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Improving and validating forest inventory information using operational harvester data

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Academic dissertation

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ABSTRACT

This dissertation evaluates the applicability of airborne laser scanning (ALS)-based forest attribute interpretation, mobile-based machine vision methods and operational harvester data for improving forest inventories and management. The research focuses on assessing the accuracy of remotely-sensed forest attributes and mobile machine vision-derived volume attributes against operational harvester data, and improving remote sensing-based volume attribute estimates by applying harvester measurements and other Big Geodata.

My first study examined the accuracy of Metsään.fi forest inventory data, derived from ALS, by comparing it to operational harvester data. The findings revealed a tendency to overestimate sawlog removals, particularly Norway spruce (*Picea abies* (L.) Karst.) in clear-cut areas, although dominant tree species were accurately determined.

My second study assessed the Trestima smartphone app for pre-harvest measurements and my results showed that an insufficient number of photographs per forest stand led to poor accuracy levels, although when the recommended data collection protocol was closely followed there was an improvement in performance. The app provided accurate estimates of Norway spruce volume but slightly underestimated Scots pine (*Pinus sylvestris* L.) volume.

My third study explored the use of operational harvester data for the prediction of sawlog volumes using Metsään.fi attributes and other Big Geodata sources. A Random Forest model provided the best results with regard to factual sawlog volumes. The model-based approach notably improved sawlog predictions for Scots pine compared to the original Metsään.fi estimates.

Findings of this thesis indicate that remote sensing and machine vision-based methods are satisfactory when timber assortments and sawlog proportions are predicted but could be improved by additions. While certain limitations remain, improved data collection practices and advanced modelling techniques can further enhance the accuracy and usability of forest inventory systems. The results of this dissertation will contribute to the development of more efficient and data-driven forest inventory practices that may facilitate better resource allocation and sustainability in Nordic forestry.

Keywords: Metsään.fi, machine vision, logging data, airborne laser scanning (ALS), timber assortments, big geodata

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Joensuu, August 2025

Ville Vähä-Konka

LIST OF ORIGINAL ARTICLES

This thesis is based on data presented in the following articles, referred to by Roman Numerals **I**–**III** in the text.

I Vähä-Konka, V, Maltamo, M, Pukkala, T, Kärhä, K (2020) Evaluating the accuracy of ALS-based removal estimates against actual logging data. Annals of Forest Science 77:1–11. https://doi.org/10.1007/s13595-020-00985-7

II Vähä-Konka, V, Korhonen, L, Kärhä, K, Maltamo, M (2024) Estimating the accuracy of smartphone app-based removal estimates against actual wood-harvesting data from clear cuttings. iForest 17:140–147. https://doi.org/10.3832/ifor4377-017

III Vähä-Konka, V, Korhonen, L, Kärhä, K, Maltamo, M (2025) Estimating timber assortment reduction and sawlog proportions with the application of harvester measurements and open big geodata. Trees, Forests and People 20, 100811 https://doi.org/10.1016/j.tfp.2025.100811

Ville Vähä-Konka was responsible for all the calculations and analyses in articles **I** and **II**. In article **III**, Lauri Korhonen provided the original codes for data extraction and k-NN model construction with simulated annealing**.** Ville Vähä-Konka was the corresponding author in all three articles.

TABLE OF CONTENT

LIST OF ABBREVIATIONS

ABA	Area-based approach
ALS	Airborne laser scanning
CCF	Continuous cover forestry
CHM	Canopy height model
FFC	Finnish forest centre
FMI	Forest management inventory
GNSS	Global navigation satellite system
ITD	Individual tree detection
k-NN	k-nearest neighbour
NFI	National Forest inventory
ND	Normalised Difference
NPV	Net present value
RF	Random Forest
SR	Spectral Ratio
TLS	Terrestrial laser scanning
WSF	Wood Supply Finland

1 INTRODUCTION

1.1 Development of forest inventories in Nordic countries

The Nordic countries have a long tradition in forest inventories that has evolved from traditional field-based approaches to advanced remote sensing techniques (Maltamo et al. 2021). The two main types of forest inventories are National Forest Inventories (NFI) and Forest Management Inventories (FMI). Nowadays, both inventory types utilise remotely sensed data but also need field measurements.

The NFI are large-scale, statistically designed forest inventories that are conducted and utilised at national or regional levels to monitor forest resources, carbon stocks, biodiversity and other ecosystem services (Maltamo et al. 2021). The FMI are designed for operational forest planning at local or forest property levels and focus on stand-level management decisions. In this thesis, the focus is on FMI and the datasets consist of the forest stands where the management decisions were made. While NFI and FMI serve different purposes, they complement each other in sustainable forest management.

Field-based inventories rely on direct observations and measurements by forestry professionals. Recent advancements in remote sensing have transformed forest inventories, improving efficiency and scalability. In Finland, remotely sensed forest information is freely available for all forest owners. Nevertheless, the increasing use of remote sensing enhances efficiency, yet field measurements remain essential for calibration and validation of the models that are developed (Maltamo et al. 2021). Future developments are expected to further refine inventory methods, thereby ensuring accurate and timely forest resource assessments.

In FMI, inventory information is obtained at the stand-level using wall-to-wall auxiliary information (Maltamo et al. 2021). The inventory cycle is typically 6–10 years and forest stands are classified by categorial attributes, such as main tree species, and measurement, modelling and predictions can be done by tree species. In this dissertation, the focus is on the three main tree species of Finland: Norway spruce (*Picea abies* (L.) Karst.), hereafter referred to as spruce, Scots pine (*Pinus sylvestris* L.), hereafter referred to as pine, and silver birch (*Betula pendula* Roth) and downy birch (*Betula pubescens* Ehrh.), hereafter referred to as birch.

Special case of FMI is the pre-harvest inventory, where wood purchasing organisations and buyers gather information on tree species-specific log length-top diameter distribution and log quality from marked stands (Pitkänen et al. 2021). Many studies have shown that remote sensing methods are not sufficiently accurate for pre-harvest measurements per se (Vergara et al. 2015, Haara et al. 2019). In particular, information on sawlog and pulpwood removal by tree species, as well as information on the quality characteristics of the trees are needed for pre-harvest inventory purposes (Holopainen et al. 2013). Over the past decade, proximal sensing methods have started to emerge in forest resource inventories. Proximal sensors are mounted on standing or mobile platforms (Mulla 2013). For example, the use of smartphones in forest inventories can be considered as proximal sensing (Talbot et al. 2017). Different smartphone applications have been used specifically for pre-harvest inventories of marked stands.

Figure 1. Field measurements remain crucial for calibration and validation of prediction models (Lusto/Metsäteollisuus ry:n kokoelma 2025).

1.2 Operational forestry

In Finland, the production of sawn wood and paper products had already commenced in the 19th century (Ministry of Agriculture and Forestry of Finland, 2025). Today, the forest industry has expanded beyond traditional paper and sawn goods to include a wide range of wood-based products, such as packaging material, as wood serves as an alternative to many fossil fuel-based materials. Given its size, Finland is among the most forest-dependent countries in the world, possessing unique expertise in forest management and the forest industry.

The forestry sector is a cornerstone of the Finnish economy, with timber and energy among the most valuable commercial forest products (Alvites et al., 2022). Effective management of this sector necessitates precise information of forests and their growing stock. Wood purchasing organisations and buyers require accurate data on sawlog and pulpwood removals prior to harvesting (Pitkänen et al., 2021). Since whole trees are seldom marketable, stems are segmented into various products (e.g. sawlogs, plywood logs, pulpwood, and energywood) with differing prices (Marshall, 2007). Quality standards are set by the customers, which include sawmills, plywood mills and pulp mills.

In 2023, industrial roundwood removals in Finland were 61 million m^{-3} (Natural Resources Institute Finland 2024). Slightly less than half of the removals were sawlogs and the remainder were pulpwood. Most of the wood in Finland is logged by three large forestry companies: Metsä Group Cooperative, UPM-Kymmene Plc and Stora Enso Plc, which are also quoted on the Finnish stock exchange (Forest 2024). With this volume of removals, precise information on the growing stock is needed to ensure that planning is efficient at both strategic and operation levels. In addition to the amount of wood, precise information about wood quality and timber assortments is also needed. In 2023, the average cost of timber harvesting was €13.29 m^{-3} (over bark) (Strandström 2023), which was 7.5% higher than in 2022. For regeneration felling, the cost was €9.85 m^{-3} in 2023, an increase of 4.6% (Strandström 2023). In 2023, the overall costs of harvesting operations were over €600 million (Strandström 2024), so more accurate information could provide substantial savings in the costs of harvesting.

In operative forest planning, the planning period is usually one month. The forest stands to be harvested are chained for the harvesting entrepreneurs and the demand for certain timber assortments comes from the mills that use the harvested wood. Wood buyers buy specific forest stands, depending on their need for different timber assortments. When the information on timber assortment removals is more accurate, planning of harvesting operations becomes more efficient. On the other hand, if the pre-harvest information is not accurate, deviations between assortment supplies and demand can occur, which will affect overall wood supply logistics, and this increases the costs and work of operative forest planning. The relative net present value (NPV) and the timing of the loggings are significantly affected by the accuracy of the input data (Holopainen et al., 2010). This is because the input data influences the simulations used in both tree- and stand-level simulators.

1.3 Current methods used in forest inventories

Different remote sensing technologies, particularly airborne laser scanning (ALS), have become operational in forest inventories (Karjalainen et al., 2020). In Finland, stand-level forest management inventories predominantly rely on a combination of remotely sensed data, local field sample plots and the k-nearest neighbour (k-NN) method (Maltamo and Packalén, 2014). Specifically, ALS is the primary method for information collection in management-oriented forest inventories in Finland. Regardless of the type of ALS-based forest resource inventory, the inclusion of field training data is mandatory. These data facilitate the development of models that link forest stand attributes, such as timber volume, to metrics derived from remote sensing (Maltamo et al., 2019). Moreover, ALS is a promising source of information for other types of forest inventories, such as NFI or pre-harvest stand measurements (Maltamo et al. 2019, Räty et al. 2019). In practical forest planning, information is required for each tree species (Packalén 2009). Thus, aerial imagery is often used to predict attributes that are difficult to predict from laser data (e.g. Packalén and Maltamo 2007; Holopainen et al. 2008).

Inventory verifications have shown that ALS-based inventory results can be more accurate for stand totals than results obtained using traditional field-based methods (Suvanto et al., 2005; Wallenius et al., 2012). In addition, both tree species-specific attributes (e.g. Packalén and Maltamo, 2007; Holopainen et al., 2010) and the measurements of individual tree attributes (e.g. Korpela et al., 2010; Vauhkonen, 2010) have been at least comparable to traditional field assessments. Nevertheless, further research is needed to improve the accuracy of tree quality assessments in ALS-based forest inventories (Wallenius et al., 2012).

The Finnish Forest Centre (FFC) collects and distributes forest inventory information on Finnish forests. This information is available in the Metsään.fi data repository, which is an electronic transaction service maintained by the FFC (Finnish Forest Centre 2019). The data includes information on stand attributes, forest use and the habitats that are important for biodiversity. Due to the amendment of the Forest Information Act, which came into force in early March 2018, much information has been made publicly available through the Metsään.fi service. Public access to the information is provided through a technical connection, provided that the transferee has the right to store and use such personal information in accordance with the Personal Data Protection Act (Laki Suomen metsäkeskuksen metsätietojärjestelmästä 2011). The amendment was a starting point for this thesis. Most of the information in Metsään.fi service is based on remote sensing, and in particular ALS data. One of the aims of this thesis was to investigate if the information is sufficiently accurate for the needs of the timber trade. Metsään.fi forest inventory data are widely used for forest management and planning.

Metsään.fi forest inventory information has been obtained using low-pulse ALS data and aerial photographs interpreted using the area-based approach (ABA) (Finnish Forest Centre 2019). ABA combines the metrics of remote sensing data with accurately measured field data. The estimation method varies bnetween inventory areas, but the k-NN approach is the most implemented (Maltamo and Packalén 2014). The resulting tree species-specific stand characteristics are predicted using a continuous grid of cells, and the stand results are aggregated from the cell results. In the case of timber assortments, the theoretical diameter distribution and tree heights are first predicted from the stand attribute estimates. The trees in the predicted diameter distribution are bucked and the theoretical sawlog reduction model developed by Mehtätalo (2002) is applied to account for defects. Correspondingly, theoretical thinning models (Äijälä 2001) are applied to determine the need for thinning. Metsään.fi estimates are also annually updated with growth models (Finnish Forest Centre 2019).

Another approach widely employed in ALS-based forest inventories is Individual Tree Detection (ITD) (Hyyppä et al. 2001, Vastaranta et al. 2012). Nowadays, ITD methods have become more common in forest mensuration as well as in operational forestry (Keefe et al. 2022). Usually, local maxima in the canopy height model (CHM) are considered to be trees and are further segmented to delineate tree crowns (Kaartinen et al 2012). From the tree heights, it is then possible to derive different attributes, such as stem volume (Hyyppä et al. 2001).

In addition, different proximal sensing applications have emerged in forest inventories in recent years. In particular, the use of smartphones for forest measurements has been studied intensively (e.g. Wu et al. 2019, Fan et al. 2020a, Fan et al. 2020b, Marzulli et al. 2020, Täll 2020, Aguilera et al. 2021, Kim et al. 2021, Pitkänen et al. 2021) due to the development of advanced remote sensors and computer vision (Kärhä et al. 2019, Wu et al. 2019). For example, a commercial app called Trestima has been developed in Finland for forest attribute estimation, especially the pre-harvest inventory of marked stands. Trestima uses monocular vision combined with the classic relascope theory (Bitterlich 1984). Stem diameter, tree height and tree species are estimated on a cloud computing platform using data that are extracted from photographs taken with a smartphone camera (Siipilehto et al. 2016, Trestima 2021).

1.4 Using harvester data in forest research

To date, research on the utilisation of harvester data for forest inventory purposes remains limited, primarily due to the complexities and high costs of collecting and integrating harvester data with remotely sensed data (Holopainen et al., 2013). Harvester data are collected for timber transaction purposes and research needs are seldom considered. However, when timber assortments are predicted, training data should include precise stand-level information on sawlog and pulpwood removals, which can only be measured with sufficient accuracy in practice by a harvester (Malinen et al. 2003). Labour-intensive field inventories have already been replaced in FMI by ALS-based methods (Vauhkonen et al. 2014). Remote sensing-based methods are more objective and can lead to more constant predictions compared to field inventories, which are more subjective because of human errors.

Previous studies that have evaluated the accuracy of ALS inventories have typically compared ALS-based estimates of stand attributes with field measurements (e.g. Wallenius et al., 2012). Attempts have also been made to use harvest data for similar comparisons (Siipilehto et al., 2016; Pesonen, 2017). In addition, harvester data have been used as training data for modelling various stand attributes such as volume, basal area and diameter distribution using laser scanning metrics as predictors (Bollandsås et al., 2011; Peuhkurinen et al., 2011; Holmgren et al., 2012; Barth and Holmgren, 2013; Hauglin et al., 2018; Saukkola et al., 2019).

Until recently, the Global Navigation Satellite System (GNSS) positioning of operational harvester data has generally been inaccurate (Lindroos et al. 2015). However, Hauglin et al. (2018) presented an approach to improve GPS positioning so that the tree level positioning error was approximately 1 m. The forest machine manufacturer, Komatsu, has promised a positioning error of only a few centimetres for their harvesters, for both the machine and the harvester head (Komatsu 2024): Hannrup and Möller (2022) studied the accuracy of the Komatsu precision-positioned harvester and obtained an error value of 0.56 m in relation to tree position.

Figure 2. Harvesters collect large amounts of information that is only marginally utilised for scientific research purposes. A John Deere 1170G harvester working in a clear-cut forest area. Photograph by Kalle Kärhä.

Furthermore, a significant challenge in using operational harvester data for scientific research is its limited suitability. For instance, data processing can substantially decrease the number of stands that are acceptable for research purposes. The main reasons that stands are discarded from a dataset can include the unavailability of remotely sensed data for the harvester stands, the fact that cuttings were made before information collection, and that geolocation information is not always available or suitable for research purposes.

1.5 Quality estimation in remotely-sensed forest inventories

The need for better estimates on timber assortments will increase in the future as climate change impacts the growth and quality of wood. However, timber quality is often missing from pre-harvest information. In earlier studies that considered the estimation of tree quality with remote-sensing, factual sawlog volumes have usually been predicted (Karjalainen et al. 2019). More efficient forest management and resource optimisation would be possible in operational forestry provided that the quality of the information obtained from remote-sensing based forest inventories could be improved. Applications that combine operational harvester data and Big Geodata (i.e. openly available georeferenced data for large areas) are one potential approach to improve the quality of estimated timber assortments (Barth and Holmgren 2013). For example, Bollandsås et al. (2011) studied the prediction of tree volume and quality characteristics in northeastern Norway and concluded that there is a need for more auxiliary information to generalise the models across stands. Korhonen et al. (2008) predicted factual sawlog volumes using mixed effects regression models with low point density ALS data and concluded that the method is suitable for operational pre-harvest estimation of sawlog volume. Sanz et al. (2021) integrated detailed timber assortments into ALS-based information and concluded that their non-parametric approach can assist in locating stands with the desired timber assortments for harvesting operations.

Alternatively, terrestrial laser scanning (TLS) can be used for the estimation of wood quality. This can be done using three-dimensional stem geometry obtained from TLS point clouds (Pyörälä et al. 2019a). In operational forestry, mobile platforms would probably work better to obtain such data (Pyörälä et al. 2019a). While Pyörälä et al. (2019b) concluded that the fusion of TLS and ALS could assist in the estimation of wood quality, TLS methods are beyond the scope of this thesis.

1.6 Objectives

The primary aim of this thesis was to investigate the accuracy of up-to-date forest inventory methods and their usability to support the timber trade, especially for pre-harvest inventory purposes. I used operational harvester data as a reference in the research. In addition, I developed methods to improve ALS-based forest information by integrating harvester measurements with forest databases and other open Big Geodata sources. Below are the specific aims for studies **I**–**III**:

(1) Validate the accuracy of remotely sensed and smartphone-based estimates of total volume, species specific volume and timber assortments in an operational context (I and II).

(2) Increase the accuracy of ALS-based predictions of sawlog recoveries by using open Big Geodata sources (III).

By addressing these objectives, this thesis aims to enhance the integration of remote sensing methods into practical forestry applications. The findings will contribute to improved forest inventory methodologies, thereby ensuring better data reliability, support for informed decision-making, and more efficient forest management.

2 MATERIALS AND METHODS

2.1 Research areas

In study **I,** most of the stands were located in southeastern Finland (Fig. 3). After removing all inconsistencies, a total of 82 clear-cut stands were selected for the study (Table 1). These comprised 121 stands with a total area of 148.3 hectares. Consequently, 79 thinning blocks were selected for the study and consisted of 149 stands with a total area of 223.6 hectares. Harvester data played a central role in study **II** as well, where 37 clear-cut stands in southeastern Finland were analysed (Fig. 3). The harvesting period was from December 2018 until August 2020. In study **III**, harvester data were extended to include 683 clear-cut stands from eastern Finland from the seashore up to the Kainuu region (Fig. 3). The study stands covered 1,250 hectares.

Table 1 Number of stands and total removals as measured by a harvester in the different studies of this thesis.

Study	Number of stands	Measured removal by harvester (m^3, solid over bark)	Main tree species
I (clear-cut)	121	33,507	Spruce
I (thinnings)	149	16,609	Pine
II	37	21,531	Spruce
III	683	318,154	Spruce

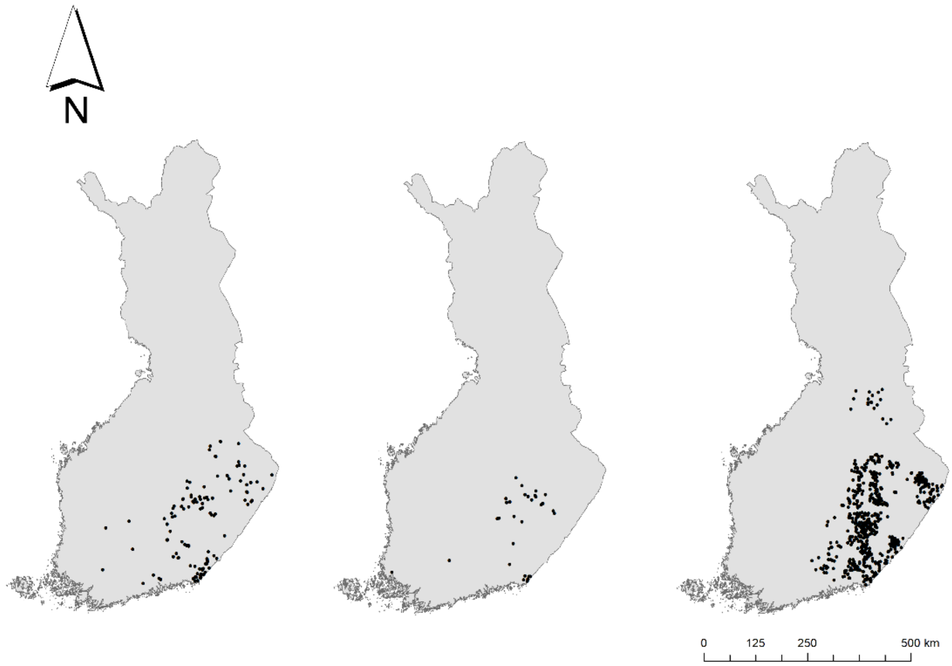

Figure 3. Location of the study stands in Finland. Datasets used in studies **I**, **II** and **III** are shown from left to right. Map data source: © EuroGeographics for the administrative boundaries (EuroGraphics 2020). [Colour online.]

2.2 Datasets

2.2.1 Harvester data

Harvester data played a significant role in the research presented in this dissertation. The harvester data included detailed information on harvested tree stems and enabled precise volume and assortment comparisons. Harvester data were used to ground truth harvested removals in each of the studies. In all studies (**I**, **II** and **III**), the harvester data included all usable stem pieces harvested from the forest stands, excluding decayed wood (i.e. offcuts) and treetops (Kärhä et al. 2019). Sawlog lengths typically varied between 3.7 and 5.5 m, but there was some variation including shorter (3.1 or 3.4 m) and longer (5.8 and 6.1 m) lengths. The minimum top diameters (over bark) of spruce, pine and birch sawlogs were 16, 15 and 17 cm, respectively. The length of pulpwood logs ranged from 2.7 to 5.0 m, with minimum top diameters (over bark) generally set at 7, 6 and 5 cm for spruce, pine and birch, respectively). Harvester measurement is regulated in Finland under the Decree of the Ministry of Agriculture and Forestry (Laki puutavaran mittauksesta 2013).

In all studies (**I**, **II** and **III**), the starting datasets were much larger than those ultimately utilised in the research. The main reasons for discarding a large proportion of the stands were the unavailability of ALS-data for the harvested stands, instances where clear-cutting had already taken place before information collection, or when geolocated information was not always suitable. Furthermore, geolocated harvester information was available only for studies **II** and **III**.

The stands selected in study **I** had to be consistent with the metsään.fi stand-level forest inventory data provided by the Finnish Forest Centre. The deviations were analysed on a case-by-case basis from the harvester files (prd and hpr) (Skogforsk 2021). At the same time, it was verified that no abnormal harvesting had occurred. In addition, incomplete logging areas were excluded from the study. Harvesting data were available per logging area, so it was possible that more than one stand may have been included in the same file. On the other hand, there could be more than one harvester file for a single stand. Each file was matched with data in the Metsään.fi inventory. When the logging data contained several stands consistent with the forest resource data, the stands were also combined in the Metsään.fi dataset.

In study **II**, the final 37 stands had accurate stand delineations derived from harvester position data (Melkas et al. 2020). In this study, I also started with a much larger dataset. Trestima-based smartphone information was available from 2,043 stands and harvester data (harvested production (hpr) files) from 29,803 stands. In these data, the stand borders were obtained from stand databases as they were before harvesting. However, in practice, the harvested areas deviated from the nominal stand borders. A preliminary analysis indicated that there were 42 matching clear-cut stands that had both Trestima and geolocated harvesting data available. In the end there were 37 study stands after discarding non-suitable stands and combining stands that were physically connected.

For studies **II** and **III**, I used stand delineations based on recorded harvester positions (Melkas et al. 2020). I began with data from over 1,600 harvested clear-cut stands, but ultimately, fewer than half of these stands were suitable for research purposes.

2.2.2 Estimated removals

Metsään.fi forest inventory data was used in studies **I** and **III**. I investigated the accuracy of Metsään.fi stand level data in study **I**. At the stand level, the Metsään.fi inventory has timber assortments, which allows for direct comparisons with actual logging data. In study **III**, the Metsään.fi grid data was used, which was then extracted to the stand-level and aggregated as area-weighted means of intersecting cells.

In study **I**, forest stand information was retrieved at the most recent available date prior to harvesting for the selected study stands. To ensure consistency, the stand delineations in Metsään.fi were compared with the actual harvested stand borders provided by the mapping system of Stora Enso. I verified that harvesting had been carried out according to the plan in order to ensure accurate volume comparisons. Total and species-specific volumes, as well as timber assortments, were analysed for Scots pine, Norway spruce and deciduous trees, primarily birch.

In Study **II**, the final 37 harvested stands included a total of 48 inventoried stands for which Trestima data had been collected (neighbouring stands are often treated as a single unit in harvesting). There may also have been a mismatch between stand boundaries. In such cases, I intersected the Trestima estimated stand polygons with the actual harvested stand polygon and estimated the Trestima volume of the actual stand using an area-weighted average. The average number of photographs taken with Trestima was 7.3 photographs per actual harvested stand, each of which is an independent sample. The number of photographs taken for each stand varied, so I classified the observed stands according to the number of photographs (three classes) as follows: ≤ 3 photographs; 4–9 photographs; ≥ 10 photographs.

In study **III**, Metsään.fi data were utilised in a similar fashion. Forest inventory information from a 2019 database provided wall-to-wall predictions of forest attributes for the study areas. As in I, the predictions were derived from ALS and aerial image data combined with field plot measurements, and generalised to a 16 × 16 m grid using a model. Stand-level estimates were subsequently extracted as area-weighted means for each selected forest stand. This approach ensured robust and consistent comparisons between remotely-sensed inventory estimates and harvester-measured logging outcomes. The Metsään.fi grid data did not have timber assortment estimates in it.

2.2.3 Open Big Geodata

In Study **III**, I had other sources of information besides Metsään.fi that could be used as predictors. First, I had the multi-source Finnish National Forest Inventory Data (MS-NFI). In the study was used tree species-specific volumes, tree species-specific volumes and other stand characteristics as map layers from 2019. In addition to field data, satellite imagery, digital map data, and other georeferenced data were used in the estimation of MS-NFI layers (Mäkisara et al. 2022). The MS-NFI attributes were extracted from corresponding raster maps for harvester stands as with the Metsään.fi data. In addition, 20 m resolution Sentinel-2 satellite image mosaic spectral bands were used in this study (Finnish Environment Institute Syke 2019). I used ten bands out of twelve, excluding the coastal aerosol and water vapour bands. To reduce the adverse effects of mosaics, I did not use the bands as such, but instead calculated 90 different normalized difference indices (ND) and spectral ratio indices (SR) for vegetation indices that are more resistant to atmospheric effects (see III for detailed formulas).

An open digital terrain model with a resolution of 10 m was also used (Land Survey of Finland 2024). Elevation above geoid was extracted as a weighted mean of pixels that intersect the stand border and was used as a predictor variable. In addition, hillshade, aspect and slope were calculated and extracted in a similar fashion. Further, a cartographic Depth-to-Water (DTW) index map was downloaded from the Paituli-download service for the study stands. A cartographic depth-to-water index (Murphy et al., 2007, 2008, 2009) was calculated from a digital terrain model and stream networks. The latter were created based on different thresholds to simulate various hydrological situations. Here, I applied a 0.5 hectare threshold that represents very moist conditions (Salmivaara et al. 2020).

A map describing the superficial deposits of Finland was downloaded from the Hakku download service maintained by the Finnish Geological Survey to obtain more detailed information of the soil in the study stands (Geology Research Centre 2018). The map had a scale of 1:200,000 and covered the whole country. In this map, the different sediments were included as polygons. In my dataset, there were a total of seven different soil types when clay and mud were combined into a single class. Also, forest vegetation zones were included in my data, as the study stands were located in two different zones: the hemi-boreal and south-boreal zones. I used subzones of the forest vegetation zones as dummy variables in my model. A temperature sum map from 2016 was also included to extract degree days for each stand. The Triangulated Irregular Network (TIN) method was used in the interpolation. Finally, geographical coordinates in the ETRS-TM35FIN coordinate system were calculated for every stand. I wanted to utilise all open geodata in my research, which could provide more accurate information with regard to timber quality and assortments (see III for all the available predictor candidates).

2.3 Statistical analysis

2.3.1 Modelling approaches

In study **III**, the predictions were implemented using k-NN imputation with the most similar neighbour (MSN) distance metric. This distance metric is based on canonical correlations that are used to derive a weighted matrix for the imputation so that the correlations between dependent and independent variables are maximised (Moeur and Stage 1995). A heuristic optimisation method called *simulated annealing* was used to find the optimal combination of predictors. This algorithm tests different predictor combinations so that the poorer solutions can also be randomly accepted for further iterations to avoid getting stuck at a local maxima (Packalén et al. 2012), although the best solution is always retained. The algorithm does not usually find the global optimum, but it will generally find a solution that is close to it. My implementation returned five different optimisation results at each run, and the best result was applied in the modelling. I also tested Random Forest (RF) modelling for total sawlog proportions and total sawlog volume. It is a powerful and flexible algorithm that can handle large and complex datasets (Breiman 2001). However, it can also be prone to overfitting, so it is important to tune its hyperparameters carefully and use regularisation techniques to prevent overfitting. Of note, Cosenza et al. (2022) were not able to overfit RF under any circumstances when testing different models in ALS-based forest inventories. Random Forest is a popular machine learning algorithm used for classification and regression tasks, and it is effective for modelling one dependent variable.

2.3.2 Accuracy assessment

Separate comparisons were made of total removals, pulpwood and sawlog removals. Comparison of timber assortments was made for pine, spruce and birch. The timber assortments of each stand selected for the study were combined in order to correspond to the timber assortments estimate of Metsään.fi. In study **I**, hardwoods were combined into a single class for sawlog and pulpwood removals. For pine and spruce, sawlog and pulpwood removals were available directly from the harvester file. Harvester data were summed, where appropriate, by harvested stand to match harvester-measured removals with Metsään.fi estimates for total volume and volume by timber assortment. Similar comparisons were made in **II** using the Trestima estimates as predictions compared to the actual harvested volumes. In study **III**, the model-produced estimates were compared to the actual harvested values.

The root mean square error (RMSE) and bias values between the harvester data and Metsään.fi estimates were calculated for total volume, tree species specific volumes and timber assortment volumes (Equations 1 and 3). In addition, the corresponding relative RMSE and biases values were calculated with Equations 2 and 4. Note that the observed value in study **I** was reduced from the predicted value and, therefore, a positive bias indicated overestimation with the Metsään.fi data. This was carried out in reverse for studies **II** and **III**, which is a more common approach in statistics. Finally, the correlation between the harvester data and Metsään.fi estimates in **I** and **II** was calculated using the Pearson product moment correlation coefficient.

$$\text{RMSE} = \sqrt{\sum \frac{(y_{obs} - y_{pred})^2}{N}}, \quad (1)$$

$$\text{RMSE-\%} = \frac{RMSE}{\bar{y}_{obs}} * 100, \quad (2)$$

$$\text{Bias} = \frac{\sum(y_{obs} - y_{pred})}{N}, \quad (3)$$

$$\text{Bias-\%} = \frac{Bias}{\bar{y}_{obs}} * 100 \quad (4)$$

where
y_{obs} = observed value at logging
y_{pred} = predicted value at logging
N = number of stands
$\bar{y}_{obs}$ = average of observed volumes
$\bar{y}_{pred}$ = average of predicted volumes

3 RESULTS

In studies **I** and **III**, Metsään.fi data was used and proximal sensing information obtained with the Trestima smartphone app in study **II**. Detailed information on the models and other specific information can be found in the original articles.

3.1 Accuracy of remote sensing-based volume and timber assortment estimates

When removals from clear-cut areas were inspected (**I**), the scatterplot between total measured removals by the harvester and estimated removals with the Metsään.fi data showed a somewhat linear relationship (Figure 4). The RMSE value associated with estimated total harvested removals in the Metsään.fi data was 26%. The bias in the data was less than 4% and the removal estimates in the Metsään.fi data were more often over- than under-estimations. However, for very large removals (> 450 m^3 ha^{-1}), the Metsään.fi data produced considerable underestimates (Figure 4).

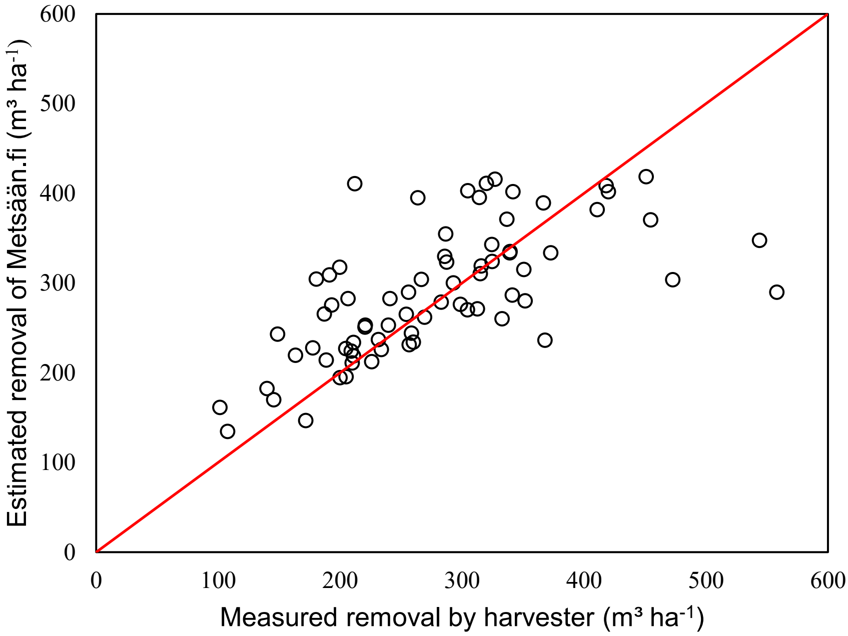

Figure 4. Scatterplot of total logging removals in clear-cut areas between measured removals by a harvester and estimated removals with the Metsään.fi inventory data.

Timber material was dominated by spruce in study **I**. In the case of spruce sawlogs, there was a rather strong relationship between measured and estimated removals with the Metsään.fi data (Figure 5). However, the RMSE% value was almost 50% and the bias value was more than 20% (Table 2). Estimated removal with Metsään.fi produced a considerable systematic overestimation in removals of spruce sawlog. The relationship was less pronounced for spruce pulpwood and the RMSE value was more than 50%. For spruce pulpwood, the bias value was nearly 30%, and the estimated removals with Metsään.fi consistently underestimated actual harvested removals (Figure 5).

Less than a quarter of the total removal was pine sawlog or pulpwood. There was a rather linear relationship between measured pine sawlog removals and the Metsään.fi estimate (Figure 5). The relative RMSE value was slightly less than 70% and the bias value averaged less than 4% (Table 2). The correlation between harvester-measured removals and the Metsään.fi estimate for pine pulpwood was the weakest, after hardwood sawlogs (Table 2). The RMSE% value was over 100% for pine pulpwood and the bias value was less than 6%. The Metsään.fi data produced a slight systematic underestimation for pine pulpwood removal. Notable was the bias value for spruce assortments and the absence of bias for pine assortments. In addition, the least accurate results were observed for hardwood assortments, which were the smallest removals in the study. Overall, the relative errors for the tree species-specific assortments were significantly greater than the error associated with total logging removals.

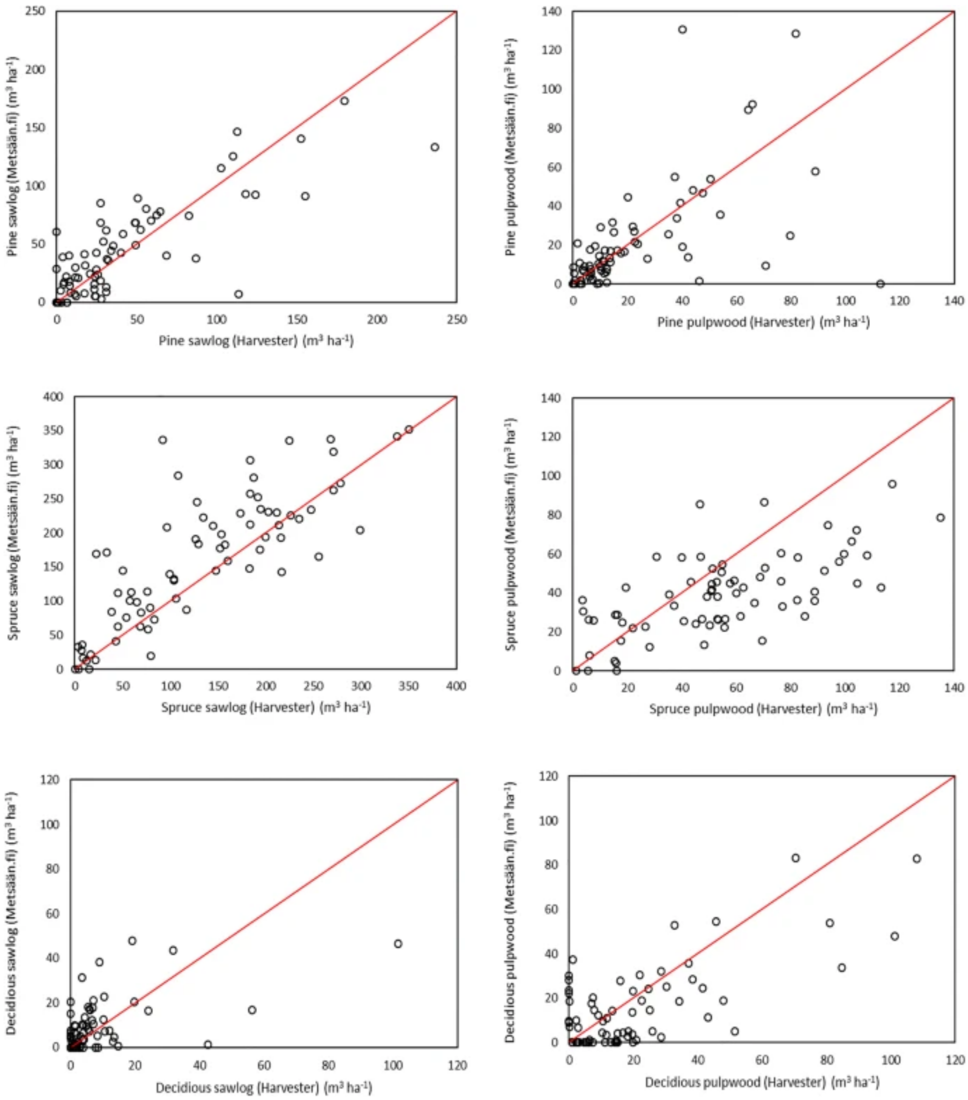

Figure 5. Tree species-specific scatterplots between timber assortment removals (as measured by a harvester) and Metsään.fi estimates.

Table 2 Root mean square error (RMSE) and bias values in clear-cuts by tree species-specific timber assortment.

Timber assortment ($m^3\ ha^{-1}$)	RMSE	RMSE%	Bias	Bias%	Correlation
Pine sawlog	27.42	67.12	-1.60	-3.93	0.81**
Spruce sawlog	63.98	48.61	-29.28	-22.25	0.81**
Hardwood sawlog	12.66	169.80	-1.06	-14.25	0.55**
Pine pulpwood	23.23	107.10	1.24	5.73	0.58**
Spruce pulpwood	30.63	54.80	16.49	29.51	0.65**
Hardwood pulpwood	20.13	97.74	3.39	16.44	0.66**

** Correlation statistically significant at 1% ($p < 0.01$)
 * Correlation statistically significant at 5% ($p < 0.05$)

In clear-cuttings, the dominant tree species was interpreted correctly in 87.7% of the stands and the kappa value was 0.7, which would imply that there was considerable consistency between the materials. According to the logging data, 54 of the 73 stands were spruce-dominated and 50 were also spruce-dominated with the Metsään.fi data. On closer inspection, it was noted that the main tree species was generally classified incorrectly in mixed forest stands (see study **I**, for more detailed information on the determination of the main tree species).

In study **I**, we also inspected the accuracy of thinning removals. The correlation between measured removals by the harvester and the estimated removal with the Metsään.fi data was weak (Figure 6). The thinning removals with the Metsään.fi data were mostly between 50 and 100 $m^3\ ha^{-1}$ and included both over- and under-estimates. The bias value was less than 1% (see Table 6 in study **I**). Correspondingly, the correlation between measured removals by the harvester and estimated removals with the Metsään.fi data was considerably lower than for clear-cutting but was still statistically significant at the 5% level. The RMSE% value was slightly above 40%. In the case of thinnings, I worked with a pine-dominated dataset in study **I**.

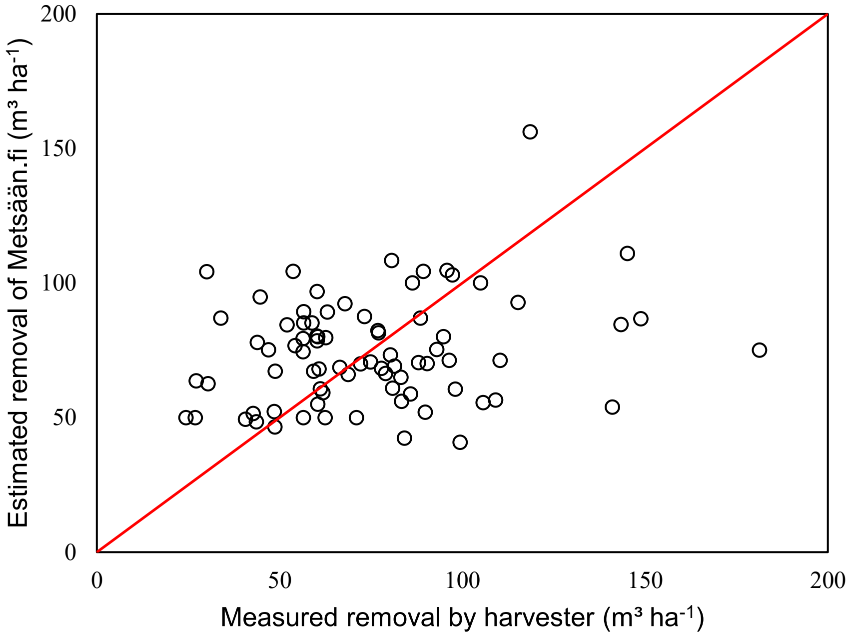

Figure. 6 Scatterplot between measured removals (in thinnings) by a harvester and estimated removals with the Metsään.fi data.

3.2 Accuracy of smartphone app-based volume and timber assortment estimates

In study **II**, I focused on the accuracy of smartphone app-based forest inventories. The correlation between the harvested and Trestima-estimated volumes was not strong when total harvesting removals were examined, but was much stronger for tree species-specific removals. The accuracy of the Trestima estimates varied greatly according to the number of photographs that had been taken in the forest stand (Figure 7). The RMSE value associated with total harvest volume was 55.3% in the ≤ 3 photographs per stand class, 27.7% in the 4–9 class and 17.7% in the ≥ 10 class (Table 3). The overall RMSE value was 32.2%. Bias values also decreased as the number of photographs increased. The Trestima estimates were more often underestimates.

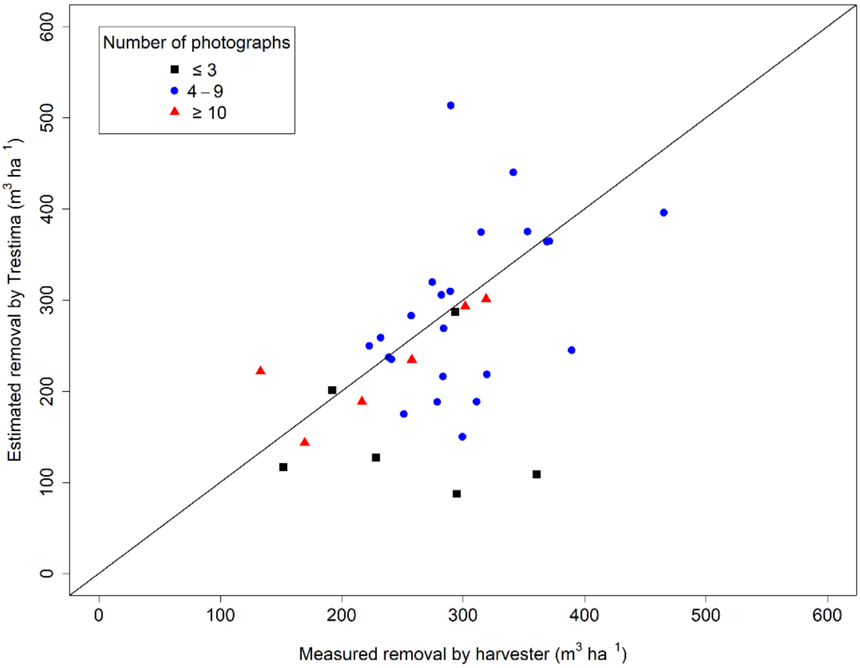

Figure. 7 Scatterplot of total logging removals between measured removals by a harvester and estimated removals by the Trestima app.

Table 3 Absolute root mean square error (RMSE) and relative (RMSE%) errors and corresponding bias values (Bias, Bias%) for total harvest removals by volume in clear-cutting according to the number of Trestima photographs taken per forest stand.

Number of pictures	RMSE	RMSE%	Bias	Bias%	Number of observations
≤ 3	140.3	55.3	98.8	39.0	6
4–9	83.7	27.7	12.4	4.1	23
≥ 10	41.3	17.7	2.5	1.1	6

In study **II**, the dataset was likewise spruce dominated, with spruce accounting for more than half the total removals. Results were weaker when tree species-specific removals were examined (see Table 4 in **II**). Even greater scattering was evident with regard to the timber assortment data (Figure 8). The RMSE values were also greater than for tree species, and ranged from 50.1% to 123% (Table 4).

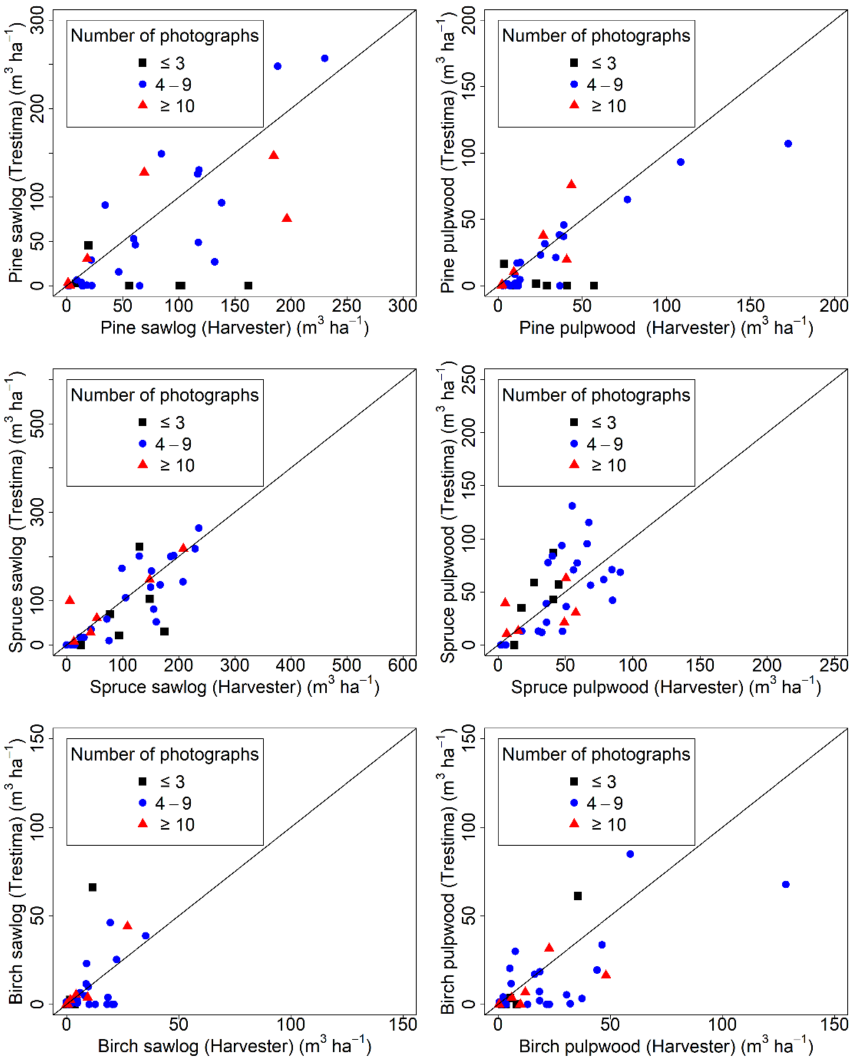

Figure. 8 Tree species-specific scatterplots between timber assortment removals in clear-cut forest stands as measured by a harvester and Trestima estimates.

Table 4 Root mean square error (RMSE) and bias values in clear-cut areas by timber assortment (m³ ha^{-1}).

Timber assortment/Number of photographs	RMSE	RMSE%	Bias	Bias%
Pine sawlog				
≤ 3	91.9	123.0	66.7	89.2
4–9	39.9	60.1	8.7	13.1
≥ 10	57.2	72.6	14.7	18.7
Spruce sawlog				
≤ 3	78.5	72.7	33.4	30.9
4–9	79.5	65.2	-9.5	-7.8
≥ 10	39.3	50.1	-14.9	-19.0
Birch sawlog				
≤ 3	22.3	687.9	-8.2	-253.3
4–9	10.7	104.4	2.4	23.6
≥ 10	7.3	102.2	-2.1	-30.0
Pine pulpwood				
≤ 3	32.9	121.4	24.1	89.0
4–9	17.2	56.4	8.2	26.9
≥ 10	16.4	79.1	-3.3	-16.1
Spruce pulpwood				
≤ 3	24.9	81.6	-16.3	-53.3
4–9	29.8	62.6	-4.1	-8.6
≥ 10	21.9	71.3	1.0	3.4
Birch pulpwood				
≤ 3	11.2	116.7	-1.2	-12.3
4–9	21.6	89.0	10.1	41.6
≥ 10	14.2	86.0	6.8	41.2

Overall, the accuracy increased as the number of photographs increased. The Error index indicated that approximately ten photographs were needed to guarantee Error Index values < 0.4 (Figure 9). This is the recommended number of photographs as stated by Trestima (Trestima 2021).

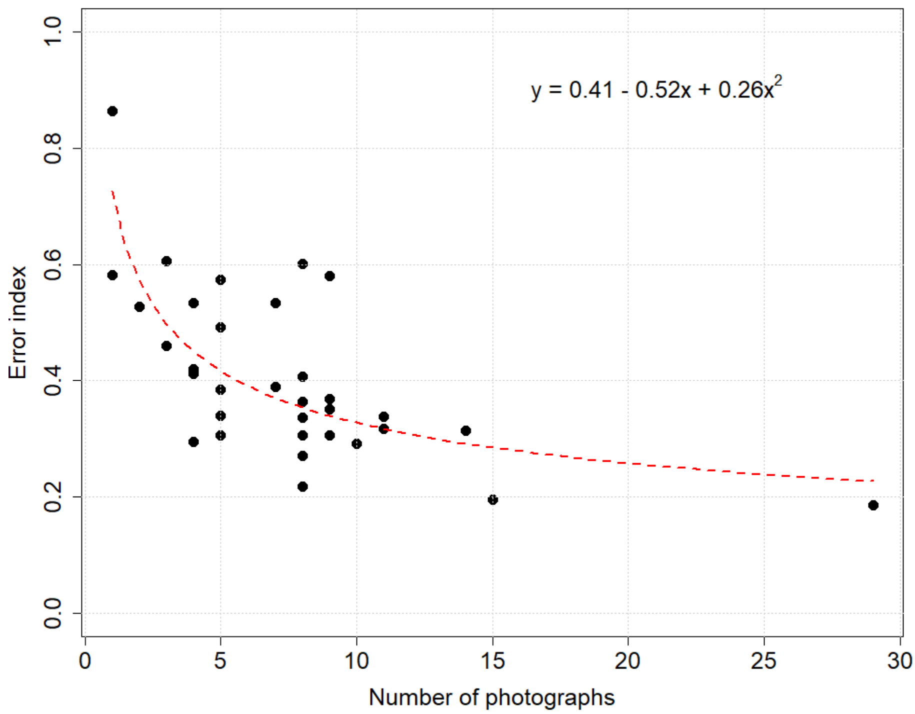

Figure. 9 Error index according to the number of photographs taken per forest stand. A degree 2 polynomial trendline is fitted to the scatterplot.

Diameter distributions between harvester and Trestima seemed consistent, when sufficient photographs were taken (Figure 10).

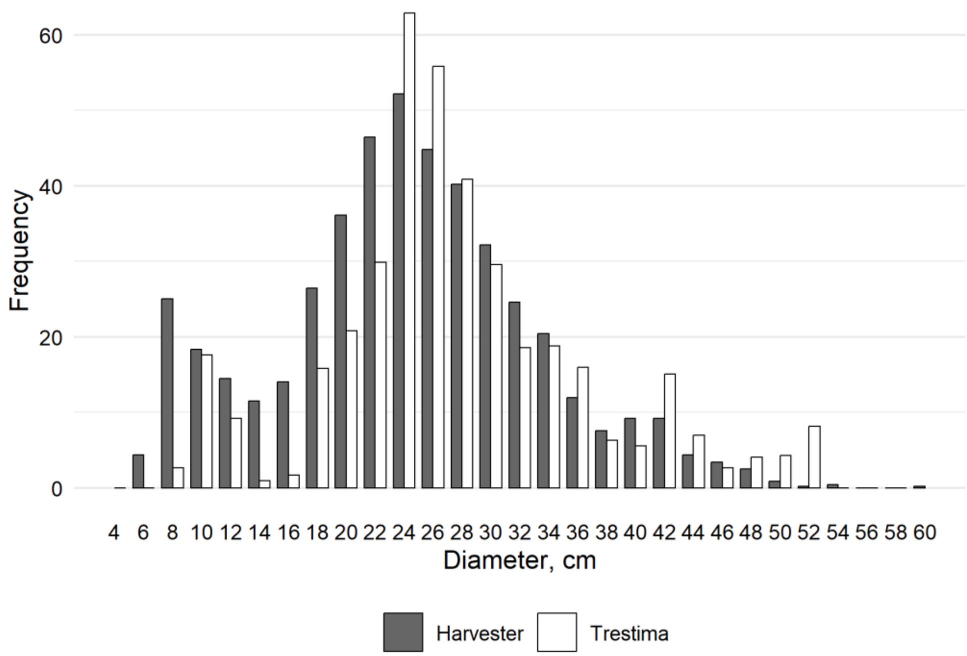

Figure. 10 Stem distribution from the > 10 photograph per stand class. In this case, 15 photographs were taken. Stem number as measured by the harvester and the Trestima app was 462 and 395, respectively. The Error index was 0.20.

3.3 Prediction of timber assortments and sawlog proportions

In study **III**, a modelling approach was used to include a quality estimation into the remotely-sensed forest inventory information. Metsään.fi grid cell information was obtained for the entire Finnish Forest Centre forest database from 2019. The accuracy of total volume was already at a better level before modelling when compared to the study **I** dataset (RMSE value: 19.2%) (Figure 11). These data were estimated using low pulse density (1 m^{-2}) ALS data, optical aerial images (50 cm resolution) and field plots.

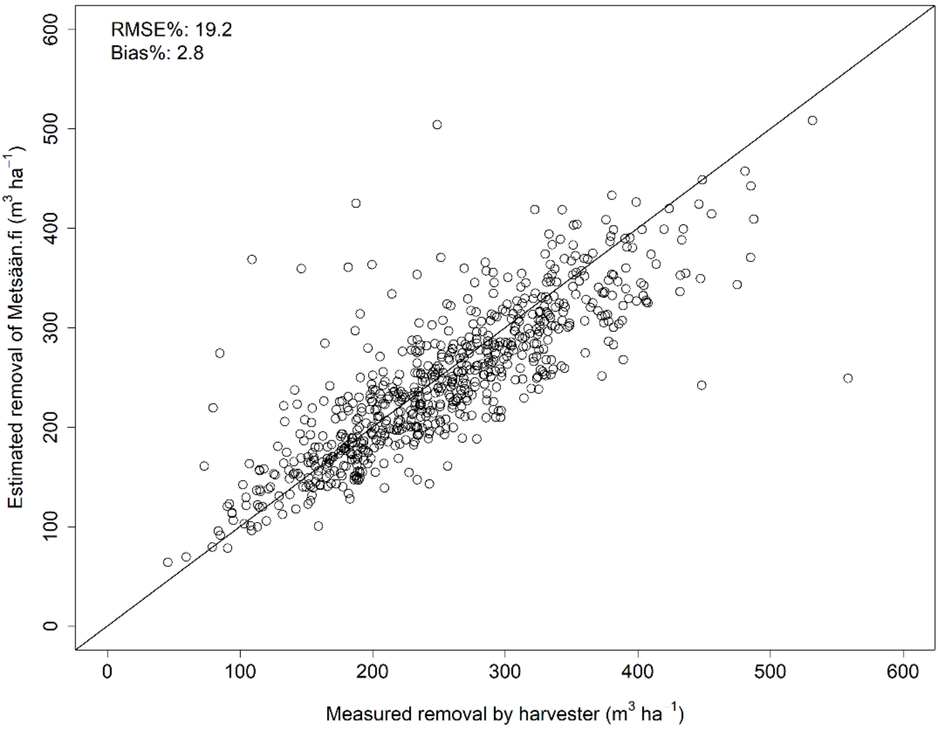

Figure. 11 Scatterplot of total logging removals in clear-cut areas between measured removals by a harvester and estimated removals with the Metsään.fi data.

The k-NN model produced the most accurate results for spruce sawlog with a relative RMSE value of 40.8% (Figure 12, and see Table 2 in **III**). Spruce sawlog and pulpwood comprised over half of the commercial volume in my dataset. For pine sawlog, the RMSE value was 59.5% (Table 2 in **III**). The model resulted in almost unbiased values for all the timber assortments (see **III** for selected predictors and available predictor candidates).

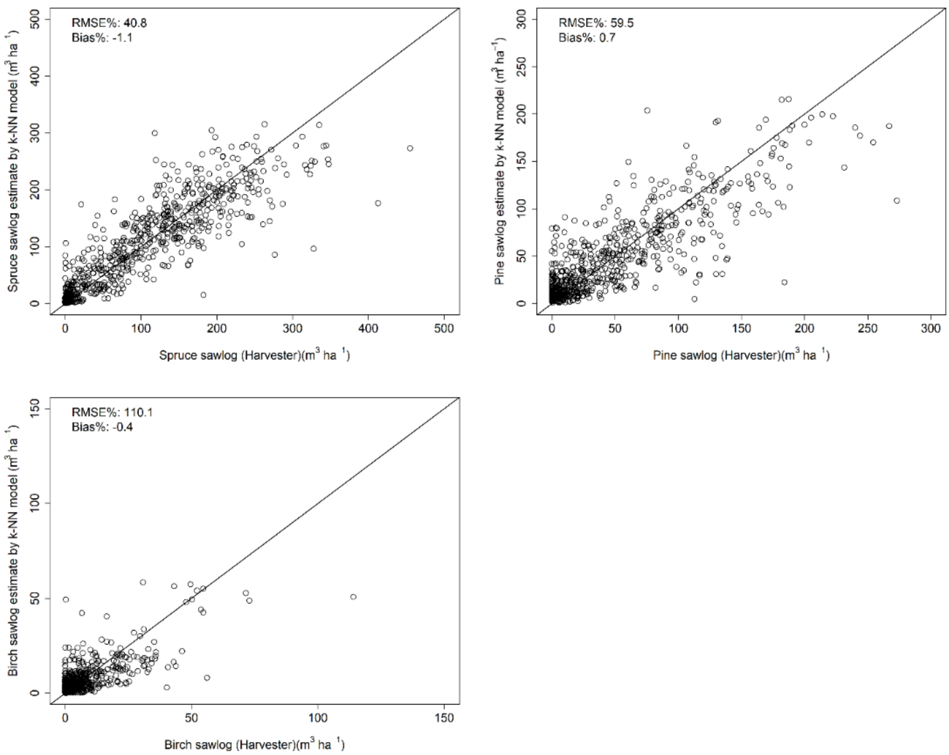

Figure 12. Tree species-specific scatterplots between observed sawlog assortments (as measured by a harvester) and estimated sawlog assortments.

In addition, I used RF and k-NN models to predict sawlog proportions (**III**). Furthermore, I used the predicted sawlog proportions from both the k-NN and RF models to calculate absolute sawlog volumes (Figure 13). I multiplied the stand-specific total volumes from the Metsään.fi grid by the total sawlog proportions obtained from the k-NN and RF models. The best result for total sawlog volume were obtained by multiplying the volume in the Metsään.fi data with the RF-estimated total sawlog proportions, which yielded a relative RMSE value of 25.3% (see Table 4 in **III**). Compared to the total sawlog volume produced by the k-NN model, the RMSE value was 2.3 percentage points smaller (Table 4 in **III**). When the total sawlog proportion predicted by the k-NN model was used instead, the result was slightly less accurate than the RF model (RMSE% value: 25.9%). Biases increased slightly when sawlog proportions from the models were used to obtain the sawlog volumes.

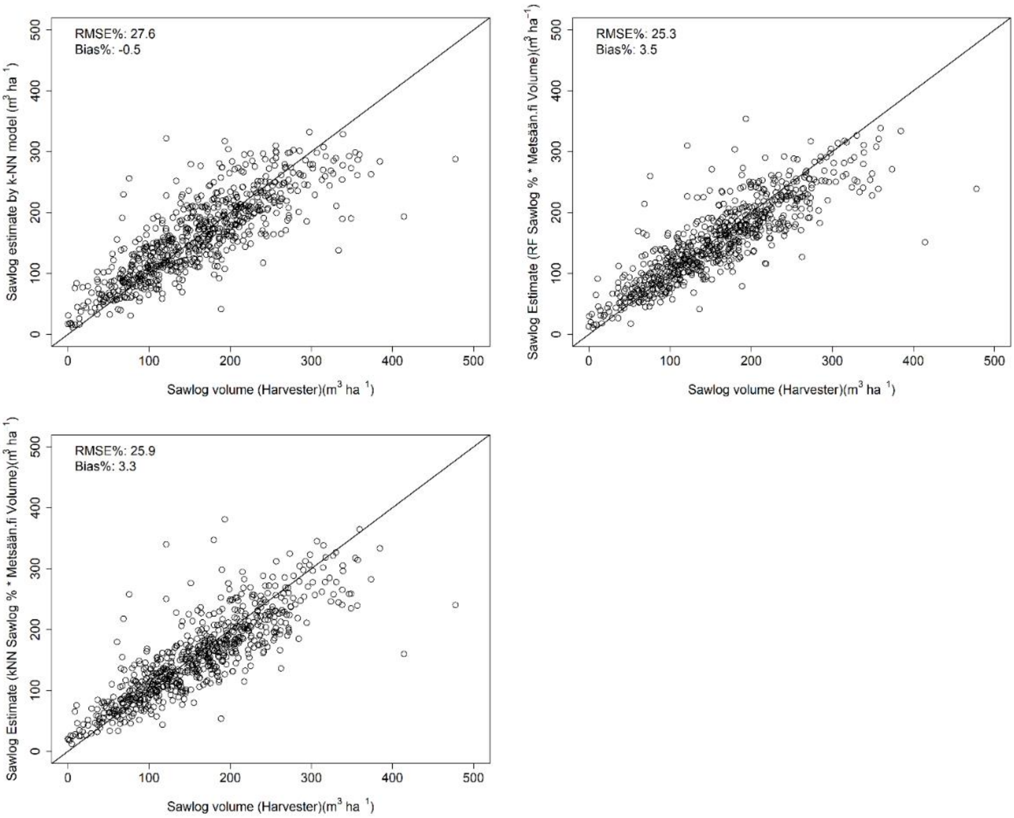

Figure 12. Scatterplots between the observed total sawlog volume (as measured by a harvester) and the total sawlog volume estimated from the direct k-NN model, the random forest (RF) sawlog percent model and the k-NN sawlog percent model.

When the Metsään.fi species-specific volumes were multiplied by the sawlog proportions obtained from the k-NN model, the accuracy of the pine sawlog volume improved by 4.7% and the resultant RMSE% value was 54.7% (Figure 13, and Table 5 in **III**). In the case of spruce sawlog volume, the relative RMSE value remained basically the same, but the relative bias value increased to 11.7% (Table 5 in **III**).

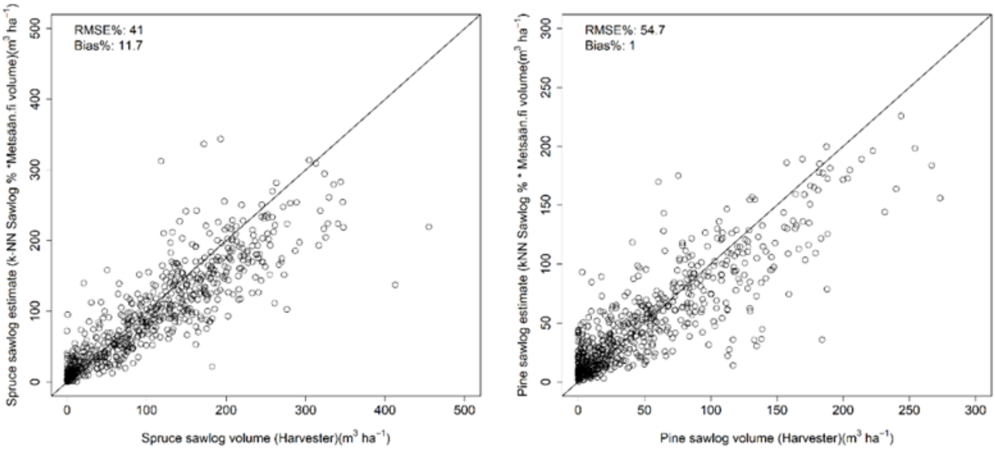

Figure 13. Scatterplot between observed spruce and pine sawlog volumes (as measured by a harvester) and the spruce and pine sawlog volumes derived from the k-NN model by multiplying the Metsään.fi species specific volumes.

4 DISCUSSION

4.1 Accuracy of current forest management inventories

The ALS-based removals estimated with the Metsään.fi data satisfactorily predicted total volume (**I**). From my studies, Metsään.fi predicts more sawlogs than are actually harvested. In the conventional timber trade, remote sensing-based information still requires on-the-ground verification but is nevertheless useful for the purposes of timber purchasing. For example, when searching for potential stands, Metsään.fi provides reliable assistance and acts as a starting point when making a timber trade assessment (Sanz et al. 2021). In addition, a field visit can help in checking tree species proportions and detecting, for example, damage to trees. Furthermore, field visits can improve the customer relationship, if visiting the forest is important for the forest owner.

The study materials used in all the studies in this thesis were located in areas where different types (and causes) of forest damage are present (Piri et al. 2019). In the wake of bark beetle (*Ips typographus* L.) damage, log-sized spruce trees may have to be used for energy purposes or converted to pulpwood. During the course of fieldwork for this thesis, the frequency of bark beetle outbreaks increased markedly (Terhonen et al. 2023). Spruce root and butt rot (*Heterobasidion parviporum*) are also prevalent in the study area (Piri et al. 2019).

In the case of spruce, the transition from sawlog to pulpwood was substantial, especially in study **I**, but the level varied by region. However, there was also a slight overestimation in pine and hardwood sawlog volumes with the Metsään.fi estimate, as well as an underestimation in pulpwood removals. In general, field measurements are required to determine the quality of the timber (Barth and Holmgren 2013), although more extensive use of harvester data could help avoid high-cost field inventories.

One factor that hinders the more extensive use of harvester data in research has been the inaccuracy of harvester positioning information. However, technology has improved rapidly in recent years. For example, Muhojoki et al. (2024) noted that the horizontal and vertical errors inherent in mobile positioning systems can be less than 15 cm and 10–30 cm, respectively. However, the accuracy of the only commercial GNSS system that is currently available to the general public is in the order of several meters. This indicates that more accurate positioning systems are still needed for machines that operate inside a dense forest canopy. In **II** and **III**, stand delineations were based on the automated algorithms presented by Melkas et al. (2020).

During thinning, the correlation between measured removals by the harvester and estimated removals with the Metsään.fi was weak (**I**). The removal of thinnings with the Metsään.fi data were mostly between 50 and 100 m^3 ha^{-1} and included both over- and under-estimates. The poor accuracy observed for the Metsään.fi data might be partly due to the thinning models employed. Thus, it is not possible to realistically deduce the amount of felling from thinnings based only on the Metsään.fi estimate. In the Metsään.fi data, consideration of the main tree species for thinnings is ambiguous, because the tree species that is suboptimal for the site may be more likely to be removed during felling. On average, thinnings were underestimated slightly more during logging than clear-cuts, although the bias was very low. This would also be the case with continuous cover forestry (CCF). As in thinning operations, all the trees in CCF are not removed from the target stand. This is difficult from the perspective of forest mensuration and planning. As such, forest planning systems need to be updated to be able to deal with CCF (Mehtätalo et al. 2024). The Finnish Forest Centre plans to bring suggestions with regard to CCF for suitable forest stands to the Metsään.fi service by the end of 2025 (Finnish Forest Centre 2025).

The accuracy of the Trestima smartphone app was found to be sufficient (**II**). It was observed that RMSE values varied significantly depending on the number of photographs taken in the targeted forest stands, and the scale of errors could be influenced by the users that collected the data. When more than 10 photographs were taken in the forest stand, the RMSE value associated with the Trestima estimate was 17.7%, corresponding to an error of approximately 71 m^3 per hectare. The bias was around 1.1%, which would indicate that Trestima slightly underestimated the removed volume. These results were more accurate than those obtained for ALS-based stand information in study **I**. However, my study included additional sources of errors, such as clear mismatches between the stand borders described in Trestima estimations and the boundaries of the actual harvested stands. Other factors may also have contributed to errors, such as the fact that retention trees and waste pieces of decayed wood were not included in the harvester data (Kärhä et al., 2019), although they were included in the Trestima-based estimates.

In study **II**, the RMSE% value was reasonably low when the total harvested volume was examined, which would suggest that the Trestima estimates are accurate when an adequate number of photographs are taken. The issue appears to lie in the operational use of Trestima, as the service pricing of the app is based on the number of photographs taken, potentially discouraging users from taking a sufficient number of photographs. In cases of large errors, it is possible that photographs were taken merely for documentation purposes, without the intent to accurately estimate stand characteristics, such as basal area. Nonetheless, errors were significant when only one photograph was taken in the forest stand. In such instances, sampling errors could be substantial, given that the entire stand is harvested. In general, subjective selection of measurement points is major source of error in this kind of inventories.

Study **II** provided new insights into the accuracy of Trestima data in operational use. The primary issue was that the app was not utilised as recommended. Pitkänen et al. (2021) concluded that Trestima can offer reasonably good pre-harvest information using simple tools, without requiring specific skills in forest mensuration. Their study setup differed from this one, as their information was derived from operational forestry use. It was also concluded that with an adequate number of photographs, Trestima can provide reasonably good pre-harvest information. Vastaranta et al. (2015) examined basal area, diameter and height measurements with Trestima and achieved excellent results. However, their study setup also differed from study **II**, as they measured at the plot level and compared the results with field measurements. Other smartphone studies have primarily focused on measuring diameter at breast height (DBH) (e.g. Fan et al., 2018; Wu et al., 2019; Woo et al., 2021). Singh et al. (2024) stated that reliable DBH measurements can be obtained when LiDAR is mounted on the newer iPhone models.

Compared to traditional field measurements, both the Trestima and Metsään.fi results show promise (**I** and **II**). Haara and Korhonen (2004) found that the RMSE value associated with stand volume was 24.8% and 21.4% after a reduction in sampling error. In traditional field measurements, stands are measured by tree species and by storey. When total stand volumes are predicted, the Trestima app achieved better results when > 10 photographs were taken. In traditional field measurements, total volume was underestimated by an average of 1.6% (Haara and Korhonen, 2004), while in my study, Trestima also slightly underestimated harvest removals. In the Metsään.fi ALS-based estimation, the error in total volume (26%) was slightly higher, but ALS inventories are continually improving.

4.2 Improving the accuracy of sawlog recoveries and timber assortment estimates by inclusion of harvester data

In study **III**, the aim was to integrate *in situ* harvester measurements of timber assortments with various types of open Big Geodata to predict timber assortments in the target stands. Existing harvester data can be effectively utilised within this framework to enhance predictions of timber assortment yield. Other Big Data sources used in this study included ALS-based forest inventory products, Sentinel-2 satellite image mosaic and MS-NFI estimates for example. My results were promising when compared to previous studies: RMSE values for spruce sawlog volumes ranged from 40.8% to 41.0%, and from 54.7% to 59.5% for pine sawlog volumes. In contrast, Peuhkurinen et al. (2008), who also used harvester data and a stem data bank, reported RMSE values that ranged from 31.8% to 34.8% for spruce sawlog volumes and 61.9% to 69.7% for pine sawlog volumes. Thus, my results were weaker for spruce sawlog but better for pine sawlog. For total sawlog volumes, obtained RMSE values varied from 25.3% to 27.6%, which are substantially more accurate. One issue in this study was that the model predicted sawlogs for target stands that did not contain any sawlogs. In study **III** operational harvester database was much larger than that used by Peuhkurinen et al. (2008), where all tasks were carried out locally in a small study area.

Errors in species-specific timber assortments were significantly larger in study **I** compared to **III**. The stand-level Metsään.fi data used in **I** included timber assortments estimated using general sawlog reduction models (Mehtätalo, 2002). In addition, Karjalainen et al. (2019) inspected pine sawlog volumes using the sawlog reduction model by Mehtätalo 2002 and obtained a RMSE value of 73.6%. Therefore, compared to previous studies, the integration of harvester measurements with forest databases and other sources of Big Geodata has the potential to noticeably improve estimates of sawlog removals.

Study **III** provided new information on the incorporation of new predictor variables into traditional forest resource estimates (Metsään.fi), allowing the integration of stand quality assessment into remote sensing-based forest inventories. Despite the extensive survey data and the wide range of available predictor variables, most of the selected predictor variables were still derived from the Metsään.fi grid data. However, the inclusion of other data sources can be promising. The Sentinel-2 satellite image mosaic emerged as the second most common source of predictor variables, suggesting that these band combinations could improve ALS-based tree species estimates. In predicting sawlog proportions from both k-NN and RF models, deciduous tree attributes emerged as important predictor variables. This is because deciduous trees of similar size tend to have lower sawlog removals as they have larger required sawlog dimension limits and are of poorer quality. The Metsään.fi data showed significant improvements over stand-level data, with smaller errors for the most accurate sawlog volume predictions than for the total volume (**I**). RMSE values for coniferous sawlogs ranged from 41-60% (**III**), while RMSE values ranged from 50-73% when Trestima was used according to the manufacturer's recommendations (**II**). The application of harvester measurements and Open Big Geodata can potentially provide more accurate estimates of sawlog removals.

4.2 Factors that affect sawlog quality and processing efficiency

Tree species and log quality characteristics are crucial factors influencing the sawlog assortment and cross-cutting processes (Barth and Holmgren, 2013). The wood species determines the range of products that can be manufactured and the potential buyers of sawn timber. In **III**, all timber was purchased by one company, although the sawlogs ended up in different regional sawmills. The sawmill industry generally adheres to strict standards regarding the size and quality of the wood it purchases. Size and quality standards vary between sawmills and regions, leading to differences in sawlog proportions. For pine, manual bucking is often used, where the harvester operator determines the lengths of the pieces, resulting in lower sawlog proportions and shorter sawlog lengths (Kärhä et al., 2017). Bucking is affected by customer requirements, and poor bucking can significantly reduce production value (Kärhä et al., 2017). Each of the big forest companies in Finland has their own price matrix, which is based on demand on the market, specific demands from the sawmills, processing capabilities as well as regional differences. In this work I have only been working with harvester data from one of these companies. Overall sawlogs are constantly priced higher than pulpwood, which should result with more precise bucking. Bucking is also affected by wood damage, and healthy spruce trees have less variation in quality, making the price of timber more stable. Pine, on the other hand, requires a more accurate quality-based bucking (i.e. un-branched stems, dead branches and green branches) and is divided into three categories according to branching. Manual bucking is more common in thinnings where smaller trees are cut. To maximize the value of sawlog production, Kärhä et al. (2017) recommended minimizing manual bucking for spruce and maximizing it for pine.

4.3 Future research

Future research should concentrate on the refinement and identification of additional techniques to accurately predict tree quality using laser scanning data. Leveraging harvester data, which was partially incorporated in the studies of this dissertation, could play a significant role in addressing this challenge (Barth and Holmgren, 2013). In addition, the use of ALS to map biodiversity should receive more investigation. For example, large tree trunks on the forest floor, which are ecologically important, can be detected using ALS-data.

Interesting topics for further research could include, for example, how to obtain more accurate information on the quality characteristics of stands by using remote sensing-based forest inventory methods. Exploration of how harvester information could be used more widely and in collaboration between different actors could be instigated, although it is recommended to have a contract between the owner and the user of the harvester data (Metsäteho 2020). In addition, the positioning accuracy of the harvester data could be improved and should be investigated (Hauglin et al. 2018). More accurate positioning of both the harvester and the harvester head will enable new applications, for example the use of ITD methods. With ITD methods and tracking, forest products can be followed in smart operational forestry from the stump to the mill where the wood is used (Keefe et al. 2022). Laser scanning technology is constantly evolving, and its benefits should be explored in practice. Higher pulse densities (e.g. 5 m^{-2}) will enable further use of ITD methodologies, while drone inventories prior to clear-cutting can be performed even without *in-situ* field measurements (Kotivuori et al. 2020). Furthermore, new sensors placed in forest machines can assist the operators in various applications, such as mapping of biodiversity indicators in managed forests (Korhonen et al. 2024) or selection of trees to be harvested (Sagar et al. 2024).

5 CONCLUSIONS

This dissertation explored advancements in remote sensing and machine vision technologies for forest inventories and operational forestry, providing novel information on their accuracy in comparison with operational harvester data. The findings from the three scientific articles that comprise this dissertation contribute to a broader understanding of how remote sensing-based methods compare with traditional field-based measurements.

Study **I** evaluated the accuracy of Metsään.fi forest inventory data derived from airborne laser scanning by comparison with operational harvester data. The study revealed that although the determination of the dominant tree species was accurate, the system tended to overestimate sawlog removals, particularly for spruce in clear-cut areas. These findings highlight the need for continuous refinement of remote sensing-based inventory methods to reduce bias and improve precision in the estimation of removals.

Study **II** examined the machine vision-based application Trestima in an operational context and identified that an insufficient number of photographs leads to weak estimation accuracy. However, when the recommended minimum of ten photographs per stand were taken, the accuracy improved significantly. While Trestima slightly underestimated the volume of harvest removals, particularly for pine, it provided unbiased estimates for spruce. The study confirmed that Trestima can be a valuable tool for forest inventories, provided that best practices for data collection are closely followed.

Study **III** investigated the use of operational harvester data for the prediction of sawlog volumes. The results demonstrated satisfactory accuracy in the estimation of total sawlog volumes, particularly for spruce, with refined model-based calculations improving predictions for pine. The RF model showed better performance over the k-NN model in predicting sawlog proportions, thereby highlighting its potential for operational implementation. Improved sawlog assortment predictions will enhance forest management efficiency and resource optimisation.

Overall, this dissertation observed the potential for remote sensing and machine vision-based methods in modern forest inventories. While challenges remain, the findings indicate that novel technologies can significantly reduce reliance on field measurements. Future advancements in remote sensing methodologies, machine learning applications and data integration strategies will further enhance the accuracy and usability of forest inventory systems, thereby contributing to more efficient and sustainable forest management practices. Use of operational harvester data also has the potential to play a significant role in this development.

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