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Measuring tree growth using terrestrial laser scanning

Ville Luoma

Department of Forest Sciences
Faculty of Agriculture and Forestry
University of Helsinki

Academic dissertation

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Author: Ville Luoma

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Thesis Supervisors:
Professor Markus Holopainen
Department of Forest Sciences, University of Helsinki, Finland

Professor Mikko Vastaranta
School of Forest Sciences, University of Eastern Finland, Finland

Docent Ville Kankare
School of Forest Sciences, University of Eastern Finland, Finland

Docent Ninni Saarinen
School of Forest Sciences, University of Eastern Finland, Finland

Pre-examiners:
Professor Petteri Alho
Department of Geography and Geology, University of Turku, Finland

Associate professor Johan Holmgren
Department of Forest Resource Management, Swedish University of Agricultural Sciences, Sweden

Opponent:
Professor Matti Maltamo
School of Forest Sciences, University of Eastern Finland, Finland

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ABSTRACT

Forests are dynamic ecosystems that are constantly changing. The most common natural reasons for change in forests are the growth and death of trees, as well as the damage occurring to them. Tree growth appears as an increment of its structural dimensions, such as stem diameter, height, and crown volume, which all affect the structure of a tree. Repeated measurements of tree characteristics enable observations of the respective increments indicating tree growth. According to current knowledge, the tree growth process follows the priority theory, where trees aim to achieve sufficient lightning conditions for the tree crown through primary growth, whereas increment in diameter results from the secondary growth. Tree growth is known to have an effect on the carbon sequestration potential of trees as well as on the quality of timber. To improve the understanding of the underlying cause–effect relations driving tree growth, methods to quantify structural changes in trees and forests are needed.

The use of terrestrial laser scanning (TLS) has emerged during the recent decade as an effective tool to determine attributes of individual trees. However, the capacity of TLS point cloud-based methods to measure tree growth remains unexplored. This thesis aimed at developing new methods to measure tree growth in boreal forest conditions by utilizing two-date TLS point clouds. The point clouds were also used to investigate how trees allocate their growth and how the stem form of trees develops, to deepen the understanding of tree growth processes under different conditions and over the life cycle of a tree. The capability of the developed methods was examined during a five- to nine-year monitoring period with two separate datasets consisting of 1315 trees in total.

Study **I** demonstrated the feasibility of TLS point clouds for measuring tree growth in boreal forests. In studies **II** and **III**, an automated point cloud-based method was further developed and tested for measuring tree growth. The used method could detect trees from two-date point clouds, with the detected trees representing 84.5% of total basal area. In general, statistically significant changes in the examined attributes, such as diameter at breast height, tree height, stem volume, and logwood volume, were detected during the monitoring periods. Tree growth and stem volume allocation seemed to be more similar for trees growing in similar structural conditions.

The findings obtained in this thesis demonstrate the capabilities of repeatedly acquired TLS point clouds to be used for measuring the growth of trees and for characterizing the structural changes in forests. This thesis showed that TLS point cloud-based methods can be used for enhancing the knowledge of how trees allocate their growth, and thus help discover the underlying reasons for processes driving changes in forests, which could generate benefits for ecological or silvicultural applications where information on tree growth and forest structural changes is needed.

Keywords: TLS, forest mensuration, LiDAR, change detection, point cloud processing, tree growth allocation

PREFACE

When writing this preface, the once so distant goal of completing a PhD degree is starting to get closer and closer. The start of this journey probably dates back to year 2012, when I still was an MSc student. Markus Holopainen and Mikko Vastaranta offered me first a job as a course assistant and then after my graduation in 2013 asked me to continue working at the University of Helsinki as a project researcher. In retrospect, those were probably the first steps towards this PhD project, even if I did not consider them as such back then. Soon after that, Ville Kankare introduced me to TLS data processing and a bit later, I was privileged to get a chance to learn everything about TLS and data collection in guidance of Ville, Mikko, Harri Kaartinen and Antero Kukko during the field campaign in Evo in 2014. Despite of continuing to work in several research projects in the following years, my PhD project started officially only in 2019 when the Finnish Cultural Foundation awarded me a three-year grant.

Since then, I have been able to concentrate on working with this thesis under inspiring and supportive guidance of my supervisors Markus, Mikko, Ville, and Ninni Saarinen. I am grateful to all you for your efforts in supporting me to complete this thesis. Especially I want to thank Markus, firstly for ensuring funding for me, but above all, for always having your door open and time for advice and discussions if I have needed it. Thank you for trusting me all these years and giving me the opportunities to follow my calling and be involved in teaching too, which I really have enjoyed. In addition to my supervisors, I want to thank Tuomas Yrttimaa. It has been a pleasure to work with you, first exchanging ideas and collecting study data together as PhD candidates. In the later phases of my thesis project, you took a role of an additional supervisor, who gave me valuable feedback and advice during the completion of this thesis. I am also thankful for the fruitful collaboration with my other co-authors Harri, Antero, Juha Hyyppä, Topi Tanhuanpää, Jiri Pyörälä and Samuli Junttila.

During these years I have been lucky to get to know so many good people in different contexts. I want to thank all the friends and colleagues in our research group and at the Department of Forest Sciences for their help and advice during my still young career as a researcher. Special thanks go to our lunch hour group of Markus, Topi, Jiri, Einari, Otto, Mohammad and Lukas for always nice and interesting discussions during the breaks.

Completion of this thesis would not have been possible without financial support for it. I want to thank the Finnish Cultural Foundation (grant numbers 00190660, 00202601 and 00220054) for my PhD grant and Academy of Finland (grant numbers 272195 and 334001). The TLS equipment from the Finnish Geospatial Research Institute made the data acquisition possible. I also want to thank people from the Evo Campus of Häme University of Applied Sciences for their cooperation and for making us always feel warmly welcome to Evo.

I want to thank my parents Pekka and Leila for being caring and supportive parents for my brother Jussi and me. I am fortunate to have friends and relatives to whom I can trust and with whom I can share the ups and downs of my life. You are important to our family and me. Finally, I want to thank my dear wife Katja and our beloved daughters Hilda and Helka for supporting me in pursuit of my goal to finish this thesis and even more importantly, that every day with you three brings smiles, joy, and love to the life of a proud father.

Helsinki, September 2022

Ville Luoma

LIST OF ORIGINAL ARTICLES

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

I Luoma V, Saarinen N, Kankare V, Tanhuanpää T, Kaartinen H, Kukko A, Holopainen M, Hyyppä J, Vastaranta M (2019) Examining changes in stem taper and volume growth with two-date 3D point clouds. Forests 10 (5), article id 382. https://doi.org/10.3390/f10050382

II Yrttimaa T, Luoma V, Saarinen N, Kankare V, Junttila S, Holopainen M, Hyyppä J, Vastaranta M (2020) Structural changes in boreal forests can be quantified using terrestrial laser scanning. Remote Sens 12 (17), article id 2672. https://doi.org/10.3390/rs12172672

III Luoma V, Yrttimaa T, Kankare V, Saarinen N, Pyörälä J, Kukko A, Kaartinen H, Hyyppä J, Holopainen M, Vastaranta M (2021) Revealing changes in the stem form and volume allocation in diverse boreal forests using two-date terrestrial laser scanning. Forests 12 (7), article id 835. https://doi.org/10.3390/f12070835

AUTHOR'S CONTRIBUTION

I) Luoma planned the study design together with his supervisors and colleagues. He collected the field reference and TLS data at the end of the monitoring period with his colleagues. He was responsible for data processing and analysis and wrote the first draft of the manuscript.

II) Luoma planned the study design together with his colleagues and supervisors. He collected the field reference and TLS data as well as pre-processed the point cloud data together with his colleagues. He was responsible for processing and analyzing the field reference and performed the data-analysis with the main author. He participated in the writing of the first draft of the manuscript with his colleagues.

III) Luoma planned the study design together with his colleagues and supervisors. He collected the field reference and TLS data as well as pre-processed the point cloud data together with his colleagues. He performed the data-analysis with his colleague and wrote the first draft of the manuscript.

TABLE OF CONTENTS

ABBREVIATIONS

Δ	delta; indicating change in tree and forest structural attributes
3D	three-dimensional
ALS	airborne laser scanning
cr	crown ratio
dbh	diameter at the breast height
$d_{6.0}$	diameter at the height of 6.0 meters
$d_{0.5h}$	diameter at the relative height of 50 %
D_g	basal area-weighted mean diameter
f	cylindrical form factor
G	mean basal area of a forest stand (m^2/ha)
g	basal area of an individual tree
H_g	basal area-weighted mean height
h	tree height
hc	height of the crown base
HDR	height to diameter ratio
MLS	mobile laser scanning
$q_{0.5h}$	normal form quotient
QSM	Quantitative structure modeling
R^2	coefficient of determination
RANSAC	random sample consensus
RMSE	root mean square error
T1	time point at the beginning of a monitoring period
T2	time point at the end of a monitoring period
TAP	stem tapering
TAP%	relative stem tapering
TLS	terrestrial laser scanning
TPH	number of trees per hectare (n/ha)
V	stem volume
V_{log}	logwood volume
V_{log}%	logwood percentage

1 INTRODUCTION

1.1 Changes in trees and forest environments

Forests are dynamic ecosystems and an essential part of the environment that is under constant change. In general, change can be defined as the act or result of something becoming different (Oxford University Press 2022). Changes may be logical, expected, sudden, slow, or even illogical, and often some kind of action is needed for a change to happen. The reasons for change vary and depend on the subject of the change as well as on the surrounding environment. For example, changes in climate have shown to have an effect on the environment (e.g., Hardy 2003) and thus on the growth conditions of forests (Lindner et al. 2010). It has been reported that changes in how trees grow in forests have occurred during recent decades (Kangas et al. 2020), even though all the underlying reasons for these changes have not been determined exactly. On the whole, all changes happening in our universe, being small or large in size, may have small- or large-scale effects on other organisms of the universe.

The occurrence of changes in the structures of trees and, through them, also in forests are of interest to many. For example, forest scientists aim to generate a better understanding of tree growth and how trees allocate growth to different structures (Pretzsch 2009). Accurate and up to date information about forests is also needed in the decision-making processes of forest management planning (Kershaw et al. 2016) and how forests could be utilized sustainably and cost-effectively around the world. Forests are of high value both on a local and global scale, and information about their changes is vital for forest owners as well as for investors. Changes in the carbon sequestration potential of forest biomass are a key factor in mitigating climate change, where detailed information about tree growth helps scientists to understand the effects of changing environments to tree and forest growth processes (Harris et al. 2021). On the other hand, ecologists are keen on studying different growth strategies of plants and how they evolve under changing growth environments (Sutherland et al. 2013).

Considering the changes occurring to trees and forests, there are several types of change, all with various underlying factors and reasons. Both biotic and abiotic factors drive change. The most typical and natural source for a change in a tree or a forest stand is natural growth, which in general is a result of the tree's genetic properties, its geographical location, and environmental conditions such as the temperature, altitude, and soil properties, as well as competition for growth resources between other organisms (e.g., Tomé and Burkhart 1989; Ericsson et al. 1996; Oliver and Larson 1996; Poorter and Nagel 2000; Craine 2005). Natural growth is an essential part of the life cycle of a tree, in which the growth process typically starts from a seed and includes the phases of developing into a sapling and further to a full-sized tree. At the end of the cycle, the tree dies of some cause (e.g., being affected and weakened by drought, insect, or storm damage) and starts decaying or is cut down on purpose, to be further utilized as raw material. An increment in any of the observable attributes of the tree can be classified as growth (Kershaw et al. 2016). The growth of a tree consists of vertical growth, where the height of a tree increases, and radial growth, where the diameter of the tree increases on any height along the stem in a time horizon. For a tree, growth may also mean the increase in, for example, stem volume, biomass, or basal area. In practice, it is also possible for a change in some of the tree attributes to be negative; for example, the biomass or volume may reduce as a result of damage to the tree or if the tree stem gets broken. These kinds of biotic changes may result from wind, storm, snow, or insect damage, spread of pathogens, or forest fires (e.g., Quine 1995; Cherubini et al. 2002; Lyytikäinen-Saarenmaa and Tomppo 2002; Gupta et al. 2015; Carvajal-Ramirez et al. 2019). All these changes resulting from natural disturbances may have an effect on the individual trees during their life cycle and thus also modify the forest structure on a scale that depends on the severity of the disturbance (e.g., Attiwill 1994). Furthermore, the changes related to abiotic factors mainly happen through the changes occurring to individual trees at first, but very often the reasons behind these changes are part of larger processes. Many anthropogenic actions related to land use, silviculture, and harvesting reshape forests, thus effecting changes on individual trees (Holopainen et al. 2014). Typically, forest operations such as thinning and harvesting reduce the number of trees and thus affect the structure of forests in the short and long term.

Spatiotemporal information is essential to be able to better follow the wide spectrum of changes occurring in trees and forests. With the acquisition of more exact and detailed information about trees and forests over time and space, a better understanding of the changes resulting from natural phenomena or human actions, as well as more accurate determination of tree growth, can be achieved.

1.2 How do trees grow?

Different theories to describe tree growth exist, but currently the prevailing assumption is the priority theory summarized by Oliver and Larson (1996). According to the theory, a tree's first priority is to maintain its respiration before using its resources to increase its size in a vertical direction or horizontally by further extending the branches of the tree crown. The increase in height or branches is defined as primary growth, wherein trees aim to ensure sufficient lightning conditions. Only after using resources for primary growth can trees concentrate on the secondary growth, which is radial growth of the tree stem. This is why trees' adaptation to the environment and balancing between growth and survival have been evaluated by focusing on the ratio between primary and secondary growth (King et al. 2006; Bartholome et al. 2013).

The progress of tree growth can indicate the state of the forest and what kind of effect the surrounding environment has on a tree. Studies focusing on tree growth and yield have shown, for example, how different thinnings and treatments affect the growth environment of a tree and thus also the tree growth itself (e.g., Pretzsch 2009; Weiskittel et al. 2011; Saarinen et al. 2021). Based on the assumptions of priority theory, it can be expected that trees that encounter less competition can use more resources for diameter growth, whereas trees experiencing severe competition when located in denser stands or suppressed by dominant trees have to allocate their resources to increasing tree height for better lighting conditions. Various studies have supported the priority theory, with results indicating that dominant and co-dominant trees that have achieved the best position in competition, as well as trees on more sparse or thinned stands, seem to be able to allocate more growth resources to secondary growth than trees amid more intense competition (e.g., Vuokila 1960; Larson 1963; Kozlowski 1971; Muhairwe 1994; Tasissa and Burkhart 1997; Peltola et al. 2002; Mäkinen and Isomäki 2004a; Mäkinen and Isomäki 2004b; Saarinen et al. 2021). This development will lead to a relatively higher rate of diameter growth, which is especially concentrated on the lower parts of the stem. This is further supported by findings (e.g., McMahon 1973; Bullock 2000; Sperry 2003; Mencuccini et al. 2011) stating that when trees are able to gain more height and may have a larger crown, they also need more supportive structures, especially in the lower parts of the stem, to ensure that the tree is capable of maintaining its vital functions. This leads to the development of a more tapered stem, since the height of the tree and the diameter of the stem in parts closer to ground level are increasing at the same time. To be able to evaluate tree growth, specific estimates have been derived from the measurable characteristics of trees. Attributes such as tapering, form quotient, form factor, and the ratio between tree height and stem diameter at breast height are used to describe the status of a tree (Kershaw et al. 2016). Changes in these attributes may also yield information about how trees allocate their growth between different parts of the stem.

However, the preferences and purposes of the end user often determine what kind of increment is sought after. For example, with increased secondary growth, trees produce more biomass or stem wood (Oliver and Larson 1996), which is prioritized when the trees are being utilized as raw material by the forest industry (e.g., Hurmekoski et al. 2018), whereas in a more suppressed position the dimensions of the trees increase more slowly and thus produce wood, which has higher density and can be more suitable for solid-wood products, for example (Moore and Cown 2017). Demands for wood quality are also important to take into account when making decisions related to forest management.

1.3 Attributes describing characteristics of trees and forests

The more exact, accurate, and up to date forest resource information is available, the better the foundation that can be created for decisions related to forests. For this purpose, forest scientists around the world have been working to improve and develop methods of measuring and estimating different attributes that describe the state of single trees and forests. One of the focus areas has been how to more precisely follow and measure changes that are constantly happening in the forests of the world.

Typically, the most used attributes to characterize trees are diameter at breast height (dbh), tree height (h), tree species, and age (Kershaw et al. 2016). In addition to these, diameters at other heights along the stem, for example at a height of 6.0 meters, and attributes describing the length and height of the tree crown are used. All these attributes have traditionally been, and are still on many occasions, determined in the field by a mensurationist or a measurement crew using devices such as calipers or measurement tapes for dbh and clinometers for measuring h (Avery and Burkhart 2015). The accuracy of determining these attributes is dependent on the tree attribute in question and the used observation method (e.g., McRoberts et al. 1994; Williams et al. 1994; Liu et al. 2011; Wang et al. 2019). Several other attributes, such as basal area, stem volume, and tree biomass, can be derived from the basic attributes with the help of allometric models developed to estimate attributes not possible to be measured directly (e.g., Laasasenaho 1982; Repola 2008; Repola 2009). However, the allometric models have not been developed for all tree species, and they are mainly designed to be used only within specific regions, which both limit their applicability in general.

Stem volume is also often used to indicate the amount of wood, since modeling the stem volume is easier than weighing the tree, especially if the aim is to keep the tree alive (Kershaw et al. 2016). Depending on the end use purpose, it is also typical that the tree is divided into different timber assortments, such as logwood and pulpwood, which have their own limits for the quality, diameter, and length of the parts of the tree trunk (Rantala 2011). Size and stem form are among the main factors determining the potential yield and quality of the timber (Uusitalo 1997; Kilpeläinen et al. 2011). With logwood normally being the most valuable part of a tree stem, for example for the sawmill industry, forest management practices are often planned and implemented to maximize its abundance (Kivinen and Uusitalo 2002).

The attributes of individual trees are then used to characterize the structure of forests by estimating forest stand-level attributes; this is conducted by summing up individual tree attributes or utilizing, for example, sampling, modeling, and remote sensing technologies. Examples of attributes characterizing forests are stem count, total volume, and basal area per area unit, as well as either arithmetic or size-weighted means of h and dbh (Kershaw et al. 2016). Typically, the estimates are either directly modeled from the tree observations, or a tree size distribution is predicted based on the measurements from the sample plots. The diameter distribution can then be used for predicting further attributes for the forest stands. Nowadays, remote sensing methods are used to provide information about forests over large areas by using, for example, area-based approaches, where airborne laser scanning (ALS) data are used to generalize field-measured forest inventory attributes over an entire inventory area (e.g., Næsset et al. 2004; White et al. 2013).

Since it still is not possible to measure all the trees within the biosphere or even within large forested areas in practice, the aforementioned solutions are essential in producing information about the forests. For effective use of these methods, accurate information about attributes of individual trees that are being measured is extremely valuable. Thus, attempts to further improve the quality of these estimates, as well as knowledge and understanding of their production, is also beneficial for the decision makers utilizing forest resource information.

1.4 Methods for detecting and measuring changes in tree and forest characteristics

A potential change in some characteristic of interest can be determined by repeating an observation at least twice with a certain period of time in between, and then by comparing the observations to each other. In the case of attributes of an individual tree, repeated measurements can give direct information about tree growth through increments in its dimensions (Kershaw et al. 2016). This is relatively easy, practical, and fast; however, when the change detection is based on conventional field measurement methods, the investigation is naturally limited to the few attributes that are commonly determined for trees. Then, the strengths, weaknesses, and limitations of those measurement methods directly affect the accuracy and variety of the available information (e.g., Elzinga et al. 2005; Guillemette and Lambert 2009; Luoma et al. 2017). In addition to this, attributes recorded by means of conventional measurement methods do not include any additional information about the environment surrounding the measured tree. There are also measurement devices, such as dendrometer bands, which are specifically developed for acquiring repeated observations over time to characterize the change in tree stem diameter on a mm-scale (Drew and Downes 2009). However, these measurements are also limited to describing the potential diameter increment only at the specific height at which the dendrometer is assembled at.

If prior observations of tree attributes have not been made, with some tree species, such as conifer trees Norway spruce (*Picea Abies* (L.) H. Karst.) or Scots pine (*Pinus sylvestris* L.), it is also possible to determine the annual height increment retrospectively, by measuring the vertical distance between annual branch whorls (Kershaw et al. 2016). In addition to this, it is also possible to use cross cuttings or increment borers to measure annual ring widths of the trees and thus determine the diameter increment during a specific time period. However, these options to measure diameter growth require destructive sampling, especially when using cross cuttings, since the tree needs to be completely cut down before any changes can be detected. The conventional methods have shown their capability to provide accurate information about forests and are widely used as a reference for developing new measurement techniques and technologies. However, some attributes are easier to measure than others, and variation in results may arise when the measurements are repeated several times—even at one time point (Luoma et al. 2017). Despite these differences being relatively small, it is worthwhile to contemplate what the absolute correct value of an attribute of interest is, and how it should be obtained.

Considering the characterization of changes in the stem form or allocation of stem volume growth of a tree, the conventional ways have included either retrospective measurements from trees that were cut down, or modeling of the attributes of interest (e.g., Weiskittel et al. 2011; Burkhart and Tomé et al. 2012; Kershaw et al. 2016). If a tree needs to be cut down for analysis, it will immediately mean the end of the monitoring period, which does not allow continuous time-series studies with several monitoring points. Furthermore, these kinds of destructive measurement operations cannot be seen as sustainable research methods, especially if performed on a larger scale. The use of models in the estimation of attributes that are not directly measurable with conventional methods, such as stem volume or biomass, is also affected by the changing environment. For example, it has been shown (Kangas et al. 2020) that trees are no longer growing the same way as they were growing roughly 50 years ago, when, for example, the stem volume and taper curve models (Laasasenaho 1982), which are still nationally commonly used in Finland, were developed. The results also showed that the stem form of Scots pine and Norway spruce trees had changed (i.e., trees belonging to same dbh-class have larger stem volume nowadays) and updates for the model parameters would be needed. This kind of evolution lays ground for the development of new solutions and methods to measure and estimate attributes of interest—either only once or repeatedly— to reveal the changes in forests. Recently, close-range laser scanning of trees has shown potential solutions and possibilities to answer these challenges by expanding the spectrum of tree measurements (e.g., Liang et al. 2018a; Calders et al. 2020).

1.5 Terrestrial laser scanning of forests

1.5.1 Technology and measurement principles

The principle of laser scanning is based on measuring the distance and direction of backscattered laser signals to derive 3D point clouds from surfaces around the laser scanning unit. In terrestrial laser scanning (TLS), currently two techniques are mainly used for the range measurements—namely phase shift and time-of-flight methods (Wehr and Lohr 1999; Dassot et al. 2011). In phase shift laser scanning the distance between the scanner and the object of interest is determined based on the amplitude modulation of the laser beam resulting from the use of continuous laser pulse. In contrast, with scanners working on time-of-flight method the distance can be calculated from the flight time of the backscattered laser signal with the help of the speed of light. With both methods, it is possible to rapidly create 3D point clouds with a millimeter-level of detail and geometric accuracy. The point clouds can be created through scans from single or multiple positions (Liang et al. 2016). If multiple scanning positions are used, the resulting point clouds from individual scans can be combined together with the help of artificial targets to form one complete point cloud over the area of interest. Typically, the whole horizontal 360° area surrounding the scanner can be scanned at once, since the scanner is placed on a tripod where it rotates horizontally. The vertical coverage is enabled by the fast-rotating vertical mirror, which also ensures a vertically complete coverage over the area, except for typically a small circular area on the ground in the nearest vicinity around the scanner, where the scanner itself causes a blind spot which cannot be observed without changing the position of the scanner (Maas et al. 2008; Wilkes et al. 2017). The development of commercial terrestrial laser scanners has led to the introduction of lighter devices with increased measurement speed and point density (Liang et al. 2022). With the current TLS-scanners it is possible to measure tens of thousands of returns (i.e., points) per square meter from each scanning position, at a distance of 10 meters.

1.5.2 Tree and forest characterization

The first TLS-based studies in the field of forest science date back to the early 2000s. The original aim of introducing TLS in forest inventories was to improve the work efficiency of data collection by replacing manual measurements with automatic data collection, as well as to open up new approaches to characterize tree attributes that could not be directly observed using conventional mensuration tools (Liang et al. 2016). In hindsight, it can be said that the original aims of replacing manual field work with TLS have not quite completely been met; despite this, TLS-based methods are nowadays utilized for measuring several different tree and forest attributes, such as dbh and h (e.g., Dassot et al. 2011; Liang et al. 2016; Calders et al. 2020). One of the reasons for this development is that research has shown that punctiliously performed point cloud data acquisition and processing can result in TLS data with single points on a millimeter-level accuracy (Wilkes et al. 2017; Liang et al. 2018a). This allows the creation of geometrically precise 3D reconstructions of trees and measurement of their dimensions comprehensively from any part of the stem, at least in theory (Hackenberg et al. 2014).

At first, solutions to locate and characterize individual trees from TLS point clouds were developed (Lovell et al. 2003; Simonse et al. 2003; Aschoff and Spiecker 2004; Thies et al. 2004; Maas et al. 2008). According to Liang et al. (2016), the two most common methods for identifying trees from TLS point clouds are based on the detection of circular shapes representing the cross-sections of trees (e.g., Aschoff et al. 2004; Maas et al. 2008) or clusters of points representing similar surface characteristics (e.g., Cabo et al. 2018; Zhang et al. 2019). Development of the sensor technology and new findings in point cloud processing approaches have widened the field of tree observations (e.g., Disney et al. 2018; Calders et al. 2020). Reconstruction of trees can be done with the help of a series of geometrical primitives, especially circular cylinders (Raumonen et al. 2013; Hackenberg et al. 2014; Åkerblom et al. 2015). To be able to reconstruct the trees, points need to be classified to represent their source, which in this case means the part of a tree they have been obtained from. An algorithm-based tree classification typically follows assumptions that characteristics of stem points have more cylindrical, vertical, and planar neighborhoods than points representing branches or foliage (e.g., Liang et al. 2012b; Raumonen et al. 2013; Olofsson and Holmgren 2016; Yrttimaa et al. 2019). The aim of the processing and the method used then determine whether the reconstruction consists of the whole tree (Raumonen et al. 2013; Hackenberg et al. 2014) or just the main stem of a tree (e.g., Liang et al. 2012b; Heinzel and Huber 2016).

The typical measurement geometry of TLS especially supports the investigation of horizontal forest structure, which favors measuring the dimensions of tree stems foremost (Dassot et al. 2011; Liang et al. 2016). Earlier research has shown the capabilities of TLS point clouds in measuring tree dbh on a level of accuracy equal to that of conventional field measurements (e.g., Henning and Radtke 2006; Huang et al. 2011; Liang et al. 2013; Kankare et al. 2014b; Cabo et al. 2018; Pitkänen et al. 2019). In contrast to single measurements of stem diameter at specific heights with, for example, calipers or measurement tapes, it is also possible to form a complete stem curve by measuring stem diameters along the stem from a point cloud. This allows for a more comprehensive investigation of the characteristics of a tree.

However, mostly due to the measurement geometry—which is optimal for horizontal investigation—the vertical characterization of trees has been noted to be more complicated with the TLS point clouds (Dassot et al. 2011; Liang et al. 2016). Due to this and the occlusion caused by other tree stems and especially tree crowns or branches, the point cloud may be particularly incomplete in the upper parts of the tree crowns, and some important information may be missing. The limited visibility from the scanner to treetops, particularly in dense forest conditions, may cause difficulties in determining the location of the tree top and in tree height measurements. Thus, the accuracy of TLS point cloud-based h measurements has been reported to fall short of that of other measurement methods (e.g., Huang et al. 2011; Olofsson et al. 2014; Kankare et al. 2014b; Cabo et al. 2018) and underestimation of h is typical. The challenges in deriving attributes characterizing the vertical structure of trees have thus been a limiting factor in making the utilization of TLS more common.

In addition to diameter and height measurements, TLS point cloud-based methods have been utilized to measure, for example, stem volume (e.g., Moskal and Zheng 2012; Ducey et al. 2014; Kankare et al. 2014a; Saarinen et al. 2017), tree biomass (e.g., Holopainen et al. 2011; Kankare et al. 2013; Yu et al. 2013; Calders et al. 2015; Disney et al. 2018), as well as tapering of the stem through creation of taper curves (e.g., Henning and Radtke 2006; Maas et al. 2008). Earlier, estimation of these attributes from standing trees required the use of modeling and prediction based on the results of diameter and height measurements, whereas now they can be directly measured from the TLS point clouds with a plot-level accuracy on an equal level to the allometric models that are in use (Newnham et al. 2015; Liang et al. 2016). Characterization of tree communities and forests can then be performed by processing the obtained point clouds thoroughly tree by tree and then summarizing the results from individual trees over the selected investigation area.

1.5.3 Detecting changes in trees and forests

One of the major strengths of using a TLS point cloud is that it enables measurements at millimeter scale without damaging trees, which separates it from some of the other operational methods that are used, for example, for tree growth measurements. Observation of stem volume and profile without destructive measurements is an especially valuable advantage when evaluating how trees allocate their growth resources. Naturally, maintaining trees undamaged can be seen as an important aspect, since it ensures continuity of monitoring studies. Another advantage of using point cloud-based methods to characterize tree growth is that the 3D reconstruction of the object of interest is available for additional analysis and comparisons even years after the actual survey itself has been made. Despite these advantages and the fact that observation of several tree attributes through TLS point clouds has already been investigated for years, tree growth, as well as changes in the structure and form of trees have, until recent years, been gaining relatively little ground in the field of TLS point cloud-based measurements.

Kaasalainen et al. (2014) used Quantitative Structure Modeling (QSM) (Raumonen et al. 2013) to investigate changes in branch volume and length of a single sample tree during a four-year period, while Sheppard et al. (2017) used QSM models to study the annual development of stem and branch dimensions of wild cherry (*Prunus avium* L.) trees over a three-year period. Mengesha et al. (2015) reported the advantages of multi-temporal TLS data in stem volume growth estimation. Changes in tree biomass were modeled by Sirinvasan et al. (2014), who reported that TLS point cloud-based canopy volume and height change observations were the best indicators of the change with a dataset of 29 loblolly pine *(Pinus taeda* L.*)* trees. Changes in forest structure have been studied, too: Liang et al. (2012a) used an automated method, which was able to detect almost all the changes resulting from harvesting on a sample plot level. Hess et al. (2018) developed a voxel-based method that was used to analyze changes in canopy occupancy over time. Still, the number of studies focusing on determining tree growth and changes from two- or multi-date TLS point clouds has stayed relatively low. Previous studies (e.g., Kaasalainen et al. 2014; Sirinvasan et al. 2014; Sheppard et al. 2017) have either been performed mainly with small samples or covered only deciduous tree species. Furthermore, the monitoring period has been short relative to the length of the life cycle of the studied tree species. The novelty of TLS technology is a restricting factor for the length of the monitoring period, since data from earlier years is needed to be able to perform change detection studies without having to wait for years for the changes to happen. However, as earlier studies (e.g., Kaasalainen et al. 2014; Sirinvasan et al. 2014; Mengesha et al. 2015; Sheppard et al. 2017) have shown, development of change detection methods and discovery of new opportunities with already-existing point cloud data are already possible under the current circumstances.

1.6 Objectives

The current understanding and knowledge of the capabilities of TLS-based methods in forest mensuration have reached the level, over the last two decades, where TLS point clouds are being used reliably and successfully to obtain attributes of individual trees and tree communities (e.g., Liang et al. 2018a; Calders et al. 2020). Yet, for TLS, there have still been certain technological and methodical restrictions and limitations that have prevented it from becoming the primary method in providing field reference information from forests. Meanwhile, the need for accurate and up to date information about forests is increasing and demands for new additional knowledge arise. Thus, based on the hierarchical structure of a forest ecosystem, understanding the growth processes of an individual tree is essential to comprehending the development of forest stands and landscapes.

Prior to this thesis, only a few studies had reported utilization of TLS point cloud-based approaches to characterize tree growth and changes in trees or forests in general (e.g., Liang et al. 2012a; Kaasalainen et al. 2014; Srinivasan et al. 2014; Sheppard et al. 2017). However, earlier studies have mainly been focused on measuring the growth of deciduous trees, with relatively small samples. To further increase the knowledge related to the use of TLS point cloud-based tree growth measurements in different environments and to broaden awareness of potential opportunities it could offer, for example, in the field of forestry, a need for further studies exists. This thesis aims to develop TLS point cloud-based methods for change detection, tree, and forest growth measurements, as well as elucidating how tree growth allocation could be effectively measured and quantified on a single tree level and among tree communities. The results and solutions of this thesis could improve the understanding of forest ecology and tree physiology in general. The new findings could also promote the use of TLS point clouds in forest monitoring applications and thus potentially increase opportunities for their operational use.

Thus, the objectives of this thesis are:
(1) Developing TLS point cloud-based tree growth measurement methods.

(2) Exploring the capability of TLS point cloud-based methods to measure tree growth in boreal forest conditions and hence detect the occurring changes in attributes characterizing individual trees and the forest structure.

(3) Enhancing understanding of how trees allocate growth into their structures in different phases of their life cycle and in different growth environments.

Two different TLS point cloud-based methods to measure tree growth from two-date data are presented in the thesis. First, a method combining TLS point cloud-based stem diameter measurements and conventional tree height measurements for measuring tree growth is presented in study **I**. Then, a fully automated point cloud processing method to measure tree growth is used in studies **II** and **III** to further investigate the feasibility of TLS point clouds to measure tree growth with a larger sample of trees from varying boreal forest conditions. Performance of these methods to measure tree growth is examined with comparisons to reference data, and the capability to detect the significant changes in tree attributes resulting from tree growth during the monitoring period is tested. The ability to measure tree growth allocation provides new, detailed information about the behavior of individual trees as well as the variation in tree growth in diverse environments. The fundamental idea behind these objectives is to aim at creating new opportunities and possibilities to identify and measure the eco-physiological phenomena shaping the structure of trees and forests by using the point cloud-based methods developed and presented in this thesis.

2 MATERIALS AND METHODS

2.1 Study sites

Two study sites, located in southern Finland, were used in the investigations of this thesis (Figure 1). The areas were “Nuuksio” (60°18’ N, 24°31’ E), located approximately 30 km northwest of Helsinki, and “Evo” (61°11’ N, 25°8’ E), located approximately 100 km north of Helsinki. Study **I** was performed in the Nuuksio study site (Figure 1), which is located in Nuuksio National Park. The national park area is 53 km^2 in total, consisting of large continuous forested areas and several lakes, with altitude varying from 27 m to 114 m above sea level. The main tree species in the study area are Scots pine and Norway spruce, but broadleaved species such as silver birch (*Betula pendula* Roth.), white birch (*Betula pubescens* Ehrh.), lime tree (*Tilia cordata* Mill.), aspen (*Populus tremula* L.), and maple (*Acer Platanoides* L.) are also represented in mixed-species forest stands. The site type in Nuuksio varies from groves to barren heaths and rocky hilltops. In 2008, a systematic network of 216 sample plots with fixed plot intervals of 100 m was established in the Nuuksio study area. Field measurements were initially carried out on the sample plots to be used as a reference mainly for airborne laser scanning research (Vastaranta et al. 2009). Later in 2008, eight plots covering the overall variation of the sample plot network were selected from the whole sample to be recorded with TLS. Prior to repeating the TLS campaign in 2017, a field control was performed, which revealed that four sample plots out of the eight original TLS plots had remained undisturbed since the first scanning. Thus, these four plots were re-scanned in 2017 and selected to be used in study **I**. The plots were located on mineral soils and the site type varied from sub-xeric to herb-rich heath forests. Scots pine and Norway spruce were the main tree species on the plots with a mixture of silver birch, lime tree, aspen, and maple also present. The forest development class varied from young thinning stands to mature forests. In study **I** the sample plots were circular, with a radius of 7.98 m and an area of 200.1 m^2.

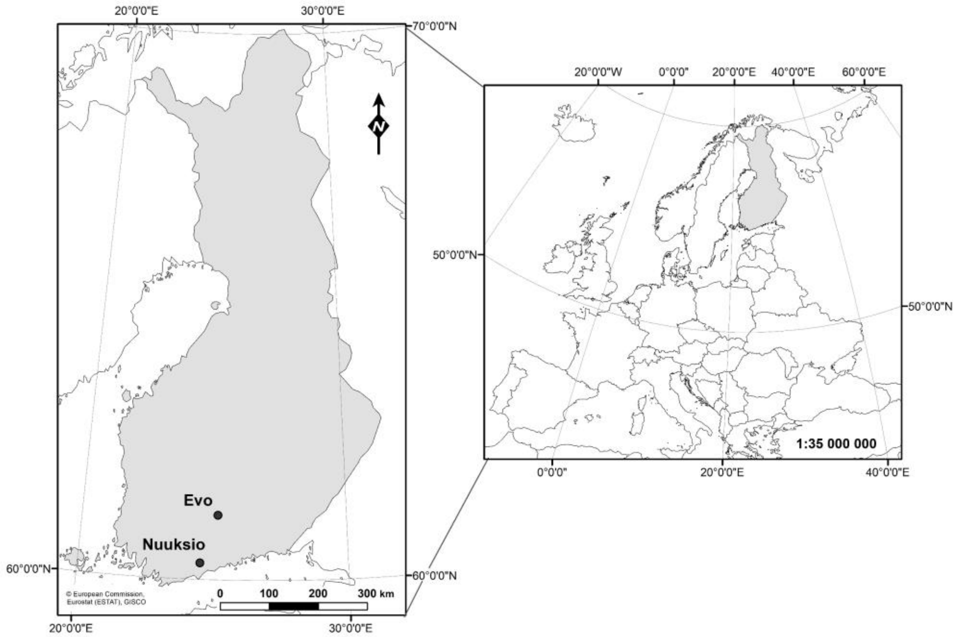

Figure 1. Map of the study site locations of the thesis. Study **I** was performed in study site "Nuuksio" and studies **II** & **III** in study site "Evo" in Finland.

Studies **II** and **III** took place in the Evo study site (Figure 1) consisting of a forested area of ~2000 ha with elevation varying from 125 m to 185 m above sea level. The forests in the Evo study site are characterized by typical southern boreal forest conditions. Scots pine and Norway spruce are the dominant tree species in the area, whereas deciduous species comprise ca. one fifth of the total stem volume. Silver birch and white birch are the main deciduous tree species in the area.

In 2014 a sample plot network was established on the study site, consisting of 91 square-shaped sample plots 32 m x 32 m in size. The sample plots were placed in such a way as to ensure that the structural variation of forests was represented (Yu et al. 2015). At the time of establishment, a complete tree-wise field inventory as well as TLS data-acquisition were performed on all the plots. The initial data collection was followed by a repeated field inventory and TLS data-acquisition campaign on 37 out of the original 91 sample plots in 2019. After the data collection, a circular sample plot was created within each of the re-measured 37 square-shaped plots to be used in studies **II** and **III**. The radius of the circular sample plot was 11 meters (380.1 m^2), with the plot center located at the center of the original square-shaped plot.

2.2 TLS point clouds

2.2.1 Data collection

TLS data acquisition in the circular sample plots of study **I** was performed in 2008 and further repeated in 2017 (Table 1). On both occasions the same measurement principle was used. A phase shift scanner Leica HDS6100 (Leica Geosystems AG, St. Gallen, Switzerland) was used with high-resolution settings, measuring up to 508,000 points per second and delivering a point cloud with 6.3-mm point spacing at 10-m distance from the scanner. The field of view was 310° vertical × 360° horizontal with an angular resolution of 0.018° in both vertical and horizontal directions. To generate a complete 3D point cloud from the sample plots, a multi-scan data collection method was used. On each of the sample plots, the scan set-up included one central scan at the plot center and four to six supplementary scans depending on the factors affecting the visibility on the circular plot (e.g., stem density, undergrowth, age of the stand, and dominant tree species). Artificial reference targets were used on the plots to enable co-registering of the unique scans to one 3D point cloud over the whole sample plot.

The first TLS data-acquisition for studies **II** and **III** was performed in 2014 using two separate phase shift scanners, a Leica HDS6100 and a Faro Focus 3D X330 (Faro Technologies Inc., Lake Mary, FL, USA) (Table 1 & Table 2). Due to limited time resources and availability of scanners in 2014, the TLS campaign was carried out by two independent field crews operating with the same scanner on different sample plots. Thus, only one and the same scanner was used per each plot. The scanners operate at wavelengths of 690 nm (Leica) and 1550 nm (Faro), measuring up to 508,000 points per second and delivering a point cloud with 6.3-mm point spacing at 10-m distance from the scanner (Table 2). The field of view was 310° vertical × 360° horizontal (Leica) and 300° vertical × 360° horizontal (Faro) with an angular resolution of 0.018° in both vertical and horizontal directions, respectively. Again, the multi-scan data collection method was applied on the plots. The center scan was performed at the plot center and the four auxiliary scans at quadrant directions (i.e., northeast, southeast, southwest, and northwest) approximately 11 m away from the plot center. Artificial reference targets were spread out on the plots to ensure the formation of a merged point cloud by co-registering the scans.

Table 1. The time points of TLS data-acquisition processes in studies **I–III**, summary of the used laser scanning devices as well as number of used sample plots and trees in respective studies.

Study	Plots	TLS trees	1st TLS scanning		2nd TLS scanning	
			Year	Scanner	Year	Scanner
I	4	35	2008	Leica HDS6100	2017	Leica HDS6100
II	37	795	2014	Leica HDS6100 & Faro Focus 3D X330	2019	Leica RTC360
III	37	736	2014	Leica HDS6100 & Faro Focus 3D X330	2019	Leica RTC360

Table 2. Summary of the technical specifications for the three terrestrial laser scanners utilized in data acquisition of studies **I–III**.

Scanner	Measurement method	Operation range	Point spacing at a distance of 10 m	Wavelength
Leica HDS6100	phase shift	1–79 m	6.3 mm	690 nm
Faro Focus 3D X330	phase shift	0.6–330 m	6.3 mm	1550 nm
Leica RTC360	time-of-flight	0.5–130 m	3 mm	1550 nm

In 2019, the same data collection procedure was repeated, but using a Leica RTC360 (Leica Geosystems AG, St. Gallen, Switzerland) time-of-flight scanner, which operates at a wavelength of 1550 nm and measures 2,000,000 points per second with a point spacing of 3-mm at a distance of 10 m (Table 1 & Table 2). The scanner delivers a hemispherical (300° vertical × 360° horizontal) point cloud with an angular resolution of 0.009° in both vertical and horizontal directions. The scanning process used in 2019 was similar to the one used in 2014 to ensure similar quality of point clouds. Only the locations of the auxiliary scans were moved a few meters further away from the plot center towards the plot corners when compared to the locations used in 2014. This adjustment was based on the findings of Yrttimaa et al. (2019) to improve the visibility and range in individual scans and thus create an even more complete point cloud over the whole sample plot area.

2.2.2 Data processing and estimation of tree and forest attributes

The point cloud data in study **I**, acquired both in 2008 and 2017 through TLS scans, were co-registered to complete point clouds over sample plots by using Z+F LaserControl software (Zoller and Fröhlich GmbH, Wangen im Allgäu, Germany) and the artificial reference targets. Trees were then manually identified from the resulting point clouds and tree-specific point clouds were extracted for the analysis by using TerraScan software (Terrasolid, Helsinki, Finland).

Due to the hemispherical measurement geometry of TLS and resulting occlusion to tree crowns, the field-measured tree height was also used as the value of h in point cloud analysis in study **I**. This aimed at removing uncertainty regarding the accuracy of TLS point cloud-based tree height measurement, which was at that time (e.g., Liang et al. 2016)—and can still be considered as—one of the most challenging attributes to be measured from TLS point cloud data. The tree-specific point clouds were analyzed with R-software (R Core Team, 2020) to fit circles with 10-cm intervals along each stem to be able to measure stem diameters and to estimate a taper curve for each tree following the method presented by Saarinen et al. (2017). In the creation of the stem curve, the validity of each diameter measurement was tested by applying maximum tapering values and comparing the results to the three previous diameter measurements to decide whether to include the measurement or exclude it as an outlier. The stem volumes were then estimated from the resulting taper curves. First, volumes of separate stem sections were defined by multiplying the cross-sectional area at the middle of the cylinder with the height of the cylinder. The volumes of stem sections were then summarized as the total stem volume (V).

In studies **II** and **III** the point cloud data acquired in 2014 were co-registered to complete point clouds over sample plots by using the Z+F LaserControl and Faro Scene (Faro Technologies Inc., Lake Mary, FL, USA) software. For these studies, the point cloud data acquired in 2019 were co-registered using Leica Cyclone software (Leica Geosystems AG, St. Gallen, Switzerland). At both timepoints, all the co-registrations were performed with the help of the artificial reference targets. The co-registered point-clouds from sample plots were then processed following an automatic method presented by Yrttimaa et al. (2020) and available in Yrttimaa (2021). At first, the point clouds were divided to separate point clouds with a raster-based segmentation procedure so that each segment represented mainly a single tree or a small group of trees, if tree crowns were overlapping (Figure 2). Then the points were classified as either stem or non-stem points based on their origin, assuming that stem points have more planar, vertical, and cylindrical neighborhoods in comparison to points describing branches and foliage (Liang et al. 2012b; Yrttimaa et al. 2019). The classification procedure iteratively searched for the desired point cloud characteristics using grid average downsampling, surface normal filtering, point clustering, and random sample consensus (RANSAC)-cylinder filtering (for more details, see Yrttimaa et al. 2020). From the tree-wise extracted point clouds, tree attributes were determined for each tree following the methods initially presented in Yrttimaa et al. (2019). The point cloud-based estimate for h was obtained by measuring the vertical distance between the lowest and highest points of each tree. Height of the crown base (hc) was defined as the height of the lowest living branches and crown ratio (cr) represented the proportion of the living tree crown from the tree height, and was calculated by utilizing h and hc according to Equation 1:

$$cr = \frac{h - hc}{h} \tag{1}$$

A taper curve was estimated for each tree from the TLS point clouds by measuring diameters along the stem and filtering potential outliers as well as interpolating missing ones using the same methods as in study **I**. Dbh as well as diameters at the height of 6.0 meters ($d_{6.0}$) and at the relative height of 50% ($d_{0.5h}$) were obtained from the taper curve (Figure 2). Basal area (g) was derived from dbh following Equation 2:

$$g = \frac{\pi * dbh^2}{4} \tag{2}$$

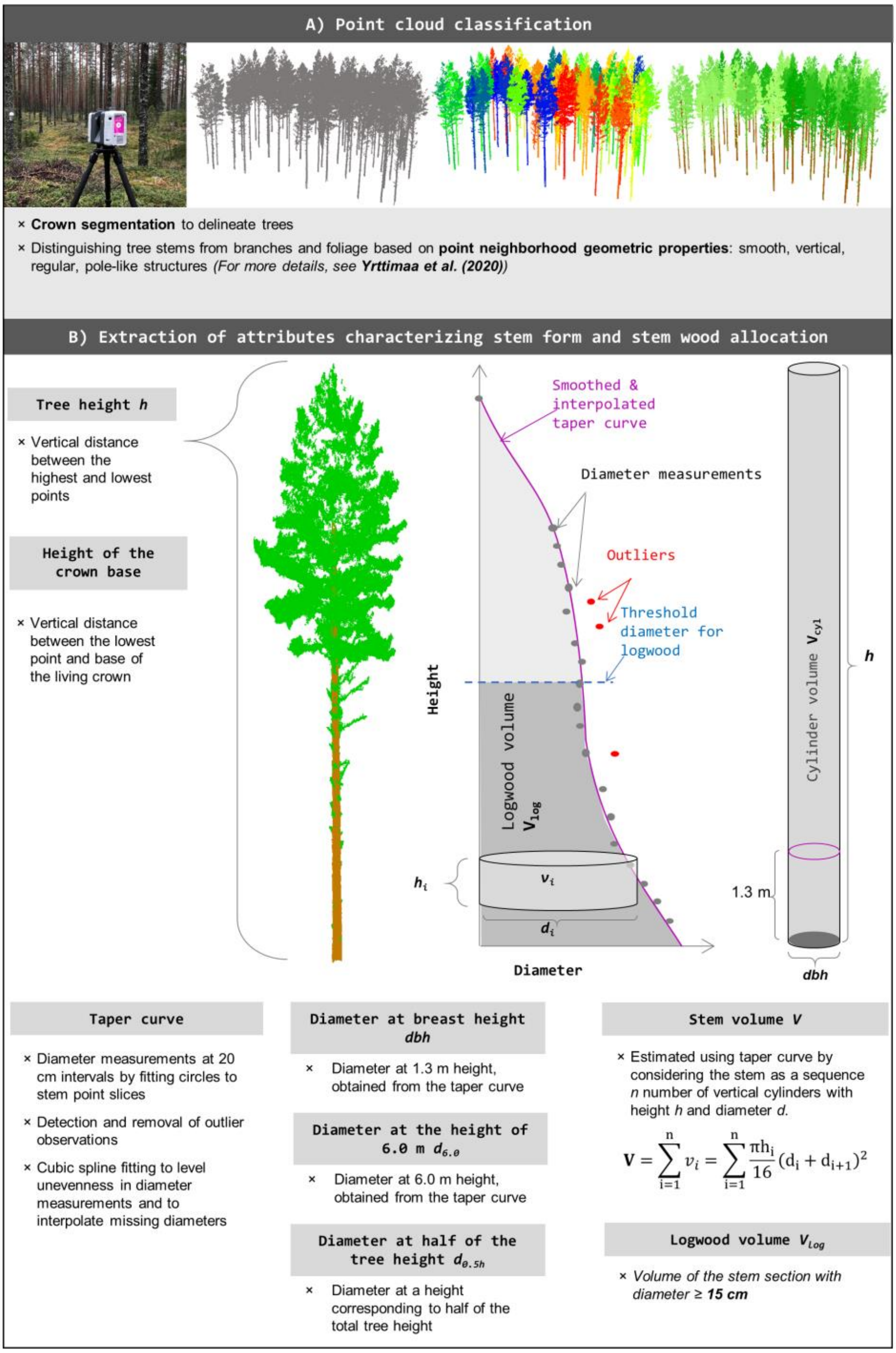

Figure 2. A graphical illustration summarizing the point cloud data processing performed in studies **II** & **III** and description of taper curve derivation as well as extraction of tree height, diameter, and volume attributes from the TLS point cloud of individual trees.

Stem tapering (TAP) and relative tapering (TAP%), cylindrical form factor (*f*), normal form quotient ($q_{0.5h}$), and height to diameter ratio (HDR) were derived from the diameter and height (i.e., dbh, $d_{6.0}$, $d_{0.5h}$, and h) measurements according to Equations 3–7:

$$TAP = dbh - d_{6.0} \tag{3}$$

$$TAP\% = \frac{dbh - d_{6.0}}{dbh} \tag{4}$$

$$f = \frac{V}{g * h} \tag{5}$$

$$q_{0.5h} = \frac{d_{0.5h}}{dbh} \tag{6}$$

$$HDR = \frac{h}{dbh} \tag{7}$$

V and logwood volume (V_{log}) were estimated using the taper curve, with V_{log} representing the volume of the part of the stem whose diameter exceeded 15 cm (Figure 2). Logwood percentage for trees ($V_{log}\%$) was calculated from estimates of V and V_{log} following Equation 8:

$$V_{log}\% = \frac{V_{log}}{V} \tag{8}$$

Forest structural attributes basal area weighted mean diameter (D_g) and basal area weighted mean height—known also as Lorey's height (H_g)—as well as mean basal area (G) and number of trees per hectare (TPH) were estimated from the attributes of individual trees at sample plot level following Equations 9–12:

$$D_g = \frac{\sum_{i=1}^{n} d_i g_i}{\sum_{i=1}^{n} g_i} \tag{9}$$

$$H_g = \frac{\sum_{i=1}^{n} h_i g_i}{\sum_{i=1}^{n} g_i} \tag{10}$$

$$G = \frac{\sum_{i=1}^{n} g_i}{A} \tag{11}$$

$$TPH = \frac{n}{A} \tag{12}$$

where n is the number of trees in a sample plot and d_i, g_i, h_i, and v_i are the dbh, basal area, height, and stem volume of the i^{th} tree in a sample plot, respectively. A is the area of the sample plot in hectares.

In study **II** 795 trees were detected from the point clouds and used in the analysis, whereas in study **III** the sample size was further reduced to 736 trees (Table 1). The number of sample trees in studies **II** and **III** was based on the success of the automated tree detection method, meaning that all the trees whose attributes could be completely characterized from the point clouds at both time points were included in the studies.

2.2.3 Characterizing tree and forest growth

Tree growth and changes in tree and forest attributes were measured by comparing the observations from the beginning and at the end of the monitoring period. The potential results of the comparisons were an increase, decrease, or no change in the attribute in question. Whether the results were defined as tree or forest growth or as a change in the attribute depended on the investigated attribute. The absolute difference (ΔX) in values of observed attributes in each study was calculated by subtracting the value of the attribute in the beginning (X_{T1}) of the monitoring period from the value of the attribute at the end (X_{T2}) of the period following Equation 13:

$$\Delta X = X_{T2} - X_{T1} \tag{13}$$

The relative change (ΔX%) of the attributes was determined by dividing the absolute change (ΔX) with the attribute value in the beginning (X_{T1}) of the monitoring period following Equation 14:

$$\Delta X\% = \frac{\Delta X}{X_{T1}} \tag{14}$$

Paired-sample *t*-tests were used to investigate whether a significant change had happened during the monitoring period in the observed attributes. The H0 in these tests stated that: “No significant change happened between the beginning and the end of the monitoring period for the attribute in question,” whereas the alternative hypothesis assumed that: “A significant change, either positive or negative, occurred during the monitoring period.”

In study **III**, two-sample *t*-tests were used to evaluate whether the changes in stem form or volume allocation between different forest conditions were significantly different. It was also analyzed whether the changes between trees on similar forest conditions and between trees from different forest conditions were significant.

2.3 Acquisition of the reference data

A tree-wise field inventory was performed in all study sites to acquire reference measurements for the analyses. In study **I**, tree species, dbh, and h of all the trees on the plot were defined during the field measurements in both 2008 and 2017. The h was measured on a 0.1-meter scale with a Haglöf Vertex Ultrasonic (Haglöf Sweden AB, Långsele, Sweden) clinometer, calibrated to current weather conditions. Dbh was determined as the mean of two caliper measurements perpendicular to each other. From the four sample plots used in study **I**, all the trees with dbh exceeding a threshold of 5 cm in 2008 and defined as alive in 2017 were classified as eligible for the study. In total, 35 trees were used in study **I**. Of the 35 trees, 10 were Scots pines, 14 were Norway spruces, five were silver birches, and six were other deciduous trees (one maple, two aspens, and three lime trees). According to the field measurements in 2008, tree size varied from 6.2 cm to 50.7 cm, and from 5.0 m to 34.0 m for dbh and h, respectively (Table 3).

For studies **II** and **III**, a tree map of each sample plot was created before the field inventory in 2014 by using manual detection of tree stems from horizontal TLS point cloud slices. Tree maps were verified and completed during the field inventory by determining the locations of undetected trees, if they exceeded the set minimum-dbh threshold of 5 cm. After completion of the tree maps, a tree-wise field inventory was performed to acquire reference measurements of tree attributes. Tree species, dbh, h, and health status (alive/dead) were recorded for all the trees. Visual interpretation was used to determine the species and health status of the trees. Steel calipers were used to measure the dbh as the mean of two measurements perpendicular to each other at the height of 1.3 m above the ground. The Haglöf Vertex Ultrasonic clinometer was used to measure h. The precision of field-measured dbh and h in 2014 were approximately 0.3 cm and 0.5 m, respectively, as reported by Luoma et al. (2017).

The field inventory was repeated in 2019 following the same principles as in the field inventory from 2014. Tree maps were updated with fallen or harvested trees as well as with trees that had reached the threshold-dbh of 5 cm during the monitoring period. Again, dbh and h were measured for all trees, as well as hc for Scots pines. Finally, from the 37 sample plots a total of 1280 trees were measured on the field both in 2014 and 2019. Of these trees, 270 (21.1%) were Scots pines, 649 (50.7%) Norway spruces, and 361 (28.2%) broadleaved

Table 3. Variation in diameter at breast height (dbh) and tree height (h) of the sample trees in studies **I–III**. The attributes are based on the results of the field inventory performed in the beginning of the respective monitoring period (i.e., year 2008 for study **I** and year 2014 for studies **II–III**). Mean, minimum (min), and maximum (max) values are reported separately for Scots pine, Norway spruce, and other trees, as well as for all trees.

Study	Species	Number of trees, n	dbh, cm			h, m		
			Mean	Min	Max	Mean	Min	Max
I	Scots pine	10	10.5	7.6	14.5	10.2	7.1	12.8
	Norway spruce	14	27.3	6.2	50.7	23.8	5.0	34.0
	Others	11	28.4	7.2	49.2	23.4	5.6	32.6
	All trees	35	22.8	6.2	50.7	19.8	5.0	34.0
II & III	Scots pine	270	20.3	5.2	59.7	17.8	5.0	34.5
	Norway spruce	649	16.9	5.0	57.9	15.2	2.2	36.6
	Others	361	14.9	5.1	59.9	17.0	2.2	32.5
	All trees	1280	16.9	5.0	59.9	16.3	2.2	36.6

trees, being mainly birches and aspen. In 2014, the mean dbh of field-measured sample trees was 16.9 cm with minimum and maximum dbh being 5.0 cm and 59.9 cm, respectively, whereas h varied from 2.2 m to 36.6 m with a mean h of 16.3 m (Table 3).

2.4 Assessment of the methods used

The performance of the automated TLS-based measurement method used in studies **II** and **III** was evaluated by comparing results from the point cloud-based measurements with the field-measured tree and forest structural attributes. The ability of the method to detect trees was assessed by investigating how large of a proportion of the field-determined trees were detected from the TLS point clouds. The accuracy of the point cloud-based tree and forest structural attributes in the beginning and at the end of the monitoring period as well as the accuracy of detected change was evaluated by using mean absolute error (bias) and root-mean-square-error (RMSE) as variables of the accuracy. Bias and RMSE were defined following Equations 15 and 16:

$$bias = \frac{\sum_{i=1}^{n}(\hat{X}_i - X_i)}{n} \tag{15}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{X}_i - X_i)^2}{n}} \tag{16}$$

where n is the number of trees or sample plots, $\hat{X}_i$ is the tree or forest structural attribute for tree i or plot i derived from the point cloud-based measurements, and X_i is the equivalent attribute based on field measurements. The relative bias (bias%) and RMSE (RMSE%) were calculated by dividing the respective absolute variable with the field-measured average value of the attribute in question. The accuracy was assessed on the tree level by tree species (Scots pine, Norway spruce, broadleaved) in study **II** as well as by forest structural group (young managed, young unmanaged, mature managed, old-growth) in study **III**. The accuracy of forest structural attributes was evaluated in general for all plots and by dividing the plots into three groups per main tree species on the sample plot (Scots pine-dominated, Norway spruce-dominated, and mixed-species sample plots). The relationship between the TLS point cloud-based and field-measured tree and forest structural attributes was further analyzed by calculating the coefficient of the determination (R^2).

3 RESULTS AND DISCUSSION

3.1 Detection of trees from TLS point clouds

As the first step of this thesis, an approach, which utilized measurement information from both TLS point clouds and conventional measurements, was selected to be investigated in study **I**. The applied method showed its capability of detection of volume growth and changes in the stem form during the nine-year monitoring period. The combination of two different sources was conducted to minimize the effect of uncertainty regarding the measurement of h from TLS point clouds, which was and is still known to be a challenge for ground-based laser scanning, especially in boreal forest conditions (Liang et al. 2016). Thus, clinometer measurements were used for determining h. Another known challenge regarding measurements from TLS point clouds is the tree detection accuracy, mainly due to the quality of point clouds (Liang et al. 2016). Since in study **I** the aim was to primarily develop and test the method to observe and measure changes in trees, all the trees used in study **I** were manually searched and detected from the TLS point clouds. Only trees that could be found in the data from both time points were investigated. Naturally, repeated observations from at least two different time points are a prerequisite for investigating structural changes in trees, but in this case this also ensured that it was possible to avoid the potential challenges of tree detection.

One of the key issues for the future use of point cloud-based measurements both in research as well as in operational use is that the method should be applicable for a large number of trees. Considering the method used in study **I**, this is not possible, since manual determination and extraction of individual trees from the TLS point clouds is time consuming and limits the capacity of trees to be processed. In addition to this, to make the measurement process effective, all the dimensions of a tree should be measured from the point clouds instead of using alternative observation methods. Even if the results and findings of study **I** were similar to the earlier studies and thus supportive of applicability of TLS point clouds to change detection in trees, certain needs for development of the point cloud-based methods to measure tree growth still existed.

Those needs were considered when implementing studies **II** and **III**. There, an automated TLS point cloud-based tree detection and measurement method was used to first identify and then measure trees located on 37 sample plots. In total, 795 out of the 1280 trees that were standing on the sample plots both in the beginning and at the end of the five-year monitoring period were identified with the used method. In total, approximately ⅔ of all trees, representing 84.5% of the total basal area, were detected at both time points. For species-specific detection accuracy, 91.3%, 85.7% and 73.3% of the total basal area of Scots pine, Norway spruce, and broadleaved trees were detected, respectively. The basal area-based detection accuracy was especially high for Scots pine and Norway spruce trees. This indicated that the method could detect the vast majority of the large—and thus the most valuable and dominant—trees on the plots. This is clearly visible also in Figure 3, which demonstrates the species-specific diameter distributions of trees detected both from TLS point clouds and by means of conventional field measurements at the end of the monitoring period in study **II**. The results also created an opportunity to consider whether the tree detection methods should be evaluated and further developed to maximize individual tree detection or, for example, basal area detection capability. The results of study **III** also revealed in greater detail the effect of the forest structure on tree detection. The individual tree detection rate in managed forest plots was over 40%-points higher than on unmanaged plots, with the detection rates being 81.7%, 77.6% and 86.5% in young, mature, and old growth managed forest plots, in comparison to a detection rate of 35.7% in unmanaged young forests. This further supports the finding that the absent trees in tree detection are mainly smaller trees, in this case especially broadleaved trees and Norway spruces, belonging to the undergrowth. However, even if most of the missing trees belong to the undergrowth, it has to be considered that if the aim is to detect all trees, the methods used can still be improved.

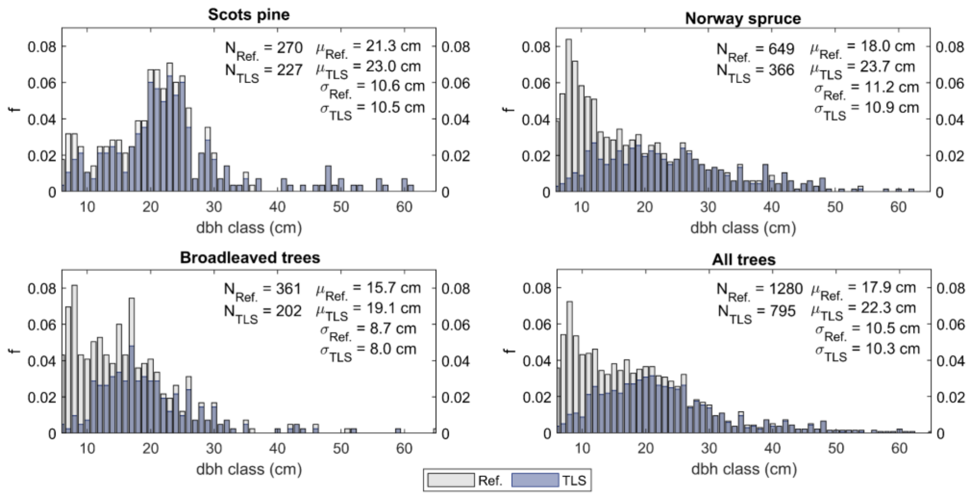

Figure 3. Species-specific (i.e., Scots pine, Norway spruce, and broadleaved trees, as well as all trees of the study) diameter at breast height (dbh) distributions of TLS point cloud-based tree detection and field inventory at the end of the monitoring period (T2, year 2019) in study **II**. The relative frequency (f) of trees is presented in 1-cm dbh classes. The colored bars represent the proportion of trees detected from the TLS point clouds. Mean values (μ) and standard deviations (σ) of dbh of TLS point cloud-based measurements (TLS) and field inventory (Ref.) are presented in the graphs.

Even if the performance of the point cloud-based method is a major factor in the success rate of tree detection, other issues also need to be considered when evaluating the success of the process. Among others, the role of the scanning set up and the selection of the data acquisition method, as well as the available resources for TLS point cloud data acquisition, play a significant role in the quality of the resulting point cloud data and thus directly affect the number of trees that are possible to be detected and further measured (Trochta et al. 2013; Abegg et al. 2017; Wilkes et al. 2017; Liang et al. 2018a; Yrttimaa et al. 2019). When the number of scans on each plot is limited (i.e., 5 scans per plot as in studies **II** and **III**), there is a high probability for occlusion, especially in dense forests, even if the scanning set-up is well-planned. The occlusion effect could possibly be reduced by performing a couple of, or even several additional, TLS-scans, or by applying completely different methods, such as mobile laser scanning (e.g., Liang et al. 2018b) to increase the point cloud coverage. When combining several scans together, the effect of wind also needs to be taken into consideration; Vaaja et al. (2016) observed in their study, that if the windspeed was 9 m/s or above during the data collection, it may have an impact on tree diameter measurements from the resulting combined TLS point clouds due to movement of the tree stem. However, a trade-off between the consumed time and the proportion of trees to be covered is an essential decision to be made to ensure a successful TLS point cloud measurement process.

Altogether, results of studies **II** and **III** show that the fully automated point cloud processing method is capable of reaching an adequate level of accuracy in tree detection regardless of certain technological, methodical, and environmental limitations related to tree detection performance. The structure of the forest, occlusion, distance from the scanner to the trees, and size of the trees all affect the probability of a tree to be detected (e.g., Wilkes et al. 2017). But, as previously mentioned, in point cloud-based tree detection the method itself can be held, at the most, only partially responsible for the missing trees because it is not possible to detect a tree if it does not exist in the point cloud at all due to insufficient scan setup with respect to the complexity of the forest stand.

3.2 Characterization of tree and forest attributes

In studies **II** and **III**, the accuracy of the automated method to measure and derive attributes from TLS point clouds was evaluated by comparing the point cloud-derived estimates to the respective field-measured reference values. In general, the bias and RMSE of dbh and g estimations was on a similar level to the accuracies reported for diameter measurements in earlier studies (e.g., Liang et al. 2016; Liang et al. 2018a). For dbh, the RMSE for all trees at the beginning (T1) and at the end of the monitoring period (T2) was 1.2 cm (5.7%) and 0.9 cm (4.1%), respectively, with no significant differences between tree species (Table 4). Thus, a strong relationship (R^2 = 0.99) between the point cloud-based and field-measured estimates of dbh and g was recorded at T1 and T2.

For h, the point cloud-based estimates were underestimated, which is typical for TLS-derived estimates of h (e.g., Liang et al. 2016). The RMSEs varied between tree species, with estimates of Scots pine h being the most accurate at T1 (2.5 m; 13.7%) and at T2 (2.4 m; 12.1%) followed by Norway spruce (4.0 m; 20.1% and 3.0 m; 14.4%) and broadleaved trees (6.3 m; 31.7% and 6.6 m; 30.8%), respectively (Table 4).

For forest structural attribute level, the point cloud-based estimates were accurate at both time points. Of the investigated attributes, the estimation accuracy of D_g, H_g, G, and TPH was evaluated on Scots pine and Norway spruce-dominated plots as well as on mixed-species sample plots. D_g was both under- and overestimated on the sample plots, with bias ranging between -0.3 cm (-0.7%) and 0.6 cm (2.4%) depending on the main tree species in a forest stand (Table 5). H_g was underestimated from -2.9 m (-10.7%) to -0.4 m (-1.9%) in all cases except for Scots pine-dominated plots at the end of the monitoring period, where overestimation was 0.2 m (1.0%). The RMSE% for D_g and H_g varied from 2.5% to 9.6% and from 2.9% to 13.1%, respectively. G and TPH were underestimated regardless of tree species, with the bias ranging from -10.5 m^2/ha (-29.2%) to -3.2 m^2/ha (-8.1%) and -659 stems/ha (-43.3%) to -47 stems/ha (-7.7%), respectively. The RMSE% of respective estimates varied from 10.6% to 35.7% for G and for TPH from 10.7% to 60.0%. The accuracies of forest structural attributes were on a similar level to the findings of a study performed in comparable conditions (Yrttimaa et al. 2019). In general, the decreased accuracy of G and TPH compared to other forest structural attributes was mainly caused by unsuccessful detection of trees from the TLS point clouds, as G and TPH were computed by summing up the number of trees or g of detected trees. For D_g and H_g, the estimated value was based on a weighted mean of dbh or h of the detected trees, and the accuracy depended on the representativeness of the sample of detected trees. Altogether, the obtained results further support the finding that if trees are not detected from the point clouds, it will also cause errors in the estimates.

Table 4. Bias and root-mean-square-error (RMSE) of TLS point cloud-based tree attribute measurements at the beginning (T1, year 2014) and at the end (T2, year 2019) of the monitoring period in study **II**. Bias and RMSE of diameter at breast height (dbh), basal area (g) and tree height (h) are presented for all trees of the study as well as separately for Scots pine, Norway spruce, and broadleaved trees. Relative bias and RMSE are reported in parentheses, respectively. Negative bias indicates underestimation.

Tree Attribute	Tree Species	Bias		RMSE	
		T1	T2	T1	T2
dbh (cm)	All trees	−0.1 (−0.3%)	0.0 (0.2%)	1.2 (5.7%)	0.9 (4.1%)
	Scots pine	−0.4 (−2.0%)	−0.3 (−1.4%)	1.1 (5.2%)	1.0 (4.5%)
	Norway spruce	0.3 (1.2%)	0.3 (1.3%)	1.3 (5.7%)	0.8 (3.3%)
	Broadleaved	−0.2 (−1.1%)	−0.0 (−0.15%)	1.1 (6.3%)	1.0 (5.3%)
g (cm^2)	All trees	−7.7 (−1.9%)	−3.4 (−0.7%)	49.3 (11.9%)	47.6 (10.4%)
	Scots pine	−21.5 (−5.1%)	−18.5 (−3.9%)	52.8 (12.5%)	60.8 (13.0%)
	Norway spruce	1.8 (0.4%)	7.4 (1.4%)	50.5 (10.6%)	32.4 (6.2%)
	Broadleaved	−9.2 (−3.1%)	−6.0 (−1.8%)	42.4 (14.5%)	53.5 (16.3%)
h (m)	All trees	−1.3 (−6.9%)	−0.7 (−3.6%)	4.4 (22.5%)	4.1 (19.7%)
	Scots pine	−0.9 (−4.8%)	−0.5 (−2.3%)	2.5 (13.7%)	2.4 (12.1%)
	Norway spruce	−0.5 (−2.6%)	0.4 (1.8%)	4.0 (20.1%)	3.0 (14.4%)
	Broadleaved	−3.3 (−16.8%)	−3.1 (−14.6%)	6.3 (31.7%)	6.6 (30.8%)

Table 5. Bias and root-mean-square-error (RMSE) of TLS point cloud-based forest structural attribute estimations at the beginning (T1, year 2014) and at the end (T2, year 2019) of the monitoring period in study **II**. Bias and RMSE of basal area-weighted mean diameter (D_g), and –height (H_g) mean basal area (G) and number of trees per hectare (TPH) are presented for all plots of the study and separately for Scots pine-, and Norway spruce-dominated as well as for Mixed-species plots. Relative bias and RMSE are reported in parentheses, respectively. Negative bias indicates underestimation.

Forest Structural Attribute	Main Tree Species	Bias		RMSE	
		T1	T2	T1	T2
D_g (cm)	All plots	0.1 (0.3%)	0.3 (0.9%)	1.4 (5.2%)	1.7 (6.0%)
	Scots pine-dominated	0.1 (0.4%)	0.6 (2.4%)	0.6 (2.7%)	0.8 (3.4%)
	Norway spruce-dominated	−0.3 (−0.7%)	−0.2 (−0.4%)	0.9 (2.5%)	1.1 (2.9%)
	Mixed-species	0.4 (1.6%)	0.4 (1.6%)	2.1 (8.4%)	2.5 (9.6%)
H_g (m)	All plots	−1.7 (−7.8%)	−0.5 (−2.1%)	2.5 (11.2%)	1.9 (7.9%)
	Scots pine-dominated	−0.4 (−1.9%)	0.2 (1.0%)	0.5 (2.9%)	0.7 (3.5%)
	Norway spruce-dominated	−2.9 (−10.7%)	−0.8 (−2.9%)	3.1 (11.6%)	1.1 (3.9%)
	Mixed-species	−1.7 (−8.0%)	−0.7 (−3.1%)	2.7 (13.1%)	2.8 (12.6%)
G (m^2/ha)	All plots	−6.5 (−20.5%)	−6.6 (19.1%)	8.5 (26.9%)	9.3 (26.9%)
	Scots pine-dominated	−5.3 (−23.6%)	−5.6 (−21.8%)	7.0 (31.1%)	8.1 (31.6%)
	Norway spruce-dominated	−3.8 (−10.2%)	−3.2 (−8.1%)	5.1 (13.5%)	4.2 (10.6%)
	Mixed-species	−9.8 (−30.2%)	−10.5 (−29.2%)	11.5 (35.5%)	12.8 (35.7%)
TPH (n/ha)	All plots	−373 (−35.2%)	−292 (−27.9%)	620 (58.5%)	515 (49.3%)
	Scots pine-dominated	−337 (−35.0%)	−268 (−26.9%)	486 (50.5%)	428 (42.9%)
	Norway spruce-dominated	−91 (−14.3%)	−47 (−7.7%)	117 (18.5%)	65 (10.7%)
	Mixed-species	−659 (−43.3%)	−536 (−36.0)	914 (60.0%)	753 (50.6%)

3.3 Measuring tree growth and detection of forest structural changes

Tree growth was measured through detecting and quantifying changes in the observed attributes. Statistically significant changes in attributes describing the size and form of the trees within the nine- (study **I**) and five-year-long (studies **II** & **III**) monitoring periods were detected in all three sub-studies of this thesis. In study **I**, development of stem form due to tree growth processes over a life cycle was detected and measured with the point cloud-based method. The results showed that a statistically significant change during the monitoring period had occurred in V, TAP, and $q_{0.5h}$ according to paired sample Student's *t*-tests, whereas there was no significant change in *f* or HDR. On average, TAP decreased, but there was variation within the plots, too. Especially for the largest trees, a marginal change in TAP was recorded, while $\Delta q_{0.5h}$ indicated that the increase in stem diameters was relatively higher in the upper parts of the stem than at breast height (i.e., 1.3 m above the ground). However, considering the low number of sample trees in study **I** and the location of the study site in Nuuksio National Park, where the forest conditions differ slightly from the ones in managed boreal forests, it is not recommended to make major conclusions about findings related to tree growth based on these results. Due to the location of the study site, the variation in tree species on each plot was probably larger than it would have been in more actively managed boreal forests. Also, the range in the size of the trees was notable within the sample plots. When taking this into account, further research with larger datasets was needed to be able to evaluate the differences in tree growth more extensively in varying forest conditions. Still, study **I** demonstrated the feasibility of using TLS point clouds to measure tree growth in boreal forests.

In studies **II** & **III**, changes in all examined attributes of individual trees were successfully detected. A significant change during the monitoring period was recorded for dbh, g, h, HDR, hc, cr, TAP%, *f*, $q_{0.5h}$, V, V_{log}, and V_{log}%. When ΔTAP%, Δf, $\Delta q_{0.5h}$, ΔV, ΔV_{log}, and ΔV_{log}% were further investigated within four different forest structural groups in study **III**, the results showed that the changes were of similar kinds in equal forest conditions. The value of TAP% decreased in all classes except for old-growth forests, but ΔTAP% was statistically significant only in the young forest class (Figure 4). This supports the understanding that the development of stem form has an equal trend in similar forest conditions (e.g., Larson 1963; Oliver and Larson 1996). Changes in the attributes describing stem form were also relatively small due to the rather short monitoring period, but it was still possible to see slight differences in tree growth processes and in trees' responses to different forest conditions.

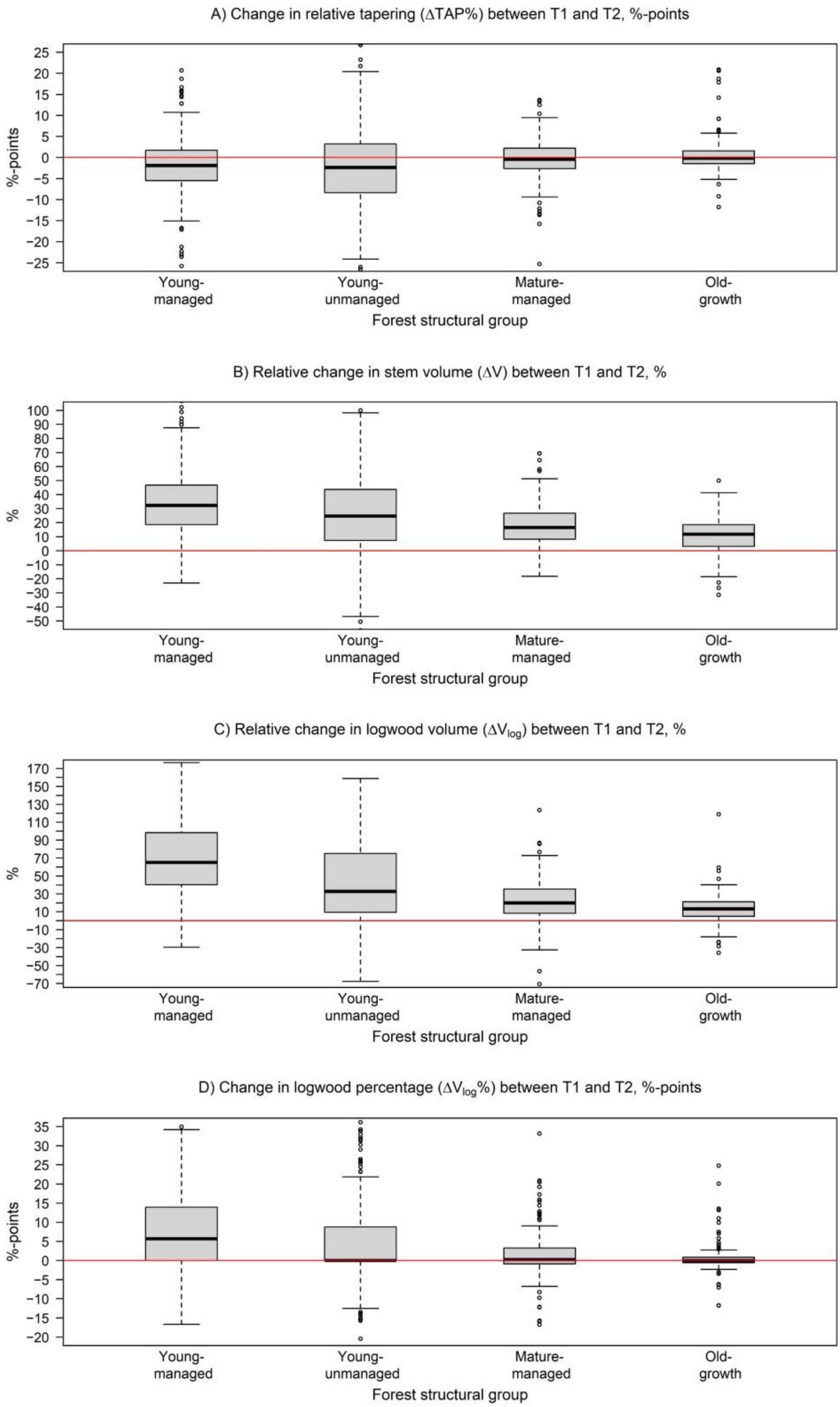
A) Change in relative tapering (ΔTAP%) between T1 and T2, %-points
%-points
B) Relative change in stem volume (ΔV) between T1 and T2, %
%
C) Relative change in logwood volume ($ΔV_{log}$) between T1 and T2, %
%
D) Change in logwood percentage ($ΔV_{log}$%) between T1 and T2, %-points
%-points
Young-
managed
Young-
unmanaged
Mature-
managed
Old-
growth
Forest structural group

FIGURE 4 (facing page). Box and whisker plots describing the variation in change of relative tapering (ΔTAP%), stem volume (ΔV), logwood volume (ΔV_{log}), and logwood percentage (ΔV_{log}%) within the forest structural groups during the monitoring period in study **III**. In the plots, the black line represents the median of change, and the box borders show the lower and upper quartile of the variation. The whiskers are used to indicate 1.5 times the interquartile range from the upper and lower quartiles. For ΔTAP% in A) and for ΔV_{log}% in D), the change is reported in percentage points. For ΔV in B) and ΔV_{log} in C), the relative change is presented in percentages. The horizontal red line is equal to no change.

When studying how trees allocate volume growth in study **III**, a significant change in V, V_{log}, and V_{log}% was expected, since the increase of these attributes as a function of time is supported by the theories related to tree growth (e.g., Oliver and Larson 1996). The obtained results showed that the applied point cloud-based methods had performed successfully in recording the occurred changes. Specifically, the V_{log} increased notably more in the groups of young managed forest (146.2%) and young unmanaged forest (76.5%) in comparison to groups of mature managed (23.5%) and old-growth forests (18.5%) (Table 6 & Figure 5). This is understandable, since the V_{log}% of trees belonging to groups of mature managed and old-growth forests has already reached such a level that, even if their growth were to continue, the increase in the proportion of V_{log} would only be minor. This is in contrast to the younger trees, where increase of V_{log} is rapid since the trees have, or are only just reaching, dimensions above the logwood threshold in large parts of their stems. There were no differences within the four forest structural groups in ΔV, but statistically significant differences were detected between the groups. This again supports the current understanding of tree growth and the effects of the surrounding environment on it. Trees in younger development phases are forced to allocate their growth efforts to vertical growth and to extend their branches to compete for light and other resources, to avoid ending up suppressed by neighboring trees (e.g., Oliver and Larson 1996). Therefore, they are not able to allocate an equal amount of resources to increase the diameter at the lower end of their stems, whereas dominant trees in mature and old-growth forests can allocate their resources to extending the stem girth, thus strengthening the supportive structure of the tree.

The accuracy of detecting changes in forest structural attributes was investigated in study **II**. The results from conventional field measurements were used as a reference for whether a statistically significant change in ΔD_g, ΔH_g, ΔG or ΔTPH had occurred on the sample plots. Detection of change with methods based on TLS point clouds was successful on all tested forest attributes except for ΔTPH. According to the field reference, there was a significant change in ΔTPH on Norway spruce-dominated and mixed-species plots, but it was not detected with point cloud-based methods. This defect is directly related to the difficulties of detecting individual trees from the plots either in the beginning or at the end of the monitoring period. The same issue was also the reason for higher errors in estimation of G and TPH from the TLS point cloud data. To improve detection accuracy, better point cloud coverage with additional scans or data acquisition from a mobile platform could be a solution (Wilkes et al. 2017; Liang et al. 2018b).

Table 6. Means and standard deviations of the estimated changes in stem volume (ΔV), logwood volume (ΔV_{log}), and logwood percentage (ΔV_{log}%) during the monitoring period in study **III** for all trees and for trees belonging to different forest structural groups. Mean change in stem volume (ΔV) and in logwood volume (ΔV_{log}) is reported as the relative change in percentages. The mean change in logwood percentage (ΔV_{log}%) is reported in percentage points. Standard deviations of the respective changes are reported in parentheses.

Forest structural group	ΔV, %	ΔV_{log}, %	ΔV_{log}%, %-points
young-managed	35.3 (27.2)	146.2 (467.1)	9.1 (13.2)
young-unmanaged	29.2 (38.7)	76.5 (220.2)	5.4 (15.2)
mature-managed	17.8 (16.1)	23.5 (34.7)	1.6 (7.3)
old-growth	10.0 (13.7)	18.5 (63.4)	0.7 (4.4)
All trees	25.4 (29.6)	67.1 (267)	4.9 (12.3)

Measurements of hc and cr for Scots pines with methods based on TLS point clouds were affected by similar challenges in vertical measurements, which had an effect on the measurements of h, too. The uncertainty in measuring h or hc also caused errors in change detection of Δhc and Δcr of Scots pines. This was expected, as the TLS point cloud data in these studies was collected on a sample plot level and the data collection process did not focus only on individual trees. To be able to perform more detailed point cloud-based measurements of crown attributes of all the sample trees, for example, the data collection should probably have been adjusted towards these targets. Typically, the collection of more comprehensive TLS point clouds with several scans targeted to an individual tree is possible if the study is more focused on individual trees and the sample size is thus significantly smaller (e.g., Saarinen et al. 2017).

Considering the point cloud-based methods for measuring tree growth and detecting forest structural changes, the novelty of TLS technology in forest inventory applications is still limiting the length of observation periods. Especially in boreal forest conditions, where the rotation time of commercially managed coniferous forests may reach up to 80–100 years, the annual diameter increment of trees may be on a millimeter level. This means that the scale of the detectable change during current monitoring periods is still relatively small, whereas longer time horizons will make the differences more distinct for the measurement methods. Even though accurate measurements at T1 and T2 are the foundation of growth analyses, the relative effect of the measurement accuracy to the growth analysis is expected to decrease with a longer monitoring period when the growth is more prominent.

3.4 Insights and implications

In this thesis, the attributes selected to be measured have already been defined for trees and forests for decades (Kershaw et al. 2016). The decision to use attributes characterizing diameter increment at a specific height, tree height increment, stem tapering, form factors, etc. to measure tree growth was made mainly due to the conventionality of the attributes. Those were the attributes for which it was in practice possible to acquire an equivalent reference with the other available methods. The ability to compare the obtained results to those obtained from earlier studies, where tree growth was measured with TLS point clouds, favored the use of those attributes, too. However, suggestions to create and take advantage of the new attributes derived from features that are measurable from TLS point clouds have emerged through the ability of TLS to characterize almost all the structural details of the trees. For example, several researchers (e.g., Seidel et al. 2011; Cattaneo et al. 2020; Saarinen et al. 2020; Jacobs et al. 2021; Uzquiano et al. 2021; Yrttimaa et al. 2022) have already started to develop and test such new point cloud-based tree attributes that have been impossible to measure using conventional methods in attempts to increase the understanding of factors affecting tree growth, such as tree crown structure and competition between trees. Following the example of recent studies, it might be recommended to consider which attributes should and can be used to measure growth of trees and forests in the future. In addition to this, the possibility of re-processing the previously collected point cloud data is an unrivaled feature of point cloud-based methods. The already-existing point clouds make it possible to gather additional information from the surrounding environment, or even determine later such attributes for trees as were neither of interest nor determined when the data was originally collected.

Altogether, the advantages of point clouds to measure trees should be utilized in full in the future when investigating tree growth. However, instead of characterizing trees and their growth using attributes designed to be measured with conventional mensuration techniques, one could fully deploy the ability of point clouds to characterize all the structural details of trees. Exploring the opportunities provided by the TLS point cloud-based methods may create possibilities to find even better indicators for some phenomena, such as tree growth, and thus contribute to extending the use of TLS point clouds even more widely among forest and other natural sciences.

4 CONCLUSIONS

The importance of the ability to observe and understand the current state and development of dynamic ecosystems, such as forests, is vital for researchers and decision makers around the world. Information about constant changes in forests can be utilized in analyzing and managing ecological, social, and economic processes and their direct or indirect effects on human well-being.

This thesis contributed to fulfilling the demand for more accurate and detailed information about changes in forests through its three main objectives. The aims of the thesis were: Firstly, to develop methods for TLS point cloud-based tree growth measurements by utilizing repeatedly acquired TLS point clouds. Secondly, to explore the capability of the developed methods in measuring tree growth in boreal forest conditions and to detect the occurring changes in attributes characterizing individual trees and the forest structure. And finally, to enhance understanding of how trees allocate resources into the growth of their structures in different phases of their life cycle as well as in different growth environments, and thus increase awareness of the functioning of the forest ecosystems.

The feasibility of TLS point clouds to measure tree growth was demonstrated in study **I**. A combination of TLS point cloud-based tree diameter measurements and traditionally measured tree height information was successfully used to detect tree growth and thus characterize the changes in size and form of individual trees during a nine-year-long monitoring period.

The fully automated TLS point cloud-based tree detection and measurement method, presented in study **II** and validated with a large number of trees, could measure tree growth in boreal forest conditions. The tree attributes were successfully characterized at T1 and T2 even though the detection accuracy of smaller trees on the plots was particularly restricted by point cloud occlusion in dense forests, which could be expected based on the existing knowledge related to the challenges of TLS point cloud-based methods. For trees that were detected at both time points, the attributes of individual trees could then be derived to quantify growth-induced changes in the forest structure.

Study **III** aimed at investigating how trees allocate growth into their structures. TLS point cloud-based measurements were utilized in investigating the allocation of tree growth and changes in attributes describing the stem form of trees. A statistically significant change in stem volume, logwood volume, and logwood percentage, as well as for attributes describing stem form (i.e., relative tapering, cylindrical form factor, and normal form quotient) was measured during the five-year monitoring period. The results also revealed environment-induced variation in tree growth that further supported the existing growth theories.

Following the findings of this thesis, the TLS point cloud-based tree growth measurement methods used could be expanded into conditions outside the boreal forests and tested with other tree species as well. The follow-up studies demand measurements from at least two time points, but even now, the already-existing point cloud data is available for creation of new time series of digitized trees and forests. The methods used can also be utilized in the future to continue the topics of current studies with extended monitoring periods. Furthermore, short-term measurements with a millimeter level of detail could also be utilized in exploring sudden shifts in tree growth, and thus improve understanding of the state of individual trees and forests in a changing environment.

This thesis has shown the capability of TLS point cloud-based methods to measure tree growth and characterize changes in forest structure. The benefits of further utilizing point cloud-based methods as measurement tools will open new worlds for ecological and silvicultural applications, and will thus undoubtedly improve the understanding of the underlying cause–effect relations driving the changes related to tree growth processes.

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