Dissertationes Forestales 326

Methods for supporting digital timber trade

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Academic dissertation

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ABSTRACT

Information on timber assortment recovery and wood quality is crucial for wood procurement planning, as the various tree species and wood dimensions and qualities may be utilized and refined in separate mills. The aim of this thesis is to improve our understanding of the timber trade in digital environments in order to support the planning of harvesting operations.

The work for the thesis was carried out in three areas, two of which (discussed in Papers I and II) were located in Eastern Finland and one (Paper III) in Southern Finland. The field data comprised tree characteristics obtained from 79, 99 and 665 sample plots (Papers I, II and III, respectively), 249 harvested stands (Paper III) and a stem quality database (Papers I and III), whereas the remote sensing material consisted of aerial imagery (Papers I and III) and airborne laser scanning (ALS) data (Papers I, II and III) covering all the sites.

With the stated overarching aim, we set out in Papers I and III to estimate timber assortment volumes, economic values and wood paying capabilities (WPC) for plots (Paper I) or stands (Paper III) with different bucking scenarios, and used the resulting timber assortment estimates to assess logging recoveries. The alternative bucking scenarios investigated were (1) bucking-to-value using maximum sawlog and pulpwood volumes but excluding quality (theoretical maximum), and (2) bucking-to-value using sawlog lengths at 30 cm intervals for Scots pine (*Pinus sylvestris* L., Papers I and III) and Norway spruce (*Picea abies* (L.) H.Karst, Paper III) and veneer logs of lengths 4.7 m, 5.0 m, 6.0 m and 6.7 m for birch (*Betula* spp., Paper III), either excluding or including wood quality indicators. The first approach resembled the state-of-the-art in Nordic forestry business circles and the second approach went beyond that. The commercial value of timber stands is substantially affected by the quantity of understorey trees, and pre-harvest clearing is typically needed when forest stands have an understorey vegetation that hinders harvesting operations. We therefore proposed a method in Paper II for estimating this need for the pre-harvest clearing of small trees (diameters at breast height < 7 cm).

The results showed that use of the methods developed in this thesis could support wood procurement practices by (1) locating valuable stands with the desired timber assortment distributions (Papers I and III), (2) identifying understorey vegetation that needs to be removed before harvesting (Paper II), and (3) reducing costs, as the number of field visits needed before harvesting will diminish (Papers I, II and III).

In conclusion, the present findings may make timber markets more competent, since the methods developed here provide detailed pre-harvest information that can be used as a decision support tool by either buyers or sellers of timber in traditional and digital marketplaces.

Keywords: timber assortment recovery; cut-to-length (CTL) harvester; pre-harvest clearing operations; wood procurement; airborne laser scanning (ALS); remote sensing.

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Joensuu, November 2021
Blanca Sanz

LIST OF ORIGINAL ARTICLES

The PhD thesis presented here is based on the following papers, which are referred to by their Roman numerals:

I. Sanz, B, Malinen, J, Leppänen, V, Valbuena, R, Kauranne, T, Tokola, T (2018) Valuation of growing stock using multisource GIS data, a stem quality database, and bucking simulation. Canadian Journal of Forest Research 48: 888–897. https://doi.org/10.1139/cjfr-2017-0172.

II. Sanz, B, Malinen, J, Heiskanen, J, Tokola, T (2020) Need for Pre-Harvest Clearing of Understory Vegetation Determined by Airborne Laser Scanning. Forests 11, article id 294. https://doi.org/10.3390/f11030294.

III. Sanz, B, Malinen, J, Sirparanta, S, Peuhkurinen, J, Leppänen, V, Melkas, T, Riekki, K, Kauranne, T, Vastaranta, M, Tokola, T (2021) Integrating Detailed Timber Assortments into Airborne Laser Scanning (ALS)-Based Assessments of Logging Recoveries. Forests 12, article id 1221. https://doi.org/10.3390/f12091221.

AUTHOR'S CONTRIBUTION

Blanca Sanz was responsible for the summary of this thesis and was the corresponding author in Papers I, II and III. In this capacity she carried out the analyses, interpreted the results and wrote the first draft of all three papers. All the co-authors contributed to the papers, with the thesis supervisors, Professor Timo Tokola (Papers I, II and III), Jukka Malinen, D.Sc. (Papers I, II and III), and Professor Mikko Vastaranta (Paper III) as the main contributors.

TABLE OF CONTENTS

LIST OF ABBREVIATIONS

ABA	Area-Based Approach
AGL	Above Ground Level
ALS	Airborne Laser Scanning
CIR	Colour Infrared
CTL	Cut-To-Length
DBH	Diameter at Breast Height
DTM	Digital Terrain Model
FFC	Finnish Forest Centre
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GSD	Ground Sample Distance
ITD	Individual Tree Detection
k-MSN	*k* Most Similar Neighbour
LDA	Linear Discriminant Analysis
$N_{DBH1–7}$	Understorey density of trees with diameters at breast height from one to seven centimetres
pp	percentage points
RGB	Red, Green and Blue
RMSE	Root Mean Square Error
SD	Standard Deviation
TAV	Timber Assortment Volume
UAV	Unmanned Aerial Vehicles
WPC	Wood Paying Capability
3D	Three-Dimensional

1 INTRODUCTION

1.1 Wood procurement in the Nordic countries

Wood procurement is a complex process that comprises not only purchasing, harvesting and transportation but also the planning and management of these activities. Different timber assortments are transported to different mills depending on the species, wood quality and timber dimensions. Especially for sawmills, procurement represents a strategic business process, since the properties of sawlogs are the main factors for the output of sawn products and the raw materials contribute around 60% of the final cost of the products. Although it is the task of the managers to optimize the incoming flow of timber assortments at a given market price, Nordic sawmills employ a customer-oriented production strategy, which means that customer orders determine the length, small-end diameter and quality distributions of the logs entering a sawmill (Helstad 2006). Thus, assessments of harvesting output must be based not only on single volumetric figures, but also on comparisons between the demand and the actual output length-diameter distributions of the logs (Kivinen et al. 2005).

Timber buyers have to make pricing choices when purchasing roundwood at a given stumpage price, so that those who can buy stands that best fit their industrial process will benefit, since in competitive markets by-products have to be sold at or below cost price. Approximately 86% of Finland's commercial roundwood is removed in stumpage sale fellings (Finnish Forest Research Institute 2014). The stumpage price (i.e. price per m^3 of standing trees), determined separately for each sale, is somewhere between the buyer's maximum willingness to pay and the seller's minimum willingness to accept (Omwami 1986). Kolis et al. (2014), examining the effects that sale and site-specific characteristics have on the stumpage prices paid to non-industrial private forest owners in Finland, concluded that (1) buyers take differences in harvesting costs into account when making purchase offers, and (2) buyers are more interested in stands with a high percentage of sawlogs.

Current digital marketplaces (e.g., www.kuutio.fi) facilitate trading in timber by providing a place where supply and demand can meet. The challenge for such a digital marketplace is the facilitation of "standing sales", where the buyer is responsible for harvesting and its costs. This is the type of sales contract that is predominantly used in Finland. One requirement for such transactions is accurate and comprehensive information on the forest area concerned, including timber assortments and harvesting conditions. These matters were previously assessed in the course of purchasing the timber, but now that this can be done in a digital environment, there is increasing pressure to reduce the number of forest visits before harvesting operations. For this purpose, it would be feasible to resort to remote sensing and geographic information system (GIS)-based methods.

The decision support system needed in the Nordic cut-to-length (CTL) method requires detailed pre-harvest information, which is used to allot raw materials to specific timber assortments and to plan harvesting operations to satisfy production needs. The most important attributes of such a system are the availability of a stem diameter distribution for each tree species present in a stand and the availability of quality information.

The productivity of CTL harvesting is affected by the type of machine used, the capabilities of the operator, and the stand and site conditions (see Kärhä et al. 2004; Nurminen et al. 2006; Jiroušek et al. 2007; Eriksson and Lindroos 2014). CTL machinery is constantly being developed (Nordfjell et al. 2010) and the operators' capabilities can be improved through training (Ovaskainen 2009) and experience (Malinen et al. 2018b). Since operator, machine type and stand conditions have critical impacts on harvesting performance, studies aimed at giving overall productivity values have to be based on large samples. In this sense only the large surveys carried out in Sweden and Finland in the 1980s and 1990s (Brunberg et al. 1989; Kuitto et al. 1994; Brunberg 1997; Nurminen et al. 2006) can be assumed to be valid representations of Nordic conditions. On the other hand, it is generally difficult to alter the stand and site conditions in order to improve productivity. One option for achieving this, of course, is to remove any understorey vegetation that may hinder visibility during harvesting, which is standard practice in the Nordic countries before harvesting (Kärhä 2006; Bergström et al. 2016). Pre-harvest clearing has been found to ease the work of harvester operators in these countries, increase their safety and productivity and improve the quality of harvesting operations (Kärhä 2006). It has also been stated (Metsäteho Ltd. 2001) that pre-harvest clearing of small trees reduces stem damage, facilitates selection of the trees to be harvested and increases bearing capacity, thereby reducing root damage. Weak visibility due to understorey vegetation also increases the risk of chain, guide bar and hydraulic tube breakages (Metsäteho Ltd. 2001). In Finland, dense understorey vegetation is the most serious problem affecting industrial roundwood harvesting in young stands (Oikari et al. 2010). It is possible to obtain data on understorey trees from the National Forest Inventory, but these are quantitative estimates and are imprecise for practical purposes (Korpela et al. 2012).

1.2 Timber assortment recovery

The value of a timber stand can be derived from the value of the roundwood in the wood processing yard, with its procurement costs deducted. These procurement costs will include harvesting and transportation costs plus the fixed overhead costs of the procurement organization, and will consequently greatly depend on the productivity and cost-efficiency of the wood procurement operations, as also will the value of any timber stand (Paper II). Forest stand conditions, timber assortment information and simulated future developments should all be taken into account when planning harvesting operations (Holopainen et al. 2014; Kankare et al. 2014; Siipilehto et al. 2016), as forest owners can use this knowledge to decide when to offer their timber for sale and from which stands it should be taken. The forest industries, in turn, optimize their production by obtaining timber assortments from the harvesting sites that best fit their feedstock needs (Kankare et al. 2014). Furthermore, industrial timber buyers acquiring roundwood for refinement can make better pricing decisions if they have detailed pre-harvest information (Paper I).

Logging recoveries comprise everything that is obtained by felling trees, including small branches, twigs, leaves and all sorts of wood. Depending on the requirements in terms of wood dimensions and quality, tree stems can be bucked into timber assortments such as grade A (i.e. branchless) butt logs, sawlogs, small-diameter logs and pulpwood, in descending order of quality and monetary value. These assortments may be utilized and refined by processing mills such as sawmills, plywood mills, pulp mills, heating plants or combined heat and power plants. Some such plants can process various tree species with particular specifications in terms of dimensions and quality, while others may process only one tree species, mixed softwood or hardwood species or both softwood and hardwood (see Malinen et al. 2007; Hyvönen et al. 2019). To optimize wood procurement planning and various end user-driven refinement processes, it is essential to know the timber assortments prior to trading and harvesting. This is especially important in countries where intensive small-scale family forestry takes place, as in the Nordic countries (see Holopainen et al. 2014).

1.3 Airborne laser scanning (ALS)-based forest inventory methods

Detailed tree data, including tree lists, have traditionally been collected by means of field measurements, but this approach has been found to be too laborious and expensive (Uusitalo 1995). Digitalization of forest information services has opened new opportunities during the last decade, and wood procurement planning and the purchasing of timber can be expected to be conducted more and more in a digitalized environment in the future, without necessarily visiting all the potential stands. Thus there is an emerging need to develop methods that provide information on the characteristics and value of a stand and the products obtainable from it. Such methods would help to reduce or remove the need for stand visits.

As regular field visits entail a comparatively high workload, active remote sensing techniques such as airborne laser scanning (ALS) represent an excellent alternative for analysing forest characteristics. ALS collects information on tree size structures in three-dimension (3D) and has been widely used to provide estimates of tree and stand-level forest inventory characteristics such as tree height (Nelson et al. 1984; Næsset 1997). Large-scale forest stand inventories based on ALS have been in use in the Nordic countries since 2002 (Næsset et al. 2004). Forest characteristics can be obtained through the area-based approach (ABA; see Paper I) or by individual tree detection (ITD; see Sun et al. 2019), but ITD requires a relatively high ALS point density, whereas ABA has been shown to work quite reliably at a comparatively low point density (roughly one pulse·m^{-2}, Maltamo et al. 2006). While overstorey trees (dominant and co-dominant trees) often have a detection rate of 90% or more in ALS data, the detection rate for understorey trees (intermediate and suppressed trees) is usually below 50% (Hamraz et al. 2017). One important source of omission errors (missed trees) is the obstruction of understorey trees by overstorey ones (Wang et al. 2016), although full-waveform ALS data detect these strata in more detail than do discrete ALS data. Nevertheless, full-waveform ALS data are less common due to the large amount of data involved and the limited processing tools available (Anderson et al. 2016; Crespo-Peremarch et al. 2018). On the other hand, branches, non-crop trees and dead trees are potential causes of commission errors (wrongly detected trees) (McCombs et al. 2003). While ALS data can be used to estimate the canopy cover quite accurately (Peuhkurinen et al. 2011), the isolation of understorey trees from overstorey ones remains a challenging task (Korpela et al. 2012). However, for the pre-harvest pruning application discussed in Paper II it is not crucial to distinguish individual plants, as the average height and density of the forest understorey form a good proxy for the necessity of pre-harvest clearing (Alam et al. 2012) and it may be quite possible to estimate these rather coarse parameters of the understorey from ALS data.

Since a certain proportion of the laser pulses will penetrate through the dominant tree canopy layer, multi-layered stands can be identified using ALS (see Zimble et al. 2003; Maltamo et al. 2005). When Maltamo et al. (2005) examined the height distributions of reflected laser pulses using the histogram thresholding method to segregate distinct tree storeys, the results indicated that multi-layered stand structures could very well be identified and quantified using ALS height data distribution statistics. Later, an object-oriented segmentation approach to multistorey stands was adopted by Hamraz et al. (2017) and Ferraz et al. (2012). The first-mentioned authors stratified the point cloud by canopy layers and segmented the trees of all sizes for each canopy layer using a digital surface model-based tree crown segmentation method. Ferraz et al. (2012) used a mean shift algorithm to segment the point cloud and allocate each segment to an appropriate vegetation layer.

ALS data can characterize canopy height, height variation and canopy density in a fairly direct manner (Bouvier et al. 2015; Vastaranta et al. 2018) and these characteristics can be linked to some of the essential indicators of wood quality (Pyörälä et al. 2019). This means that ALS data can be used to decide which stands are more liable to have a particular log quality distribution. While some quality variables are easy to model, many others can be hard to predict accurately, since aspects such as local variation and historical stand development (including silvicultural treatments of the stands) are not captured by the laser data. Moreover, timber quality depends on internal and external stem properties, and some of the internal factors are not disclosed until the logs are processed at the mill (Bollandsås et al. 2011).

Species-specific forest inventory characteristics such as stem number, basal area, volume and mean diameter and height can be predicted from ALS data and aerial images together with field-measured sample plots (White et al. 2013; White et al. 2016; White et al. 2017), after which species-specific diameter distributions can be estimated at the stand level through statistical relationships (Gobakken and Næsset 2004; Peuhkurinen et al. 2008; Siipilehto et al. 2016). The predicted data can then be used in taper curves and timber assortment reduction models to estimate timber assortment volumes (TAVs) at the stand or tree level (Laasasenaho 1982; Mehtätalo 2002; Kangas and Maltamo 2002). Thus tree size distribution models can convert information obtained at the stand level into tree-level data (Maltamo et al. 2018). It should be noted, however, that all the predictions involved in the previous steps introduce some measure of uncertainty (Holopainen et al. 2010; Karjalainen 2020).

1.4 Objectives and hypotheses

The main aim of the timber trade from the buyer's perspective is typically to deliver the required raw materials to the different mill locations and at certain specific times. To do that, stands that are available for harvesting are considered within a predefined wood sourcing area and harvesting procedures are allocated to secure a continuous flow of feedstock for further processing. In order to perform this complex spatiotemporal optimization task, it is important to know about the timber assortments to be found in each stand within the given wood sourcing area, and especially the quality of the stems in each possible stand, before trading and harvesting (Papers I and III). This knowledge can support timber trade as well as the planning and preparation of harvesting operations. It should also be borne in mind in this context that the planning and preparation of harvesting operations will affect the costs and will be further reflected in the commercial value of each stand (Papers I, II and III). This commercial value will be referred to here as the wood paying capability (WPC). To understand this phenomenon and to provide methods for supporting digital timber trade, the following hypotheses were formulated:

(1) Useful WPC estimates for Scots pine (*Pinus sylvestris* L.) can be obtained if ALS data and aerial images are used together with sample plots and a stem quality database, since these data can predict species-specific stem volumes and qualities, and WPC depends on the volume and value of the stems (Paper I).

(2) The need for pre-harvest clearing can be estimated using ALS data because these data can characterize the density of the vegetation below the overstorey, which includes the small

trees that cause a need for pre-harvest clearing when they hamper harvesting operations (Paper II).

(3) Detailed timber assortments for Scots pine, Norway spruce (*Picea abies* (L.) H.Karst.) and birch (*Betula* spp.) can be estimated by means of ALS data, aerial images, sample plots and a stem quality database, because these data can predict species-specific stems, and different timber assortments in terms of their dimensions and qualities can be obtained by means of bucking simulations based on these stems (Paper III).

2 MATERIALS

2.1 Inventory areas and field data

Three forest areas were studied in this thesis, two of them (Site I, Paper I, and Site II, Paper II) located in Eastern Finland and the third (Site III, Paper III) in Southern Finland (see Figure 1). The main tree species in these areas were Scots pine, Norway spruce and birches. Scots pine was the dominant tree species at Site I, whereas Norway spruce was the prevailing species at Site III.

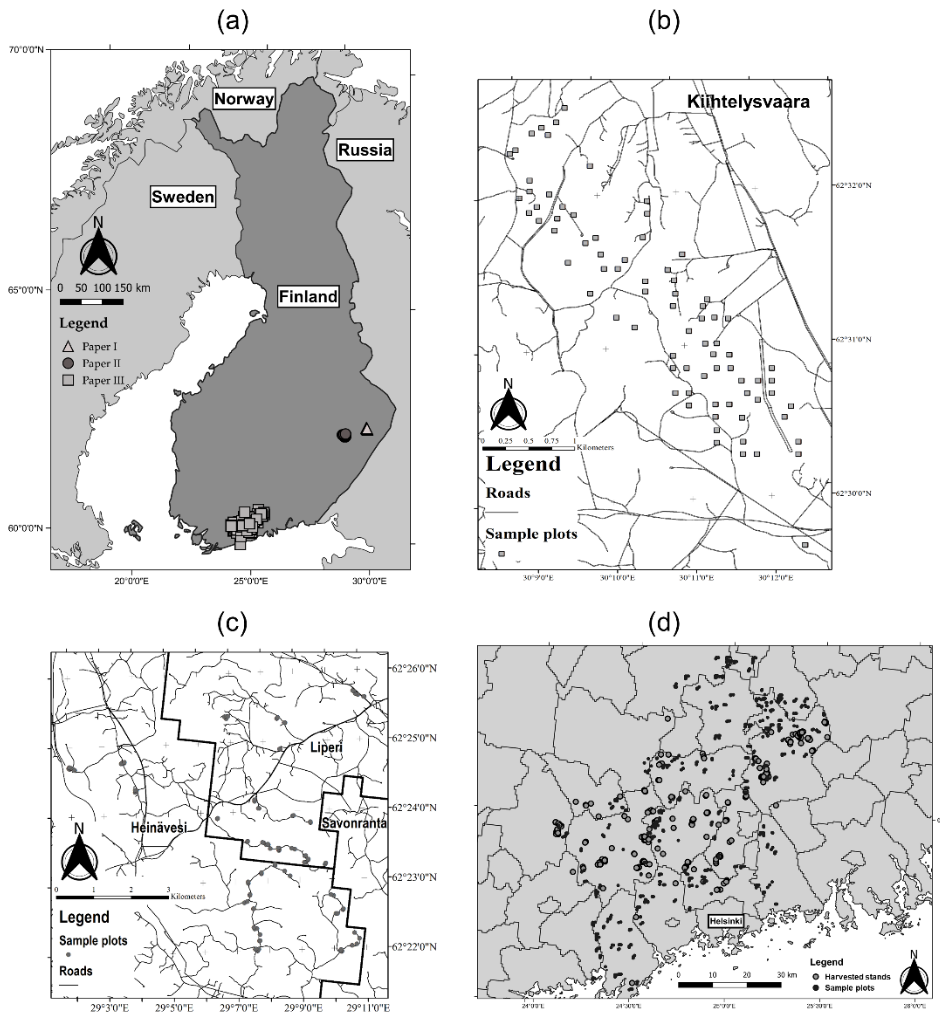


Figure 1. (a) Location of the forest areas studied in Finland; (b) sample plots at Site I (Paper I); (c) sample plots at Site II (Paper II); (d) sample plots (black circles) and harvested stands (grey circles) at Site III (Paper III).

The field data for Site I consisted of a stratified sample of 79 square plots, locations of which were determined subjectively in order to guarantee that the sample covered the full range of variability in forest conditions. The measurements were made in May and June 2010. The sample plots varied in size, being either 20 × 20 m, 25 × 25 m or 30 × 30 m according to their stand development class. Height, diameter at breast height (DBH) and species (Scots pine, Norway spruce or birch) were recorded for all of the trees inside the plots with a DBH > 4 cm or height > 4 m. Statistics concerning the sample plots are presented in Table 1.

Table 1. Forest characteristics on the 79, 99 and 665 sample plots at Sites I, II and III, respectively, the 249 harvested stands considered at Site III, and in the stem quality databases employed at Sites I and III.

		Variable	**DBH**	**Height**	**Density**	**Volume**	**Basal area**	**Norway spruce basal area**	**Scots pine basal area**	**Birch basal area**
			cm	m	stems $\cdot ha^{-1}$	$m^3 \cdot ha^{-1}$	$m^2 \cdot ha^{-1}$	$m^2 \cdot ha^{-1}$	$m^2 \cdot ha^{-1}$	$m^2 \cdot ha^{-1}$
Site I	Sample plots	Min.	8.1	8.7	467	79.5	13.8	0.0	0.0	0.0
		Mean	15.0	14.4	1259	197.6	24.6	8.2	18.3	3.3
		Max.	28.4	24.1	2875	502.2	40.1	40.0	33.5	22.7
		SD	4.0	3.3	566	73.6	6.2	12.2	8.8	5.4
Site II	Sample plots	Min.			0		6.0	0.0	0.0	0.0
		Mean			3455		17.5	6.9	6.7	3.9
		Max.			11926		34.0	31.0	28.0	20.5
		SD			2817		5.3	7.7	6.9	5.0
Site III	Sample plots	Min.	5.0	4.7	60	7.0	2.3	0.0	0.0	0.0
		Mean	19.8	16.8	1398	193.9	22.1	9.9	7.4	4.7
		Max.	47.3	32.7	8205	693.3	52.2	52.2	40.9	38.2
		SD	8.7	5.9	1091	127.9	10.2	11.9	9.7	6.2
	Harvested stands	Min.	7.4	7.5	33	8.8	1.2	0.0	0.0	0.0
		Mean	22.4	19.3	520	235.0	21.5	14.8	2.4	3.5
		Max.	41.0	25.1	1093	565.2	50.6	38.0	20.4	28.0
		SD	3.9	2.3	218	110.5	9.0	8.6	3.8	3.7
		Variable						**OMT**	**MT**	**VT & CT**
Sites I and III	Stem quality database	Number of sample trees						903	6589	5076
		Norway spruce						630	3588	254
		Scots pine						273	3001	4822
		Stems including an external defect (%)						57.6	55.0	80.0
		Norway spruce						43.7	39.2	39.4
		Scots pine						89.7	73.9	81.5

Note: Min.: Minimum; Max: Maximum; SD: standard deviation; DBH: basal area-weighted mean diameter at breast height (cm); Height: basal area-weighted mean height (m); Density, stems$\cdot$ha^{-1}, considering stems with a DBH > 4 cm or height > 4 m in Paper I, with a DBH > 1 cm and DBH < 7 cm in Paper II, and with a DBH > 5 cm in Paper III; OMT: *Oxalis-Myrtillus* site type; MT: *Myrtillus* site type; VT & CT: combined *Vaccinium* (VT) and *Calluna* (CT) site types, or corresponding peatland site types.

The field data for Site II were collected in July and August 2017. Altogether, 99 circular sample plots were photographed in order to estimate the need for pre-harvest clearing. The centre of each plot was identified using global positioning system (GPS) devices with an accuracy of < 0.5 m. The plots were selected subjectively with the aim of having approximately one third of each of the plots dominated by Scots pine, one third by Norway spruce, and one third by birches. In dense forests with small trees, sample trees were typically selected from plots of different sizes, depending on the DBH (Fridman et al. 2014). Here trees with a DBH under seven centimetres were defined as understorey trees, and for the purpose of determining the understorey tree density, each plot contained two concentric circular sample plots with fixed radiuses of three and five metres. In the three-metre plots the DBH and the species of all the trees with a DBH between one and seven centimetres ($DBH_{1–7}$) were recorded, while in the five-metre plots the same measurements were carried out for all the trees with a DBH between four and seven centimetres ($DBH_{4–7}$). The understorey tree density of all the trees with a $DBH_{1–7}$ ($N_{DBH1–7}$) varied from 0 to 11 926 stems·ha^{-1}, with an average of 3455 stems·ha^{-1} (see Table 1).

An online e-questionnaire survey among subscribers to the Finnish Facebook group “Forest machine operators”, which included over 8000 members at the time of the survey, was organized to compile our reference dataset. The questionnaire contained images taken within the plots, and respondents were asked to classify each plot into one of five classes: (1) no need for pre-harvest clearing; (2) pre-harvest clearing would help harvesting; (3) pre-harvest clearing recommended; (4) a great need for pre-harvest clearing; and (5) compulsory pre-harvest clearing (see Figure 2). Replies were received from 66 respondents, representing 56 harvester operators, 10 forwarder operators, four forest experts, five students, six forest owners, and one other person. In some cases, the same respondent fell into more than one category (e.g. a forwarder operator and forest owner) (Site II).

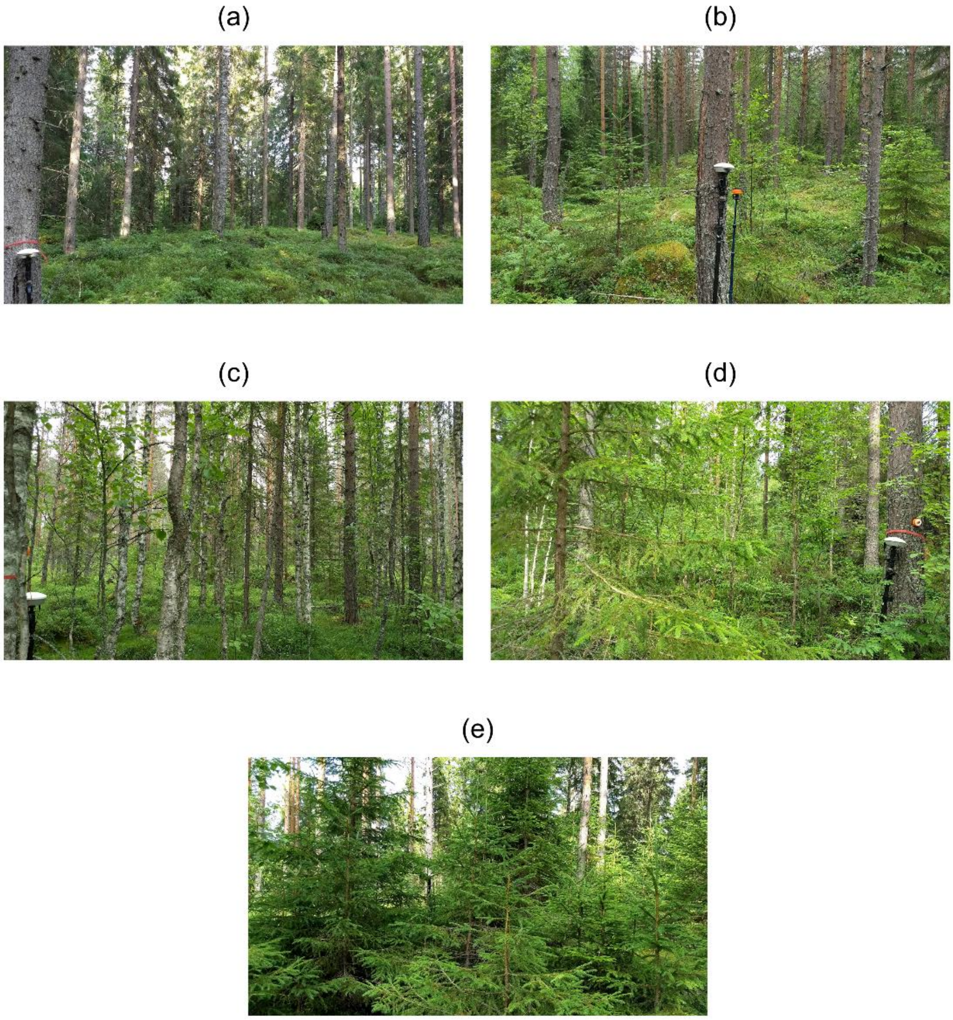


Figure 2. Photographs representative of each pre-harvest clearing class used in the e-questionnaire survey (Site II). (a) Class 1, no need for pre-harvest clearing; (b) class 2, pre-harvest clearing would help harvesting; (c) class 3, pre-harvest clearing recommended; (d) class 4, a great need for pre-harvest clearing; and (e) class 5, compulsory pre-harvest clearing.

The field data for Site III were collected between May and September 2015 by the Finnish Forest Centre (FFC). A total of 831 circular sample plots were designated in forests of varying structure based on the existing stand register information. In view of possible further analyses, those plots that were located in seedling stands were removed from the data. The remainder then comprised 665 plots (Figure 1) with a radius of 5.64 m, 9.00 m or 12.62 m depending on the tree density and development class, following the general FFC guidelines

(Suomen Metsäkeskus 2018). The locations of the sample plots were defined with a global navigation satellite system (GNSS) device capable of achieving sub-metre accuracy after post-processing. Species and DBH were defined for all of the trees with a DBH larger than 5 cm, and the height of every fifth tree was measured. Callipers and clinometers were used for these measurements. The heights of all the trees were also estimated using DBH as a predictor in locally calibrated species-specific allometric models, and volumes were calculated using species-specific allometric models based on DBH and height (Laasasenaho 1982). Forest inventory characteristics for the sample plots were computed from the measured or predicted tree characteristics. Descriptive statistics for the sample plots are presented in Table 1.

Site III also yielded harvester data covering altogether 202 428 stems and collected from 249 clear-cut stands (Figure 1) between June 2015 and September 2016. Each stem was located by reference to the harvester's GNSS, i.e. using the geographical coordinates recorded for each tree, which represent the location of the harvester at the time of cutting, not the original location of the stem. In addition to the geographical coordinates, the data recorded for each stem included tree species, diameters at 10 cm intervals along the stem, length, volume and timber assortment information. Although the data were collected using different harvesters, all of them recorded the same body of data according to the harvester production (HPR) standards and the standard for forest data and communication (StanForD) (Skogforsk 2018). Statistics based on the harvester data are shown in Table 1. Among the clear-cut stands there were 170, 12 and 10 stands dominated by Norway spruce, Scots pine and birch, respectively, where domination was taken to imply that a single tree species accounted for more than 60% of the total basal area. The collection, pre-processing and fitting of the harvester data were performed by Metsäteho Ltd. (Vantaa, Finland) in cooperation with the forest companies and harvester manufacturers (for a more detailed description, see Saukkola et al. 2019).

2.2 Remote sensing materials

The aerial images for Site I were acquired on 31 May 2009 using a Vexcel camera at a flight elevation of 7500 m above ground level (AGL). The ground sample distance (GSD, i.e. spatial resolution) was 45 cm. The ALS data were then collected on 26 June 2009 using an Optech ALTM Gemini laser scanning system from 600 m AGL with a field of view of 26° and a swath width of 320 m. The sensor was pointed in the nadir direction. A side overlap of 55% was used, and the pulse repetition frequency of 125 kHz resulted in an average point density of 11.9 pulses$\cdot$m^{-2}. The original ALS point cloud was normalized using a digital terrain model (DTM) with 1 m resolution that was generated by classifying points as ground or non-ground points, as described by Axelsson (2000). The ALS files were preprocessed to alter the Z value to represent elevation AGL (dZ files). Echoes with AGL heights < 1 m and > 40 m were masked out, because the low echoes were considered to be mainly reflected from the ground and the high ones were considered to be too elevated to represent the vegetation of that area. ALS features as defined by Næsset (2002) were calculated at the plot and grid cell levels using the remaining echoes, the features at the grid cell level being computed over a regular grid of 25 m × 25 m cells covering the entire scanning area (Site I). A summary of the remote sensing material used for Sites I, II and III can be found in Table 2.

Table 2. Remote sensing material for Sites I, II and III.

		Site I	Site II	Site III
Aerial images	Collection date	31 May 2009		June and August 2015
	Camera	Vexcel camera		Vexcel (Denver, CO, USA), Ultra Cam UCXp and S/N UC-SXp
	Flight elevation (m AGL)	7500		5000
	GSD (m)	0.45		0.3
ALS data	Collection date	26 June 2009	2, 3 and 10 July 2016	June and August 2015
	Sensor	Optech ALTM Gemini laser scanning system	Optech Titan sensor on a fixed-wing aircraft	Leica ALS60 SN6114 system (Leica Geosystems AG, Heerbrugg, Switzerland)
	Flight elevation (m AGL)	600	1000	2050
	Pulse repetition frequency (kHz)	125	250	114.6
	Average point density (pulses·m^{-2})	11.9	6.6 (1550 nm channel) 8.0 (1064 nm channel) 3.1 (532 nm channel)	1.8
	DTM resolution (m)	1	0.5	2
	Ground speed (m·s^{-1})		77	160
	Scan angle (°)	26	40	20

Note: AGL: above ground level; GSD: ground sample distance; ALS: airborne laser scanning; DTM: digital terrain model.

The multispectral ALS data for Site II were collected on 2, 3 and 10 July 2016 using an Optech Titan sensor on a fixed-wing aircraft travelling at 1000 m AGL, recording with a strip width of 655 m. The ground speed was 77 m·s^{-1}, the scan angle 40° and the pulse repetition frequency 250 kHz. This Optech Titan sensor has three independent active imaging channels working at wavelengths of 1550, 1064, and 532 nm. The average pulse densities per flight line were 6.6 pulses·m^{-2}, 8.0 pulses·m^{-2} and 3.1 pulses·m^{-2} for these three channels, respectively. The original ALS point cloud was normalized using a DTM with 0.5 m resolution that was built up by classifying points as ground or non-ground points, as explained by Axelsson (2000). After that, the ALS point altitudes (Z) were normalized to altitudes AGL (dZ) using the DTM. We then filtered the point cloud using a height threshold and considered only those points with heights from zero to three metres for the remainder of the analysis.

The ALS data for Site III were collected between June and August 2015 using a Leica ALS60 SN6114 system (Leica Geosystems AG, Heerbrugg, Switzerland) at 2050 m AGL. The ground speed was 160 $m \cdot s^{-1}$, the scan angle 20°, the beam divergence 0.22 mrad (1/e) and the pulse repetition frequency 114.6 kHz. The density of the first-echo pulses was 1.8 hits per m^2. The original ALS point cloud was normalized using a DTM with 2 m resolution and generated by classifying points as ground or non-ground points, as described by Axelsson (2000). The aerial images were obtained within the same time window, using Vexcel (Denver, CO, USA), Ultra Cam UCXp and S/N UC-SXp imaging sensors. The area was covered by 194 images in total. The flying height was 5 km and the GSD approximately 0.3 m. The images were delivered as 16-bit visible light (red, green and blue, RGB) and colour infrared (CIR) composites. In addition, 8-bit orthorectified images were provided by the data vendor (Blom Kartta Oy, Helsinki, Finland).

3 METHODS

3.1 Tree list predictions (Papers I and III)

Tree characteristics were predicted from the stem quality database and ALS data using ABA (Figure 3). The ALS-based estimates provided a full coverage over the target area and a detailed stem quality database was then used to impute stem quality characteristics with additional details (e.g. the presence of surface flaws such as scars or checks and defects such as decay or a broken main crown). The stem quality database contained information which is difficult to measure automatically in an ALS survey or even during standard field sample plot measurement campaigns.

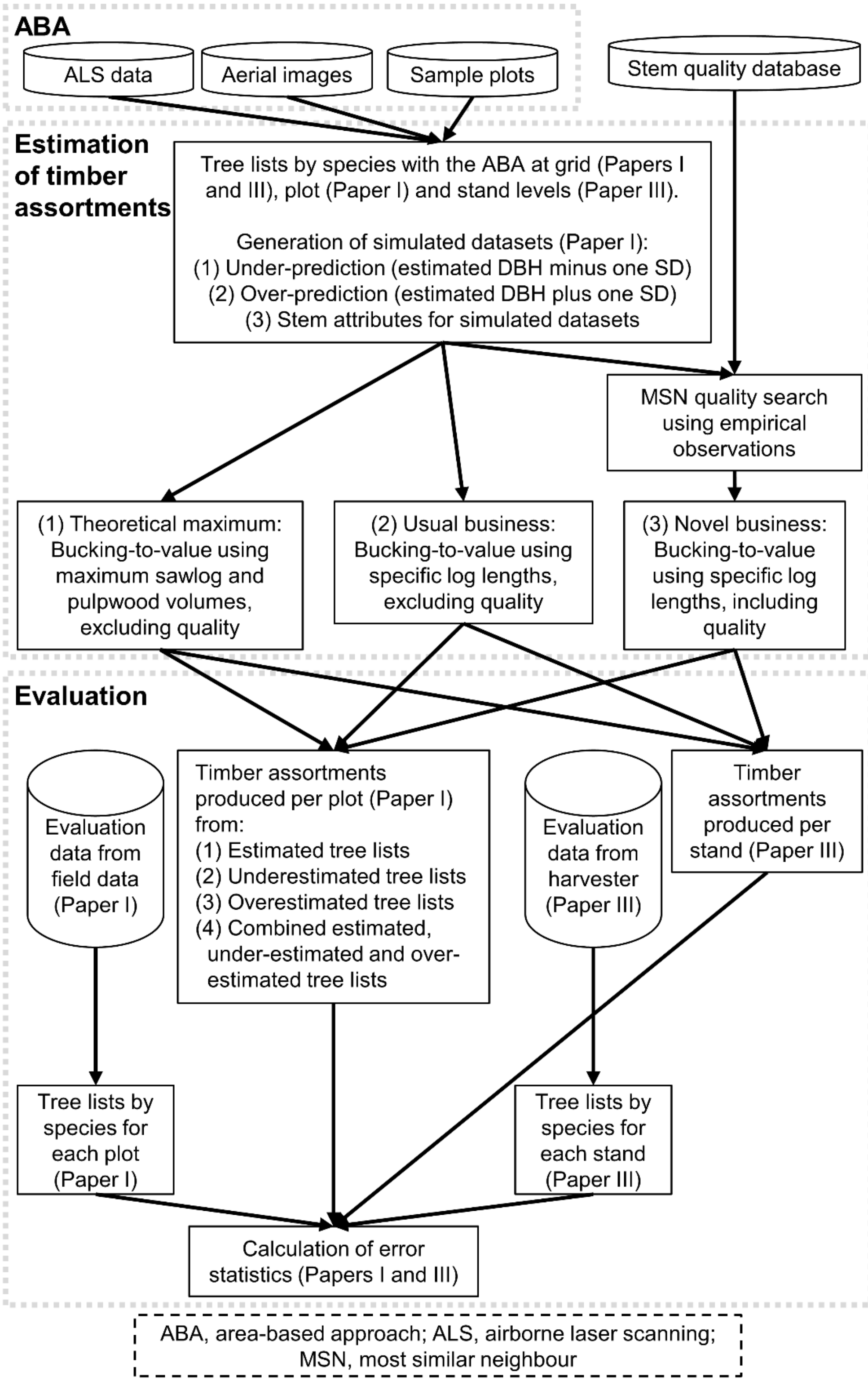

ABA
ALS data
Aerial images
Sample plots
Stem quality database
Estimation of timber assortments
Tree lists by species with the ABA at grid (Papers I and III), plot (Paper I) and stand levels (Paper III).
Generation of simulated datasets (Paper I):
(1) Under-prediction (estimated DBH minus one SD)
(2) Over-prediction (estimated DBH plus one SD)
(3) Stem attributes for simulated datasets
MSN quality search using empirical observations
(1) Theoretical maximum: Bucking-to-value using maximum sawlog and pulpwood volumes, excluding quality
(2) Usual business: Bucking-to-value using specific log lengths, excluding quality
(3) Novel business: Bucking-to-value using specific log lengths, including quality
Evaluation
Evaluation data from field data (Paper I)
Timber assortments produced per plot (Paper I) from:
(1) Estimated tree lists
(2) Underestimated tree lists
(3) Overestimated tree lists
(4) Combined estimated, under-estimated and over-estimated tree lists
Evaluation data from harvester (Paper III)
Timber assortments produced per stand (Paper III)
Tree lists by species for each plot (Paper I)
Tree lists by species for each stand (Paper III)
Calculation of error statistics (Papers I and III)
ABA, area-based approach; ALS, airborne laser scanning; MSN, most similar neighbour

Figure 3 (facing page). Flowchart of the methods followed to obtain the timber assortments and error statistics (Papers I and III).

The ALS data were fused with the aerial image data by the back-projecting ALS method, i.e. every ALS point was combined with the information from unrectified aerial image scenes to avoid geometric errors (see Valbuena et al. 2011). The point cloud data including spectral information from aerial images were then used to derive numerous features for each grid cell describing the height, density and spectral data distributions. The grid size used was 25 m by 25 m cells in Paper I and 16 m by 16 m cells in Paper III. The features were based on those described by Junttila et al. (2010), and included percentiles from the height distribution of both the first and last echo data, the density at given absolute and relative heights, and the mean and SD of the height observations. Linearizing transformations of the features were calculated as well. The spectral distribution features included mean and SD calculated from the spectral distributions of the absolute and relative height thresholds. Spectral distributions were estimated for the red, green and near infrared bands and for the band ratios.

These studies made use of the ABA at grid level through the medium of the ALS data and aerial image data, using the field data as a reference, to estimate tree lists for Scots pine (Papers I and III), Norway spruce and birch (Paper III) (for more details of the ABA, see White et al. 2013; White et al. 2017). The field data used here were derived from 79 sample plots in Paper I and 665 sample plots in Paper III.

The tree lists generated were lists of trees in the area of interest with details of the species, DBH, height and stem volume of each tree. This information was then compressed in the form of tree size distributions presenting the frequencies of trees of a similar size.

The statistical approach used to produce the estimates contained in the tree lists for both of these studies was the *k*-MSN method (Moeur and Stage 1995; Packalén and Maltamo 2007), based on the sample plot data and the ALS data fused with the aerial image data.

First, an initial set of predictor variables explaining the species distribution (percentages of Scots pine, Norway spruce and birch by volume), total volume, total basal area and mean tree size was selected using correlations (of importance for the species) and regression analysis (of importance for the total values). Then a canonical correlation analysis was employed that involved an exhaustive search for the selected initial set of predictor variables, carried out by testing different feature combinations and minimizing the root mean square errors (RMSEs) of the species volumes, basal area and mean tree size. The number of most similar neighbours was set at six in Paper III, which means that every grid cell was allotted to the six most similar sample plots and their MSN weights. Tree lists (also known as stem lists) were predicted for each grid cell and weighted by the average of the trees measured from the six most similar sample plots. In Paper I, the two MSNs were used to estimate the stand density and the single MSN for estimating the DBH and height frequency distributions, in order to avoid averaging between the trees. The information from the predicted tree lists at the grid level was aggregated at the plot level in Paper I and at the stand level in Paper III.

K-MSN imputation produces a tree list with a weight for every tree in the reference data occurring in the plot or stand. For further analyses, each imputed tree list was transformed to a list that contained only complete trees. This was done by means of a sample from the tree lists estimated by the ABA, the stems then being divided into 2 cm diameter classes in Paper I and 1 cm diameter classes in Paper III, weighted by their probability of occurrence and assigned the corresponding number of trees for each diameter class. The stems selected in the sample were identified in terms of species, DBH, height and volume as obtained from the

ABA data (see Figure 3). Two more sets of tree lists were generated in Paper I in order to examine the effect of design bias at the plot level by using under- and over-predictions of one standard deviation (SD) from the estimated DBH (see Figure 3).

3.2 Bucking methods and wood paying capabilities (WPC, Papers I and III)

Two alternative tree lists were available for each stand: one obtained directly from the harvester data and the other based on the ABA (see Figure 3, Paper III). Since tree lists and timber assortments obtained from the harvester data were always used for reference purposes, we set out to compare these two approaches. First, we calculated the differences in the volume estimates between the ABA and harvester data in order to reveal the errors caused by the tree list prediction, and second, we assessed the differences in timber assortments between the ABA and harvester data that were attributable to the tree list prediction and the simulated bucking. In this second case we further evaluated three bucking options for the tree lists: (1) bucking without any reductions due to length requirements or quality (Scenario 1), (2) bucking with reductions due to length requirements (Scenario 2), and (3) bucking with reductions due to length requirements and quality (Scenarios 3 and 4) (see Figure 3 and Table 3). Timber assortments were also calculated in Paper I for these four scenarios, each produced using one of the following data sets: (1) the measured field data, (2) the estimated data, and, when testing for design bias, the tree list generated with either underprediction (3) or overprediction (4) of the estimated DBH by 1 SD.

Table 3. Distinctions between the calculation scenarios for Scots pine (Papers I and III), Norway spruce and birch (Paper III).

	Bucking method	**Timber assortments**	**Quality in-cluded**
Sce-nario 1	Maximum sawlog and pulpwood volumes	Sawlogs Pulpwood	No
Sce-nario 2	Scots pine and Norway spruce: sawlog lengths at 30 cm intervals Birch: veneer logs of lengths 4.7 m, 5.0 m, 6.0 m and 6.7 m	Sawlogs Pulpwood	No
Sce-nario 3	Scots pine and Norway spruce: sawlog lengths at 30 cm intervals Birch: veneer logs of lengths 4.7 m, 5.0 m, 6.0 m and 6.7 m	Sawlogs Pulpwood	Yes
Sce-nario 4	Sawlog lengths at 30 cm intervals	Grade A butt logs (only for Scots pine) Sawlogs Small-diameter logs Pulpwood	Yes

Species-specific taper curve models including DBH and height as the other inputs were used to taper the stems in the tree lists from the harvester data, the field data and the ABA (Laasasenaho 1982). When quality was not considered, the bucking-to-value simulator used the tapering of the stems, the tree species and the species-wise bucking objectives, whereas when quality was taken into account, the same simulator employed external quality expressed in terms of vertical stem sections fulfilling different timber assortment quality requirements as specified by the Finnish forest companies (Malinen et al. 2018a). The external quality that affected bucking was estimated in Scenarios 3 and 4, in which a stem quality database was used with the MSN method (Malinen et al. 2014; Malinen et al. 2018a) (see Figure 3). For these two scenarios, technical defects in the target stems were estimated by selecting the most similar stem from the quality database in terms of the stand variables, DBH and height of the stem. The stem quality database contained over 13 000 trees measured for dimensions and evaluated for stem quality (Malinen et al. 2014). The quality assessment was based on visual estimation of the occurrence of technical defects (forks, knots, crooks, scars, sweeps, branchiness, etc.). The database was compiled for various research projects at the Finnish

Forest Research Institute between 1998 and 2010 (for a more detailed description and the geographical coverage of the database, see Table 1 and Malinen et al. 2018a).

The minimum top-end diameters and minimum and maximum lengths used in the bucking were as presented in Table 4, and the taper curve models of Laasasenaho (1982) were used to determine the theoretical sawlog volume, which is the stem volume exceeding the minimum diameter, considering minimum diameters of 15, 16 and 18 cm for Scots pine, Norway spruce and birch, respectively, and minimum lengths of 3.7 m for Scots pine and Norway spruce and 4.7 m for birch.

The unit prices for the TAVs for Scots pine in Paper I were EUR 58$\cdot$m^{-3} for grade A butt logs, EUR 55$\cdot$m^{-3} for other sawlogs, EUR 25$\cdot$m^{-3} for small-diameter logs, and EUR 17$\cdot$m^{-3} for pulpwood. The corresponding unit prices for the TAVs in Paper III were EUR 67$\cdot$m^{-3} for Scots pine grade A butt logs, EUR 67$\cdot$m^{-3} for Norway spruce sawlogs, EUR 64$\cdot$m^{-3} for Scots pine sawlogs, EUR 45$\cdot$m^{-3} for birch sawlogs, EUR 33$\cdot$m^{-3} for Norway spruce small-diameter logs, EUR 29$\cdot$m^{-3} for Scots pine small-diameter logs, EUR 22$\cdot$m^{-3} for Norway spruce pulpwood, EUR 20$\cdot$m^{-3} for Scots pine pulpwood, and EUR 19$\cdot$m^{-3} for birch pulpwood. These were typical stumpage prices paid in Finland in week 4 of 2017 (Paper I) and in week 16 of 2021 (Paper III) (Metsäkustannus Oy 2021). The total volumes were solid volumes over bark calculated from the stump to the top of the stem.

Table 4. Minimum and maximum parameters used in bucking for Scots pine (Papers I and III), Norway spruce and birch (Paper III).

		Minimum diameter (cm)	Mini-mum length (m)	Maxi-mum length (m)	Mini-mum WPC (EUR·m^{-3})	Maxi-mum WPC (EUR·m^{-3})
Scots pine	Grade A butt logs	21.0	2.8	6.1	68	129
	Sawlogs	15.0	3.7	5.8	57	98
	Small-diameter logs	12.0	3.1	4.0	28	65
	Pulpwood	7.0	2.8	5.2	17	17
Norway spruce	Sawlogs	16.0	3.7	6.1	62	98
	Small-diameter logs	12.0	2.8	4.9	31	65
	Pulpwood	7.0	2.8	5.2	26	26
Birch	Sawlogs	18.0	4.7	6.7	55	65
	Pulpwood	7.0	2.8	6.1	17	17

Note: The wood paying capability (WPC) values shown here are the ones used in Paper III.

The WPC figures used in bucking can be defined as the residual values that a purchaser can pay for wood when all the other costs are deducted from the sales price (Paavilainen 2002). We calculated the WPC for each plot (Paper I) and stand (Paper III) as the value divided by the volume obtained with the bucking-to-value simulator. It should be noted that WPC is size-dependent (given that larger logs are generally more valuable) and depicts the range in which values may vary (see Table 4).

The RMSE, relative RMSE (RMSE%), bias, relative bias (bias%) and SD of the difference between the measured and estimated values were calculated for the timber assortments to compare the volumes, WPC results and values obtained for the estimated data with those for the reference data. The RMSE and RMSE% were used to assess the accuracy of the various methods relative to the reference:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{j=1}^{n}(y_{ij} - \hat{y}_{ij})2}{\mathrm{n}}} \quad (1)$$

$$\mathrm{RMSE\%} = \frac{RMSE}{\bar{y}_i} \times 100 \quad (2)$$

where y_{ij} is the reference value of variable *i* in stand *j*, $\hat{y}_{ij}$ is the estimated value of variable *i* in stand *j*, $\bar{y}_i$ is the average of the reference values for variable *i* and n is the number of observations.

The bias and bias% of the estimates were calculated as follows:

$$\text{Bias} = \frac{\sum_{j=1}^{n}(y_{ij} - \hat{y}_{ij})}{n} \tag{3}$$

$$\text{Bias\%} = \frac{\text{Bias}}{\bar{y}_i} \times 100 \tag{4}$$

3.3 Evaluation of the need for pre-harvest clearing (Paper II)

The procedure for estimating the need for pre-harvest clearing using the ALS data required the following steps: (1) pre-processing of the point cloud, (2) calculation of height statistics for the voxels and prediction of the need for pre-harvest clearing, and (3) definition of the operational needs for pre-harvest clearing using the results obtained from the model. We used two alternative concepts to determine the need for pre-harvest clearing, the first relying on the operators' opinions (five and three classes) and the second on predicting the number of stems in the understorey vegetation and applying the rules developed in the forest industry.

In the first approach, the classes of need for pre-harvest clearing were based on the e-questionnaire survey. The average value for each plot was calculated as the nearest integer to the average for all the answers (from one to five) within the plot. After that, the 99 plots were divided into the five classes based on the average value per plot. To calculate the variation in the forest professionals' perceptions within the class represented by each average value, the numbers of observations with an answer equal to one, two, three, four, or five were divided separately by the total number of observations with an answer equal to the average value for the class. The e-questionnaire was used to classify each plot into one of five classes, but if we assume that three classes are enough for operational decision-making, we can combine some of the classes. The original classes one and two, for example, both indicate a low need and can just as well be combined, class three is evidently an uncertain class, but the original classes four and five represent a distinct need for pre-harvest clearing. Thus we have three new classes, where class one indicates little need for pre-harvest clearing, class two an uncertain need and class three an evident need.

For an in-depth description of the vegetation structure, as illustrated in Figure 4, we constructed voxels with a base of 1.5 m by 1.5 m and a height of 1.5 m or 3 m around the centre of each sample plot. This left us with 72 voxels that were fully contained within the 5 m radius data for the plots (i.e. 24 in the XY direction by 3 in the Z direction) for each plot for which the ALS features were calculated. For this purpose the ALS points were split geometrically by voxels, and the ALS data from the three channels were used together to estimate the need for pre-harvest clearing. The density (i.e. the number of ALS points) and the maximum, minimum, mean, SD, skewness and kurtosis of the density per plot and per voxel were calculated from the ALS data.

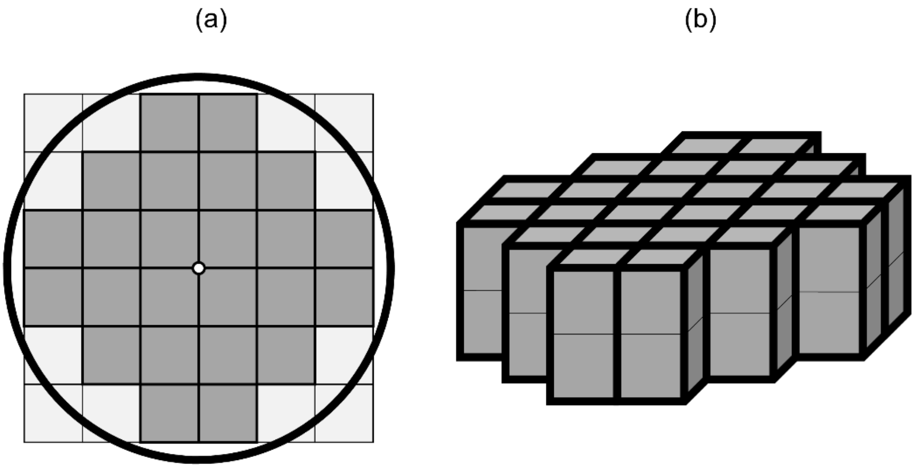


Figure 4. (a) 2-dimensional distribution of the voxels (dark grey) in a circular plot of radius five metres (black circle). The size of each voxel was 1.5 m × 1.5 m. (b) 3-dimensional distribution of the same voxels. The size of each voxel was 1.5 m × 1.5 m × 1.5 m or 1.5 m × 1.5 m × 3 m.

A linear discriminant analysis (LDA) with cross-validation was carried out using the ALS density distribution statistics of the voxels as predictor variables and the mean values of all the answers per plot regarding the need for pre-harvest clearing (five classes) according to the e-questionnaire survey data as response variables (professionals' opinions). When five classes were employed, the LDA used the mean values from the survey data per plot as response variables and the following ALS density distribution statistics for the voxels as predictor variables: $N_{P0–1.5}$, $Max_{V0–1.5}$, $Max_{V1.5–3}$, $Max_{V0–3}$, $Mean_{V0–3}$, $SD_{V0–1.5}$, $SD_{V1.5–3}$, $SD_{V0–3}$, $Skew_{V1.5–3}$, $Skew_{V0–3}$, $Kurt_{V0–1.5}$, $Kurt_{V1.5–3}$ and $Kurt_{V0–3}$. Where P, plot; V, voxel; 0–1.5, heights from zero to 1.5 metres; 1.5–3, heights from 1.5 to three metres; 0–3, heights from zero to three metres; N, point density; Max, maximum; Mean, mean; SD, standard deviation; Skew, skewness; Kurt, kurtosis. The predicted classes were evaluated in terms of the overall accuracy and the kappa index.

For the second approach, the needs for pre-harvest clearing were estimated based on the understorey tree density, the features measured in the field being separately related to the e-questionnaire survey results and to the ALS-derived features. On the other hand, the understorey densities of the trees with $N_{DBH1–7}$ were compared with the mean of the answers given in the e-questionnaire and a linear model was formulated to predict the density of the corresponding trees. The density distribution statistics from the ALS data presented earlier were used as predictor variables in this model and the densities of trees with $N_{DBH1–7}$ were used as response variables. Stepwise variable selection criteria were used to define independent variables. The continuous variables were evaluated using the coefficient of determination and the RMSE.

We concluded the study with a determination of the need for pre-harvest clearing based on the number of understorey trees by comparing the predicted understorey tree densities with the need for pre-harvest clearing as stated by the forest professionals. First, we divided the plots into the three classes presented above from the e-questionnaire survey results. Second, we performed a LDA using the understorey densities of the stems as measured in the field, with $N_{DBH1–7}$ as predictor variables and the three classes from the e-questionnaire survey data as response variables. Third, we predicted the three classes from this LDA and the number of stems with $N_{DBH1–7}$ estimated from regression model 1.

4 RESULTS

4.1 Volume, value and wood paying capability (WPC) estimates by timber assortments (Papers I and III)

The RMSE% of the bucking estimates for sawlog volume when quality estimation was included (Scenario 3) was 11.2 percentage points (pp) higher than when quality was not considered (Scenario 2) and 12.2 pp higher for sawlog value. In the case of the estimates for both pulpwood volume and value, the RMSE% when considering quality (Scenario 3) was 6.0 pp higher than when the bucking estimates were based only on dimensions (Scenario 2). Use of the bucking objectives reduced the sawlog volume by 1.0%. The bucking estimates based on dimensions and external quality (Scenario 3) produced 30.0% less sawlog volume and 30.9% less sawlog value than those based only on dimensions (Scenario 2). Due to the lower small-end diameter requirements of small-diameter logs, the total volume of all sawlog assortments combined (i.e. the sum of the volumes of grade A butt logs, sawlogs and small-diameter logs in Scenario 4) was 25.4% higher than the sawlog volume based on external quality without grade A butt logs and small-diameter logs (i.e. the sawlog volume in Scenario 3). In the same way as for volume, the total value of the combined sawlog assortments (Scenario 4) was 22.5% higher than the sawlog value based on external quality without grade A butt logs and small-diameter logs (Scenario 3). Prediction error statistics for WPC with respect to the various timber assortments are shown in Table 5 (Paper I).

Table 5. Wood paying capability estimates for the timber assortments and their error statistics at the plot level (79 plots, Paper I) and at the stand level (249 stands, Paper III).

	Paper I				**Paper III**						
	Scots pine (*Pinus sylvestris*)				**Norway spruce (*Picea abies*)**			**Scots pine (*Pinus sylvestris*)**			
	Scenario 2	Scenario 3	Scenario 4		Scenario 2	Scenario 3	Scenario 4	Scenario 2	Scenario 3	Scenario 4	
Total											
Average WPC based on ABA data (EUR·m^{-3})	47.9	36.1	42.3		63.3	61.5	62.9	61.1	51.3	59.6	
RMSE%	48.2	47.9	44.4		25.7	24.8	24.1	62.7	64.4	66.1	
Bias (EUR·m^{-3})	−6.5	−3.2	−2.8		4.6	4.0	3.7	−9.0	−8.5	−11.1	
SD (EUR·m^{-3})	12.1	9.0	10.2		16.9	15.8	15.7	31.5	26.3	30.1	
Sawlogs											
Average WPC based on ABA data (EUR·m^{-3})	74.7	73.5	75.2		79.5	79.2	79.4	72.3	70.2	69.0	
RMSE%	38.5	44.2	52.1		28.7	29.0	29.0	66.0	65.5	68.7	
Bias (EUR·m^{-3})	−6.2	−6.8	−5.3		3.4	3.3	3.3	−13.5	−13.1	−13.8	
SD (EUR·m^{-3})	3.2	3.5	3.2		23.6	23.7	23.9	36.5	35.1	35.4	
Pulpwood											
Average WPC based on ABA data (EUR·m^{-3})	17.0	17.0	17.0		25.2	25.2	25.2	15.6	15.6	15.6	
RMSE%	32.7	32.7	32.7		19.3	19.3	19.3	63.7	63.7	63.7	
Bias (EUR·m^{-3})	−1.1	−1.1	−1.1		0.5	0.5	0.5	−2.8	−2.8	−2.8	
SD (EUR·m^{-3})	0.0	0.0	0.0		4.9	4.9	4.9	7.7	7.7	7.7	
Grade A butt logs (1) or small-diameter logs (2)			**(1)**	**(2)**			**(2)**			**(1)**	**(2)**
Average WPC based on ABA data (EUR·m^{-3})			103.1	53.8			35.9			93.6	46.9
RMSE%			137.5	41.7			22.3			75.5	75.8
Bias (EUR·m^{-3})			15.3	−4.8			0.6			−21.1	−10.9
SD (EUR·m^{-3})			7.3	3.1			8.1			50.6	25.1

Note: WPC: wood paying capability; ABA: area-based approach; RMSE%: relative root mean square error; SD: standard deviation.

Regarding the effect of design bias at the plot level on volumes, values and WPC in Paper I, when quality estimation was excluded, the bias for volumes and values was negative for sawlogs but positive for pulpwood, whereas when quality estimation was included it was negative for both sawlogs and pulpwood. When quality estimation was included the RMSE% of the bucking estimates for the differences between the field data and the combined data for the underestimated (tree lists with the estimated DBH minus SD), overestimated (tree lists with the estimated DBH plus SD) and estimated results (combined data) was 2.5 pp lower than the RMSE% of the bucking estimates for the differences between the field data and the estimated data (uncombined data) for sawlog volume, and 3.4 pp lower for sawlog value. When only dimensions were considered, the RMSE% was 5.9 pp higher for the combined data than for the uncombined data where sawlog volume was concerned and 7.6 pp higher for sawlog value. Inclusion of the quality estimate for pulpwood did not change the RMSE% for volume and value with respect to the bucking estimate obtained only with dimensions, the RMSE% of the combined data being 11.8 pp higher than that of the uncombined data for the bucking estimate including quality and 6.2 pp higher for the bucking estimate obtained using only dimensions.

The RMSE% values of the bucking estimates for sawlog volume for Norway spruce, Scots pine and birch were 0.2 pp lower, 0.7 pp lower and 12.9 pp higher, respectively, when considering quality (Scenario 3) than when quality was not considered (Scenario 2). In the case of pulpwood volume, the RMSE% values of the bucking estimates were 1.3 pp lower, 49.7 pp lower and 1.0 pp higher, respectively, for the same species when quality was also estimated (Scenario 3) than when it was not considered (Scenario 2). The bucking predictions reduced the total volume most in the case of Scots pine (28.6% in the harvester data and 11.8% in the ABA data) and least in the case of Norway spruce (6.9% in the harvester data and 5.7% in the ABA data). Use of the bucking objectives reduced the sawlog volume for Norway spruce, Scots pine and birch by 4.1%, 0.9% and 22.9%, respectively, in the harvester data, and 5.0%, 1.1% and 26.7%, respectively, in the ABA data. The differences in WPC estimates are shown in Table 5 (Paper III).

The residual errors in the TAVs obtained for Scots pine (Papers I and III), Norway spruce and birch (Paper III) and in the values for the various scenarios are shown in Figures 5 (Paper I) and 6 (Paper III). Figures 5a and 5b show that the residual errors for Scots pine decreased as the sawlog volume and value increased. They also show that pulpwood follows a similar trend to that seen in sawlogs, but the residual errors were larger, especially for pulpwood value. In the same way, Figures 6c and 6d show that the residual errors for Scots pine decreased as the sawlog volume and its value increased. Norway spruce followed a similar trend, although in this case there were few stands with high residual errors for large volumes and values (Figures 6a and 6b). The most scatter residuals for both volume and its value occurred in the case of birch (Figures 6e and 6f).

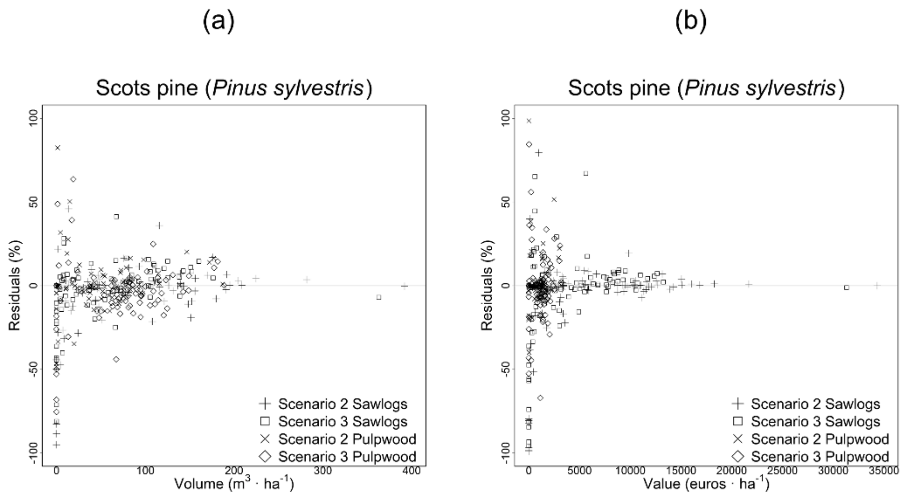
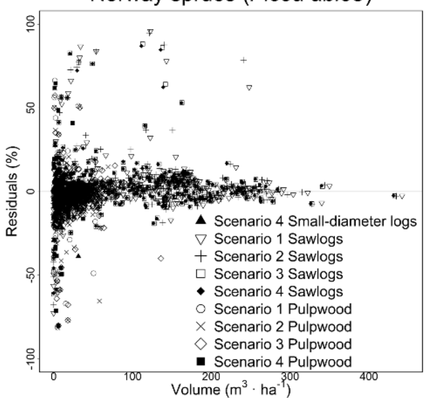


Figure 5. Residual errors for the timber assortment volumes (TAVs) (a) and values (b) for Scots pine (Paper I).

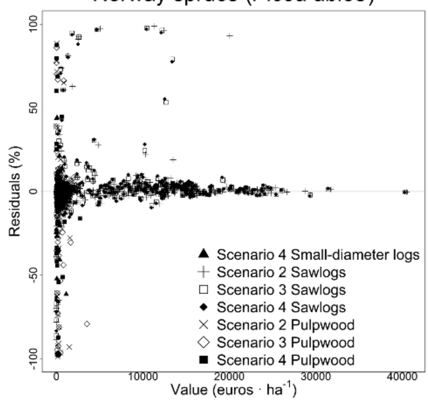
(a)

Norway spruce (*Picea abies*)



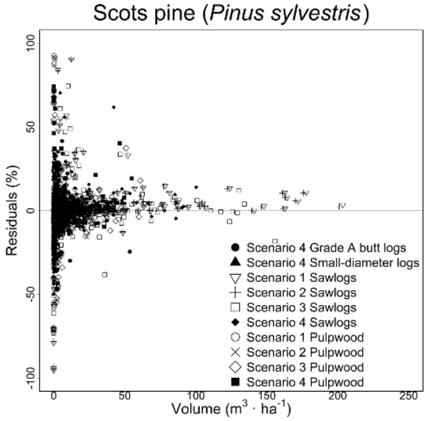
(b)

Norway spruce (*Picea abies*)



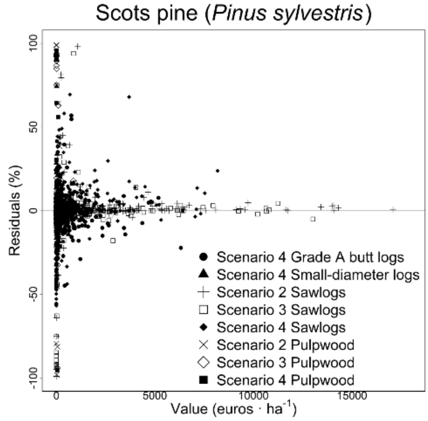
(c)

Scots pine (*Pinus sylvestris*)



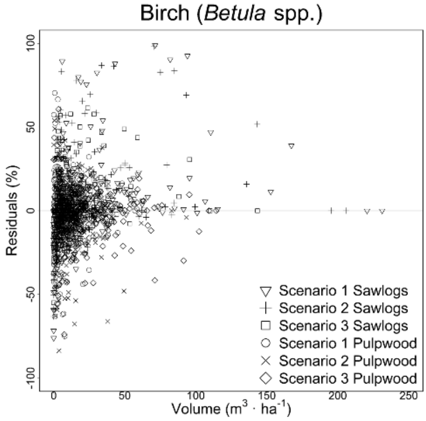
(d)

Scots pine (*Pinus sylvestris*)



(e)

Birch (*Betula* spp.)



(f)

Birch (*Betula* spp.)

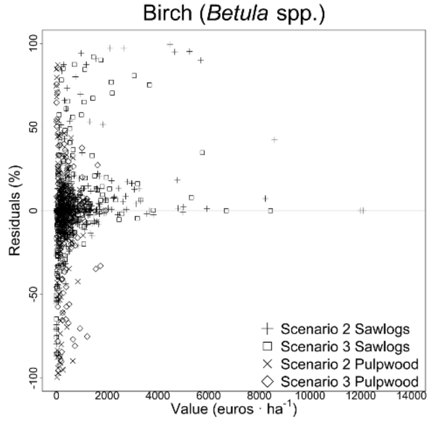


Figure 6 (facing page). Residual errors for the timber assortment volumes (TAVs) for Norway spruce (a), Scots pine (c) and birch (e), and values for Norway spruce (b), Scots pine (d) and birch (f) (Paper III).

4.2 Estimated need for pre-harvest clearing (Paper II)

It was noticeable that the perceived need for pre-harvest clearing varied between the professionals. Classes one and five showed a high level of agreement among them (87.9% and 76.8%, respectively), but in the case of classes two, three and four about 30% of the professionals were in agreement with the average value. On the other hand, 91.2% of the respondents' perceptions were within one class of the average value. The understorey tree density was shown to correlate with the forest professionals' opinions given in the e-questionnaire (Figure 7a) and with the ALS data (Figure 7b).

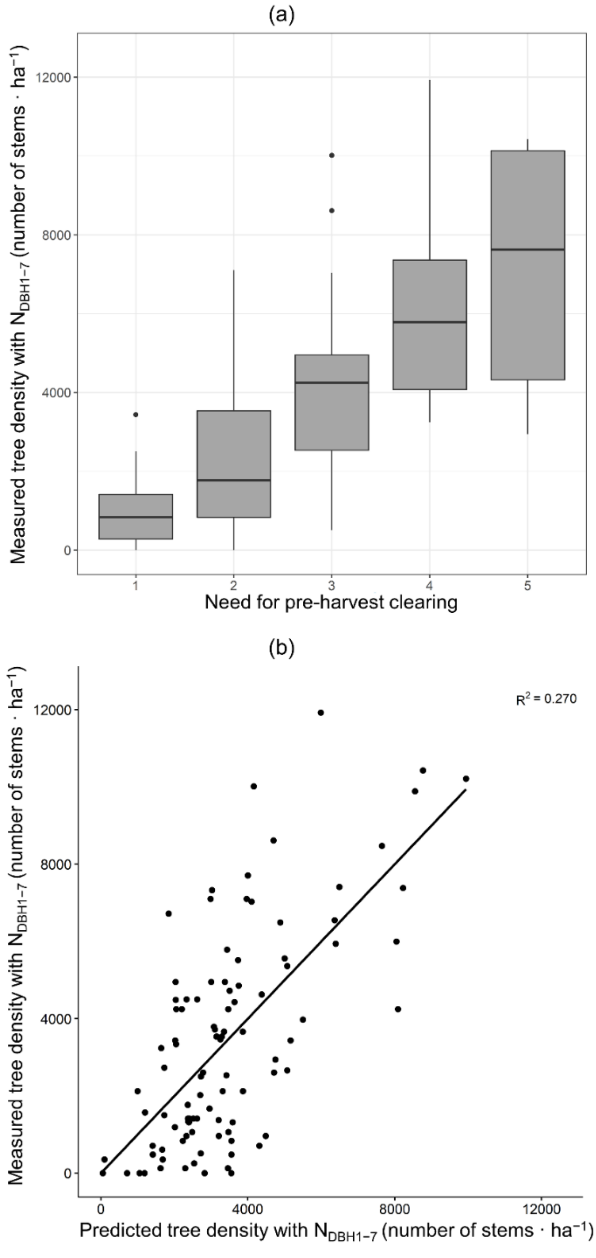


Figure 7. (a) Box plots of the measured understorey tree densities (trees with diameters at breast height from one to seven centimetres, $N_{DBH1–7}$) versus the need for pre-harvest clearing, based on the answers given in the e-questionnaire: 1, no need for pre-harvest clearing; 2, pre-harvest clearing would help harvesting; 3, pre-harvest clearing recommended; 4, a great need for pre-harvest clearing; 5, compulsory pre-harvest clearing. (b) Measured densities of trees with $N_{DBH1–7}$ versus densities of trees with $N_{DBH1–7}$ as predicted by model 1. The solid line is a regression line.

To evaluate the need for pre-harvest clearing, the first approach used a LDA with cross-validation to predict this need (in five or three classes) within the plots from the ALS density distribution statistics for the voxels. When three classes were considered (Table 6), the LDA predicted them with 63.6% accuracy. This LDA used the mean values from the e-questionnaire survey data per plot as a response variable and the next ALS density distribution statistics of the voxels as predictor variables: $N_{P0–1.5}$, $Max_{V0–1.5}$, $Max_{V1.5–3}$, $Max_{V0–3}$, $Min_{V0–3}$, $SD_{V0–1.5}$, $SD_{V1.5–3}$, $SD_{V0–3}$, $Skew_{V1.5–3}$, $Skew_{V0–3}$, $Kurt_{V0–1.5}$, $Kurt_{V1.5–3}$ and $Kurt_{V0–3}$, where Min = minimum. Little need for pre-harvest clearing (class one) was the best-predicted class, with an accuracy of 81.6%, whereas the accuracy was 40.0% when the need was uncertain (class two) and 52.0% when it was evident (class three).

Table 6. Need for pre-harvest clearing of understorey trees in three classes based on the e-questionnaire survey mean field data values versus values estimated from (1) the airborne laser scanning (ALS) linear discriminant analysis (LDA) or from (2) the ALS model 1 and field data-based LDA classes.

(1) ALS LDA						(2) ALS model 1 and field data-based LDA classes					
	Field data values						**Field data values**				
	1	**2**	**3**	**To-tal**	**Accu-racy (%)**		**1**	**2**	**3**	**To-tal**	**Accu-racy (%)**
Esti-mated values from (1)						Esti-mated values from (2)					
1	40	14	8	62	64.5	1	46	16	13	75	61.3
2	6	10	4	20	50.0	2	2	8	2	12	66.7
3	3	1	13	17	76.5	3	1	1	10	12	83.3
Total	49	25	25	99		Total	49	25	25	99	
Accu-racy (%)	81.6	40.0	52.0			Accu-racy (%)	93.9	32.0	40.0		

The classes are: 1, little need for pre-harvest clearing; 2, uncertain need for pre-harvest clearing; 3, evident need for pre-harvest clearing. Overall accuracy (1): 63.6%. Cohen kappa (1): 0.39. Weighted kappa (1): 0.47. Overall accuracy (2): 64.6%. Cohen kappa (2): 0.37. Weighted kappa (2): 0.41.

The second approach used a linear model to predict the number of trees within the diameter range from one to seven centimetres ($N_{DBH1–7}$, model 1). This was:

$$N_{DBH1–7} = 2102.343 - 451.017 \times N_{P1.5–3} - 230.582 \times Max_{V0–1.5} + 625.300 \times Max_{V1.5–3} + 207.317 \times Max_{V0–3} - 210.453 \times Mean_{V0–1.5} + 12992.500 \times Mean_{V1.5–3} + 1425.248 \times SD_{V0–1.5} - 3099.624 \times SD_{V1.5–3} - 1131.531 \times SD_{V0–3} - 2283.163 \times Skew_{V0–1.5} + 1953.650 \times Skew_{V1.5–3} + 1753.099 \times Kurt_{V0–1.5} - 450.967 \times Kurt_{V1.5–3} - 971.578 \times Kurt_{V0–3} \quad (5)$$

The 5-fold cross-validation-based relative RMSE of model 1 was 75.8%, the residual standard error 2620 stems·ha^{-1}, and the adjusted coefficient of determination 0.270. In order to determine the need for pre-harvest clearing based on the understorey tree density, the trees used for prediction with regression model 1, $N_{DBH1–7}$, were assigned to three classes using field data-based LDA classes. Model 1 determined the need for pre-harvest clearing with an accuracy of 64.6% (Table 6).

5 DISCUSSION

5.1. General

This thesis was aimed at understanding and supporting wood procurement practices, with the expectation of making timber markets more efficient by supplying each user with more suitable timber for processing. The focus of Papers I and III was on introducing a method for measuring timber volume, its value and the WPC by timber assortments for Scots pine (Papers I and III) and also Norway spruce and birch (Paper III). On the other hand, the idea of Paper II was to facilitate assessment of the need for pre-harvest clearing, which is required when forest stands have an understorey vegetation that hampers harvesting operations.

Many forest companies have distinct guidelines for the pre-harvest clearing of understorey vegetation, but the need for this and its assessment are considered controversial for a number of reasons. Studies differ in the size of the understorey, the proportions of the various tree species in it, the working methods of the harvester operator, the harvesting machinery used, the time interval between pre-clearance and harvesting and the seasons when the various operations are carried out (Kärhä 2006). In any case, it is important to note that the understorey trees that are located between the machine and the stem to be harvested will more probably hinder the operator’s visibility and the movement of the harvester head than any other understorey trees (Kärhä 2006).

There are many reasons why different species are used for particular products and this affects how they are traded. Grade A butt logs represent a branchless grade, but Norway spruces have branches all the way down. Veneers can be fabricated from high quality spruce butt logs, but these are often traded at the same price as sawlogs. Norway spruces are not used for poles, since poles are impregnated and Norway spruce is unsuitable for this. There are only a few small sawmills in Finland that deal in birch, so birch sawlogs are almost entirely veneer logs, but for simplicity these are referred to here as sawlogs. It is for this reason that the lengths of veneer logs differ from the actual sawlog lengths (multiple veneer logs are obtained according to the width of the lathe). Residual wood is woody biomass which can be collected for energy use or left in the forest to decay and fertilize the next generation of trees, thereby increasing biodiversity.

5.2. Estimates by tree species (Papers I and III)

In Paper I, some of the bucking results for maximum theoretical sawlog volumes excluding quality estimation (Scenario 1) and for sawlog and pulpwood volumes excluding quality estimation (Scenario 2) are alike, and the RMSE% results for volumes and values are quite similar. This is partially caused by the fact that the value estimate is a weighted version of the volume estimate (calculated by multiplying the volume by the unit prices for the TAV). The RMSE% becomes slightly higher if quality estimation is considered. In the approach that considers four timber assortments (Scenario 4), the bucking objectives included grade A butt logs and small-diameter sawlogs in addition to conventional sawlogs and pulpwood, and the more complicated bucking objectives certainly introduce some error into the estimates. On the other hand, raising the number of timber assortments increased the weighting on external quality. The RMSE% values show that the variables used are quite efficient in predicting dimensions but slightly less so in predicting log quality. On the other hand, the estimates that take account of quality include additional usable information for the decision-maker, even though their predictive ability is poorer. The estimates are more robust for pulpwood than for sawlogs (the errors are smaller), but RMSE% increases progressively as we introduce (1) bucking, (2) quality and (3) assortments. The method presented here allows the recognition of grade A butt logs, the value of which is high, thus increasing the value and WPC of this timber assortment, but it underestimates sawlogs and overestimates pulpwood when quality is not an issue and underestimates both when quality is considered. It thus provides a conservative estimate for the total value of the stand. The stem quality database had been collected from a large geographical area, of which the test site was a rather small part. Thus a small-area approach of this kind is evidently more sensitive to local differences.

In Paper III the bucking of maximum sawlog and pulpwood volumes excluding quality estimation (Scenario 1) and of all sawlog and pulpwood volumes excluding quality estimation (Scenario 2) also had similar outcomes. Overall, it can be deduced from the RMSE% values that the combination of a *k*-MSN search (in the existing stem quality database) and the ALS data presented here can be used to predict both dimensions and log quality. It is also the case that the RMSE% values for both Norway spruce and Scots pine are smaller for sawlogs than for pulpwood volumes, whereas the RMSE% values for birch are slightly larger for sawlogs than for pulpwood volumes. When three or four timber assortments were considered (Scenario 4), the bucking of grade A butt log volumes (for Scots pine) and small-diameter log volumes (for Scots pine and Norway spruce) produced larger RMSE% values than the bucking of sawlog volumes. In this context it seems that our approach can help to locate the stands that are likely to be more valuable and have the desired timber assortment distributions.

For all the timber assortments (i.e. grade A butt logs, sawlogs, small-diameter logs and pulpwood) and all three tree species (Norway spruce, Scots pine and birch) the RMSE% values for the WPC were smaller than those for the volume. The probable reason for this is that while the volume of each timber assortment is only influenced by the proportion of that timber assortment per unit volume, the WPC is affected by the size of the logs as well (i.e. large logs from overstorey trees are usually more valuable than small logs from understorey ones). However, even though understorey trees are less valuable, the commercial value of timber stands is substantially affected by the amount of these understorey trees (Paper II).

Hou et al. (2016) estimated the ABA-derived diameter distribution in the same forest area that was used for Paper I but without applying any species identification procedure in *k*-MSN, and obtained the following RMSE% results for total, sawlog and pulpwood volumes, respectively: ~35%, ~40% and ~65% for Scots pine, ~90%, ~85% and ~190% for Norway spruce, and ~180%, ~230% and ~215% for deciduous species. When predicting DBH distributions in this way, they set $k = 3$ and used 1 cm DBH classes. In our case k was set to 1 to avoid averaging between trees and 2 cm DBH classes were used to ensure continuous DBH distributions with a relatively small number of trees per plot. More accurate estimates of DBH distributions could be achieved by examining more sample plots. The standard operational ALS data processing method was used in this study, and the approach presented by Hou et al. (2016) could slightly improve the results. The forest concerned (Site I) is predominantly Scots pine and is a good area for studying the effect of using diameter distributions and product yield simulations, as the role of tree species is minimized, even though it is still present to some extent.

Other studies have similarly estimated TAVs. Holopainen et al. (2010); Siipilehto et al. (2016); Vähä-Konka et al. (2020), and the present authors (in Papers I and III), for example, used an ABA based on ALS data to assess the amount of harvestable timber and its value, whereas Malinen et al. (2014) used non-parametric estimation and a decision support tool employing empirical data from sample plots. Holopainen et al. (2010) reported RMSE% results of 79.2% for sawlog volume and 167.6% for pulpwood volume in the case of Scots pine, 33.6% for sawlog volume and 46.7% for pulpwood volume where Norway spruce was concerned, and 78.6% for sawlog volume and 218.5% for pulpwood volume in birch, while Siipilehto et al. (2016) obtained RMSE% values of 41.1% for total volume, 40.1% for sawlog volume, and 52.8% for pulpwood volume when studying Scots pine. Likewise Vähä-Konka et al. (2020) reported RMSE% values of 67.1% for sawlogs and 107.1% for pulpwood in Scots pine, 48.6% for sawlogs and 54.8% for pulpwood in Norway spruce, and 169.8% for sawlogs and 97.7% for pulpwood in the case of deciduous trees (mainly birch). In Paper I we reported RMSE% results of 52.0% for total volume, 209.5% for grade A butt logs, 89.9% for sawlogs, 42.8% for small-diameter logs and 49.4% for pulpwood in Scots pine, whereas in Paper III we obtained 162.0% for grade A butt logs, 152.1% for sawlogs, 206.8% for small-diameter logs and 163.1% for pulpwood in Scots pine, 42.5% for sawlogs, 66.4% for small-diameter logs and 64.4% for pulpwood in Norway spruce, and 157.1% for sawlogs, and 89.5% for pulpwood in birch. By contrast, Malinen et al. (2014) reported RMSE% values of 6.7% for grade A butt logs, 7.1% for sawlogs, 2.5% for small-diameter logs and 7.1% for pulpwood when considering both Scots pine and Norway spruce.

5.3. Need for pre-harvest clearing (Paper II)

When predicting the number of understorey trees with $N_{DBH1–7}$ with regression model 1 using the ABA, we recorded a relative error of 75.8%, which is not directly sufficient for decision making. However, when the estimates were converted to the three classes used in that decision making the accuracy of the classification was reasonable (64.6%). Other researchers who have estimated the understorey vegetation by means of ALS data have reported that the species, height and crown shape of the neighbouring tall trees had a great influence on the rate of detection of the suppressed trees (Wang et al. 2016). Point density also decreased in the lower canopy layers, depending significantly on the number of layers (Hamraz et al. 2017), the results being typically affected by variation in the tree size structure. Su and Bork (2007) used an average density of 0.54 pulses·m^{-2} and were not able to estimate the understorey vegetation cover and height precisely. When pulse densities between one and 10 per m^{-2} were used the variation in the identification rate was 38–70% for intermediate trees and 14–30% for suppressed trees (Solberg et al. 2006; Ferraz et al. 2012; Wang et al. 2016). Several authors have also used average densities between 10 and 20 pulses·m^{-2}. Maltamo et al. (2004) detected less than 40% of the understorey trees, and Maltamo et al. (2005) succeeded in predicting the density and height of understorey trees with regression models that had coefficients of determination of 0.87 for density and 0.76 for height. Vega et al. (2014) detected 41%, 42% and 50% of the non-dominant trees in three forest types, while Paris et al. (2016) detected 71.8% of the understorey trees. When a very high density of 50 pulses·m^{-2} was employed it was possible to detect 68% of the understorey trees (Hamraz et al. 2017). In addition, Duncanson et al. (2014) used a very high pulse density with detection rates of 35% for intermediate trees and 21% for suppressed trees.

The results show that the stem number-based approach differs slightly from direct estimates of the need for pre-harvest clearing. Both can be used to support forest operations, but direct need-based estimation (LDA) should cover all the aspects that are of importance for operators, while the stem number-based approach requires clear criteria and should be tested further. Here the understorey density was estimated with the latter approach for trees with $N_{DBH1–7}$ (model 1). The regression model might have been overfitted, but the forest structure in Finland is very heterogeneous and visibility below the main canopy layer requires detailed information from various height zones. Further studies are needed to assess the usefulness of optimized and stable biometric models for this purpose. Both approaches estimated the need for pre-harvest clearing with an accuracy of 64% when three classes were considered and 5-fold cross-validation was used without an independent dataset. The method will need to be tested with different forest structures and datasets in the future.

LDA can be used directly when taking forest management decisions, and likewise, regression model 1 could be employed directly for decision making if we had clear criteria for determining the amount of interference from the understorey vegetation. In this case, however, our material did not include many dense stands. Kärhä (2015) states that in operational forestry the cutting work is hindered when the understorey of more than 1.5 m in height exceeds 1100–2000 stems·ha^{-1}, so that pre-clearance should be carried out in such cases. On the other hand, Bergström et al. (2016), evaluating the effects of the density of the understorey on the operational efficiency of a bundle harvester in early fuelwood thinnings in northern Sweden, showed that pre-clearance had no significant effect on the time taken up by harvesting and bundling work. Their understorey trees were of diameters below 2.5 cm at breast height, however, and the biomass removed was collected into bioenergy bundles.

Furthermore, it should be noted that a bundle harvester can be used for energy wood thinning, but not for CTL harvesting.

The reference material concerning the needs for pre-harvest clearing was collected from an e-questionnaire answered by forest professionals. The survey had a scale of five answers instead of three to avoid losing resolution, so that class four, for instance, means that harvesting is very difficult but possible, whereas class five implies that it is not possible without pre-clearing. For operational decision making, however, three classes are enough to separate two reliable alternatives and one uncertain class for further inspection. If the forest professionals had had the chance to decide between three classes rather than five, their answers may have been different. Nevertheless, we believe that most of the outcomes would have been similar to the classification we created when we reduced the number of classes from five to three. The perceptions of the need for pre-harvest clearing expressed by forest professionals and the variations in these are dependent on personal preferences (i.e. some professionals are willing to adapt to different circumstances whereas others require more stable conditions). The method could point reliably to plots that have little need for pre-harvest clearing and those that do have a need for it, although there were several plots here where the need existed but was fairly low, and then it was rather difficult to determine the necessity for clearing. For that reason, some flexibility based on current resources should be retained in decisions as to whether pre-harvest clearing in a given stand should be carried out or not.

5.4. Limitations and potential research directions

Although we used ALS data for prediction purposes, our field data in Paper III were collected from a large area, allowing inferences to be made with regard to subpopulation parameters and indirect estimators or predictors to be used that borrow information from other geographical areas. This partly affected the bias introduced into the design by the use of different vegetation zones, stem shapes and other geographically related factors. Special attention needs to be focused on the covariance structure of the training area data as compared with the target area when non-parametric estimation is used (Tokola and Heikkilä 1997). The attribute value distribution of the reference database is important in the *k*-MSN method, and if the target population has a different covariance structure in its major variables this can lead to design bias. For example, the reason why the RMSE% and bias% values quoted in Paper III are larger for Scots pine and birch than for Norway spruce is that Norway spruce is the main tree species in our material (see Table 1) and our estimation method was focused on getting better results for the main tree species than for the minor ones.

The methods presented here can be further improved (1) with denser ALS data (which should enable better tree list predictions), (2) by having a more representative database for the *k*-MSN search (such as more plots from near the target area), (3) by using more precise harvester data (in the case of Paper III), and (4) by collecting more extensive stem quality data with terrestrial laser scanning (which should improve stem quality estimation). The taper curve models of Laasasenaho (1982) used in Papers I and III are old, but they were compiled using extensive data and they are still used in operational forestry in Finland. The two main novelties in Paper III are (1) that the investigation was implemented using a real-life forest inventory area and its related data sources, and (2) that this choice of material was supplemented with enhanced methodological developments such as the use of a bucking-to-value simulator, the use of harvester data as a reference source and the imputation of tree lists from sample plots in the ABA.

Laser scanning data from unmanned aerial vehicles (UAV) open up new possibilities for estimating forest growing stock volumes based exclusively on such UAV laser scanning data (Puliti et al. 2020). The use of UAV in the civilian market has increased enormously over the last five years or so (Puliti et al. 2019), and this rapid growth is expected to continue (Watts et al. 2012), as UAVs offer greater operational flexibility than other platforms (such as manned airborne vehicles) and can be used for data collection under a wider variety of atmospheric conditions (Whitehead and Hugenholtz 2014). UAVs can provide excellent resolution (e.g. a few centimetres for the imagery collected) and data density (between 60-1500 points·m^{-2} for the laser scanning data) (Puliti et al. 2015). Nevertheless, civilian UAVs are restricted to use over areas of up to 10 km^2 when complete coverage is required (Whitehead et al. 2014) and light-weight sensors are used and significantly smaller areas when relying on heavier and more energy-consuming laser scanning systems (Puliti et al. 2019). For larger areas there are alternative remote sensing platforms that become more cost-effective for achieving complete coverage (Heaphy et al. 2017). Data collected by UAVs from multispectral, hyperspectral or laser scanning sensors, for example, can be employed for several purposes, such as forest inventories (Puliti et al. 2015; Puliti et al. 2018) or monitoring forest health by detecting physiological stress in mature plantations (Dash et al. 2017). UAV-based data collection has a potential in the long term, and high density point clouds from unmanned ALS systems offer great possibilities for small area forest inventories (Kukkonen et al. 2021). Where wood procurement is concerned, however, we need to cover landscapes, regions, administrative areas and even beyond, and it is difficult to cover sufficiently large geographical areas with the current UAV technology and cost structure. There is a substantial need to develop concepts and data fusion techniques to improve the quality of information services in this field of expertise.

Purchasing, harvesting, transportation, storage and handling, and manufacturing are the five major functions in the wood procurement supply chain (Lang and Mendell 2012). As these supply chains are dynamic networks of complex information and material flows between forestry, transport, and industry stakeholders (Kogler et al. 2021), this thesis is intended to contribute to wood procurement by improving our understanding of timber stand valuation, since it provides the information needed to define appropriate value and timber assortment distributions for harvestable timber stands.

5.5. Conclusions

In order to understand the complex wood procurement process and support the planning of harvesting operations, this thesis presents approaches designed to obtain detailed pre-harvest information from ALS data, aerial images, sample plots and a stem quality database. Information gathered with the methods developed here could reduce the need for field visits and therefore cut costs, as well as assisting in the performing of digital timber sales and improving the operational environment for digital timber marketplaces (Papers I, II and III).

Moreover, the LDA and linear model-based approaches proposed in Paper II could offer a means of enhancing the guidelines for the pre-harvest clearing of understorey vegetation. Both of these approaches were based on the information that ALS can provide regarding the lower vegetation layers in forests and proved capable of generating new information to support the planning of forest harvesting operations.

The ABA was used to estimate tree lists for Scots pine (Papers I and III), Norway spruce and birch (Paper III) per plot (Paper I) and per stand (Paper III). These tree lists were later bucked into different timber assortments, and the timber volumes, values and WPC of these assortments were reckoned. Thus the methods developed in Papers I and III can be used for assessing forest stand conditions, and especially the amounts of the various timber assortments, when planning harvesting operations. Nevertheless, more studies will be needed in order to improve the parameters and establish the restrictions that might be implemented in this non-parametric approach. This thesis provided an understanding of the locations, conditions and appraisal of harvestable timber stands, and may thus have contributed towards solving the current bottlenecks in the digital timber trade.

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