**Dissertationes Forestales 307**

# Predicting commercial tree quality by means of airborne laser scanning

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Academic dissertation

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## ABSTRACT

Airborne laser scanning (ALS) is widely used to predict the total volume of trees in a forest stand. However, in operational forestry, it is usually not sufficient to consider the total volume only, because the various tree species and timber assortments are priced differently. As tree quality strongly affects how harvested logs are assigned to different timber assortments, tree quality information prior to harvesting, for example, would improve the planning of harvesting operations. The main aim of this thesis was to test different methods to predict tree quality, especially sawlog volume, by means of ALS.

The three sub-studies of this thesis were implemented using datasets from eastern Finland (3 datasets) and south-eastern Norway (1 dataset). All the study forests were dominated by Scots pine (*Pinus sylvestris* L.) or Norway spruce (*Picea abies* (L.) Karst.). The first study focused on the effects of transferring tree-level models between inventory areas. In the second study, various methods to predict plot-level (30 m × 30 m) sawlog volume were tested. The third study focused on the field-calibrations of stand-level merchantable and sawlog volumes by using basal area measurements. All the ALS-based predictions were made with either linear mixed-effects models or k-nearest neighbor imputations at the tree or plot-levels (15 m × 15 m).

The results showed that there is only weak correlation between the ALS metrics and tree quality. Nevertheless, sawlog volume predictions with relative root mean squared error values between 20–30 % were obtained after aggregations to the 30 m × 30 m and stand-levels. Moreover, the study-specific results showed that a notable decrease in accuracy can be expected when tree-level models are transferred between inventory areas, and that basal area information is not generally useful to increase the accuracy of sawlog volume predictions in Norway spruce dominated stands.

**Keywords:** LiDAR, sawlog volume, crown base height, timber assortments, remote sensing

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Joensuu, November 2020

Tomi Karjalainen

# LIST OF ORIGINAL ARTICLES

This thesis is based on the following three papers, which are referred to by Roman numerals in the text.

**I.** Karjalainen T., Korhonen L., Packalen P., Maltamo M. (2019). The transferability of airborne laser scanning based tree-level models between different inventory areas. Canadian Journal of Forest Research 49(3): 228–236. https://doi.org/10.1139/cjfr-2018-0128

**II.** Karjalainen T., Packalen P., Räty J., Maltamo M. (2019). Predicting factual sawlog volumes in Scots pine dominated forests using airborne laser scanning data. Silva Fennica 53(4): 17 p. https://doi.org/10.14214/sf.10183

**III.** Karjalainen T., Mehtätalo L., Packalen P., Gobakken T., Næsset E., Maltamo M. (2020). Field calibration of merchantable and sawlog volumes in forest inventories based on airborne laser scanning. Canadian Journal of Forest Research. In press. https://doi.org/10.1139/cjfr-2020-0033

Tomi Karjalainen was responsible for all the calculations and analyses in papers **I** and **III**. In paper **II**, he was responsible for all the analyses, and for all the calculations, except for the construction of the tree lists with the k-nearest neighbor imputation, which were constructed by co-author Janne Räty. The author was also the corresponding author of all three papers.

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## ABBREVIATIONS

| | |
|---|---|
| ABA | Area-based approach |
| AIC | Akaike information criterion |
| ALS | Airborne laser scanning |
| CBH | Crown base height |
| CHM | Canopy height model |
| CTL | Cut-to-length |
| DBH | Diameter at breast height |
| DTM | Digital terrain model |
| D6 | Diameter at the height of 6 meters |
| EBLUP | Estimated best linear unbiased predictor |
| H | Height |
| ITD | Individual tree detection |
| k-MSN | k-most similar neighbor |
| k-NN | k-nearest neighbor |
| LME | Linear mixed effects |
| LOOCV | Leave-one-out cross validation |
| MD% | Mean difference (relative) |
| NFI | National forest inventory |
| PP | Percent point |
| PRF | Pulse repetition frequency |
| RMSE% | Root mean squared error (relative) |
| SRM | Sawlog reduction model |
| STD | Single tree detection |
| TLS | Terrestrial laser scanning |
| UAV | Unmanned aerial vehicle |
| Vlog | Theoretical sawlog volume |
| 3-D | Three-dimensional |

# 1 INTRODUCTION

## 1.1 Commercial tree quality

In general, the forestry sector is based on the utilization of sawlogs, pulpwood and energy wood. The mechanical forest industry uses sawlogs to produce different timber products, whereas the chemical forest industry uses pulpwood to produce, for example, various paper, pulp, or cardboard products. Energy wood usually consists of logging residuals and the logs of low-value species, which are burned in one form or another to produce energy.

Different properties are required from the timber end-products, so not all the trees are suitable to be sawn. Due to supply and demand, forest industry companies are generally able to pay more for trees that can be sawn to produce high-end timber products. For example, the price (€ m-3) of sawlogs in Finland has traditionally been about 2–3 times greater than the price of pulpwood (Natural Resources Institute Finland 2019). Therefore, sawlog volume is by far the most influential attribute that affects the monetary value of the growing trees.

Sawlogs can be categorized into numerous, more specific, timber assortments, such as small diameter sawlogs and veneer logs. As these species-specific assortments realize different prices, the evaluation of all the assortments separately would result in more detailed information. However, the data used in this thesis were not sufficiently detailed to allow for an assessment of the different sawlog assortments, so sawlog volume will be predicted at the general level. Nevertheless, as the division between sawlogs and pulpwood is clearly the most influential with respect to the value of the growing stock, the absence of more detailed information from the different timber assortments is only a minor drawback that will not greatly affect the general conclusions.

In some cases, the term "technical" has been used in combination with tree quality (e.g. Maltamo et al. 2009a), although it often includes attributes (in addition to the attributes related to sawlog requirements), such as ring width and branch angle, which are not taken into account during harvesting operations. Indeed, the pricing of sawlogs in Finland is based only on volume, not on the quality of the wood: the same price is paid regardless of ring width, for example, even though it affects the density and the strength of the wood (e.g. Pihlajamaa and Jantunen 1995), and thus, the strength grade and the optimal end-use of the timber products (Hautamäki et al. 2010). Therefore, as tree quality in the practical roundwood trade is considered via the quality requirements of the sawlogs, it is justified in this thesis to define tree quality from a commercial aspect rather than a technical one.

There are many requirements that determine whether a tree stem is suitable to be sawn or not. It should be noted that the requirements for sawlogs differ among practitioners, i.e. there is no unambiguous definition of a sawlog. However, the requirements for sawlogs are well established and are similar between Norway, Sweden, and Finland, located mostly in the boreal zone. First, the species must be suitable for sawing. In Norway, Sweden, and Finland, sawlogs are bucked mainly from Scots pine (*Pinus sylvestris* L.) or Norway spruce (*Picea abies* (L.) Karst.), but also from birch (*Betula* spp.) in some cases. Second, the tree must be sufficiently sturdy. For example, a minimum diameter of 15–17 cm is commonly applied in Finland for pine, spruce, and birch sawlogs, which means that the diameter at breast height (DBH) is even larger. Varying minimum lengths are also applied for sawlogs.

The remaining requirements for sawlogs are usually related to specific defects that are not permitted, e.g., sawlogs in Finland are generally not allowed to deviate by more than 1 cm within a 1 m distance. Curving in multiple directions prevents the bucking of sawlogs completely. Cracks, decay, blue fungal infection, insect holes or internal items are not permitted either. In high-quality butt sawlogs, all branches are disallowed, although in regular pine sawlogs, the maximum diameter for a living branch is set at 6 cm, and at 4 cm for a dead branch (Keski-Suomen Metsäkeskus 1999). In Sweden and Norway, the requirements for pine and spruce sawlogs are similar to Finland (SDC 2014). Examples of Scots pine trees with good and poor commercial qualities are illustrated in Fig. 1.

As the requirements for branches are quite restrictive, different attributes related to the properties of the tree crown can be used to provide indicative estimates of tree quality. The height of the lowest dead branch (i.e. dead branch height) and the starting point of the contiguous living crown (i.e. crown base height, CBH) describe, at least indirectly, the theoretical proportion of the stem that is suitable for sawlog production, provided there are no other defects (Maltamo et al. 2010). In addition, the lowest branches of trees in forests usually start to die and fall off due to the decreasing levels of sunlight caused by increased competition. This self-pruning is more intensive in the denser forests, so CBH can also be utilized to determine the urgency of silvicultural operations (Vauhkonen 2010a). On the other hand, competition between trees in young stands has been shown to improve the quality of young pines (Turkia and Kellomäki 1987), so it is beneficial to regenerate the pine stands with a large number of stems. Moreover, site fertility affects the expected quality, especially in the case of Scots pine, so that the quality is usually better in poorer sites (Lämsä et al. 1990). In addition, genetics affect the tree quality, so tree breeding can also be utilized (Haapanen et al. 2016).

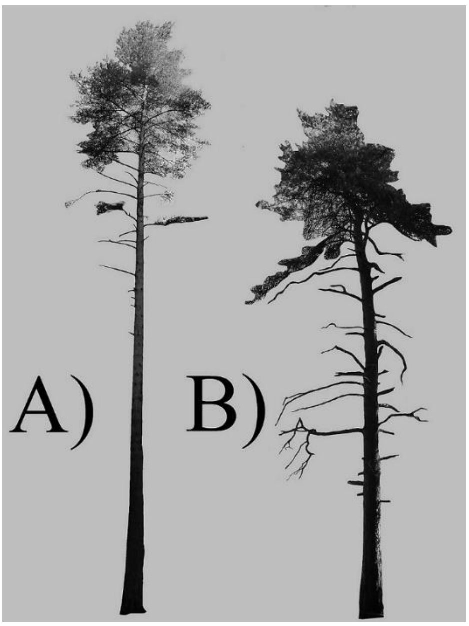


**Figure 1.** Examples of Scots pine trees of A) good commercial quality, and B) poor commercial quality. Pine B) has a slightly crooked butt and numerous thick dead branches on the lower part of the stem. In contrast, pine A) has a straight and branch-free stem.

### 1.2 Airborne laser scanning-based forest inventories

Many remote sensing techniques, such as satellite imagery, aerial imagery, and radar data can be utilized in forest inventories (Hyyppä et al. 2000). However, when the different techniques have been compared, the most accurate stand-level results have usually been obtained with airborne laser scanning (ALS) (Magnusson 2006). Moreover, in the case of many forest attributes such as mean height, basal area, and total volume, ALS often results in even better stand-level accuracies than those obtained with visual assessments during field-visits (Haara and Korhonen 2004; Uuttera et al. 2006). Consequently, in many countries (e.g. Norway, Sweden, and Finland), ALS data is intensively used in operational stand-level forest management inventories (Næsset 2014; Maltamo and Packalen 2014).

In ALS, an aircraft, usually a fixed-wing airplane, is equipped with a laser scanner. There are two main types of data that laser scanners can produce: full-waveform data (see Hollaus et al. 2014) and small-footprint, discrete-return data. In this thesis, only discrete ALS datasets were used. While the aircraft flies at an altitude of between 500 m and 2 km, the laser scanner emits laser pulses downwards. When the pulses hit the ground or vegetation, they backscatter and the ALS sensors detect these backscattering echoes (even multiple echoes per emitted pulse), and the precise time that each pulse has travelled before the returning echoes are received. Thus, by utilizing the known speed of light and the exact position and orientation of the scanning system, a three-dimensional (3-D) position where the backscattering occurred can be calculated. Eventually, an accurate 3-D georeferenced point cloud can be constructed by merging the positions of the separate echoes together. In forestry applications, the point density typically varies from < 1 to dozens of pulses $m^{-2}$, depending on factors, such as the sensor used and the flying altitude.

In the prediction of forest attributes, the utilization of ALS data is usually based on statistical modelling of the relationship between the field measurements and the ALS echoes. Two main approaches are the so-called area-based approach (ABA) (Næsset 2004a; Næsset 2014) and individual tree detection (ITD) (Vauhkonen et al. 2012). In Finnish operational area-based ALS inventories that typically cover between 100,000–500,000 hectares, the number of plots needed for training data is around 500–800, and the plots are measured comprehensively from different site types with different ages to minimize the need for extrapolation (Maltamo and Packalen 2014). All the field-measured plots are positioned with a sub-meter accuracy using a global positioning system to allow the accurate linkage of ALS data and field measurements (Gobakken and Næsset 2009). For each tree with DBH > 5 cm, the DBH is measured and the tree species is recorded. In addition, tree heights (H) are measured from a subset of trees in each plot (Metsäkeskus 2018).

In ABA, the ALS metrics are calculated from the ALS echoes that are extracted within the field measured plots. Usually, the horizontal coordinates of the extracted echoes are ignored, and the metrics are calculated only from the height distribution of the echoes. Before the ALS metrics are calculated, the ALS data are normalized so that the height of each echo describes the height with respect to the ground-level. In addition, ALS data are commonly separated into different echo groups according to the type of echoes (first, last, intermediate). ALS metrics that are usually calculated separately for each echo group are the maximum, mean, median, standard deviation, coefficient of variation, mode, and variance of heights of ALS echoes. In addition, different canopy height percentiles (1, 5, 10, 15, 20...80, 90, 95, 99) and proportional canopy densities are usually calculated. Modern laser scanning instruments can also record the intensity of all echoes. Intensity describes the power of the backscattered echoes and it has been utilized in a forestry context, for example, in tree species classification

(Ørka et al. 2009). Intensity metrics are calculated with the same principle as the metrics based on echo heights, i.e. they describe the distribution and the percentiles of the intensity values of the ALS echoes.

The relationship between the ALS metrics and forest attributes is then modelled to allow the prediction of forest attributes for the area of interest, possibly in a wall-to-wall manner. For wall-to-wall predictions, the inventory area is tessellated into a grid with a cell-size that usually corresponds to the area that was also used with the sample plots (Næsset 1997a). For example, the sizes of grid cells in operational ALS inventories in Finland are fixed to 16 m × 16 m (256 m$^2$) (Metsäkeskus 2016). The same ALS metrics are calculated for each grid cell as for the plots, and the predictions of attributes of interest are then made according to the ALS metrics. In general, for stand volume predictions, a relative root mean squared error (RMSE%) value of approximately 10–15 % can be expected with ABA (Næsset 2007). However, for seedling and sapling stands, the accuracy of ABA predictions is generally poor (Maltamo and Packalen 2014).

In contrast, the ITD approach can be implemented with many different methods. In the widely used raster-based method, the measured and field-positioned trees are linked to the segments that are delineated from the raster-based canopy height model (CHM). First, the CHM with the desired resolution is interpolated from the above ground heights of ALS echoes (e.g. Hyyppä et al. 2001) and smoothed to obtain the correct number of local maxima from the canopy (Koch et al. 2014). The local maxima are considered as treetops, and the segments that represent the individual tree crowns are then delineated using, for example, a watershed algorithm (Vincent and Soille 1991). The corresponding ALS metrics (as for the plots in ABA) are then calculated for each tree using the ALS echoes within the segments, and the relationship between the measured trees and the ALS metrics is further modelled to produce tree-level predictions. However, a more straightforward method is to use ALS-based tree heights to predict, for example, DBH or the volume of a tree, directly without field measurements. If required, the tree-level predictions can be aggregated to stand-level predictions (see e.g. Koch et al. 2014, for other ITD approaches).

The essential problem with ITD is that not all the trees are detected (Persson et al. 2002). However, the trees that are not detected are usually smaller in diameter, and so their proportion of the total plot volume is minor. For example, Persson et al. (2002) detected 71 % of the trees but 91 % of the total volume. The detection rate is affected by the detection algorithm used and its parameterization (Kaartinen et al. 2012). In addition, difficulties in tree species recognition also affect the accuracy of ITD (Vauhkonen 2010b), and successful detection of individual trees also requires greater density (thus more expensive) ALS data than ABA (Peuhkurinen et al. 2011). Consequently, ITD has not been used in large-scale operations as commonly as ABA. Nevertheless, ITD has the potential to produce accurate pre-harvest information, especially in mature stands where the tree crowns do not overlap, where understory trees have been removed during thinning, and where the tree species is already known (Vastaranta et al. 2014).

### 1.3 Currently used approach to predict stand-level sawlog volumes in Finland

In Finnish operational ALS-based forest inventories conducted by the Finnish Forest Centre (Metsäkeskus 2017), the current approach to predict stand-level volumes for different species-specific timber assortments includes multiple steps, which all accumulate uncertainty in the essential predictions. First, ALS data and aerial images are used to produce species-specific predictions for all the attributes of interest, such as volume and mean height. Stand-level species-specific diameter distributions are then predicted (Maltamo and Gobakken 2014), and the tree-level sawlog volumes for these predicted trees are further estimated using taper curves and various sawlog reduction models (Mehtätalo 2002). Stand-level predictions are finally obtained by aggregating all the tree-level sawlog volume predictions together.

The sawlog reduction models are usually fitted with datasets that represent geographically large areas, and the used predictors typically have only a loose relationship with actual tree quality. For example, a sawlog reduction model for Scots pine in southern Finland (Mehtätalo 2002), includes predictors, such as tree age, DBH, the x,y-coordinates, height above sea level, and different site types (according to Cajander 1949). The capability of such models to adjust to local, stand-specific conditions is very poor. Naturally, even more inaccuracy can be expected when the sawlog reduction models are applied to predicted trees, instead of those that actually grow in the stand.

Overall, it can be assumed that in a single stand, the accuracy of sawlog volume predictions produced with the above-mentioned procedure can be very poor. Holopainen et al. (2010) compared the accuracies of predicted sawlog volumes between two inventory methods based on ALS and aerial images, and the traditional stand wise field inventory (SWFI). The ALS and SWFI were first used to predict stem distributions, and then taper curves and sawlog reduction models were used in bucking to predict the tree-level sawlog volumes. Holopainen et al. (2010) took into account all the errors related to (1) inventory, (2) generation of stem distributions, and (3) stem-form prediction and simulated bucking. The accuracies were validated at the stand-level against harvester data. The resulting RMSE% values for pine, spruce and birch sawlog volumes were 79.2 %, 33.6 %, and 78.6 %, respectively, when the stem distribution was based on the ALS inventory. With SWFI, the corresponding RMSE% values were 234.6 %, 32.5 %, and 256.4 %, respectively, i.e. notably larger, except in the case of spruce, which was clearly the most dominant species (87 %) in the study area. Consequently, the combined errors also had a great influence on the predicted total value of the growing stock, as the RMSE% values were 23.8 % and 33.4 % for ALS and SWFI, respectively. However, Holopainen et al. (2010) noted that their results and their generalizability should be carefully considered as their data consisted of only 12 clear-cut stands.

For the first time, Vähä-Konka et al. (2020) investigated the accuracy of Finnish ALS-based forest inventory data (Metsäkeskus 2017) against operative harvester data. They used large-scale field data from 121 mainly spruce-dominated clear-cut stands (148.3 ha, ~40,000 $m^3$), and focused on the species-specific volumes by timber assortment (pulpwood or sawlog). The RMSE for the dominant spruce sawlog volume was 64 $m^3ha^{-1}$ which corresponds to RMSE% of 48.6 %. The RMSE% for the spruce pulpwood was 54.8 %. In the case of pine and deciduous timber assortments the corresponding results were even less accurate. The sawlog volumes were commonly overestimated whereas the pulpwood volumes were underestimated. Vähä-Konka et al. (2020) concluded that better methods to predict the quality of harvested trees are needed, and that harvester data have high potential to be effectively utilized in the inventories.

### 1.4 Predicting commercial tree quality with ALS data

The effects of commercial tree quality culminate in cuttings when part of the sawlogs are usually downgraded to pulpwood due to defects (Malinen et al. 2007; Barth et al. 2015).

Therefore, meaningful predictions of tree quality attributes, especially sawlog volume, requires that the tree species and diameter distributions are known or are predicted first. Only when the growing stock is known or is predicted to be sawlog-sized and of a suitable species, is it meaningful to also predict the quality attributes that may reduce the sawlog volumes. Consequently, the theoretical sawlog volume in which the required species-specific diameter–length dimensions are considered, but the defects are not, is also a very informative tree quality attribute.

Quality related tree- or forest-level attributes can be predicted by means of ALS data in the same way as the more traditional attributes. Thus, sawlog volume, theoretical sawlog volume and CBH, as well as various other quality related attributes (Bollandsås et al. 2011), can be predicted if suitable training data is available. Alternatively, some approaches that are based directly on the 3-D structure of segmented ALS echoes have also been developed for the prediction of CBH, for example (Holmgren and Persson 2004; Popescu and Zhao 2008; Vauhkonen 2010a). With these approaches, no training data are needed to produce the predictions. However, some local field data is likely useful to reduce bias, just like in the case if tree heights are determined directly from the ALS data.

### *1.4.1 Sawlog volume*

In the case of sawlog volume, the collection of training data is a challenge as currently there are only two approaches to carry it out: (1) visual bucking of the standing stock, or (2) harvesting with a modern cut-to-length (CTL) harvester. Both approaches have some serious drawbacks, and research related to the topic is sparse. Also, terrestrial laser scanning (TLS) and laser scanners mounted on unmanned airborne vehicles (UAV) flying under the canopy (Hyyppä et al. 2020) or at low altitude above the canopy (Windrim and Bryson 2020) have the potential to be used to measure stem forms, and to detect defects from tree stems, but they have not been used in practice to date.

In visual bucking, the stem of a sawlog-sized tree is visually inspected from all directions for any defects that would prevent the bucking of sawlogs. The start and end points of these defects are recorded to separate the parts of the stem that are not suitable for inclusion in a sawlog. The actual “bucking” is implemented afterwards. First, diameter and length are estimated for the parts of the tree that fulfil the quality requirements, by using taper curves that employ DBH, H and possibly diameter measurements at upper heights as well, such as 6 m (D6). These partial stems are then bucked into logs, while the required diameter-length dimensions of sawlogs are also considered. For example, the minimum length can be set at 3.7 m, which ensures that no parts of a stem shorter than this length can be cut to sawlog. The same taper curves are also used to calculate the theoretical sawlog volume. First, the height at which the defined minimum diameter of the sawlog is reached, is predicted with taper curves. Then, the stem below that height is bucked into sawlogs with length restrictions also considered, so that the sum of the volume of the bucked sawlogs is maximized.

The problem of visual bucking is that it is very laborious and, therefore, expensive to carry out – especially at the operational scale where the costs would be unrealistic. In practice, visual bucking is also somewhat subjective and measurement errors may occur. Moreover, as only external defects can be detected, visual bucking might not be appropriate for all species. For example, Norway spruce quite often exhibits butt rot or decay, which may be difficult to detect by visual assessment only. For Scots pine, internal defects are less common (e.g. Uusitalo 1997) and, therefore, visual bucking is more suitable.

The accuracy of sawlog volume predictions produced with visual bucking depend completely on the decisions and professionalism of the fieldworker. In fact, also the ground truth for the sawlog volume of an individual tree is difficult to determine unambiguously with a CTL harvester. This is because in operational cuttings the eventual sawlog volume of any given tree is affected by the applied bucking approach. Therefore, the accuracy and reliability of visual bucking is very case-specific and difficult to validate in practice. Nevertheless, visual bucking is implemented in Finnish National Forest Inventory (NFI) measurements, but only a proportion of the trees per plot are assessed. To determine accurate sawlog volumes for the whole plot, each sawlog-sized tree should be visually bucked, which would be very time-consuming.

Another avenue for the collection of sawlog volume information is the use of modern CTL harvesters. The computer in a modern CTL harvester measures and records, among other things, diameter at 10 cm intervals along the stem and uses these measurements and length measurements to calculate the volume for each bucked log. These volumes are then saved into stem and harvester production files. Therefore, the collection and utilization of sawlog volume information by means of CTL harvester is inherently easy. Nonetheless, the main problem of harvester-based sawlog volume information has been the lack of accuracy in the positioning of trees. Typically, as for example in the study of Holmgren et al. (2012), the spatial accuracy of harvester-based tree data has been about 10 m. This is because the positioning system has usually been mounted on the back of the harvester, and for each harvested tree the position has been determined as the position of the machine at the time of felling. In other words, the movement of the boom, which may move up to 10 m around the machine, is often completely ignored. In addition, the positioning of the moving harvester often includes inaccuracies caused by the positioning system used, local topography, weather conditions and forest structure. Even in clear-cuts, the shading of large standing trees can be assumed to weaken the positioning of an occasionally but repetitively moving machine (Kaartinen et al. 2015). The accuracy of approximately 10 m for tree positions is not suitable for ALS–based inventories where the overall accuracy is related to the error in the positioning of plots (Gobakken and Næsset 2009). In addition, effective utilization of harvester data, especially with ABA, from cuttings other than clear-cuts is difficult (Saukkola et al. 2019). However, retention trees, which may be required by the forest certificate system (e.g. PEFC, FSC), are also problematic because they should be manually positioned and measured. The bucking approach used in this instance and the professional abilities of the driver also affect the distribution between the accruals of sawlog and pulpwood volumes (Kuusisto and Kangas 2008).

Nevertheless, the versatile potential of harvester-based data in modern forestry has been recognized (Lindroos et al. 2015; Kaartinen et al. 2015), and systems that provide sub-meter accuracy for tree positions have been experimentally developed in recent years (Hauglin et al. 2017). These systems record the angles and directions of the moving parts of the boom, and, therefore, the position of the tree can be accurately calculated with respect to the positioning system that is mounted on the top of the machine. The harvester manufacturer Komatsu Forest (Umeå, Sweden) has also recently integrated such a system into their harvesters (Saukkola et al. 2019), but there are no publications or official reports about the accuracy for tree positions. However, at least in one Finnish experiment (Melkas and Riekki 2017) sub-meter accuracy for tree positions was not reached.

Due to limited availability of the quality information of the logs, the quality of trees has been completely ignored in some studies where sawlog volume has been predicted (Peuhkurinen et al. 2007; Vauhkonen et al. 2014), or the quality has been predicted with stem data banks that have originated from other areas (Peuhkurinen et al. 2008). Few studies have addressed cases where sawlog volume has been predicted locally with ALS data. Widely differing datasets and methods have been used in these studies, which complicates the comparison of the results. For example, it can be assumed that the level of homogeneity, with respect to tree quality and species proportions of the studied stands, has a considerable effect on total accuracy. Nevertheless, with ABA in boreal forests, the resulting RMSE% values for the predicted sawlog volumes have been between 20–30 % at both the plot- and stand-level.

Bollandsås et al. (2011) used harvester-based sawlog volume information in modelling. However, they did not obtain the exact position for each harvested tree, so they used the position of the harvester at the time of felling to determine the grid cell that each harvested tree was located in. To minimize the effects of geo-referencing errors between the ALS and field data, Bollandsås et al. (2011) used uncommonly large grid cells (50 × 50 m: 0.25 ha) in modelling. Despite the large-sized grid cells, the authors reported that due to inaccuracies in positioning, approximately 20–25 % of the harvested trees were still assigned to the wrong grid cells. Nevertheless, they fitted a model with sawlog volume as the response variable and ALS metrics as the predictors. The resulting RMSE% value was 24 % at the 50 × 50 m level.

Korhonen et al. (2008) bucked field measured trees with a taper curve and then estimated sawlog volumes by employing an existing sawlog reduction model (i.e. they did not have local measured information of tree quality). The sawlog volumes of the trees within the same sample plots were summed together, and two linear mixed effect models with sawlog volume as the response variable and ALS metrics as predictors were fitted separately for pine and spruce dominated plots. Finally, they used real harvester data from 14 clear-cut stands to validate the accuracy of model predictions in a wall-to-wall manner. The pine model was used on three stands, and the spruce model on the remaining 11 stands. The resulting stand-level RMSE% value for sawlog volume was 18 %.

Studies where sawlog volume has been predicted outside Nordic countries by means of ALS data are really rare. In mixed hardwood forests in USA, Hawbaker et al. (2010) used regression models to predict also the sawlog volume for circular plots with a radius of 15.25 m. At best, they obtained an $R^2$ value of 0.65 for the sawlog volume model. In tropical loblolly pine (*Pinus taeda* L.) plantations, on the other hand, Silva et al. (2017b) used the Random Forest method and obtained a RMSE% value of 7.7 % for the predicted sawlog volume in 20 m × 30 m plots. However, in both Hawbaker et al. (2010) and Silva et al. (2017b) the estimates for sawlog volumes in the field data were based solely on the requirements about DBH and log lengths, not any defects as in Nordic countries. Even though the qualitative defects might not have as large of an effect to sawlog volume in USA and Brazil as in Nordic countries, the results of Hawbaker et al. (2010) and Silva et al. (2017b) should be rather compared to theoretical sawlog volume in Nordic countries. In addition, the more accurate predictions of Silva et al. (2017b) compared to what have been observed in boreal forests can at least partly be explained by the greater homogeneity of the trees in intensively managed plantations. Nonetheless, it is clear that balanced comparison between results obtained in different continents and different forest zones is really difficult.

Sawlog volume can be predicted also on tree level. Kankare et al. (2014b) predicted the sawlog volume for 144 individual Scots pines with ALS, TLS, and a combination of both (TALS). With TLS and TALS, they first estimated DBH, D6 and H from the laser point cloud, and then employed them in stem curve models. With ALS, H was observed from the point cloud, then used as an input to predict DBH, and the stem curves were then predicted using H and predicted DBH. Finally, sawlog and pulpwood volumes were estimated by bucking the stems, while considering the minimum diameters for sawlogs. The predictions were validated against harvester measurements. The RMSE% values associated with predicted sawlog volumes were 22.1 %, 21.7 %, and 36.0 %, for TLS, TALS, and ALS, respectively. Kankare et al. (2014b) did not consider the defects in bucking, and 11 of the harvested trees were extreme outliers with respect to quality. The omission of those 11 trees from the analysis decreased RMSE% values to 17.5 %, 16.8 %, and 34.7 %, respectively. The notable change in the RMSE% values emphasizes the importance of considering defects in sawlog volume predictions. Barth et al. (2015), on the other hand, reported that in most cases the ALS-based tree-level predictions for different species-specific timber assortments were more accurate than the predictions based on traditional field work. However, they did not provide any numerical results for the sawlog volume predictions, only graphical histograms.

In addition to sawlog volume, sawlog proportion can also be modelled. Sawlog proportion determines the proportion of wood that is suitable for bucking of sawlogs in the total volume of all trees within the stand. Thus, sawlog proportion describes more the average quality (sawlog reduction) of the trees than the actual sawlog volume. This aspect is emphasized if the total volume cannot be predicted accurately. In an abstract for a conference, Hauglin et al. (2018b) reported a RMSE% value of 28.7 % for the predicted sawlog proportion. Maltamo et al. (2009a) also predicted the sawlog proportion, but at the tree-level. They used k-MSN in their predictions, and the resulting RMSE% value was 8.7 % for sawlog proportion of individual Scots pine trees. These trees were visually bucked in the field to determine the sawlog volumes.

### *1.4.2 Crown base height*

Whereas the collection of sawlog volume information for training data is a challenge, measurement of the CBH of a tree is rather straightforward. Provided that tree height is measured, for example, with an ultrasound instrument (e.g. Haglöf Sweden 2016), as is often the case nowadays, the additional measurement of CBH takes only a few seconds. However, if tree height is not measured for each tree but only for some sample trees, then the relative laboriousness of measuring CBH for each tree may be too onerous. Nevertheless, as a consequence of the ease of field measurements and the evident relationship with tree quality, numerous studies that include the prediction of CBH either at the tree-level (e.g. Pyysalo and Hyyppä 2002; Maltamo et al. 2009a), the plot-level (Dean et al. 2009; Bollandsås et al. 2011; Maltamo et al. 2018), or both the tree- and plot-level (Næsset and Økland 2002; Maltamo et al. 2006) have been published. In addition, the relationship between CBH and the forest fuel has been identified (Gajardo et al. 2014), thus providing motivation for research into the prediction of CBH by ALS in those parts of the world where the risk of forest fires is also great, and where the tree quality aspect is of less importance (Riaño et al. 2004; Andersen et al. 2005; Erdody and Moskal 2010; Gonzalez-Ferreiro et al. 2017).

In published studies, various methods have been used to predict CBH. For example, Maltamo et al. (2010) compared different approaches to predict the mean crown height in Norway spruce dominated stands. They tested multiple methods in which the ALS data was utilized in three ways by (1) using statistical modelling, (2) directly analyzing the properties of the 3-D point cloud, or (3) combining 1 and 2. They validated the results at the actual stand-level by utilizing harvester data, and the resulting RMSE values varied between 1.7 and 3.6 m. Methods based on regression analysis and the alpha shape technique (Vauhkonen 2010a) have been found to be the most suitable for the prediction of CBH. Furthermore, Maltamo et al. (2018) compared four different alternatives to predict plot-level CBH in Scots pine dominated forests in eastern Finland: (1) k nearest neighbor (k-NN) imputation with full field-measured tree lists that included CBH measurements as training data, (2) tree-level mixed-effects model, (3) plot-level alpha shape (Vauhkonen 2010a), and (4) plot-level regression analysis. Thus, alternatives 1, 2, and 4 were based on statistical modelling and alternative 3 was based on the direct interpretation of the point cloud. The resulting RMSE% values for the basal-area-weighted mean CBH were between 20.9–29.6 %. The conclusion was that the k-NN imputation approach would be the most suitable for Finnish ALS-based multivariate forest management inventories (Maltamo and Packalen 2014), as it would be sufficient to just add CBH to the set of field measured attributes.

In general, the accuracy of predicted CBH has usually been from one to several meters. Maltamo et al. (2010) concluded that a minimum error of 1 m seems inevitable if CBH is predicted with ALS data, due to the structure of the lower parts of the canopy. Regardless, the comparison of results between datasets should be carried out with caution as the variation within the data has a strong effect on the resulting accuracy. Moreover, tree species proportions have been shown to affect the accuracies of the different alternatives (Maltamo et al. 2018).

Despite the promising results and the evident relationship with tree quality and various other interesting attributes, CBH has not yet been measured in practical inventories (e.g. Maltamo and Packalen 2014). One reason could be that the additional and more accurate information gained has not been considered sufficiently useful to cover the extra financial costs (see Kangas et al. 2010). However, k-NN based plot-level predictions of CBH, with RMSE values between 1–1.5 m, could be incorporated into ALS-based forest management inventories rather easily and cost-efficiently (Maltamo et al. 2018). Predictions with such accuracy could potentially be utilized in practice when cuttings are scheduled and prioritized between stands (Maltamo et al. 2010; Kangas et al. 2012).

### 1.5 Potential approaches to increase the cost-effectiveness of ALS-based inventories

The total costs of an ALS inventory consist of multiple parts (see Næsset 2014). Perhaps the most evident sections for any cost-savings are the acquisitions of ALS data and field training data. Flying an airplane or a helicopter is always expensive, so one option for savings is to decrease the flight time. For example, the higher that a plane flies, the wider is the strip covered and scanned at ground-level. Thus, when the flying altitude is increased, less adjacent flight lines (i.e. less flight time) are needed to cover the whole inventory area. There is a tradeoff between the flight altitude and the point density in the resulting ALS point cloud, although a slight decrease in point density might not be crucial (Gobakken and Næsset 2008; Jakubowski et al. 2013). On the other hand, the maximum flying altitude of an ALS sensor is determined by parameters, such as the pulse repetition frequency (PRF), and greater PRF values may produce more noise in the dataset (Næsset 2014). Indeed, the effects of flying altitude have been evaluated in numerous studies (e.g. Næsset 2004b; Yu et al. 2004; Goodwin et al. 2006; Næsset 2009; Keränen et al. 2016). In addition, the angle of view of the ALS sensor can also be amplified to increase strip width, although this will possibly affect the resulting 3-D point cloud in a negative way (Holmgren et al. 2003; Keränen et al. 2016). Nevertheless, as approaches to increase the cost-effectiveness of ALS data acquisition have been studied comprehensively elsewhere, the topic will not be addressed further in this thesis.

In general, the total costs associated with labor are high. Therefore, measuring field sample plots comprehensively around the inventory area is expensive. However, if the predictions are to be based on statistical modelling of the relationship between the biophysical properties of the trees and the ALS data (e.g. operational ABA inventories), then field data is essential. In each operational ALS inventory, hundreds of field-plots need to be measured (Maltamo and Packalen 2014). Therefore, numerous approaches to decrease the amount of essential field work have been suggested, such as the use of existing NFI field data (Maltamo et al. 2009b; Tuominen et al. 2014; Hollaus et al. 2007; Hollaus et al. 2009; Nilsson et al. 2017). The number, size, positioning accuracy, and the sampling of the field plots can also be optimized (Gobakken and Næsset 2008; Gobakken and Næsset 2009; Maltamo et al. 2011; McRoberts et al. 2014). In this thesis, two approaches were included that aim to increase the cost-quality ratio of field work of ALS inventories: (1) the transferability of ALS-based tree-level models between inventory areas, and (2) field calibrations of existing predictions. These approaches will be introduced in the following sections.

### *1.5.1 Transferring ALS-based tree-level models between inventory areas*

The amount of field work can be reduced by transferring ALS-based models between inventory areas. This means that the models fitted with ALS and field data from one inventory area are applied to a new area where only ALS data is available. Thus, in an ideal case, none or only a small amount of field data needs to be collected from the new validation area. This would result in considerable savings. However, the primary problem of transferring models between inventory areas is that the scanning parameters (point density, flying altitude, PRF, scanning angle etc.) used in the ALS data acquisition are selected in a case-by-case basis to be as suitable as possible for the area in question. As seen in the previous section, the effects of changing these parameters have been studied to determine the optimal balance between costs and accuracy. In addition to scanning parameters, the ALS sensor that is used also affects the resulting 3-D point clouds (Næsset 2005; Næsset 2009; Korpela et al. 2010), as specifications, such as pulse width and pulse energy are unique (Næsset 2014). Differences in any of the details related to ALS data acquisition between inventory areas may result in systematic differences after the models are transferred (Næsset 2014).

In addition to differences in the acquisition of ALS data, the forest structure (e.g. species proportions) or the structure of crowns of individual trees may also vary notably and systematically between different geographical locations, restricting the distance that the training area and new inventory area can be located from each other. Ideally, the training area should cover all the variation in the new inventory area. In Finland, for example, movement of only a few hundred kilometers in a south-north direction may result in a notable change in mean volume due to variations in climate and topography (Korhonen et al. 2017).

The transferability of ALS-based models has been studied previously, but only at the plot- or stand-level using ABA. For example, Uuttera et al. (2006) used plot-level models fitted in one area in central Finland (Suvanto et al. 2005) and transferred them to two other inventory areas located 300 km south and 150 km west from the training area. The same ALS sensor, with essentially the same scanning parameters, was used in all three areas during the acquisition of ALS data. Nevertheless, the RMSE% values for the predicted attributes clearly increased due to the transfers: for example, the RMSE% value associated with stand volume changed from 9.8 % to 17.8 % and 18.8 %. Uuttera et al. (2006) also reported that regression models, originally fitted in Norway by Næsset (2002), resulted in corresponding RMSE% values of 24–28 %.

Different ALS and field datasets have also been used simultaneously for prediction purposes. For example, Næsset et al. (2005) combined ALS and field plot data from two inventory areas, located about 100 km apart, for the prediction of several typical forest attributes, and noted that the use of models fitted with data from both areas did not provide a clear advantage compared to using models fitted with regional data only. Næsset et al. (2005) concluded that data from different inventories should not be pooled together before careful examination of the similarities in forest conditions and the details related to acquisition of ALS data. They also suggested that at least a small sample of local data should be collected for model training.

Similarly, Suvanto and Maltamo (2010) used data from two separate inventory areas. The areas were located 120 km apart in eastern Finland, and the ALS data were acquired using different sensors and scanning parameters. Suvanto and Maltamo (2010) used mixed estimation, with one of the areas used for auxiliary data, and the other (with a varying number of plots) as a sample from the target area. Plots from the target area were also tested independently. Their results showed that, in the case of volume, a local model fitted from approximately 50 plots that were measured only from the target area, provided predictions that were as accurate as the alternative mixed estimation model that was fitted with the same local plots plus the auxiliary data from the other area. Thus, the usefulness of having auxiliary data from a previous inventory proved to be rather limited in this instance.

The simultaneous use of multiple ALS datasets in different areas has been examined in many studies, even at the national scale. Næsset and Gobakken (2008) successfully used 10 different ALS datasets to predict above- and below-ground biomass in southern Norway, while Kotivuori et al. (2016) constructed nationwide regression models for volume, biomass and dominant height using data from nine different ALS inventories from around Finland. For volume and biomass, their nationwide models produced less accurate predictions than the regional models, presumably due to differences in forest structure and ALS data characteristics. However, a clear improvement was obtained with local calibrations that were based on 20 measured plots. Furthermore, Kotivuori et al. (2018) employed various additional calibration variables, such as location, degree days and temperature information, and were able to improve the performance of a nationwide stem volume model. In Sweden, Nilsson et al. (2017) used data from hundreds of separate ALS inventories that covered almost the whole country, with a single inventory area (i.e. “block”) covering approximately 20 km × 50 km. In total, 13 scanning sensors were used for the collection of ALS data. A pool of 11,500 NFI plots was available in the model construction process, but rather than using all the available plots for all blocks, Nilsson et al. (2017) always selected the 350 nearest plots (of which approximately 70 were further discarded) to fit the block-wise models. At the plot-level, the resulting RMSE% values for predicted stem volume were 22.2 %, 25.1 %, and 19.2 % in northern, mid, and southern Sweden, respectively. Gopalakrishnan et al. (2015) used 1800 field sample plots and data from 76 different ALS inventories in southeastern USA and built regression model for dominant height for 120 m × 120 m cells. The resulting RMSE value was 3 m, thereby indicating the suitability of their method to produce wall-to-wall maps over large areas.

However, the transferability of tree-level ALS-based models between different inventory areas has not been comprehensively studied. The practical advantage of good transferability of tree-level models would be most evident in such cases where the aim is to obtain information from mature stands to ease the planning of harvesting operations. As timber assortment specific ABA predictions have so far resulted in somewhat unreliable accuracies (Holopainen et al. 2010), more detailed, tree-level information derived in an ITD inventory could be a viable solution (Vastaranta et al. 2014). Ideally, local tree data banks, including careful field measurements and tree-level ALS metrics for each tree, could be constructed, and whenever a new area is then scanned, the tree-level predictions could be produced without field visits by using only the nearby tree data banks. Primary targets would be remote, mature stands with preferably some silvicultural thinnings carried out in their recent history: the detection of individual sawlog-sized trees without omission and commission errors on such stands (for definitions, see e.g. Breidenbach and Astrup 2014) would be realistic, as the crowns of the remaining trees most likely do not overlap each other (Vauhkonen et al. 2012). Also, prior knowledge of species would exclude at least most of the problems related to tree species recognition. In ITD, correct species recognition is crucial because the relationship between the crown characteristics and the main stem form are very species-specific (Kalliovirta and Tokola 2005).

### *1.5.2 Field calibrations of existing predictions*

Another avenue to increase the cost-quality ratio of ALS-based forest inventories is to increase the quality of existing predictions by carrying out some sort of local calibration. The potential, and even necessity, of using calibrations to increase the accuracy of transferred ALS-based models was introduced in a previous section. Additional field work always increases the total costs, but even a small number of local measurements are likely to improve the accuracies. Mixed-effects modeling offers a framework for calibrations, as local field-measurements can be used to predict the random effects for the group (area) of interest. The fixed part of the model is first fitted to provide predictions for an average group, and the calibrated predictions can then be obtained by summing the random effects to the fixed part of the model. Mixed-effects models can be used even if the new area of interest is not located within the inventory area that was used for model training. For example, Korhonen et al. (2019) transferred tree-level linear mixed-effects models from one (training) inventory area to two (validation) inventory areas. The accuracy of predictions decreased due to transfers, but a notable improvement was obtained with calibrations based on local measurements.

In general, calibrations that utilize the correlation between different attributes are particularly useful, if the time taken with field measurements differs. Such calibrations can be carried out with seemingly unrelated multivariate models. For example, diameter and height measurements have traditionally been used to calibrate volume models (Lappi 1991). Maltamo et al. (2012) calibrated ALS-based tree-level models, and they constructed seemingly unrelated mixed-effects models for DBH, H, CBH, volume and dead branch height of Scots pine, and tested the effects of using 1–10 sample trees from a stand in the calibration. Only some of the attributes of interest were measured from the sample trees to provide calibrated predictions for all the attributes of interest. In most cases, accuracy increased in combination with the number of sample trees used. The greatest improvement was obtained for volume and dead branch height predictions. Maltamo et al. (2012) stated that the practicality of the method is evident when the stands are field visited before clear-cutting decisions are made, for example.

The original ALS-based predictions for attributes related to commercial quality, at least in Finnish forests, are not considered sufficiently accurate for the needs of planning of harvesting operations. Therefore, forestry practitioners have adjusted their actions so that the stands are most often visited in the field before any decisions with respect to, for example, bidding are made. Consequently, if mature stands are already visited, then it is not expensive to carry out some simple measurements in the stand during that visit. By utilizing cross-model correlations, these measurements can be used to calibrate the predictions of other attributes of interest as well.

### 1.6 Aims and motivation

The overall aim of the current thesis was to develop methods for the prediction of commercial tree quality by using ALS data and field measurements. New approaches that aim to make ALS-based forest inventories more cost-efficient were also studied. The specific aims for studies **I**–**III** were as follows:

**Study I**. To study the effects of transferring ALS-based tree-level models between inventory areas on the accuracy of predicted tree-level quality attributes.

**Study II**. To test different alternatives to predict sawlog volumes for Scots pine dominated 30 m × 30 m plots by means of ALS data. The performance of an existing tree-level sawlog reduction model was also evaluated.

**Study III**. To study the effects of calibrations based on basal area measurements on the accuracy of stand-level predictions for merchantable and sawlog volume.

As seen in section 1.3, it is clear that more accurate predictions for sawlog volume would be beneficial for all the participants in the roundwood trade. From the forest practitioner's point of view, more accurate sawlog volume predictions would assist in the planning and scheduling of harvesting operations. More accurate knowledge of the volumes of different timber assortments would be a step towards precision forestry, in which cuttings can be cost-efficiently allocated to optimal stands. Furthermore, forest owners would also obtain better information on the economic value of their forest estate, which again would enhance forest management and timing of silvicultural operations.

## 2 MATERIALS AND METHODS

Studies **I-III** were implemented using different methods, approaches, and datasets. A summary of the main differences between studies are provided in the Table 1. More detailed information will be provided in the following sections. In study **I**, the commercial tree quality was considered indirectly through the theoretical sawlog volume and CBH, whereas in studies **II** and **III**, the sawlog volume was the main attribute of interest. Note that sawlog volume in **II** was denoted as "factual sawlog volume" to emphasize the distinction with "theoretical sawlog volume".

### 2.1 Research areas and field data

Field data from four different study areas were used in studies **I**–**III**. Three of the areas were located in eastern Finland and one was located in south-eastern Norway (Fig. 2). In all study areas, the forests were boreal and were dominated by Scots pine or Norway spruce. Some deciduous trees, such as birch, were also common. In all areas, the used field data were collected from mature stands with basal areas of approximately 20–30 $m^2ha^{-1}$ and with 500–1000 stems $ha^{-1}$. The four areas are briefly introduced next.

**Liperi (62° 28′ N, 29° 02′ E; Eastern Finland)**. The Liperi dataset was used in studies **I** (referred to as A1) and **II**. In Liperi, the forests are mostly privately owned, and the level of management depends on the owner. The Liperi field data were collected in summer 2017 from 30 m × 30 m plots. In each plot, DBH, CBH, and H of every tree with DBH ≥ 5 cm were measured. All the trees were also accurately positioned (Korpela et al. 2007; **I**). In addition, all the sawlog-sized (DBH ≥ 16 cm) Scots pine trees were visually bucked to estimate the sawlog volume for each tree. The following requirements for sawlogs were applied during the field work: maximum curving of 1 cm within 1 m distance (no curves on multiple directions), and maximum diameter of 4 cm for dead and 6 cm for living branches. Any decay, blue stain -fungi infection, insect holes, cracks, or internal items were not allowed either. The sawlog volumes were calculated afterwards (see section 1.4.1) using minimum log length of 3.7 m and minimum small end diameter of 15 cm for the applicable stem parts. The bucking was implemented so that the sawlog volume was maximized. The accuracy of visual bucking was not validated against real harvester measurements in this inventory. However, it can be assumed that the used sawlog volume estimates were at least fairly accurate, and therefore adequate for the purpose. In study **I**, we used 47 plots that included at least five sawlog-sized Scots pine trees, and in study **II**, we used 41 Scots pine dominated plots.

**Kiihtelysvaara (62° 31′ N, 30° 11′ E; Eastern Finland)**. The Kiihtelysvaara dataset was used only in study **I** (referred to as A2). The forests in Kiihtelysvaara are privately owned. The field data were collected in 2010 and included 66 plots with plot sizes of 20 m × 20 m, 25 m × 25 m, or 30 m × 30 m. Aside from the variable plot sizes, the plot measurements mostly followed the same procedure as in the Liperi dataset, and the position of each tree was also determined.

**Koli (63° 03′ N, 29° 53′ E; Eastern Finland)**. The Koli dataset was used only in study **I** (referred to as A3). Here, the field data were collected in 2006 from a conservation area in the Koli National Park extension. The park was established in 1991, so no silvicultural operations were implemented in the 15 years prior to field measurements. The positioning of plots and trees within plots were implemented differently to Liperi and Kiihtelysvaara, but the same attributes were measured for each tree.

**Table 1.** An overview of the three studies. A = Liperi, B = Kiihtelysvaara, C = Koli, D = Romerike, ITD = individual tree detection, ABA = area-based approach, k-NN = k-nearest neighbor, LME = linear mixed-effects model, CBH = crown base height, DBH = diameter at breast height, H = height.

| | Study **I** | Study **II** | Study **III** |
|---|---|---|---|
| Study areas used | A, B, C | A | D |
| Field data | Inventory | Inventory | Harvester |
| Level of ALS analysis | ITD | ABA | ABA |
| Statistical methods | k-NN | LME, k-NN | LME |
| Response variables | CBH, theoretical sawlog volume, (DBH, H, volume) | Sawlog volume, theoretical sawlog volume, sawlog reduction | Sawlog volume |

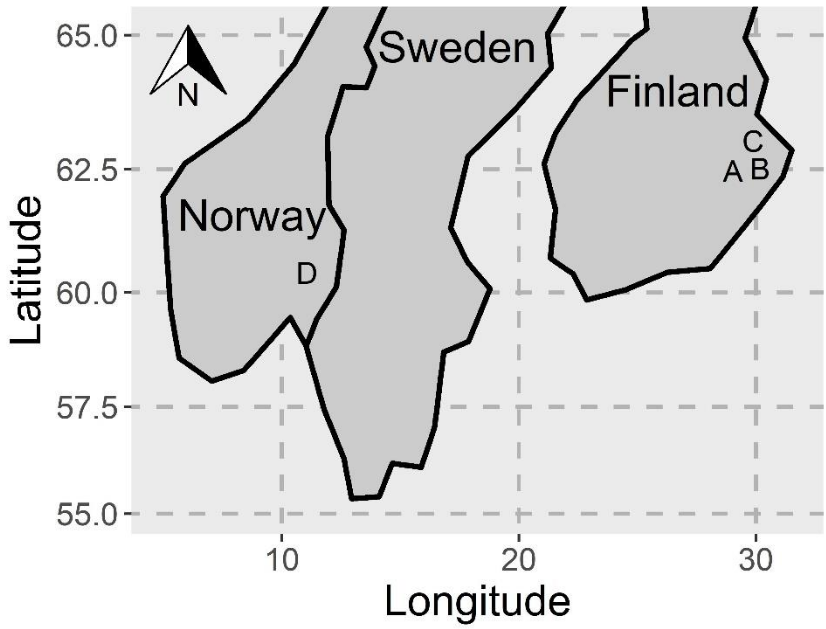


**Figure 2.** The locations of the four study areas. A = Liperi, B = Kiihtelysvaara, C = Koli, D = Romerike. The map was created in the R software.

**Romerike (60° 25′ N, 11° 4′ E; South-Eastern Norway)**. The Romerike dataset was used only in study **III**. The field data were collected from Norway spruce dominated clear-cut stands between January and October 2017 with a John Deere 1270E CTL harvester. The harvester was equipped with a positioning system that provided sub-meter accuracy for the position of each harvested tree. For more details of this positioning system, see Hauglin et al. (2017) and Hauglin et al. (2018). For each harvested tree, the merchantable and sawlog volumes were obtained from the production file that was created by the harvester during harvesting. The sawlog volumes were summed from the possible more specific sawlog assortments.

## 2.2 ALS data

### *2.2.1 Collection of ALS datasets*

The most essential details in regard to the ALS datasets from the different study areas are shown in Table 2. An Optech Titan sensor (used in Liperi) provided multispectral ALS data, but only the channel with a wavelength of 1064 nm (near-infrared) was used in studies **I** and **II**. The 1064 nm wavelength is commonly used in ALS sensors (Pfennigbauer and Ullrich 2011), and it has also been found to be effective in the prediction of many forest attributes (Dalponte et al. 2018). The same wavelength was also used in all the other study areas.

**Table 2.** Scanning details of the study areas. PRF = Pulse repetition frequency, Inst.1 = Optech Titan, Inst. 2 = Optech ALTM Gemini, Inst. 3 = Optech ALTM 3100, Inst. 4 = Leica ALS70.

| | Liperi | Kiihtelysvaara | Koli | Romerike |
|---|---|---|---|---|
| Scanning time | 7/2016 | 6/2009 | 7/2005 | 7/2013 |
| Instrument type | Inst. 1 | Inst. 2 | Inst. 3 | Inst. 4 |
| Flying altitude (m) | 850 | 600 | 900 | 3000 |
| PRF (kHz) | 250 | 100 | 100 | 105 |
| Mean pulse density ($m^{-2}$) | 13.2 | 14.7 | 5.2 | 0.7 |
| Used in studies | **I**, **II** | **I** | **I** | III |

### *2.2.2 Processing of ALS data*

Raw ALS data must be processed to obtain the aboveground height for the echoes. A common procedure that was also followed in this thesis is to initially classify the ALS echoes to ground hits and vegetation hits (Axelsson 1999), and then to interpolate a Digital Terrain Model (DTM) with Delaunay triangulation from the ground hits. The aboveground height of each non-ground echo is then calculated as the vertical distance from the DTM. First (first of many + only), last (last of many + only), and intermediate echo groups were used in this thesis. Study-specific details related to the use of ALS data are provided in the following section.

### *2.2.3 Study **I***

In study **I**, the ITD approach was used, as we were particularly interested in the transferability of ALS-based tree-level models. The field measured plots were 30 m × 30 m. To ensure the complete segmentation of trees that were also located close to the plot borders, we extracted the ALS echoes for plots using 5 m buffers. For each of these 40 m × 40 m areas, the CHM with a 0.333 m resolution was computed by stacking multiple partial CHM bottom-up. These partial CHM were interpolated from triangulated irregular networks computed from the ground echoes and from the echoes above 2, 5, 10, 15, 20 and 25 m height thresholds. This procedure, described in a step-by-step manner by Isenburg (2014), effectively prevented the appearance of pits and empty pixels in the CHM, and thus, improved the segmentation process (Khosravipour et al. 2014).

These plot-level CHM were the basis for the actual ITD processes that were implemented with the rLiDAR package (Silva et al. 2017a) in the R statistical computing environment (R Core Team 2017). First, the pit-free CHM were low-pass Gaussian filtered to improve the subsequent tree detections. Local maxima (i.e. treetops) were searched from the filtered CHM with a fixed window size of 5 × 5 raster cells and a height threshold of 8 m using the rLiDAR function FindTreesCHM. The tree crowns were then delineated into segments using the local maxima with expected maximum crown radius of 3.6 m (rLiDAR function ForestCAS). These segments and field-measured trees were then linked together using the known positions of the trees. Next, only those segments that were known to include only one sawlog-sized Scots pine tree (and possibly one or more small understory trees that have only a minor effect on the ALS echo distribution of the segment) were included in the study. Finally, the ALS echoes within each segment were extracted, and the tree-level ALS metrics were calculated with respect to these echoes. First and last echo groups were again used separately. In addition, the plot-level ALS metrics were calculated using only first echoes and linked to each tree in the plot. This was carried out because the plot-level ALS metrics provide information related to the neighborhood of an individual tree (Maltamo et al. 2012). In addition to heights of ALS echoes, we calculated different metrics using the intensity of the ALS echoes. However, as three different ALS datasets were used in the study, and it is known that the magnitude of intensities can vary remarkably between datasets (Hopkinson 2007; Korpela et al. 2010), the regional intensity distributions were examined first. There appeared to be clear differences between areas, so ultimately only a few relative metrics, which describe the intensity distribution, were accepted in the study.

#### *2.2.4 Study **II***

We used ABA in study **II**. First, 30 m × 30 m sample plots were divided into four 15 m × 15 m subplots to better correspond to the commonly used plot/cell sizes and to quadruple the number of plots in the training data. We were able to do this as the position of each tree was recorded during the field measurements. For each 15 m × 15 m plot, ALS metrics were calculated in three different ways by using only first, last, and intermediate echo groups. The subplot-level forest attributes of interest were summed from individual trees within the subplot in question.

#### *2.2.5 Study **III***

We used ABA in study **III**, and the size of the grid cells was 15 m × 15 m. However, instead of measured sample plots, the field data was point-wise and included all the trees that were harvested from the clear-cut stands. As we did not possess geometries for stand borders, we had to process the data before ABA could be applied. First, we built polygons of tree positions by the creation of two-dimensional alpha shapes (Edelsbrunner 1983) using the alphahull R package (Pateiro–Lopez and Rogriguez–Casal 2016). An alpha value of 10 was used to produce useful borders for the stands. The same value for alpha was also used for the same purpose with the same data by Hauglin et al. (2018) and Maltamo et al. (2019). Then, we laid a separate grid over each stand. On each stand, we systematically iterated multiple positions for the grid, and finally chose the position where the number of accepted 15 m × 15 m cells was maximized. A cell was accepted if at least 215 (of 225) 1 m × 1 m sub-cells intersected the clear-cut stand (polygon) that was created with the alpha shape. When the position of the grid was determined, the ALS metrics were calculated for each 15 m × 15 m cell by separately using first and last echoes. The cell-level forest attributes of interest were summed from individual trees within the 15 m × 15 m cell.

### 2.3 Prediction of the attributes

#### *2.3.1 k-Nearest Neighbor imputation*

The nonparametric k-NN imputation was used in studies **I** and **II**. The approach has been used in numerous previous studies (e.g. Hudak et al. 2008; Latifi et al. 2010). In the k-NN imputation, the values for the response variables of validation units are predicted from the k nearest training units. The k nearest neighbors are chosen by minimizing the distance calculated from the values of the predictor variables between the training and validation units. For k, a fixed value of 5 was used in studies **I** and **II**. In studies **I** and **II**, the MSN (most similar neighbor) was used as the distance metric in the imputations to select the most similar neighbors (Moeur and Stage 1995).

In study **I**, individual Scots pine trees were used as units, which means that for each pine tree from the validation area (Kiihtelysvaara and Koli), five most similar pines with respect to the predictor variables were searched from the training area (Liperi). The response variables for the target pines were then calculated as weighted averages from the response variables of the five most similar trees from the training data. The prediction of all attributes of interest were implemented simultaneously to ensure logical predictions (Eskelson et al. 2009). The predictor variables for the imputation were selected by manually testing the candidate ALS metrics as predictor variables and minimizing the observed RMSE% value. To avoid overfitting, the aim was to employ less than 10 different predictor variables (Packalen et al. 2012). The k-NN imputations were carried out in the R environment (R Core Team 2017) with the yaImpute package (Crookston and Finley 2008).

In study **II**, k-NN imputation was used to retrieve the five most similar plots for each plot using leave-one-out cross-validation (LOOCV) (see section 2.4). The procedure results in tree lists (Temesgen et al. 2003) from which the response variables can be calculated for the target plots. The selection of response variables was carried out with the algorithm proposed by Packalen et al. (2012). This algorithm is based on a heuristic optimization algorithm known as Simulated Annealing (Kirkpatrick et al. 1983) and it aims to minimize the cost function (weighted mean RMSE% value over all response variables) by solving the NN model repeatedly over a fixed number of times. The resulting five most similar plots were weighted with respect to their similarity to the target plot. The weights and the response variables of these five plots were then used to calculate the response variables for the target plot as weighted averages.

### *2.3.2 Linear mixed-effects models*

Linear models with ALS metrics as predictors have been commonly used in the prediction of many forest attributes (Næsset 1997b). However, in a forestry context, the field data often have a grouped structure, as many trees are measured within one plot, or many plots are measured within one stand. For example, due to properties of the site, two Scots pine trees from the same stand are generally more alike than two Scots pine trees from different stands. The variance-covariance structure between observations affects the standard errors of the estimated regression coefficients, so ignoring within group correlations in the model construction phase may lead to severe problems in parameter estimates and model inference (Mehtätalo and Lappi 2020). Therefore, instead of regular linear models that are fitted with the ordinary least squares method and the assumption that the residuals are uncorrelated, linear-mixed effects (LME) models should be used to take the correlation structure into account. Therefore, LME models were used in studies **II** and **III**, and the models were fitted with the lme function in the nlme package (Pinheiro et al. 2019) in R software (R Core Team 2017). The Restricted Maximum Likelihood approach was used in the model fitting (Fahrmeir et al. 2013).

In LME models, the group effects are modelled as random variables, i.e. the group effects are the same for all members within the group and are different between members of different groups. There can be one or more random effects in a mixed-effect model. In this thesis, a total of six LME models were constructed (excluding the three models in study **II** that were simply expanded by the addition of a site type dummy as an additional predictor). Five of these models included only a random intercept, whereas one of the models also included random slope as a predictor, in addition to random intercept. The general form of each of these models is shown in Eq. 1.

$$y_{ij} = \boldsymbol{x}'_{ij}\boldsymbol{\beta} + \boldsymbol{z}'_{ij}\boldsymbol{b}_i + \epsilon_{ij} \tag{1}$$

where $i$ indicates the group, $j$ indicates member $j$ of group $i$, $y$ is the value of the response for the $j^{th}$ observation of group $i$, $\boldsymbol{x}$ is the vector that includes the values of the predictors for the $j^{th}$ observation of group $i$, $\boldsymbol{\beta}$ is the vector of regression coefficients, $\boldsymbol{z}$ is the vector of predictors in the random part for the $j^{th}$ observation of group $i$, $\boldsymbol{b}$ is the vector of random effects, and $\epsilon$ is the residual for observation $j$ of group $i$. If the model only includes a random intercept, then $\boldsymbol{z}$ = 1 and the length of $\boldsymbol{b}$ is 1. Each additional random effect increases the length of $\boldsymbol{b}$ by one. The predictor in question is also added to vector $\boldsymbol{z}$. Furthermore, the model for group $i$ with $n$ observations, $p$ predictors and $s$ random effects is shown in Eq. 2.

$$\boldsymbol{y}_i = \boldsymbol{X}_i\,\boldsymbol{\beta} + \boldsymbol{Z}_i\,\boldsymbol{b}_i + \boldsymbol{\epsilon}_i \tag{2}$$

where vector $\boldsymbol{y}_i$ includes the values of the $n$ observations in group $i$, $\boldsymbol{X}_i$ is a $n \times p$ matrix that includes the predictors for the $n$ observations, $\boldsymbol{\beta}$ is a vector that includes the $p$ regression coefficients, $\boldsymbol{Z}_i$ is a $n \times s$ matrix that includes the $s$ random predictors for the $n$ observations, $\boldsymbol{b}_i$ is a vector that includes the $s$ random effects and $\boldsymbol{\epsilon}_i$ is a vector that includes the residuals for the $n$ observations in group $i$. These matrices and vectors are illustrated in Mehtätalo and Lappi (2020).

Local information is required to predict and utilize the random parts of the model. However, these random effects can also be predicted for new groups that were not used in the training data. In general, LME models are especially useful in cases where the aim is to improve the accuracy of existing predictions by calibrations (Maltamo et al. 2012). Such a case was also considered in study **III**. LME models are also excellent in cases where a model must be calibrated for a new area with just a few field measurements (Korhonen et al. 2019).

In the LME models in study **II**, the group effects were considered by adding a random intercept in the model. However, the predictions were based only on the fixed effects because local information would not be realistically available in the practical application. The three LME models, with (factual) sawlog volume, theoretical sawlog volume and sawlog reduction as the response variables, were constructed by manually testing different sets of the most potential ALS metrics as predictors. The groups with the greatest number of potential predictors were found by initially employing all candidate ALS metrics as predictors and then dropping the least significant predictors in steps, until the p-value of each remaining predictor was < 0.001. RMSE%, mean difference (MD%), and homoscedasticity of residuals were evaluated in the selection of the final predictors.

In study **III**, cross-model correlations of residual errors and random effects needed to be estimated at the start and then utilized in the calibrations. Therefore, a multivariate seemingly unrelated mixed-effect model was constructed. Initially, the models for the three attributes of interest, i.e. basal area, merchantable volume (volume of all logs that passed the harvester head) and sawlog volume, were constructed separately. Again, the eventual predictors were chosen by manual testing, where both numerical and visual criteria were applied. The structure of the random part of the model was also evaluated using Akaike Information

Criteria values (Fahrmeir et al. 2013). Even though overparameterization of the random part of the model is less of a concern than if the random part is too simple (Mehtätalo and Lappi 2020), we attempted to constrain the number of random parameters to one or two in a single model, to avoid later problems with the convergence of the multivariate model. In addition to the fixed and random parts of the models, adequate variance function and correlation structure were examined for each response in order to model heteroscedasticity and the dependence among the within-group errors, respectively. Finally, the three models were merged into one multivariate seemingly unrelated mixed-effects model (Mehtätalo and Lappi 2020). Stand-level random effects were predicted by employing the Estimated Best Linear Unbiased Predictor (EBLUP) (Mehtätalo and Lappi 2020). In study **III**, the utilization of EBLUP was based on the measured sample plots and on the ALS metrics that were calculated for these plots. If the realized value of the plot measurement/measurements was/were different with respect to the original model predicted by the ALS metrics of the plots, then the random stand effects were adjusted with respect to the residuals of the calibration plots. The locally calibrated predictions were obtained when the predicted random effects were added to the prediction that was based only on fixed effects. The principle of EBLUP is described in detail in Appendix A in study **III** and will not be discussed in more depth in this thesis.

### *2.3.3 Alternatives to predict the attributes related to commercial tree quality*

In this thesis, commercial tree quality was determined through sawlog volume, theoretical sawlog volume and CBH. Sawlog volume was predicted in studies **II** and **III** with 10 alternatives, whereas theoretical sawlog volume (denoted as "Vlog" in study **I**) and CBH were predicted only in study **I**, using k-NN imputation at the tree-level (see section 2.3.1). In addition, theoretical sawlog volume was predicted in study **II** as an auxiliary attribute to allow various chained predictions for sawlog volume. The definitions for the 10 alternatives to predict sawlog volume are provided below to aid in the inference of the results and discussion sections of this thesis. More detailed information can be found from the corresponding studies **II** and **III**. The alternatives that were introduced in study **II** will be referred to here with the same codes (e.g. 2a), and the alternative presented in study **III** will be, instead, referred to here as 7. Sawlog volume was predicted at the 15 m × 15 m level in all approaches.

(1) Theoretical sawlog volume was calculated by taper curves that employ H, DBH and D6 (if available) of a tree. For pine, a tree-level sawlog reduction model (SRM) for pines in southern Finland (Mehtätalo 2002) was also applied. The prediction of tree-level Scots pine sawlog volumes was obtained by subtracting the modelled sawlog reduction from the theoretical sawlog volume. For other species, the theoretical sawlog volume was also used as the sawlog volume because they were not visually bucked during field work. These tree-level predictions were then summed to the plot-level. ALS data was not included in this alternative; thus, this alternative provided the theoretical level of accuracy that can be obtained when information of actual tree quality is not available.

(2a) LME model with sawlog volume as the response variable and ALS metrics as predictors.

(2b) Alternative 2a + site type dummy variable as an additional predictor in the LME model.

(3a) LME model with theoretical sawlog volume as the response variable and ALS metrics as predictors. The prediction for sawlog volume was obtained by subtracting SRM from the modelled theoretical sawlog volume.

(3b) Alternative 3a + site type dummy variable as an additional predictor in the LME model.

(4a) LME models for both theoretical sawlog volume and sawlog reduction. The prediction for sawlog volume was obtained by subtracting the latter from the former.

(4b) Alternative 4a + site type dummy variables as additional predictors in the LME models.

(5) k-Nearest Neighbor imputation (tree lists) of plot-level sawlog volume.

(6) k-Nearest Neighbor imputation (tree lists) of plot-level theoretical sawlog volume. The prediction for sawlog volume was obtained by subtracting SRM from the imputed theoretical sawlog volume.

(7) A multivariate seemingly unrelated LME model for basal area and merchantable and sawlog volumes. The prediction for sawlog volume was obtained directly from the model. The tree-level sawlog volumes needed in the model training were obtained from spatially accurate harvester data.

## 2.4 Leave-one-out cross-validation

To avoid overly optimistic results, LOOCV was used in studies **I** and **II**. In study **III**, the data was divided into separate training and validation stands, so cross-validation was not needed. In LOOCV, the predictions are always produced by excluding the observation in question from the training data and, possibly the observations from the same group as well (e.g. from the same stand). In study **I**, LOOCV was applied only when the results were calculated for the training data (Liperi). In study **II**, the neighboring 15 m × 15 m subplots were always excluded from the training data, the models were fitted, and predictions were made in turn for each subplot.

## 2.5 Accuracy assessment

The accuracies of the various predictions were assessed using RMSE% (Eq. 3) and MD% (Eq. 4). In studies **I** and **II**, the MD% was denoted as BIAS%.

$$\mathrm{RMSE\%} = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}} \times \frac{100}{\bar{y}} \tag{3}$$

$$\text{MD\%} = \sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)}{n} \times \frac{100}{\bar{y}} \tag{4}$$

where $n$ is the number of observations, $y_i$ is the observed value for observation $i$, $\hat{y}_i$ is the predicted value for observation $i$, and $\bar{y}$ is the mean of the observed values. In study **I**, the difference within the RMSE% and MD% equations was calculated as "predicted - observed": in the case of RMSE% this does not make any difference, however it results in a sign change in the case of MD%. Therefore, to avoid confusion in the interpretation of the results, MD% values that were obtained in study **I** were also transformed in this thesis to "observed - predicted".

In studies **I**, **II** and **III**, accuracy was assessed at the tree-level, the 30 m × 30 m plot-level, and the stand-level, respectively. In study **II**, the predictions for adjacent 15 m × 15 m subplots were aggregated to 30 m × 30 m plots. In study **III**, the initial predictions were made for 15 m × 15 m cells, but the predictions were then aggregated to the stand-level (enabled by the comprehensive harvester data). In addition, the results of calibrations in study **III** were calculated as the average of 500 repeats to minimize the effects of randomness in the calibration plot sampling. In general, aggregations from the 15 m × 15 m level to a larger scale were well justified, as there is also a strong interest in stand-level results in practical forestry.

# 3 RESULTS

The results obtained in studies **I**–**III** are summarized in this section. The studies had considerably different and specific objectives, so the results were generally incomparable, with the exception of the prediction of sawlog volume in studies **II** and **III**. Detailed information related to the constructed LME models (**II** and **III**) is not provided in this thesis summary.

**Table 3.** Relative root mean squared error (RMSE%) and mean difference (MD%) values associated with predicted sawlog volumes across the 10 alternatives. Results are provided at the 15 m × 15 m level and after aggregation. See section 2.3.3 for detailed definitions of the 10 alternatives. Alt. = alternative, *15* = 15 m × 15 m level, *A* = Aggregated.

| Alt. | Study | *15*: RMSE% | *15*: MD% | Aggregation to: | *A*: RMSE% | *A*: MD% |
|---|---|---|---|---|---|---|
| 1 | **II** | 33.02 | -10.26 | 30 m × 30 m | 29.08 | -10.26 |
| 2a | **II** | 30.85 | -0.44 | 30 m × 30 m | 22.69 | -0.44 |
| 2b | **II** | 29.46 | -0.91 | 30 m × 30 m | 20.92 | -0.91 |
| 3a | **II** | 35.94 | -10.19 | 30 m × 30 m | 27.16 | -10.19 |
| 3b | **II** | 34.44 | -10.50 | 30 m × 30 m | 25.27 | -10.50 |
| 4a | **II** | 33.94 | -1.77 | 30 m × 30 m | 25.11 | -1.77 |
| 4b | **II** | 32.89 | -1.98 | 30 m × 30 m | 23.78 | -1.98 |
| 5 | **II** | 36.47 | 3.20 | 30 m × 30 m | 27.31 | 3.20 |
| 6 | **II** | 40.73 | -7.98 | 30 m × 30 m | 30.03 | -7.98 |
| 7 | **III** | 53.98 | 4.96 | stand-level | 22.17 | 9.33 |

### 3.1 Prediction of sawlog volume

Sawlog volume was predicted in studies **II** and **III** in 10 different ways. These results are shown in Table 3. For better comparability, accuracy at the 15 m × 15 m level is also provided (Note: these details were not included in the original papers. See Fig. 1 in **II** for scatterplots at the 30 m × 30 m level).

The RMSE% values associated with the different sawlog volume predictions were, in general, between 21–30 % after aggregation to the 15 m × 15 m level or to the stand-level. Prior to aggregation, the RMSE% values were between 29–41 % in alternatives 1–6 from study **II,** and 54 % in alternative 7 from study **III**. Therefore, aggregation to the 30 m × 30 m level in study **II** decreased the RMSE% value by approximately 4–10 %, and by almost 32 % (to the stand-level) in study **III**.

The smallest RMSE% value (20. 9 %) was obtained with alternative 2b that employed an LME model for sawlog volume and included the site type dummy variable as an additional predictor. Alternative 7 (study **III)** was also based on an LME model, with sawlog volume as the response variable, but site type information was not included in the model. Alternative 7 resulted in a slightly smaller RMSE% value (22.2 %) compared to alternative 2a (22.7 %). The alternatives that were based on k-NN imputations (i.e. 5 and 6) had clearly weaker accuracy than the alternatives that were based on the LME models (2, 3, 4, 7).

Some trends were also evident with the MD% values associated with predictions. In particular, the predictions in study **II**, which included the sawlog reduction model of Mehtätalo (2002) (i.e. alternatives 1, 3 and 6), resulted in clear overestimates, with MD% values between -8 and -10 %. The MD% values for alternatives 1–6 were similar at both the 15 m × 15 m and the 30 m × 30 m levels due to the balanced structure of the data, i.e. each 30 m × 30 m plot consisted of exactly four 15 m × 15 m subplots. On the other hand, the rather large MD% values associated with alternative 7, i.e. approximately 5 % at the 15 m × 15 m level and 9.3 % at the stand-level, denoted differences in the ALS and field data between the training and validation datasets that were used in study **III**.

In study **II**, the prediction of sawlog volume was also tested at the tree-level by employing the sawlog reduction model formulated in Mehtätalo (2002) for 1235 sawlog-sized Scots pine trees. The tree-level performance of the model appeared to be quite poor: the RMSE% value was 73.6 and the MD% value was -18.0 %. The smallest and largest obtained sawlog reductions were 15.4 % and 63.1 %, respectively, with an average sawlog reduction of 32.4 %. The residual errors associated with the predicted sawlog volumes are plotted against the observed relative sawlog reduction in Fig. 3. It can be seen that if the observed relative sawlog reduction was < 20 %, the sawlog reduction was too strong, and thus, the sawlog volume predictions, produced with the sawlog reduction model, resulted in underestimates. On the other hand, if the observed relative sawlog reduction was > 60 %, then the sawlog reduction was not sufficiently strong, and the predicted sawlog volume yielded clear overestimates. Between those two thresholds, the performance of the model was clearly better. In addition, we tested the performance of the sawlog reduction model with different subsets of pine: the smallest RMSE% value (30.4 %) was obtained with flawless pine trees, and the MD% value was 27.8 %. See Table 7 in study **II** for a detailed description of the different subsets.

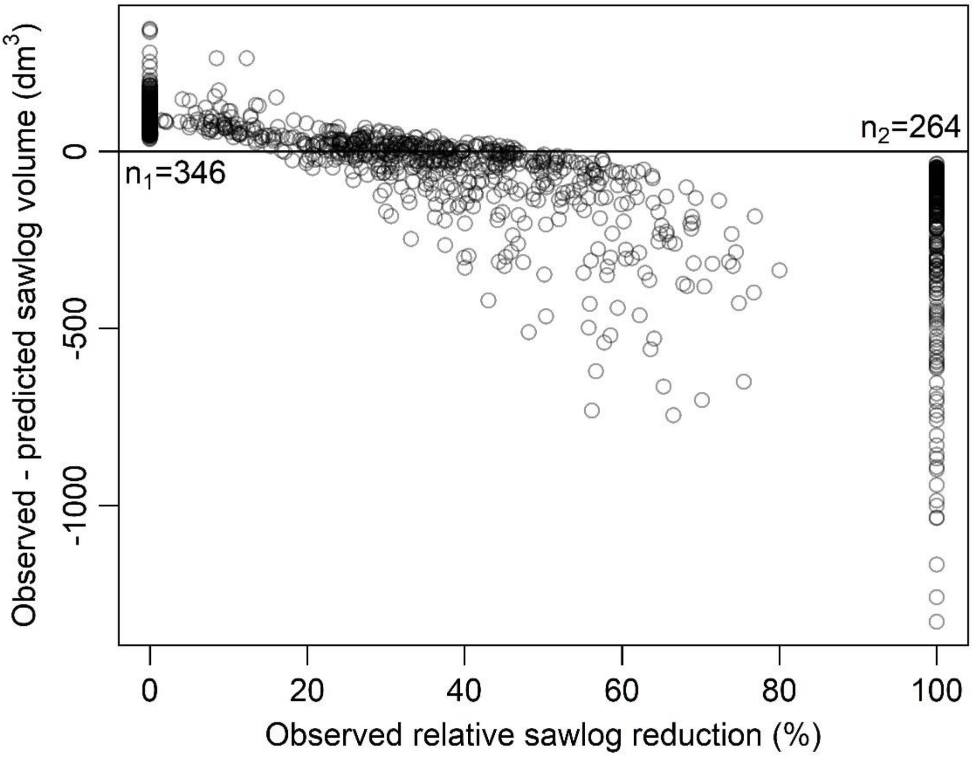


**Figure 3.** Residual errors (i.e. the observed tree-level sawlog volume - sawlog volume estimated with the sawlog reduction model described in Mehtätalo 2002) plotted with respect to the observed relative sawlog reduction. $n_1$ = number of flawless pine trees, $n_2$ = number of fully defective pine trees. The observed sawlog volumes were obtained by visual bucking.

### 3.2 Prediction of tree-level theoretical sawlog volume and crown base height

Tree-level theoretical sawlog volume and CBH were predicted in study **I** with k-NN imputation with two different sets of predictor variables. The first set (denoted as “H-model” in study **I**) included five height-based ALS metrics: (1) the maximum height of first echoes, (2) the 55$^{th}$ percentile of height of last echoes, (3) the 90$^{th}$ percentile of height of first echoes, (4) the standard deviation of heights at the plot-level, and (5) the 15$^{th}$ percentile of heights at the plot-level. The second set of predictor variables (denoted as “I model” in study **I**, “HI-model” in this thesis) also included two intensity-based ALS metrics, in addition to the five aforementioned height-based ALS metrics that were included in the H-model. Thus, there were a total of seven different predictor variables in the HI-model. The two intensity-based predictor variables were the coefficient of variation of intensity and the skewness of intensities.

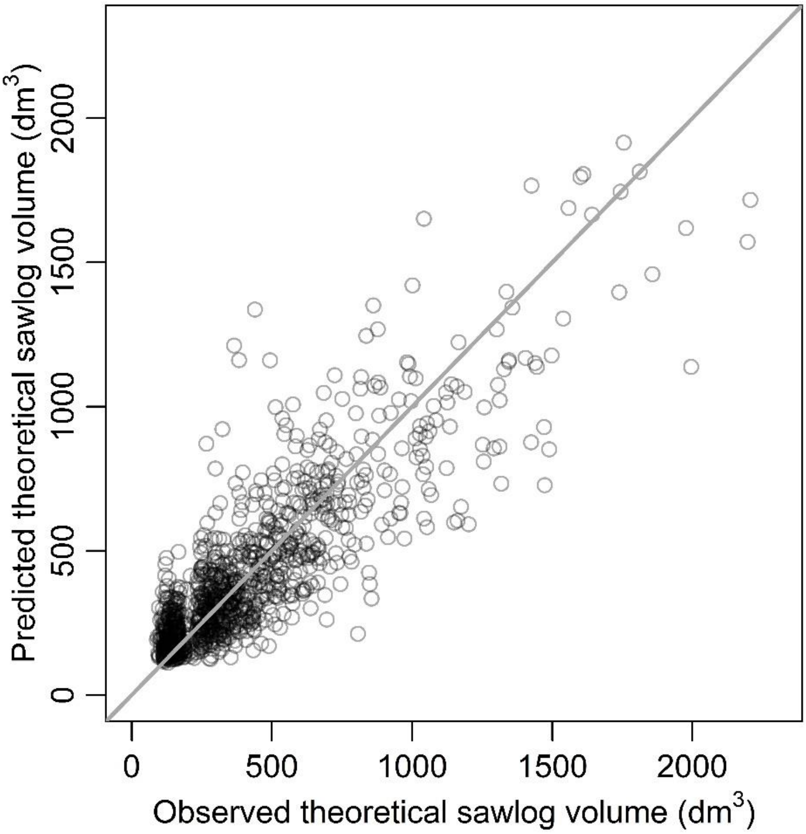


**Figure 4.** Observed vs. predicted theoretical sawlog volumes for individual sawlog-sized Scots pine trees in the Liperi dataset. Only height-based ALS metrics were used as predictors (H-model).

In the case of theoretical sawlog volume, the RMSE% values with LOOCV in the training data (Liperi) were 39.76 % and 38.16 % for the H-model and HI-model, respectively. The corresponding MD% values were 0.19 % and 0.57 %. Thus, the inclusion of intensity-based ALS metrics to the set of predictors had a small effect on the accuracies. The observed vs. predicted (only H-model) values for the theoretical sawlog volume are shown in Fig. 4.

The RMSE% and MD% values associated with CBH in the training data were 13.39 % and -0.10 % for the H-model, and 13.26 % and -0.13 %, for the HI-model, respectively. Thus, the difference between the final accuracy in the predictions between the H-model and the HI-model in this case was only marginal. The observed vs. predicted (only the H-model) values for CBH are shown in Fig. 5.

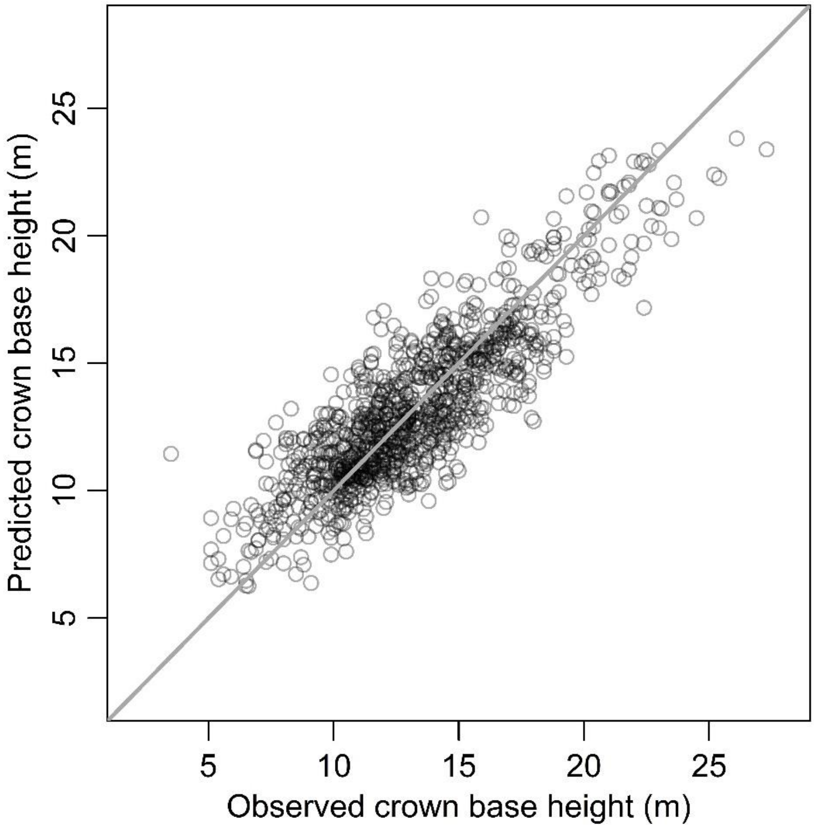


**Figure 5.** Observed vs. predicted crown base heights for individual sawlog-sized Scots pine trees in the Liperi dataset. Only height-based ALS metrics were used as predictors (H-model).

### 3.3 Transferability of tree-level models

The transferability of the tree-level models between inventory areas was only studied in study **I**. The changes in RMSE% and MD% values caused by the transference of the models from the training area (Liperi) to the validation areas (Kiihtelysvaara and Koli) are illustrated in Fig. 6. As expected, the accuracies decreased in every case due to the transfer. In the case of DBH, especially, the difference in the RMSE% values between the Liperi and Kiihtelysvaara areas was quite small: 13.8 % vs. 15.0 % for the H-model, and 13.5 % vs. 14.8 % for the HI-model. The addition of two intensity-based ALS metrics to the set of predictor variables changed the sign of the MD% in all three areas.

The RMSE% values associated with height predictions increased by approximately 3 % for both areas. However, the MD% values in Kiihtelysvaara were positive (approximately 3 %), whereas in Koli they were negative (about -2 %). Therefore, in comparison to Liperi, the laser pulses in Kiihtelysvaara appeared to penetrate the tree crown more deeply before the first return, whereas in Koli the laser pulses backscattered closer to the actual treetop.

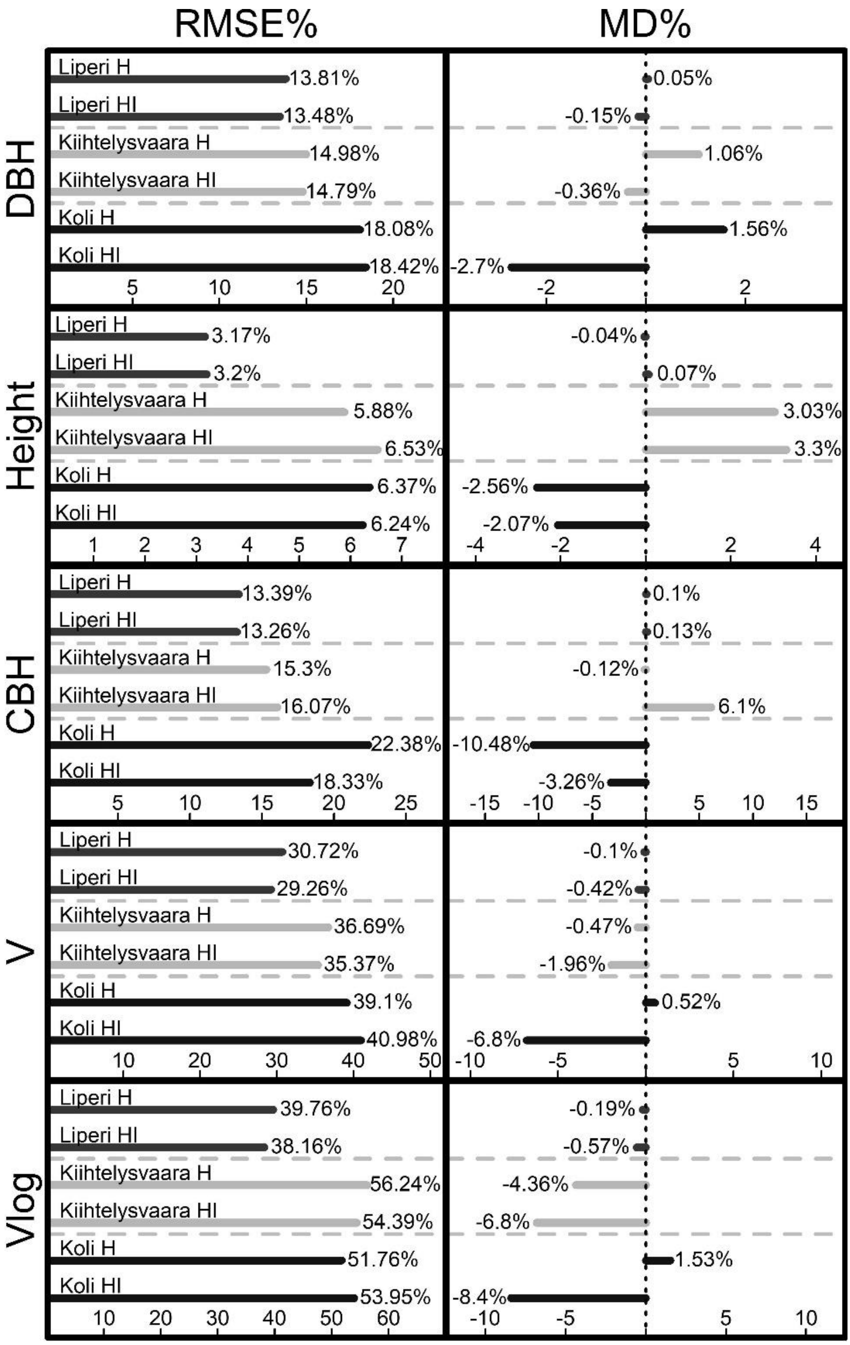


**Figure 6.** Tree-level relative root mean squared error (RMSE%) and mean difference (MD%) values in the training area (Liperi), and after transfer to two validation areas (Kiihtelysvaara and Koli). Two different sets of predictors (H and HI) were used in the k-NN imputations. DBH = diameter at breast height, CBH = crown base height, V = volume, Vlog = theoretical sawlog volume.

Also, in the case of CBH predicted with the H model, the difference in RMSE% values between Liperi and Kiihtelysvaara was relatively small (13.4 % vs. 15.3 %), and the post-transfer MD% value was only -0.1 %. In Koli, the corresponding post-transfer RMSE% and MD% values were much larger, 22.4 % and -10.5 %, respectively. This indicates notable systematic differences in the crowns of sawlog-sized Scots pine trees, or in the functioning of ALS sensors between the Liperi and Koli areas.

From the viewpoint of harvest planning and the roundwood trade, volume related attributes are the most important. For example, the RMSE% value associated with volume for the H-model in the Liperi area was approximately 30.7 %. Transferring the model to other areas decreased the accuracy further, and the corresponding RMSE% values were 36.7 % and 39.1 % in Kiihtelysvaara and Koli, respectively. As expected, the accuracies were even worse for theoretical sawlog volume: the RMSE% value associated with the H-model was approximately 39.8 % in Liperi, and the post-transfer RMSE% values were 56.2 % and 51.8 % in Kiihtelysvaara and Koli, respectively. Thus, theoretical sawlog volume was the only attribute that resulted in smaller RMSE% values in Koli than in Kiihtelysvaara. This applied for the HI-model as well.

### 3.4 Effects of field calibrations on the accuracy of predicted merchantable and sawlog volumes

Calibrations were evaluated in study **III**. For details of the multivariate model and the correlation between responses, see paper **III**. The effects of using 1–10 angle gauge measurements to calibrate a seemingly unrelated multivariate mixed-effects model to the stand in question are illustrated in Fig. 7. Note that the results were calculated over 15 validation stands and as averages of 500 repeats, to smooth out the effects of randomness in the calibration plot sampling.

For merchantable volume, the advantage of the calibration was clear: the RMSE% value with fixed effects only was 15.8 % and was 11.9 % with 10 plots. Correspondingly, the MD% value also changed from -9.1 % to -6.8 %. The slope of the curve started to approach zero slowly, i.e. the benefit of each additional measured plot was smaller with addition of more measured plots. On the other hand, it appeared that the correlation between basal area and sawlog volume was not sufficiently strong to notably improve the accuracy of predictions. In fact, the MD% values even increased from 9.3 % to 12.3 % with 1–10 plots, respectively.

Moreover, as only one set of measurements would be carried out on each stand in practice, the distribution of the effects of individual calibration procedures was further analyzed for angle gauge calibrations of merchantable volume (see Fig. 7 in study **III**). When one plot was used for the calibration, approximately 67 % of the calibrations resulted in increased accuracy. The mean improvement in the predicted stand-level merchantable volume was 0.5 percent points (pp), while the corresponding values for 10 plots were 75.8 % and 3 pp. With 2–9 plots, the results were found between the extremes described above. However, the variation in the effects of the calibrations also clearly increased as more plots were used, i.e. the most increased and decreased accuracies of calibrated predictions were obtained with 10 plots. This is logical; the more plots that are measured, the more the residuals of measured plots can adjust the predicted random effects to wrong direction with respect to majority of the cells in the stand. Nevertheless, the results showed that it is unlikely that the calibrations cause decreased accuracy in the merchantable volume predictions.

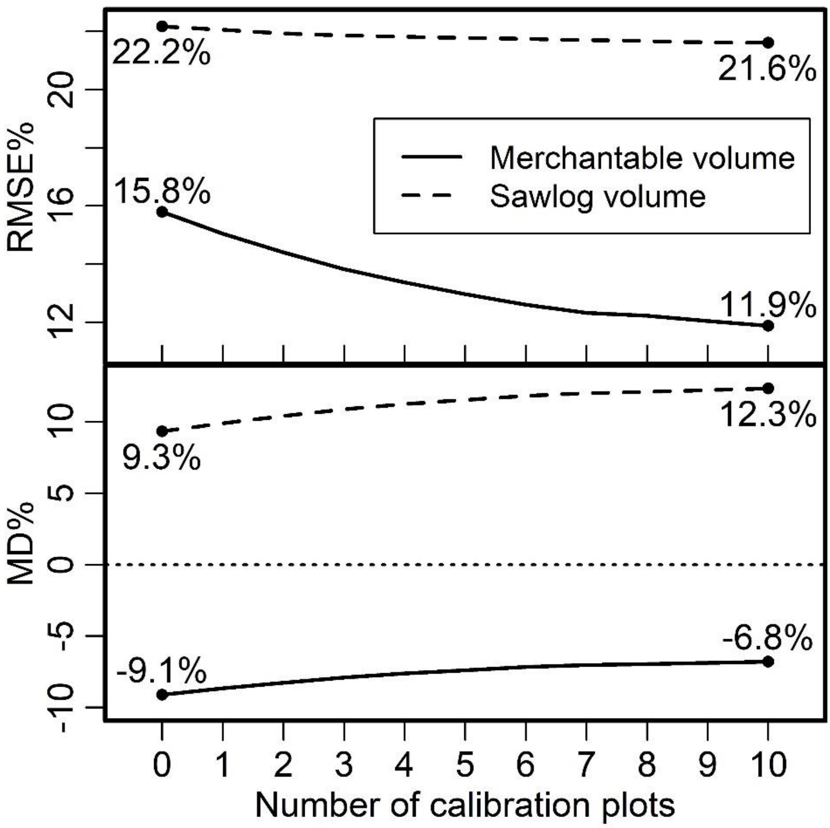


**Figure 7.** Relative root mean squared error (RMSE%) and mean difference (MD%) values associated with merchantable and sawlog volume predictions when 0–10 angle gauge plots were used in the calibration.

An example of when sawlog volume was calibrated with angle gauge measurements is provided in the boxplot in Fig. 8. The accuracy of the calibrated predictions decreased on average, and the variance of the effects of calibrations clearly increased as more plots were used. With one plot, 53.5 % of the calibrations resulted in decreased accuracy with a mean of -0.2 %, while the corresponding values with 10 plots were 55.2 % and -0.8 %. Thus, regardless of the number of calibration plots, it was more likely that the accuracy of predictions just decreased and, therefore, such calibrations are not meaningful in practice.

# 4 DISCUSSION

The primary aim of this thesis was to test a range of alternatives to predict the commercial quality of trees by means of ALS data. In Finland, for example, the accuracy of stand-level volume predictions has been found to be notably better in ALS–based inventories than for

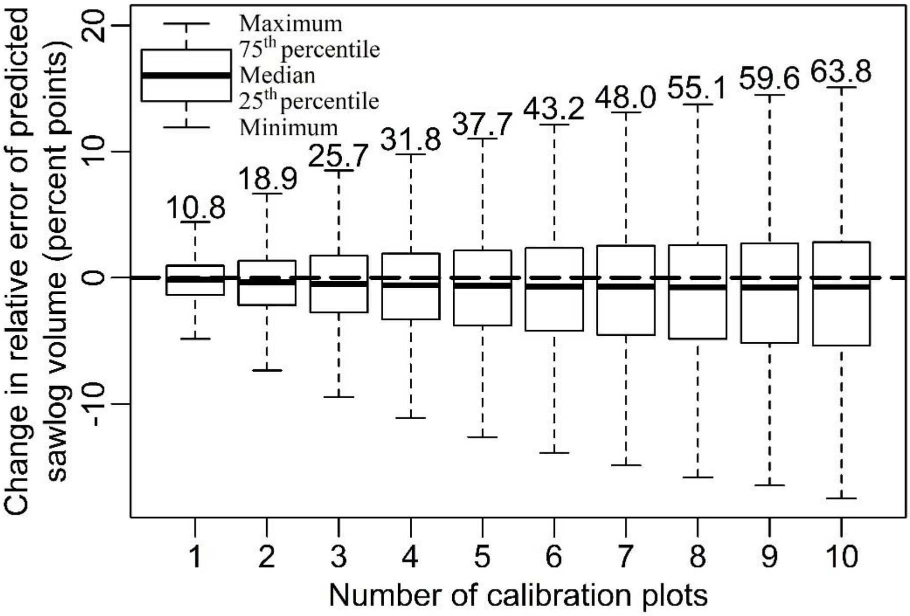


**Figure 8.** Change in relative error (i.e. [observed-predicted]/observed × 100) of predicted sawlog volume of a stand when 1–10 angle gauge plots are used instead of the fixed effects of the model only (7,500 observations for each box). Above the y = 0 line, the calibrated prediction is more accurate than the prediction based only on the fixed part of the model. Variances are provided numerically above each box.

the previous method known as "inventory by compartments" (Haara and Korhonen 2004). Nevertheless, field visits are still needed for reliable estimates of tree quality and the expected accruals of different timber assortments in the upcoming cuttings. Therefore, more accurate remote sensing–based tree quality information would assist in the efficient planning and scheduling of harvesting operations. Consequently, less storage of felled trees would be needed, at least in theory, as the stands could be cut more precisely when such wood material that is on a specific stand is needed. More accurate tree quality information would also provide forest owners with a better estimate of the value of their forest resource.

Sawlog volume was predicted at the 15 m × 15 m level, and the results were validated at the 30 m × 30 m and the stand-level in studies **II** and **III**, respectively. The results indicate that some degree of correlation between ALS data and sawlog volume exists when the assessment is made at the plot- (30 m × 30 m) or stand-level. However, overall prediction accuracy was heavily dependent on the aggregations where over- and under-estimations of the individual cells cancelled each other out.

In fact, sawlog volume could have also been predicted at the tree-level in study **I**. However, the obtained accuracy for theoretical sawlog volume, which does not take into account tree defects, was already very weak: tree-level RMSE% values were 39.8 % and 38.2 % in the training data. Of course, predictions for individual trees are rarely interesting in forestry, so the results should have been aggregated to the plot-level to help in the interpretation of their practical usefulness, and aggregations would probably have increased the accuracy of the predictions. However, such aggregations were not plausible and meaningful, as we accounted for only the sawlog-sized Scots pine trees, rather than all the trees in the plots. Nevertheless, it is most likely that the accuracy of the predictions would have decreased even more if the defects were considered, in addition to the stem dimensions. A similar finding was also observed by Kankare et al. (2014b) where removal of 11 qualitative outliers (from a total of 144 trees) from the dataset notably increased the accuracies of predicted sawlog volumes. The RMSE% value of 34.7 % associated with ALS-based sawlog prediction without qualitative outliers (Kankare et al. 2014b) is somewhat comparable to the RMSE% values of 39.8 % and 38.2 % that were obtained for theoretical sawlog volume in the training data in study **I**.

Barth et al. (2015) used ALS data to first predict the DBH and H for individual trees. Then they predicted the tree-level volumes by using species-specific volume functions. While bucking the stems into different timber assortments, they took the defects into account by generating realistic levels of simulated stem defects based on existing harvester production files from the study area. However, the results were provided in graphical form only, which disables the further comparison between the results of this thesis. In general, the possibilities of accurately predicting tree-level sawlog volume by means of ALS seem very restricted. This is because most of the laser pulses in ALS hit the tree crown or the surrounding ground instead of the main stem of the tree. It can be hypothesized that most of the defects that affect the sawlog volume of a tree do not clearly correlate with the properties of the tree crown. Thus, crooks in the stem or thick branches, for example, are difficult to observe from above, even if ALS data with a high point density (e.g. dozens of pulses $m^{-2}$) were available. In some cases, the defects are completely internal (e.g. butt rot, blue stain fungi), which might not be detectable even in the field before the tree is felled. In such cases, it is evident that vertical airborne laser pulses cannot observe the defects. Of course, internal defects in some cases may be so severe that the vigor of the tree is also weaker and so, therefore, the tree crown is sparser and might exhibit a different color. In such cases, utilization of the intensity of ALS pulses and different wavelengths could help identify the symptoms (Kantola et al. 2013) and indicate non-suitable sawlogs.

## 4.1 Prediction of sawlog volume with ABA

With ABA, the ALS metrics are calculated from the above ground heights of the ALS echoes within the modelling units (15 m × 15 m cells in this thesis). Therefore, direct observation and classification of any defects that could cause sawlog reduction on an individual tree is basically impossible. Thus, the prediction of sawlog volume with ABA is based on the phenomenon that sawlog volume is more or less correlated to total volume, which in turn can be predicted quite accurately by means of ALS and ABA. Consequently, the accuracies associated with final sawlog volume predictions are heavily affected by the homogeneity of the data used with respect to tree quality. The effect of coincidence is the greater the more variation in quality there is in the field data. If the predictions are made with k-NN, it can be assumed that somewhat similar neighbors with respect to 3-D structure will be chosen, but the accuracy of predictions are highly prone to coincidence. However, extreme values caused by coincidence can be avoided by increasing the value of k. On the other hand, with the linear model the poor correlation between sawlog volume and ALS metrics leads to a poor model fit and inaccurate predictions.

Based on the findings of this thesis and previous studies, it would seem that in boreal Scots pine or Norway spruce dominated forests RMSE% values of approximately 20–30 %

can be obtained at both the plot- and stand-level when sawlog volume is predicted using ALS data and ABA. This is more accurate than what have been observed in studies where the sawlog volume predictions have been derived by applying sawlog reduction models to stems predicted with ALS (Holopainen et al. 2010; Vähä-Konka et al. 2020; see section 1.3). However, here the focus was on the total sawlog volume, not on the species-specific sawlog volumes as in Holopainen et al. (2010) and Vähä-Konka et al. (2020). Even though studies **II** and **III** were carried out in Scots pine and Norway spruce dominated stands, respectively, focusing on the total sawlog volume instead of the species-specific ones probably enhanced the resulting accuracies.

Comparison to traditional field work without the utilization of any ALS data (see e.g. Maltamo and Packalen 2014) is a challenge due to lack of adequate reports and studies where the accuracy of sawlog volume predictions based on subjective field work has been evaluated. In Sweden, Barth et al. (2015) did compare the accuracy of traditional field work to predictions based on ALS data and ITD approach. The results were validated against harvester data. In the case of spruce and pine sawlog volumes, the ALS-based predictions were more accurate than those based on traditional field work. In Finland, on the other hand, Haara and Korhonen (2004) used data that included predictions for various stand-level attributes assessed by dozens of forest planning experts. In the case of theoretical sawlog volume predictions, the mean error was 28.2 % in mature stands. It was also reported that the variation in predictions between experts was notable. Thus, also when compared to subjective and laborious field work, the methods based on straightforward modelling of sawlog volume by means of ALS data appear to provide more accurate predictions.

When evaluating the applicability and goodness of the results of the presented methods outside the Nordic countries, it should be kept in mind that boreal forests are generally very homogeneous with respect to e.g. species-proportions. In Nordic countries, the most common and also the most important commercial species are the Scots pine and Norway spruce, and the number of different deciduous trees is small. In central Europe, for example, the number of different commercially important deciduous trees is already notably greater which complicates the prediction of sawlog volume at large-scale. In addition, the practices considering e.g. the applied logging methods and the number and pricing systems of different timber assortments vary notably between countries around the world. To the best of this author’s knowledge, there are no studies from other parts of the world to which the results of this thesis could be reasonably compared to.

### *4.1.1 Reasons for the differences in obtained results*

The post aggregation RMSE% values associated with predicted sawlog volumes in studies **I** and **II** were of similar magnitude and are in line with the findings of earlier studies (e.g. Bollandsås et al. 2011). However, there were clear differences in the original 15 m × 15 m accuracies between studies **II** and **III**. In study **II**, the best RMSE% value of 30.9 % (alternative 2a) was obtained without auxiliary site type information, whereas the corresponding RMSE% value in study **III** was 54 % (alternative 7). Both alternatives were based on mixed-effects models and, thus, were the most logical for further comparison. The difference in the pre-aggregation accuracies could probably be explained by the many differences in the datasets and methods. These differences are elaborated below.

First, the sawlog volume information was collected with different methods: in study **II**, visual bucking was used, whereas sawlog volume information was acquired with a CTL harvester in study **III**. Moreover, in study **II**, only sawlog-sized Scots pines were visually bucked. In Finland, sawlogs are generally bucked from spruce and birch trees as well, so trees other than pine cannot be completely ignored. Therefore, theoretical sawlog volume was also used as the sawlog volume for spruce and deciduous trees. This means that spruce and deciduous trees were assumed to be flawless, which obviously would not be the case in practice. This assumption affected some of the results. For example, the results of alternative 1 were too optimistic, as the sawlog volume for spruce and birch was predicted without errors, i.e. the relative weighting of the performance of the SRM was smaller. For alternative 2, on the other hand, any conclusions as to the eventual effect of ignoring the quality of spruce and birch are difficult to be drawn. On mixed species plots, the observed sawlog volumes would have been smaller if the quality of spruce and birch were also considered. However, it is not known how it would have affected the regression coefficients and, furthermore, the accuracies of predictions. Potentially, the increased variability of the plots would have resulted in poorer model fits in LOOCV, and thus, less accurate predictions. Nonetheless, the proportion of spruce and deciduous trees was small, so it can be hypothesized that the total effect of assuming that spruce and birch were flawless was only minor.

In study **III**, on the other hand, the sawlog volume was obtained only for spruce and pine: in Norway, birch or other deciduous trees are not generally bucked to sawlogs. Therefore, the presence of deciduous trees complicated the prediction of sawlog volume as they could not be identified and separated from coniferous species. In study **III**, the proportion of deciduous trees was 5.7 % of the total merchantable volume, so the effect of deciduous trees on the results should not be completely ignored. Overall, it seems that the differences in the methodology used in the acquisition of sawlog volume data were favorable for study **II**, thus, partly explaining the better performance.

The second major difference occurred between the study areas. From the outset, species dominance differed between areas; the forests in Liperi were dominated by Scots pine (about 85 % of total theoretical sawlog volume), whereas in study **III**, Norway spruce was clearly the most common tree species (about 87 % of total merchantable volume). The quality requirements for sawlogs are quite similar between pine and spruce excluding the properties of acceptable branches: for spruce sawlogs the branch-related requirements are usually less restricted than for pine sawlogs (SDC 2014). Consequently, it can be assumed that CBH is more correlated to quality in pines than in spruce. In Liperi, the 30 m × 30 m plots were mature and mostly dominated by Scots pine. Based on previous studies that predicted CBH by means of ALS (e.g. Maltamo et al. 2018), it can be assumed that the mean plot-level CBH could have been predicted with an accuracy of 1–2 m in Liperi as well. Thus, as such relatively accurate quality related information (for Scots pine stands) can be extracted from ALS data, it is plausible that Scots pine dominated stands are generally more suitable for the prediction of sawlog volume than Norway spruce dominated stands. This hypothesis is also supported by Korhonen et al. (2008), where separate sawlog volume models for pine and spruce were fitted. The RMSE values of the models were 18.9 and 40.1 $m^3$ $ha^{-1}$, respectively. However, it should be noted that there were only three pine dominated stands in the validation data.

Moreover, the two study areas were also located geographically far from each other, one in eastern Finland (Liperi) and the other in south-eastern Norway (Romerike). It is clear that weather and general growth conditions differ between these areas. Location and weather conditions affect, for example, the probability and severity of the occurrence of biotic and abiotic disturbances, which further affect the quality of the trees. For example, the probability of insect caused damage (that completely prevents the bucking of sawlogs) is presumably greater in south eastern Norway than in eastern Finland. However, the datasets used here did not include detailed information about the defects, so the effects of different locations on the accuracies of sawlog volume predictions is not known.

Thirdly, the ALS datasets were also very different. In study **II**, point density, for example, was 13.2 pulses m$^{-2}$, whereas it was approximately 0.7 pulses m$^{-2}$ in study **III**. However, a greater point density with ABA does not automatically mean better performance, as shown by e.g. Gobakken and Næsset (2008). It is possible that the differences in the ALS datasets did not have any clear effect on the prediction of sawlog volume as individual defects cannot be detected in any case. More studies that evaluate the prediction of sawlog volumes with diverse datasets and methods (e.g. k-NN vs. LME-models) are needed to determine the most optimal methods for different conditions. More accurate sawlog volume predictions are needed for mixed species stands as well, and aerial images could potentially be used as auxiliary data to produce species-specific sawlog volume estimates (Maltamo and Packalen 2014).

### *4.1.2 Acquisition of training data*

From the perspective of operational inventories, the collection of training data is the greatest bottleneck that prevents the prediction of sawlog volume by means of ALS. Visual bucking is too laborious and expensive to be carried out at an operational scale. Harvester-based data, on the other hand, offer a straightforward and cost-effective way to record the sawlog volumes of trees. In general, harvesters could provide a huge amount of data for many purposes, especially if the spatial accuracy of the data was good (Lindroos et al. 2015). One approach is the use of local tree data banks consisting of ALS data and accurate measurements for each tree (as described in section 1.5.1). However, the time-window for the utilization of local harvester data is rather short as the data needs to be collected, preferably, within 12-months following the acquisition of the ALS data. Indeed, systems that provide submeter accuracy for the position of harvested trees have recently been developed for study purposes (Hauglin et al. 2017), but more product development is needed to upgrade all the required systems for operational use. Solutions with an accuracy of approximately 5 m have also been introduced (Melkas and Riekki 2017; Saukkola et al. 2019), and as interest in precise positioning of harvested trees is substantial, it can be assumed that accurately positioned harvester data will become more readily available and utilized in the future. Such data will provide a really cost-effective mean to predict also the sawlog volume in ALS-based inventories.

Alternatively, different laser scanning procedures carried out at ground level (TLS, mobile laser scanning, personal laser scanning) or with an UAV below the canopy, could potentially be used to estimate sawlog volumes. With these approaches, external defects and the tree diameters at different heights should be observable (Kankare et al. 2014a, Kankare et al. 2014b, Liang et al. 2014; Bauwens et al. 2016). However, these approaches do not provide spatially comprehensive data, so they could be used mainly to replace visual bucking and other manual measurements during the field sample plot measurements of ABA inventories (Lindberg et al. 2012). Another potential approach, at least for intensively managed plantations, is to collect the ALS data above the canopy but from a low flying altitude (e.g. < 100 m above ground). Depending on the ALS instrument and the aircraft the instrument is attached to, the resulting point density can be several hundred points m$^{-2}$ and also the individual tree stems may be well visible in the point cloud allowing the evaluation of taper (Windrim and Bryson 2020). However, the areal coverage of this approach is not suitable for large-scale inventories either. All of the aforementioned approaches also need more research and development before they can be effectively utilized in practice. Therefore, the problem of the collection of sawlog volume training data still exists in late 2020.

*4.1.3 The limited potential of ABA in the prediction of sawlog volume*

It would seem that if predictions with RMSE% values notably smaller than 20 % are required, then stand-specific auxiliary quality information must be collected in the field. This is because tree quality does not correlate strongly with the canopy layer. Such ground-level or otherwise highly detailed information can be acquired by visual evaluation/bucking and, potentially in the future, by laser scanners mounted on backpacks or UAV. Other information, such as site type (study **II**) or CBH, may be useful, particularly in Scots pine dominated stands. Bollandsås et al. (2011) and Peuhkurinen et al. (2007) have suggested that more auxiliary data is needed to improve ALS-based sawlog volume predictions.

In the Romerike dataset, the within-stand correlation between the sawlog and merchantable volumes (= indirect description of how much the tree quality varies within a stand) was 0.83 (on average), which indicates that tree quality evaluation should be effectively generalizable to the stand-level. The same finding was also supported where sawlog volume predictions were derived as the mean of 10 field sample plots (Appendix B in study **III**), as the overall RMSE% value was only 4.2 %. Of course, the stands must always be meticulously delineated for good generalizability.

## 4.2 Transferability of tree-level ALS-based models

The total costs of an ALS inventory would decrease if existing field measurements from previous inventories could be effectively utilized in the new area of interest. Even though ITD is not (at least yet) operationally used, tree-level models have the potential to produce accurate quality-related predictions on mature stands. Thus, good transferability of ALS-based tree-level models between inventory areas would allow for the establishment of local tree data banks (see section 1.5.1) from which new predictions could be derived automatically. This topic was assessed in study **I**, where the effects of transferring tree-level models from one inventory area (Liperi) to two other areas (Kiihtelysvaara and Koli) were tested. The focus was only in correctly detected sawlog-sized Scots pine trees, i.e. the traditional problems of ITD, related to tree detection and species recognition, were ignored. Therefore, the tree-level results obtained in study **I** are generalizable only to mature pine dominated stands with no overlapping tree crowns.

As shown in previous ABA studies (Uuttera et al. 2006), the accuracy of each prediction decreased due to transfer. For some attributes, such as DBH and CBH, the decrease was only minor, whereas for volume-related attributes the decrease was more severe. In most cases, the resulting accuracy was better in Kiihtelysvaara than in Koli, thereby indicating differences in the ALS data acquisitions and/or structural properties of the forests. For example, it appeared that the laser pulses in Kiihtelysvaara penetrated the tree crowns deeper before backscattering, than in Liperi. In contrast, the first echo backscattered closer to the treetop in Koli than in Liperi. Consequently, height (H) was systematically underestimated in Kiihtelysvaara and was overestimated in Koli. It is probable that these results were mostly caused by differences in the acquisition of ALS data, although the structural differences in tree crowns cannot be excluded either (Gaveau and Hill 2003). Nevertheless, the ALS sensor and the scanning parameters are selected on a case-by-case basis in practice, so the arrangement in study **I** was considered realistic.

The effects of varying forest structures, on the other hand, should be minimized by transferring models only to nearby areas, and by a comprehensive training dataset that covers the variation in the validation areas. Obviously, this can be a challenge, as the local forest structure is always affected by local growth conditions and silvicultural activities carried out in the past, for example. Nevertheless, the training data in study **I** were comprehensive, and the distances between the training and validation areas were less than 100 km. In fact, the Koli study area is located in a protection area where no silvicultural activities had been carried out in the 15 years prior to the inventory. The Liperi and Kiihtelysvaara areas, on the other hand, were mostly privately owned, and thus, more intensively managed in general. This aspect could account for the larger systematic differences in tree crowns observed between the Liperi and Koli areas, and thus, partly explain the less accurate post-transfer results in Koli (compared to Kiihtelysvaara). Of course, the tree crowns may be different for other reasons as well.

The remaining reasons for the poor transferability to Koli can be explained by the differences in the acquisition of ALS data. All the areas were scanned with a different ALS sensor, so it is likely that the sensor used in Koli behaved differently and produced different ALS point clouds compared to the sensor used in Liperi. Differences in the penetration of laser pulses before the first return have already been pointed out here, so other differences are also likely (e.g. Næsset 2009). For instance, the pulse density (5.2 pulses $m^{-2}$) was clearly smaller in Koli than in Liperi (13.2 $m^{-2}$) and Kiihtelysvaara (14.7 $m^{-2}$) (Table 2). Consequently, the average number of first echoes backscattered from each tree crown was 147 in Koli, but was 243 and 276 in Liperi and Kiihtelysvaara, respectively. The notably sparser pulse density in Koli is another plausible explanation for the less accurate results. Nevertheless, it appeared that the Liperi and Kiihtelysvaara datasets corresponded with each other better than the Liperi and Koli datasets, and therefore, a set of more similar neighbors in k-NN was found for the pine trees in Kiihtelysvaara than in Koli.

It should be noted that study **I** was only a case study, i.e. with different inventory areas the results could have been notably different. In addition, problems with tree detection and tree species recognition also accumulate uncertainty in practical applications. Moreover, stem attributes are, in general, a challenge to predict from the properties of tree crowns, so some degree of decrease in accuracy can always be expected when tree-level models are transferred from the training area to new inventory areas. In particular, the accuracies of volume-related predictions seem to be prone to larger decreases. It is probably too optimistic to transfer models without any field measurements to the new area. Instead, to obtain more accurate predictions, even a small number of measurements should be carried out to calibrate the models in the new areas (Korhonen et al. 2019).

### 4.3 Field calibrations of merchantable and sawlog volumes

In practical forestry, mature stands are usually field visited before clear-cutting. If the stands are physically visited, carrying out some simple manual measurements during the visit should not increase the total costs dramatically. Thus, only a little extra effort would be required to obtain more accurate predictions, especially if the correlation between the different attributes can be utilized so that an easily measurable attribute can be used to calibrate another attribute that is laborious to be measured. In the future, automatic measurements, such as personal laser scanning, could potentially be utilized as well. In study **III**, the potential of using 1–10 manual angle gauge measurements to calibrate merchantable and sawlog volumes was tested. The initial predictions were made with LME models, and the calibrations were based on the prediction of stand-level random effects using basal area measurements and cross-model correlations of residuals and random effects.

The results showed that the accuracy of stand-level merchantable volume predictions can be increased with basal area information. In the absence of calibrations, the RMSE% value was 15.8 %, and decreased to 11.9 %. with 10 angle gauge measurements. However, the correlation between basal area and sawlog volume was not sufficiently strong, in general, to successfully calibrate the sawlog volume predictions. On some stands, the accuracy of the sawlog volume prediction was slightly increased, but no common factor with respect to forest conditions on those stands could be extracted.

Merchantable volume consists of the volume of all logs that pass the harvester head, regardless of the timber assortment. Therefore, compared to the total volume of a stem, only the volumes of the tree top and the above-ground stump are excluded from the merchantable volume. It can be assumed that the variation in the relative volumes of the tree top and the above-ground stump are rather constant between harvested trees, i.e. the merchantable volume is highly correlated to total volume. In traditional field work, mean height and basal area measurements have been used to approximate the total volume ($m^3$ $ha^{-1}$) (Nyyssönen 1954). Thus, as mean height was generally provided by the ALS data, and basal area was manually measured, it was not surprising that the accuracies of merchantable volume predictions were improved by the implemented calibrations.

Sawlog volume, on the other hand, includes a lot of uncertainty that is caused by the various requirements for species, dimensions, and the qualitative properties of the stem, in particular. A grid cell with only mature birch trees would result in no sawlog volume, whereas the sawlog volume for mature spruce or pine dominated cell could be dozens of cubic meters. Therefore, deciduous trees reduce the correlation between the ALS point cloud and the sawlog volume. In addition, same basal areas may consist of numerous small trees, or of a few large trees. Of course, it can be assumed that on mature stands, large clusters of small diameter trees are unlikely, but as minimum diameters are applied for sawlogs, a substantial basal area that constitutes smaller trees would result in a small (or even zero) sawlog volume.

The correlation between basal area and sawlog volume is further reduced by the possible defects in the tree stems. The effects of basal area on tree quality are anything but unambiguous, especially for Norway spruce. For Scots pine, large stem numbers in young stands usually improve the quality with respect to branches (Lämsä et al. 1990). However, due to tending of the seedling stand, self-thinning and possible silvicultural thinnings during the rotation time, the basal area of a mature stand is not dependent on the average growing space in the young phase. On the other hand, poor quality trees are usually removed in thinnings, so in that sense, a smaller basal area could indicate better quality on average if compared to a stand without intensive thinning. However, thinnings decrease the competition between the remaining trees, allowing them to grow faster than without thinning. Therefore, the timing of thinning affects the sawlog volume as well, as does possible fertilization applications. Overall, as tree quality is affected by many factors (e.g. genetics, site type, competition, past silvicultural activities that include possible logging scars, abiotic and biotic disturbances) it can be assumed that the correlation between basal area and tree quality is weak. Furthermore, the more defects in a tree, the weaker the correlation between basal area and sawlog volume.

Even though the accuracy of sawlog volume predictions was not generally increased by calibrations, it is obvious that if the stands are visited, the external tree quality could also be visually assessed during the visit. This method would be subjective but by applying it as “a sawlog reduction model” to the merchantable volume, it could result in improved accuracy of estimates. Consequently, no initial predictions for sawlog volume would be needed, i.e. the collection of (expensive) training data for sawlog volume models would not be needed either.

In study **III**, angle gauge plots were also compared to fixed radius plots. Using an angle gauge is fast, but some inaccuracy is introduced when the estimates are merged to the fixed-sized calibration plots. Moreover, as accurate *in-situ* positioning of the plots may take several minutes (Valbuena 2014), the fixed radius plot could be delineated, while the plot is being positioned, and the DBH of all included trees could also be measured in that time. However, the results from study **III** showed that fixed radius plots yielded only slightly more accurate calibrations. Therefore, angle gauge plots appear to be the more practical alternative to measure the basal area for the calibration.

# 5 CONCLUSIONS

Predicting commercial tree quality, especially sawlog volume, by means of ALS remains a challenge. However, the results from this dissertation seem to verify that in boreal forests sawlog volume predictions with an RMSE% value of approximately 20–30 % should be obtainable for both plot- and stand-levels by means of ALS data. Whether predictions of this accuracy are adequate for its adaptation in practice remains unclear. Consequently, more studies with a wider range of datasets and methods are needed to demonstrate the applicability of predicting sawlog volume by means of ALS on a larger scale and in different types of forests. The problems related to the acquisition of training data for sawlog volume models also needs to be solved. Harvester collected data has considerable potential for this purpose, provided that each harvested tree can be automatically positioned with a sub-meter accuracy. To obtain sawlog volume predictions with a RMSE% value notably less than 20 %, the collection or measurement of some auxiliary stand-specific quality information from below the canopy is also required. In mature boreal forests, tree quality often is somewhat constant within a stand, thus, effectively allowing the generalization of a few field measurements to the entire stand-level.

The study-specific results in this thesis have also shown that it is unlikely that basal area information can be utilized to improve the accuracy of sawlog volume predictions in boreal, Norway spruce dominated forests. For the calibration of merchantable volume, on the other hand, basal area information is likely to be sufficient. In addition, a notable decrease in accuracy can be expected when tree-level ALS-based models are transferred from the training area to new inventory areas.

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