		301		149.8			**II, III**
Kangasniemi	2013		301		181.2			**II, III**
Sulkava	2011	570	301	173.4	175.4	90.3	18.6	**I, II, III**
Orivesi	2015		301		191.2			**III, III**
Sastamala	2014		301		186.0			**II, III**
Virolahti	2013	724	301	179.4	186.3	93.5	17.8	**I, II, III**
Hyvinkää	2015		301		178.5			**II, III**
Turku	2012	716	301	180.9	183.3	93.6	18.8	**I, II, III**

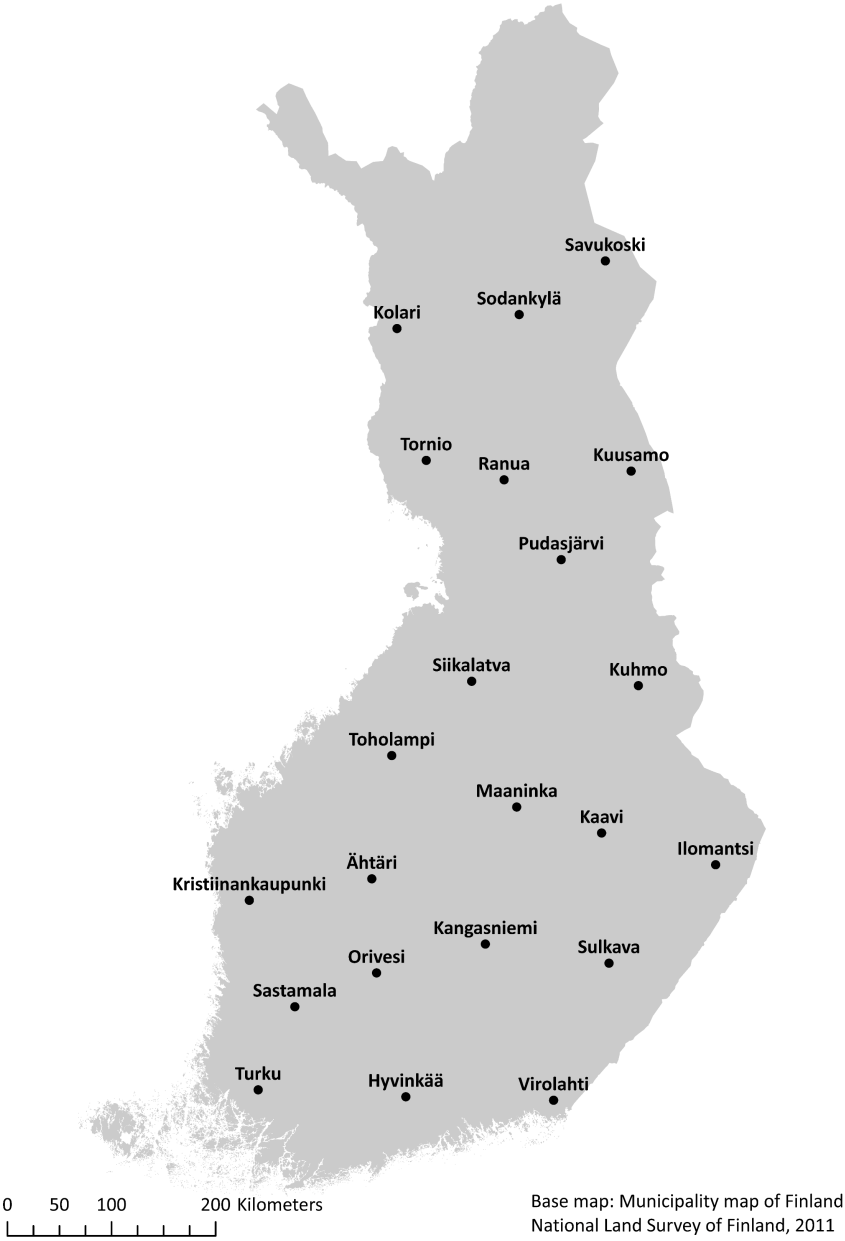

Figure 1. Locations of inventory areas of nationwide datasets (**I**, **II**, **III**).

2.1.2 ALS data

The nationwide ALS data were collected from the same inventory areas as the nationwide field data, i.e., the dataset consisted of 22 ALS acquisitions from different geographical areas of Finland. A total of 12 different ALS sensors from two manufacturers were used (Leica and Optech). The single-pulse-in-the-air mode was used in 17 of the areas and multiple-pulses-in-the-air scanning mode in five of the areas. The PRF varied from 50,000 to 71,800 Hz with single-pulse mode and was either 114,600 or 136,500 Hz with multiple-pulses mode. Flying altitude varied between 1675 and 2200 m and the half scan angle was either 15° or 20°. Average pulse density between the areas varied from 0.5 to 1.2 points m^{-2}. All ALS datasets were acquired in leaf-on conditions. The ALS sensors and their settings are presented in Table 2. In study **I**, ALS data from nine areas were used. In studies **II** and **III**, ALS data from all 22 areas were utilized. Digital terrain models (DTM) were used to calculate above-ground heights for the ALS echoes. The DTM were created by Delaunay triangulation using the methods described by Axelsson (2000). The ALS datasets for sample plots were provided by Blom Kartta Oy, TerraTec Oy and Arbonaut Oy. The ALS data were used to calculate various height and density metrics to the sample plot-level. Calculation of ALS metrics is described in Section 3.1.

Table 2. Manufacturer (Manuf.), individual scanner unit (Unit), pulse type (P. type), acquisition year (Year), flying altitude (Alt.) (m), pulse repetition frequency (PRF) (Hz) and half scan angle (HSA) (degrees) of the nationwide airborne laser scanning (ALS) data acquisitions. Roman numerals indicate the ALS datasets used in studies **I**, **II** and **III**.

Inventory area	Manuf.	Unit	P. type	Year	Alt.	PRF	HSA	Study
Savukoski	Leica	E	Multi	2015	2200	136,500	20	**II, III**
Sodankylä	Optech	F	Single	2015	1890	70,000	20	**II, III**
Kolari	Optech	B	Single	2013	1950	50,000	15	**I, II, III**
Kuusamo	Leica	H	Single	2014	2000	63,700	15	**II, III**
Ranua	Optech	A/B	Single	2012	1750	70,000	20	**I, II, III**
Tornio	Leica	C	Single	2013	1950	71,000	20	**I, II, III**
Pudasjärvi	Leica	I	Single	2015	1800	60,000	20	**II, III**
Kuhmo	Leica	J	Multi	2014	2150	114,600	20	**II, III**
Siikalatva	Optech	B	Single	2013	1950	50,000	15	**I, II, III**
Toholampi	Optech	B	Single	2012	1750	70,000	20	**I, II, III**
Maaninka	Leica	K	Multi	2015	2000	114,600	20	**II, III**
Kaavi	Leica	K	Multi	2014	2000	114,600	20	**II, III**
Ilomantsi	Leica	L	Single	2013	2000	58,900	15	**II, III**
Ähtäri	Optech	A	Single	2013	1730	70,000	20	**I, II, III**
Kristiinankaupunki	Optech	G	Single	2015	1890	70,000	20	**II, III**
Kangasniemi	Leica	H	Single	2013	1675	60,000	20	**II, III**
Sulkava	Optech	A	Single	2011	2000	50,000	15	**I, II, III**
Orivesi	Optech	G	Single	2015	1850	70,000	20	**III, III**
Sastamala	Optech	G	Single	2014	1850	70,000	20	**II, III**
Virolahti	Leica	D	Single	2013	1900	71,800	20	**I, II, III**
Hyvinkää	Leica	J	Multi	2015	2050	114,600	20	**II, III**
Turku	Optech	B	Single	2012	1750	70,000	20	**I, II, III**

2.1.3 Calibration data

A total of 31 continuous or discrete variables from multiple data sources were used to account for the geographical and environmental conditions throughout Finland. The data were used in the calibration of nationwide forest attribute models or in model prediction (**II**, **III**). The calibration variables were divided into five categories: 1) location, 2) site, 3) climate, 4) spectral, and 5) tree-species composition. A summary of the data is presented in Table 3.

Geographical location in study **II** was addressed by x- and y-coordinates in the ETRS-TM35FIN coordinate system (m) by orthometric height (m) (© National Land Survey of Finland 2015–2016), by forest vegetation zones and sub-zones (© Finnish Environment Institute (SYKE) 2015), and by distance from the coastline (km) (© European Environment Agency 2015). Finland is covered by four forest vegetation zones: 1) hemi-boreal, 2) south-boreal, 3) mid-boreal, and 4) north-boreal (Figure 2), while zones 2–4 are further divided into sub-zones (2a–2c, 3a–3c and 4a–4d). Distance to the nearest coastline was calculated as Euclidean distance (**II**). Site properties in study **II** were described by site fertility and sediment classes. Site fertility classes 1–7 were present in the nationwide data, where small class number indicates fertile site and large class number indicates infertile site (© Natural Resources Institute Finland (Luke) 2013; Tomppo and Halme 2004). An alternative site fertility variable was also created where the most infertile site classes 4–7 were pooled. Sediment classes present in the nationwide data included a total of ten surface and eight base sediments (© Geological Survey of Finland 2010). More details on the fertility and sediment classes can be found in Appendix B in study **II**.

The main categories for the climate related variables used in study **II** were degree days (i.e., effective temperature sum), monthly mean temperature and monthly precipitation. Degree day data were also used in study **III**. The nationwide degree day layer was interpolated as presented by Ojansuu and Henttonen (1983) using the degree day data from 1951 to 1980 provided by Luke. In addition to continuous degree day observations, degree days were also assigned to three classes as recommended by Äijälä et al. (2019): 1) degree days > 1200, 2) degree days ≤ 1200 and > 1000, and 3) degree days ≤ 1000 (**II**). Monthly mean temperature and monthly precipitation data were used to calculate a total of eight different calibration variables (Table 3) (© Finnish Meteorological Institute 2000–2013). To simplify the calculations, the growing season was assumed to continue from May to September nationwide. The spectral variables in study **II** were extracted from MODIS satellite data. Reflectance composite was 005 MOD13Q1 product, courtesy of the NASA Land Processes Distributed Active Archive Center (LP DAAC), and the USGS / Earth Resources Observation and Science (EROS) Center (© NASA LP DAAC, 2011–2015). A total of four bands and two indices were used (Table 3).

Tree species composition information was extracted from multi-source national forest inventory (MS-NFI) data, which provides the NFI predictions in 16 × 16 m spatial resolution and is created by combining the NFI field data with information from satellite images and other map data sources (Mäkisara et al. 2019). In study **II**, MS-NFI-based tree species information was used to calculate dominant tree species classes and tree species proportions (Table 3) (© Natural Resources Institute Finland (Luke) 2015a; © Natural Resources Institute Finland (Luke) 2015b). In study **III**, species information from MS-NFI was used to disaggregate the inventory units to coniferous and deciduous dominated sites when the nationwide model was applied to the test area (see Section 3.3) (© Natural Resources Institute Finland (Luke) 2017). In study **II**, inventory area-wise medians of MS-NFI-based total stem volumes were also tested in calibration (see Section 3.2).

Table 3. Variables used to account for the geographical and environmental conditions throughout Finland. Roman numerals indicate the variables used in studies **II** and **III**.

Group	Variable	Description	Unit	Study
1	x	In ETRS-TM35FIN coordinate system	Meter	**II**
1	y	In ETRS-TM35FIN coordinate system	Meter	**II**
1	cdist	Distance from the sea	Kilometer	**II**
1	elev	Elevation from the sea level	Meter	**II**
1	v.s.zone	Vegetation sub-zone (classes 1, 2a–2c, 3a–3c and 4a–4d)	Class	**II**
2	site.a	Site fertility (classes 1–7)	Class	**II**
2	site.b	Site fertility (classes 1–4)	Class	**II**
2	soil.a	Surface sediment (classes 1–10)	Class	**II**
2	soil.b	Base sediment (classes 1–8)	Class	**II**
3	d.d.	Degree days (The effective temperature sum)	°C	**II, III**
3	d.d.cl	Geographical zones divided by degree days (classes 1–3)	Class	**II**
3	tmean.a	Mean of the monthly temperatures	°C	**II**
3	tsd.a	Standard deviation of the monthly mean temperatures	°C	**II**
3	tmean.b	Mean temperature of the growing season	°C	**II**
3	tsd.b	Standard deviation of the mean temperatures of growing seasons	°C	**II**
3	pmean.a	Mean of the monthly precipitations	Millimeter/month	**II**
3	psd.a	Standard deviation of the monthly precipitations	Millimeter	**II**
3	pmean.b	Mean of the annual monthly precipitation sums of the growing season	Millimeter/ 5 month	**II**
3	psd.b	Standard deviation of the annual monthly precipitation sums of the growing season	Millimeter	**II**
4	red	MODIS red reflectance (Band 1, 620–670 nm)	16-Bit signed integer	**II**
4	NIR	MODIS near-infrared reflectance (Band 2, 841–876 nm)	16-Bit signed integer	**II**
4	blue	MODIS blue reflectance (Band 3, 459–479 nm)	16-Bit signed integer	**II**
4	MIR	MODIS mid-infrared reflectance (Band 7, 2105–2155 nm)	16-Bit signed integer	**II**
4	NDVI	MODIS normalized difference vegetation index	16-Bit signed integer	**II**
4	EVI	MODIS enhanced vegetation index	16-Bit signed integer	**II**
5	dts	Dominant tree species (classes 1–4)	Class	**II**
5	pine.p	Proportion of pine	Percentage	**II**
5	spruce.p	Proportion of spruce	Percentage	**II**
5	birch.p	Proportion of birch	Percentage	**II**
5	ot.p	Proportion of other tree species	Percentage	**II**
5	decid	Deciduous dominated (True = 1, False = 0)	Logical	**III**

2.2 Small area drone inventory data (III)

2.2.1 Field data

The additional field data used in study **III** consisted of square 30 m × 30 m test plots from the research area in Liperi, eastern Finland. The field work was conducted in 2017. The area is dominated by coniferous trees, although deciduous sites are also present. The 19 sample test plots were selected subjectively so that there was variability in tree species and age class among the data. Heights and diameter were measured from all trees with DBH ≥ 5 cm. The locations of each tree were solved in the field using ALS-based ITD map and field triangulation (Korpela et al. 2007). Each sample plot was further divided into smaller 15 × 15 m cells, which resulted in a total of 76 forest inventory units. Volume (V) for each test plot was estimated by 1) calculating tree-level stem volumes by tree species (pine, spruce and birch) using the two parameter (DBH and H) models described in Laasasenaho (1982), 2) aggregating tree-level estimates to the cell-level, 3) scaling the estimates to the hectare level (m^3 ha^{-1}), and 4) calculating the total stem volume for each test plot as a mean value of four cells. The average V in the 19 test plots was 237.8 m^3 ha^{-1}. Figure 2 shows the location of the small area drone inventory data with respect to the nationwide inventory areas.

2.2.2 Drone data

Drone images for the Liperi test plots were collected using a DJI Inspire 1 rotary-wing drone and Zenmuse x3 digital camera in 2017. The images were captured with a forward overlap of about 90% and with a side overlap of about 60%. Flying altitude was 75 m and the ground sampling distance (GSD) was 3.2 cm. Images were captured in varying weather conditions, i.e., sunny to cloudy, and calm to slightly windy conditions. However, the most hazardous imaging conditions were avoided (strong wind, rain, etc.). The DIPC were created using the Agisoft Photoscan software (AgiSoft PhotoScan Professional 2017). The average point density of the DIPC was approximately 1148 points m^{-2}. The DIPC were adjusted horizontally and vertically using ALS datasets from the same area as GCP or other georeferencing methods were not used. In the horizontal adjustment, the DIPC were shifted so that the correlation between the DIPC and ALS (Optech Titan, see Section 2.2.3) based on canopy height models (CHM) reached the maximum value. In the vertical adjustment, DIPC altitude was corrected by calculating the difference between the ground observations of ALS (© National Land Survey of Finland 2016) and DIPC data, and by adding the difference to the DIPC data. Finally, DIPC heights were scaled to above ground-level using DTM created from the ground observations of ALS (© National Land Survey of Finland 2016).

2.2.3 ALS data

The ALS data for the test plots in Liperi were acquired using an Optech Titan multispectral ALS sensor in 2016. The data were acquired in leaf-on conditions. Optech Titan operates on three channels (channel 1 = 1550 nm, channel 2 = 1064 nm, channel 3 = 532 nm), but only data from channel 2 were used in this thesis. Pulse density in channel 2 was approximately 12.4 point m^{-2}. Multiple-pulses-in-the-air mode and half scan angle of 20° were used. The PRF was 250,000 Hz, flying altitude was 850 m and lateral overlap 55%.

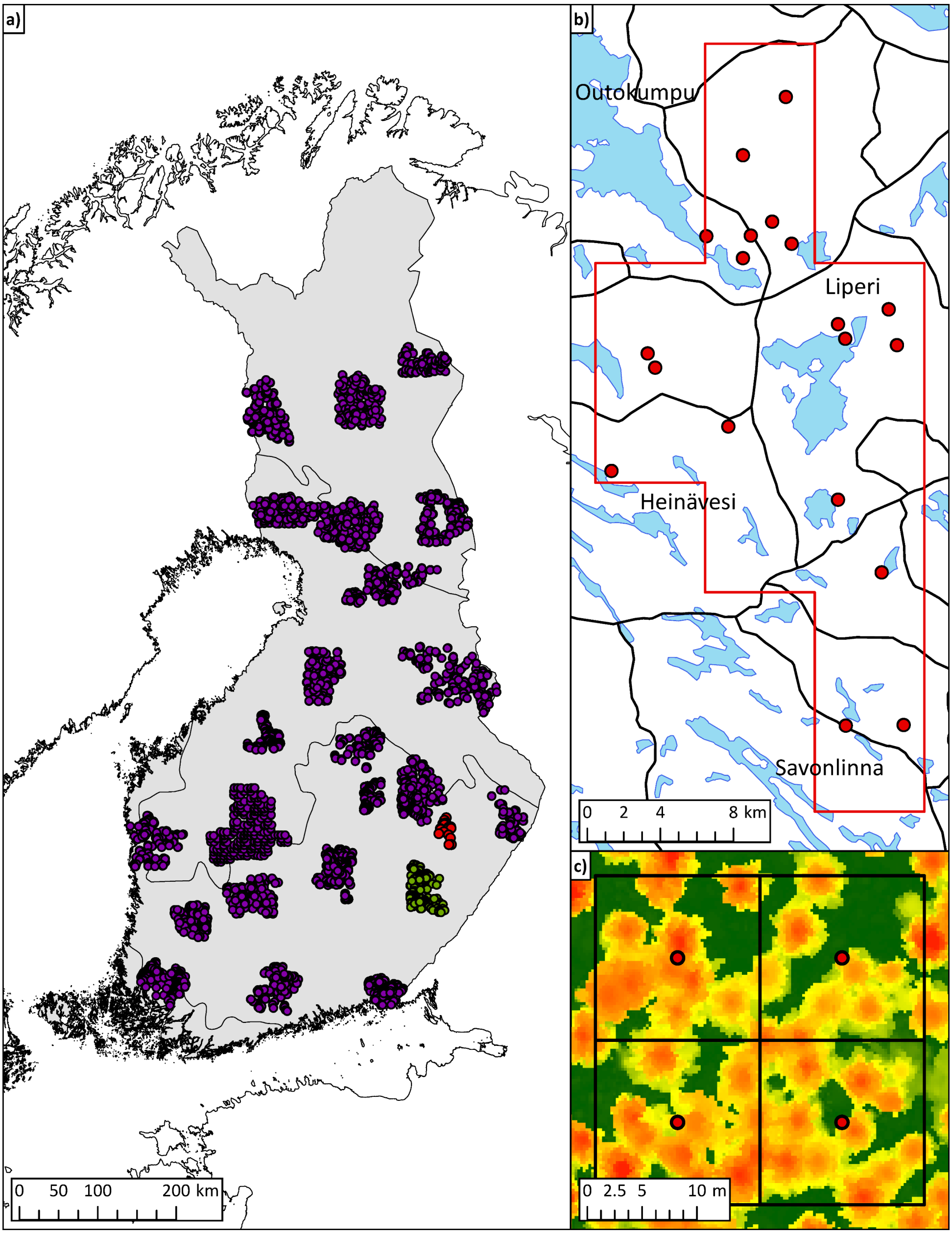

Figure 2. a) Test plots in Liperi (red points) with respect to the nationwide field data used in studies **II** and **III** (purple and green points) within the forest vegetation zones. The Sulkava area (green points) was considered as the nearest inventory area with similar growth conditions and species distributions. b) Locations of the test plots in Liperi. c) One of the 30 × 30 m test plots deviated to four 15 × 15 m cells with a drone image point cloud-based (DIPC) canopy height model (CHM). Base maps: a) © National Land Survey of Finland 2011; © Finnish Environment Institute (SYKE) 2015, © European Environment Agency 2015, b) © National Land Survey of Finland 2018.

3 METHODS

3.1 Modelling and validation of nationwide ALS-based forest attribute models (I, II)

In this thesis, two basic ALS-based nationwide models for V (**I**, **II**), one basic nationwide model for AGB (**I**) and one basic nationwide model for Hdom (**I**) were formulated. The term "basic" is used here for models that were fitted using only ALS metrics as predictor variables. The modelling process was divided into three steps: 1) calculation of ALS metrics for the sample plots, 2) variable selection and model fitting, and 3) validation. The basic nationwide models were fitted using OLS estimation (see Chapter 4.4.1 in Mehtätalo and Lappi 2020) by utilizing the sample plots from multiple inventory areas in the same model (n = 6230 in study **I**, n = 6402 in study **II**).

The following ALS metrics were calculated for each plot: mean, standard deviation, maximum, density percentages and height quantiles (**I**, **II**). The metrics were calculated from both first (F) and last (L) echo categories. First echoes included the original echo categories of "first of many" and "only", and last echoes included the categories of "last of many" and "only". In the preliminary tests in studies **I** and **II**, the nationwide models were observed to be more transferable between the ALS datasets when the height threshold (e.g. echo height $\geq$ 2 m) for ALS height metrics was ignored. Therefore, all the echoes from the first and last echo categories were used when calculating the ALS metrics. Height quantiles were calculated using the quantile function in the R software (quantile type 7) (R Core Team 2017; Hyndman and Fan 1996). The density percentages, in turn, were calculated by dividing the number of echoes over a certain threshold by the number of all echoes. Table 4 shows the variables used in each study.

The basic nationwide V and AGB models were fitted using two ALS metrics as predictor variables, while the basic nationwide Hdom was fitted with one ALS metric. For example, the linear model with two ALS predictors was as follows:

$$\hat{y} = \beta_0 + \beta_1 ALS_1 + \beta_2 ALS_2 \tag{1}$$

where
$\hat{y}$ is the response variable (V, AGB or Hdom),
$ALS_{1\text{–}2}$ are the predictor variables calculated from ALS data, and
$\beta_{0\text{–}2}$ are the model coefficients.

The selection of regression models was conducted using a comprehensive investigation of predictor variables. In other words, the nationwide models were fitted with all possible variable combinations and the best model form was selected by means of the smallest root mean square error (RMSE) value (Equation 4). Square root, logarithmic, polynomial (**I**, **II**) and inverse transformations (**II**) for predictor variables were also tested. In addition, the use of square root transformations for response variables was examined.

Table 4. Airborne laser scanning (ALS) variable groups and variable settings used in studies **I**, **II** and **III**.

Variable group	Used variables	Study
mean	havgF and havgL	**I**
standard deviation	hstdF and hstdL	
maximum	hmaxF and hmaxL	
density percentages	veg1/2/3/…/23/24/25F and veg1/2/3/…/23/24/25L	
height quantiles	h5/10/15/…/90/95/99F and h5/10/15/…/90/95/99L	
mean	havgF and havgL	**II**
standard deviation	hsdF and hsdL	
maximum	hmaxF and hmaxL	
density percentages	veg1/2/3/…/23/24/25F and veg1/2/3/…/23/24/25L	
height quantiles	h1/2/3/…/97/98/99F and h1/2/3/…/97/98/99L	
mean	havgF	**III**
median	hmedF	
standard deviation	hstdF	
maximum	hmaxF	
density percentages	veg0.5/2/5/10/15/20F	
height quantiles	h5/10/15/…85/90/95F	

Square root transformation of a response variable requires a bias correction when the predicted response value is transformed back to its original scale (Chapter 5.4 in Lappi 1993). The bias-corrected predicted value was calculated as follows:

$$\hat{y} = \left(\beta_0 + \beta_1 ALS_1 + \beta_2 ALS_2\right)^2 + \sigma^2 \quad (2)$$

where the bias correction is the residual variance (σ^2)

$$\sigma^2 = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n} \quad (3)$$

where
y_i is the observed value of attribute y in sample plot *i*,
$\hat{y}_i$ is the predicted value of attribute y in sample plot *i*, and
n is number of sample plots.

The nationwide models were validated by leave-one-inventory-area-out cross validation. The error rates of the nationwide models were compared to the error rates of the regional ALS models, i.e., compared to models fitted for individual inventory areas using in-situ field measurements. The regional models were selected in the same manner as the nationwide models. In study **I**, a total of nine regional models were fitted for each response variable (V, AGB and Hdom). In study **II**, a total of 22 regional models for V were fitted. Each regional model was leave-one-plot-out cross validated. The performance of cross validated nationwide and regional models was compared using inventory area-wise RMSE and MD (mean difference) values:

$$\text{RMSE} = 100 \times \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} / \bar{y} \quad (4)$$

$$\text{MD} = 100 \times \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n} / \bar{y} \quad (5)$$

where $\bar{y}$ is the mean value of attribute y and other abbreviations are the same as in Equation 3. In this thesis summary, and in studies **I** and **II**, a negative MD value denotes systematic overprediction and a positive MD value denotes systematic underprediction. In study **III**, the interpretation of MD was opposite (negative value denotes underprediction and positive value denotes overprediction). The summary statistics (minimum, maximum, mean, median, standard deviation) of inventory area-wise RMSE and |MD| (absolute value of mean differences) values were used to compare the results at the nationwide level. In the summary statistics, absolute MD values were used because the negative and positive MD values would have canceled each other out. The nationwide models are denoted with the abbreviation N and regional models by R.

3.2 Calibration of nationwide ALS-based models (I, II)

Calibration of the nationwide models was undertaken to improve the inventory area-wise performance of the models. Calibrations were tested with four main scenarios: 1) calibration with a small number of new sample plots (**I**), 2) calibration with additional predictor variables (**II**), 3) calibration with existing sample plots from nearby inventory areas (**II**), and 4) calibration through MS-NFI predictions (**II**). In calibration scenarios 2–4, it was assumed that new field measurements were not needed. The performance of the calibration scenarios was compared to the basic nationwide models and regional models based on inventory-wise RMSE and MD values. The summary statistics of the RMSE and |MD| values associated with each calibration scenario were used to compare the results at the nationwide level.

Calibration with a small number of new sample plots was conducted using mixed-effect models and the best linear unbiased predictor (BLUP) estimator (Chapter 5.4.1 in Mehtätalo and Lappi 2020). Mixed-effect models were fitted using the same predictor variables as in the basic nationwide V, AGB and Hdom models. Inventory areas were defined as groups, i.e., inventory area-wise random effects were estimated for model intercept and predictors. The calculations were simulated with the following steps: a) leave inventory area *j* out, b) fit nationwide mixed-effect models for V, AGB and Hdom with other inventory areas, c) select 20 of sample plots from area *j*, d) predict new group effects with the BLUP-estimator, and e) predict V, AGB and Hdom for the remainder of the plots in area *j* using new group effects, where *j* is the order number of the inventory area. The simulation was repeated 10,000 times. A small number of sample plots from each inventory area was randomly selected based on the stratification of the sample plots by the ALS metric havgF. The inventory area-wise RMSE and MD values were calculated as the mean RMSE and MD values from 10,000 simulations. Calibration with a small number of new sample plots is denoted by SN.

Calibration with the additional predictor variables was studied for 29 calibration variables that were used to account for the geographical and environmental conditions throughout Finland (Table 3, with the exception of variables decid and v.s.zone). Calibration variables were assumed to bring more predictive power for the nationwide ALS based model, which improves the inventory area wise predictions. Either 1, 2 or 3 additional variables were added to the basic nationwide V model and new coefficients were estimated with OLS. The models were leave-one-inventory-area-out cross validated and the final model forms were selected based on the smallest mean |MD| value. The calibrations with additional variables were denoted either AV1, AV2 or AV3, depending on the number of additional variables used in the calibration.

Calibration with the existing sample plots from nearby inventory areas was performed in two ways. The first alternative (NN1) was conducted as follows: a) select inventory area *j*, b) select the 200 nearest sample plots from the nearest inventory areas based on Euclidean distances calculated between the center of area *j* and sample plot centers of the other inventory areas, c) refit the basic nationwide V model using the 200 nearest sample plots, and d) apply the refitted model for area *j*. In the second alternative (NN2), the 200 nearest sample plots for the target inventory area were selected from the same vegetation sub-zone (v.s.zone in Table 3). If 200 sample plots from the same vegetation sub-zone were not available, sample plots from the most similar sub-zone were used. In addition, if the area was separated into multiple vegetation sub-zones, the calibration was repeated for each sub-area separately.

Calibration with the MS-NFI information was conducted by matching the inventory area-wise V median value associated with the nationwide model predictions to the corresponding median value of the MS-NFI based predictions. The MS-NFI V was extracted for the nationwide sample plot data from MS-NFI rasters (16 × 16 m) (see Section 2.1.3). The MS-NFI-based calibration was performed using leave-one-inventory-area-out cross validation routine. Two variations of this scenario were tested. The first alternative was simulated as follows: a) leave inventory area *j* out, b) predict V for area *j* using the basic nationwide model, c) calculate the V median value for area *j* from plot-level V predictions of the basic nationwide model, d) calculate the V median value for area *j* from plot-level V predictions of MS-NFI, and e) determine the calibration coefficient for the nationwide model so that plot-level predictions would result in the same V median value for area *j* as MS-NFI (NFI1). The second alternative was conducted with the same simulation but only used the sample plots for which the ALS-based prediction was > 0.5 × MS-NFI prediction and < 2 × MS-NFI prediction (NFI2). The second alternative was expected to ignore loggings and other major inconsistencies between the ALS and MS-NFI data. The time difference between the ALS inventories and MS-NFI was ± 2 years.

3.3 Prediction of forest attributes for small areas using ALS-based models and drone image data (III)

The DIPC inventory without new field measurements was studied in three steps: 1) selection of ALS metrics that were similar to DIPC metrics, 2) fitting the ALS-based nationwide and regional V models using selected ALS metrics, and 3) prediction of V in the Liperi test plots (Figure 2) using ALS-based V models with DIPC metrics as predictor variables.

First, the ALS and DIPC metrics were calculated for 15 × 15 m cells of the Liperi test plots. The calculated ALS metrics are presented in Table 4. It was assumed that ALS metrics from the first echo category (F) would correspond better to the DIPC metrics than the ALS metrics from last echo category (L) and so only first echoes were used. Corresponding DIPC metrics were calculated using all point observations. The ALS metric was considered as a candidate variable of a model, if a) Pearson's correlation coefficient (r^2) between the ALS and DIPC metrics in the Liperi test plots was > 0.9, and b) coefficients β_0 and β_1 of relationship function

$$\mathrm{DIPC_m} = \beta_0 + \beta_1 \mathrm{ALS_m} \tag{6}$$

were between −1.0 and 1.0 and 0.9 and 1.1, respectively. Coefficients were estimated with OLS.

In the second step, the model forms for the nationwide and regional ALS models were selected based on the smallest RMSE values (see Section 3.1). However, in study **III**, the number of degree days was assumed to be the best variable to account for the geographical and environmental conditions throughout Finland (d.d. in Table 3). Therefore, the nationwide model was fitted with three predictor variables that assumed that the best model form would include two ALS metrics and degree days. Regional models were fitted using the sample plots from the Sulkava area, which was assessed to have similar forests to the Liperi test area. Degree day information was not included in the regional models, i.e., only two ALS metrics were used. Alternatives to the nationwide and regional models were also constructed in which the dominance of deciduous trees was used as a dummy variable. While fitting the models with OLS, it was found that the residual variance of V increased with respect to the predictions. For that reason, the final models in study **III** were fitted with a nonlinear form assuming a power type variance for residual errors:

$$\mathrm{var}(e_i) = \sigma^2 \mathrm{h95}_i^{2\delta} \tag{7}$$

where
e_i is the residual error for plot i,
$\mathrm{h95}_i$ is the 95% height quantile of first echoes for plot i, and
σ and δ are estimated parameters.

Model coefficients and σ were estimated with nonlinear generalized least squares (NGLS) and δ with maximum likelihood (Chapters 7.5 and 8.3.3 in Pinheiro and Bates 2000; R Core Team 2017; Chapter 7.2.6 in Mehtätalo and Lappi 2020; Pinheiro et al. 2022). As an example, the final nationwide model with dummy variable is presented as follows:

$$\hat{y} = \beta_0 + (\beta_1 + \beta_2 \mathrm{ALS_{m1}} + \beta_3 \mathrm{ALS_{m2}} + \beta_4 \mathrm{d.d.} + \beta_5 \mathrm{decid})^2 \tag{8}$$

where
d.d. is degree days, and
decid is a dummy variable for dominance of deciduous trees.

In the last step, ALS-based nationwide and regional models were applied to the Liperi test plots with DIPC data. Then, V was predicted to the 15 × 15 m cells using DIPC metrics as predictor variables. In alternative scenarios, where the models were fitted with a dummy variable, MS-NFI data (© Natural Resources Institute Finland (Luke) 2017; Tomppo and

Halme 2004) were used to disaggregate the test plots as either coniferous and deciduous dominated before the prediction (decid in Table 3). Predictions were further aggregated to the 30 × 30 m test plots. Error rates were compared with the RMSE and MD values. The scenarios where nationwide and regional ALS-based models were applied using DIPC metrics without disaggregation are denoted by NatDIPC and RegDIPC, respectively. The corresponding abbreviations for scenarios with disaggregation to coniferous and deciduous dominated inventory units are denoted by $\mathrm{NatDIPC_D}$ and $\mathrm{RegDIPC_D}$.

The RMSE and MD values associated with the nationwide and regional models were also compared to the performance of the corresponding local scenarios. The local ALS models were fitted using ALS and field data from the 15 × 15 m cells of the Liperi test area. In the local scenarios, the ALS model was applied to the same data that was used to fit the model. Disaggregation to coniferous and deciduous dominated in the local prediction was performed with field observations. The RMSE values associated with local scenarios represent the lowest possible error rates with ALS data and local field measurements. The local scenarios with and without disaggregation were denoted by LocALS and $\mathrm{LocALS_D}$, respectively.

Finally, the uncertainty of the results in the 30 × 30 m plots was examined by the model-based 95% confidence intervals:

$$\hat{y}_i \pm 1.96\sqrt{\widehat{\mathrm{var}}(\hat{y}_i)} \tag{9}$$

where $\widehat{\mathrm{var}}(\hat{y}_i)$ is the estimated model-based variance of the predicted mean V value in test plot *i* (details of variance estimation can be found in study **III**).

4 RESULTS

4.1 Nationwide models (I, II)

The most essential outputs of this thesis are the nationwide ALS-based forest attribute models. The basic models with the model coefficients for nationwide V, AGB and Hdom models are presented in Table 5. All of the predictor variables in the nationwide V, AGB and Hdom models were statistically significant.

The first (Equation 10) and the second (Equation 11) basic nationwide V models were fitted using sample plots from 9 and 22 inventory areas, respectively. Although the first sample (**I**) covered a geographically much smaller area than the second sample (**II**), both models had the same predictor variables: 1) average height of first echoes (havgF), and 2) 95% quantile of last echoes (h95L). The only difference between the V model forms was that the predictor variable transformations were used only for the first model (**I**). In the training data, RMSE (27.8% vs. 28.5%) and adjusted R-square values (0.88 vs. 0.87) of the nationwide V models were very similar. Note that the RMSE value in the training dataset for the basic nationwide V model in study **II** was not previously reported in the original article. Likewise, the adjusted R-square values for the nationwide models in study **I** are reported only in this thesis summary.

Both the V models and the nationwide AGB model used havgF as a predictor variable. The second predictor for AGB was the maximum value of last echoes (hmaxL). The RMSE and the adjusted R-squared values for the nationwide AGB model in the training data (27.2% and 0.87) were comparable to the V models. The high percentiles of first echoes had a strong correlation with Hdom, which resulted in 95% quantile of first echoes (h95F) selected as the best predictor for the nationwide Hdom model (Equation 13). The RMSE value associated with the nationwide Hdom model (6.7%) in the training data was only a quarter of the RMSE values associated with the V and AGB models. The adjusted R-square value of the Hdom model (0.96) was close to one.

Table 5. The basic nationwide models presented in studies **I** and **II** for stem volume (V), above-ground biomass (AGB) and dominant height (Hdom).

Nationwide model	Equation number	Inventory areas (n)	Study
$V = 2.0923 + (0.7622 + 3.3582 \times \sqrt{havgF} + 0.0100 \times h95L^2)^2$	(10)	9	**I**
$V = 2.3512 + (3.1063 + 0.5834 \times havgF + 0.3038 \times h95L)^2$	(11)	22	**II**
$AGB = 1.1161 + (-0.4247 + 0.1494 \times hmaxL + 2.5196 \times \sqrt{havgF})^2$	(12)	9	**I**
$Hdom = 3.1475 + 0.9855 \times h95F$	(13)	9	**I**

The summary statistics of the leave-one-out cross validated nationwide and regional models are presented in Table 6. The summary statistics were calculated from inventory area-wise RMSE and |MD| values. The RMSE and MD values in study **I** are presented from that perspective only in this thesis summary. It should also be noted that the median values for the regional RMSE and |MD| values were not previously reported in study **II**.

The results presented in Table 6 show that the regional V and AGB models had mean RMSE values approximately 4–5 percentage points lower than the corresponding nationwide models. The differences between the regional and nationwide maximum RMSE values were even higher; about 6–8 percentage points. However, there were also areas where the nationwide V and AGB models performed similar to the regional models, e.g., differences in minimum RMSE values were only about 1–2 percentage points. The region-wise RMSE values associated with the nationwide V and AGB models exhibited a wide range, which was also observed in the standard deviations. In turn, the |MD| values associated with the nationwide V and AGB models varied from 1% to 19%, and the mean of the |MD| values was between 8% and 10%.

The performance of the nationwide Hdom model was almost similar to the regional Hdom models. The mean RMSE value associated with the regional models was only one percentage point lower than the mean RMSE of the nationwide model. The main reason for the difference was that the nationwide Hdom model did not perform well in one area (Tornio). If that area was removed from the results, the difference between the regional and nationwide mean RMSE values was only marginal (0.4 percentage points). In addition, with the exception of the Tornio area, the |MD| values associated with the nationwide Hdom model were close to zero.

Table 6. Summary statistics of root mean square error (RMSE, %) and absolute mean difference (|MD|, %) values of leave-one-out (inventory area or plot) cross validated nationwide (N) and regional models (R) models for stem volume (V), above-ground biomass (AGB) and dominant height (Hdom). The |MD| values associated with the regional models were always close to zero and are not presented here. Statistics are summarized from the regional RMSE and MD values presented in studies **I** and **II**.

Scenario		N				R			
Forest attribute		V	V	AGB	Hdom	V	V	AGB	Hdom
Study		**I**	**II**	**I**	**I**	**I**	**II**	**I**	**I**
Inventory areas (n)		9	22	9	9	9	22	9	9
RMSE	Min	23.0	21.2	22.3	5.4	21.7	19.9	20.2	5.2
	Max	32.9	35.8	33.8	11.4	26.8	28.0	25.4	6.7
	Mean	28.1	28.6	27.9	7.0	24.0	23.9	23.2	6.0
	Median	28.0	28.4	27.3	6.6	24.3	23.6	23.5	6.3
	Sd	3.3	4.3	3.4	1.8	1.6	2.3	1.4	0.6
|MD|	Min	2.0	0.6	2.6	0.2	--	--	--	--
	Max	18.2	19.3	18.7	9.1	--	--	--	--
	Mean	9.7	8.3	9.1	2.2	--	--	--	--
	Median	8.8	7.9	8.0	1.7	--	--	--	--
	Sd	5.5	5.6	5.3	2.7	--	--	--	--

4.2 Nationwide model calibration (I, II)

The nationwide V models were calibrated with ancillary data without additional field measurements. A total of seven calibration scenarios (AV1–3, NN1–2, NFI1–2) were compared to the uncalibrated nationwide model (N) and to the regional models (R). The results were also compared to the calibration scenario where new field measurements were simulated (SN). The nationwide V models with calibration variables (scenarios AV1–3) and their coefficients are presented in Table 7. Summary statistics of all calibration scenarios for V are presented in Table 8. Noted that the median values for the regional RMSE and |MD| values were not previously reported in study **II**.

The best calibration performance was attained by simulating new field measurements and calibrating the nationwide V models with the BLUP-estimator (SN). Compared to the basic nationwide V model in study **I** (N), the mean RMSE value decreased by about 2 percentage points and the mean |MD| value by about 8 when the calibration plots from each inventory area were used (SN). It is also notable that the maximum |MD| value was 14 percentage points lower after the simulation with the new field measurements (N vs. SN). The mean RMSE value associated with the new field measurements (SN) was only about 2 percentage points greater than the mean RMSE value associated with the regional models (R). The results of SN scenario for nationwide AGB model were in line with the nationwide V model (see study **I** for details). The nationwide Hdom model did not benefit significantly from the calibration plots as the uncalibrated model had already exhibited small error rates (**I**).

The results reported in study **II** showed that the additional variables (AV1–3) decreased the mean RMSE value associated with the nationwide model from 1 to 3 percentage points compared to the basic nationwide model (N). Although, the number of inventory areas varied between studies **I** and **II**, the similar RMSE mean values indicate that the RMSE values decreased similarly when three additional calibration variables (AV3) were used as when measuring the small number of new sample plots from the target area (SN). However, the additional calibration variables (AV1–3) decreased the mean |MD| values less than the new calibration plots (SN). Compared to the basic nationwide model (N) in study **II**, the mean and maximum |MD| values decreased by about 3 percentage points when the three additional calibration variables (AV3) were used. From the AV scenarios, AV3 had the lowest mean and median |MD| values, although the lowest extreme and standard deviation |MD| values were in AV2. The best performing additional calibration variables for the AV scenarios were degree days (d.d. and d.d.cl in Table 3), proportion of pine and birch from MS-NFI (pine.p and birch.p) and standard deviation of the monthly precipitations (psd.a). Details on how the other calibration variables decreased RMSE and |MD| values can be found in Section 3.2 in study **II**.

With regard to RMSE statistics, calibration with the MS-NFI information (NFI2) performed similar to the calibration with the two additional calibration variables (AV2). However, with regard to |MD| statistics, the NFI2 calibration was closer to AV3 than to AV2. The results indicated that the extreme |MD| values were more common when elimination of systematic inconsistency between the MS-NFI and ALS data was not used (NFI1 vs. NFI2), i.e., elimination of inconsistencies is a required step in the MS-NFI-based calibration. The calibration scenarios NN1 and NN2, where nationwide models were refitted using sample plots from nearby inventory areas, resulted in greater mean and median values for region-wise |MD| values than were observed for NFI1 and NFI2. Major differences between the NN and NFI scenarios were not found with regard to mean and median RMSE values. However, it should be noted that the standard deviation value associated with the region-wise RMSE values in the NN2 scenario was slightly lower than in the NFI2 scenario, although the maximum RMSE value in NN2 was notably higher. The use of vegetation sub-zones in sample plot selection (NN2) resulted in lower mean |MD| values compared to the distance-based approach (NN1).

The spatial distribution of MD values in the basic nationwide model (N) and the best calibration scenarios from each calibration category where additional field measurements were not used (AV3, NN2 and NF2) are visualized in Figure 3. The spatial distribution shows that the basic nationwide model (N) systematically underpredicted (positive MD values) for the northern part of Finland and systematically overpredicted (negative MD values) for the southern part. The basic nationwide model (N) also had greater mean |MD| value for the northern part. Each calibration scenario improved the MD values, especially for the northern part of the country. In some of the inventory areas, calibration improved the MD value and even changed the MD sign. The most uniform spatial distribution was obtained using three additional variables in the nationwide model (AV3).

In study **I**, with the basic nationwide V and AGB models, the region-wise MD values associated with the Optech scanners were, on average, greater than the values associated with the Leica scanners. However, very different results were observed in study **II**: a) with the basic nationwide V model, the mean and standard deviation values associated with |MD| for Leica were 8.8% and 5.3%, and 7.7% and 6.1% for Optech and b) after the AV3 calibration, the mean and standard deviation values associated with |MD| were 6.8% and 5.2% for Leica, and only 4.5% and 3.3% for Optech, respectively. Note that these findings from study **II** were not reported in the original article.

Table 7. Calibrated nationwide models for stem volume (V) presented in study **II**.

Nationwide model	Equation number	Inventory areas (n)	Study
$V = 2.1481 + (d.d.cl + 3.4000 + 0.6593 \times havgF + 0.2892 \times h95L)^2$	(14)	22	**II**
$V = 2.0561 + \begin{pmatrix} d.d.cl + 2.4441 + 0.6981 \times havgF + \\ 0.2715 \times h95L + 0.1272 \times \sqrt{pine.p} \end{pmatrix}^2$	(15)	22	**II**
$V = 1.8895 + \begin{pmatrix} 4.6931 + 0.7383 \times havgF + \\ 0.2332 \times h95L - 0.2266 \times \sqrt{birch.p} + \\ 0.0019 \times psd.a^2 - 2.2607 \times 10^{-6} \times d.d^2 \end{pmatrix}^2$	(16)	22	**II**

Note: In equation 14, d.d.cl is −1.2686 when d.d. > 1200, d.d.cl is −0.8267 when d.d. ≤ 1200 and > 1000, and 0 otherwise. In equation 15, d.d.cl is −1.1695 when d.d. > 1200, d.d.cl is −0.7490 when d.d. ≤ 1200 and > 1000, and 0 otherwise.

Table 8. Summary statistics of root mean square error (RMSE, %) and absolute mean difference values (|MD|, %) of the nationwide (N) stem volume models (V) with different calibration scenarios (SN, AV1–3, NN1–2, NFI1–2) and regional models (R). Statistics are summarized from the regional RMSE and MD values presented in studies **I** and **II**. SN refers to the calibration with new field measurements from the target area, AV to the calibration with additional calibration variables, NN to the calibration using data from the nearest inventory areas, and NFI to the calibration based on multisource national forest inventory data (MS-NFI).

Scenario		N		SN	AV1	AV2	AV3	NN1	NN2	NFI1	NFI2	R	
Forest attribute							V						
Study		**I**	**II**	**I**	**II**	**II**	**II**	**II**	**II**	**II**	**II**	**I**	**II**
Inventory areas (n)		9	22	9	22	22	22	22	22	22	22	9	22
RMSE	Min	23.0	21.2	23.3	20.9	20.9	20.2	20.9	22.9	20.1	20.1	21.7	19.9
	Max	32.9	35.8	28.3	34.9	33.9	34.4	36.8	38.5	36.7	33.5	26.8	28.0
	Mean	28.1	28.6	25.9	27.3	27.1	25.9	27.7	27.7	27.8	27.4	24.0	23.9
	Median	28.0	28.4	26.3	27.8	27.7	25.5	27.6	27.4	27.7	27.1	24.3	23.6
	Sd	3.3	4.3	1.6	3.7	3.5	3.9	3.5	3.5	4.3	3.7	1.6	2.3
|MD|	Min	2.0	0.6	0.3	0.1	0.1	0.7	0.0	0.1	0.5	0.7	--	--
	Max	18.2	19.3	3.9	18.8	14.3	16.7	17.9	20.5	22.0	16.3	--	--
	Mean	9.7	8.3	1.8	6.7	5.9	5.6	7.0	6.6	6.2	5.9	--	--
	Median	8.8	7.9	1.5	6.8	6.0	5.0	6.0	6.3	4.0	4.9	--	--
	Sd	5.5	5.6	1.3	4.6	3.9	4.4	5.3	5.2	6.2	4.4	--	--

Note: Inventory area-wise RMSE and MD values associated with the SN scenario were calculated as the mean RMSE and MD values from 10,000 simulations.

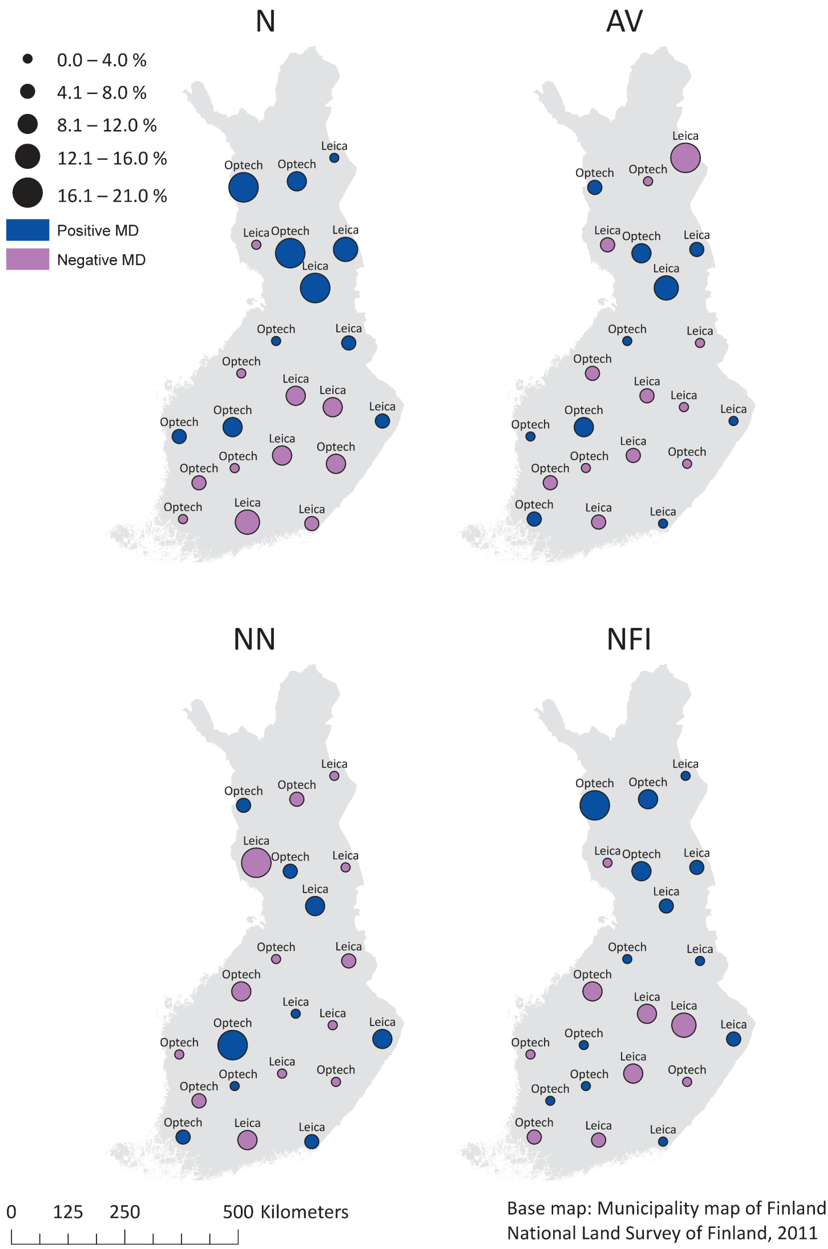

Figure 3. Inventory area-wise absolute mean difference (|MD|, %) values with the basic nationwide model (N) and with the best calibration scenarios from each calibration category (AV, NN and NF) without new field measurements (study **II**). AV refers to the calibration with additional calibration variables, NN to the calibration that used data from the nearest inventory areas, and NFI to the calibration based on multisource national forest inventory data (MS-NFI). Optech and Leica refers to the manufacturer of the used airborne laser scanning sensor.

4.3 ALS-based models in DIPC-based forest inventories (III)

The results of study **III** highlighted the ALS metrics that are usable in forest attribute models when the models are utilized in DIPC-based forest inventories. Two nationwide and two regional V models were established with ALS data and their predictive performance was assessed with DIPC data. The nationwide models are shown in Table 9 and the RMSE and MD values associated with the different inventory scenarios are shown in Table 10.

From the calculated ALS metrics (Table 4), only 45% were comparable to the DIPC metrics. The metrics that described the dominant tree layer were the most similar between the ALS and DIPC datasets (h60–h95, havg, hmax, d15–20). This result is logical since DIPC data do not include observations that are not visible from the images. Height metrics for low percentiles (h5–h55), which represent the understory, and the density metrics (d0.5–d10) with small threshold values were not similar between the ALS and DIPC data.

The nationwide V models used in the DIPC-based prediction (Table 9) were quite similar to the nationwide V models presented in studies **I** and **II** (Tables 5 and 7). In the first model (Equation 17), the predictor variables were: average height of first echoes (havgF), 95% quantile of first echoes (h95F) and degree days. In the second model (Equation 18), the 85% quantile of first echoes (h85F) was used instead of the 95% quantile. If the site was deciduous dominated, the predictions of the second model were systematically adjusted with the estimated constant (decid).

The RMSE values in studies **I** and **II** were reported for the circular sample plots used in operational inventories (radius between 9 m and 12.65 m). However, in study **III**, the results of a DIPC-based inventory were reported for larger 30 × 30 m test plots. In aggregation of V from 15 × 15 m cell to the 30 × 30 m test plot-level, the RMSE value decreases as the errors compensate for each other. The fact that aggregation decreases the RMSE value indicates that the RMSE values presented in studies **I** and **II** are not directly comparable to the results in study **III**. Nevertheless, it is still worth noting that the RMSE value in the scenario where the nationwide V model (Equation 17) was used in the DIPC inventory and inventory units were not disaggregated to coniferous and deciduous dominated (NatDIPC) was the same as the mean of the region-wise RMSE values associated with the nationwide V model with three additional calibration variables (AV3) (25.9%, see Tables 8 and 10) (**II**, **III**). In turn, the RMSE value in the scenario where the nationwide V model was used in the DIPC inventory with disaggregation of inventory units (Equation 18; NatDIPC$_D$) was the same as the lowest RMSE value observed from the cross validated regional V models (R) (about 20%) (**I**, **II**, **III**). In other words, the disaggregation of sample plots to coniferous and deciduous dominated in the nationwide DIPC scenarios decreased the RMSE value by about 6 percentage points. In contrast to the RMSE values, the MD values of the studies are comparable, since aggregation of V from 15 × 15 m to the 30 × 30 m level does not change the MD value. The results showed that the |MD| values associated with the nationwide DIPC scenarios (10.4% and 9.6%) were closer to the mean |MD| value associated with the basic nationwide model (N) (8.3%) than the mean |MD| values associated with the nationwide calibration scenarios without additional field measurements (AV1–3, NN1–2, NFI1–2) (5.6%–7.0%) (**II**, **III**). Disaggregation of inventory units only improved the MD value by about 1 percentage point in the nationwide DIPC scenarios.

In the DIPC-based inventory, the use of the regional models from the Sulkava area, instead of the nationwide models, improved the MD values. The MD value associated with the regional scenario using disaggregation (RegDIPC$_D$) was approximately 9 percentage points better than the MD value of the corresponding nationwide scenario (NatDIPC$_D$), i.e., ALS-based model from Sulkava area using disaggregation of inventory units to coniferous and deciduous dominated resulted in a MD value close to zero. Improvements in the RMSE values were also observed; the RMSE value associated with scenario $\mathrm{RegDIPC_D}$ was 7 percentage points lower than the value for $\mathrm{NatDIPC_D}$. In the local DIPC scenarios, MD values were essentially absent and RMSE values were generally the lowest.

Although there were clear differences in the RMSE and MD values associated with the nationwide and regional scenarios, the observed versus predicted values of these scenarios were quite similar (Figure 4). In scenarios NatDIPC and $\mathrm{NatDIPC_D}$, 84.2% and 89.8% of the confidence intervals included the observed stem volume, respectively. Corresponding values for scenarios RegDIPC and $\mathrm{RegDIPC_D}$ were 84.2% and 94.7%, respectively. In the local scenarios, all the observations were inside the confidence intervals.

Table 9. Nationwide models for stem volume (V) presented in study **III**.

Nationwide model	Equation number	Inventory areas (n)	Study
$V = 4.89585 + \left(0.69467 \times \mathrm{havgF} + 2.11538 \times \sqrt{\mathrm{h95F}} - 1.34654 \times \left(\frac{\mathrm{d.d.}}{1000}\right)^2\right)^2$	(17)	22	**III**
$V = 5.18609 + \left(2.80389 + 0.72222 \times \mathrm{havgF} + 2.00006 \times \sqrt{\mathrm{h85F}} - 3.18360 \times \frac{\mathrm{d.d.}}{1000} - 2.16066 \times \mathrm{decid}\right)^2$	(18)	22	**III**

Note: decid = 1 in deciduous dominated and decid = 0 in coniferous dominated sites.

Table 10. Root mean square error (RMSE, %) and mean difference values (MD, %) of stem volume predictions for the 30 × 30 m test plot in the Liperi area with nationwide (Nat), regional (Reg) and local (Loc) models (study **III**). DIPC refers to the drone image point cloud-based prediction and ALS to airborne laser scanning. D denotes the scenarios where test plots were disaggregated to coniferous and deciduous plots before the prediction.

Scenario	NatDIPC	$\mathrm{NatDIPC_D}$	RegDIPC	$\mathrm{RegDIPC_D}$	LocALS	$\mathrm{LocALS_D}$
RMSE	25.9	20.0	24.1	13.1	14.1	7.9
MD	−10.4	−9.6	−5.7	−0.9	−0.2	−0.3

Note: In study III, the corresponding MD values are presented as opposite, i.e., systematic overpredictions are positive values.

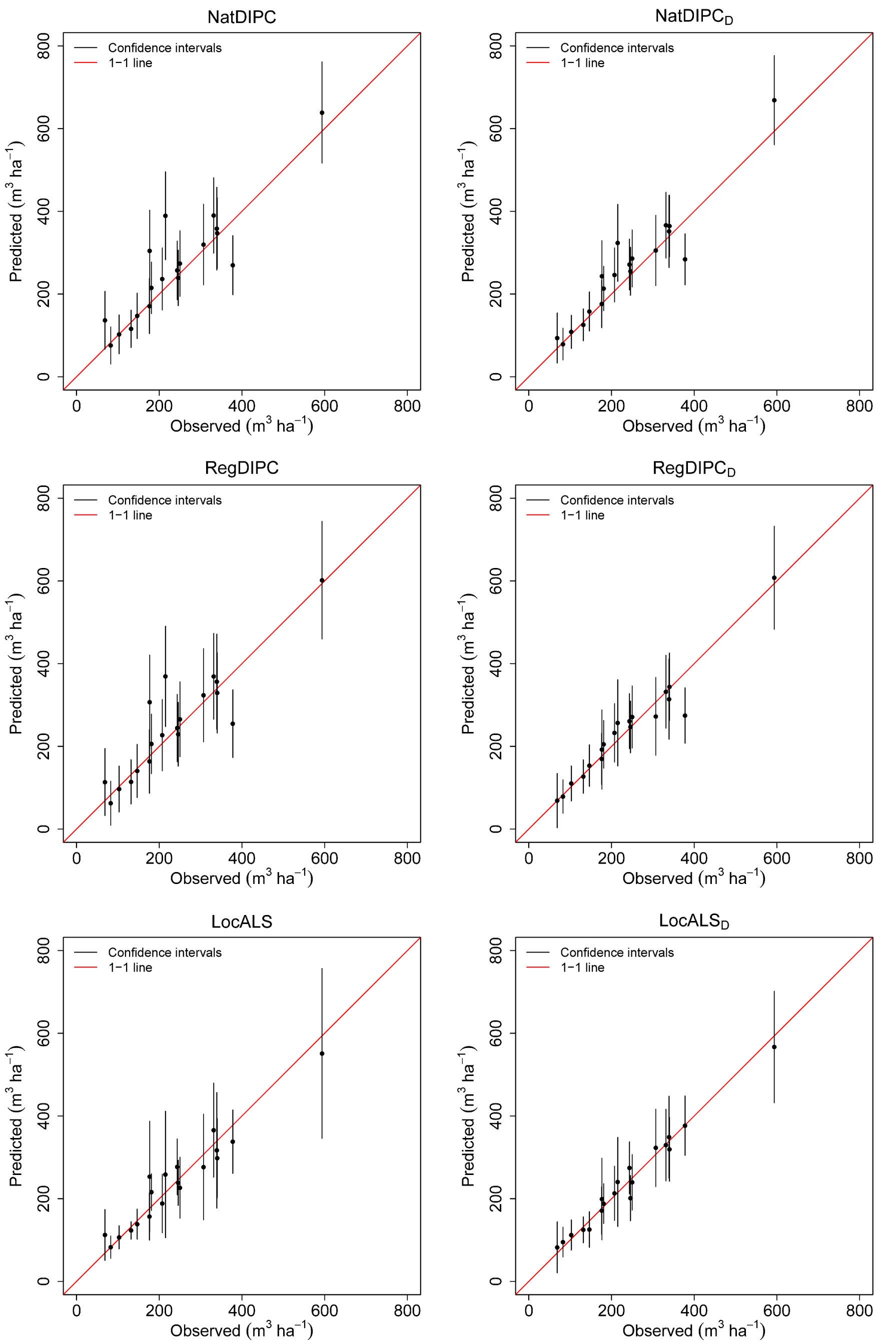

Figure 4. Observed (m^3 ha^{-1}) versus predicted stem volumes (m^3 ha^{-1}) with 95% model-based confidence intervals for the 30 × 30 m test plots in the Liperi area using nationwide (Nat), regional (Reg) and local (Loc) prediction scenarios (study **III**). DIPC refers to the drone image point cloud-based prediction and ALS to airborne laser scanning. D denotes the scenarios where test plots were disaggregated to coniferous and deciduous plots before the prediction.

5 DISCUSSION

5.1 Is the prediction of forest attributes without new in-situ field measurements possible using nationwide ALS-based models?

The main objective of this thesis was to predict forest attributes without new in-situ field measurements using ALS-based models. One possible solution is to fit a model that uses sample plots distributed over a large area and to then use it for predictions elsewhere. In general, the results of this thesis demonstrated that nationwide ALS-based model performance was associated with moderate error rates, especially when geographical and environmental information were used in conjunction with the ALS data. Systematic errors in the nationwide models were minimized when degree days, precipitation and tree species proportion information was included in the predictive models. However, calibration of nationwide models with a small amount of field data from the target area is recommended, provided the training data from the target areas is easily available.

To examine nationwide predictions, one nationwide model for Hdom (**I**), one nationwide model for AGB (**I**) and a total of seven nationwide models for V (**I**, **II**, and **III**) were constructed. Different growing conditions, especially between the northern and southern parts of Finland (Table 1; Section 1.3), lead to systematic regional errors in nationwide V and AGB predictions, especially when calibration for the nationwide models is not used (N) (**I**, **II**). Using the basic nationwide V models (N), extreme underpredictions were observed for the northern part of Finland, with considerable overpredictions observed for the southern part. For V, nationwide model calibration with a small number of sample plots from the target area had the best calibration effect. The RMSE distributions in study **I** showed that with suitable sample plot combinations, scenario SN would provide even smaller RMSE values than the regional models (R). The observed benefit of the calibration plots is in line with findings of de Lera Garrido et al. (2022). They concluded that 20 calibration plots would result in predictions comparable to the local models when spatially or temporally transferred models are applied to the target area. However, it should also be noted that solely using a small number of sample plots from the target area (e.g., 40 plots) may be sufficient for V prediction (Suvanto and Maltamo 2010; Gobakken et al. 2013).

In the absence of in-situ field measurements, the RMSE values of the nationwide V models were the most comparable to the RMSE values of the regional models (R) when the models were calibrated with additional variables: degree days, precipitation, and proportion of birch trees (AV3). The environmental and geographical information in the ALS-based models minimized the number of extreme MD values. The smallest mean |MD| value and the most uniform spatial distribution of MD values for V without new in-situ field measurements were also obtained using the model with three additional variables. As V and AGB are similar and closely correlated forest attributes, this resulted in comparable RMSE and MD values in the basic nationwide models. The similarity of these attributes indicates that the additional variables would also decrease the error rates of the nationwide AGB model. The nationwide Hdom model would probably not benefit to any great extent from calibration with additional variables as the uncalibrated model had performed well in almost all of the inventory areas. The results in study **I** showed that even calibration with a small number of sample plots from the target area (SN) did not result in major improvements in the nationwide Hdom predictions.

In general, refitting of nationwide models using sample plots from the nearest inventory areas (NN) or calibration with MS-NFI data (NFI) did not perform as well as calibration with additional variables. However, the results indicate that NN calibration could be useful in some of the inventory areas if nearby available sample plots provide a good representation of the target area. ALS assisted plot selection for NN calibration should be considered in the future (Maltamo et al. 2011; Gobakken et al. 2013). In addition, MS-NFI data could provide good calibration for the inventory area, provided inconsistencies (such as loggings) between the datasets are reliably detected and taken into account.

The findings related to the extreme MD values in the nationwide predictions of V and AGB are in line with other studies (e.g., Uuttera et al. 2006; Tompalski et al. 2019; van Ewijk et al. 2020). The extreme MD values observed regionally in the nationwide prediction are probably related to the different species distributions in the different regions. Bouvier et al. (2015), for example, showed that fitting separate models for coniferous, deciduous and mixed sites improved the MD values. Maltamo et al. (2016) also highlighted that species disaggregation is an important factor in large area predictions and that separate models by species should be considered in pine and deciduous dominated regions, while a common model of all tree species could be used in spruce dominated regions. In this thesis, the proportions of pine and birch were also important variables in calibration scenarios AV2 and AV3. Based on the model coefficients (Equations 15 and 16), a greater proportion of pine increases the value of V, while a greater proportion of birch decreases the value of V. In turn, study **III** showed that disaggregation of the prediction units to coniferous and deciduous dominated would provide sufficient information for the calibration. It should be noted that all the tree species variables in this thesis were extracted from MS-NFI data. However, the MS-NFI based attributes may exhibit high error rates at the pixel-level (Mäkisara et al. 2019), which affect the corresponding variables. Therefore, information from former stand-level management inventories (Minguet 2013; Kangas et al. 2020) or high-resolution satellite images (Kukkonen et al. 2018; Piispanen 2019) should also be considered as additional variables to account for tree species.

Other geographical and environmental variables that were important in the nationwide prediction were degree days and standard deviation of the monthly precipitations. Degree days was always selected for the nationwide V models. The coefficients of degree days were negative in each model. The negative coefficient of degree days indicates that V was reduced when degree days increased along a north to south gradient and can be explained by the different height-diameter relationships in northern and southern Finland. Trees in southern Finland have smaller diameters than trees with the same height in northern Finland, which correspondingly results in larger V values for the same height trees in the north. The trees in the south grow taller and are, therefore, more slender than trees with the same height in the north (Korhonen et al. 2021). Standard deviation of the monthly precipitations, in turn, had a positive coefficient in the nationwide V model (Equation 16), i.e., high standard deviation of the monthly precipitations in an area indicates a generally greater V value. Moreover, mean annual precipitation was found to be a better calibration variable than the corresponding variable calculated for the growing season (Section 3.2 in study **II**). It is probable that the deep snow layer provides frost protection for the root system in winter (Sutinen et al. 2014) and available melt water may relieve the stress of the trees in spring, which has positive effects on V. Excluding peatlands, summertime precipitation is usually the main variable that limits forest growth in Finland (Henttonen et al. 2014).

In addition to the geographical and environmental variables, the ALS sensor and acquisition settings can influence the error rates (Næsset 2005; Næsset 2009; Hopkinson

2007; Keränen et al. 2016). In study **I**, the ALS data were acquired with Leica scanners in 22% of the regions. The corresponding value in studies **II** and **III** was 50%. In the other regions, Optech scanners were used. In Section 4.2, it was reported that MD values associated with the Leica scanners were, on average, greater than with Optech scanners using the basic nationwide model (N, **II**). After the calibration with additional variables (AV3), the mean |MD| difference between Leica and Optech increased. The calibration scenario AV3 improved the MD values, especially from the inventory areas where the Optech scanners were used. Calibration was found to affect more the areas scanned with Optech, because the ALS data from the Optech scanners were more homogenous than ALS data within areas scanned with Leica (see Table 2). It should be noted that even scenario AV3 probably did not account for all the environmental and geographical effects. Therefore, the comparison between the Optech and Leica scanners is not completely unbiased. The results of AV3 could probably be improved further if the nationwide models were fitted separately by the manufacturer or if the sensor unit was used as a dummy variable. However, the sensor or manufacturer information in nationwide models were not used in this thesis because the technology is constantly developing, and new scanner models are introduced every year. Moreover, if models are also targeted for use with DIPC data, the ALS sensor information in the prediction cannot be used.

5.2 Are ALS-based models transferable to DIPC data?

This thesis illustrated that ALS-based models are transferable to DIPC data provided the point cloud metrics used in the ALS models are selected carefully, i.e., the predictor variables are similar between the datasets. Especially, the point cloud metrics that represent the upper canopy are good predictor candidates for the models. The results of the DIPC-based inventory in the Liperi test area also indicated that sample plots from a nearby ALS inventory area with similar growth conditions and species distributions is recommended instead of nationwide data. Likewise, the inventory unit disaggregation to deciduous and coniferous dominated forests should be performed before predictions to ensure lower error rates.

In general, the error rates of ALS-based models with DIPC data were in line with studies where both the models and the predictions were based on DIPC data (Puliti et al. 2015, Tuominen et al. 2015, Ota et al. 2017). The ALS-based nationwide models exhibited greater error rates in the Liperi test plots than the ALS models fitted using sample plots from the nearby inventory area (Sulkava). The difference between the nationwide and regional model performance was especially notable when disaggregation of the test plots to coniferous and deciduous dominated forests was used before the predictions. The nationwide model with disaggregation (NatDIPC_D) tended to show greater systematic overprediction compared to the corresponding regional model (RegDIPC_D). The RMSE value for V reported by Puliti et al. (2015) was relatively close to the RMSE value reported here for RegDIPC_D.

Tompalski et al. (2019) noted that ALS-based models can be transferred to IPC data in the same area with acceptable error rates, which also demonstrates the similarity between the ALS and IPC metrics. The empirical test in study **III** showed that height-related DIPC metrics, such as h60–h95, havg and hmax, were similar to corresponding ALS metrics. However, it was also observed that DIPC data tended to produce systematically greater values than ALS data for some of the predictor variables (e.g., havg). The reason for that tendency is that most of the DIPC observations are from the upper part of the canopy layer, i.e., DIPC data do not include the understory observations that are not visible from the images (Lisein et al. 2013), although ALS data does penetrate through the canopy. Greater predictor variable values lead to systematic overpredictions if these variables are included in the models. Even though nationwide models can produce systematic errors at the regional-level (**I**, **II**), it can be concluded that overpredictions of ALS-based models in the Liperi area were at least partly caused by the use of DIPC metrics in the predictions (**III**). The systematic differences between DIPC and ALS metrics may level out in forests with a dense canopy cover (White et al. 2015).

Weather conditions, such as variable cloud conditions and wind, could also affect the quality of DIPC and subsequent prediction error rates (Dandois et al. 2015). However, the effect of variable illumination on the error rates was not observed here, although the images were collected under both sunny and cloudy conditions. Wind conditions during the Liperi data acquisition were rather stable. One error source in DIPC-based predictions may be the geolocation accuracy of the DIPC data and the height normalization of the point observations. In study **III**, DIPC data were adjusted horizontally and vertically with ALS data, and DIPC heights were normalized based on ALS DTM. If ALS data are not available, one option is to use DIPC-based DTM in height normalization (Kukkonen et al. 2021a). As DIPC-based normalization may perform poorly in areas with a dense canopy, the metrics that are not dependent on the DTM should be studied more in the future (Giannetti et al. 2018).

5.3 Further studies

Studies **I**, **II** and **III** have inspired several other studies. First, Piispanen (2019) created normalization functions between Sentinel-2 and Landsat 8 satellite images and used the information from the pooled image bands to calibrate the basic V model presented in study **II** (Equation 11). Their results showed similar mean RMSE values for calibrated model using the pooled red and short-wave infrared bands (**II**) than in AV3. However, the mean |MD| values with pooled image bands remained greater. Aaltonen (2019) studied the effects of height-diameter ratios, basal area weighted median diameter and numbers of stems per hectare as predictor variables in regional-level basal area predictions. They used sample plots from the subset of the regions presented in study **II** (n = 10). The results illustrated that in most of the studied areas, number of stems resulted in the relatively greatest decrement in regional-level RMSE values and noted the importance of height-diameter ratios in prediction. It would be an interesting option to interpolate general diameter-height relationship rasters for the whole of Finland and to test the information as additional variables in nationwide models. Most recently, Toivonen et al. (2021) predicted Hdom and V for the Liperi test plots by examining multiple ALS-based models from different regions in DIPC-based predictions. They used the same data and estimation methods presented in study **III** to fit fixed ALS-based Hdom and V models for all 22 regions. They obtained smaller error rates for the Liperi test area using a regional ALS-based V model from Hyvinkää (Figure 1) than using the model from Sulkava. In future studies, one option to improve the DIPC-based predictions would be to create an approach to select the optimal set of training plots from multiple regions for the model construction.

The operational forest inventory and the planning of forest management usually requires species-specific predictions from the forest inventories (Maltamo and Packalen 2014). Therefore, the next step is to examine species-specific predictions without new in-situ field measurements. One possible option is to use satellite image data in species-specific prediction (Kukkonen et al. 2018). Kukkonen et al. (2021a) have already demonstrated the use of spectral information from Sentinel-2 images in the prediction of species proportions in DIPC-based forest inventories without new in-situ field measurements. Species proportions were then used to derive the species-specific V predictions. In the study of Kukkonen et al. (2021a), total V was predicted similarly to our approach in study **III** using the ALS-based model from a nearby area and DIPC metrics in the prediction. The results reported by Kukkonen et al. (2021a) are promising; the species-specific error rates for V were in line with the traditional ALS-based inventories (e.g., Packalén and Maltamo 2007, Kukkonen et al. 2018, Kukkonen et al. 2019a, Kotivuori et al. 2021). In the context of nationwide ALS inventories, satellite images of species proportions should be similarly tested. Separate species-specific nationwide models for the main tree species should also be considered. For species-specific nationwide models, standardization of predictor variables between the different geographical areas may be required (Rana et al. 2022).

In addition to the nationwide species-specific predictions, the calibration of nationwide models should be further studied. For example, it would be interesting to study the calibration of the nationwide models using regional NFI sample plots in conjunction with ALS data. However, ALS and NFI data would have different acquisition years in many areas and therefore growth prediction for the field data should be used to eliminate the differences. The re-use of the existing sample plots and ALS data should also be more deeply studied when a new inventory is implemented for the same area (de Lera Garrido et al. 2020). The ITD-based samples (e.g., from drone LiDAR) from the target area would also be one possible option to simulate field training data for nationwide model calibration. Likewise, the statistical modelling could be improved. For example, the effects of multicollinearity and different modelling techniques should be tested. Multicollinearity of the predictor variables could be problematic, especially when the correlation of predictors varies notably between the separate inventory areas (Werkowska et al. 2017; van Ewijk et al. 2020). Tompalski et al. (2019) also reported that V models fitted with the random forest model may be more transferable between the inventory areas than OLS models. It would be useful to create calibration maps for the nationwide models to ensure the easy calibration of the predictions. In addition, the possibility of engaging local forest professionals to advise on the most appropriate model for transfer to a particular target area should be investigated.

6 CONCLUSIONS

This thesis investigated the prediction of forest attributes without new in-situ field measurements in ALS and DIPC-based forest inventories. Prediction of forest attributes is possible with moderate error rates using nationwide ALS-based models. Systematic errors are minimized when the nationwide models are calibrated with geographical and environmental variables, such as degree days, precipitation, and tree species proportions. However, the local calibration of nationwide models with a small number of sample plots is recommended, provided the local training data is easily available. Forest attribute prediction by applying ALS-based models with DIPC metrics is possible if the metrics used as predictor variables are pre-selected carefully. In particular, ALS metrics that describe the upper canopy layer are recommended when the ALS models are used with DIPC data. According to this thesis, a model from a nearby region may perform better than the corresponding nationwide model when DIPC metrics are used in the predictions. Moreover, a model from a nearby region may perform particularly well if the inventory units are disaggregated to coniferous and deciduous dominated before the predictions. In the future, species-specific predictions without new in-situ field measurements should be studied with nationwide models. The re-use of existing ALS and field datasets when a new inventory for the same area is implemented should also be studied further.

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