Dissertationes Forestales 230

Developing laser scanning applications for mapping and monitoring single tree characteristics for the needs of urban forestry

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Academic dissertation

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ABSTRACT

Urban forests provide various ecosystem services. However, they also require fairly intensive management, which can be supported with up-to-date tree-level data. Until recently, the data have been collected using traditional field measurements. Laser scanning (LS) techniques provide efficient means for acquiring detailed three-dimensional (3D) data from the vegetation. The objective of this dissertation was to develop methods for mapping and monitoring urban forests at tree level.

In substudy I, a method (MS-STI) utilizing multiple data sources was developed for extracting tree-level attributes. The method combined airborne laser scanning (ALS), field measurements, and tree locations. The field sample was generalized using the non-parametric nearest neighbor (NN) approach. The relative root mean square error (RMSE) of diameter at breast height (DBH) varied between 18.8–33.8%.

The performance of MS-STI was assessed in substudy II by applying it to an existing tree register. 88.8% of the trees were successfully detected, and the relative RMSE of DBH for the most common diameter classes varied between 21.7–24.3%.

In substudy III, downed trees were mapped from a recreational forest area by detecting changes in the canopy. 97.7% of the downed trees were detected and the commission error was 10%. Species group, DBH, and volume were estimated for all downed trees using ALS metrics and existing allometric models. For the DBH, the relative RMSE was 20.8% and 34.1% for conifers and deciduous trees respectively.

Finally, in substudy IV, a method utilizing terrestrial laser scanning (TLS) and tree basic density was developed for estimating tree-level stem biomass for urban trees. The relative RMSE of the stem biomass estimates varied between 8.4–10.5%.

The dissertation demonstrates the applicability of LS data in assessing tree-level attributes for urban forests. The methods developed show potential in providing the planning and management of urban forests with cost-efficient and up-to-date tree-level data.

Keywords: Urban forest inventory, Urban forestry, Laser scanning, Trees outside forests

PREFACE

The Great Race for the PhD started in 2011, although I did not know it then. I had just finished my master's thesis when, in the long corridor of the fourth floor of the Forestry building Mikko Vastaranta, my soon-to-be mentor in both science and racing, let me know there was a vacancy for a post graduate racer in their team. The team leader, Markus Holopainen, had just negotiated a fresh sponsor deal that would just cover the racing license of a beginner. This meant that their team now had a free jersey for someone to wear. So why not. There I was, at the starting line of a 43 000 hour race for my PhD.

I would not dare to say that I was well prepared when the pistol went off. My split times from the first quarter implied that there were some serious defects in both my riding skills and fitness. I had already run into several drops and step-ups which could have driven me to drop out of the race, but the team kept me going. On the course, there were several teammates whose rear tire I found myself following repeatedly as the heat of the race got hotter. Ville Kankare guided me through the treacherous switchbacks of point-cloud software and Ninni Saarinen taught me to always define whether the risk of getting a flat tire was statistically significant or not before hitting the rock gardens of biometry at full speed. Juha Raisio was our eyes and ears in the urban obstacle course of Helsinki, providing our team with nearly anything we found ourselves in need of. Finding myself nearly exhausted in the final backbreaking ascent of field reference, Mikko Niemi was there to unleash all his brute force to keep me going.

As the race drew closer to its end, I found a nice pace from two professionals Heikki Setälä and Vesa Yli-Pelkonen. Following them closely in the straights of scientific writing, reaching nearly supersonic speed, I found myself closer to the finish than ever. On the last dusty berms, Jari Vauhkonen shined his laser light and showed me the line to ride. As the goal began to shimmer somewhere in the imaginary horizon of academic endeavors, Tuomo Kauranne and Timo Tokola, both honored members of the race jury, gave me the last precious directions on how to proceed to the finish. At that point I knew the race would soon be over.

Here, near the finish line I look back at the past 41 600 hours. Even in the direst times, I have been able to trust that the coaching and team management were in sure hands, as Markus and Mikko were accompanied by assistant coaches Juha Hyyppä, Hannu Hyyppä and Petteri Alho. Eventually, with the irreplaceable help I have received from all the team members, fellow racers, spectators and cheering fans (Thank you, Iidu!), it seems that I am now ready to finish the race. Anyhow, it is not all about the result of the race, it is the quality of the ride that matters.

Before breaking the tape, I would like to thank all my sponsors for the fruitful co-operation during the race. Finishing would not have been possible without the financial and material support from the Finnish Cultural Foundation, Center of Excellence in Laser Scanning Research, Helsinki Metropolitan Region Urban Research Program, and the City of Helsinki.

Topi Tanhuanpää September 1st 2016 Helsinki

LIST OF ORIGINAL ARTICLES

This thesis consists of an introductory review followed by four research articles. Research articles I–III are printed with permission from the publishers, whereas article IV is a submitted manuscript.

I Saarinen N., Vastaranta M., Kankare V., Tanhuanpää T., Holopainen M., Hyyppä J., Hyyppä H. (2014). Urban-tree-attribute update using multisource single-tree inventory. Forests 5(5): 1032–1052.
http://dx.doi.org/10.3390/f5051032

II Tanhuanpää T., Vastaranta M., Kankare V., Holopainen M., Hyyppä J., Hyyppä H., Alho P., Raisio J. (2014). Mapping of urban roadside trees–A case study in the tree register update process in Helsinki City. Urban Forestry & Urban Greening 13(3): 562–570.
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III Tanhuanpää T., Kankare V., Vastaranta M., Saarinen N., Holopainen M. (2015). Monitoring downed coarse woody debris through appearance of canopy gaps in urban boreal forests with bitemporal ALS data. Urban Forestry & Urban Greening 14(4): 835–843.
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IV Tanhuanpää T., Kankare V., Setälä H., Yli-Pelkonen V., Vastaranta M., Raisio J., Holopainen M., Niemi M. (2016). Assessing above-ground biomass of open-grown urban trees: a comparison between existing models and a volume-based approach. Urban Forestry & Urban Greening. Manuscript.

AUTHOR CONTRIBUTION

Topi Tanhuanpää was the main author in articles II–IV, where Tanhuanpää was responsible for developing the research design, processing and analyses of the data, and method development. Tanhuanpää also organized and led the collection of the field data. In article I, Ninni Saarinen was the main author, responsible for the analyses, model development, and accuracy assessment. Ville Kankare collected the field data and processed the TLS data. Tanhuanpää participated in designing the study and in the manuscript development. Juha Hyyppä and Hannu Hyyppä guided the development of the original study design. In article II, Juha Hyyppä, Hannu Hyyppä, and Petteri Alho supervised the study. In articles II and IV, Juha Raisio was responsible for supplying the data sets and contributed the preliminary design of the studies. In article IV, Ville Kankare, Mikko Vastaranta, Markus Holopainen, and Mikko Niemi participated in collecting the reference data. In article IV, Heikki Setälä and Vesa Yli-Pelkonen supervised the study and guided the development of the study design. Juha Raisio had a central role in organizing the field measurements. In articles I–IV, all co-authors contributed to both the writing and the revision processes. All the articles were planned together with supervisors Markus Holopainen and Mikko Vastaranta.

TABLE OF CONTENTS

ABSTRACT 3
PREFACE 4
LIST OF ORIGINAL ARTICLES 5
AUTHOR CONTRIBUTION 6
ABBREVIATIONS 9
INTRODUCTION 11
- Background 11
  - Urban forests 12
  - Management of urban forests 13
  - Urban forest information 13
- Airborne laser scanning 15
- Terrestrial laser scanning 16
- Objectives of the thesis 17

Materials 19
- Study areas 19
  - Seurasaari 19
  - The Central Park of Helsinki 19
  - Myllypuro 20
- LS data sets 20
  - ALS data 20
  - TLS data 20
- Field data 21
  - Seurasaari 21
  - The roadside trees of Helsinki 21
  - The Central Park of Helsinki 21
  - Myllypuro 21
- Additional data sets 22

METHODOLOGICAL OVERVIEW 22
- Processing of ALS data sets 22
  - Creation of height models (studies I, II, and III) 22
  - Change detection (study III) 23

Tree delineation (studies I, II, and III)....23
Extraction of ALS metrics (studies I, II, and III)....23
Prediction of tree attributes using field-measured training data (studies I and II)..24
Processing of TLS data sets....24
Deriving the tree map and tree metrics manually from TLS data (study I)....24
Semi-automatic stem diameter measurements from TLS point clouds (study IV).25
Assessment of result accuracy....26
RESULTS AND DISCUSSION....27
Study I: The use of multiple data sources in predicting and updating tree-level information for existing tree locations....27
Study II: Updating the tree characteristics of an existing tree register with ALS data. 27
Study III: Developing a monitoring method for detecting downed trees in urban forest areas through changes in canopy structure. 28
Study IV: Developing an estimation method for adding new attributes to urban tree registers. 29
CONCLUSIONS....31
REFERENCES....34

ABBREVIATIONS

3D	Three-dimensional
AGB	Aboveground biomass
ALS	Airborne laser scanning
CHM	Canopy height model
DBH	Diameter at breast height
DSM	Digital surface model
DTM	Digital terrain model
ED	Ecosystem disservice
ES	Ecosystem service
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
GSD	Short ground sample distance
IMU	Inertial measurement unit
ITD	Individual tree detection
kNN	k-nearest neighbor
LS	Laser scanning
MLS	Mobile laser scanning
MS-STI	Multi-source single-tree inventory
nDSM	Normalized digital surface model
NN	Nearest neighbor
OBIA	Object-based image analysis
RF	Random Forests
RMSE	Root mean square error
RS	Remote sensing
TLS	Terrestrial laser scanning
VRS	Virtual-reference station

INTRODUCTION

Background

Trees and forests benefit mankind in many ways. These benefits can be bundled under the term ecosystem services (ES), and they can have local along with global effects (Daily et al. 1997). As an example of a local ES, trees provide shelter and form habitats for various species, thus affecting biodiversity. As for global effects, trees also sequester and store atmospheric carbon, which affects the climate and slows down global warming. The two example ES mentioned above are produced by all trees, regardless of where they grow. However, the number of ES increases when considering trees growing near to or even amongst people. These urban trees and forests provide various ES as they directly affect the everyday lives of people. Urban trees, for example, lower the temperatures in built areas through evapotranspiration and shading (Bolund and Hunhammar 1999; Hardin and Jensen 2007), help in managing storm water run-off (Xiao and McPherson 2002; Valtanen et al. 2014;), and enhance aesthetic values in built environments (Hauru et al. 2015). Still, the interaction between people and urban trees also results in issues that have negative effects. These issues are so-called ecosystem disservices (ED) (see e.g. Lyytimäki et al. (2008)). A common element of ED in cities is a general wish to avoid or reduce them. For urban trees such ED include e.g. trees that fall down during storms harming people or infrastructure and litter fall that has to be removed from the streets (Lyytimäki et al. 2008; Lyytimäki and Sipilä 2009).

The total economic value resulting from urban forest-related ES is fairly complicated to define (Bolund and Hunhammar 1999). Although not representing the total costs resulting from ED, summing up the costs of tree pruning, removing fallen leaves etc., gives an estimate of the direct losses resulting from managing ED. To better understand, evaluate, and manage both ES and ED, more detailed data from urban forests are sought for. As with rural forests managed primarily for benefiting the forest owner through e.g. timber production, the management efficiency in urban forests would also benefit from more accurate knowledge of trees. Tree-level information in the form of e.g. tree registers enables the accurate allocation of various treatments, such as tree pruning or removing hazardous branches, which lowers the overall costs of avoiding ED and enhancing the existing ES. However, collecting tree-level data manually is costly and the price increases with the number of recorded attributes. Typically, the recorded attributes are fairly easy and fast to measure in the field, like diameter at breast height (DBH) and tree height (Nielsen et al. 2014).

The cost of the data also affects the tree registers that already exist. Urban forests change over time due to natural tree growth, but more sudden events also affect them. Storms and snow damage may occur in the same way as in rural forests, although human activities are typically the biggest factor changing the urban environment. For example, trees are removed because of e.g. construction work, and hazardous trees are replaced with new saplings. To be up-to-date and hence useful, both types of change should be recorded in urban tree registers. However, the high costs of repeating the manual field measurements is a significant hindrance for keeping the registers up to date.

Mapping applications have utilized remote sensing (RS) data for decades. Aerial photographs began this development in the early 1900s (Campbell and Wynne 2011). Since then, the range of available RS methods has increased from airborne to spaceborne methods, i.e. satellite images. Due to the lower altitude of the sensors, airborne methods can offer higher spatial resolution, which is why they are typically preferred to spaceborne methods in detailed surveying. Spaceborne methods with coarser resolution have typically been used for thematic mapping e.g. for land-use maps (e.g. Weng 2002; Herold et al. 2002). In recent years, cities around the world have taken steps towards the three-dimensional (3D) mapping of urban environments. The detailed 3D data can be transformed into 3D city models following e.g. the CityGLM standard (Gröger and Plümer 2012). In the form of structured models, the data can be utilized in various fields of urban planning and management. Digital photogrammetry and more recently laser scanning (LS) have established their positions as operational means for acquiring accurate 3D information.

The LS methods used in RS are typically divided into three types. Airborne laser scanning (ALS) is used in the city-wide mapping of vertical structures, e.g., ground elevation or rooftops, whereas ground-based terrestrial laser scanning (TLS) and mobile laser scanning (MLS) are utilized to capture horizontal structures, such as building facades, in detail. ALS-based methods for assessing forest resources are already in operational use in the field of forestry (Maltamo and Packalen 2014), and methodologies utilizing TLS and MLS are being developed for sample plot measurements (Kukko et al. 2012; Liang et al. 2016). However, operational LS applications for acquiring tree-level data are still rare. The main reasons for this are challenges in mapping the location and species of the trees and the higher data costs (Hyyppä et al. 2008; Vastaranta et al. 2011; Kaartinen et al. 2012; White et al. 2013; Vastaranta et al. 2014; Vauhkonen et al. 2014a).

Currently, LS data are collected from cities for various urban mapping purposes. In addition to the more traditional applications, such as creating city-wide elevation models or surveying built environments, the data can be also utilized in other fields. This thesis describes methods that utilize LS data for acquiring tree-level attributes from urban forests, and thus, contemplates the fields of urban forestry and RS.

Urban forests

The term urban forest has different meanings depending on the point of view. It can be seen as a special type of forest located inside or in the vicinity of cities, and if so e.g. built parks are left outside the definition (e.g. Tyrväinen 2001). Wider descriptions also include other wooded areas including strips of roadside trees and single scattered trees in parks and yards (e.g. Nowak et al. 2001). The two definitions can be seen as European and North American viewpoints to the subject, and their differences arise from the local customs and traditions in managing urban trees (Konijnendijk et al. 2006). Urban forests can be divided into several different subtypes of wooded urban land. Here, urban forests are divided into four groups. Typically, the subtypes are classified into their own groups by the city plan, each with their own characteristics also. The subtypes differ e.g. in terms of tree density, tree species distribution, and maintenance priority class.

1. Roadside trees grow in between or in the immediacy of roads or walkways. This group is managed actively to maintain road safety, visibility, and landscape characteristics.

2. Yard trees are single isolated trees or small groups of trees growing in urban yards. Property owners are usually responsible for the management of these trees.

3. Park trees are single trees or groups of trees growing in public parks. The park areas vary from sparse intensively managed lawn-dominated areas to dense, near-forest conditions. Management intensity varies with the location and management class of the park.

4. Recreational forests are forest-like park areas with managed main trails. Outside the trails, management is rare.

Management of urban forests

The growing environment of urban trees often differs from rural surroundings. Especially trees growing in densely built areas or roadsides in particular face stress that is typical only for urban areas. Limited growing space above and under ground, heat stress, and toxic compounds in the soil and air (Bassuk and Whitlow 1985; Sieghardt et al. 2005) are examples of the harsh conditions that urban trees grow in. In addition, the chance of radical changes is relatively high in urban environments. Changes in the surrounding infrastructures can cause stress in the form of e.g. rapid changes in light conditions or physical damage to the roots, stem, or crown. The harsh and changing growing conditions mean that trees may have to be treated in various ways to keep them alive and, on the other hand, safe for city residents.

In addition to the growing conditions, the management of most urban forest subtypes also differs greatly from that of rural forests. However, there are also significant differences within urban forests. Management intensity varies a lot between various subtypes of urban forests. The trees growing within built areas or next to roads (i.e., roadside trees, yard trees, and park trees) usually receive the most intensive care. Considering e.g. the roadside trees in the city of Helsinki, a typical management chain includes planting the tree and ensuring successful rooting by watering and supporting the stem. Depending on location, after becoming successfully rooted the trees growing in surroundings with high risk of physical damage to the stem are often protected with various gear, i.e. a metal cage around the stem. The cage protects a young tree's stem, but has to be removed as the tree grows. The trees are rarely cut down for timber, but are often kept alive as long as possible, to uphold the ES they provide. Eventually, because of aging or stress, the condition of the tree weakens. At this point the tree crown may have to be pruned to keep it safe for people. In the end, the tree has to be removed and replaced with a new plant. As the treatments alter the surroundings and result in costs, it is typical that they are kept to a minimum. Hence, the treatments are often allocated to single trees or small groups of trees with similar characteristics.

Management needs are fairly different in urban recreational forests compared to forest-like parks. Although some trees might be planted, they are often left to grow up naturally without watering, protective gear, or pruning. As the tree grows old it may even be left to die, fall down, and decay. In such surroundings the management actions are not allocated as precisely as e.g. for roadside trees. The management resembles that of rural forests without the commercial cuttings, and treatments are often performed for forest areas or compartments. Nevertheless, the preferable aim of the management is often to preserve and enhance the ES provided by the trees (e.g. Tyrväinen et al. 2005).

Urban forest information

Urban forest information is collected to manage the trees and green areas sustainably and efficiently both in the short (i.e. maintenance) and long terms (i.e. strategic planning

(Gustavsson et al. 2005). There is also growing interest in quantifying the ES that urban forests provide (Bolund and Hunhammar 1999; Nowak et al. 2008; Gómez-Baggethun et al. 2013; Livesley et al. 2016). Hence, the need for information is two-fold. Detailed data are needed for allocating tree maintenance, and on the other hand, for providing reliable estimates of city-level ES. However, the need for detail also varies within urban forests. It is typical that the most significant trees or the trees receiving the most maintenance, e.g. street trees, are mapped in more detail than trees growing in less central locations, e.g. forest-like urban parks. The most detailed information concerns single trees and accurate tree location is often an essential part of the data. Tree-level data have to be collected individually for each tree, whereas large area estimates are based on sample plots. Sample-based approaches are efficient and provide accurate estimates for large areas, but without additional information the estimated attributes cannot be generalized for any specific tree or area.

Tree registers are a common method for managing tree-level information. The registers are used e.g. for keeping record of significant trees (The Tree Register 2013; City of Sydney 2013), but also for more formal information such as tree-level data for urban forest management (Helsingin kaupungin rakennusvirasto 2014). For urban forest management, the registers should contain at least the essential tree attributes such as DBH and height. Also, when setting up a tree register, accurate positioning of the trees is essential. To be widely applicable in various urban planning, the register must also be maintained. The information should be matched with changes caused by e.g. tree growth or the replacement of single trees. As growth models for urban trees are scarce and the replacement of trees is highly irregular, updating the registers solely by using models is not possible. Hence, register updating must be based on observing each tree. Collecting tree-level information creates challenges in acquiring the tree data needed for both setting up and maintaining the data. Tree locations have traditionally been determined manually by using e.g. tachymeter measurements, the visual interpretation of aerial images or measurements utilizing global positioning system (GPS). DBH has been measured using a caliper (or a tape measure for girth) and tree height using a clinometer. Manual field measurements are both time-consuming and expensive (e.g. McRoberts and Tomppo 2007). The more trees and attributes measured per tree, the costlier the data. The high cost of the measurements also affects how well the register is maintained, i.e. how often repeating the measurements can be afforded.

Although manual field measurements are still common in operational urban forestry (Nielsen et al. 2014), RS-based methods have been studied fairly widely. Utilization of RS data enables wall-to-wall estimates of tree-level or area-based variables with a limited amount of field measurements (Schipperijn et al. 2005; McRoberts and Tomppo 2007). In such RS-based mapping solutions, a field sample is generalized for the area using RS data as auxiliary information. Applications aiming to produce area-level estimates of urban forest attributes typically utilize coarse resolution data such as medium-resolution satellite images (e.g. Myeong et al. 2006). Object-based image analysis (OBIA) has become more popular with the availability of high spatial resolution RS data and commercial software designed especially for the needs of OBIA (Blaschke 2010). Aerial images and high-resolution satellite images have been utilized together with OBIA in mapping e.g. urban forest cover (Moskal and Zheng 2011) and tree species (Pu and Landry 2012).

LS techniques have also been studied during recent years for their use in urban forest assessment. The introduction of LS-based methods has enabled various tree-level approaches for mapping urban forests. Holopainen et al. (2013) compared three LS-based methods (ALS, TLS, and MLS) regarding their suitability in detecting individual trees in an urban park. TLS-based methods were found to measure tree locations with the highest accuracy. However, the high costs of TLS data were seen as a hindrance for assessing wall-to-wall data over large areas. Although tree detection and location accuracy of ALS-based estimates were not as good as those derived from TLS, ALS was considered a promising method for assessing urban forests, especially in combination with additional information of tree locations. ALS has been utilized both as an independent method and as part of a fused data set for assessing urban forests. Shrestha and Wynne (2012) used ALS data for estimating tree-level attributes for urban trees. The trees were delineated manually from the point clouds and tree-level estimates were derived from linear regression models based on field-measured reference data. In Alonzo et al. (2014) high-density ALS data were fused with hyperspectral airborne imagery for mapping urban trees at tree level. Trees were delineated automatically using watershed segmentation and both the spectral and ALS data were used for determining tree species. In Omasa et al. (2008), TLS and ALS data were fused for visualizing and measuring biophysical parameters from park trees.

Airborne laser scanning

The ALS methodology, like all LS methodologies, is based on repeated range measurements between the laser scanner and the scanned object. The range measurements are performed by measuring the time-of-flight, i.e. the time a single laser pulse travels from the scanner to the object and back to the scanner (Wehr and Lohr 1999). An ALS system is typically mounted on a small aircraft such as an airplane or helicopter. The scanning system includes a laser scanner, which emits and receives the laser energy, and devices that are used to determine the exact position, speed, and orientation. The position and speed of the aircraft are determined using the Global Navigation Satellite System (GNSS), whereas the orientation is determined with an inertial measurement unit (IMU). A single emitted laser pulse reflects from the scanned object resulting in a back scattering signal, whose intensity varies as a function of time. This intensity curve, or waveform is used for the range measurements. Two alternative methods exist for recording the back scattering laser data (Lim et al. 2003). In the so-called discrete return approach, the waveform is analyzed on the fly for reducing the amount of data. The approach seeks for the local maxima from the waveform. The maxima exceeding a predetermined intensity threshold value are stored as range measurements. The measurements are often referred to as echoes or laser points. The alternative method records and stores the entire backscattering waveform. This so-called full-waveform approach is more data intensive, as the amount of collected data from each emitted pulse is much higher than with the discrete return approach. Because of the amount of the data, both storage and analysis of the full-waveform data are more demanding but, on the other hand, also provide more detailed information from the scanned object. The quality of ALS data is most often described with the number of emitted pulses per area, i.e. pulse density that varies from less than one pulse to tens of pulses per m^2, depending on the sensor used, scanning altitude, and flying speed.

ALS-derived metrics describe well the height and density of forest areas and single trees. These metrics have been found to be good predictors for forest attributes (e.g. Næsset 2002; White et al. 2013). In addition to attributes describing forest areas, ALS metrics can also be utilized for predicting attributes for single trees (Hyyppä and Inkinen 1999). ALS data used for detecting single tree crowns has typically been denser than data used for describing forest areas. However, forest structure and the detection method have been found to have a more significant effect on detection accuracy than the point density of the ALS data (Kaartinen et al. 2012; Vauhkonen et al. 2012). Tree crowns have been extracted both directly from the ALS point clouds (e.g. Wang et al. 2008; Liu et al. 2013) and from ALS-derived height models (e.g. Koch et al. 2006). During the last decade, the prediction of forest attributes using ALS data has been established as an essential part of operational forest assessment, whereas the low detection accuracy of suppressed trees and higher data costs have hindered the operational utilization of ALS-based single-tree measurements in the forest environment.

Prediction of tree-level attributes from ALS point clouds can be separated into two main approaches. Firstly, attributes, such as tree height, crown width, and tree location, can be estimated directly from the point clouds (Persson et al. 2002). Typically, the height value of the highest point inside a crown segment is used as an estimate for tree height, whereas crown width can be estimated with the x-y distance between the points at opposite edges of the segment. Tree location is typically determined as the x- and y-coordinates of the highest point (i.e. tree top) or as the mean x- and y-coordinates of all points inside a crown segment. Alternatively, ALS metrics can be used in conjunction with field-measured tree data. In these modellng approaches the aim is to measure the characteristics of interest from the field sample and create a model explaining the field-measured characteristics with ALS metrics. Both regression models (e.g. Hyyppä et al. 2001; Næsset and Økland 2002) and non-parametric nearest neighbor (NN) approaches (Vauhkonen et al. 2010; Yu et al. 2011) have been utilized in predicting tree-level attributes. If available, existing allometric models can also be utilized together with ALS data for predicting tree attributes (e.g. Hyyppä et al. 2001). However, the models used must fit the specific environment and e.g. the tree species they are used for. This must be borne in mind also in urban areas, where the tree species are numerous and growing conditions vary significantly in terms of light, space, and soil (McHale et al. 2009).

Terrestrial laser scanning

A TLS system consists of a stationary scanner that measures the environment and objects around it. The static scanner is typically mounted on a tripod and positioned within the area of interest. A 360-degree horizontal measurement coverage is achieved by rotating the scanner unit around its axis, whereas vertical coverage is typically limited to 310 degrees from below by the scanner and its mount. The range measurements of terrestrial laser scanners are performed utilizing either time-of-flight, i.e. the same method as in ALS, or phase shift of the laser beam (Kukko 2013). Whereas time-of-flight measurements are performed from a pulsed laser, phase shift measurements utilize a continuous phase modulated laser beam. The range between the scanner and the scanned object is determined from the phase difference of the emitted and received laser beam. By utilizing the orientation of the scanner (horizontal and vertical angle) and the defined range, a 3D position (X, Y, and Z) can be calculated for each measurement. Compared to ALS, the point density of the TLS point clouds is significantly higher, typically tens of thousands of points per m^2. The scanning direction of the TLS result in more detailed measurements from vertical structures such as tree trunks (Figure 1). The point density is at its highest right next to the scanner, and decreases as a function of distance from the scanner. The environment also affects the point density of the final point cloud. All objects in the measured area block the laser beam and therefore result in blind spots in the final point cloud. Hence, it is common that covering a larger area with satisfactory TLS data requires multiple scans. A typical TLS setup for measuring tree attributes in a forest plot consists of one central scan and additional scans around it (e.g. Holopainen et al. 2013). The scanning locations are chosen so that no blind spots remain. For combining, i.e. co-registering the scans, a set of identical reference targets is set in the scanned area, and placed so that they can be detected from several scanning positions (e.g. Kankare et al. 2014). In the co-registration process, an internal coordinate system is formed for the point cloud and no external coordinate system is required. However, if desired the point cloud can be registered in an external coordinate system by positioning the reference targets and the scanning locations with GNSS (Liang et al. 2016). The measurement accuracy of TLS data is typically in millimeters, and accurate measurements can thus be performed directly from the TLS point clouds (e.g. Liang et al. 2014).

Terrestrial laser scanning enables fast and detailed measurements from its surroundings. It has been suggested as an option for the manual measurement of field references in forest environments (e.g. Tansey et al. 2009). In addition to measuring basic tree attributes, i.e. tree height and DBH, the TLS point clouds have been utilized e.g. in defining stem curve, biomass, and quality of individual stems (e.g. Liang et al. 2016).

Objectives of the thesis

The aim of this study was to develop LS-based methods for assessing tree-level information from urban forests and maintaining the tree registers. Here, maintaining a tree register is divided into I) updating the tree-level attributes, such as DBH and height, and II) updating other changes such as downed or removed trees in the tree register. As the LS-based methods enable detailed measurements of single trees, this study also aimed at III) introducing new tree-level attributes that can be derived from sample trees using TLS data.

Studies I and II contemplate on updating tree-level attributes. The method utilizing multiple data sources in updating tree-level attributes is developed and tested in study I. In study II, the method is applied in an updating process of an existing tree register in diverse

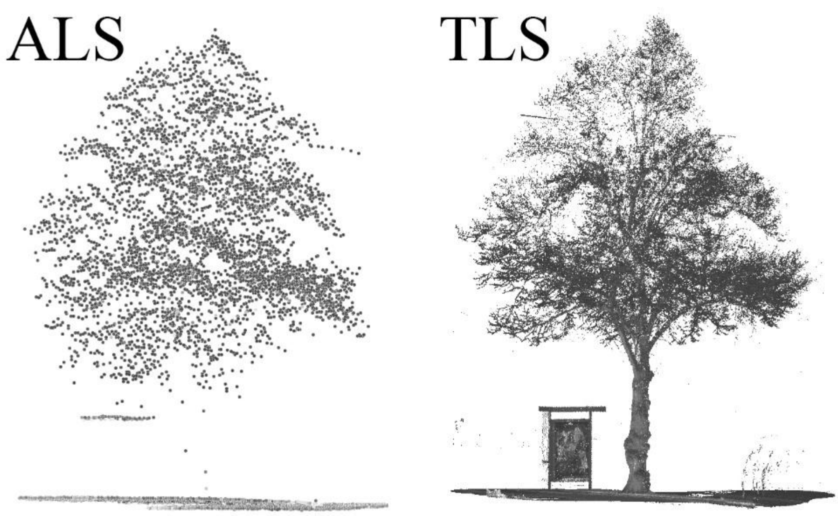

Figure 1. A single roadside linden (*Tilia sp.*) illustrated using ALS data (on the left) and TLS data (on the right).

urban conditions. Both the accuracy and shortcomings of the automatic method are evaluated and discussed. In study III, downed trees are detected by utilizing bitemporal ALS data. The size and quality of the downed trees are estimated with existing allometric models. Study IV describes a non-destructive TLS-based method for deriving stem biomass for urban roadside trees. The objectives for studies I–IV were formulated in the following way:

I. The use of multiple data sources in predicting and updating tree-level information for existing tree locations.

   Extensive field measurements of single trees are expensive and thus urban tree data are often out of date. The aim of the first study was to introduce a multi-source inventory method for updating tree-level attributes to an existing tree register. The method utilized field-measured sample trees whose attributes were generalized for the entire tree register using the NN method and wall-to-wall ALS data.

II. Updating the tree characteristics of an existing tree register with ALS data.

   The aim of the second study was to apply the ALS-based method, introduced in study I, to update an existing citywide tree register and to assess method accuracy when applied to roadside trees in diverse urban conditions.

III. Developing a monitoring method for detecting downed trees in urban forest areas through changes in canopy structure.

   Maintaining tree registers also requires detecting more dramatic changes caused e.g. by downed trees. The aim of the third study was to develop a method for mapping the downed trees in a recreational forest area using bitemporal ALS data. In addition, we aimed to estimate the type, diameter, and volume of the downed trees without field-measured training data.

IV. Developing an estimation method for adding new attributes to urban tree registers.

   Detailed TLS data enable tree-level measurements that have not been applicable when using traditional field measuring equipment. In the final fourth study the aim was to develop a non-destructive method for assessing stem biomass for single trees. TLS data and existing information on wood basic density was utilized in determining the stem biomass for roadside trees. In addition, the study aimed at quantifying the performance of existing allometric biomass models in urban roadside environments.

MATERIALS

Study areas

All studies were conducted in urban forests within the borders of the city of Helsinki, Finland (Figure 2). The study areas cover various types of urban forests from roadside trees in the city center to forest-like conditions in the Central Park of Helsinki.

Four different study sites were utilized. Study II looked at the city of Helsinki as a whole, while three smaller study sites were used in studies I, III, and IV.

Seurasaari

Study I was conducted in the Seurasaari area, approximately 5 km from the city center. Seurasaari has been a public park since 1890 and is nowadays a popular recreation area. Seurasaari covers approximately 46 ha consisting of homogenous urban forests. The northern part is a well-managed urban park with scattered oaks (*Quercus robur*) as the dominant tree species and grass as the under-story vegetation. The southern part is denser and less managed urban forest with varying under-story vegetation. The area is easily accessible through a dense network of outdoor constructed paths.

The Central Park of Helsinki

The Central Park is a recreational forest area located near the city center. Forests in the area are dominated by Norway spruce (*Picea abies* (L.) H. Karst.), the remainder being mainly mixtures of silver birch (*Betula pendula* Roth) and Scots pine (*Pinus sylvestris* L.). Since the forests form an important body of recreational areas, the primary focus in the management of the forests is to maintain their ability to offer a place for recreational activities for city

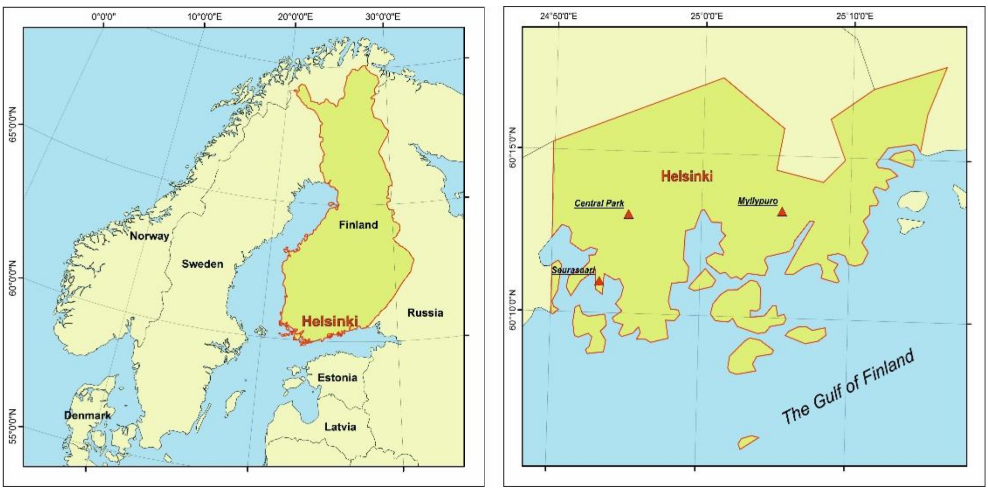

Figure 2. The location of the city of Helsinki and the study areas of Seurasaari, the Central Park, and Myllypuro within Helsinki

residents. Hence, various aspects considering biodiversity, accessibility, and safety have to be taken into account. When cuttings are made, it is typical that only single hazardous trees near the main trails are removed.

Myllypuro

The Myllypuro study site consists of a short section of roadside in Myllypuro, eastern Helsinki. It represents a typical urban growth environment for roadside trees. The ground surface is covered with grass and bordered by paved surfaces on two sides. The roadside trees in the area originate from the 1960s.

LS data sets

ALS data

The discrete return ALS data were collected as part of the City of Helsinki's urban mapping campaigns in consecutive years from 2009 to 2012 (Table 1). Only part of the city was scanned every year, and the scanners and scanning parameters varied. However, the pulse densities were around 20 pulses/m^2 in all data sets. As multiple returns were recorded with all scanners, the densities of the final point clouds varied from 20 to tens of points per m2.

TLS data

TLS data were collected in 2010 in the Seurasaari study area. A total of 52 scans were made to cover the study area. The individual scans were co-registered, i.e. combined using spherical reference targets and Cyclone software (Leica Geosystems). The RMSE of the registration ranged from 2.3 mm to 6.3 mm. The central scans along with at least one reference target were positioned with a GNSS virtual-reference station (VRS) and a tachymeter.

The Myllypuro study area was scanned from 35 scan locations with Z+F IMAGER 5006h (Zoller and Fröhlich GmbH, Wangen im Allgäu, Germany). The individual scans were co-registered using two-sided reference targets, whose coordinates (x, y, and z) were measured with a Leica TCRP1203 tachymeter (Leica Geosystems AG, Heerbrugg, Swizerland). The registration was performed with LFM software (LFM Software Limited, Manchester, United Kingdom) resulting in a mean registration error of 5 mm. The summary of TLS data is presented in Table 2.

Table 1. Summary of the ALS data used in studies I–III.

Data acquisition	Pulse density	Scanner	Used in studies
May, 2009	20 pulses/m^2	TopEye S/N 724	II and III
May, 2010	20 pulses/m^2	Leica ALS 50-II	II
March, 2011	20 pulses/m^2	Optech 3100	I
May, 2011	20 pulses/m^2	Leica ALS 70	II
May, 2012	20 pulses/m^2	Riegl ALS LMS-Q680i	II and III

Table 2. Summary of the TLS data used in studies I and IV.

Data acquisition	Point spacing at 10 m	Scanner	Used in studies
September, 2010	6.3 mm	Leica HDS6100	I
August, 2014	1.6 mm	Z+F IMAGER 5006h	IV

Field data

Seurasaari

In Seurasaari, 389 trees were measured from the study area. The trees were first identified from a predefined TLS tree map, after which the DBH was determined for each tree. The measured DBH varied between 31 mm and 482 mm, and the arithmetic mean was 268 mm.

The roadside trees of Helsinki

The field data for mapping the characteristics for the roadside trees of Helsinki covered 1241 trees. All sample trees where identified on-site from aerial photos and measured for DBH. Tree height was additionally measured for 574 (i.e. roughly every second) sample trees with a Vertex height measurement device (Haglöf Sweden AB, Långsele, Sweden). To choose the measured trees, all roadside trees in the tree register were first divided into 14 species groups. The field measurements were then allocated to 14 species groups according to their relative size. In addition, within the groups the measured trees were chosen so that the entire diameter range was covered.

The Central Park of Helsinki

The field data from the Central Park of Helsinki was used for validating the automatic detection of downed trees. Trees determined as downed according to the automatic approach were checked in the field. The downed trees were found using ALS-based tree maps. The study area was simultaneously inspected for any downed trees or stumps not detected by the automatic approach. The age of all downed trunks or stumps was estimated ocularly and those that had fallen outside the study period were ignored. Tree species and DBH were recorded from every downed trunk. If only a stump was found, species and stump diameter were recorded and DBH was estimated using an allometric model (Laasasenaho 1975). The field measurements were used in the allometric models (Laasasenaho 1982) to calculate volume estimates for every downed tree.

Myllypuro

The field data in the Myllypuro area consisted of 12 silver birches. The trees were cut down and weighed with Dini Argeo TLN300 (Modena, Italy, 5 g divisions) scales to gain their fresh weights. The stem and branches where weighed separately. A sample disc from the stem and three samples from the branches were taken from two randomly selected trees. The samples were weighed to gain fresh and dry weights with Precisa XT4200C (Dietikon, Switzerland, 0.01 g divisions) precision scales. The dry mass was weighed after drying the samples at 103 °C for three days.

Additional data sets

When defining the tree parameters for the roadside trees of Helsinki in study II, two additional data sets were used. The city's tree register was used for choosing the trees included in the field sample. The utilized register data included tree species, DBH, and location. Aerial images were additionally used for identifying the sample trees in the field. The images were acquired in April 2012 using an UltraCam Xp aerial camera, and had a ground sample distance of 5 cm.

METHODOLOGICAL OVERVIEW

Processing of ALS data sets

Detecting individual trees from the ALS data includes at least three stages. The necessary stages are detecting the trees, extracting the features describing each tree, and finally, estimation of tree attributes (e.g. Hyyppä and Inkinen 1999; Persson et al. 2002). In studies I–III ALS-based height models were used in detecting the trees, tree-level features were extracted from the ALS point clouds, and tree attributes were estimated either by using either a field reference with non-parametric methods or existing allometric models. In addition to the three basic components of individual tree detection (ITD), change detection was also utilized in study III.

Creation of height models (studies I, II, and III)

The height models are typically raster format data. The cell size of the models describes the spatial accuracy and determines the minimum size of variation distinguishable from them. To produce a height model with high resolution, the point density of the ALS data must also be sufficient. A cell size of 0.5 m or less has typically been considered sufficient for detecting single tree crowns (e.g. Lévesque and King (2003)).

Using discrete return ALS data, a digital terrain model (DTM) is determined from the lowest laser points within a grid cell (Axelsson 2000). The procedure is prone to overestimating the height of the ground (e.g. Hyyppä et al. 2005) at sites with dense ground vegetation. A digital surface model (DSM) is produced for assessing canopy height. A DSM is created from the highest laser points. The actual height estimate of the canopy, i.e. the canopy height model (CHM), also referred to as a normalized digital surface model (nDSM), is derived by subtracting the DTM values from the DSM. CHM typically underestimates the height of the canopy (e.g. Hyyppä and Inkinen 1999). The underestimation results from overestimation of the DTM, but also from underestimation of the DSM. A laser pulse rarely hits the highest point of the tree crown rather than somewhere very close to it.

Change detection (study III)

Changes in forest canopy can be monitored with bi-temporal data sets. Comparing the CHMs of an area from two separate occasions (time points T1 and T2) reveals the changes in height values. This method can be used for estimating tree growth along with e.g. spotting new openings in the canopy. Vastaranta et al. (2012) proposed a method for detecting snow-damaged trees in the boreal forest utilizing bitemporal medium-density ALS data. The point cloud data were transformed into CHMs with a spatial resolution of 0.5 m. The proposed method detected 66.3% of the downed stems, which accounted for 80.6% of the total volume of the downed trees. Relative size and crown volume were found to explain the detection of damaged trees best. Also utilizing ALS-derived CHMs, Yu et al. (2004) utilized bitemporal data and change detection in the automatic detection of harvested trees and forest growth. DTM compensation was also used when determining tree growth. The method detected 73.5% of the harvested trees, whereas the standard error of stand-level tree growth varied between 10 cm and 15 cm.

Tree delineation (studies I, II, and III)

As CHM describes the height variation of the canopy, individual tree crowns can be detected from it as peaks. However, the detection of a single tree depends on its position within the canopy with respect to the trees nearby and the cell size of the CHM. Two closely related approaches, watershed segmentation (Hyyppä and Inkinen 1999; Persson et al. 2002; Yu et al. 2011; Kaartinen et al. 2012) and pouring algorithm (e.g. Straub and Koch 2011) are commonly used for delineating individual tree crowns from CHMs. Prior to the extraction of crown segments, the CHM is filtered to smooth out the noise, i.e. the small-scale height fluctuations in the CHM. Here, a typical approach is to use a moving filter widow (see e.g. Hyyppä et al. 2001; Koch et al. 2006). The actual segmentation begins by first finding the local minima (or maxima, if the pouring algorithm is used), i.e. the treetops from the smoothed CHM, and then growing the regions around the minima cell by cell. A neighboring cell is attached to the region if it has a value higher than or equal to the edge of the region. The crown segments are used for selecting the points from ALS data representing each tree.

Extraction of ALS metrics (studies I, II, and III)

In ITD, the points describing single tree crowns are utilized in calculating various metrics that can be used as tree attribute predictors (e.g. Vauhkonen et al. 2010). The metrics have been calculated from discrete return ALS data. Perhaps the most common types are the metrics describing the height distribution of the ALS point cloud, e.g. the percentage of points reflecting below a certain height percentile (e.g. Yu et al. 2011). Textural metrics (Haralick et al. 1973) and metrics describing the geometrical properties of the tree crown have also been used (Vauhkonen et al. 2009). When calculating the metrics, points near the ground are often discarded as data near the ground are likely to contain points from the ground vegetation and other objects, e.g. rocks in forest-like areas or cars in urban environments that affect the calculations.

Prediction of tree attributes using field-measured training data (studies I and II)

Covering the variation of tree attributes between tree species, size classes, and sites with traditional parametric approaches, such as linear regression, is demanding. In the case of citywide tree registers, it is likely that several allometric models would have to be created for every predicted attribute. Hence, in studies I and II, a non-parametric k-nearest neighbor (kNN) approach was utilized for modeling the tree attributes. A single model is typically enough to cover the entire variation, as long as all strata are covered in the field sample. However, possibly the most significant aspect is the versatility of the created model. Utilizing kNN, practically any number of attributes can be added into one model and imputed for all trees, whereas in parametric approaches a separate model is needed for every attribute.

The kNN method imputes attributes from a field-measured sample to uninventoried trees (or plots). The method first searches the k field-measured trees that are statistically closest to the unmeasured tree in terms of auxiliary data, e.g. ALS metrics collected for all trees. The attributes of the unmeasured tree are imputed as e.g. the distance-weighted average of the k field-measured trees (Crookston and Finley 2008). When using a large set of ALS metrics as auxiliary data, the features best describing the similarity of objects are chosen to be used in the imputation process. Random Forests (RF) (Breiman 2001) is a machine-learning algorithm often utilized in feature selection (e.g. Falkowski et al. 2010). In RF a set of regression trees is determined for each target value. In each tree a pre-defined number of predictors is used to classify the training data, i.e. the field-measured trees into "branches". A regression tree is ready when each of its "branches" contains only one field-measured tree. Two-thirds of the field data were used for training and one-third for testing the performance of each tree. When estimating the tree metrics with RF, i.e. imputing the model, the modeled tree is compared against all regression trees in terms of predictors, or the ALS metrics in the case of studies I and II. The comparisons result in the probabilities between the tested tree and the trees in the training data to be classified in the same final branch. The target values for the modeled tree are determined from the trees in the training data with the highest probability values.

Processing of TLS data sets

Co-registered TLS point clouds were used in studies I and IV to obtain direct measurements from the trees in the study area. The measurements were performed manually in study I, while being partly automated in study II.

Deriving the tree map and tree metrics manually from TLS data (study I)

In study I, the TLS point clouds were utilized in two ways. First, a tree map was extracted from the point cloud. A horizontal slice was extracted from the point cloud at a height of 1.3 meters. In this cross section, the tree locations appeared as circles formed from laser points from the stem. Locations, as well as DBHs of single trees were manually identified from this cross section, where individual stems appeared from above as circles. The same cross section was used for manually determining the DBH for all mapped trees.

Semi-automatic stem diameter measurements from TLS point clouds (study IV)

In study IV, the non-tree objects and branches were first removed manually from the point cloud. After clearing the point cloud, the remaining stem points were used in defining the diameters from the stem up to 60% of the tree height. The stem points were divided into "logs" according to their height value, the first log being 0.25 m and the consecutive log 0.5 m high. For each log, a circle was fitted into the XY coordinates of the extracted points using the least squares method. The circles were used in two alternative ways to estimate log diameters. In the first approach, the circle diameters were used as such to estimate the log diameters. In the second approach, the circle diameters were utilized in fitting a spline function describing the stem diameter at various heights. The log volumes were determined using the Huber formula (Formula 1). As the visibility of the upper part of the stem was rather poor above a height of 60% (Figure 3), the volume of the remaining stem part stem was estimated as a cone (Formula 2).

$$V = \sum_{i=1}^{j} \frac{(\pi d_i)^2}{4} * h_i, \tag{1}$$

$$V = \frac{1}{3}\pi \left(\frac{d}{2}\right)^2 h, \tag{2}$$

where d_i is the diameter of the log in the middle, h_i the length of the log, h the height of the cone, and d the bottom diameter of the cone.

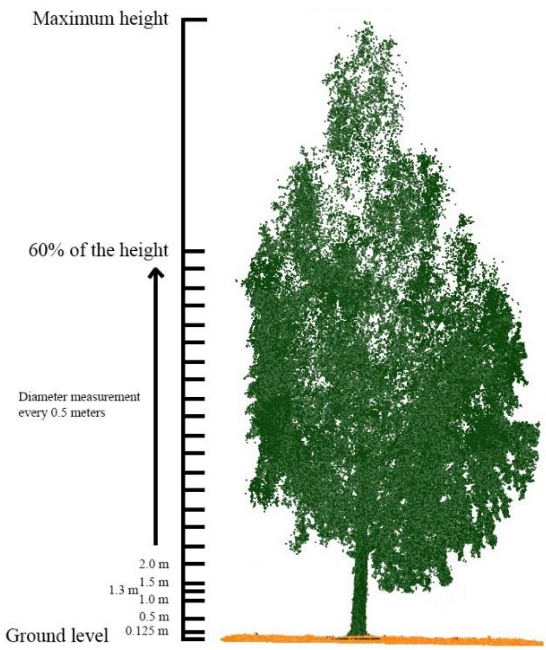

Figure 3. Illustration of a TLS point cloud of a birch tree at the Myllypuro research site.

Assessment of result accuracy

The accuracy of tree-level (studies I, III–IV), diameter class-level (study II), and area-level (study III) results were evaluated by calculating root mean square error (RMSE) (Formula 3), relative RMSE (Formula 4), bias (Formula 5), and relative bias (Formula 6):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}}, \quad (3)$$

$$RMSE\,\% = 100 * \frac{RMSE}{\bar{y}}, \quad (4)$$

$$bias = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n}, \quad (5)$$

$$bias\,\% = 100 * \frac{bias}{\bar{y}}, \quad (6)$$

where n is the number of observations, y_i the observed, $\hat{y}_i$ the predicted, and $\bar{y}$ the mean value.

In addition, the correctness of the estimated diameter distributions was also evaluated in study I. The evaluation was performed by calculating the Reynolds error index (Formula 7) (Reynolds et al. 1988), which describes the difference between the estimated and detected distributions:

$$EI = \sum_{i=1}^{k} w_i \left| f_i - \hat{f}_i \right|, \quad (7)$$

where k is the number of classes, w_i is the weight of class i, f_i is the true number of trees in height class i, and $\hat{f}_i$ is the predicted number of trees in height class i. An alternative error index taking also the total number of trees into account was calculated according to Packalén and Maltamo (2008):

$$e = \sum_{i=1}^{k} 0.5 \left| \frac{f_i}{N} - \frac{\hat{f}_i}{\hat{N}} \right|, \quad (8)$$

where k is the number of classes, f_i is the true number of trees in class i, $\hat{f}_i$ is the predicted number of trees in class i, N the true number, and $\hat{N}$ the predicted number of trees on the plot.

When determining the accuracy of detecting single trees, the relative detection rate (Formula 9) and Cohen's Kappa coefficient (Formula 10) were used. The relative detection rate can be considered simply as a percentage of correctly detected trees, whereas Cohen's Kappa is used to describe the quality of classification.

$$det\,\% = \frac{n_{correct}}{N} * 100, \quad (9)$$

$$K = \frac{p_0 - p_e}{1 - p_e}, \quad (10)$$

where N stands for the total number of observations, $n_{correct}$ the number of correct observations, p_0 the observed number of correct observations, and p_e the number of correct observations that would be expected by chance.

RESULTS AND DISCUSSION

Study I: The use of multiple data sources in predicting and updating tree-level information for existing tree locations.

Much of urban forestry is based on managing individual trees. Essential characteristics of single trees, e.g. location, DBH, height, and tree species are measured and stored in tree registers. Tree-level data have typically only been collected for sparsely growing trees in central locations. However, also some denser and forest-like areas may be of great importance in terms of e.g. recreation. In study I, a multi-source single-tree inventory (MS-STI) method combining a tree map, ALS, and field data was introduced. The tree map was first derived manually from TLS data, after which the key attributes (DBH, height, and crown width) were predicted for the trees. The attribute prediction was performed using ALS-based predictors and field measurements in kNN modeling in combination with RF. In addition to attribute prediction, RF was also used in analyzing the effect of the number of predictors and neighbors used in the modeling chain. The method was tested in a managed park and a forest-like area in the Seurasaari recreational area. MS-STI can be used as such for creating new tree registers, whereas TLS measurements can be omitted for updating an existing tree register with known tree locations.

When the use of 1–23 ALS-based predictors was tested, the relative tree-level RMSE of DBH varied between 18.8% and 20.1% in the managed park area and between 25.0% and 33.8% in the forest-like area. The suitable number of predictors was found to be six for the managed park and seven for the forest-like area. When analyzing the effect of altering parameter k between one and five, the best results were obtained when setting k as 1 in the managed park, and as 5 in the forest-like area. The stem distributions resulting from the DBH estimates were also compared to the field-measured distributions. Considering the relative error index, the stem distribution from the forest-like area was more accurate than that estimated from the managed park. For both areas, the smallest and largest DBH classes were omitted as the value of k increased. When comparing the resulting relative error index to those in Vauhkonen et al. (2014b), the results from the forested area were better and results from the park area were at the same level.

Study II: Updating the tree characteristics of an existing tree register with ALS data.

The validity of tree registers is highly dependent on the age of the data stored in them. All standing trees grow at least to some extent, and because of the diversity of tree species, and special and diverse characteristics of the urban growth environment the possibilities of estimating this change using existing models are limited (McHale et al. 2009; Picard et al. 2012). Hence, keeping the tree registers up-to-date requires repeated measurements. In study II, an existing roadside tree register was updated for DBH and height information using ALS data and the MS-STI method introduced in study I. The study tested the applicability of a fully automatic detection procedure for a tree register update.

The method discovered 17 568 (88.8%) of the 19 777 register trees (Figure 4). DBH and height were modeled for the discovered trees from a field sample utilizing a combination of kNN and RF. The relative tree-level RMSE of the predicted DBH varied between 21.7% and 40.6% depending on the diameter class. The RMSE varied between 21.7% and 24.3% for trees with DBH of 10–50 cm, representing 86.5% of the trees The relative tree-level DBH bias varied between -29.3% and 19.1%. For predicted tree height the relative tree-level RMSE varied between 9.6% and 14.5% and the relative tree-level bias between -1.1% and 4.0%. For the DBH, the relative RMSE was the biggest in the extreme DBH classes, i.e. in the case of the smallest and largest trees. For tree height, the relative RMSE was highest for small trees and lowest for the largest trees. Considering the accuracy of the DBH estimates, Yu et al. (2011) achieved similar results in a forest environment, also using non-parametric methods. Height estimate accuracy was poorer than those reported in previous studies (e.g. Persson et al. 2002; Maltamo et al. 2009).

Study III: Developing a monitoring method for detecting downed trees in urban forest areas through changes in canopy structure.

Changes in urban areas are rapid and many of them cannot be estimated reliably with existing models. Changes in the canopy can be defined using bitemporal data sets. ALS point clouds from two dates enable detecting changes in the forest canopy heights. In study III, ALS data from 2009 and 2012 were used for detecting trees that had downed during the study period. Decaying wood provides habitats for various species and hence affects the biodiversity (Harmon et al. 1986; Karjalainen and Kuuluvainen 2002). ALS-derived CHMs from 2009 and 2012 were utilized to detect the areas damaged by storms during the study period. The damaged areas, i.e. the emerged canopy gaps, were mapped by detecting areas where canopy height had lessened from 2009 to 2012. The emerged canopy gaps and the locations of trees detected from the 2009 ALS data were compared, which allowed the identification of downed trees (Figure 5). Once the downed trees were detected, their key attributes (species, DBH, and volume) were estimated using existing allometric models. As

Figure 4. A road section at Katajanokka harbor with detected roadside trees highlighted.

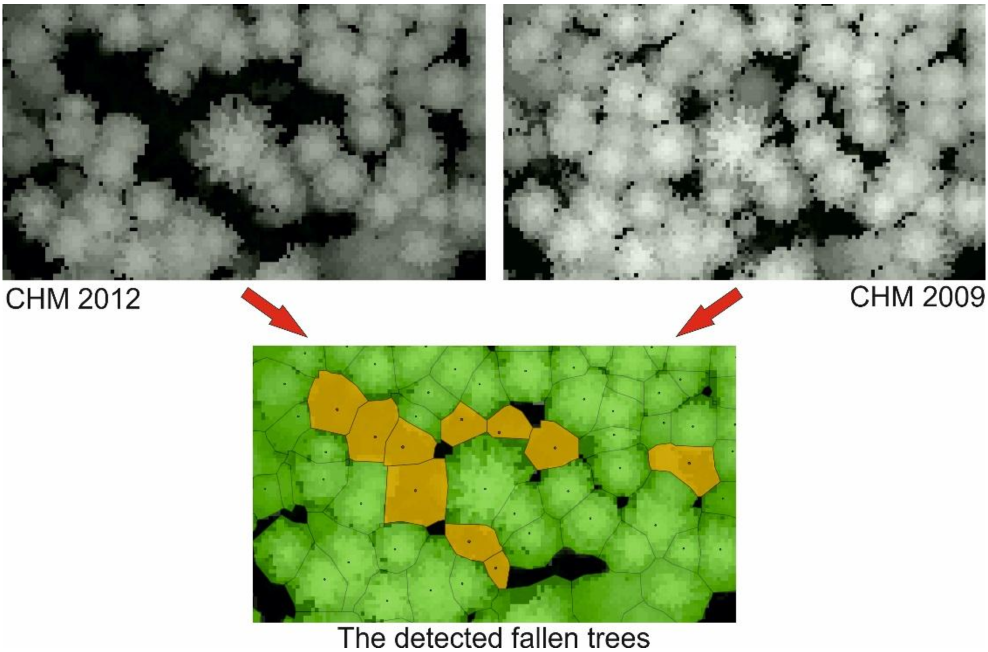

Figure 5. The CHMs from 2009 and 2012 were utilized in detecting the downed trees. The locations of the detected downed trees are highlighted in the lower picture.

all attributes were estimated using ALS-based metrics, there was no need for field-measured training data.

A total of 200 downed trees were detected with the developed method. From the observations, 180 were confirmed in the field as downed trees (97.8% of the total). 20 observations (10.0%) were false, caused by tilted trees and errors in tree delineation. Downed conifers were separated from broadleaved trees with an accuracy of 89.0% (kappa 0.76). For the detected downed trees the relative RMSE of DBH was 20.8% and 34.1%, and the relative DBH bias was 1.6% and 6.7%, for conifer and broadleaf species respectively. The results concerning the detection of the downed trees was good. In previous studies, direct ALS-based detection methods have found between 41% (Lindberg et al. 2013) and 75% (Mücke et al. 2013) of the downed stems.

The proposed method does not provide the total amount of deadwood in the area. However, when repeated for a longer time, the method would enable creating detailed maps including the amount, size class, age, and type (deciduous or conifer) of decaying wood. The maps would benefit e.g. urban biodiversity conservation. Another application for the method would be assessing the amount of carbon stored in decaying wood.

Study IV: Developing an estimation method for adding new attributes to urban tree registers.

Tree species, DBH, and tree height are often used as the core attributes describing urban trees. The attributes are fairly simple to define in the field and give an overall description of

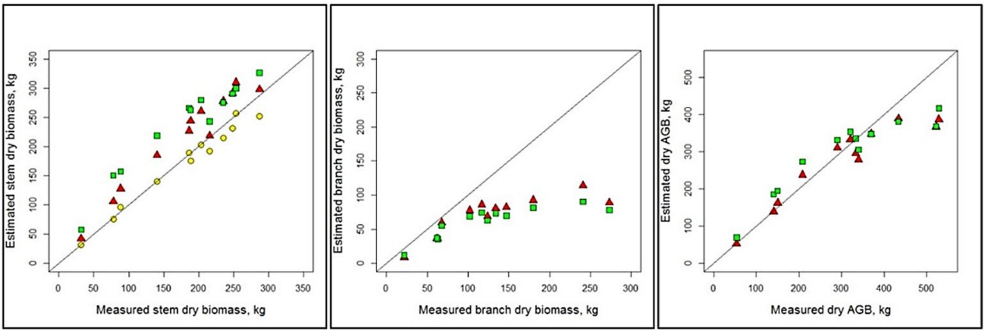

Figure 6. Estimated stem biomass (left), branch biomass (middle), and total aboveground biomass (right) plotted against a field reference. Triangles (red) represent the estimates from allometric biomass model 1, squares (green) the estimates from allometric biomass model 2, and circles (yellow) the TLS-based estimates.

the tree's characteristics. More advanced tree characteristics are usually derived from these basic attributes through various models (e.g. Shrestha and Wynne 2012; Lee et al. 2016). However, urban tree-specific models are rare. For example, biomass modeling has traditionally required destructive sampling, which is rarely applicable to urban surroundings. TLS measurements enable detailed 3D measurements from the trees, which can be used for accurately defining tree volumes. When combined to tree basic density, the volumes can be transformed into biomass estimates. In study IV, the applicability of two forest-based biomass models, utilizing DBH and tree height as predictors, was investigated for 12 urban silver birches. In addition, the tree-level stem biomass was estimated for the study trees by two approaches utilizing TLS measurements and basic density.

The results show that both tested forest-specific biomass models resulted in biased estimates for both stem and branch biomass (Figure 6). On average, the field-measured percentage of biomass allocated to the branches was 40.6%, whereas the two models estimated branches to cover from 20.3% to 23.8% of the total biomass. The relative RMSEs of stem biomass estimates were 22.4% and 33.0% for the two models tested and the relative biases were 20.0% and 31.1%. For branch biomass the relative RMSEs were 60.1% and 67.2% and the biases were -45.6% and -51.8%. The underestimate of branch biomass was greatest for the largest trees. The relative RMSEs of stem biomass for the two TLS-based methods varied between 8.4% and 10.5% and the relative biases between -4.5% and 0.6%. For the introduced TLS-based method, the RMSE of stem biomass varied between 8.4% and 10.5% and the bias between -4.5% and 0.6%. The results show the potential of TLS-based data in measuring new parameters for urban tree registers and in acquiring training data, e.g. for the kNN procedure.

CONCLUSIONS

Urban forest data consists largely of tree-level data that are stored in tree registers. The registers contain information concerning the trees that is essential for maintaining the urban tree resource. Such attributes include e.g. DBH, height, location, and tree species. The data on single trees has traditionally been collected using manual field measurements, and to some extent also through the visual interpretation of aerial images. Tree-level data are expensive to collect, which above all, affects the rate at which the existing registers are updated. Based on the results presented in this thesis, laser scanning methods provide efficient means for both setting up and maintaining tree registers and urban forest information.

In this thesis, laser scanning-based methods were developed for mapping, updating, and monitoring urban forests at the tree level. The first two studies focused on creating and updating tree registers. In study I, a TLS-based tree map was utilized in modeling tree-level parameters for urban park area using ALS data and field measurements. In study II, a citywide tree register was updated using an automatic process utilizing ALS data and field-measured sample trees. In study III, a monitoring application was developed for assessing downed trees in a recreational urban forest area. DBH, volume, location, and species group of downed trees were detected using bitemporal ALS data and existing allometric models. It is known that the performance of allometric models is often highly dependent on the conditions where the models have been developed (e.g. Kalliovirta and Tokola 2005; Piccard et al. 2012). In study IV, a TLS-based method was developed for obtaining tree-level estimates for stem biomass, and compared to two existing biomass models based on allometric relations.

ALS-based detection of individual tree crowns proved to reliably detect the trees. In study II, 88.8% of the existing register trees could be linked unambiguously to a formed crown segment, i.e. an ALS-derived tree candidate. The remaining 11.2% of the tree candidates contained multiple trees. For updating every tree in the tree register, such crown segments have to be divided so that ALS metrics can be calculated for every tree crown. The division of the crown segments can be done either manually, like in study I, or by utilizing some automatic procedures (e.g. Liu et al. 2013; Rahman and Rashed 2015).

When combined with ITD at the start of the monitoring period (T1), the changes in the canopy height model (T2-T1) can be addressed to single trees. In study III, the combination was utilized in mapping the downed trees, and in combination with existing allometric models for DBH and volume, the number and size of the trees was estimated without field-measured training data. In the case of existing tree registers, the methodology could be utilized in detecting significant changes in the register trees, e.g. mapping the sites were single trees have been removed.

Study IV showed that applying existing allometric biomass models of forest trees in urban conditions may result in significant bias, especially when the allocation of biomass between the stem and the branches is considered. In study IV, TLS measurements were successfully utilized in estimating stem biomass. However, in the same study the percentage of branches of the total tree aboveground biomass (AGB) averaged 40.6%. To achieve complete biomass estimates also including branches, the measurement and modeling strategy should be developed further. Although costly for the mapping of large areas, TLS measurements show potential in measuring smaller areas in high detail. Considering the amount of information, the method can also be considered fairly cost-effective. A possible solution for estimating tree biomass at the single tree level for large areas would be to impute the TLS-based biomass estimates of the sample trees for all trees in the area using the kNN procedure and ALS data.

For estimating DBH, the combination of kNN resulted in fairly reliable DBH estimates for the majority of the trees. However, for trees with the smallest and largest DBHs, relative RMSE and relative bias were clearly higher than for the more common DBH classes. The phenomenon stems from at least two sources. Firstly, in kNN when $k > 1$, the size of the smallest tree tends to be overestimated and the size of the largest tree underestimated. This is because tree-level estimates are formed as a mean value from k sample trees. The increment of k intensifies the averaging effect. Secondly, the ALS metrics best explaining tree diameter are typically strongly related to tree height. However, trees with the same height rarely have the same DBH. This is especially true in urban forests, where trees are pruned in various ways. The growth environment also strongly affects the height-DBH ratio of trees. Despite the inaccuracies in the extreme DBH classes, kNN can be considered an efficient and convenient tool for modeling parameters for urban trees. Its strengths are that multiple attributes can be predicted using the same model and that the relation of resulting estimates are logical as they stem from existing trees.

There are still challenges left to solve in applying the LS methods in urban forests. For example, interpretation of tree species is demanding from the single wavelength laser data even in commercially managed rural forests, with a limited number of tree species. In urban forests the task is even more demanding, as they typically consist of tens of different tree species. However, the issue has been engaged e.g. in Alonzo et al. (2014), where promising results were achieved by fusing ALS and hyperspectral data. In their study, 29 of the most common tree species of Santa Barbara were classified with an accuracy of 83.2% (kappa 82.6). In future studies, the fusion of ALS data and other RS material with higher spectral resolution, e.g. multiple wavelength ALS data, aerial images, or satellite images with short ground sample distance (GSD), should be investigated. Another important aspect is that the methods proposed in this thesis do not cover the mapping of trees in all urban areas. For example, the majority of trees in the city of Helsinki are located in areas where tree registers with accurate tree locations do not exist, i.e. the trees are not included in the city’s tree register. These areas consist mainly of park areas and recreational forests. In such areas, discovering the locations of individual trees to centimeter-class accuracy would require extensive measurements utilizing, e.g. TLS or MLS data, whereas ALS data would be sufficient for sub-meter accuracy. The extensive field measurements can be justified in central park areas, whereas the method is likely to be too costly in recreational forests. For some of these areas, a sufficient level of mapping accuracy and detail could be achieved even with methods similar to those traditionally utilized in commercially managed forests (see e.g. Koivuniemi and Korhonen 2006), resulting in compartment-level estimates of forest attributes.

For matching the ALS-derived tree candidates, the accuracy of the a priori tree locations is important. Poor location accuracy of an existing tree register greatly affects the percentage of matched trees, especially for young trees and trees with small crown diameter (e.g. *Alnus glutinosa* F. ´Pyramidalis´ or *Populus tremula* L. ´Erecta´). In park areas trees are not as evenly dispersed as e.g. roadside trees are. Single tree crowns are hard to identify from dense clusters of deciduous park trees solely from ALS data. Here, accurate locations are needed when partitioning the clustered tree crowns. To receive extensive tree-level data from park areas, new methods for producing tree maps should be tested. TLS data were used for producing the initial tree maps in study I. Using multiple TLS measurements in determining the tree locations and even tree attributes (e.g. DBH) for tree registers is highly accurate (Liang et al. 2016), but often considered too costly to apply to large areas. However, in urban environments the exact location of a mapped tree is often a more important attribute than the exact diameter of the tree. As the TLS-derived tree location accuracy exceeds that derived from ALS, applying the TLS method for establishing primary tree registers in the most important locations might still be applicable. An MLS system could also be utilized to achieve the accurate location data more cost-efficiently. An MLS system consists of a TLS scanner, an IMU, a GNSS, and a moving platform (e.g. a car or a quad bike), and tree positions can be derived from the acquired data the same way as from TLS data (Holopainen et al. 2013).

LS-based methods provide various enhancements in mapping and monitoring urban forests. ALS data enables the automatic detection and attribute prediction of single trees with a limited amount of field data. The method's cost-efficiency makes repeated updating of tree attributes possible, which enhances the quality and applicability of the tree-level data. Whereas ALS enables covering large areas with high precision from above the canopy, TLS measurements from under the canopy take the level of detail even further. TLS point clouds can be used in introducing new tree parameters, which have been too costly or complicated to measure by traditional means. Combining wall-to-wall ALS data, detailed tree-level measurements from TLS data, and kNN estimation of tree parameters, the new tree-level parameters can be added into citywide tree registers. The new parameters can be used in modeling tree-related ecosystem services and disservices in urban environments.

Accurate and up-to-date tree-level information benefits the management of urban forests in several ways. The trees can be taken better into account in all urban planning. Management actions for the trees can also be allocated more accurately and efficiently, and the cost of the actions can be predicted more accurately. In more forest-like areas, such as recreational forests, the detailed data can be utilized e.g. when mapping sites potentially hosting endangered species. In this thesis, LS methods for creating such tree-level data were developed, tested, and applied.

Looking back at the objectives of this thesis concerning the development of methods for assessing tree-level information and maintaining the tree registers, it can be concluded that they were met. A method for updating tree-level attributes was developed and also tested in demanding urban surroundings. The results showed that the introduced method can be used to automatically produce tree-level estimates for roadside trees and hence update an existing tree register. A method for detecting downed trees was also developed and tested. Although not directly applied to a tree register, the method clearly showed its potential in locating strong tree-level changes. Finally, a TLS-based field measurement method was introduced for assessing stem biomass.

However, the methods introduced are not complete. Three key points should be emphasized in the future. Firstly, reliable information on tree species is an important part of urban forestry at the operational level, and hence, it should be addressed when further developing the automatic mapping of trees. Secondly, the errors in tree delineation are still causing inaccuracies in mapping individual trees, especially, if the mapping procedure is conducted solely with ALS data. Thirdly, considering the estimates of urban biomass, the TLS-based modeling of branch biomass should be studied further.

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