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Analysing the human–machine–forest interaction in cut-to-length harvesters equipped with a mobile laser-scanning system in thinning operations

Johannes Pohjala

School of Forest Sciences
Faculty of Science, Forestry and Technology
University of Eastern Finland

Academic dissertation

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Author: Johannes Pohjala

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Thesis supervisors:
Professor Kalle Kärhä
School of Forest Sciences, University of Eastern Finland, Joensuu, Finland

Professor Juha Hyyppä
Finnish Geospatial Research Institute FGI, Espoo, Finland

Associate Professor Ville Kankare
Department of Geography and Geology, University of Turku, Turku, Finland

Chief R&D and Technology Officer Juha Inberg
Ponsse Plc, Vieremä, Finland

Pre-examiners:
Senior Scientist Dipl.-Ing. Dr. Franz Holzleitner
Institute of Forest Engineering, Universität für Bodenkultur Wien, Austria

Professor Dr. Luc LeBel
Université Laval, Québec, Canada

Opponent:
Associate Professor Dan Bergström
Department of Forest Biomaterials and Technology, Swedish University of Agricultural Sciences (SLU), Umeå, Sweden

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ABSTRACT

Thinning intensity, timing and tree selection can substantially influence forest growth and the rate of carbon sequestration. Remote sensing-based forest planning increasingly incorporates tree-level estimates alongside stand-level assessments so information on the status of the trees must be transferred effectively to the harvester operator. This doctoral thesis evaluated the current state of development of tree-level operator guidance systems based on mobile laser scanning (MLS) and their potential to improve thinning operations in the future.

Study **I** examined the effect of prior tree marking on cutting productivity and harvesting quality in thinnings. Prior tree marking increased cutting productivity by an average of 2.7–2.8% through reduction in the time spent during the boom-out and moving, and also helped the operator maintain the target density of the remaining trees.

Study **II** investigated the effect of tree-level guidance (with the laser scanning-based thinning density assistant (TDA) system from Ponsse Plc.) on cutting productivity in thinnings, the workload experienced by harvester operators and the overall profitability of the investment. At the pioneering implementation stage, the guidance system modestly improved productivity (by 1.0–1.2%), and less experienced operators reported benefiting from the system. Improved implementation could unlock greater benefits in both productivity and harvesting quality.

Study **III** evaluated the capacity of MLS to measure harvesting quality attributes and to improve harvesting quality with the TDA in thinning stands. The results showed strong agreement between MLS-based assessments and traditional field measurements, while also highlighting the need to develop new methodologies. Harvesting quality met the recommendations for sustainable forest management on almost all reference and TDA plots.

The findings show that tree-level guidance can improve operators' productivity by 1–3% while helping to maintain good harvesting quality, with greater benefits achievable through improved usability and a more immersive user experience. However, achieving investment feasibility requires other, intangible value streams both from and to all stakeholders.

Keywords: assistance system, forest machine, wood harvesting, quality, productivity, time study, profitability

Pohjala, J. (2026) Mobiililaserkeilaimella varustettujen hakkuukoneiden ihminen–kone–metsä-vuorovaikutuksen analyysi harvennushakkuilla. Dissertationes Forestales 395. 49 s. https://doi.org/10.14214/df.395

TIIVISTELMÄ

Harvennuksen voimakkuus, sen ajoitus ja poistettavien puiden valinta voivat merkittävästi vaikuttaa metsän arvokasvuun ja hiilen sitoutumiseen. Kuviotason tarkastelun rinnalla kaukokartoitukseen perustuva metsäsuunnittelu hyödyntää nykyään myös puukohtaista estimointia, ja puiden tiedot on siksi tulevaisuudessa siirrettävä tehokkaasti myös hakkuukoneenkuljettajalle. Tämä väitöskirja keskittyi mobiililaserkeilaukseen perustuvan puutason kuljettajaopastuksen nykyisen kehitystason ja tulevan potentiaalin tarkasteluun harvennushakkuiden kehittämisessä.

Tutkimus **I** tarkasteli ennakkoleimauksen vaikutusta hakkuun tuottavuuteen ja korjuujäljen laatuun harvennuksissa. Ennakkoleimaus lisäsi hakkuun tuottavuutta keskimäärin 2,7–2,8 % vähentämällä hakkuulaitteen viennin ja työpistesiirtymisten ajanmenekkiä sekä auttoi kuljettajaa ylläpitämään jäljelle jäävän puuston tavoitetiheyden.

Tutkimus **II** tarkasteli Ponsse Oyj:n kehittämän Harvennusavustin-tuotekonseptin vaikutusta harvennushakkuiden hakkuun tuottavuuteen, hakkuukoneenkuljettajien kokemaan työkuormitukseen sekä yleistä investoinnin kannattavuutta. Konseptivaiheessa oleva järjestelmä paransi tuottavuutta maltillisesti (1,0–1,2 %). Kokemattomat kuljettajat kokivat hyötyvänsä järjestelmästä. Käytettävyyttä parantamalla voitaisiin saavuttaa huomattavasti suurempia hyötyjä niin hakkuun tuottavuudessa kuin korjuujäljen laadussakin.

Tutkimus **III** arvioi mobiililaserkeilauksen ja Harvennusavustin-tuotekonseptin kykyä mitata korjuujäljen laatua sekä parantaa harvennuksen laatua. Tulokset osoittivat vahvaa yhteneväisyyttä mobiililaserkeilaukseen perustuvien arvioiden ja perinteisten maastomittausten välillä, mutta toivat samalla esiin tarpeen kehittää uusia menetelmiä. Hakkuujäljen laatu täytti suurimman osan kestävän metsätalouden suosituksista sekä vertailu- että harvennusavustin-aloilla.

Tulokset osoittavat, että kuljettajan puutason opastus voi parantaa tuottavuutta 1–3 % ja samalla kohentaa korjuujäljen laatua. Vielä tätäkin suurempien hyötyjen arvioidaan olevan saavutettavissa käytettävyyden ja käyttäjäkokemuksen parantamisen myötä. Investoinnin korkean hinnan vuoksi kannattavuuden saavuttaminen edellyttää kuitenkin lisäarvoa, joka syntyy osin myös saavutettavista aineettomista hyödyistä kaikille sidosryhmille.

Asiasanat: avustavat järjestelmät, metsäkone, puunkorjuun laatu, aikatutkimus, tuottavuus, kannattavuus

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Harjavalta, 9th June 2026

Johannes Pohjala

LIST OF ORIGINAL ARTICLES

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

I Pohjala J, Vahtila M, Ovaskainen H, Kankare V, Hyyppä J, Kärhä K (2024) Effect of prior tree marking on cutting productivity and harvesting quality. Croat J For Eng 45(1): 25–42. https://doi.org/10.5552/crojfe.2024.2213

II Pohjala J, Kankare V, Hyyppä J, Kärhä K (2025) Effects of a mobile LiDAR-based thinning density assistant (TDA) system on harvester operator performance. Eur J For Res 144: 1301–1322. https://doi.org/10.1007/s10342-025-01808-y

III Sagar A, Pohjala J, Muhojoki J, Dhital A, Kaartinen H, Kärhä K, Järvelin K, Ghabcheloo R, Hyyppä J, Kankare V (2026) Utilising mobile laser scanning point clouds to assess harvesting quality in thinning stands. Sci Remote Sens 13, 100374. https://doi.org/10.1016/j.srs.2026.100374

Johannes Pohjala is the author of this doctoral thesis synthesis and is responsible for its structure, analytical reasoning and scientific conclusions. The author's specific contributions to each article are presented below.

I Johannes Pohjala (JP) was the main author of the article. Mika Vahtila (MV), Kalle Kärhä (KK) and Heikki Ovaskainen (HO) conceptualised the study. MV collected the data. JP conducted the data analysis. JP wrote the draft version of the manuscript. JP, MV, HO, Ville Kankare (VK), Juha Hyyppä (JH) and KK revised and approved the final version of the manuscript.

II JP was the main author of the article. JP and KK conceptualised the study. JP collected the data and conducted the data analysis. JP developed the methodology used to model the time consumption of moving. JP wrote the draft version of the manuscript. JP, VK, JH and KK revised and approved the final version of the manuscript.

III Anwar Sagar (AS) and JP were the corresponding authors of the article. JP and AS conceptualised the study. JP, AS and Harri Kaartinen (HK) collected the data. AS, JP and Ville Kankare (VK) developed the methodology. AS, JP and Jesse Muhojoki (JM) developed the software. AS wrote the original draft of the section on the detection of defective trees, JP wrote the original draft of the section on harvesting-quality attributes using mobile laser scanning and tree-maps and AS and JP jointly drafted the section on how the TDA guidance system influences harvesting quality. AS, JP, JM, Anubhav Dhital, HK, KK, Kalervo Järvelin, Reza Ghabcheloo, JH and VK revised and approved the final version of the manuscript.

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ABBREVIATIONS AND DEFINITIONS

3D	Three-dimensional
ABA	Area based approach
ADAS	Advanced driver assistance system
AI	Artificial intelligence
ALS	Airborne laser scanning
ANOVA	Analyses of variance
ANCOVA	Analyses of covariance
AR	Augmented reality
CCF	Continuous cover forestry
CFM	Conventional field measurements
CTL	Cut-to-length
DBH	Diameter at breast height
DSS	Decision support system
GIS	Geographic information system
GNSS	Global navigation satellite system
hpr	harvested production
ITD	Individual tree detection
LiDAR	Light detection and ranging
m^3	Cubic metre (solid over bark)
MLS	Mobile laser scanning
MV	Machine vision
OBC	On-board computer
RMSE	Root mean square error
RMSE-%	Percentage root-mean-square error
RQ	Research question
SFM	Best practices for sustainable forest management in Finland
SLAM	Localisation and mapping
TDA	Thinning density assistant
TLS	Terrestrial laser scanning

1 INTRODUCTION

1.1 Thinning in forest management

Thinnings play a crucial role in sustainable forestry as they direct stand growth and development (Cameron 2002; Kellomäki 2022; Zhang et al. 2024). In the future, the proportion of thinnings within overall silvicultural activity is expected to increase as thinning is generally considered more socially acceptable as a wood harvesting method (Ribe 2006) and has, in many regards, a smaller environmental impact than clear-cutting (Keenan and Kimmins 1993; Nieminen et al. 2018; European Commission 2021). In this context, measures that support biodiversity, enhance forest resilience to disturbances, maintain habitat quality across forest age classes and influence carbon sequestration in the remaining trees are increasingly relevant in all silvicultural practices (Nabuurs et al. 2017; Kuuluvainen and Gauthier 2018; Mäkelä et al. 2023).

Thinning methods are commonly categorised in the literature as below thinning, above thinning, quality thinning and systematic thinning (Kellomäki 2022). In Finland, thinning from below is the most common method, in which the selection of trees to be removed focuses on suppressed and poor-quality trees. However, it is not a universal thinning method that always results in optimal economic outcomes (Pukkala et al. 2015). The choice of thinning method and the subsequent selection of trees to be removed is a multifaceted challenge that reflects the skills and expertise of the forest owner, the forester or the machine operator. The primary distinction between these approaches lies in the criteria used to select the trees for removal. In addition, the selection of cuttings within continuous cover forestry (CCF) are often even more complex and challenging to implement (Brunner et al. 2025). Ultimately, a shared objective across all thinning methods is to optimise competition dynamics and forest structure, remove damaged or suppressed trees and maintain a balanced spatial distribution of the remaining trees based on their space requirements and growth potential in alignment with the optimal desired forest management target (Niemistö et al. 2018; Saarinen et al. 2020; Kärhä et al. 2021; Kellomäki 2022).

Forest management planning is primarily conducted at the estate- and stand-levels (Maltamo et al. 2021). Decisions on thinning regimes are based on forest inventory data, which can be collected either through conventional field measurements (CFM) or derived from remote sensing data (White et al. 2016; Maltamo et al. 2021). Based on this information, forest growth and silvicultural treatments can be simulated and optimised over the rotation period to maximise the forest owner's objectives (Bettinger et al. 2009). In practice, decision-making with regard to thinning timing and intensity often follows established guidelines and thinning models (e.g. Äijälä et al. 2019). Stand-level forest management decisions for operational use are increasingly based on remote sensing data, primarily airborne laser scanning (ALS) and photogrammetry, which provide sufficient accuracy for operational forest planning while reducing the need for labour-intensive and costly CFM. However, the estimation of timber quality attributes and the planning of environmentally sensitive site features still require stand-level field visits.

1.2 Mechanised thinning operations

The mechanisation of forest operations has significantly altered the nature of the human work involved in the process (Silversides 1997; Kanninen 1999). Today, wood harvesting in Finland is almost entirely mechanised (Strandström 2025) with approximately 70 million m^3 (solid over bark) of industrial roundwood harvested each year, with slightly over 40% originating from thinning stands (Strandström 2025). Unless otherwise stated, all volumes are reported as cubic metres solid over bark (m^3 SOB), hereafter denoted as m^3. In 2025, the total harvested area in Finland was approximately 805,000 ha, of which 19% were first thinnings, 48% later thinnings, 4% CCF, 25% regeneration cutting and 4% other cuttings (Natural Resources Institute Finland 2025). Worldwide, the cut-to-length (CTL) harvesting method accounts for an estimated 580 million m^3 of wood annually (Lundbäck et al. 2021).

The CTL harvesting method consists of two operations: felling and delimbing the trees with the harvester into various timber assortments directly at the stump and forwarding of the processed assortments to the roadside landing with a forwarder. The time consumption and productivity of these machines is influenced by a wide range of factors. In general terms, the environmental and working conditions, operator characteristics, work methods and techniques, machine specifications and organisational factors all influence the time consumption and productivity of the mechanised harvesting operations. More specifically, cutting productivity of single-grip harvesters is significantly dependent on the stem size of the removed tree (e.g. Kärhä et al. 2004; Nurminen et al. 2006; Spinelli and Magagnotti 2013): the work time per cubic metre increases when the size of the stem decreases. Removal density affects the time spent *moving* (Lageson 1997; Kärhä et al. 2018). Tree distribution may also affect productivity (Spinelli and Magagnotti 2013) as does the number of timber assortments that are bucked (Nurminen et al. 2006), the tree species (Nurminen et al. 2006), branchiness (Glöde 1999), the terrain and steepness (Spinelli et al. 2010), the silvicultural methods employed (e.g. thinning type; Lageson 1997) and the undergrowth trees (Kärhä and Bergström 2020). In addition to these technical factors, one of the most significant determinants of productivity are human factors (Sirén 1998; Kärhä et al. 2004; Väätäinen et al. 2005; Ovaskainen 2009; Purfürst 2010; Wenhold et al. 2020), which include cognitive, psychological and motor abilities (Manner 2021).

Technically, CTL forest machines are highly advanced. Sensors and computers are an important part of harvesting work. Harvesting instructions, bucking matrixes and maps are transmitted to the on-board computer (OBC) of modern CTL machines. The harvester operators are responsible for planning the strip road network within the forest stand and selecting trees to be removed during their work (Kärhä et al. 2021), although harvesting maps and instructions are often clarified with field markings with biodegradable marking ribbons; the boundaries of the harvesting area and sub-areas, as well as locations that pose risks to machine operations, such as power lines, soft mires, and small ponds or similar water bodies that may pose a risk of machines becoming stuck. In addition, areas or individual trees that are to be excluded from harvesting for environmental reasons are marked.

While this decision-making process employed by harvester operators can be supported by prior tree marking, a method widely used internationally (e.g. Yeo and Stewart 2000; Ontario Ministry of Natural Resources 2004; Spinelli and Magagnotti 2013; Self and Baker 2017; Holzleitner et al. 2019), it is rarely applied in Scandinavian boreal forests, being largely limited to the harvesting of utility poles. One method to mark trees chosen for removal is illustrated in Figure 1. Etymologically, the widely used Finnish term *"leimikko"* and the

Figure 1. An example of a prior tree marked first thinning (the marking indicated by a circle). *Photo courtesy of* Mika Vahtila

Swedish "*stämplingspost*" both refer to a harvesting area where the trees designated for removal were traditionally punched with an axe prior to harvesting operation.

Prior tree marking causes additional costs in wood procurement operations, which are difficult to offset through improvements in harvesting productivity and quality. However, the benefits of the method, namely improved tree selection, highlight the importance of tree-level data as a key component of precision forestry (Havreljuk et. al 2014; Holzleitner et al. 2019).

1.3 Harvesting quality in mechanised thinning

Even when well planned, thinning can also cause a negative impact on the forest by causing damage to the soil, residual trees, water bodies and habitats (Sirén 1998; Ampoorter et al. 2012; Cambi et al. 2015). Harvester and forwarder operators are responsible for balancing the productivity and quality of the thinning work. High costs associated with CTL harvesting machinery and thus the demand for high productivity levels, have led to more intensive thinning practices (Lageson 1997; Mäkinen et al. 2006; Bianchi et al. 2024), a projection already presented by Vuokila (1970). However, due to improvements in forest machinery, operator skills and worksite planning, high productivity does not lead to an increased rate of stem damage (Harstela 1996; Holzleitner et al. 2019).

Nevertheless, harvesting quality still leaves room for improvements. Inspections conducted by the Finnish Forest Centre (mainly for 2022–2023 thinned stands) revealed that only 26% of thinning operations in Finland met the recommendations for Best Practices in Sustainable Forest Management (SFM) (Äijälä et al. 2019), while 65% were rated as satisfactory and 9% were found to be in violation of the Finnish Forest Act (Finnish Forest Centre 2024). The most significant challenge over the years has been excessively heavy thinning intensity, which might lead to economic losses, and lower rates of carbon dioxide sequestration/carbon storage (Vuokila 1981; Hynynen and Arola 1999; Mäkipää 2023; Mäkinen and Isomäki 2024a; 2024b). Moreover, the risk of windthrow and snow damage increases as thinning intensity increases particularly under changing climate conditions (Wallentin and Nilsson 2014).

The assessment of harvesting quality in the mechanised era has required substantial methodological advancements in measurement techniques to ensure comparability of results (Sirén 1998). Many of these methods are still widely applied in Fennoscandia (Bergkvist and Staland 2003; Iittiläinen et al. 2003; Leivo et al. 2023), as well as in other regions globally (Strubergs et al. 2024; Laajalehto 2025) by forest owners, forest companies, harvesting contractors and public authorities. However, assessment of harvesting quality is both time-consuming, expensive and is conducted during or, more often, months after the thinning operation, while at the same time resulting in only limited data coverage compared to harvested areas (Sirén 1998). In addition, machine operators conduct self-monitoring using the known boom length and global navigation satellite system (GNSS) position as a reference (Niemistö 1992; Kymäläinen et al. 2024). Self-monitoring may include measuring the density of remaining trees by species, diameter at breast height (DBH), dominant height, and stand description, as well as recording the count and location of retention trees and dense areas for game (Haataja et al. 2014). The requirement for self-monitoring imposes a time burden on the operator, thereby diminishing operational efficiency.

Digital applications enable the collection of significantly larger and more objective datasets from operational environments for post-harvest analysis. A key objective in harvesting quality monitoring is to automatically measure and record data related to harvesting quality during operations (Ovaskainen 2019; Tarvainen et al. 2025). This is made possible by the various sensors integrated into the harvester or forwarder. For example, stand-specific strip road-network-related harvesting quality attributes (e.g. width and spacing) can be determined from the GNSS positioning data in the forest machines, which is available in the harvested production (hpr) file (Hannrup et al. 2021; Ovaskainen and Riekki 2022; Strubergs et al. 2024). Stem damages can also be assessed using machine-vision-based methods (Palander et al. 2019). However, canopy-induced signal loss often limits GNSS performance, making sub-meter position accuracy difficult to achieve (Noordermeer et al. 2021; Faitli et al. 2024; Liu et al. 2025). To the best of my knowledge, no significant progress has been reported that would advance image-based stem-damage detection beyond the conceptual idea.

1.4 From stand-level to tree-level forest inventories

Laser scanning technologies provide high-resolution three-dimensional (3D) point-cloud data that capture forest structure at varying spatial resolution (e.g. point density, p m^{-2}) (Liang et al. 2022). Moreover, ALS data and aerial imagery are used to estimate stand-level and species-level forest attributes over wide areas using either the area-based approach (ABA;

Holmgren and Persson 2004) or individual tree detection (ITD; Hyyppä & Inkinen 1999) (White et al. 2013; Vastaranta et al. 2014; Yrttimaa et al. 2025). Of these, ABA has traditionally been more widely applied, while ITD has gained increasing interest in recent years (Hyyppä et al. 2024). An example of the application of ITD is the Forest database, which provides nationwide forest inventory data for Finland at the level of individual trees (Metsakanta.fi 2026, based on Hyyppä et al. 2024). These capabilities align with the frameworks of precision forestry (Heinimann 2007; Kovácsová and Antalová 2010; Holopainen et al. 2014) and smart forestry (Ehrlich-Sommer et al. 2024), which enhance decision-making and operational efficiency through sensor-based and data-driven technologies applied in forest inventories and planning.

Terrestrial laser scanning (TLS) or mobile laser scanning (MLS) as ground-based light detection and ranging (LiDAR) systems provide dense point cloud data, which is essential for precise single-tree measurements, such as tree detection and stem curve estimation. Specifically, TLS captures fine-scale structural details from static ground-based positions (Liang et al. 2016; Calders et al. 2020) and MLS collects dense point cloud data from moving platforms, thereby enabling efficient wall-to-wall scanning of forest environments at ground level while maintaining high spatial resolution (Lin et al. 2010; Jaakkola et al. 2010; Holopainen et al. 2013; Melkas et al. 2014; Di Stefano 2021; Sevgen and Abdikan 2023). With the use of advanced laser scanning techniques, high-resolution individual tree attributes, such as DBH, height, volume and biomass, can be estimated with high precision (Lin et al. 2010; Jaakkola et al. 2010; Holopainen et al. 2013; Bauwens et al. 2016; Hyyppä et al. 2020; Neudam et al. 2022; Faitli et al. 2024). They can also be used to assess wheel rut depths (Salmivaara et al. 2018). In addition to basic metrics, high-resolution point clouds enable the measurement of detailed information of tree stem and crown metrics, growth and growth allocation patterns, quality assessment models and defect detection (Liang et al. 2016; Saarinen et al. 2020; Saarinen et al. 2022; Sagar et al. 2024; Tavi et a. 2025). However, automated tree species identification remains a challenge, regardless of whether machine vision or LiDAR-based approaches are employed (Åkerblom et al. 2017; Carpentier et al. 2018; Boudra et al. 2021). This detailed structural information can also be used for purposes, such as gathering training data for ALS-based tree-level inventories (Kärhä et al. 2025), optimising bucking operations (Murphy et al. 2010; Prendes et al. 2023) and optimising tree selection (Niemi et al. 2025) for example, using forest digital twin technologies (Buonocore et al. 2022; Shanmugam et al. 2025).

Harvesters and forwarders can be equipped with sensors (Figure 2) that can collect and analyse point cloud data, which allows for *in-situ* processing of the acquired data (Faitli et al. 2024). The system developed by Faitli et al. (2024) achieved a root mean square error (RMSE) value of 3–4 cm when estimating DBH in real-time mode and 2–3 cm depending on the distance of trajectory. However, the absolute localisation error can exceed 2 m in the real-time mode, even when robotic simultaneous localisation and mapping (SLAM) are used (Faitli et al. 2024).

Multisource data fusion can enhance the precision of forest attributes estimations (Balestra et al. 2024). Overall, real-time data processing capabilities in the operational use of MLS and machine vision (MV) pose a significant challenge compared to post-processing (da Silva et al. 2021; Faitli et al. 2024). Despite the challenges, these technologies enable the detection of individual trees, thereby offering a practical trade-off between accuracy and operational flexibility, transitioning from stand-level to tree-level forest and wood supply chain management (Keefe et al. 2022).

Figure 2. The cabin of a Ponsse Scorpion King harvester. The Ouster LiDAR OS0 is mounted on a bar located beneath the front windshield. *Photo courtesy* of Johannes Pohjala

1.5 Operator assistance systems in CTL harvesters and forwarders

The human–machine–environment interaction in CTL harvesters refers to the micro-level dynamics of work system processes during harvesting operations. This interaction is predominantly manual, involving intensive use of manipulators and complex decision-making (Gellerstedt 2002; Häggström 2015; Dreger et al. 2023). Operators visually gather environmental information and integrate this information with forest management objectives while simultaneously maintaining productivity. Conversely, certain aspects of machine movements and feedback are already highly automated. These are discussed in more detail in the following sections. Cognitive ergonomics plays a key role in designing interfaces and workflows that support mental workload and decision-making. However, continuous manual control limits opportunities to improve efficiency (Gellerstedt 2002). Increasing automation levels is the next step toward enhancing productivity in forest machine operations but requires advanced sensing systems (Westerberg 2014).

A classification of automation levels has been introduced to enable a systematic understanding of forest machinery automation, either throughout the timber value chain (Lindroos et al. 2017; Kreis et al. 2025), or more specifically for CTL machines, distinguishing between the crane and the base unit (Seppälä 2020). In general, CTL forest machines are categorised at level 1 on the 0–5 automation scale (SAE international 2021), but certain tasks or sub-cycles within their operation may reach more advanced levels. These systems can be broadly categorised into Advanced Driver Assistance Systems (ADAS), Decision Support Systems (DSS) and machine control systems. In simplified terms, ADAS provide real-time, active operator assistance by monitoring the environment and supporting machine operation, while DSS serve as tactical planning tools that enhance decision-making before or during work tasks. Machine control systems utilise sensors, GNSS technologies and 3D models to accurately guide and coordinate machine operations. Together, these system types illustrate the continuum from operator assistance to operational control in modern machinery.

Forest harvesters and forwarders are already extensively equipped with assistance systems, which improve the efficiency, safety and precision of harvesting operations. In addition to enhancing machine performance, these systems support operators by simplifying decision-making (Hellström et al. 2009; Westerberg 2014), reduce cognitive and physical workload, and allow the operators to focus on more critical aspects of the work (Kymäläinen et al. 2024). Lighting systems and reverse cameras enhance safety, while OBC, map-based guidance including GNSS position and bucking systems provide highly valuable information to the operator about the machine, the stand, the terrain and optimal bucking (Uusitalo et al. 2004; Kauppinen et al. 2016; Kymäläinen et al. 2024; Strahlendorff et al. 2024). Boom-tip control and automatic cab levelling ease the tasks of the operator and increase productivity (Gellerstedt 1998; Hartsch et al. 2023; Manner and Lundström 2025). Advancements in assistance technology in forest machines underscore their critical role in modern forestry. However, a shift towards precision forestry, from the stand-level to the single tree-level, requires more intelligent and immersive solutions in forest machines.

Novel robotics, artificial intelligence (AI), control systems and sensor fusion will enable the development and employment of entirely new types of assistance systems to support harvester operators. For example, dynamic crane motion control can assist operators in executing smoother and more efficient movements (La Hera and Ortiz Morales 2019; Lindroos et al. 2019). In the future, intelligent coaching systems are expected to provide real-time feedback, guiding operators in optimising their work practices (Manner 2024). Real-time observations of forest conditions can be achieved by integrating remote sensing data, such as ALS, to assess forest trafficability (Kankare et al. 2019) or to monitor biodiversity indicators (Korhonen et al. 2024). This enables continuously updated, site-specific information to be accessed directly via the OBC, thereby supporting more informed and adaptive planning based on dynamic map layers.

The ability to recognise the surroundings of a harvester or forwarder is a critical technology to automate machine movements as well as for the long-term vision for unmanned forestry vehicles (Gellersted 2002; Lindroos et al. 2019; Hyyti 2023; La Hera et al. 2024; Semberg et al. 2024). This vision closely aligns with the approaches seen in Industry 4.0 and Agriculture 4.0 (Holzinger et al. 2024a), which emphasise large-scale automation and reduced human involvement. However, an alternative technological pathway may adopt a more human-centric approach, integrating human expertise and experiential knowledge through human-in-the-loop systems (Holzinger et al. 2024b). This helps to address the challenges described by Moravec's Paradox, which illustrates how tasks that are intuitive for humans can be unexpectedly complex for AI systems (Moravec 1988).

The development of real-time harvesting quality monitoring systems enables operators to detect and respond to harvesting quality issues during operations. Several developers are currently developing concepts for harvesting quality control in thinning stands, either based on forest machine data (Hannrup et al. 2021; Tarvainen et al. 2025) or an MLS-based tree mapping systems, such as the Thinning Density Assistant (TDA) or Nordic Forestry Automation (NFA 2026), to support harvester operators during thinning operations (Figure 3). The system generates a real-time tree-map of the harvesting site using MLS frames, visualises the machine's position relative to surrounding trees and adjacent strip roads, and provides feedback on thinning intensity. Although detailed technical

Figure 3. An operator's view showing the Opti-5G system of a Ponsse machine, with a GoPro Hero 8 camera mounted on the windscreen with a suction cup. A Ponsse Thinning Density Assistant (TDA) display is positioned in the centre, and a reversing camera is positioned on the pillar. *Photo courtesy of* Johannes Pohjala

specifications are still emerging, the system is part of a broader movement toward AI-enabled SFM.

Recent advances in MLS-based operator assistance systems have created a clear need to understand their actual impact on harvesting productivity, quality and operators' workload (Kärhä et al. 2025). While ADAS, such as the TDA and Nordic Forestry Automation's AI-enhanced guidance systems offer first-of-their-kind applications for visualising tree density, strip-road spacing and width, their effectiveness in supporting real-time decision-making during thinning operations remains uncertain. In addition, there is still limited knowledge regarding which harvesting and tree-quality indicators can be reliably estimated from high-density point cloud data collected during harvesting operations. Finally, a reliable approximation of the overall cost-effectiveness of implementing MLS-based systems in forest machinery is still unclear. As outlined above, the full benefit of MLS-based systems is comprised of several interrelated components. These gaps highlight the need for research into the integration of MLS and AI technologies for operational decision support, harvesting quality documentation and sustainable forest management.

1.6 Objectives

The aim of this thesis was to investigate the opportunities and challenges of utilising close-range remote sensing techniques based on MLS to support harvester operators in forest thinning operations. The thesis placed particular emphasis on tree-level guidance, its impact on operator productivity and harvesting quality in thinnings. Moreover, it explored methods through which MLS can be utilised to generate information related to harvesting quality, thereby supporting the operator in decision-making. This thesis addressed the following research questions (RQs):

RQ1) How does the tree-level guidance provided to machine operators affect work productivity?
RQ2) How does the tree-level guidance provided to machine operators affect harvesting quality?
RQ3) How can point cloud–derived tree attributes be used to enhance operator guidance and reporting in thinning operations?
RQ4) How do these improvements influence the overall profitability of thinning operations?

2 MATERIALS AND METHODS

2.1 Overview of research stands, operators and datasets

Time-study data were collected in central and eastern Finland (Figure 4) in August–September 2018 (Study **I**) and in March and September 2023 (Study **II**). The study sites ranged from two oligotrophic *Vaccinium vitis-idaea* type sites, one of which was located on

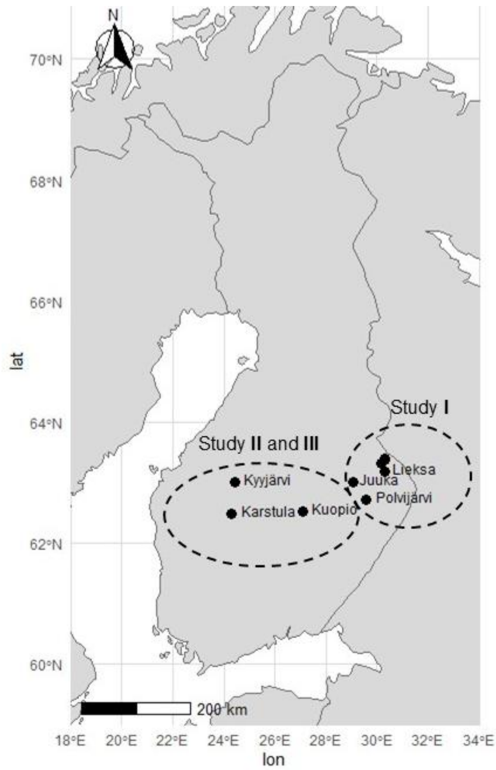


Figure 4. Locations of the study sites in central and eastern Finland (Studies **I-III**)

Table 2. Locations and details of the forest stands where the studies were conducted. Stand fertility types (fertility class) are defined as follows: 2 = herb-rich heath forests, 3 = mesic heath forests and 4 = sub-xeric heath forests. DBH = diameter at breast height.

Stand	Location	Fertility class	Main tree species	Age, yrs	Area, ha	Dom. height, m	DBH, cm	Density, stems ha^{-1}
Study I								
1	Lieksa	4	*P. sylvestris*	35	1.18	13.7	12.7	1720
2	Polvijärvi	3	*B. pendula*	27	0.69	17.5	14.6	1380
3	Lieksa	4	*P. sylvestris*	37	0.76	13.6	14.1	1530
4	Lieksa	3	*P. sylvestris*	35	1.28	15.2	15.0	1880
5	Lieksa	4	*P. sylvestris*	50	1.95	16.8	18.4	740
6	Lieksa	3 and 4	*P. sylvestris*	48	1.58	17.2	17.4	900
7	Lieksa	3	*P. sylvestris*	52	1.26	18.3	19.1	750
8	Juuka	3	*P. sylvestris*	58	1.28	20.2	21.6	630
Study II–III								
1	Kyyjärvi	4$_a$	*P. sylvestris*	37	2.6	17.0	15.6	1137
2	Karstula	4	*P. sylvestris*	55	4.3	20.4	18.0	896
3	Kuopio	2	*B. pendula*	27	1.6	18.0	13.8	1277
4	Kuopio	2	*B. pendula*	42	1.9	20.4	16.1	875

a) Located on peatland

peatland, to eutrophic *Oxalis-Myrtillus* type forests. For a more detailed description of the classification, cf. Cajander (1926). The dominant tree species were either Scots pine (*Pinus sylvestris* L.) or birch (*Betula* spp.). Furthermore, most of the stands were interspersed with Norway spruce (*Picea abies* (L.) Karst.), which typically occurred in the lower canopy layer. Forest workers performed pre-clearance of undergrowth trees where necessary. All the stands were thinned from below. Descriptions of the study stands are summarised in Table 2.

2.2 Time study: data and data collection methods

The time-study data from the cutting operation was collected using a video camera, primarily in daylight (Study **I**), but also partially under low light conditions (Study **II**). The video camera was attached to the cabin of the harvester (Figure 2). In studies **I** and **II**, the total duration of the videos were 28.7 hours and 37.0 hours, respectively. The time elements followed the division used by Kärhä et al. (2004) and Nurminen et al. (2006), in which each work cycle consisted of up to six elements: *boom-out*, *felling*, *processing*, *boom-in*, *moving* and *miscellaneous time*. The time-study material joined and matched with the hpr data, which enabled observation of the time consumption of cutting work in relation to stem volume.

Study **I** included time-study data from 4,825 trees and 463 m^3 of harvested timber (solid over bark). Similarly, study **II** included data from 4,967 trees and a total of 490 m^3 of harvested timber, of which 449 trees were felled during nighttime operations. In study **I**, the average volume of removal was 0.063 m^3 in first thinnings and 0.148 m^3 in later thinnings. In study **II**, the overall average volume harvested was 0.102 m^3, which included both first and later thinnings. A description of removals is provided in Table 3.

In study **I**, all selected harvester operators had at least 10 years of experience in forest thinning. In study **II**, three operators had 15 or more years of experience, while two had less than five years (3 and 4 years) (Table 4). Based on experience, it can be assumed that all operators in study **I** had reached their final performance level, whereas for two operators in study **II** this learning process presumably is still ongoing. The operators used harvesters that they regularly operate as part of their employment. Operator A was unfamiliar with the TDA system, whereas the other four operators had less than one year of experience using it in their daily work (Study **II**).

Table 3. Description of study stands by thinning type and treatment. The thinning types are abbreviated as FT (first thinning) and LT (later thinning). Treatments were M (marked), TDA (thinning density assistant used during harvesting), and R (reference).

Study I								
Stand	Thinning type	Treatment		Removals			Thinning intensity, %	Total removals, n
		M, TDA or R	Plots, n	m^3 ha^{-1}	Stem count, stems ha^{-1}	Stem volume, m^3		
1	FT	M	3	29	637	0.05	37	379
		R	3	46	872	0.05	50	506
2	FT	M	2	58	631	0.09	48	225
		R	3	62	766	0.08	53	255
3	FT	M	2	43	639	0.07	45	276
		R	2	50	894	0.06	55	294
4	FT	M	2	63	903	0.07	48	644
		R	2	72	983	0.07	52	559
5	LT	M	4	32	250	0.13	32	289
		R	4	31	227	0.14	32	180
6	LT	M	3	32	278	0.12	47	227
		R	3	55	429	0.13	37	328
7	LT	M	2	36	302	0.12	37	187
		R	2	41	246	0.16	36	158
8	LT	M	2	64	243	0.26	37	160
		R	2	60	256	0.24	43	158
Study II								
1	FT	TDA	5	45	502	0.09	44	532
		R	6	56	600	0.09	53	895
2	LT	TDA	9	53	396	0.14	44	396
		R	6	45	318	0.13	35	318
3	FT	TDA	5	41	620	0.06	48	558
		R	4	47	787	0.07	61	535
4	FT	TDA	6	52	440	0.11	50	440
		R	5	43	450	0.10	51	450

Table 4. Technical and background information on operators and harvesters.

Study	Operator	Age, yrs	Work experience, yrs	Manufacturer	Model	Harvester head	Boom reach, m
I	A	36	21	Komatsu	931.2	C123	11
	B	34	10	Ponsse	Scorpion King	H6	11
	C	50	28	John Deere	1170 E	414	10
	D	36	16	John Deere	1170 E	413	11
II–III	A	-	19	Ponsse	Scorpion King	H6	11
	B	-	3	Ponsse	Scorpion King	H6	11
	C	-	15	Ponsse	Scorpion King	H6	11
	D	-	4	Ponsse	Scorpion King	H6	11
	E	-	30	Ponsse	Scorpion King	H6	11

2.3 Time study analysis

Research on forest work has been conducted to measure and compare the performance of existing or proposed human–machine–environment systems (Björheden et al. 1995). System productivity is defined as the ratio between outputs and inputs. In forestry, this is affected by many factors, such as the skills of the operators, the characteristics of the machinery and forest stand conditions (Magagnotti and Spinelli 2012). Generalisable results in forest work studies require careful experimental design, representative sampling and robust statistical methods (Steinlin 1955; Magagnotti and Spinelli 2012).

A comparative time study was used as the work study method as it has a long methodological tradition in forestry work research. The methodological assumption of this research approach relies on the theoretical idea that the relative time consumption between different work methods remains the same regardless of who performs the work, provided the same operator tests all the methods (Lindroos 2010).

A comparative time study with factorial design was employed to examine how prior tree marking and the use of a TDA can affect time consumption on different work elements and productivity (Study **I-II**). Prior tree marking and a TDA were the treatments under study, each with two levels (reference and prior tree marking in study **I**, reference and the TDA in study **II**). The operator was treated as a blocking factor to account for the inherent variability among operators. Stem volume and removal density were adjusted by regression variables to ensure they were set at the same level for all operators in the analysis. Tree species and time of day (day, night) were treated as blocking factors. *Boom-out* had only a very small positive relationship with stem volume so it was analysed using solely descriptive statistics and time consumption estimations were based on average time consumption values.

Regression analysis with the appropriate variable transformations was applied to fit time consumption for *felling*, *processing* and *moving*. In study **I**, *moving* was modeled as a single model for all operators at the plot-level, whereas in study **II**, it was modeled separately for each operator using GNSS-derived machine position data from a hpr file. Using this approach, both the total moving time and the number of trees removed within the 20 × 20 m grid cells along the strip roads were computed (Figure 5).

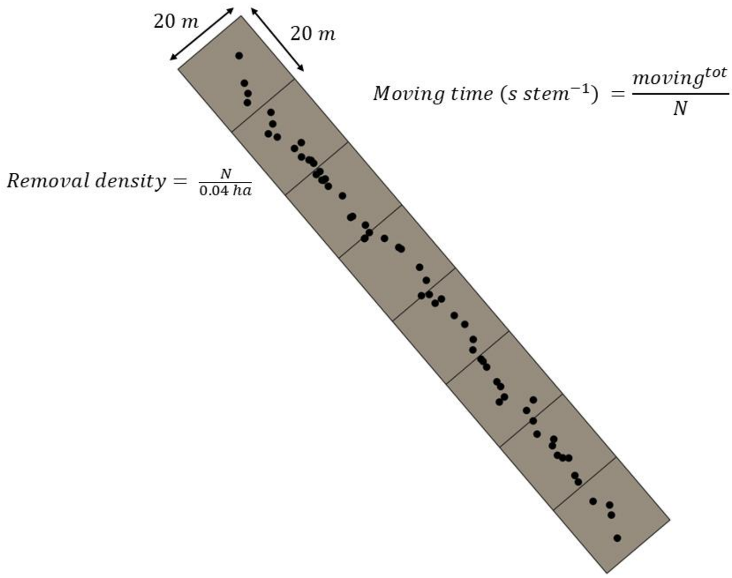


Figure 5. Illustrative map of the method used to model the time spent *moving* in Study **II** using hpr data. The black dots represent the recorded harvester positions when each tree was cut. *Moving* time per stem (s stem^{-1}) was calculated by dividing the total *moving* time (*moving*^{tot}) within each 20 × 20 m grid cell by the number of harvested stems (*N*) inside the specific cell. *Removal density* (stems ha^{-1}) was derived by dividing the number of harvested stems (*N*) by an area of 0.04 ha.

The average total effective time consumption by the operator was calculated by summing the modelled time consumption of the individual work elements. In study **I**, the tasks of *felling*, *processing* and *boom-in* were combined. The summation of the work elements is expressed in Eq. (1)

$$T_{tot} = y_1 + y_2 + y_3 + y_4 + y_5 + y_6 \quad (1)$$

where T_{tot} = total effective time consumption spent *cutting* (s stem^{-1}), y_1 = *boom-out* (s stem^{-1}), y_2 = *felling* (s stem^{-1}), y_3 = *processing* (s stem^{-1}), y_4 = *boom-in* (s stem^{-1}), y_5 = *moving* (s stem^{-1}) and y_6 = *miscellaneous* time (s stem^{-1}).

The total effective time consumption spent *cutting* was then converted into effective hourly productivity (P_e; m^3 E$_0^{-1}$), as expressed in Eq. (2). This measure is also referred to as productive machine hour productivity.

$$P_e = 3600\ x\ (x_1/T_{tot}) \quad (2)$$

where P_e = effective hourly productivity (m^3 E$_0^{-1}$); x_1 = stem volume (m^3); T_{tot} = total effective time spent during *cutting* (s stem^{-1}). Effective hourly productivity was converted into gross-effective hourly productivity (m^3 E$_{15}^{-1}$), also known as scheduled machine hour productivity, which included delays shorter than 15 minutes, and to correct the bias between the time study and the follow-up study using coefficients proposed by Kuitto et al. (1994) as expressed in Eq. (3)

$$P_{ge} = \frac{P_e}{1.197 \times 1.276} \tag{3}$$

where P_{ge} = gross-effective hour productivity (m^3 E_{15}^{-1}); P_e = effective hour productivity (m^3 E_0^{-1}).

Both parametric and non-parametric statistical tests were applied in the analyses, and included t-test, Mann-Whitney U test, two-way analyses of variance (ANOVA) and analyses of covariance (ANCOVA). Parametric tests assume normal distribution and homogeneity of variances, while non-parametric tests, such as the Mann-Whitney U test, are more robust to violations of these assumptions and are suitable for ordinal data or non-normally distributed samples. A significance level of $\alpha \leq 0.05$ was used to determine statistical significance. The t-statistics were calculated to evaluate differences between group means under the assumption of normally distributed data.

2.4 Harvesting quality: data and collection methods

Harvesting quality data were collected after the harvesting operations. The datasets contained the variables listed in Table 5 at both the plot- and stand-levels. These data were obtained through CFM (Studies **I** and **III**) and MLS (Study **III**). The MLS assessment utilised point cloud data collected with the MLS setup, which consisted of a backpack-mounted system equipped with a suite of advanced technologies that included a ZEB Horizon laser scanner sensor with IMU and a 360° camera from GeoSLAM Ltd. (GeoSLAM 2026).

Trees were automatically detected using the method developed by Hyyppä et al. (2020), which enabled the estimation of individual tree locations and characteristics. This process resulted in a highly detailed tree-map dataset (Figure 6), which enabled the estimation of harvesting quality and its comparison with CFM in Study **III**.

Table 5. Harvesting quality attributes, units used and measurement methods in Studies **I** and **III**. DBH = diameter at breast height, CFM = Conventional Field Measurements, MLS = Mobile Laser Scanning and GIS = geographic information system (GIS)-based analysis using GNSS positions derived from harvester data (HPR files).

Variables	Units	Study **I**	Study **III**
Stem density	stems ha^{-1}	CFM	CFM and MLS
Basal area	m^2 ha^{-1}	–	CFM and MLS
Dominant height	m	CFM	CFM and MLS
DBH	cm	CFM	CFM and MLS
Strip road width	m	CFM	CFM and MLS
Strip road spacing	m	GIS	CFM and MLS
Thinning intensity	%	CFM and GIS	CFM, MLS and GIS
Stem damages	%	—	Full inventory
Remaining defected trees	n	CFM	—

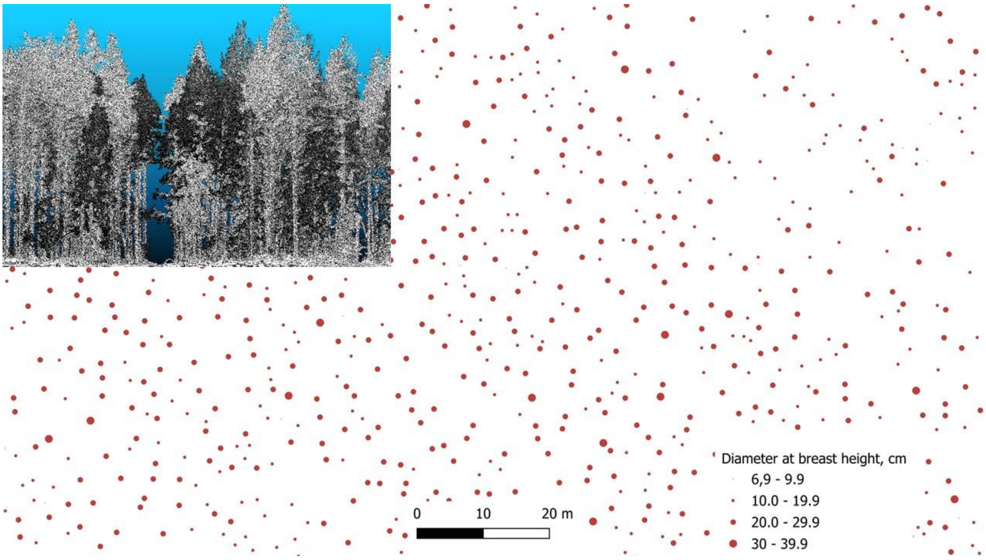


Figure 6. Examples of raw point-cloud data and the tree-map showing the identified stems classified into four diameter at breast height (DBH) classes.

Harvesting quality variables were measured *in-situ* using circular plots and *ex-situ* using point-cloud-based tree-map data. Study **I** focused on the most important attributes related to harvesting quality in thinnings, while Study **III** included a broader assessment that covered the density of the remaining trees, basal area, DBH, dominant height, strip road width and strip road spacing, estimated from both CFM and point cloud data. In addition, Study **I** assessed the presence of remaining defective or diseased trees, while Study **III** evaluated the stem damage, such as stem wounds or bark removal, caused by harvesting operations (Leivo et al. 2023).

2.5 Harvesting quality analysis

The accuracy of the MLS-derived estimates relative to the reference field data in Study **III** was evaluated for each structural variable using RMSE, the percentage root-mean-square error (RMSE-%) and bias. Both RMSE and RMSE-% measure the prediction error, while bias and bias% quantify the systematic error. They are shown in Eqs. (4–7).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i^{MLS} - x_i^{ref})^2} \tag{4}$$

$$RMSE\% = \left(\frac{RMSE}{\bar{x}}\right) \times 100 \tag{5}$$

$$BIAS = \frac{1}{n}\sum_{i=1}^{n}\left(x_i^{MLS} - x_i^{ref}\right) \tag{6}$$

$$BIAS\% = \left(\frac{Bias}{\bar{x}}\right) \times 100 \tag{7}$$

where n is the number of observations, x_i^{MLS} and x_i^{ref} are values obtained from MLS and the corresponding reference field data value, respectively for the i-th observation. $\bar{x}$ is the mean of the reference field data values.

2.6 Profitability and operator workload

The profitability of the TDA depends on the purchase price, the proportion of thinning during harvesting, annual expenses and the return requirement of the investments. The cost-saving benefit of the TDA is equal to its impact on gross-effective time (E_{15}). In the calculation of machine costs, variable costs were €43.78 h^{-1}, with an annual work time of 2,699 hours calculated with 85% of direct work time on site. The net present value (NPV) of the investment was calculated by discounting the cash flows (acquisition cost, cost savings, maintenance costs, residual value) and is described in Eq. 8.

$$NPV = \sum_{t=0}^{T} \frac{cashflow_t}{(1+r)^t} \tag{8}$$

where NPV = Net Present Value; cash flow = *cash flow* in year t; t = time period (year); T = total time during which the cash flow occurred; r = discount rate.

In addition to the data collected using advanced forest technology applications, one dataset consisted of workload assessments gathered through the NASA Task Load Index (NASA TLX) (Hart and Steveland 1988) questionnaire, which evaluates perceived cognitive and physical workload during harvesting. The six measured dimensions of workload were mental demand, physical demand, temporal demand, performance, effort and frustration, each assessed on a 10-point scale that ranged from 0 (low) to 10 (high). In addition, the questionnaire included two questions related to whether the TDA helped operators maintain the target number of remaining trees and, more generally, how useful they perceived the system.

3 RESULTS

3.1 Work element time consumption

Differences in the relative distributions of effective time consumption across the work elements were small between the reference and prior tree marking treatments (Table 6), as well as between the reference and the TDA (Studies **I** and **II**). Only a minor difference in the relative proportion of *boom-out* was observed, which decreased by 2 percentage points, while the differences in the other work elements were 1 percentage point or less (Studies **I** and **II**).

The operator's time spent on individual work elements, standardised by harmonised stem size and removal, is illustrated in Figures 7 and 8. Systematic differences between treatments were observed only in the *boom-out* and *moving* work elements. In contrast, no statistically significant or generalisable differences were found for *felling, processing, boom-in* or *miscellaneous* time elements. Consequently, these elements were modelled without including the treatment effects of prior tree marking (Study **I)** or the TDA (Study **II)**. It should be noted, however, that statistically significant differences were detected at the level of individual operators in these elements, although no consistent trend was seen across all operators.

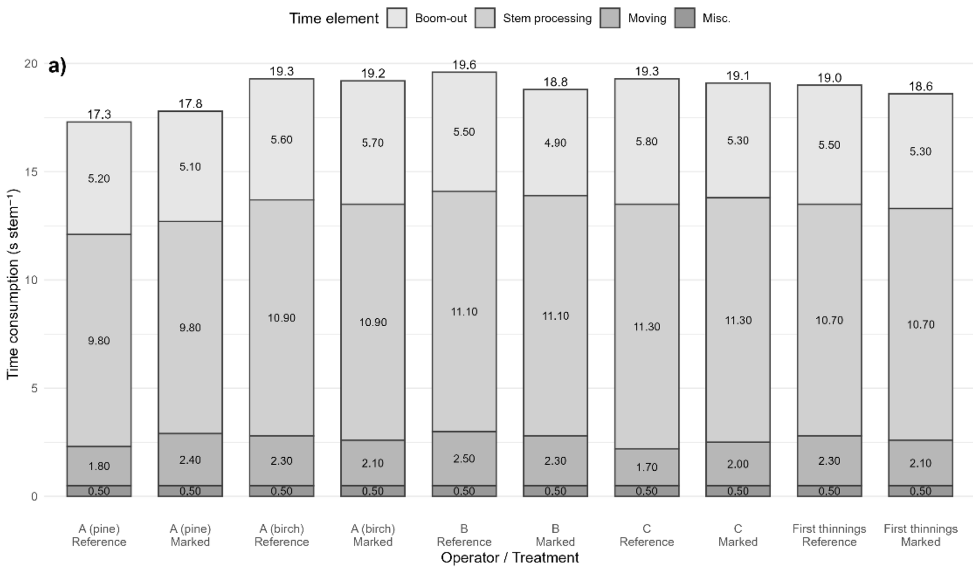
The average time consumption of *boom-out* was 5.2 s stem^{-1} in the marked first thinnings and 5.5 s stem^{-1} in the reference first thinnings but was not statistically significant (Study **I**). However, in later thinnings, the time consumption for *boom-out* averaged 5.2 s stem^{-1} in marked stands and 5.6 s stem^{-1} in reference stands, which was statistically significant ($U = 345.0$, $p < 0.05$). The results showed that the TDA reduced the average *boom-out* time from 6.6 s stem^{-1} to 6.3 s stem^{-1} and had a weak but statistically significant effect ($F = 6.3$, $p < 0.05$) (Study **II**). The effect of prior tree marking on the time spent *boom-out* ranged from −13% to +12%, while the effect of the TDA ranged from −15% to +10% across individual operators (Studies **I** and **II**).

Removal density ($F = 138.7$, $p < 0.001$) and operator ($F = 13.6$, $p < 0.001$) had a statistically significant effect on the time spent *moving* (Study **II**). Prior tree marking reduced *moving* time with an average of 0.2 s stem^{-1} in later thinnings, but the TDA did not significantly affect *moving* time ($F = 0.73$, $p = 0.39$). Notably, there were substantial (106%) relative differences between operators in the time spent *moving* (Study **II**).

In study **I**, the combined processing time element (i.e. the sum of *felling*, *processing* and *boom-in*) was significantly correlated with stem volume. Similarly, in Study **II**, both *felling* and *processing* times showed a significant correlation with stem volume ($t = 5.646$, $p < 0.001$; $t = 14.199$, $p < 0.001$). However, prior tree marking did not have a statistically significant effect in either first or later thinnings (Study **I**). Likewise, the TDA did not systematically affect the time spent *felling* or *processing*, although night-time cutting appeared to increase *processing* time by approximately 0.5 s stem^{-1} ($F = 10.60$, $p < 0.01$) (Study **II**).

Table 6. Distribution of average work elements (*boom-out*, *felling*, *processing*, *boom-in*, *moving* and *miscellaneous*) as proportions of the total effective work time. TDA = Thinning Density Assistant.

	Study **I**				Study **II**	
Work element	First thinning		Later thinning		First and later thinning	
	Marked, %	Reference, %	Marked, %	Reference, %	TDA, %	Reference, %
Boom-out	28.2	29.7	35.0	33.0	21.7	23.9
Felling	23.9	23.0	22.5	23.0	24.3	23.2
Processing	31.5	32.1	20.7	20.5	32.1	33.4
Boom-in	3.7	2.9	4.1	3.4	1.6	1.4
Moving	11.3	10.1	15.9	18.0	12.2	10.6
Miscellaneous	1.4	2.2	1.8	2.1	8.1	7.6
Total	100.0	100.0	100.0	100	100.0	100.0



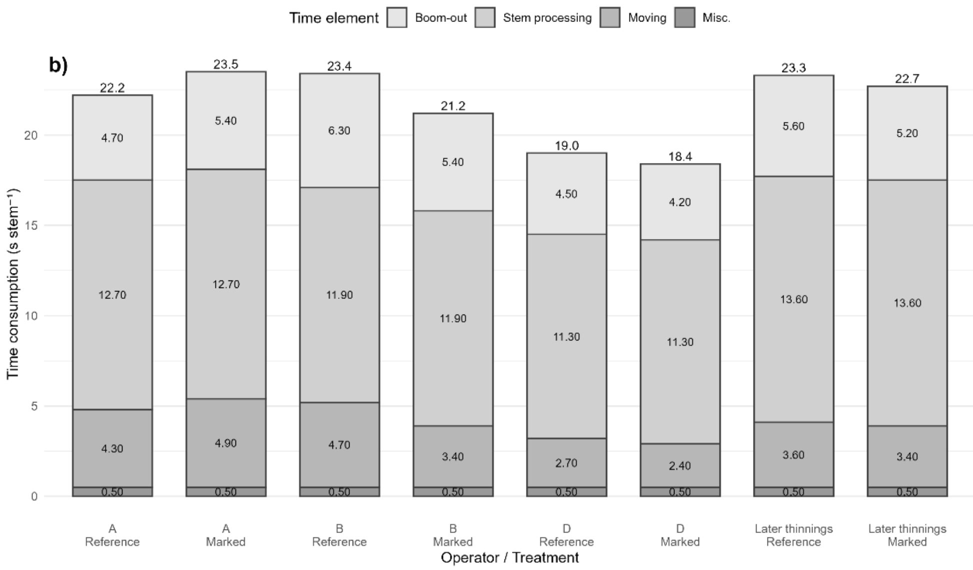


Figure 7. Total effective time consumption of each operator (Study **I**), with a stem volume of 0.06 m^3 removed in the first thinning a), and 0.15 m^3 removed in the later thinning b). Removal density was set at 800 stems ha^{-1} in the first thinning and 300 stems ha^{-1} in the later thinning. The final two columns show the overall average for first thinning and later thinning.

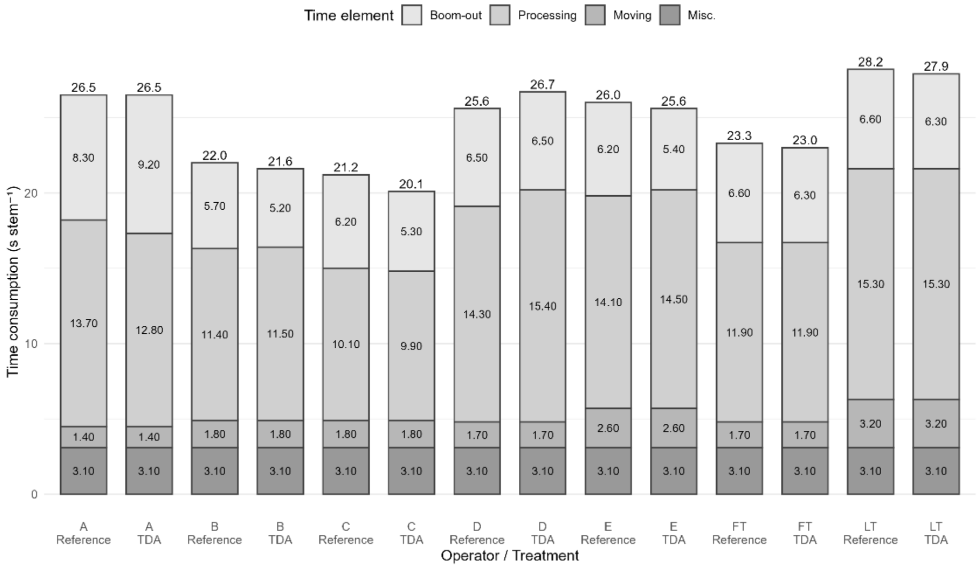


Figure 8. Total effective time consumption with a stem volume of 0.06 m^3 removed in the first thinnings (Study **II**). Removal density was set at 800 stems ha^{-1}. The final two columns show the overall average for first thinning (FT) and later thinning (LT) results. In later thinning stands, the average stem volume was set at 0.13 m^3, with removal density at 300 stems ha^{-1}.

3.2 Productivity, profitability and perceived workload

Neither prior tree marking nor TDA resulted in statistically significant improvements in productivity, despite observed increases in over half of the operators (Studies **I** and **II**). Effective hourly productivity is presented in Figure 9. Prior tree marking reduced the productivity gap between the most and least productive operators from +12.5% to +7.9% in first thinnings and from +18.4% to +13.0% in later thinnings (Study **I**). This trend was not observed with the TDA; instead, the opposite occurred: the relative difference between the most and least productive operators increased from +22.0% to +26.4% in first thinnings and from +24.3% to +30.7% in later thinnings (Study **II**). Although cutting at night slowed processing and reduced productivity by 1.5%, the benefit of the TDA did not increase under night-time conditions (Study **II**). Although younger operators seemed to perceive the TDA as more useful, this finding should be interpreted with caution due to the exceedingly small sample size in Study **II** (n = 5), which included only two operators under 30 years of age.

The acquisition of the system becomes economically viable only at approximately €2,900–4,200 (which corresponds to a NPV of €0) (Study **II**). However, if the machine is used exclusively for thinning, and productivity reaches the level observed with prior tree marking, the profitable acquisition price could increase to approximately €14,000 (Study **II**). Depending on the proportion of thinnings and the technological stage of development of the system, cost savings achieved solely through increased productivity are estimated to range between €1,000–3,000 per year.

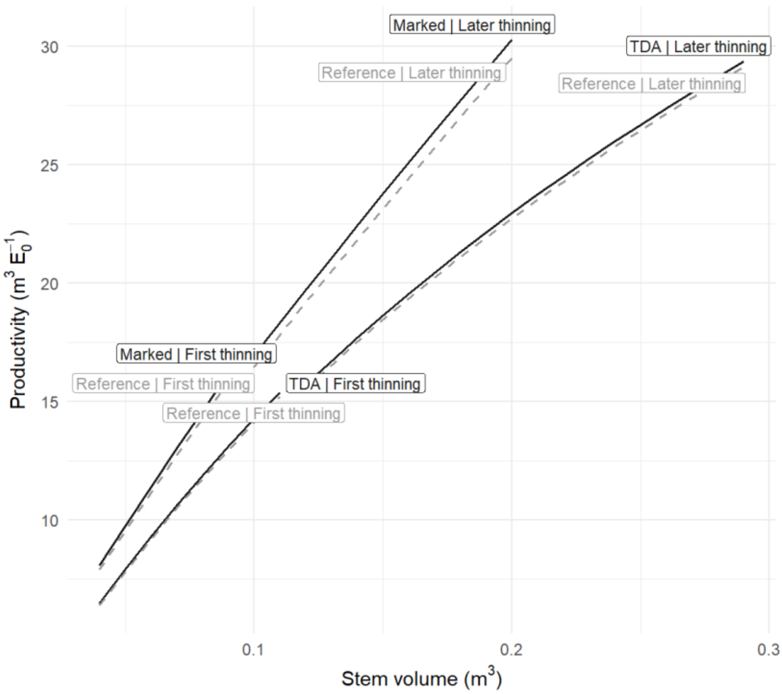


Figure 9. Cutting productivity modeled for marked and reference stands (Study **I**) and for the Thinning Density Assistant (TDA) and reference stands (Study **II**) during first and later thinnings as a function of removed stem volume. Removal intensity for Scots pine was set at 800 stems ha^{-1} in first thinnings and at 300 stems ha^{-1} in later thinnings.

The results showed that the TDA did not significantly increase or decrease workload. However, differences between age groups were observed: operators under 30 years of age found TDA to be slightly beneficial, primarily in supporting decision-making, work planning and maintaining work quality. In contrast, among more experienced operators, the TDA slightly increased physical activity, mental and physical effort, as well as perceived stress.

3.3 Estimating stand characteristics and strip road attributes using MLS technology

The MLS-derived estimates showed variable accuracy across stand stocking attributes, but overall, MLS provided consistent results despite minor systematic deviations. Stem density was underestimated in young, structurally heterogeneous stands. This slightly reduced average accuracy (RMSE = 113.1 stems ha^{-1}, bias = −9.7 stems ha^{-1}). Basal area tended to be slightly overestimated (RMSE = 3.1 m^2, bias = 1.5 m^2), partly because DBH estimates were statistically larger (0.6–2.5 cm) than reference values, though distributions aligned well (RMSE = 2.5 cm, bias = 1.6 cm). Dominant height showed the best agreement with the reference data (RMSE = 1.0 m, bias 0.1 m). Strip road width estimations were based on the regression model presented in Table 7, which achieved an average accuracy error of 0.4 m.

Table 7. Statistical information of the model for strip road width estimation (m). Independent variables are stem count (trees m^{-1}) within a 5 m range of the centre of the strip road and density of the remaining trees (Density, trees ha^{-1}).

Coefficient	Estimate of Coefficient	Standard Error	t-value	Significance
Intercept	6.15	0.39	15.589	< 0.001***
Stem count	11.53	3.74	-3.084	< 0.01**
Stem count^2	29.34	11.51	2.549	< 0.05 *
Density	0.000834	0.00089	-0.937	0.36
R^2 = 0.41, RSE 0.41, F = 8.41*** on 3 and 33 DF				

Likewise, an estimation of strip road spacing had an average accuracy of 1.5 m, with a bias toward underestimations (bias = −0.8 m).

3.4 Effect of operator guidance on harvesting quality

In study **I**, a larger proportion of the reference plots were thinned below the lower limit recommended by SFM guidelines compared to marked plots. Notably, in first thinnings, such shortfalls occurred only in reference stands, whereas in later thinnings, both reference and marked stands fell below the lower limit, although the shortfall was smaller in marked stands. The thinning intensity was almost 6% lower in the marked stands compared to the reference stands in both first and later thinnings, but the difference was not statistically significant (F = 4.15, p = 0.08).

Furthermore, prior tree marking helped the operator to maintain strip road spacing within the SFM guidelines (> 20 m), which reduced the tendency for strip road spacing to “drift” toward 30 m. In addition, strip road width more often remained closer to the recommended value (< 4.5 m). The most common tree defect was forking. However, prior tree marking had no effect on the number of remaining forked trees. In contrast, other defects occurred slightly more often in reference stands, which suggested a minor difference in quality outcomes. This indicates that prior marking may have influenced thinning outcomes (Study **I**).

A state-of-the-art TDA system can collect and visualise thinning density and strip road spacing data during forest operations (Study **II**). The birch-dominated first thinning stand presented the greatest difficulty for operators to keep the basal area and density of the remaining trees within SFM recommendations, whereas the other stands largely remained within the prescribed limits. Stem damage rates remained below the 5% guideline, which amounted to 1.9% in the reference plots and 2.3% in the TDA plots. The average thinning intensity was slightly lower in the TDA plots (45%) than in the reference plots (50%); however, differences in either stem-damage percentage or thinning intensity were not statistically significant. At this stage, harvesting quality did not differ significantly between treatments (TDA vs. reference), as both treatments met SFM recommendations (Study **III**).

4 DISCUSSION

4.1 General perspectives on tree-level guidance and the use of MLS data

The development of modern timber harvesting increasingly builds on the principles of precision forestry, where operations are optimised at both the stand-level and at the level of the individual trees. In thinning operations, the selection of removal trees must be economically viable, while the trees left standing should remain vigorous, structurally balanced and capable of sustained growth. In order to achieve these aims, the systems should accurately perceive and interpret stand structure and present this information to the operator in a clear and intuitive format. Tree choice is one of the central operational challenges for machine operators in mechanised thinning.

As a close-range remote sensing method, MLS provides highly detailed tree-level information that can enhance operator situational awareness and support a more systematic way of working. Tree-level attributes derived from MLS-based point cloud data can be used to support both real-time decision-making and the monitoring of harvesting quality. The aim of this thesis was to evaluate how guidance systems may influence work productivity, harvesting quality and its reporting, and ultimately the economic profitability of operations.

4.2 Evaluation of study data and methods

The high number of repetitions required for a manual time study, the nine participating operators (four operators in Study **I** and five operators in Study **II**) and the control of nuisance variables (e.g. stem volume and removal density) were the strengths of the time studies in this dissertation. Furthermore, the methodological advances presented here facilitate more precise modelling of the time spent *moving* during harvesting operations, which represents up to one quarter of the total effective work time. Notably, this approach enables the evaluation of operator effects during *moving* by significantly increasing the number of observations and adding interaction terms into the model.

The participating operators in the studies were skilled and experienced harvester operators. Their work was highly fluent, which may obscure the potential effects of prior tree marking or assistance systems, such as TDA. Conversely, their performance is inherently difficult to improve through ADAS, DSS or machine-control aids.

The harvesting quality data included the most important and commonly used variables (excluding rutting) for assessing harvesting quality in thinnings, as operators had limited ability to affect strip road planning. Studies **II** and **III** demonstrated that tree-maps derived from point clouds can be used to assess harvesting quality. However, improvements are necessary, as the data must be collected from point clouds and processed in real time during cutting to avoid generating extremely large point clouds or by merging them at a later processing stage. In Study **III**, information on individual trees was aggregated from plot-level tree-maps, finally forming a complete stand-level dataset. This step was highly labour-intensive and is not directly applicable to practical harvesting quality assessment.

Based on the productivity results observed here, the effective productivity of harvesting operations in Finland has developed steadily over the past three decades (Figure 10). The results from this dissertation show that effective productivity is 21 $m^3\ E_0^{-1}$ (Study **I**) and 17

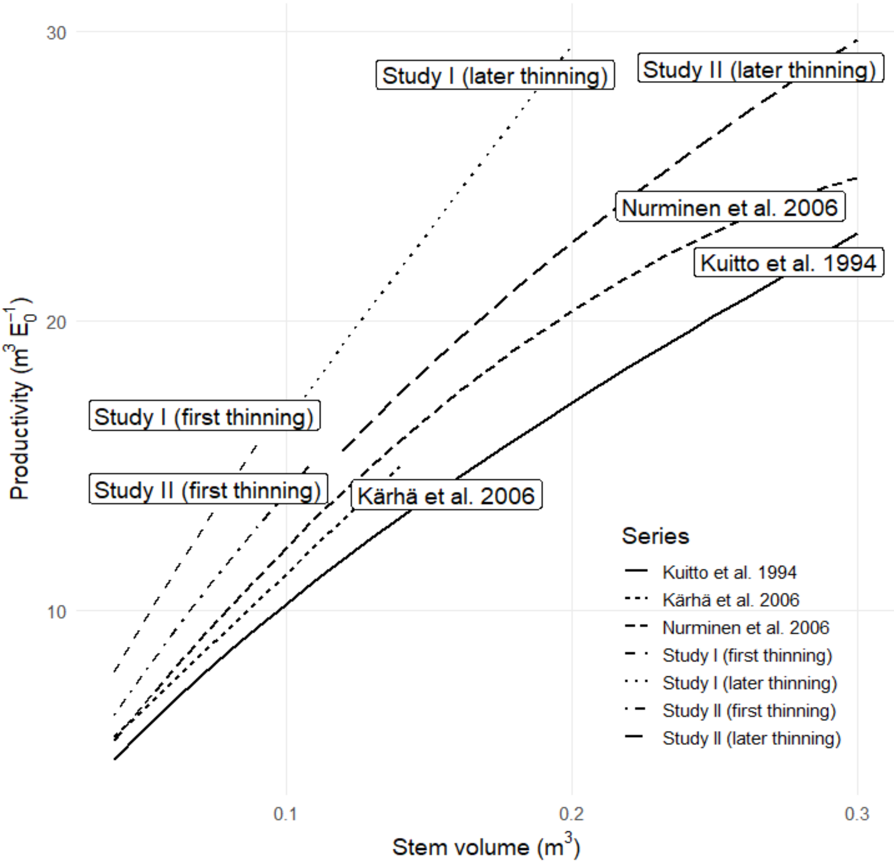


Figure 10. The development of effective-hour productivity over the past 30 years. The figure includes the productivity models proposed by Kuitto et al. (1994), Kärhä et al. (2006) and Nurminen et al. (2006) for pine cutting.

m^3 E$_0^{-1}$ (Study **II**) with an average stem volume of 0.13 m^3. When compared to recent follow-up studies, these figures are slightly higher than those reported in Scandinavia, where Eriksson and Lindroos (2014) found a value of 14.0 m^3 E$_0^{-1}$ and Jylhä et al. (2019) reported 15.1 m^3 E$_0^{-1}$.

The higher productivity levels seen in Studies **I** and **II** can be attributed to technological development, to the skill level and experience of the participating operators, as well as the relatively easy work sites. Adequate competency as a thinning operator can be reached in eight to nine months (Björheden 2001; Purfürst 2010; Wenhold et al. 2020), but full proficiency as a thinning operator can require up to five years of experience (Gellerstedt 2002). As the operators had no prior experience with prior tree marking, they may not have been able to fully benefit from its potential advantages (Study **I**). This may have led to an overly weak investment case in study **II**.

The NASA-TLX dataset, which measures operators' cognitive and physical workload, only included the five operators who took part in study **II**; therefore, the results should be interpreted with caution and cannot be generalised to the broader operator population.

4.3 Tree-level guidance systems for CTL harvesters

4.3.1 Time consumption and productivity

Stem size and removal density have a significant impact on cutting productivity, as documented in multiple earlier studies (Kärhä et al. 2004; Nurminen et al. 2006; Spinelli and Magagnotti 2013). As is typical in forest work studies, the influence of human factors was considerable, and the results showed a degree of variability that limits definitive conclusions. In the present work, productivity differences between harvester operators were 13% in Study **I** and 31% in Study **II**. These findings support those of Kärhä et al. (2004) and Väätäinen et al. (2005), who reported that operator-level productivity differences during thinning operations could be as high as 40–42%, although the variation seen here was lower. Such differences arise from factors that include boom and harvester head movements, an efficient working pace and proactive planning of harvesting tasks and tacit knowledge (Väätäinen et al. 2005)

Prior tree marking improved effective hourly productivity for three of the four operators in Study **I**, and the TDA improved productivity for four of the five operators in Study **II**, although the improvement was marginal for three of them. Prior tree marking affected the *boom-out* and *moving* time elements (Figure 7), while the TDA showed an effect on the *boom-out* element (Figure 8). The effect of prior tree marking was, to some extent, associated with lower operator productivity; however, this trend was not seen with the TDA. Based on the limited amount of night-time data, night work appears to slightly reduce cutting productivity.

Prior tree marking improved effective hourly productivity by slightly less than 3%, while the TDA increased productivity by only 1% (Figure 9). However, the relative benefit of prior tree marking or the TDA for the operators did not reach statistical significance. No previous results exist for thinning density guidance systems, but with regard to prior marking, the findings are broadly consistent with (though smaller than) the 20% improvement suggested by Bort (2005). In contrast, the results appear to conflict with those reported by Kellogg and Bettinger (1994), Spinelli and Magagnotti (2013) and Holzleitner et al. (2019), where marking did not increase thinning productivity, as well as with Kuitto and Mäkelä (1988), who found that *de facto* marking reduced productivity. Earlier studies on operator assistance systems have generally reported only minor productivity gains and substantial variation among operators in the benefits achieved, even when operators expressed generally positive experiences with the novel technology (cf. Englund 2015; Manner and Lundström 2025).

Tree marking tended to narrow the productivity gaps between operators (Study **I**), while the TDA showed the opposite pattern (Study **II**). This variation in results may account from unfamiliarity with the novel system, usability issues, working routines and methods, as well as operators' motivation toward modern technology. However, this raises an important question: can part of the experienced operators' tacit knowledge be transferred to less experienced operators to guide optimal working techniques and thereby narrow the performance gap between the least and most productive operators? Such transferable elements may include, for example, selecting edge trees along strip roads and planning work at the harvesting site (Ovaskainen 2009), or providing in-the-loop feedback on working techniques and harvesting quality in thinnings (Manner 2024), thus supplementing the otherwise limited feedback available to operators (Kymäläinen 2025).

Despite these conflicting findings, the results support the statement that the productivity of cutting work can be improved by easing the planning and decision-making duties of harvester operators with assistance systems (Ylimäki et al. 2012; Kärhä et al. 2021). A challenge lies in deciding what information should be provided to the operator and how it should be presented. Operators are concerned that cognitive workload may increase if frequent double-checking, confirmation or disregarding of suggestions becomes necessary due to anomalies or errors (Kymäläinen 2025). Therefore, accessible and intuitive AI systems that meaningfully complement human actions are desirable, in line with the vision of Agriculture 5.0 (Holzinger et al. 2024a).

Improvements in the usability and immersive experience using augmented reality (AR) of the TDA system could unlock greater efficiencies and productivity gains when integrated with other technologies to semi-automate actions or sub-tasks currently performed by the operator, thereby freeing time for other time activities. Examples could include automatic tree species recognition or notification of irregular stem geometry (i.e. bend or crooked stems) and real-time harvesting quality monitoring (Sagar et al. 2024; 2026). In addition, as positioning accuracy improves, digital geofencing will be increasingly utilised, which will aid operators near no-go areas (Lumperoinen et al. 2025).

To conclude, substantial productivity improvements are unlikely to be achieved through a single assistance or controlling system, but rather through the sensor fusion and integration of multiple aids within a comprehensive human-machine-environment interaction framework. It remains to be seen whether effective-hour productivity will continue to improve at the pace experienced over the last decades (Figure 10). In that case, productivity would need to increase by more than 10% over the next 20-year development period, primarily with the aid of assistive systems. Alternatively, autonomous machines may have entered the forest by then, once again revolutionising harvesting work.

4.3.2 Harvesting quality

The operators performed better at maintaining targeted thinning density in prior tree marked stands, whereas operator tree selection in reference stands led to surprisingly low stand densities compared with the recommendations given by the SFM (Study **I**). A similar effect was not observed in the state-of-the-art TDA system; with a few exceptions, harvesting results with and without the TDA were adequate and complied with SFM recommendations (Study **III**). The thinning intensity, expressed as the ratio of removed to remaining trees, approached statistical significance, and was some percentages lower in the prior tree marked plots and the TDA plots compared to the reference plots (Studies **I** and **III**). This indicates a solid baseline upon which the TDA may offer additional benefits as it continues to develop.

Study conditions (stand structure, species composition and terrain) likely influenced the results. In Study **I**, the initial stand densities were low and stand structure was irregular, especially in the later-thinning stands, which has been one primary reason for excessively intensive thinning in Finland (Poikela and Äijälä 2006). The TDA had no statistically significant effect on the harvesting outcome. This result may have been influenced by the skilled operators. They might have worked more carefully than usual and relied primarily on their own professional judgement rather than on TDA guidance. Limited prior experience with the system may have reduced trust in its recommendations, further lessening its impact on harvesting quality.

The combination of MLS, ITD and AI may enable the automation of tasks that have traditionally relied on manual measurements and human expertise, such as the selection of individual trees to be removed (Packalen et al. 2020; Sun et al. 2022; Pukkala et al. 2025), and where trees selected for removal or retained for future growth are typically identified through prior marking. This marking can be made from a digital twin of the stand (Shanmugam et al. 2025). By utilising point cloud data, key tree attributes, such as DBH and height, can be used to calculate the slenderness ratio (height/DBH), assess stem curvature and evaluate crown vitality, for example based on the proportion of live crowns (Pitkänen et al. 2022). Trees with sufficient light, growing space, water and nutrients exhibit balanced growth patterns, which promote diameter increment, leading to more valuable sawlogs.

4.3.3 Economic feasibility as an investment

From an R&D perspective, the cost of the investment can be seen as an investment in all future financial benefits achieved with LiDAR technology in forest machinery. The revenue model for MLS-based assistance systems is built on several value-creating hypotheses: long-term improvements in operational productivity, enhanced harvesting quality, automated collection of environmental data, chain of custody in the wood supply chain and a reduction in social costs associated with work-related strain. Therefore, the incentive currently rests with all responsible actors, as markets for environmental data, for example, remain uncertain and difficult to monetise. From a forest machine entrepreneur's perspective, to remain commercially viable, the cost of the equipment should remain within a few tens of thousands of euro (Study **II**). One potential approach is to retrofit existing machines already in operation, as forest machinery fleets are renewed at a relatively slow pace.

The development of LiDAR technology in forest machines is pioneering and in its early stages. The results are only applicable at this level of implementation. For instance, the operator must look at a separate screen and match it with the surrounding trees while simultaneously engaging in other cutting tasks, which is not an optimal method for presenting information to the operator. Moreover, the maximum benefit of the system in profitability calculations was based on the benefit achieved through prior tree marking, which may underestimate the actual performance potential of the tree-level guidance system (Studies **I** and **II**).

Low-cost and existing data sources, such as hpr files (Tarvainen et al. 2025; Holmström 2026), may provide a financially rational solution for monitoring and operational guidance in the current operational environment. However, MLS offers clear advantages for the future development of semi-autonomous and autonomous harvesters. Consequently, assistive technologies that help operators retain the most vigorous trees during thinning operations remain highly valuable.

The MLS system can detect and document the location and quality of remaining trees, retention trees and thinning intensity (Study **III**). In addition, it can document buffer zones and generate large-scale environmental data and reference material in real time (Faitli et al. 2024; Kafle et al. 2025). Thinning intensity, timing and tree selection have the potential to significantly enhance forest growth and carbon sequestration rates (Hynynen and Arola 1999; Hynynen et al. 2023; Mäkipää 2023). The potential financial benefit that results from successful thinnings over a full rotation may, in theory, reach several thousand euro per hectare (Mäkipää 2023).

Automating harvesting quality reporting and operational monitoring are key capabilities that may deliver substantial added value and cost savings in the future. However, these capabilities should be further examined through long-term studies that include a more diverse range of thinning stands. Enhancing chain-of-custody tracing of logged stems throughout the supply chain can generate significant added value (Keefe et al. 2022). Furthermore, documenting the specified proportion of broadleaf trees in a stand, as recommended or required by SFM frameworks or forest certification schemes, can likewise contribute additional value.

Work-related cognitive and physical load in the forest machine sector have considerable societal costs (Kymäläinen 2025). Among CTL harvester operators, work ability is greatest in younger operators but declines and becomes increasingly variable with age. Younger operators found the TDA significantly more useful than their older colleagues (Study **II**). Younger operators may possess a greater need for assistance systems capacity than their older counterparts with regard to the adoption of new assistance systems and operational practices. This is likely associated with a greater need for the assistance systems, as well as higher cognitive flexibility and adaptive learning abilities observed in younger individuals (Fazi et al. 2025; Radović et al. 2025).

4.4 Future perspectives on developing assistant systems for harvester operators

High-quality and dense laser scanning data enables automatic single-tree detection. National airborne laser-based derived tree datasets, such as the Forest database (metsakanta.fi 2026), could be used as prior stand information, which can then be further updated during harvesting using MLS-based methods to capture tree attributes in greater detail (Faitli et al. 2024). This information could support the optimisation of thinning intensity and the design of the strip road network. Research is needed to optimise individual-tree growth by accounting for tree characteristics and growth-limiting environmental factors, such as light availability, soil conditions and competition (Saarinen et al. 2020; Ronoud et al. 2022; Saarinen et al. 2022; Ronoud et al. 2024). Such understanding will support the development of decision-making logic to identify the trees that should be removed or retained in thinning from below, thinning from above and in CCF. Recommendations should include those trees chosen to remain as the strip road edge along the strip road (Ovaskainen 2009) at the work locations.

To work at the single tree-level, the system must recognise that a stand is not homogeneous but composed of smaller micro-stands (Mustonen et al. 2008; Saksa et al. 2021) and, from the operator's perspective, individual work locations (Ovaskainen 2009). Therefore, within-stand variability should be taken account when providing guidance to the operator. Prior information on stand-level species composition is also valuable for the operator, because SFM and certification frameworks recommend or require the maintenance of a specified proportion of broadleaf trees in managed stands. The minimum requirement is to be able to distinguish conifers from broadleaves, although identification of all major tree species would be highly valuable to advance automation. These considerations further emphasise the need to integrate prior tree information with real-time data collection to enable effective operator assistance systems. In addition, systematic monitoring and documentation of harvesting operations for stakeholders, such as forest owners, authorities, certification bodies and the forest industry, can be seen as a promising method to ensure transparency in the forest sector.

Information on the stand, individual trees, harvesting quality and biodiversity can be presented to the operator through voice guidance, haptic feedback and AR- or HUD-based solutions (Kärhä et al. 2025). Although operators are accustomed to traditional maps, comparing a tree map with the actual environment during harvesting work is challenging; therefore, more intuitive and informative visualisation methods are needed. One option is to present the data as a 3D landscape model, with or without photo texturing as surface visualisation. Such a 3D representation may feel more natural to the operator, reduce misinterpretation and improve decision-making compared to traditional 2D map-based displays.

Operators who are still in the learning phase represent an important group that deserve particular attention in research. How can their work be supported so that they reach full proficiency as rapidly as possible and be encouraged to stay in the profession rather than leave? Semi-automated machines and digital systems can help and guide operators. However, additional technology-based skill requirements for both novice and experienced operators create a need for research to decide what data should be displayed, how it should be visualised for the operator, and what kind of training is required to ensure effective use (Kärhä et al. 2025). The cognitive implications of these systems for operators, including mental workload, usability and training requirements are unknown.

The findings of this thesis, together with the outlined future perspectives, highlight the importance of MLS-based operator-guidance systems (state-of-the-art ADAS and DSS) in thinning operations, demonstrating the types of operational information that can be displayed to the operator during harvesting, and systematically documented for stakeholders. Highly accurate point clouds, when combined with machine-vision systems in forest machines, also support the development of robotics in harvesters and forwarders. This will represent a major step towards achieving Level 2 automation in forest machinery. In the long term, such robotics-based solutions may lead to substantial cost savings, particularly as skilled labour becomes increasingly scarce (Visser and Obi 2017).

5 CONCLUSIONS

Accurate tree-level information, collected in advance over large areas using ALS and close-range remote sensing, such as MLS, can be used to optimise tree selection and enable increasingly precise operator guidance and documentation in thinning operations. These capabilities offer the potential for scalable benefits, which include improved productivity, higher harvesting quality, reduced operator workload, enhanced documentation and the collection of training data for ALS-based tree-level inventories. Accordingly, there is a clear need to evaluate the effectiveness and accuracy of such data-driven systems with regard to supporting real-time decision-making during thinning operations.

This thesis assessed the potential of these systems in three studies. Study **I** imitated a decision-support system that advises operators on optimal tree removal where trees were marked manually. Study **II** evaluated a TDA system that indicated the locations of remaining and removed trees, identified trees that were too close to each other, provided the distance to the previous strip road, and examined investment feasibility in terms of harvesting productivity. Study **III** explored the use of point-cloud-derived tree-maps for operator guidance, monitoring and reporting.

Prior tree marking improved cutting productivity by slightly less than 3%, whereas the TDA system increased productivity by only 1%. Both effects showed considerable variation among operators and did not reach statistical significance. However, prior tree marking and the TDA reduced the average time spent during *boom-out* (positioning harvester head for cut), while prior tree marking reduced the time spent *moving* as well. Current TDA implementation already provides clear benefits. Although its performance does not yet fully match the results achieved with prior tree marking (Study **I**), continued development of single-tree level guidance is expected to enable performance at a comparable level of approximately 3% (RQ1).

Prior tree marking improved harvesting quality by maintaining the targeted number of remaining trees and helped to keep strip road spacing on target. The state-of-the-art Ponsse TDA system did not improve harvesting quality compared with the reference plots; experienced and skilled operators were able to achieve good results regardless. Tree-level guidance appeared to reduce average thinning intensity by about 5–6%. These results suggest that productivity and harvesting quality can be improved through tree-level guidance (RQ2). The full benefits for both productivity and harvesting quality may only be realised with immersive systems, such as AR.

The backpack-mounted MLS system provided consistent results during post-processing, despite minor systematic deviations in stocking attributes, harvesting-quality indicators and even certain wood-quality characteristics. In contrast, real-time analysis of point clouds from the MLS sensors mounted on a harvester is much more of a challenge. At present, harvester-mounted MLS can reliably detect and document the location of remaining trees, retention trees, thinning intensity and strip-road spacing (RQ3), but accurate estimation of attributes, such as DBH and tree height remains challenging.

At its current stage of development, the MLS-based assistance system does not offset its costs when evaluated solely from a productivity perspective (RQ4). However, harvester automation will continue to advance irrespective of individual system choices. Therefore, MLS is likely to be integrated into harvesters in any case and, as such, does not constitute an additional cost factor. In contrast, a well-implemented TDA system has the potential to increase productivity by approximately 3%. Importantly, the benefits of MLS-based systems extend well beyond productivity improvements and include optimised bucking, improved harvesting quality and documentation, reduced labour and field-travel requirements, and the large-scale acquisition of reference data on forest resources. The monetary value and broader intangible benefits associated with these aspects, such as improved environmental and biodiversity outcomes, are therefore expected to substantially exceed those associated with productivity improvements alone.

This dissertation contributes to the development of single-tree level operator guidance systems on CTL harvesters, and can be regarded as groundwork for future semi-autonomous and autonomous forest-harvesting solutions, ultimately enabling higher productivity and reduced environmental impacts in the long term.

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