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Characterizing tree communities in space and time using point clouds

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Academic dissertation

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ABSTRACT

To better understand the underlying processes of many natural phenomena, accurate observations and measurements must be carried out in space and time. Considering forest ecosystems, monitoring the development and dynamics of tree characteristics is essential in this regard. An era of three-dimensional (3D) sensing techniques and point clouds has revolutionized individual tree observations, enabling measurements at an unprecedented level of detail. The feasibility of using point clouds to characterize trees and tree communities in space and their development in time was investigated in this thesis. The objective was to develop point cloud–based methods for distinguishing and characterizing trees and downed dead wood and to test the feasibility of the developed methods in boreal forest conditions.

Point cloud–based methods for detecting and characterizing forest structure were developed in studies **I–III**. Downed dead wood trunks could be distinguished from the undergrowth vegetation and near-ground objects by means of their regular, cylindrical geometry. Smooth, cylindrical surfaces and vertical continuity, on the other hand, were the key characteristics of point cloud structures to separate woody structures of standing trees from foliage and a tree stem from branches. The methods were tested in diverse boreal forest structures to validate these methodological principles.

The feasibility of the developed methods for characterizing trees and tree communities in space and time was tested in studies **II–V**. The structural complexity of a tree community was noted as the most important factor affecting tree-detection accuracy. High performance of the point cloud–based method was achieved on managed forest stands with a low degree of variation in tree size distribution. In controlled thinning experiments, thinning intensity was found to be a more significant factor affecting the performance than thinning type (i.e. thinning from below, thinning from above, and systematic thinning). The hemispherical measurement geometry of terrestrial point clouds was successfully complemented with aerial point clouds acquired from above the canopy to improve the vertical characterization of trees and tree communities. Finally, the capacity of bitemporal terrestrial point clouds to characterize changes in the structure of trees and tree communities was demonstrated. If there was an increase or decrease in the attributes of trees within a tree community detected with conventional forest mensuration techniques, a similar outcome was achieved with the point clouds.

The findings of this thesis improve the current knowledge of the feasibility of using point cloud–based methods in observing tree characteristics. Detailed 3D reconstruction of forests expands the spectrum of tree observations, as the dynamics of trees and tree communities can be monitored in more detail. This increases the understanding of processes shaping ecosystems and provides new approaches to improve ecological knowledge.

Keywords: close-range sensing, terrestrial laser scanning, LiDAR, point cloud processing, forest monitoring

PREFACE

The seed for this thesis was sown in the autumn of 2016 when Mikko and Markus suggested that I could join the group of laser scanning researchers and assist in some research projects alongside my bachelor's thesis. Somehow, they recognized my research abilities before I did, for which I am grateful. Later, I ended up working with terrestrial laser scanning point clouds, aiming to develop a method for downed dead wood monitoring, which I intended to be the topic of my master's thesis. I realized that it wasn't the easiest topic to begin with, but I wanted to try, as I was surrounded by inspiring and encouraging people. Suddenly, I noticed that I was involved in investigating research topics with accomplished researchers, and the work I was doing was significant for the scientific community. Then I realized that as a researcher, I could make use of my abilities in a meaningful way, and it became clear to me that I should pursue a doctoral degree. However, a transition to the University of Eastern Finland hadn't come into my mind until Mikko mentioned the opportunity during one of our meetings related to the progress of my master's thesis. Although the past four years at the University of Helsinki had treated me well, I decided to listen to my instincts and leave Viikki for Joensuu in September 2018.

Now, two years and eight months later, I can say that I have more than enjoyed my time in North Carelia, but it wouldn't have been possible without the people around me. First and foremost, I would like to express my gratitude to Mikko and Ninni, who made it easy for me to settle down and guided me through my first steps in a new environment. Besides being helpful coworkers and supervisors of this thesis, they have become great friends too. I have spent countless hours discussing topics related to science and life in general while skiing or riding bicycles with Mikko. I have shared the office with Ninni, and together we have had a blast while trying to improve our understanding of natural phenomena. Also, I can't forget to mention the support I have had from my family during the past years. My beloved parents, Eeva-Liisa and Esa, as well as my brothers Tuukka and Miika, have always supported the decisions I have made and been interested in my wellbeing as well as the research topics I have taken on. They have always been there whenever I've needed them. I have also been lucky to have Aliisa next to me, as she has brought some balance in my everyday life.

Conducting research is teamwork and thus rarely possible without many kinds of support. My work has been financially supported by the Academy of Finland (especially grant numbers 272195, 337127 and 337810). During my short career as a scientist, Mikko as well as Juha and Markus have ensured that I have been able to fully concentrate on research every day without worrying about funding or anything related. They have provided all the equipment and research infrastructure to make this thesis possible. Ville L was there to guide me in everything related to terrestrial laser scanning data acquisition for my master's thesis, and since then, we have been an efficient duo collecting data in the field and doing research together. Ville K, Samuli and Topi have provided peer support as well as an example for me to follow in my research career. Einari, Jiri and Mohammad complete the list of great colleagues with whom I have had the privilege to work. Thank you all!

Ylämylly, April 2021

Tuomas Yrttimaa

LIST OF ORIGINAL ARTICLES

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

I Yrttimaa T, Saarinen N, Luoma V, Tanhuanpää T, Kankare V, Liang X, Hyyppä J, Holopainen M, Vastaranta M (2019) Detecting and characterizing downed dead wood using terrestrial laser scanning. ISPRS J Photogramm 151: 76–90. https://doi.org/10.1016/j.isprsjprs.2019.03.007

II Yrttimaa T, Saarinen N, Kankare V, Liang X, Hyyppä J, Holopainen M, Vastaranta M (2019) Investigating the feasibility of multi-scan terrestrial laser scanning to characterize tree communities in southern boreal forests. Remote Sens 11(12), article id 1423. https://doi.org/10.3390/rs11121423

III Yrttimaa T, Saarinen N, Kankare V, Hynynen J, Huuskonen S, Holopainen M, Hyyppä J, Vastaranta M (2020) Performance of terrestrial laser scanning to characterize managed Scots pine (Pinus sylvestris L.) stands is dependent on forest structural variation. ISPRS J Photogramm 168: 277–287. https://doi.org/10.1016/j.isprsjprs.2020.08.017

IV Yrttimaa T, Saarinen N, Kankare V, Viljanen N, Hynynen J, Huuskonen S, Holopainen M, Hyyppä J, Honkavaara E, Vastaranta M (2020) Multisensorial Close-Range Sensing Generates Benefits for Characterization of Managed Scots Pine (Pinus sylvestris L.) Stands. ISPRS Int J Geo-Inf 9(5), article id 309. https://doi.org/10.3390/ijgi9050309

V 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

AUTHOR'S CONTRIBUTION

I) Yrttimaa planned the experiment and collected field reference and terrestrial laser scanning (TLS) data together with his colleagues, developed the automatic point cloud processing method to detect fallen trees, conducted all the analyses and wrote the first draft of the manuscript.

II) Yrttimaa planned the study design together with his supervisors, developed and implemented the point cloud processing methods to characterize standing trees, conducted all the related analyses and wrote the first draft of the manuscript.

III) Yrttimaa participated in planning the study design and collected field reference data from the sample plots together with his colleagues. He pre-processed all the TLS-data, developed further the point cloud processing methods from study **II**, conducted all the analyses and wrote the first draft of the manuscript.

IV) Yrttimaa planned the study design and collected field reference data from the sample plots together with his colleagues. He was responsible for matching the terrestrial and aerial point cloud datasets and extracting the tree attributes from the point clouds using the methods developed in study **III**. He wrote the first draft of the manuscript.

V) Yrttimaa planned the study design and collected field reference and TLS data at the end of the monitoring period together with his colleagues. He conducted all the analyses using the point cloud processing methods developed in studies **II–III** as well as wrote the first draft of the manuscript.

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ABBREVIATIONS

Δ	delta; indicating change in tree and forest structural attributes
3D	three-dimensional
ALS	airborne laser scanning
CHM	canopy height model
CMOS	complementary metal–oxide–semiconductor
cr	crown ratio
dbh	diameter at the breast height
d-h-ratio	diameter-height ratio
D_g	basal area-weighted mean diameter
DTM	digital terrain model
H_g	basal area-weighted mean height
h	tree height
hc	height of the crown base
G	mean basal area of a forest stand (m^2/ha)
g	basal area of an individual tree
GC	Gini coefficient
GNSS	global navigation satellite system
IMU	inertial measurement unit
MLS	mobile laser scanning
PLS	personal laser scanning
R^2	coefficient of determination
RANSAC	random sample consensus
RMSE	root mean square error
SfM	structure from motion
T1	time point at the beginning of a monitoring period
T2	time point at the end of a monitoring period
TLS	terrestrial laser scanning
TPH	number of trees per hectare (n/ha)
V_{mean}	mean volume (m^3/ha)
UAV	unmanned aerial vehicle
ULS	UAV-borne laser scanning

1 INTRODUCTION

1.1 Observing phenomena shaping trees

Forests are an important part of the biosphere, as they provide a variety of ecosystem services, such as biodiversity and carbon sequestration, that are essential for maintaining human well-being on Earth. Forests harbor the majority of terrestrial biodiversity (FAO and UNEP 2020), encompassing a diversity of vegetation structures on a global scale, providing habitats for more than 80% of all terrestrial animal and plant species (Aerts and Honnay 2011; Barrett et al. 2018). Forests' role in the global carbon cycle is undisputed: Atmospheric carbon is bound into biomass and soil, making forests a large and persistent carbon sink (Pan et al. 2011). Forests are, like other ecosystems, hierarchically organized, consisting of coupled subsystems (O'Neill et al. 1986) and, most importantly, tree communities. Trees are the defining component of forests (FAO and UNEP 2020), and the functional traits of trees more or less determine the functioning of tree communities and forest ecosystems (Tilman, Isbell, and Cowles 2014). Therefore, the underlying mechanisms driving forest ecosystem processes can only be understood by knowing the characteristics of its individuals, trees. Being an essential part of forest ecosystems, trees are a natural monitoring unit in forest resource and biomass assessments (Crowther et al. 2015). To gain new scientific knowledge and improve understanding of phenomena shaping forest ecosystems, it is essential to develop new approaches to observe and measure trees and tree communities in space and time.

Scientific knowledge is, by definition, information gathered in an organized and systematic enterprise and condensed into testable laws and principles describing the universe (Wilson 1999; Heilbron 2003). In natural sciences, generating new scientific knowledge builds on observations and repeatable experiments for testing hypotheses that are formulated according to the observations and current knowledge to propose explanations for the investigated phenomena (Avissar et al. 2013). Besides repeatability and connectivity to past research, scientific knowledge is concisely formulated and expressed by mensuration (Wilson 1999). Mensuration refers to numerical quantitation of attributes of an object or event, which enables objective comparison between the attributes of other objects or events (Pedhazur and Schmelkin 2013). For scientific knowledge, mensuration provides unambiguous generalizations of laws and theories when a natural phenomenon can be quantified with measures using universally accepted scales and units.

A natural phenomenon is defined as a process or event in nature that can be observed to happen or exist (Oxford University Press 2020). Biological processes are an example of natural phenomena of high interest for understanding and explaining the functioning of organisms. A biological process, in turn, refers to a series of actions driven by biochemical reactions that occur in living organisms and involve alteration, consumption or production of entities (Mossio, Montévil, and Longo 2016). In forestry, which is a field of natural science, tree growth is a commonly investigated biological process (Binkley et al. 2010). It consists of a hierarchy of physiological processes at the level of cells, tissues and leaves, defining structural biomass allocation at an individual tree level and, eventually, through the hierarchy of organisms, the growth of tree communities and dynamics of forest ecosystems (Landsberg and Sands 2011a).

Processes that shape tree structure and alter its functioning can be observed through the functional traits of trees that reflect the tree's interaction with biotic and abiotic environments

(Reich et al. 2003; Brym et al. 2011; Hérault et al. 2011). Functional traits, in general, refer to plant morphological, anatomical and phenological characteristics that influence its ecological performance by affecting the growth, reproduction or survival of a plant (Violle et al. 2007). In forest sciences, these characteristics are usually described using various structural attributes of trees and tree communities, and observations of these attributes provide quantitative means to study the underlying processes. The attributes can be observed using either direct or indirect measurements or allometric models (Kershaw et al. 2016). Direct measurements refer to measures of length and mass with a standard unit of measure such as a measuring tape and a weighing scale. However, for convenience and practicality, the measurements may employ geometry, trigonometry or knowledge of the speed of light or sound to base the observations on (van Laar and Akça 2007; Kershaw et al. 2016). Dendrometers, instruments that provide accurate measurements of tree dimensions, are often built on these principles (Clark et al. 2000). Nevertheless, sometimes, observing the tree attributes involves destructive measurements that are not practical to be conducted in the field. On such occasions, statistical models can be used to estimate the unknown attribute by making use of allometric relationships between the attributes already known (Landsberg and Sands 2011b; Kershaw et al. 2016).

To put this into context, detailed characterization of tree attributes is the key to uncovering the underlying ecological processes driving the functioning of trees, tree communities and forest ecosystems in space and time. Improved understanding of a natural phenomenon requires even more detailed observations, which justifies the need for new methods to observe and measure trees through their characteristics. This methodological knowledge gap is also listed among the most important ecological research topics (Sutherland et al. 2013). In forest sciences and forestry, an era of point clouds has revolutionized individual tree observations, enabling measurements at an unprecedented level of detail and providing new approaches to improve ecological knowledge (Disney et al. 2018; Calders et al. 2020).

1.2 Characterizing trees with point clouds

1.2.1 Techniques to acquire a point cloud

A point cloud is a set of points in space representing the three-dimensional (3D) structure of an object or environment. Each point in a point cloud has assigned 3D coordinates (x,y,z) to define its position in space and is accompanied by attributes to characterize the object attributes, such as spectral information or point classification. Generating a point cloud involves 3D measurements from the object of interest to characterize its 3D structure, and the two prevalent techniques for this task are laser scanning and photogrammetry (Baltsavias 1999; Wehr and Lohr 1999; Leberl et al. 2010). Laser scanning is an active remote sensing method that emits and receives laser beams to measure distance between the scanner and the reflecting object surface to define its position in space with 3D coordinates (Wehr and Lohr 1999; Lefsky et al. 1999; Lefsky et al. 2002). The distance measurements employ the velocity of light waves in a given medium and the time delay that occurs between the emitted and received laser signal (Bachman 1979). The time delay can be observed by using time-of-flight or phase measurement techniques (Wehr and Lohr 1999). As the name implies, the time-of-flight approach is based on recording the time it takes for a laser pulse to travel the round trip from the scanner to the reflecting object and back to the scanner. Phase measurement techniques, in turn, use a continuous wave of light with modulated amplitude or frequency, and the phase difference between the emitted and received waveform is used to compute the respective time delay. Once the time delay (τ) is recorded using either of these techniques, the distance (p) between the scanner and the reflecting object can be computed according to Equation 1:

$$p = (c / n) * (\tau / 2). \tag{1}$$

, where *c* is the velocity of light in vacuum (299.792.458 m/s) and n is the refractive index of air that depends on air temperature, pressure and humidity. Once the location and the orientation of the scanner, as well as the direction to which the laser beam was emitted, are known, the distance measurement can be converted to a 3D coordinate. Usually, the backscattered laser signal intensity is also recorded to provide spectral information of the target surface (Wehr and Lohr 1999; Höfle and Pfeifer 2007).

Instead of direct distance measurements for point cloud generation, as in laser scanning, the photogrammetric approaches rely on indirect reconstruction of the 3D structure of the target object from overlapping images (Baltsavias et al. 2008; Leberl et al. 2010). The key principle of image-based 3D reconstruction is to identify the target object from a set of images acquired from different viewpoints by using triangulation of the corresponding points of the object in the images (Hartley and Zisserman 2004). Searching for the matching points within images is carried out using computer vision algorithms such as structure from motion (SfM; Westoby et al. 2012) and dense matching (Leberl et al. 2010; Remondino et al. 2014).

In a forest environment, most often, close-range sensing methods are used for detailed characterization of trees and tree communities through point clouds (Morsdorf et al. 2018; Iglhaut et al. 2019). Close-range sensing refers to an approach to acquire information from trees and tree communities remotely within a distance ranging approximately from 1 meter to 100 meters. Sensors employing either laser scanning technology or photogrammetric approaches are attached on static or kinematic, terrestrial or aerial platforms to enable the sensor-platform system to acquire point clouds to characterize trees and tree communities from different viewpoints. Close-range laser scanning technologies can be divided into terrestrial and aerial systems according to the data acquisition geometry (Vosselman and Maas 2010). Terrestrial close-range laser scanning technologies are further considered either terrestrial laser scanning (TLS) or mobile laser scanning (MLS) depending on whether the scanner platform is static or kinematic, respectively (Liang et al. 2016; Morsdorf et al. 2018). Aerial close-range laser scanning to suit for detailed characterization of trees refers to unmanned aerial vehicle (UAV)–based systems that enable a relatively low altitude for detailed point cloud acquisition (Jaakkola et al. 2010, 2017; Kellner et al. 2019). Close-range photogrammetry, on the other hand, offers an affordable alternative to laser scanning for producing aerial or terrestrial point clouds to characterize trees (Iglhaut et al. 2019). In forest applications, image-based point clouds are typically obtained by terrestrial or aerial means either using a regular hand-held digital camera or an UAV-borne system as a platform.

1.2.2 Terrestrial close-range sensing methods to characterize trees

Terrestrial point clouds for detailed characterization of trees can be acquired by the means of TLS, MLS or terrestrial close-range photogrammetry. TLS was initially developed for precision surveying applications in which the laser scanner is placed on a tripod approximately 1 to 2 m above the ground level to acquire a detailed, hemispherical point cloud of the scanner surroundings with a millimeter-level of detail (Dassot, Constant, and Fournier 2011; Wilkes et al. 2017). In a forest environment, TLS point cloud can be used to automatically derive tree attributes (Lovell et al. 2003; Simonse et al. 2003; Aschoff and Spiecker 2004; Thies and Spiecker 2004; Thies et al. 2004; Henning and Radtke 2006; Maas et al. 2008). However, TLS is capable of characterizing only trees that are visible to the scanner, or, more specifically, only the sides of the trees that are facing towards the scanner. Occlusion, the incapability to provide a complete characterization of the target object or environment, is a major factor affecting the performance of TLS-based tree observations (Béland et al. 2014; Abegg et al. 2017; Liang, Hyyppä, et al. 2018). Thus, it is usual in forest applications to combine multiple TLS scans acquired from different locations or view angles to characterize the complete structures of trees (Côté, Fournier, and Egli 2011; Liang et al. 2016). In this multi-scan approach, the point clouds from individual scans are registered together using artificial reference targets that are visible from each scan location and feature a retro-reflective surface (Wilkes et al. 2017). Of all the terrestrial close-range sensing techniques, multi-scan TLS is considered the standard of accuracy in the characterization of trees and tree communities (Liang et al. 2018) at the cost of being a relatively time-consuming approach to covering entire forest stands (Dassot, Constant, and Fournier 2011; Newnham et al. 2015).

Attached to a kinematic platform, MLS aims to reach the accuracy of TLS point clouds with improved cost-efficiency in data acquisition (Holopainen et al. 2013; Liang, Hyyppä, et al. 2014). MLS combines a laser scanner with inertial measurement unit (IMU) and global navigation satellite system (GNSS) to provide information about the orientation and position of the system to enable on-the-move recording of the surrounding 3D structure (Bauwens et al. 2016; Cabo, Del Pozo, et al. 2018). Compared to TLS, a more rapid point cloud data acquisition can be achieved with the MLS system when the laser scanner is attached to a mobile platform such as a car (Holopainen et al. 2013; Forsman, Holmgren, and Olofsson 2016), an all-terrain-vehicle (Tang et al. 2015; Kukko et al. 2017; Liang, Kukko, et al. 2018) or an unmanned ground vehicle (Pierzchała, Giguère, and Astrup 2018). Mobility in more diverse terrain and forest conditions can be further improved with a human-operated MLS by means of a hand-held (Ryding et al. 2015; Bauwens et al. 2016; Marselis et al. 2016; Bienert et al. 2018; Cabo, Del Pozo, et al. 2018; Chen et al. 2019; Stal et al. 2020; Hunčaga et al. 2020) or backpack laser scanner (Liang, Wang, et al. 2015; Hyyppä, Kukko, et al. 2020; Liang, Kukko, et al. 2018), also called personal laser scanning (PLS). However, the greatest challenge related to the applicability of MLS technology in detailed tree measurements is the insufficient positional accuracy caused by a limited GNSS signal inside the forest canopy, which leads to geometric inaccuracy and additional noise in the resulting point cloud due to georeferencing errors (Kaartinen et al. 2015; Kukko et al. 2017). This challenge has been addressed with a simultaneous localization and mapping (SLAM) method (Öhman et al. 2008; Tang et al. 2015; Forsman, Holmgren, and Olofsson 2016; Kukko et al. 2017; Pierzchała, Giguère, and Astrup 2018), in which a map of the unfamiliar forest environment is generated to improve the IMU-GNSS-based solution for localizing the MLS system.

Recent findings demonstrate that the geometric accuracy and point density of an MLS point cloud generally fall short of the respective characteristics of a multi-scan TLS point cloud (Balenović et al. 2021). Tree density and the presence of undergrowth vegetation complicate the forest structure and make it challenging for any terrestrial close-range sensing technique to provide unoccluded point cloud representation of trees, but with MLS, this effect is even more prominent (Ryding et al. 2015; Bauwens et al. 2016; Liang, Kukko, et al. 2018). However, in favorable conditions, the performance of MLS point clouds to characterize trees is comparable to that of TLS (Chen et al. 2019; Cabo, Del Pozo, et al. 2018; Gollob, Ritter, and Nothdurft 2020; Hyyppä, Yu, et al. 2020).

Besides laser scanning, a terrestrial point cloud for tree characterization can be obtained by means of terrestrial close-range photogrammetry (Hunčaga et al. 2020). This technique involves acquisition of digital images from several locations, depicting the forest scene from different viewpoints to achieve a sufficient multi-view image coverage for detailed 3D reconstruction of trees (Mokroš, Výbošťok, et al. 2018; Iglhaut et al. 2019; Piermattei et al. 2019). The image-based terrestrial point clouds can be acquired using consumer-grade equipment and software, making it a low-cost and user-friendly alternative to TLS and MLS systems (Liang, Jaakkola, et al. 2014; Iglhaut et al. 2019). Terrestrial close-range photogrammetry has proven to be feasible in characterizing tree stem attributes (Mikita, Janata, and Surový 2016; Surový, Yoshimoto, and Panagiotidis 2016; Mokroš, Liang, et al. 2018; Mulverhill et al. 2020), but comparisons shows that its performance still falls short of that of TLS (Liang, Wang, et al. 2015; Hunčaga et al. 2020).

1.2.3 Aerial close-range sensing methods to characterize trees

In contrast to terrestrial close-range sensing, point clouds obtained using aerial close-range sensing techniques provide a different viewpoint for observations, which benefits the tree crown characterization (Aicardi et al. 2017; Morsdorf et al. 2018). Due to different measurement geometry, aerial close-range sensing techniques allow cost-efficiency in 3D data acquisition, with more detailed characterization of upper parts of the tree crowns, enabling accuracy, especially in estimates of attributes related to tree height and crown dimensions (Wallace et al. 2012; Wallace, Musk, and Lucieer 2014; Guerra-Hernández et al. 2017). Most often, an aerial close-range point cloud is acquired with a UAV equipped with IMU and GNSS sensors to provide information from the exact position and orientation of the aerial platform, as well as with an imaging sensor that is either a laser scanner (Jaakkola et al. 2010; Wallace et al. 2012) or a digital camera (Westoby et al. 2012; Puliti et al. 2015). Characteristics of an aerial point cloud and its feasibility of characterizing trees depends on whether the technology used in the 3D reconstruction is laser scanning or close-range photogrammetry. UAV-borne laser scanning (ULS) provides detailed characterization of upper parts of the tree crowns but, in favorable conditions, also enables the reconstruction of the tree stem and measurements related to its dimensions (Chisholm et al. 2013; Brede et al. 2017; Jaakkola et al. 2017; Puliti, Breidenbach, and Astrup 2020), although the performance of terrestrial point clouds is not matched in this regard (Liang et al. 2019; Hyyppä, Yu, et al. 2020).

A more affordable alternative to ULS is UAV photogrammetry; it requires less expertise to be operated, and high-quality point clouds can be acquired even with consumer-grade equipment and processing software (Westoby et al. 2012; Dandois and Ellis 2013; Iglhaut et al. 2019). The point clouds based on UAV photogrammetry can be used for 3D reconstruction of tree crowns (Lisein et al. 2013; Gatziolis et al. 2015; Bonnet, Lisein, and Lejeune 2017; Guerra-Hernández et al. 2017; Mohan et al. 2017) and tree species classification when coupled with hyperspectral imaging (Nevalainen et al. 2017) but fall short of characterizing terrain information through dense canopies (Puliti et al. 2015; Tomaštík et al. 2017). Occlusion limiting the visibility to the ground and lower parts of trees can be reduced by combining UAV photogrammetry with terrestrial point clouds to obtain a comprehensive characterization of a forest stand (Mikita, Janata, and Surový 2016; Aicardi et al. 2017).

1.2.4 Expanding the spectrum of tree observations using point clouds

The use of terrestrial point clouds can complement or even replace the conventional tree mensuration techniques employing calipers, clinometers and measurement tapes (Liang et al. 2016). While the conventional non-destructive tree mensuration techniques only provide information on a few tree attributes, typically those related to tree height and stem diameter (Kershaw et al. 2016), the point cloud–based methods expand the spectrum of tree observations through detailed 3D modelling of a tree structure (Newnham et al. 2015). A terrestrial point cloud obtained by means of close-range sensing methods can reach up to a millimeter-level of accuracy (Wilkes et al. 2017), enabling geometrically accurate tree model reconstruction (Hackenberg et al. 2014). However, the presence of different-sized trees and undergrowth vegetation, as well as both woody and leafy components, makes a point cloud extremely complex from the modelling perspective (Côté, Fournier, and Egli 2011; Disney et al. 2018). Thus, point cloud classification approaches to distinguish different forest components are needed before the tree structures can be reconstructed.

Most of the point cloud classification approaches that are aiming at distinguishing woody material from foliage and tree stems from other forest vegetation rely on differences in the geometry of different forest components. A tree stem often features rather smooth vertical and cylindrical structures, which are utilized in separating woody structures from foliage (Liang, Litkey, et al. 2012; Raumonen et al. 2013; Olofsson and Holmgren 2016; Cabo, Ordóñez, et al. 2018; Wang et al. 2018; Vicari et al. 2019; Zhang et al. 2019). Point cloud classification methods may benefit even more from approaches also employing spectral information revealing differences in the spectral features between woody and leafy components (Zhu et al. 2018). Once the structures of interest have been distinguished, the 3D structure of a tree can be reconstructed by using a series of geometrical primitives, preferably circular cylinders (Åkerblom et al. 2015), which reduces the amount of data to be processed and enables a detailed characterization of tree attributes.

Automated point cloud processing techniques have been developed for detailed, non-destructive characterization of attributes related to tree stem dimensions, such as diameter at breast height (dbh) and tree height (Simonse et al. 2003; Aschoff and Spiecker 2004; Pfeifer et al. 2004; Thies et al. 2004; Watt and Donoghue 2005; Maas et al. 2008), as well as stem profile and volume (Liang, Kankare, et al. 2014; Olofsson and Holmgren 2016; Sun et al. 2016; Saarinen et al. 2017; Pitkänen, Raumonen, and Kangas 2019). Coupled with information obtained from the branching structure (Kankare et al. 2013; Pyörälä et al. 2018), the biomass estimates can be improved with observations derived directly from the point clouds (Yu et al. 2013; Calders et al. 2015; Stovall et al. 2017). Detailed 3D reconstruction of trees and tree communities also enables the modelling of tree crown structure (Henning and Radtke 2006; Barbeito et al. 2017; Trochta et al. 2017; Ritter and Nothdurft 2018) to better understand phenomena such as the competition between trees (Metz et al. 2013). Combining spectral information with geometric features expands the spectrum of observable phenomena, including such things as tree decline (Junttila 2019). Besides versatile observations in space, these point clouds provide a digital archive of the reconstructed trees and tree communities, enabling virtual revisits to forest for retrospective measurements and time series analyses.

Despite the benefits related to the detailed characterization of trees and tree communities, the terrestrial point cloud–based characterizations often fall short of maintaining the same performance across different forest conditions. Variation in forest structure and tree density and the occurrence of undergrowth vegetation affect the performance of point cloud–based methods by influencing the visibility of the structures of interest in the terrestrial point clouds (Abegg et al. 2017; Liang et al. 2018; Olofsson and Olsson 2018; Gollob et al. 2019). However, controlled experiments to investigate the influence of these performance-affecting factors in diverse forest conditions have been lacking. Due to the hemispherical point cloud acquisition geometry, the terrestrial point clouds often fail to characterize the vertical structure of trees and tree communities (Wang et al. 2019). In this regard, aerial point clouds acquired from above the canopy provide a detailed description of the upper parts of the tree crowns but, on the other hand, may have limited visibility to the tree stem (Jaakkola et al. 2010; Wallace et al. 2012; Brede et al. 2017; Liang et al. 2019; Puliti, Breidenbach, and Astrup 2020). A solution for a complete characterization could be to integrate terrestrial and aerial point clouds to make the most of both techniques (Mikita, Janata, and Surový 2016; Aicardi et al. 2017). However, the benefits of using this multisensorial approach in characterizing trees and tree communities have not yet been investigated in varying forest conditions.

Despite the fact that during recent years, tremendous effort has been put into developing point cloud processing methods to characterize trees, validation of the methods has been based mainly on a limited number of sample plots capturing one small structural variation at a time. In this regard, (Liang, Hyyppä, et al. 2018) made a significant contribution by investigating the performance of 18 TLS point cloud processing methods to characterize trees in varying boreal forest conditions using 24 sample plots. Nonetheless, there still exists a knowledge gap regarding the performance of point cloud–based methods to characterize larger tree communities and forest stands. To characterize the phenomenon of interest, e.g. forest growth, the point cloud–based methods need to provide comprehensive characterization of trees and tree communities in space but also in time. Repeated observations enable monitoring of the dynamics of trees and tree communities, which is important in understanding the processes shaping them. For example, Luoma et al. (2019) demonstrated the feasibility of TLS in detecting changes in tree stem shape, but more evidence is needed to understand the capabilities of TLS in forest monitoring, especially in diverse forest conditions.

Besides living trees, dead wood is an important forest structural characteristic, as it preserves biodiversity by providing habitat for many threatened species while storing carbon decades after the tree death has occurred (Harmon et al. 1986; Franklin, Shugart, and Harmon 1987). Therefore, the abundance of dead wood can be used as an indicator of biodiversity. However, past studies regarding the use of terrestrial point clouds to characterize forest structure have focused on detecting and measuring the standing trees, while less attention has been paid to downed dead wood monitoring. The first attempt to detect fallen trees from TLS point clouds was presented by Polewski et al. (2017). Although their method revealed the existence of downed dead wood within an area of interest, no information on the dead wood quality attributes was provided.

1.3 Objectives and hypothesis

This thesis investigates the feasibility of point cloud–based methods in characterizing trees and tree communities to better understand their development over time and builds around two main objectives and related hypotheses. The first objective is to develop automatic point cloud processing methods for characterizing trees and downed dead wood from terrestrial point clouds. This can be formulated into two hypotheses (H1–H2), whose validity is tested in studies **I–III**:

H1. Fallen trees can be distinguished from the undergrowth vegetation and other near-ground objects such as stones and stumps by means of their regular, cylindrical geometry (study **I)**.

H2. A tree stem can be distinguished from other forest structural characteristics based on its pole-like structure that features smooth and vertical surfaces with cylindrical geometry (studies **II–III**).

The second objective is to test the feasibility of the developed methods for characterization of trees and tree communities in space and time. The related three hypotheses (H3–H5) are formulated as follows, and their validity is tested in studies **II–V**:

H3. Increased density and structural complexity of tree communities, as well as the use of a scan setup with incomplete point cloud coverage, are expected to decrease the performance of the developed methods to characterize trees and tree communities (studies **II–III**).

H4. Combining terrestrial and aerial point clouds will improve tree community characterization (study **IV**).

H5. Growth of trees and the dynamics of tree communities during a five-year monitoring period can be detected and quantified using bitemporal TLS point clouds (study **V**).

2 EXPERIMENTAL SETUP AND STUDY MATERIALS

2.1 Study sites and field inventory data

The four study sites used in this thesis are located in southern Finland in Evo (61°19.6′ N 25°10.8′ E), Palomäki (62°3.6'N 24°19.9'E), Pollari (62°4.4'N 24°30.1'E) and Vesijako (61°21.8'N 25°6.3'E; see Figure 1). Studies **I**, **II** and **V** were conducted in the Evo study site, which represents varying southern boreal forest conditions covering both managed and unmanaged, young and mature, single-species and mixed-species, and single-layered and multi-layered forest stands where Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) H. Karst.) and birches (*Betula* sp.) were the dominant tree species. In 2014, 91 rectangular sample plots with an area of 1024 m^2 (32 m × 32 m) were established to cover the structural variation of forests within the vicinity (see e.g. Liang, Hyyppä, et al. 2018). A basic suite of tree attributes were measured in the field for all the 8785 trees on the sample plots with dbh exceeding 5 cm. Tree species and health status (alive/dead) were defined using visual inspection and dbh was measured with calipers as a mean of two diameter measurements perpendicular to each other at the height of 1.3 m above the ground. Tree height and height of the crown base were measured using an electronic clinometer. Stem volume was then estimated using species-specific volume equations and dbh and tree height as explanatory variables (Laasasenaho 1982).

All the 91 sample plots were used in study **II**, while a subset of 20 sample plots were selected for study **I** according to the existence of downed dead wood. Field reference for the locations, dimensions and quality attributes of the 304 individual downed dead wood trunks with diameter exceeding 5 cm was acquired in 2017. For each trunk, tree species was visually defined, while the length and diameters were measured using tape measure and calipers, respectively.

Of the total number of 91 sample plots, a subset of 37 sample plots were re-measured in 2019 to cover a five-year monitoring period for study **V**. The tree maps were updated in the field with missing trees (i.e. fallen or harvested during the monitoring period) and new trees (i.e. trees with dbh exceeded the 5 cm threshold since the last measurement). Dbh, tree height and height of the crown base were re-measured for 1280 trees following the same measurement protocol as in 2014.

Studies **III** and **IV** were conducted in the study sites of Palomäki, Pollari and Vesijako, which were initially established in 2005 by Natural Resources Institute Finland (Luke) to investigate the effect of different thinning types and thinning intensities on the growth and development of Scots pine trees and the dynamics of Scots pine stands. Each study site is characterized as managed Scots pine stands consisting of nine rectangular sample plots (27 sample plots in total) with an area varying between 900 m^2 (30 m × 30 m) and 1200 m^2 (30 m × 40 m), where the experimental design includes three different thinning types (thinning from below, thinning from above, systematic thinning from above) with two levels of thinning intensity (intensive, moderate) (Saarinen et al. 2020). Reference measurements for the 2204 trees on the sample plots were obtained during leaf-off season 2018–2019. Tree species, crown layer (dominant, co-dominant, suppressed) and health status (alive, dead) were recorded from each tree within a plot (i.e. tally trees) using visual inspection. Dbh was measured for all the tally trees with calipers as an average of two diameter measurements perpendicular to each other at the height of 1.3 m above the ground. About half of the trees (928) were selected as sample trees, for which tree height and the height of the crown base were also measured using an electronic clinometer. Heights of the tally trees were estimated with allometric models that were calibrated for each sample plot using the sample trees. Stem volume was estimated for all the trees using the volume equations by (Laasasenaho 1982).

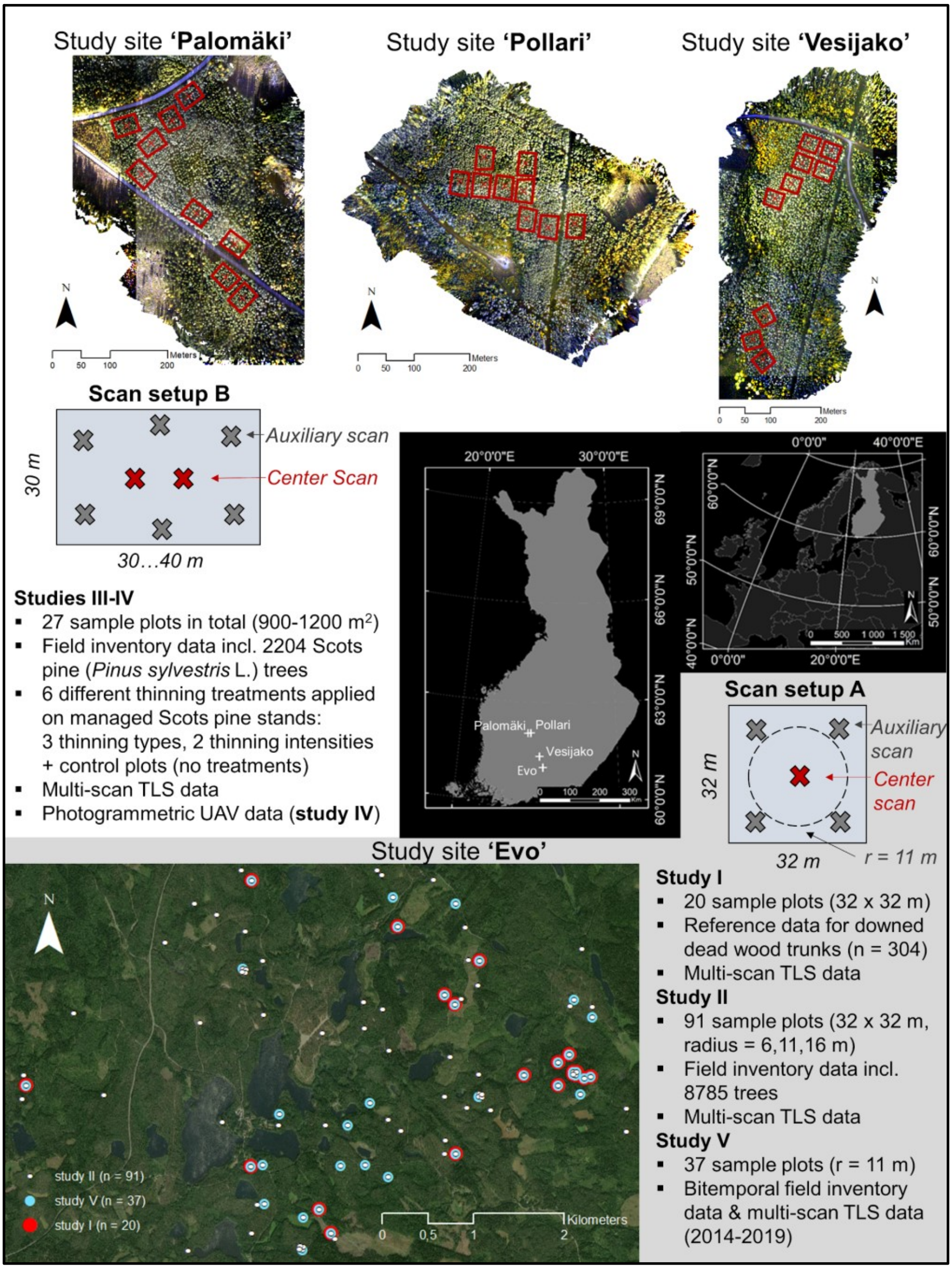

Figure 1. Description of the study site locations and the experimental design of each substudy of this thesis. TLS data refers to point clouds acquired using terrestrial laser scanning, while UAV data refers to aerial point clouds acquired from an unmanned aerial vehicle.

2.2 Point cloud data

2.2.1 Terrestrial point cloud data

TLS was used to acquire the terrestrial point clouds since it sets the baseline for the accuracy that is expected to be reached with the other terrestrial close-range sensing methods (Liang, Hyyppä, et al. 2018). TLS data acquisition campaigns were conducted by collecting the TLS data from several locations systematically placed around the sample plot or a stand (i.e. the multi-scan approach). There were minor differences in the applied scan setups between the study sites. One center scan with four auxiliary scans (five scans in total, referred to as scan setup A) were used in the Evo study site (studies **I**, **II** and **V**) whilst two center scans with six auxiliary scans (eight scans in total, referred to as scan setup B) were used in the Palomäki, Pollari and Vesijako study sites (studies **III** and **IV**; see Figure 1). In the scan setup A, the center scan was located at the plot center, and the auxiliary scans were placed evenly around it at the quadrant directions (i.e. north-east, south-east, south-west, and north-west). In the scan setup B, the two center scans were placed near the plot center approximately a few meters apart from each other, and the six auxiliary scans were evenly distributed around the plot center, with preference given to locations near the plot borders. Locations of the auxiliary scans were adjusted in the field to ensure maximum visibility, in other words, to avoid placing the scanner next to a large tree that would block the laser from digitizing other trees behind it.

Four different terrestrial laser scanners were used in the TLS data acquisition campaigns: A Leica HDS6100 (Leica Geosystems, St. Gallen, Switzerland) phase shift scanner was used in studies **I, II**, and **V**; a Faro Focus 3D X330 (Faro Technologies Inc., Lake Mary, FL, USA) phase shift scanner was used in study **II**; a Trimble TX5 3D (Trimble Inc., Sunnyvale, California, United States) phase shift scanner was used in studies **III** and **IV**; and a Leica RTC360 3D time-of-flight scanner was used in study **V**. All the scanners were operating at 1550 nm wavelength and delivered a hemispherical point cloud with a 300° to 310° vertical and 360° horizontal field of view. Angular resolution in the laser measurements varied from 0.009° (Trimble TX5 3D, Leica RTC360 3D) to 0.018° (Leica HDS6100, Faro Focus 3D X330).

Individual scans from each sample plot were registered together to obtain a merged point cloud. The registration was completed using spherical reference targets that were evenly distributed on each sample plot considering that all the targets were visible from the center scan locations and at least three of them from the auxiliary scan locations. The number of reference targets used in the registration was five or six, depending on the stand density. In the Evo study site, the reference targets were attached to trees at the height of approximately 2 m. In 2014 (study **II**), the exact locations of the reference targets were measured using a total station and ground control points. Magnets and steel plates were used for mounting the reference targets to the trees, which made it easier to repeat the TLS campaign in 2017 (study **I**) and 2019 (study **V**) using the exact same locations. In the Palomäki, Pollari and Vesijako study sites (studies **III** and **IV**), the reference targets were mounted on tripods at the height of approximately 1 m above the ground. The point cloud registration was conducted by fitting spherical objects (of equal size as the real ones) to the points that represented the reference targets in the individual point clouds. Then, a 3D transformation between the point clouds was computed to rotate and translate the auxiliary scan point clouds with respect to the center scan point cloud. As a result, the point clouds could be merged with a millimeter-level of accuracy.

2.2.2 Aerial point cloud data

UAV photogrammetry was applied in study **IV** to provide a cost-efficient approach to acquire aerial point cloud data for augmenting terrestrial point clouds in vertical forest characterization. The aerial point cloud data was acquired from the Palomäki, Pollari and Vesijako study sites using a Gryphon Dynamics quadcopter equipped with an Applanix APX-15-EI UAV positioning system consisting of a multiband GNSS, an IMU and a Harxon HX-CHX600A antenna and two Sony A7R II digital cameras that had complementary metal-oxide-semiconductor (CMOS) sensors of 42.4 megapixels with Sony FE 35 mm f/2.8 ZA Carl Zeiss Sonnar T* lenses. The two cameras were mounted on +15° and −15° oblique zenith angles to enhance the 3D reconstruction of trees. With a flying altitude of 140 m and a flying speed of 5 m/s, a total of 1916 images were captured, resulting in 1.42 cm to 1.87 cm ground sampling distance, 87% to 90% forward and 78% to 83% side overlaps at the ground level, depending on the study site. Eight ground control points were precisely measured for each study site using a Topcon Hiper HR real-time kinematic GNSS receiver (Topcon, Tokyo, Japan). The photogrammetric processing was carried out using Agisoft Metashape Professional software (Agisoft 2019) by following a similar processing workflow as that presented in Viljanen et al. (2018). Dense UAV point clouds were obtained with a reprojection error of 0.65–0.70 pixels, a point cloud resolution of 3.11–3.53 cm/pixel and a point density of 804–1030 points/m^2, depending on the study site.

3 POINT CLOUD PROCESSING METHODS

3.1 Pre-processing

The merged point clouds were first normalized, in other words, the z-coordinates were converted from heights above sea level to heights above the ground using a digital terrain model (DTM) as a reference. In study **I**, the DTM was generated by searching for the lowest z-coordinates among the points in 0.5 m × 0.5 m grid cells. Linear interpolation and a 3 × 3 -pixel moving average filtering were used to smooth out cross errors below or above the ground surface. In studies **II–V**, the TLS point cloud normalization was conducted using LAStools software (Isenburg 2017) and a workflow presented by Ritter et al. (2017). First, points representing ground surface were extracted to generate the DTM based on a triangulated irregular network. The generated DTMs were then used to normalize the multi-scan TLS point clouds.

In study **I**, the analyses were based on a subset of points with z-coordinates ranging between 0 m and 1 m above the ground, which was the expected range for downed dead wood occurrence in the forests of the study area. In studies **II–V**, the analyses were focused on standing trees, and thus, the ground points were removed to reduce the amount of data to be processed. A mixed-pixels filtering protocol was carried out to remove noisy points originating from inaccurate range measurements that occur when the laser beam intersects with objects smaller than itself.

It is generally known that a photogrammetric point cloud acquired from above the forest cannot be used for characterizing topography under the forest canopy (e.g. White et al. (2013)). Thus, the photogrammetric UAV point cloud data used in study **IV** was not capable of providing a sufficient characterization of the ground surface to enable accurate DTM generation, and thus, a publicly available 2 m × 2 m DTM (National Land Survey of Finland) was used to normalize the UAV point clouds.

3.2 Detecting and characterizing downed dead wood (study I)

A point cloud–based method for detecting and characterizing downed dead wood was developed in study **I**. The aim in dead wood detection was to identify the locations of the butt-end and the top-end of a dead wood trunk, to then be able to delineate the respective point cloud structure representing the trunk for measuring its dimensions. The detection method was based on the assumption that a dead wood trunk lying on the ground could be distinguished from the undergrowth vegetation and other near-ground objects such as stones and stumps by means of its regular, continuous, cylindrical geometry (see Figure 2). These structures were identified by first removing a set of points that obviously originate from the ground surface (i.e. z-value smaller than a set threshold value, z_{min}). Thus, the remaining point cloud represented structures clearly rising from the ground surface. The next step involved filtering the point cloud to keep only the structures with cylindrical geometry. From the methodological point of view, at this point, the point cloud consisted of inliers and outliers, inliers being the cylindrical structures representing dead wood trunks, and outliers being other near-ground objects and vegetation. Random sample consensus (RANSAC; see Bolles and Fischler (1981)) was utilized when fitting cylinders to this noisy point cloud data, aiming to keep the inliers and filter out the outliers. RANSAC-cylinder filtering was iteratively applied for one 0.5 m × 0.5 m point cloud tile at a time to cover the whole sample plot.

Continuity and regularity were the distinguishing characteristics separating downed dead wood trunks from other cylindrical near-ground structures that remained in the filtered point cloud. These characteristics were investigated by converting the point cloud into a binary raster image (2 cm × 2 cm) and applying image processing and segmentation techniques. Morphological opening and closing were applied to strengthen the distinction of regular-shaped image segments. An image segment was classified as a dead wood segment if its ellipticity, measured as eccentricity (ε), reached a set threshold value (ε_{min}). It was assumed that a dead wood trunk was represented by a single image segment or by a set of subsequent parallel image segments. Thus, the orientation and location of each image segment with respect to another were investigated to merge the segments possibly representing the same trunk. The image segments were then used to delineate and extract point clouds representing each dead wood trunk.

Dead wood quality attributes such as length, diameter and volume were estimated from the extracted point clouds. Length of the dead wood trunk was obtained as a length of the image segment representing the trunk. Diameters were measured along the dead wood trunk by applying point cloud filtering and cylinder fitting. Surface normals were computed for each point according to its neighborhood to distinguish smooth and planar surfaces representing the surface of dead wood trunk. Then, RANSAC-cylinder fitting was used to obtain diameter measurements at 10 cm intervals along the trunk. The consecutive diameter observations tended to vary due to point cloud occlusion and epiphytes growing on the trunk surface, and thus the diameter observations were filtered with a cubic spline curve. The trunk volume was eventually estimated by considering the trunk as a sequence of horizontal cylinders.

3.3 Point cloud classification to detect standing trees (studies II–III)

An automatic method for detecting individual standing trees from TLS point clouds was first implemented in study **II** and further developed in study **III**. The methodology combines elements from several earlier studies on principles to distinguish tree stems from foliage and other non-woody structures based on their geometric properties, such as smooth and cylindrical surfaces (e.g. Liang, Litkey, et al. 2012; Raumonen et al. 2013; Hackenberg et al. 2014) and vertical continuity of point cloud structures (e.g. Cabo, Ordóñez, et al. 2018; Zhang et al. 2019). A series of point cloud processing techniques including grid average downsampling, surface normal filtering, point cloud clustering and RANSAC-cylinder filtering were implemented and applied to identify these characteristics from the point clouds (see Figure 2). The point cloud was downsampled into a regular grid to even the point spacing because, in TLS data, the point cloud density tends to vary with distance to the scanner. Surface normals were computed for each point according to its neighborhood to filter out non-vertical surfaces. The filtered points were clustered, and the cluster dimensions were examined to filter out small, non-vertical point cloud structures obviously not representing a tree stem. RANSAC-cylinder filtering was applied to validate the cylindrical geometry of a point cloud structure.

Considering that a sample plot point cloud consisted of more than 100 million points and represented tens of trees, it had to be processed in smaller units to achieve reasonable computing performance. First, canopy segments (including none, one, or more trees) were extracted from a detailed canopy height model (CHM), and the sample plot point cloud was partitioned according to the canopy segments. The canopy-segmented point clouds were then split into horizontal point cloud bins, and a point cloud classification procedure was applied for each point cloud bin to separate points representing the tree stem (i.e. stem points) from points representing branches and foliage (i.e. non-stem points). The point cloud classification procedure first aimed to find the base of the tree stem from the lowest point cloud bin, as the lower part of a tree stem is often well characterized due to a low number of occluding branches and favorable point cloud acquisition geometry. Once the stem points representing the base of the tree were extracted, the realized stem location and dimensions were used to guide the classification procedure in the following point cloud bins. The classification procedure proceeded upwards along the stem, bin by bin, until the treetop was reached. As a result, the entire sample plot point cloud was classified into stem points and non-stem points by individual trees, which enabled detailed point cloud–based measurements to retrieve tree attributes such as dbh and tree height and the estimation of forest structural attributes such as the number of trees per hectare (TPH) and mean basal area (G).

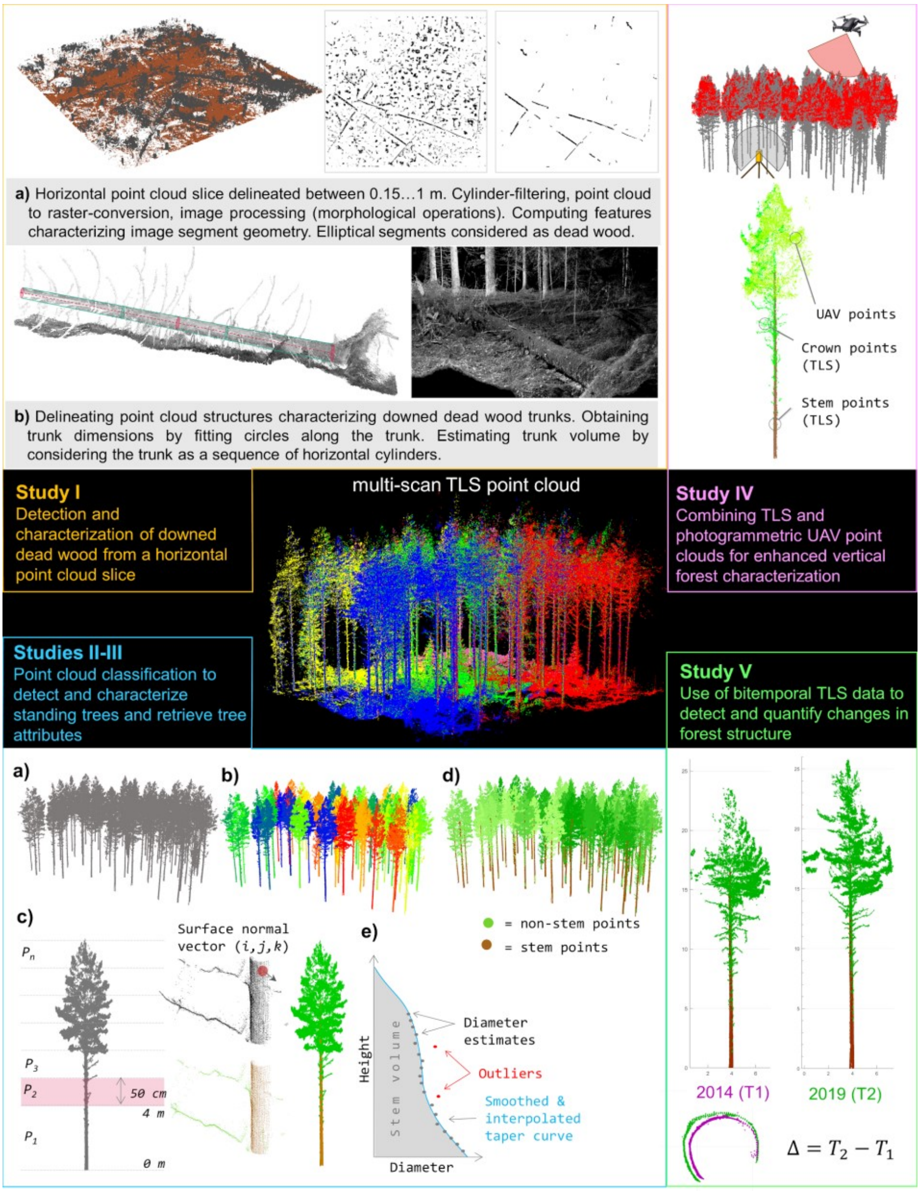

Figure 2. Outline of the point cloud processing methods implemented in this thesis. Study **I**: Downed dead wood trunks were detected from point clouds based on their cylindrical, regular geometry. Studies **II–III**: Individual trees were detected from multi-scan terrestrial laser scanning (TLS) point clouds (a-b); point cloud structures representing stem were distinguished from non-stem points based on point neighborhood characteristics (c-d). Tree attributes such as diameter at breast height, tree height and stem volume were extracted from the classified point clouds (e). Study **IV**: Aerial point clouds acquired from an unmanned aerial vehicle (UAV) were merged with TLS point clouds. Study **V**: TLS point cloud–derived estimates for tree and forest structural attributes obtained at the beginning (2014) and at the end of the monitoring period (2019) were compared to examine changes.

3.4 Characterizing trees and tree communities (study II)

Once the stem points and non-stem points were classified as explained in Section 3.3, attributes characterizing the structure of trees and tree communities were estimated using a point cloud–based method implemented in study **II**. Tree attributes such as dbh, basal area (g), tree height (h) and stem volume (v) were estimated for each tree by modelling the point cloud structures with geometric primitives such as circles and cylinders. The aim was to obtain a taper curve characterizing the stem profile, in other words, the stem diameter as a function of tree height. This involved measuring the diameters along the stem by fitting circles or cylinders at certain height intervals and using a cubic spline curve to level unevenness in the diameter measurements by following the procedure presented in Saarinen et al. (2017). The diameter was forced to be zero at the height that equaled the height of the highest point of the tree (i.e. tree height). Stem volume was computed as a piecewise integral of the taper curve by considering the stem as a sequence of vertical cylinders.

Forest structural attributes such as basal area-weighted mean diameter (D_g), basal area-weighted mean height (Lorey's height, H_g), G, TPH and mean volume (V_{mean}) were estimated by aggregating the tree attributes at the sample plot level according to Equations 2–6.

$$D_g = \frac{\sum_{i=1}^{n} d_i g_i}{\sum_{i=1}^{n} g_i} \tag{2}$$

$$H_g = \frac{\sum_{i=1}^{n} h_i g_i}{\sum_{i=1}^{n} g_i} \tag{3}$$

$$G = \frac{\sum_{i=1}^{n} g_i}{A} \tag{4}$$

$$TPH = \frac{n}{A} \tag{5}$$

$$V_{mean} = \frac{\sum_{i=1}^{n} v_i}{A} \tag{6}$$

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

3.5 Merging terrestrial and aerial point clouds (study IV)

Aerial and terrestrial point clouds were combined in study **IV** to enhance the vertical characterization of trees and tree communities. The point clouds were registered and merged by manually searching for common tie points for each sample plot and computing a 3D transformation matrix based on the tie point coordinates to align the data sets. This resulted in multisensorial point cloud data that was then used to detect and characterize trees and tree communities using the point cloud–based methods developed in studies **II–III**.

3.6 Quantifying changes in trees and tree communities (study V)

Changes in tree and forest structural attributes were quantified in study **V** by subtracting the attributes derived from the point clouds at the beginning of the monitoring period (2014, T1) from the respective attributes derived from the point clouds at the end of the monitoring period (2019, T2). At tree level, changes in dbh (Δdbh), g (Δg) and h (Δh), as well as diameter-height ratio (Δd-h-ratio), height of the crown base (Δhc) and crown ratio (Δcr), were analyzed. To complete this task, additional tree attributes were computed at T1 and T2. The d-h-ratio was computed as the ratio between dbh and height. The hc was determined by searching for a height threshold for each tree for which an increase in crown horizontal dimensions was recorded. This was done by first binning the non-stem points into horizontal slices with a height of 20 cm, then computing a convex hull around the bin points projected to XY-plane, with hc being determined at the height where the convex hull area exceeded a 1.5 m^2 threshold and the perimeter-to-area ratio for the convex hull was smaller than two. The threshold values of these parameters were chosen by pre-investigating the characteristics of the crown features with respect to the field-measured hc. The cr was computed as the proportion of the height of a living crown from the tree height (cr = (h − hc)/h). At plot level, changes in TPH (ΔTPH), G (ΔG), D_g (ΔD_g) and H_g (ΔH_g) were analyzed based on aggregated tree level attributes (See Equations 2–6).

3.7 Performance analyses

Performance of the implemented point cloud–based methods to characterize forest structure were assessed by using a set of accuracy measures assessing how well the point cloud-derived characterization of the forest structure corresponded to the characterization that was based on the reference measurements and field observations. This required searching for a corresponding field-measured tree or dead wood trunk for each point cloud–derived tree or dead wood trunk. Bias and root mean square error (RMSE; Equations 7–8) were used as accuracy measures for assessing the deviation between the point cloud–derived and field-measured tree and forest structural characteristics:

$$bias = \frac{\sum_{i=1}^{n}(\hat{X_i} - X_i)}{n} \tag{7}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{X_i} - X_i)^2}{n}} \tag{8}$$

where *n* is the number of trees or sample plots, $\hat{X_i}$ is the point cloud-derived tree attribute or forest structural attribute for tree *i* or plot *i*, and X_i is the corresponding attribute based on field measurements.

It should be noted that there is variation in the precision of caliper and clinometer measurements (Luoma et al. 2017) and errors in the stem volume estimates from allometric models. Nevertheless, these are generally considered as the reference values for point cloud-derived estimates for tree and forest structural attributes within the scientific community and, thus, also in this thesis.

Accuracy of the point cloud–based method to detect downed dead wood trunks and standing trees were assessed using correctness and completeness as accuracy measures. Correctness measures how large a part of the point cloud-derived trees was successfully matched with field-measured trees. Completeness measures how large a part of the field-measured trees was able to be detected from the point clouds. At the sample-plot level, the completeness indicates how large a part of the field-measured TPH was characterized with the point cloud–based method. Similarly, the completeness was computed with respect to G and V_{mean} to provide more insight into assessing how well the tree population was characterized by the point cloud–based method.

Performance of the point cloud–based method to detect and characterize downed dead wood was investigated in study **I**. Besides field-measured reference, performance of the automatic method was also compared to the performance of visual interpretation of the point clouds, which was assumed to represent the highest level of accuracy that could be achieved by using the point clouds with the given scan setup.

In study **II**, the effects of scan setup and forest structural heterogeneity on the performance of the point cloud–based method were investigated. With a fixed scan setup (scan setup A), different-sized circular sample plots were used to demonstrate the effect of having the auxiliary scans located either inside the plot (16 m radius), on the plot border (11 m radius) or outside the plot (6 m radius). It was assumed that it would be more favorable to have the auxiliary scans at the plot borders to ensure point cloud completeness, that is, that the trees become scanned from multiple directions. Forest structural heterogeneity was measured with Gini coefficient (GC) describing the size diversity based on variation in dbh distribution:

$$GC = \frac{\sum_{j=1}^{n}(2j - n - 1)g_j}{\sum_{j=1}^{n} g_j(n - 1)} \tag{9}$$

where n is the number of trees in a sample plot and g_j is the basal area of the j^{th} tree, j being the rank of a tree in ascending order from 1, …, n based on the basal area. The GC is a scalar value between 0 and 1, with a higher value indicating a more complex forest stand. The effect of stand structural heterogeneity on the accuracy of the point cloud–based method was evaluated by analyzing the errors of the point cloud–based estimates for the plot-level forest inventory attributes with respect to the GC.

The effects of thinning treatments on the performance of the point cloud–based forest characterization were investigated in study **III**. The accuracy of detecting trees and estimating tree and forest structural attributes was assessed by thinning type and intensity. A one-sample *t*-test was used in pairwise investigations to examine whether the estimation error of tree and forest structural attributes in one thinning treatment significantly differed from the errors of the respective estimates of other thinning treatments. The ability of the point cloud–based method to provide consistent performance in similar forest conditions was investigated by analyzing the variation in the accuracy measures among sample plots with the same thinning type and intensity and comparing the range of variation in accuracy measures between different thinning treatments.

The benefits of using multisensorial point clouds in characterizing forest structure, especially its vertical component, were investigated in study **IV**. The performance of detecting trees and measuring tree and forest structural attributes using the multisensorial data (TLS and UAV point clouds combined) was compared with the respective performance when using only TLS data. Coefficient of determination (R^2) was used to measure how large a part of the variation in the field-measured tree and forest attributes could be characterized by the point cloud–based methods.

In study **V**, paired sample *t*-tests were used to determine whether the point cloud–based estimates for tree and forest structural attributes at the beginning of the monitoring period (time point one, T1) significantly differed from the respective estimates at the end of the monitoring period (time point two, T2). The accuracy of quantifying changes in the tree attributes was assessed by tree species (Scots pine, Norway spruce, and broadleaved trees). The accuracy of quantifying changes in the forest structural attributes was assessed by main tree species of the sample plot (Scots pine–dominated, Norway spruce–dominated, and mixed-species sample plots).

4 RESULTS

4.1 Method development for characterizing forest structure

4.1.1 Performance of detecting and characterizing downed dead wood (study I)

It was possible to detect and measure the dimensions of downed dead wood trunks using the automatic point cloud–based method implemented in study **I**. The dead wood trunk locations were distinguished based on their cylindrical and regular geometry, and the respective point cloud structures were delineated to measure the trunk dimensions. In this regard, the validity of H1 was confirmed. The key methodological finding was that the downed dead wood trunks appeared as regular-shaped image segments that were strongly elliptical, in fact, more elliptical than most of the other near-ground objects. This is because the length of a dead wood trunk is often several times larger than its diameter, and such an object appears more regular and lineal than stones, stumps or hummocks. The point cloud–based method was found to be sensitive to two parameters, namely z_{min} defining the lower limit of point cloud delineation and ε_{min} defining the minimum ellipticity of an image segment to be classified as downed dead wood trunk. Sensitivity analyses resulted in the parameter values of 15 cm for z_{min}, and 0.98 for ε_{min} providing robust performance across different boreal forest conditions. Decreasing the parameter values resulted in slightly more dead wood trunks being detected at the cost of commission errors (i.e. falsely detected trunks). Increasing the parameter values, on the other hand, improved the correctness of the method at the cost of decreased completeness.

The dead wood trunks that were detected from the point clouds accounted for 68% of the total volume of dead wood. Correctness of dead wood detection was 76% and varied between 50% and 100% across the sample plots. Dead wood dimensions (i.e. diameter and length) were noticed to be the most important factors affecting the detection accuracy, with large trunks being detected more accurately than small trunks. The larger the dead wood dimensions were, the more distinguishable and regular structures they formed. Of the total volume of dead wood with mid-diameter larger than 30 cm, 86% was automatically detected. Considering that large-diameter dead wood is more valuable for biodiversity than small-diameter dead wood (Andersson and Hytteborn 1991; Bader, Jansson, and Jonsson 1995), the quantity of ecologically important dead wood could be characterized. However, 28% of the field-measured dead wood trunks remained undetected even if the point clouds were visually inspected. Completeness in dead wood detection could be improved with visual interpretation of point clouds, which resulted in detecting 83% of the total dead wood volume. It should be noted that here the TLS data was acquired using a scan setup initially designed to characterize standing trees. In other words, the scan locations were not selected to specifically prefer dead wood mapping.

Mid-diameter, length and volume of the downed dead wood trunks were computed after detecting and delineating the respective point cloud structures from the sample plot point cloud. The mid-diameter was overestimated by 3.2 cm and 4.1 cm, and the length was underestimated by 5.5 m and 2.6 m depending on whether the dead wood trunks were detected using the automatic method or visual interpretation of point clouds, respectively.

4.1.2 Performance of detecting and characterizing standing trees (studies II–III)

Individual trees were delineated from the TLS point clouds from the total number of 118 sample plots. The point clouds representing the individual trees were further classified into stem points and non-stem points using the point cloud classification procedure implemented in study **III**. This allowed measuring the tree attributes and estimating forest structural attributes using the automatic point cloud–based method implemented in study **II**. The performance of the point cloud–based method was assessed in varying forest conditions in study **II**. There, the overall correctness and completeness of tree detection were 93.6% and 66.2%, respectively. The group of trees that were detected from the point clouds represented 88.3% of the total basal area and 91.3% of the total stem volume of all the field-measured trees. This indicated that trees that were detected from the point clouds were larger in dbh and height than trees that remained undetected (Figure 3). In study **III**, the performance assessments were conducted on single-layered, managed Scots pine stands. There, the overall correctness and completeness of tree detection were 100% and 98.8%, respectively. The total volume of the trees that were detected from the point clouds accounted for 99.5% of the total volume of all the field-measured trees in study **III**. These figures reflect high accuracy of the point cloud–based method in detecting point cloud structures representing tree stems, which confirms the validity of H2.

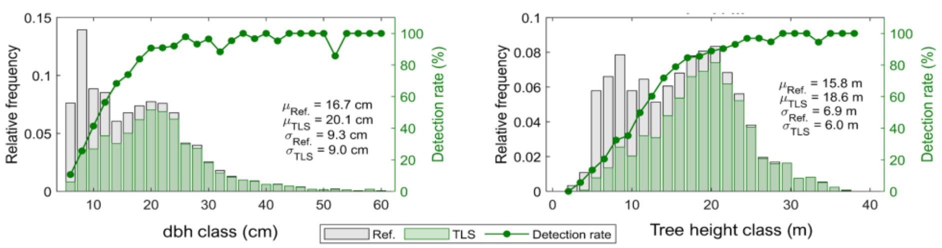

Figure 3. Completeness in tree detection by diameter at breast height (dbh) and tree height classes. The colored bars represent the proportion of field-measured reference trees (Ref.) that were detected from the terrestrial laser scanning (TLS) point clouds. The lines represent the respective tree detection rate by tree size classes (adapted from study **II**). The mean values (μ) and their variation (σ) are presented for reference and for TLS-detected trees as well.

4.2 Feasibility of point cloud–based methods to characterize forest structure

4.2.1 Effect of scan setup and forest structure (studies II–III)

The effects of scan setup and forest structural complexity on the performance of the point cloud–based method to characterize forest structure were investigated in study **II**. By default, the auxiliary scans were located approximately at the circumference of the circular 11 m radius sample plots, resulting in point clouds where the trees became scanned from multiple directions. This scan setup resulted in RMSEs of 3.1 cm (12.3%) for D_g, 1.3 m (5.9%) for H_g, 5.1 m^2/ha (18.4%) for G, 498 n/ha (51.7%) for TPH and 43.1 m^3/ha (15.3%) for V_{mean}. The results showed that the point cloud–based method could capture 83% of the plot-level variation in D_g, 95% in H_g, 86% in G, 67% in TPH and 94% in V_{mean}. Decreasing the sample plot radius from 11 m to 6 m resulted in a scan setup in which the auxiliary scans located outside of the sample plot enhanced the point cloud completeness. This reduced the magnitude of bias in the estimates of forest structural attributes but did not significantly (p > 0.05) affect the tree detection accuracy (Figure 4), or the RMSEs in the estimates of G and TPH. RMSE in the D_g estimates slightly decreased, whereas the RMSEs in the estimates for H_g and V_{mean} increased. Increasing the sample plot radius from 11 m to 16 m, on the other hand, decreased the point cloud completeness, as the auxiliary scans were located inside the sample plot. This affected unequal point cloud quality in terms of point cloud completeness: Trees near the plot center were scanned from multiple directions, whereas trees near the plot borders were scanned from only the side facing towards the plot center. Increase in the plot radius decreased the accuracy of estimating density-related forest structural attributes, namely G, TPH and V_{mean}, while no significant (p > 0.05) effect was noticed in tree detection accuracy or in estimating D_g and H_g (Figure 4). Performance of the point cloud–based method decreased even further when the sample plot size was enlarged into a rectangular 32 m × 32 m sample plot, in which the point cloud completeness was less favorable for trees located near the plot corners.

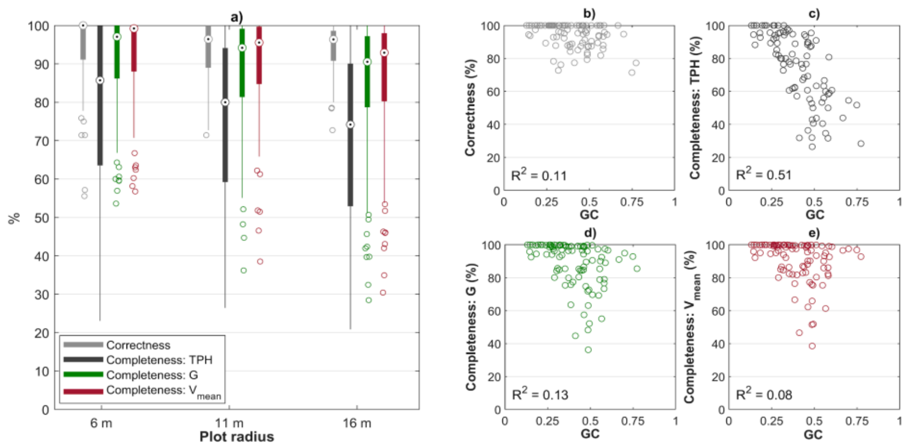

Figure 4. Correctness in tree detection as well as completeness in detecting the number of trees per hectare (TPH), mean basal area (G) and mean volume (V_{mean}) with respect to sample plot size (a), and forest structural heterogeneity (b-e) measured as the Gini coefficient (GC). Coefficient of determination (R^2) indicates the relationship between the accuracy measures and GC (adapted from study **II**).

Forest structural complexity was noticed to affect the performance of the point cloud–based method. The GC accounted for 51% of the variation in completeness of tree detection (Figure 4). When the sample plots were organized according to the performance of tree detection, over 96% correctness of tree detection and 80%, 94% and 96% completeness of detecting TPH, G and V_{mean}, respectively, were achieved for the top 50% of the sample plots. This demonstrates that high performance can be achieved in favorable forest conditions with the point cloud–based method. Variation in the accuracy measures increased with increasing variation in GC (Figure 4), which indicates that high performance in tree detection can be expected on sample plots with a low degree of tree size variation.

In study **III**, different thinning treatments (including control plots with no thinnings) were applied on managed Scots pine stands to investigate in more detail how forest structure affects the performance of the point cloud–based method of characterizing trees and tree communities. The thinning treatments had been applied under similar forest conditions, thus representing controlled variation in horizontal and vertical forest structure. On average, dbh and tree height were underestimated by 0.10 cm (0.5%) and 0.30 (1.6%) m, respectively. RMSE in dbh estimates was 0.70 cm (3.4%), while in the tree height estimates, the RMSE was 1.64 m (8.4%). Accurate estimates for tree-level attributes aggregated to accurate estimates at the plot-level as well, as a relative RMSE of less than 5.5% was recorded for all the structural forest attributes. Correctness and completeness in tree detection remained at the same level regardless of the applied thinning type or intensity. However, in general, higher accuracy in the estimates for tree and forest structural attributes was achieved for sample plots in which thinnings were carried out (Figure 5). Furthermore, thinning intensity was considered to affect the performance more than thinning type. Accuracy in estimating dbh (RMSE 3.0–4.1%), D_g (RMSE 1.1–1.7%) and V_{mean} (RMSE 4.8–5.9%) was consistent across the sample plots with different treatments, including control plots without any thinning treatments. In the case of all the other attributes, the performance of the point cloud–based method was significantly lower for control plots compared to thinned plots. Tree height was estimated most accurately (RMSE 4.5%) in sample plots in which thinning from above was carried out, while the lowest accuracy was obtained for control plots (RMSE 11.0%). In the case of H_g and G, the estimation accuracy remained at the same level for thinned plots (RMSE 2.2–2.3% and 2.5–2.9%, respectively) while being lower for control plots (RMSE 5.0% and 4.5%, respectively). TPH was estimated most accurately for sample plots where thinning from below was carried out (RMSE 0.7%), followed by thinning from above (RMSE 1.2%), systematic thinning (RMSE 1.9%) and control plots (RMSE 7.5%).

The experimental design of study **III** also enabled investigating how consistent performance can be expected when the point cloud–based method is applied under similar forest conditions. In general, more variation in the accuracy measures was recorded for control plots than for thinned sample plots (Figure 5). Range of variation in completeness in tree detection varied from 0.0% to 2.3% between the thinning treatments, while for control plots, the respective range of variation was 8.2%. Variation in the errors of H_g, G, TPH and V_{mean} estimates was significantly ($p < 0.05$) smaller for thinned plots than for control plots. Intensive thinning led to more consistent accuracy of the estimates of tree height, G and V_{mean}. The same applied with H_g, except for sample plots with thinning from above, in which moderate thinning intensity resulted in smaller variation in the estimation errors. In the case of dbh and D_g, the variation in the estimation errors was similar regardless of the applied treatments.

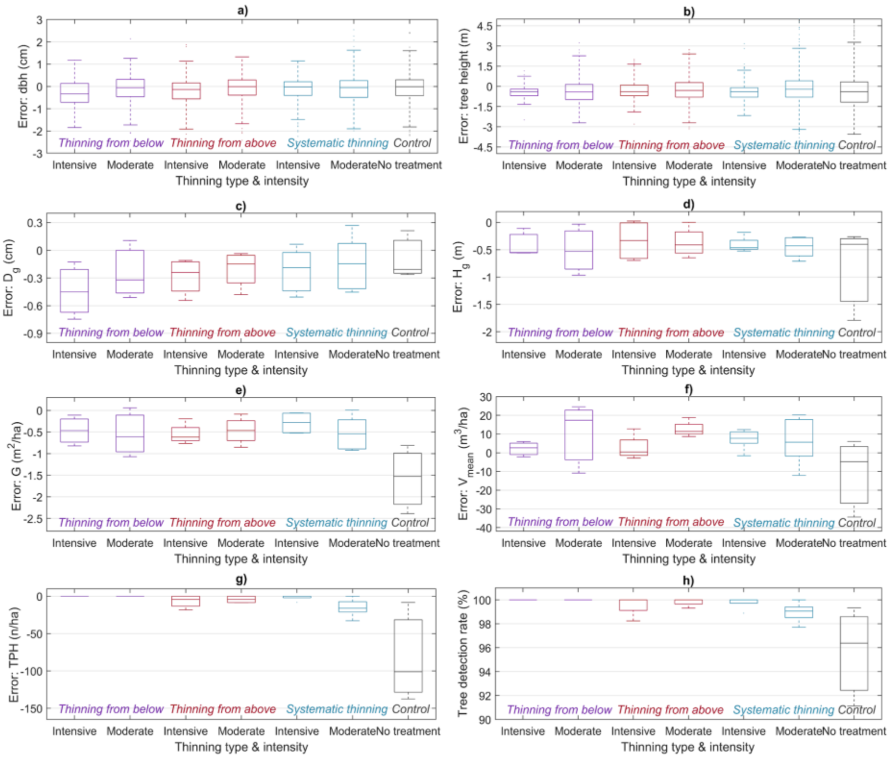

Figure 5. Variation in the errors of the point cloud-derived estimates for tree attributes such as a) diameter at breast height (dbh) and b) tree height; plot-level forest structural attributes such as c) basal area-weighted mean diameter (D_g), d) basal area-weighted mean height (H_g), e) mean basal area (G), f) mean volume (V_{mean}) and g) the number of trees per hectare (TPH) as well as h) tree detection rate between different thinning treatments (adapted from study **III**).

Altogether, the findings obtained from studies **II–III** confirmed the validity of H3 by demonstrating the effect of scan setup and stand structure on the performance of the point cloud–based method in characterizing trees and tree communities. Increased complexity in the horizontal and vertical forest structure led to decreased and inconsistent performance. On the other hand, the performance could be improved by using a scan setup that enhances point cloud completeness.

4.2.2 Benefits of using the multisensorial approach to characterize trees (study IV)

Feasibility of complementing terrestrial point clouds with aerial point clouds (i.e. the multisensorial approach) to enhance forest characterization was investigated in study **IV**. Bias in tree height estimates was decreased from -0.65 m (-3.3%) to -0.33 (-1.7%) when the multisensorial approach was used instead of just TLS point clouds. Respectively, at the sample plot level, the bias decreased from −0.75 m (−3.6%) to −0.45 m (0.58%) and the RMSE from 0.88 m (4.3%) to 0.58 m (2.8%). The photogrammetric UAV point cloud contributed to enhancing the characterization of the upper parts of the canopy, and thus, no improvement in horizontal forest characterization (i.e. dbh, D_g, G, and TPH) was recorded. However, as the accuracy of estimating V_{mean} is influenced by the accuracy of both vertical and horizontal forest characterization, the use of the multisensorial approach slightly improved the accuracy of V_{mean}, as the RMSE decreased from 14.55 m^3/ha (6.2%) to 12.81 m^3/ha (5.4%). These results showed that the use of the multisensorial approach improved vertical forest characterization (Figure 6), confirming the validity of H4.

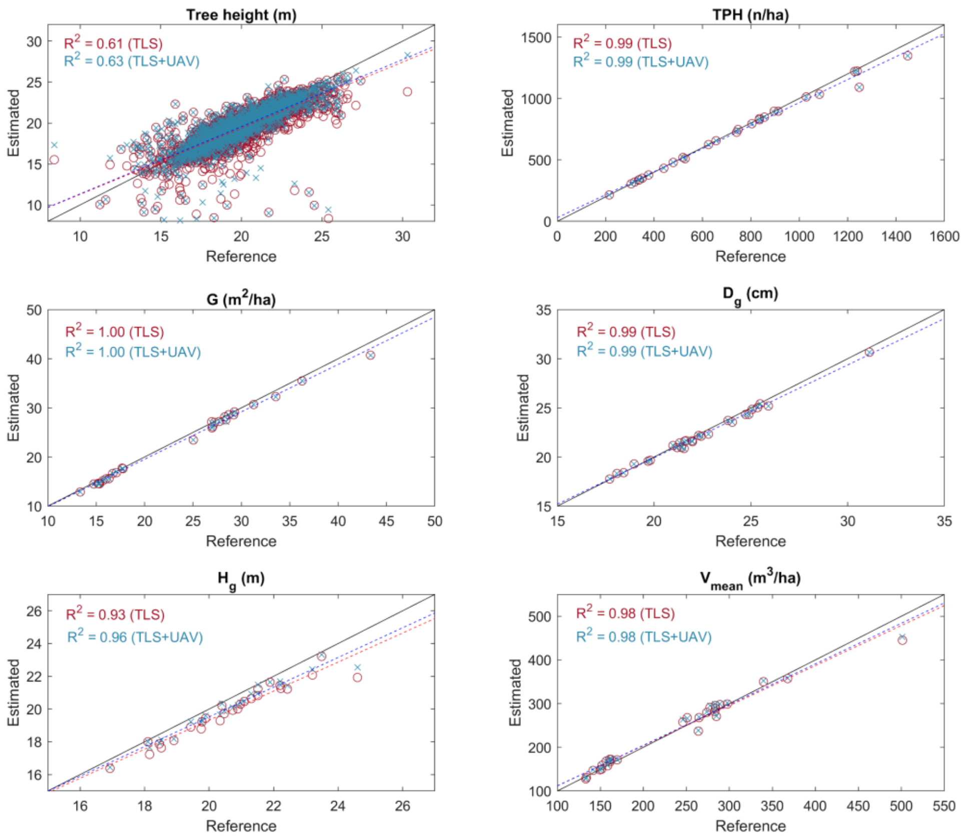

Figure 6. Coefficient of determination (R^2) indicating the relationship between the field-measured (Reference) and point cloud–derived (Estimated) estimates for tree height, number of trees per hectare (TPH), mean basal area (G), basal area-weighted mean diameter (D_g) and mean height (H_g) as well as mean volume (V_{mean}) when using terrestrial laser scanning (TLS) and the combination of TLS and photogrammetric airborne point clouds acquired from an unmanned aerial vehicle (UAV). The estimated values are based on TLS and the multisensorial approach (TLS+UAV). The solid black line represents the 1:1 relationship between the reference and the estimated values (adapted from study **IV**).

4.2.3 Capacity of TLS to characterize changes in forest structure (study V)

Bitemporal TLS data was used in study **V** to detect and quantify changes in tree and forest structural attributes. A total of 795 trees with basal area representing 84.5% of the total basal area of all the field-measured trees were detected at both time points, 2014 (T1) and 2019 (T2). The results showed that forest structure could be characterized in space and time using the point cloud–based methods developed in studies **II** and **III**. In dbh and tree height, there was an average increase of 1.16 cm and 1.40 m recorded in the field, whereas the use of the point cloud–based method resulted in an average increase of 1.26 cm and 1.99 m, respectively. Paired sample *t*-tests indicated that the arithmetic mean of the point cloud–based dbh and tree height estimates at T1 significantly ($p < 0.01$) differed from the arithmetic mean of dbh and tree height estimates at T2, which was true in the case of all the other tree attributes as well. This can be interpreted to mean that, if there was an increase or decrease in the attributes of trees within a tree community recorded in the field using calipers and a clinometer, a similar outcome (i.e. statistically significant increase or decrease in the respective attributes) was achieved with automatic processing of bitemporal point clouds. In general, the tree attributes of Scots pines and Norway spruces were estimated more accurately in space and time than the tree attributes of broadleaved trees, while changes in the horizontal structure of trees were estimated more accurately than changes in the vertical structure of trees. The point cloud–based method could explain 44–53% of Δdbh and 34–56% of Δg (Figure 7a-b). Changes in the vertical structure of trees were detected most accurately for Scots pine trees, for which 34–35% of Δh, Δhc and Δcr, as well as 20% of Δd-h-ratio, could

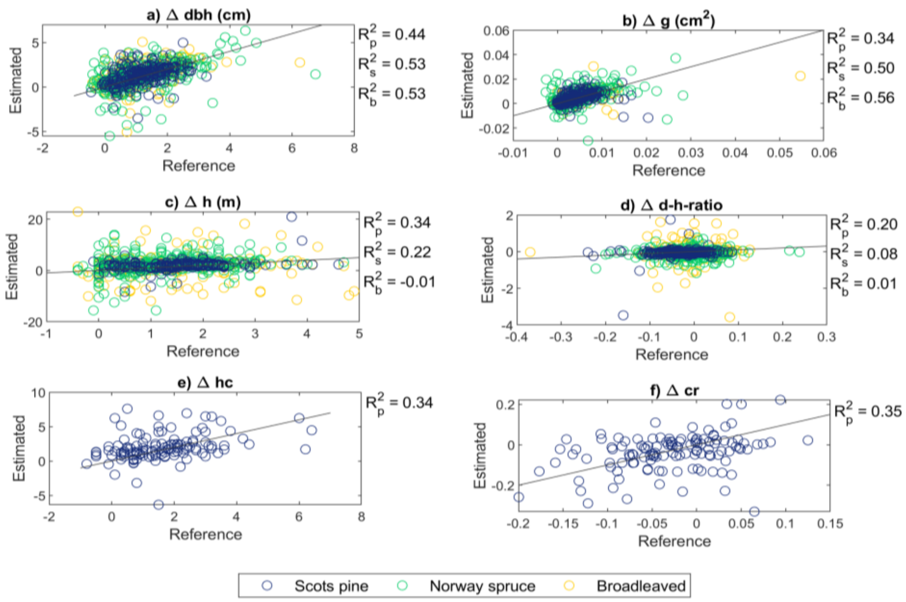

Figure 7. Coefficient of determination (R^2) indicating the relationships between the field-measured (Reference) and point cloud–derived estimates (Estimated) of changes in tree attributes such as diameter at breast height (Δdbh), basal area (Δg), tree height (Δh), diameter-height ratio (Δd-h-ratio), height of the crown base (Δhc), and crown ratio (Δcr) by tree species. The solid black line represents the 1:1 relationship between the reference and the estimated values (adapted from study **V**).

be explained with the point cloud–based method (Figure 7c-f). RMSE in estimates of Δdbh and Δh were 1.13 cm (97.4%) and 3.53 cm (251.6%), respectively. Considering these figures, it should be noted that the observed five-year change in dbh (1.16 cm) was within the accuracy of point cloud–derived estimates for dbh (RMSE 0.90–1.18 cm). In the case of tree height, the observed change (1.40 m) was below the accuracy of point cloud–derived estimates for h (RMSE 4.10–4.37 m).

Similarly to changes in the tree attributes, changes in the forest structural attributes could be detected with the point cloud–based method. In D_g, H_g and G, there was an average increase of 1.28 cm, 1.29 m and 2.86 m^2/ha recorded in the field, respectively, while the use of the point cloud–based method resulted in an average increase of 1.44 cm in D_g, 2.52 m in H_g and 2.75 m^2/ha in G. Paired sample *t*-tests indicated that the arithmetic mean of the point cloud–based estimates at T1 significantly ($p < 0.01$) differed from the arithmetic mean of the respective estimates at T2. In the case of TPH, there was an average decrease of 14 n/ha recorded in the field, whereas the point cloud–based method signified an average increase of 66 n/ha across the sample plots. However, the differences in both the field-observed and point cloud–derived estimates between T1 and T2 were not considered statistically significant ($p > 0.05$). In general, the changes in forest structural attributes of Scots pine–dominated and Norway spruce–dominated sample plots were characterized more accurately than the respective attributes of mixed-species sample plots.

Altogether, the findings of study **V** confirmed the validity of H5. Nevertheless, it should be noted that the five-year monitoring period is a relatively short time frame in the lifespan of trees in boreal forests, meaning that the observable changes in the structure of trees are small and, thus, prone to measurement errors.

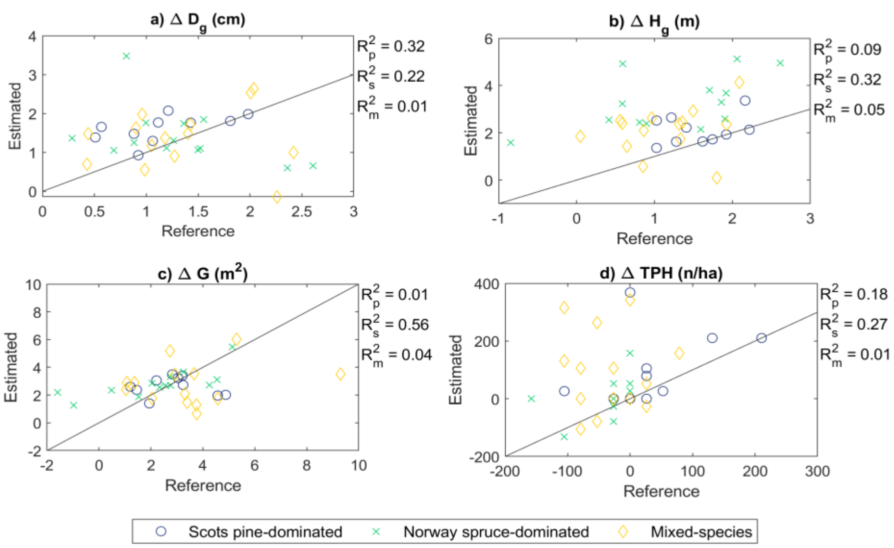

Figure 8. Coefficient of determination (R^2) indicating the relationships between the field-measured (Reference) and point cloud–derived estimates (Estimated) of changes in forest structural attributes such as basal area-weighted mean diameter (ΔD_g) and -height (ΔH_g), mean basal area (ΔG), and the number of trees per hectare (ΔTPH) by dominant tree species of a sample plot. The solid black line represents the 1:1 relationship between the reference and the estimated values (adapted from study **V**).

5 DISCUSSION

5.1 Major findings of the thesis

5.1.1 Trees can be detected from point clouds based on their regular and cylindrical geometry

The objective of this thesis was to develop point cloud–based methods for detecting and characterizing trees and downed dead wood, and to test the feasibility of the developed methods for characterizing trees and tree communities in space and time. The objective was formulated into five hypotheses (H1–H5), which were tested in the substudies of this thesis. According to H1, the fallen trees were expected to be detected from the undergrowth vegetation and other near-ground objects by means of their regular, cylindrical geometry. The validity of H1 was confirmed in study **I**, which was among the first attempts to use TLS point clouds in detecting and characterizing downed dead wood. The results showed that especially large-diameter downed dead wood trunks were accurately detected from the point clouds using an automatic point cloud processing approach that only relied on the geometric features of the trunks. It should be noted that these large-diameter downed dead wood trunks are very important for biodiversity in boreal forests (Andersson and Hytteborn 1991; Bader, Jansson, and Jonsson 1995).

The experimental design of study **I** consisted of 20 sample plots with a wide range of variation in forest structures, thus supporting the applicability of the method and the validity of the results. Earlier work by Polewski et al. (2017) presented a TLS-based method for detecting downed dead wood with comparable detection accuracy to study **I**, although the analyses were carried out in less complex forest conditions. However, the significant contribution of study **I** was that it demonstrated the feasibility of the point cloud–based method to also provide information about the quality attributes of dead wood trunks. Accuracy in estimating the diameter of a dead wood trunk (RMSE ~6 cm) did not reach the level of the expected accuracy when estimating the diameters of standing trees (RMSE ~1–2 cm; Liang, Hyyppä, et al. (2018)), which is explained by different conditions near the forest floor, where dead wood trunks are lying on the ground among undergrowth vegetation, shrubs and stones. Altogether, the results of study **I** confirmed the feasibility of using TLS in detecting and characterizing essential biodiversity indicators, such as large-diameter downed dead wood trunks in diverse boreal forest conditions.

H2 proposed that a tree stem can be detected from other forest structural characteristics based on its pole-like structure, which is characterized by smooth and vertical surfaces with cylindrical geometry. H2 was based on earlier findings on the differences in the geometric features of different forest structural characteristics. It was already known that the smooth and cylindrical surfaces (Liang, Litkey, et al. 2012; Raumonen et al. 2013; Hackenberg et al. 2014) as well as the vertical continuity of point cloud structures (Cabo, Ordóñez, et al. 2018; Zhang et al. 2019) were the key features to enable the automatic detection of tree stems from terrestrial point clouds. These principles were combined in studies **II–III** for developing a robust point cloud–based method to detect the point cloud structures representing individual trees and classify the woody structures from foliage. The performance of the method was tested on two study sites to confirm the validity of H2 in diverse boreal forest conditions. The current trend in the past studies regarding the use of terrestrial point clouds to characterize trees and tree communities has been that the study sites for validating the performance of the point cloud–based methods have covered only a small variation in forest structures at a time. In this regard, studies **II–III** contributed by introducing a rather unique experimental design with which to validate the H2. The experimental design of study **II** consisted of 91 sample plots including young and mature, managed and unmanaged, and dense and sparse tree communities. In study **III**, the 27 sample plots represented managed Scots pine stands with controlled variation in forest density and tree size distributions due to different thinning treatments applied on otherwise similar stands. The reported correctness and completeness in tree detection were comparable to the expected accuracy of a TLS-based method in boreal forest conditions (Liang, Hyyppä, et al. 2018), highlighting the feasibility of the use of terrestrial point clouds to reconstruct trees and tree communities in varying boreal forest conditions.

Accurate tree detection and point cloud classification enabled the retrieval of the tree attributes using point cloud–based measurements employing the fitting of geometric primitives such as circles or cylinders into the classified point cloud structures. Comparison of the state-of-the-art point cloud–based methods to characterize trees revealed that an RMSE of 1–2 cm in dbh estimates was generally obtained in boreal forests (Liang, Hyyppä, et al. 2018). It should be noted that there is variation also in the conventional tree measurements. For example, Luoma et al. (2017) reported a 0.3 cm precision in dbh measurements in boreal forest conditions. In this regard, the results of study **III** proved the capability of terrestrial point cloud–based methods to reach the accuracy level of conventional caliper measurements in observing dbh in managed Scots pine stands, as a sub-centimeter level of accuracy (RMSE 0.7 cm) in dbh estimates was obtained. In addition, studies **II–III** showed that accurate tree detection combined with detailed individual tree characterization resulted in accurate estimates of forest structural attributes. This was a significant contribution to the current understanding of the capabilities of TLS-based forest characterization, as the previous studies were focused mainly on investigating only the accuracy of individual tree characterization. The experimental design supported the validity of analyses by providing a large number of observations with variation at the tree and tree community levels. The total number of 10.989 trees on 118 sample plots was used in the studies.

5.1.2 Forest structure affects the performance of a point cloud–based method to characterize trees and tree communities

H3 of this thesis proposed that increased density and structural complexity of tree communities and use of a scan setup with incomplete point cloud coverage are expected to decrease the performance of the developed point cloud–based methods to characterize trees and tree communities. It was generally known that these are the main factors causing point cloud occlusion and, thus, limiting the capability of a point cloud–based method to provide a comprehensive reconstruction of trees and tree communities (Watt and Donoghue 2005; Abegg et al. 2017; Olofsson and Olsson 2018; Gollob et al. 2019). However, controlled experiments aiming to investigate the influence of these factors in diverse forest conditions were lacking. The experimental design of studies **II–III** provided unprecedented conditions for investigating the factors affecting the performance of a point cloud–based method in characterizing trees and tree communities. The results of studies **II–III** supported the earlier findings by (Liang, Hyyppä, et al. 2018) that trees considered small in terms of dbh and height were more likely to remain undetected by the terrestrial point clouds than larger trees. The proportion of small trees tended to increase as the variation in tree size distribution within a tree community increased, making the forest structure also more complex. Study **II** showed that this resulted in the decrease of the performance of a point cloud–based method as a function of increased structural complexity. In addition, the results of study **III** demonstrated an improved performance on managed forest stands where thinning treatments were carried out, with more intensive thinning leading to higher accuracy. Considering the effect of scan setup, the results of study **II** showed that when applying the multi-scan approach, it is beneficial to place the auxiliary scans approximately at the circumference of the sample plot to ensure the acquisition of a high-quality point cloud in terms of point cloud completeness.

5.1.3 Forest characterization benefits from the combined use of terrestrial and aerial point clouds

A generally recognized challenge in using TLS technology to characterize trees and tree communities has been its limited capacity of providing comprehensive characterization of vertical forest structure (Liang et al. 2016; Wang et al. 2019). Due to the hemispherical measurement geometry, the upper parts of tree crowns often remain occluded by neighboring trees even if the multi-scan approach is used in TLS data acquisition. Proposing a solution for this challenge, H4 suggested that tree community characterization could be improved by using the multisensorial approach of combining terrestrial and aerial point clouds. The validity of H4 was tested in study **IV**, in which photogrammetric UAV-borne point clouds were combined with TLS point clouds to enhance the characterization of vertical forest structure, a concept which Aicardi et al. (2017) demonstrated feasible for forestry applications. The results of study **IV** showed that, compared to the use of TLS point clouds only, improvement in the accuracy of tree height estimates as well as in the estimates of H_g and V_{mean} was obtained when the photogrammetric UAV and the TLS point clouds were combined. The experimental design consisted of 2204 trees on 27 sample plots established on managed Scots pine stands where rather high performance in the characterization of trees and tree communities had already been reached when using the TLS point clouds only. However, the difference between the multisensorial and TLS-based approaches in the forest characterization performance theoretically should be greater in forests including more variation in the horizontal and vertical structure.

Similar outcomes have been reported in earlier studies comparing terrestrial and aerial close-range sensing techniques in vertical forest characterization. Mikita, Janata and Surový (2016) combined terrestrial and aerial close-range photogrammetry to obtain a comprehensive characterization of an old-growth forest stand and reported an RMSE of 1.02 m (3.0%) for tree height of 118 Norway spruces. Wang et al. (2019) used low-altitude helicopter-borne laser scanning data for measuring the height of 1174 individual trees in 18 sample plots and concluded that the underestimation of tree height was decreased from 1.21 m to 0.12 m when the aerial point cloud was applied instead of TLS point clouds. Liang et al. (2019) compared the performance of tree height estimation using TLS, MLS and ULS point clouds in 22 sample plots and showed that the use of aerial point cloud data provided the highest accuracy in tree-height estimates, especially on sample plots with complex forest structure. Brede et al. (2017) compared the performance of TLS and ULS in characterizing height of trees and tree communities through CHMs and concluded that ULS provided more accurate characterization of the top of tree crowns in varying forest conditions. However, compared to these studies, study **IV** contributed by demonstrating high performance of the multisensorial approach also in estimating forest structural attributes characterizing tree communities. RMSE in H_g estimates was decreased from 0.88 m (4.3%) to 0.58 m (2.8%) when the TLS point cloud was augmented with UAV photogrammetry.

5.1.4 Growth of trees and tree communities can be detected using bitemporal point clouds

Building upon the recognized high performance of the point cloud–based methods to accurately characterize trees and tree communities in space, H5 proposed that the growth of trees and tree communities during a 5-year monitoring period can be detected and quantified using bitemporal TLS point clouds. The validity of H5 was investigated in study **V**, in which the experimental design consisted of 1280 trees in 37 sample plots representing diverse boreal forest conditions. The size and the shape of the sample plots were adjusted according to the findings of study **II** to match the scan setup. The results of study **V** showed that if there was an increase or decrease in the attributes of trees within a tree community recorded in the field using calipers and a clinometer, a similar outcome (i.e. a statistically significant increase or decrease in the respective attributes) was achieved by using bitemporal point clouds and the point cloud processing methods developed in studies **II–III**, confirming the validity of H5. In this regard, study **V** made a significant contribution to the current understanding of the capacity of terrestrial point clouds to detect changes in tree attributes under diverse forest structures.

Thus far, past studies have demonstrated the feasibility of using TLS in characterizing changes in individual trees and tree communities, but comprehensive investigations on the accuracy of the point cloud–based methods in diverse forest conditions have been lacking. Liang, Hyyppä, et al. (2012) reported that TLS-derived bitemporal changes accounted for 92% of the changed basal area due to harvesting on five sample plots. Changes in individual tree biomass have been analyzed with multi-temporal TLS data by detecting changes in the branching structure of a Norway maple (*Acer platanoides* L.) tree (Kaasalainen et al. 2014) or by modelling with TLS point cloud–derived parameters characterizing the structure of loblolly pines (*Pinus taeda* L.) over time (Srinivasan et al. 2014). Changes in the structure and form of 21 wild cherry (*Prunus avium* L.) trees were analyzed in Sheppard et al. (2017) to estimate changes in tree biomass. Hess et al. (2018) analyzed the spatiotemporal dynamics in canopy occupancy in four sample plots using a voxelized TLS data covering one growing season, while Kunz et al. (2019) analyzed the temporal dynamics of tree morphology on 30 sample plots when investigating the neighborhood interactions of trees. Altogether, these studies have aimed to demonstrate the potential of point cloud–based methods for characterizing forest dynamics in 3D space or detecting changes in the structure of individual trees with controlled experiments. In this regard, Luoma et al. (2019) contributed by investigating the feasibility of using bitemporal TLS data covering a nine-year monitoring period to detect changes in the shape of 35 tree stems in four sample plots in boreal forest conditions. They came to a similar conclusion as that of study **V** in regard to the capacity of TLS in detecting changes in tree attributes, although a five-year monitoring period was used in study **V**, which is a generally accepted time frame for investigating the growth of trees in boreal forests. In this respect, study **V** represents the first attempt to use TLS for investigating changes in tree and forest structural attributes in varying forest conditions with a large number of samples. The outcomes of study **V** contribute to the current knowledge by highlighting the feasibility of TLS-based characterization of trees and tree communities in space and time.

5.2 Constraints and future perspectives

5.2.1 Applicability of the developed methods and obtained findings

Feasibility of the point cloud–based methods developed in this thesis to characterize downed dead wood and standing trees was validated in southern boreal forest conditions. Although the experimental design included diverse forest conditions, from single-layered, single-species and managed forests to multi-layered, mixed-species and unmanaged forests, the boreal forests have some key structural characteristics that need to be taken into account when considering the applicability of the results of this thesis. The study sites were dominated by three main tree species: Scots pine, Norway spruce and birches, which are typically characterized by a regular stem form. From the methodological perspective, this makes it rather straightforward to detect point cloud structures representing a tree stem, either standing or lying on the ground, based on its pole-like, regular structure. However, the validity of this methodological assumption could not be tested with heavily bifurcated trees, which were lacking from the experimental design of this thesis. Another consideration regarding the forest conditions within the study sites involves the dimensions of the observed trees. Despite the fact that there was a large variation in dbh and height of the trees included in the experimental design of this thesis (see, for example, Figure 3), on average, the trees were 17.2 cm in dbh (ranging from 5.0 cm to 71.9 cm) and 16.4 m (1.5–37.5 m) in height. While these figures are representative of the forest conditions within the study sites, it should be noted that in temperate, subtropical, and tropical forests, the trees tend to grow faster and larger, forming more complex forest structures (Pan et al. 2013). Thus, it is evident that conclusions regarding the validity of the hypothesis within forest conditions completely different to boreal forests cannot be drawn based on the experiments of this thesis only. Therefore, comparable experiments carried out in different forest biomes are needed to validate the applicability of the findings of this thesis beyond the southern boreal forest zone.

Obviously, some practical considerations affected the point cloud data acquisition protocols, which were not always specifically optimized for investigating the validity of each hypothesis of this thesis. Firstly, for detecting and characterizing downed dead wood in study **I**, the TLS data were collected using a scan setup initially designed for digitizing the standing trees. The auxiliary scans were placed somewhat evenly around the sample plots without taking the spatial distribution of dead wood into account. Furthermore, the data acquisition geometry was not considered favorable for downed dead wood mapping, as the laser scanners were mounted on tripods approximately 1.5–2.0 m above the ground. In this regard, the results of study **I** rather demonstrated the feasibility of simultaneously mapping both downed and standing trees with terrestrial point clouds. On the other hand, considering that the sides of dead wood trunks that are facing towards the ground cannot be characterized anyway, a laser-based aerial point cloud collected from above the canopy or from inside the canopy could provide an improved measurement geometry for more comprehensive characterization of downed dead wood. Secondly, all the point cloud data for this thesis were acquired outside the growing season, in leaf-off conditions, to enable flexibility of the timing of measurement campaigns. During the growing season, point cloud data acquisition and field inventory must be carried out almost simultaneously to ensure that both datasets represent the same structural states. The use of point clouds collected during leaf-off conditions specifically supports the characterization of deciduous trees and reduces the occlusion effect of undergrowth vegetation. The influence of using point clouds collected during the growing season instead of leaf-off point clouds to the performance of the point cloud–based method cannot be addressed based on the experiments of this thesis.

5.2.2 Technological and methodological constraints

In this thesis, point cloud processing methods were developed to characterize downed dead wood and standing trees. The methods rely solely on the geometric features of the objects of interest; in other words, no information other than the 3D-coordinates of the generated point clouds was used. On one hand, ignoring the spectral information limits the analyses to the geometric features only. Previous studies demonstrate that the use of backscattered laser intensity, even at multiple wavelengths, enables the utilization of spectral features that, accompanied with the geometric features, could expand the spectrum of point cloud–based tree measurements, such as analyzing the health status of a tree (Junttila 2019). On the other hand, however, the use of geometric features only simplifies both the implementation and applicability of the methods, as there is no need to calibrate the intensity values before making use of the spectral information of the target. When it comes to point cloud–based dead wood characterization, the dead wood quality attributes extracted from the point clouds in study **I** were related to the dimensions of the dead wood trunks. However, many threatened species are dependent from dead wood in terms of certain dimensionless features such as tree species, water content and the stage of wood decay (Jonsell and Weslien 2003; Similä, Kouki, and Martikainen 2003). In this regard, the use of a combination of both geometric and spectral features could be beneficial in extracting these characteristics with the point cloud–based methods. Similarly, point cloud classification methods to separate woody and non-woody components may benefit from approaches employing spectral information, as presented by (Zhu et al. 2018). This could presumably improve the performance of the point cloud–based methods in characterizing trees and tree communities, especially in complex forest structures in which point cloud occlusion causes incomplete characterization of trees. However, the feasibility of making use of spectral features alongside the geometric features in characterizing trees and tree communities could not be answered based on the experiments carried out in this thesis.

Another methodological constraint is related to the general capability of the point cloud technology to fully reconstruct the 3D structure of all the forest structural characteristics of interest. It is generally known that point cloud occlusion causes incomplete reconstruction of trees and tree communities with terrestrial point clouds, especially in complex forest structures (Béland et al. 2014; Abegg et al. 2017; X. Liang et al. 2018). To a large extent, horizontal occlusion caused by trees and undergrowth vegetation can be coped with by using merged point clouds, by which multiple individual point clouds acquired from different locations are registered together. The results of this thesis demonstrated that this approach enabled the characterization of trees and tree communities with high accuracy, especially in managed forests. However, in forests with dense canopies, the capacity of terrestrial point clouds to characterize the top of tree crowns becomes limited due to the hemispherical measurement geometry. To overcome this challenge, study **IV** proposed a multisensorial approach whereby aerial point clouds were used in combination with terrestrial point clouds. Although the enhancement of the multisensorial approach was incremental in characterizing the vertical structure of the single-species and single-layered Scots pine stands, the reconstruction of more complex forest structures may benefit even more from point clouds that have been collected using sensors providing different measurement geometries. However, recent studies have demonstrated that the acquisition of terrestrial point clouds from mobile platforms could improve the vertical characterization of trees and tree communities as well. According to Hyyppä, Yu, et al. (2020), the use of point clouds acquired with a handheld laser scanner to estimate tree heights was observed to reach the accuracy of the ULS-based approach. Advances in sensor technology and solutions for accurate positioning inside the forest canopy will enable the mobile close-range sensing methods to collect data with improved geometric accuracy and point densities close to TLS. This will facilitate the shift from static to mobile point cloud generation approaches in the future.

6 CONCLUSIONS

To better understand the underlying processes of natural phenomena, accurate observations and measurements are needed. Considering forest ecosystems, monitoring the dynamics of tree characteristics is essential in this regard. Thus, the feasibility of using point clouds to characterize trees and tree communities in space and their development in time was investigated in this thesis. The first objective of this thesis was to develop point cloud–based methods for detecting and characterizing trees and downed dead wood. Study **I** demonstrated that large-diameter downed dead wood trunks that are ecologically most valuable were able to be detected from the undergrowth vegetation and other near-ground objects with high accuracy by means of their regular, cylindrical geometry. The results proved that a TLS-based mapping method is a noteworthy option for providing information regarding the spatial distribution and quantity of the ecologically most valuable dead wood and the quality attributes that are based on dead wood trunk dimensions. Studies **II–III**, on the other hand, strengthened the current knowledge of the methodology to detect and characterize individual standing trees. Smooth, cylindrical surfaces and vertical continuity were the key characteristics of point cloud structures to separate woody structures from foliage and a tree stem from branches. An automatic point cloud processing method was developed for this task, and its performance was validated in diverse forest structures to confirm its robustness in southern boreal forest conditions.

The second objective of this thesis was to test the feasibility of the developed point cloud–based methods for characterization of trees and tree communities in space and time. Studies **I–III** revealed that the performance of point cloud–based methods was strongly influenced by the accuracy of the method used to detect different forest structural characteristics such as individual trees or downed dead wood trunks. The greater the size of a tree or a dead wood trunk, the more accurately it was detected from the point clouds. In study **II**, the structural complexity of a tree community was observed to be the most important factor affecting tree-detection accuracy. High performance of the point cloud–based method was achieved on managed forest stands with low degree of variation in tree size distribution. Controlled experiments in study **III** revealed that intensive thinnings led to more spacious canopy structures favoring the point cloud–based characterization of trees and tree communities, with thinning type (i.e. thinning from below, thinning from above, and systematic thinning) being less relevant in this regard. In turn, investigations in study **IV** resulted in the conclusion that combining aerial and terrestrial point clouds enhances the performance of a point cloud–based method in vertical characterization of managed forests. Photogrammetric UAV point clouds were considered feasible in augmenting TLS point clouds to characterize the top of tree crowns. Finally, the performance of point cloud–based methods to characterize changes in the structure of trees and tree communities was investigated in study **V,** with bitemporal TLS data covering a monitoring period of five years. The results showed that if there was an increase or decrease in the attributes of trees within a tree community recorded in the field, a similar outcome was achieved with the point cloud–based method.

In general, the findings of this thesis improve the current knowledge of the feasibility of using point cloud–based methods in characterizing tree and forest structural attributes in space and time. The major contribution of this thesis is based on comprehensive experiments that advance the state of the art in how point cloud technology expands the spectrum of tree observations by enabling non-destructive approaches to characterize trees and tree communities. With the ability of point cloud–based methods to directly and repeatedly observe the characteristics of a living organism, its dynamics and responses to a changing environment can be monitored without modelling or destructive sampling. This implies that the underlying physio-ecological processes driving natural phenomena such as tree growth can be characterized and understood more comprehensively. Thus, it is expected that the use of point cloud technologies will improve our ecological understanding regarding the functioning of trees, trees communities and forested ecosystems.

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