Dissertationes Forestales 216

Predicting vegetation characteristics in a changing environment by means of laser scanning

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Academic dissertation

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ABSTRACT

Accurate and up-to-date information concerning vegetation characteristics is needed for decision-making from individual-tree-level management activities to the strategic planning of forest resources. Outdated information may lead to unbeneficial or even wrong decisions, at least when it comes to the timing of management activities. Airborne laser scanning (ALS) has so far been successfully used for applications involving detailed vegetation mapping because of its capability to simultaneously produce accurate information on vegetation and ground surfaces. The aim of this dissertation was to develop methods for characterizing vegetation and its changes in varying environments. A method called multisource single-tree inventory (MS-STI) was developed in substudy I to update urban tree attributes. In MS-STI stem map was produced with terrestrial laser scanning and by combining the stem map with predictors derived from ALS data it was possible to obtain improved estimates of diameter-at-breast height but also to produce new attributes such as height and crown size. Boat-based mobile laser scanning (MLS) data were employed in substudy II to map riverbank vegetation and identify changes. The overall classification accuracy of 73% was obtained, which is similar to accuracies found in other studies. With multi-temporal MLS data sets changes in vegetation were mapped year to year. In substudy III, open access ALS data were combined with multisource national forest inventory (NFI) data to investigate the drivers associated to wind damage. The special interest was in ALS-based predictors to map areas with wind disturbance and apply logistic regression to produce a continuous probability surface of wind predisposition to identify areas most likely to experience wind damage. The results demonstrated that a combination of ALS and multisource NFI in the modelling approach increased the prediction accuracy from 76% to 81%. The dissertation showed the capability of ALS and MLS for characterizing vegetation and mapping changes in varying environments. The developed applications could increase and expand the utilization of multi-temporal 3D data sets as well as increase data value. The results of this dissertation can be utilized in producing more accurate, diverse, and up-to-date information for decision-making related to natural resources.

Keywords: Forest inventory, forest mensuration, LiDAR, remote sensing, mapping, change detection, monitoring

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A researcher does not work in solitude, as there are plenty of people cooperating in each paper which was also true with this dissertation. The thesis brought together researchers with various backgrounds and enabled collaboration with interfaces of different disciplines, which was one of my great motivations along the way. Without experts on laser technology and varying applications this thesis would not have been possible. That is why I’m ever grateful to all my co-authors: Ville Kankare, Matti Vaaja, Harri Kaartinen, Antero Kukko, Anttoni Jaakkola, Eliisa Lotsari, Topi Tanhuanpää, Eija Honkavaara, and Paula Litkey for your valuable collaboration and hard work. Thank you Ville for the pictures and figures! I would like to give my special thanks to Petteri Alho for recruiting me to his project, without even knowing me, which was the initial boost for this thesis, as well as Mike Wulder and Joanne White for their valuable knowledge, but also for giving me the possibility to visit the Pacific Forestry Centre. Victoria will always be at second home to me, thanks to the Crawford and Wulder families.

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LIST OF ORIGINAL ARTICLES

This thesis consists of an introductory review followed by three research articles. All the articles are reprinted with kind permission of the publishers.

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 Saarinen, N., Vastaranta, M., Vaaja, M., Lotsari, E., Jaakkola, A., Kukko, A., Kaartinen H., Holopainen, M., Hyyppä, H., Alho, P. (2013). Area-Based Approach for Mapping and Monitoring Riverine Vegetation Using Mobile Laser Scanning. Remote Sensing 5(10): 5285–5303. http://dx.doi.org/10.3390/rs5105285

III Saarinen, N., Vastaranta, M., Honkavaara, E., Wulder, M.A., White, J.C., Litkey, P., Holopainen, M., Hyyppä, J. (2016). Using Multi-Source Data to Map and Model the Predisposition of Forests to Wind Disturbance. Scandinavian Journal of Forest Research 31(1): 66–79. http://dx.doi.org/10.1080/02827581.2015.1056751

Author's contributions

Ninni Saarinen was the main author of all three articles and was responsible for the analyses, calculations, model development, and accuracy evaluation as well as for leading the review processes. All articles were planned together with the supervisors. The reference and TLS data for article I were collected by Ville Kankare and Matti Vaaja. Ville Kankare also processed the TLS data sets. The remote sensing data sets for article II were collected by Harri Kaartinen, Antero Kukko, Anttoni Jaakkola, Matti Vaaja, Eliisa Lotsari, and Petteri Alho. The preprocessing of the data was performed by Harri Kaartinen, Antero Kukko, Anttoni Jaakkola, and Matti Vaaja. Eija Honkavaara and Paula Litkey collected and preprocessed the data for article III. All articles were improved by the contributions of the co-authors at various stages of the analyses, writing, and review processes.

TABLE OF CONTENTS

ABBREVIATIONS

2D; 3D	Two-dimensional; three-dimensional
4D	Three-dimensional but also including a time dimension
ABA	Area-based approach
AGB	Above-ground biomass
AIC	Akaike’s information criteria
ALS	Airborne laser scanning
CHM	Canopy height model
CWD	Coarse woody debris
DBH	Diameter-at-breast height
D_g	Basal area-weighted mean diameter
DSM	Digital surface model
DSI	Digital stereo imagery
DTM	Digital terrain model
FOV	Field of view
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
H_g	Basal area-weighted mean height
IMU	Inertial measurement unit
LAI	Leaf Area Index
LiDAR	Light detection and ranging
MLS	Mobile laser scanning
MMS	Mobile mapping system
MS-STI	Multisource single-tree inventory
nDSM	Normalized digital surface model
NDVI	Normalized difference vegetation index
NFI	National forest inventory
NLS	National Land Survey of Finland
NN	Nearest neighbor
R^2	The coefficient of determination
REDD	Reducing Emission from Deforestation and Degradation in Developing Countries
RMSE	Root-mean-square error
SAR	Synthetic aperture radar
SE	Standard error
SfM	Structure from motion
STD	Standard deviation
SWFI	Stand-wise field inventory
TLS	Terrestrial laser scanning
TOF	Time of flight
UAV	Unmanned aerial vehicle
UTC	Universal Time, Coordinated

INTRODUCTION

Background

Vegetation and various vegetated environments, e.g. forests, play an important role in preventing and precluding erosion, in nature conservation, and climate change. Various vegetation provides products and services utilizable (by humans) to provide the living and increase our well-being. Information concerning vegetation and natural resources is gathered at several different scales from tree-level attributes to global-scale land cover types. Regardless of the inspection level and from where the information is collected from, the cognizance of natural resources is needed in decision-making, whether by urban planners for management activities concerning individual trees, by authorities locating flood risk areas, by private forest owners for handling their properties, or politicians and decision-makers for international conventions. Information used in decision-making is required to be accurate and up-to-date to avoid unfavorable decisions. Thus, a need exists for efficient and applicable inventory methods for different parts of the world to map natural resources, especially vegetation, accurately and often enough. There is an additional need to develop methods and applications for mapping different changes in varying environments.

These environments may include urban surroundings with roadside trees, parks, and recreational forested areas, but also riverbanks with various vegetation types as well as larger managed forest areas. When characterizing vegetation, classification is the traditional means of describing it. A basic classification of vegetation can be based on land use or land cover species distribution, or more detailed information on height or density. Green urban areas are classified based on utilization purposes but also according to habitats, whereas riverine vegetation can be described based on species distribution. Definitions for vegetation from different environments usually follow the traditional forest-type theory (Cajander, 1909), where forest habitats are classified based on indicator species thriving in certain soil and moisture conditions of forest and mire types. According to the theory by Cajander (1909) similar vegetation will develop in equivalent habitats despite changes. Finland has been divided into three climatic zones and each habitat is represented by one or more forest type according to the indicator species and species distribution. This forest type theory has been applied in assessing vegetation productivity, but it is also important when functions of forest ecosystems are of interest since forest ecosystems follow the forest type classification. Biodiversity is one key element in nature conservation and forest type classification constitutes the basis for identifying important habitats (e.g. conserved by law in Finland). One example of vegetation characteristics is forest productivity, which can be assessed based on dominant stand height at a certain age. Traditional forest attributes include, e.g. basal area and volume, which are interesting in wood production, whereas biomass, leaf area index (LAI), canopy coverage, and forest health are characteristics that have become increasingly interesting in relation to climate change. In addition, features describing stand tolerance against natural disturbances, such as wind, could be included when depicting the stand. In this case the characteristic in question could be susceptibility to wind disturbance. Vegetation characteristics can determine upcoming management activities, thus information of these characteristics are needed.

Changes in vegetation, e.g. growth, and biodiversity development, can happen gradually over time, or they can take place suddenly. Rapid changes can either be planned (e.g. forest management actions) or unexpected like erosion or natural disturbance events such as storms, flooding, drought, or fire. Changes in urban vegetation are related to removing vegetation because of constructing city infrastructure, but also because in cases where they pose danger to citizens (i.e. old and damaged trees). Flowing water causes erosion as well as the transportation and accumulation of sediments that may remove vegetation or impede its survival. Natural disturbances are viewed as a hindrance to the productivity of managed forests (e.g. Quine, 1995) because they usually modify forest structure by damaging trees but can also cause other disturbances such as diseases. For example in Finnish legislation requires fallen trees to be removed from forests during the following growing season to prevent pest outbreaks. These disturbance events are nevertheless part of the natural succession cycle of forests, thus increasing heterogeneity and biodiversity. Although one of the goals of current forest management activities is to ensure biological biodiversity (Lindemayer and Franklin, 2002), they may also weaken the disturbance resiliency of managed forests (Holling, 2001). New management procedures are thus needed to maintain the heterogeneity and biodiversity of managed forests but also their resilience to natural disturbance, characteristics that might become more important with a changing climate and accompanying changes in disturbance regimes (Westerling et al. 2006; Seidl et al. 2011; Seidl et al. 2014). Perspective thus affects how changes are seen, especially in relation to forests. On the other hand, gradual change such as vegetation growth takes place where vegetation exists, e.g. in urban environments, on river-banks, and in forests.

Laser scanning is an active remote sensing technique providing three-dimensional (3D) information from objects. Nilsson (1996) presented the principles for the utilization of airborne laser scanning (ALS) in forest inventory and research in this field has been active ever since. ALS has proven to be a cost-efficient technique for retrieving accurate information of vegetation characteristics from large areas and it has been applied in operational use for predicting forest inventory attributes. This methodology is focused on predicting forest inventory attributes at the plot or stand levels, but methods producing single-tree-level information are still studied, although the first methods were presented as early as 1999 (see e.g. Hyyppä and Inkinen, 1999). There is growing interest for providing more detailed information efficiently on the single-tree level. Recent research has therefore also focused on other laser scanning techniques for mapping vegetation characteristics, such as terrestrial and mobile laser scanning (TLS and MLS). The advantage of TLS and MLS compared to ALS is more detailed 3D data (even at a millimeter level of detail), although they are not suitable for the vegetation mapping of large areas.

Inventory of vegetation characteristics

National forest inventory (NFI) has been the traditional means of collecting forest resource information. In Finland, the first NFI was concluded in the 1920s and was based on systematic line sampling. Currently (NFI9–NFI12) clusters of field plots are placed systematically to cover the entire country, which enables the gathering of national- and regional-scale forest information. Nowadays approximately 20% of NFI field plots are measured annually, covering all of Finland and the measurements of roughly 81 000 field plots are executed in a period of five years. In addition, Landsat thematic mapper (TM) satellite images are applied to provide forest resource information of areas smaller than would be possible with the utilized sampling design of field plots. The other traditional means of collecting information on forest resources has been stand-wise field inventory (SWFI), which has been applied for forest management planning purposes in Finland for over 60 years. SWFI is based on field measurements where species-specific information is determined using Bitterlich sampling for each compartment, thus including information about location contrary to NFI. In addition to forest inventory attributes, forest type, development class, and future management activities are determined. To distinguish compartments, aerial images have been applied before the actual fieldwork. Forest management planning is traditionally targeted at private forest owners to urge them in committing to timber production but also to self-active management to actuate private investments (Ollonqvist, 2001). In recent years, issues concerning biodiversity and its protection as well as recreational purposes have been included in the forest management plans, but also in strategic forest planning based on NFI information. Nowadays, the planning processes have enabled the participation of forest owners so as to take their perspectives more into account, but also to ensure sustainable wood production (Ingemarson, 2004; Hujala et al. 2008; Hujala, 2009).

Uncertainty in forest resource information can result in unfavorable decisions, which can lead to economic losses for the forest owner (e.g. Holopainen et al. 2010b; Mäkinen et al. 2010). Precise measurements and accurate models are thus needed for predicting stand-level forest attributes. An inventory of forest attributes has been performed in ten-year cycles, but changes in these attributes are not usually recorded although growth is predicted by means of statistical models. Another challenge is that past management activities or disturbance events are not stored in the same place with forest inventory information. In other words, SWFI has not been applied to vegetation monitoring. Traditionally, NFI and permanent field plot distribution have been the means of long-term forest resource monitoring (i.e. growth, health, biodiversity, carbon balance) in Finland. Although the NFI field plot network is dense enough for mapping these changes on a national and regional level, the accuracy is not sufficient for stand-level monitoring.

An inventory of recreational forests in urban environments has also been based on a ten-year SWFI cycle, but park and roadside trees have not been systematically inventoried. Urban trees usually mainly include roadside trees and some parks trees, and the information gained from them are managed through tree registers. A traditional tree register contains information of species, size, and location for each tree in the register. Tree registers for urban areas are used in city and environmental planning, locating old trees that are hazardous (for citizens), and biodiversity monitoring. Mapping roadside trees is particularly essential for allocating needed management activities for trees that are interfering with lamp posts, buildings, or driver visibility at road junctions, but also to reduce the costs of maintenance actions. In urban environments, trees and forests have less economic value through timber but their importance is in recreation, aesthetics, and biodiversity, and improving air quality (see e.g. Ode and Fry, 2002; Tyrväinen et al. 2005; Nowak, 2006; Bernath and Roschewitz, 2008). Plans for city parks are mainly thematic maps, where built and natural objects, detailed vegetation classification (e.g. grass, broad-leaved tree, high/low conifer/broad-leaved bush) as well as upcoming modifications and changes are presented. Citizens have the possibility to participate in the planning process, which is a common approach in management planning in urban or forested areas. With an up-to-date tree register containing roadside and park trees and stand-level attributes, maintenance activities in green urban areas could be better scheduled and allocated, and maintenance costs could thus be reduced. Tree registers strongly rely on the age of tree data, thus new updating procedures are needed to record the effects of frequent changes in urban trees.

Vegetation acts as an interface between flowing water and the soil in riverine environments, thus increasing vegetation cover on the land is one of the most effective methods to prevent soil erosion. Mapping and monitoring riverside vegetation is important for improving the understanding of river channel evolution and fluvial modeling. Models of river dynamics have been limited to information on river channel topography, water level elevation, and river channel surface roughness (e.g. Dietrich and Smith, 1983; Brasington et al. 2000; Ferguson et al. 2003; Rumsby et al. 2008). Traditional means of collecting elevation information has included time-consuming field measurements (e.g. tachymeter) or inaccurate contour lines of topographical maps. Consequently regular vegetation inventory of riverbanks is also scarce, despite the knowledge that river bends lacking vegetation can experience up to ten times greater erosion than vegetated banks (Beeson and Doyle, 1995). Information of the vegetation cover on riverbanks would therefore provide data for mapping and modeling erosion risk. Riverbank erosion processes are complicated in cold climate conditions, thus understanding these processes can be enhanced by accurate information of riverside vegetation and its changes. In Finland, areas of flood damage have been mapped but the requirements (i.e. EU directives) of updating flood maps and flood-risk maps obligate authorities to produce up-to-date and more detailed maps. Information of the vegetation characteristics on riverbanks could be used in improving the models applied in producing flood maps and flood-risk maps, thus enhancing the information provided by these maps.

Laser scanning techniques

Airborne laser scanning

ALS is an active remote sensing technique typically based on time-of-flight (TOF) measuring. The sensor transmits a laser pulse to an object and the receiver measures the time spent for the laser to travel from the sensor to an object and back (Wehr and Lohr, 1999). The scanner includes a positioning system that relies on the global navigation satellite system (GNSS) and the location of the sensor is registered (Figure 1). In addition, an inertial measurement unit (IMU) also enables the documentation of a sensor’s position and orientation. These records produce a detailed 3D point cloud (x, y, z), permitting accurate recoding of the object’s location and position in this three-dimensional space.

Specifications regarding ALS data acquisition include scan angle, pulse repetition frequency, flying altitude, swath overlap, and returns per pulse (Baltavias, 1999). In addition to these specifications, the structure of an object (vegetation in this case) has an effect on the produced point cloud. Discrete return systems used more commonly in ALS utilize the TOF measurement principle where single laser pulses are emitted and can register up to five returns from each laser pulse from objects without a well-defined surface. Another possibility is to record the shape of a returning laser pulse and convert it to digital waveform. However, methods associated with sensors recoding the full waveform of laser pulses are still under development compared to methods applying discrete laser data. The mapping range of the TOF measurement system is several thousand meters (e.g. ALS in forestry application is executed at altitudes between 400 m and 4000 m). The area illuminated by a laser beam is called a footprint, its diameter is normally 0.1–3.8 m, and it is calculated based on the aperture of the laser, range, and angular divergence of the beam. The size of a footprint affects the spatial resolution of an object that can be detected, although laser returns can be detected from objects smaller than the footprint, e.g. electric power lines (Ackermann, 1999). Because of the large size of the footprint and heterogeneous surface of the vegetation, one laser pulse can penetrate through the canopy and thus result in several backscattered returns. The first return is expected to rebound from the top of the vegetation canopy and the last returns are considered to be hits from the ground. The receiver records 3D coordinates of these returns and the point cloud is generated based on these coordinates. Because the length of the laser pulse is longer than the needed accuracy (meters vs. centimeters) the precise measurement of a laser return in real time is required. In addition to the number of returns and their TOF, the intensity of a discrete laser beam is usually recorded. Intensity is the maximum amplitude of a discrete laser beam (Baltsavias, 1999). The data acquisition specifications affect the spatial coverage and density of the point data: a large scan angle and a higher flying altitude or speed will result in a lower density of measured points on the ground but enable larger area coverage (Petrie and Toth, 2009). High pulse repetition frequency, on the other hand, enables larger measurement density (i.e. density of measured points on the ground). In addition, the complexity of the target area (terrain type, flatness of terrain, and vegetation characteristics) also affects the quality of laser point clouds (Hyyppä et al. 2005).

Straatsma and Middelkoop (2006) presented that during the leaf-off season a laser pulse is able to penetrate deeper through the vegetation compared to the leaf-on season but the intensity is higher during the growing season. In leaf-on conditions the penetration rate of a laser pulse (i.e. transmittance of a laser pulse through the canopy to the ground) is approximately 20–40% in European coniferous and deciduous forests (Ackermann, 1999) and 20–50% in Finnish coniferous forests (Ahokas et al. 2011). Leaf-off conditions have been found suitable for classifying ground points from points emitted from the vegetation and thereby it is possible to generate a raster representing terrain and elevation, called a digital terrain model (DTM) (Raber et al. 2002). However, the difference between DTM from leaf-on and leaf-off data in boreal coniferous-dominated forests has been reported to be less than 5 cm in a low-altitude ALS survey (Hyyppä et al. 2005). Several methods exist for generating DTM from the laser point cloud and a summary of these can be found in Hyyppä et al. (2005). Forest structure, i.e. forest canopy and the amount of understory vegetation, greatly affects DTM accuracy because most laser points are emitted from vegetation. As first returns are expected to hit the highest points of the vegetation, they are used in generating a raster of the digital surface model (DSM) representing the highest objects.

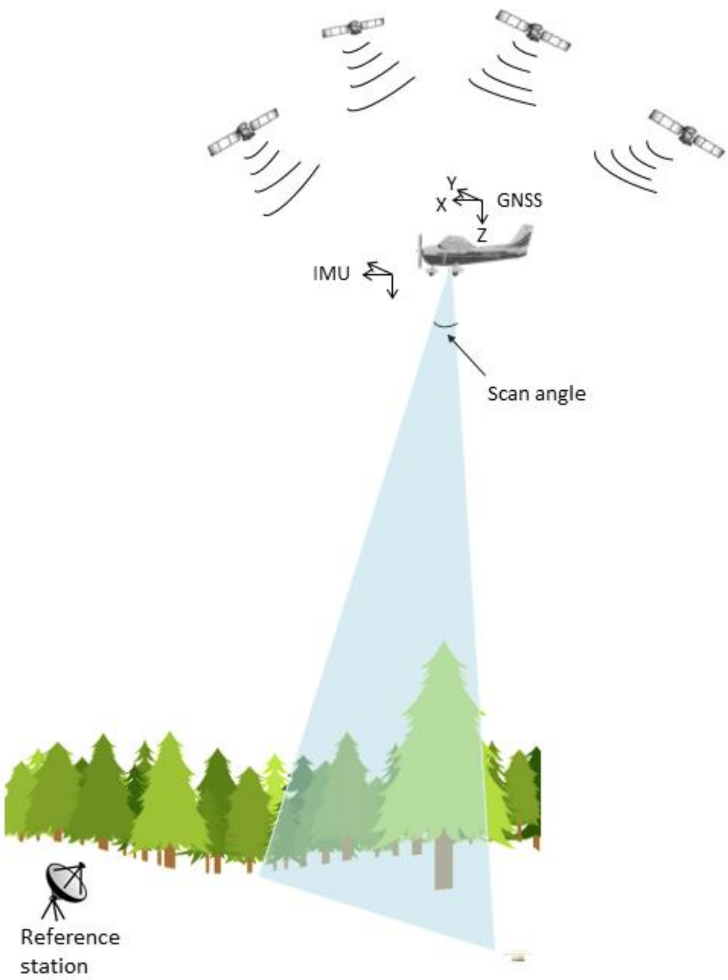

Figure 1. The principle of airborne laser scanning (ALS): A global navigation satellite system (GNSS) enables accurate positioning whereas the inertial measurement unit (IMU) measures and records scanner orientation. The sensor measures the time a laser pulse travels from the scanner to an object and back: the difference between the emitted and received pulse is the distance between the sensor and the object. These distances can be transformed into coordinates based on the position and orientation of the scanner, resulting in a three-dimensional point cloud.

DSM is generated by classifying the uppermost reflections and interpolating missing points to a certain grid size. To find out the height of the vegetation, a canopy height model (CHM) is created by subtracting DTM from DSM, which can also be called a normalized digital surface model (nDSM). ALS has been put into operational use during recent years, and forest resource information has been gradually acquired throughout Finland using ALS. The National Land Survey of Finland (NLS) has acquired ALS for updating and improving the quality of the national elevation model while concurrently providing information of vegetation height. The NLS has provided ALS data operationally since 2008. Openly available ALS data currently (2016) covers approximately 60% of Finland's land area and according to the NLS ALS data covering the entire land area of Finland will be available by 2020. By then multi-temporal ALS data will be available in several areas, thus monitoring environmental changes will be possible. In addition, high-density multi-temporal ALS data are obtainable from urban areas, e.g. the City of Helsinki has used ALS data for urban planning purposes such as the mapping of buildings, roads, and other built objects since 1999. However, applicable ALS data covering the entire city were available for the first time in 2015. Such 4D data are needed for various monitoring applications intended for change detection but also for predicting possible changes in the future.

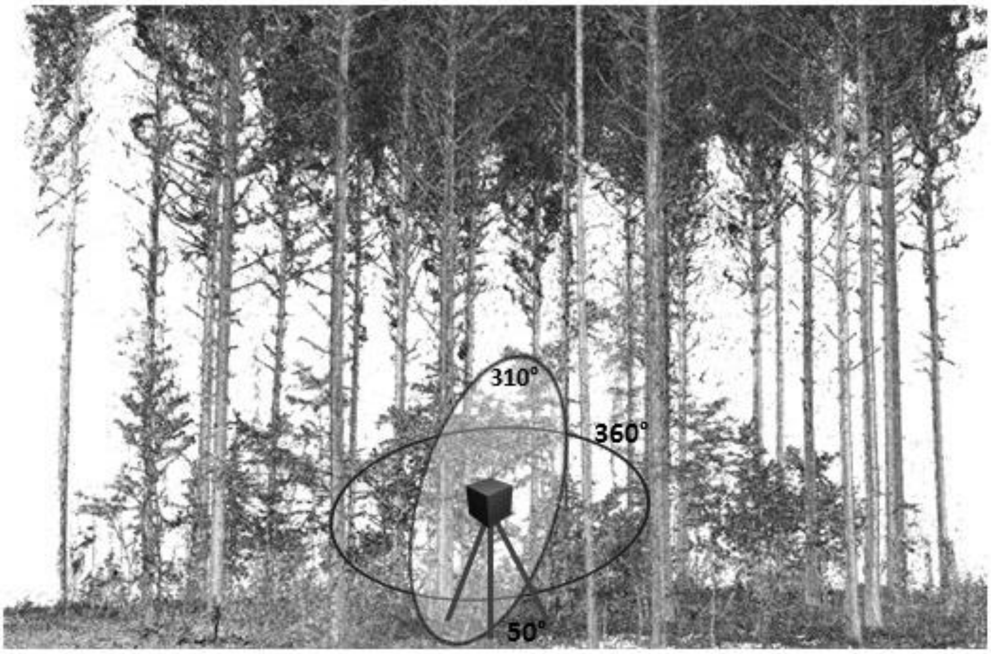

Figure 2. Principles of terrestrial laser scanning (TLS): the scanner is place on a tripod and turns 360 degrees, while vertical coverage is slightly less (310–360 degrees) because the area beneath the tripod (50 degrees at the most) is not covered. The three-dimensional point cloud is produced based on the phase difference between the emitted and received continuous laser beam.

Terrestrial and mobile laser scanning

Terrestrial laser scanning (TLS) is usually performed from a fixed position, where a laser scanner is mounted on a tripod. It is therefore suitable for smaller areas than ALS (i.e. one forest stand), but on the other hand with TLS it is possible to gain more detailed information, even at the millimeter level. A laser scanner on a tripod can use the same TOF measuring technique as ALS or phase-shift ranging. Phase-shift ranging utilizes continuous amplitude modulated wave and detects the phase-shift between the emitted and received signal, thus enabling the calculation of distance. Commercial TLS scanners typically provide 360 degrees for a horizontal field of view and 310 to 360 degrees for a vertical field of view where only the ground below the instrument and the tripod is not covered (Figure 2). Footprint as a term is not used in relation to TLS, but spot size is applied. Spot size is a few millimeters (e.g. 3 mm for Leica HDS6100 and 3.3 mm for Faro Photon120) when a laser beam is emitted and the beam divergences are 0.22 mrad and 0.16 mrad for Leica HDS2000 and Faro Photon 120, respectively. Angular resolution defines the angular difference between two laser beams and determines, along with beam divergence, the distance measurement accuracy and distance to an object, and how detailed observations from an object can be measured, i.e. the maximum number of points. TOF sensors usually have a longer maximum range compared to phase-shift measurements (up to 200 m), while the distance measurements in phase shift have been more accurate. However, the difference in distance accuracy between these two sensor types is decreasing. Point density compared to ALS sensors is clearly higher, e.g. it is possible to gain approximately 25 000 points per m^2 at the scanner level with a single scan at a distance of 10 meters using the Leica HSD6100, which was used in this thesis. Point density decreases as the distance to the scanner increases.

Instruments utilizing phase-shift ranging do not generate several returns compared to TOF, because the first contact to an object yields backscattering to the receiver. Thus, only objects that are directly visible by the sensor can be measured, hence vegetation cover, density, and measuring geometry affect the resulting point cloud and its applicability (Liang et al. 2012b). To avoid inaccuracies caused by blind spots (i.e. obstacles in front of the targets) multiple scans from different locations can be used to capture the entire area of interest. This way data gaps caused by other vegetation (e.g. tree trunks, branches or understory) can be minimized when multiple scans are combined and co-registered as one point cloud. The co-registration of multiple scans can be executed using artificial reference targets (spheres) that have been placed around the inventory area. Object-based registration was presented by Liang and Hyyppä (2013), where co-referencing is performed with no artificial reference targets but a stem-location map is created automatically from each individual scan and these maps are then merged together.

It is also possible to mobilize a laser scanner by mounting it on an all-terrain vehicle (Figure 3), a boat, or backpack, thus referred to as mobile laser scanning (MLS). MLS can utilize the same TOF or phase-shift measuring technique as TLS; the fundamental difference is the moving platform but also the evenness of data and the perspective. A mobile platform enables more spatial coverage and more even point clouds along the way of the platform, but the viewing direction to an object also remains fixed (e.g. Hyyppä et al. 2009). However, point density is similar compared to TLS. Like ALS, MLS also typically relies on GNSS and IMU for geo-referencing the data (Grejner-Brzezinska, 1999). However, one of the greatest challenges for MLS is that dense canopies can shade the positioning system (GNSS) and reduce position accuracy (Holopainen et al. 2013; Kaartinen et al. 2015). MLS data acquisition can be performed during continuous movement or by utilizing the stop-and-go method where data quality is closer to the data produced by TLS. With stop-and-go it is additionally also possible to improve mapping accuracy by avoiding data gaps. MLS was developed to capture features or objects invisible from above and to provide larger spatial coverage than TLS can reach.

Both TLS and MLS provide a dense point cloud, and both methods have currently been used in research related to urban and managed forests (e.g. Holopainen et al. 2013; Kankare et al. 2014a; Kankare et al. 2014b). Other environmental applications for TLS and MLS have included measuring snow cover and depth where intensity has been utilized (Kaasalainen et al. 2008; Prokop, 2008; Prokop et al. 2008; Kaasalainen et al. 2011). Kaasalainen et al. (2008) demonstrated that TLS is capable of detecting even small changes in snow cover depth. Prokop et al. (2008) compared TLS to tachymeter measurements and gained an accuracy of 4.5 cm with a long-range scanner (capable of measuring up to 800 m). Kaasalainen et al. (2011) reported MLS applicability in the accurate profiling of snow surface roughness, which was supported by Jaakkola et al. (2014). MLS has been studied in mapping riverine environments, especially their topography and elevation (Alho et al. 2011; Bitenc et al. 2011; Glennie et al. 2013). Vaaja et al. (2011a) obtained a root-mean-square error (RMSE) between 2.3 cm and 7.6 cm for MLS-based DTM for non-vegetated point bars, but the accuracy decreased for vegetated point bars (RMSE between 15.7 cm and 28.4 cm), whereas Lotsari et al. (2014) gained better results: the RMSE for non-vegetated point bars varied between 3.0 cm and 4.2 cm with similar sensors. Vaaja et al. (2011b) combined MLS and panoramic images to detect changes in river topography, and they concluded that merged data improved the interpretation of land cover, thus provided more information on fluvial geomorphology and river dynamics and offering a good way of visualizing erosion and deposition areas.

A clear difference between ALS, TLS, and MLS is the measuring geometry, which in ALS is almost directly from above (usually ± 20°) and nearly horizontal in TLS and MLS. ALS is thus more suitable for measuring height and height structure properties (i.e. density) while TLS and MLS provide information on the horizontal structure of vegetation, e.g. tree trunks, crowns, and lower vegetation. ALS provides a fairly even point cloud because all objects are more or less at the same distance from the sensor, whereas the point density in TLS and MLS varies drastically as the distance between the sensor and an object changes. An advantage of TLS and MLS compared to ALS is the high spatial accuracy for mapping and monitoring applications, but they work best where visibility is not an issue (e.g. open areas and mature stands without undergrowth). Different laser scanning techniques for characterizing vegetation are presented in more detail in the following sections.

Figure 3. Laser scanner developed by the Finnish Geospatial Research Institute mounted on an all-terrain-vehicle.

Remote sensing data in predicting vegetation characteristics

2D remote sensing data

Remote sensing provides information on vegetation from large areas and has enabled shift from inventory to mapping where vegetation characteristics can be combined with knowledge of locations. Species is a basic vegetation characteristic, and visual interpretation of multispectral aerial images enables separating conifers and deciduous trees. However, this is slow and subjective, and algorithms for automatic species recognition have therefore been developed (Waser et al. 2010; Heikkinen et al. 2011; Korpela et al. 2011; Pant et al. 2013). Waser et al. (2010) compared five aerial cameras in classifying thirteen land cover and eight tree species classes. Heikkinen et al. (2011) concluded that 88% classification accuracy for Scots pine (*Pinus sylvestris* L.), Norway spruce (*Picea abies* (L.) Karst.), and birch (*Betula sp.*) can be obtained if modeling the sunlit and shaded areas of trees and multiple measurements are taken for every tree. Pant et al. (2013) were able to reach 98% overall accuracy for the same study area with simulated multispectral bands. Gougeon et al. (1999) concluded that the spectral signature of closely related species and broad intra-species variations impede the classification. In addition, the applicability of hyperspectral imaging with tens of hundreds of bands has been investigated with regards to species classification (Yu et al. 1999; Becker et al. 2007; Dalponte et al. 2009). Becker et al. (2007) suggested that at least seven bands from visible and near-infrared wavelengths are needed to obtain a minimum 85% classification accuracy for coastal wetland vegetation. Dalponte et al. (2009) concluded that classification accuracy depends on the classifier because not all algorithms can exploit the extensive data from the hyperspectral sensors. Although capable of capturing more varying spectral information, one disadvantage of these hyperspectral images compared to multispectral images is their lower spatial resolution (cf. Clark et al. 2005; Korpela et al. 2011). In addition to species, aerial images have been applied in vegetation type (Holopainen and Jauhiainen, 1999) and habitat (Holopainen and Wang, 1998) mapping. In addition to aerial photographs, space-borne multispectral images have been studied for land cover classification (Hansen et al. 2003; Sedano et al. 2005) and vegetation mapping applications (Wang et al. 2004). Toivonen et al. (2007) applied Landsat TM satellite images for classifying river and waterbodies in Western Amazonian lowlands that are closely related to the forest classification system in the area (Junk and Furch, 1993). Wulder et al. (2000) applied aerial images in locating individual trees and concluded that the size of a tree crown and spatial resolution of imagery are the limiting factors in detecting individual trees. Hyyppä et al. (2000) compared various 2D aerial and space-borne sensors in estimating mean height, basal area, and volume at stand level and their results showed that it was possible to estimate mean height with lowest relative standard error.

Airborne laser scanning

Classification of vegetation type

Vegetation class is one of the principal ways of characterizing vegetation, which can be done based on generally differentiated land cover types or broad species composition, but vegetation density, height, and species-distribution represent more-detailed classification criteria. Vegetation classification is needed for land use and environmental management. Rutzinger et al. (2008) applied object-based analysis and obtained over 90% accuracy in automatically classifying laser points reflected from urban trees and shrubs. Collin et al. (2010), on the other hand, applied ALS intensity to developing an ALS-based vegetation index for distinguishing salt-marsh habitats by way of a per-pixel Maximum Likelihood classifier. A semi-automatic image segmentation system for classifying short (<1.2 m), intermediate, and tall (>5.0 m) floodplain vegetation was presented by Cobby et al. (2001) and Mason et al. (2003). The vegetation density of deciduous lowland floodplain forests was mapped with ALS and a percentage index was calculated for the laser returns, which improved the accuracy compared to the ecotype approach that utilizes lookup tables for each ecotype (Straatsma, 2008). Korpela et al. (2009) reported that an ALS-based surface model correctly matched the actual mire surface patterns and using ALS the accuracy of mire habitat classification was improved compared to optical data. However, high standard deviation (Davenport et al. 2000) and large prediction error (Cobby et al. 2001) of the lowest vegetation cover types with ALS predictions may require other sources of information as well. For example, hydrodynamically relevant surface characteristics for land cover types are derived from lookup tables (Straatsma and Baptist, 2008). Aerial images in combination with ALS data have also been applied in mapping and classifying vegetation. Chust et al. (2008) applied Maximum Likelihood classification in mapping coastal vegetation habitats and concluded that a combination of ALS data and airborne multi-spectral images improved the reliability of habitat mapping compared to ALS alone. Nevertheless, Zlinszky et al. (2012) were able to detect non-wetland features with 97% accuracy and identify 72–80% of six wetland vegetation classes correctly with ALS, also including reed health categories.

Species recognition

One of the challenges with ALS is the adequate classification accuracy of tree species. Brandtberg et al. (2003) were able to distinguish three deciduous species groups with ALS data acquired in leaf-off conditions with accuracy varying from 41% to 50%. Moffiet et al. (2005) concluded that the proportion of single laser returns showed potential in species recognition and obtained a classification accuracy of 77% for recognizing poplar box (*Eucalyptus populnea* F.Muell.) and white cypress pine (*Callitris glaucophylla* F.Muell.). Kim et al. (2009) applied intensity from discrete ALS data and were able to distinguish broadleaved trees and conifers with 83.4% accuracy. ALS sensors recoding full waveform of the laser beam have been studied in recognizing tree species and results have indicated the applicability of full-waveform ALS in tree species classification compared to discrete ALS (Lindberg et al. 2014; Vaughn et al. 2012; Yu et al. 2014). Lindberg et al. (2014) demonstrated that including waveform variables in species identification improved classification accuracy from 53% to 71% compared to discrete ALS, whereas Vaughn et al. (2012) reported an improvement from 79.2% to 85.4% in species classification accuracy. Yu et al. (2014) obtained similar results with low-density waveform ALS data: classification accuracy improved from 52.3% to 73.4% when waveform features were applied. Hovi et al. (2016) also compared discrete ALS intensity and waveform ALS in identifying different tree species and concluded that waveform improved results (from 78% to 88% with automatically segmented trees), especially when the only returns were applied because their waveform intensity was the most important feature in tree species recognition. Reitberger et al. (2008) implemented the canopy height model (CHM) to identify trees and applied waveform intensity to distinguish conifers and deciduous trees and were able to obtain an overall accuracy of 85% with leaf-on data and even 96% accuracy for leaf-off conditions. Furthermore, a combination of multispectral aerial images and ALS has been proposed to overcome the challenges of tree species identification. Classification accuracies between 83% and 96% have been achieved in managed forests with this combination (Holmgren et al. 2008; Ørka et al. 2012). In addition, hyperspectral aerial imagery in combination with ALS has been used in managed forests (e.g. Ørka et al. 2013; Dalponte et al. 2014) and urban environments (Zhang and Qiu, 2012; Alonzo et al. 2014). In these studies ALS was applied for delineating individual trees and the spectral information from aerial imagery was utilized for species recognition, which has proven to produce more accurate results. A combination of aerial images and ALS has also been applied in retrieving species-specific forest inventory attributes (e.g. basal area, volume, diameter distribution) in managed forests (Packalén and Maltamo, 2006, 2007, 2008; Packalén et al. 2009). However, promising results for species recognition have been obtained with discrete ALS data only: Holmgren and Persson (2004) were able to separate Norway spruce and Scots pine with 95% accuracy and Liang et al. (2007) obtained 90% overall classification accuracy in distinguishing conifers and deciduous trees when applying first and last returns.

Detecting tree location

Location is the main attribute for an individual tree, especially in urban environments. ALS has provided detailed enough information available for identifying, recognizing, and characterizing individual trees and therefore for recording tree location (Hyyppä and Inkinen, 1999). Various techniques exist for identifying and locating trees, but several studies (Hyyppä and Inkinen, 1999; Friedlaender and Koch, 2000; Ziegler et al. 2000; Hyyppä et al. 2001a; Koch et al. 2006; Vega and Durrieu, 2011; Yu et al. 2011; Kaartinen et al. 2012b; Vauhkonen et al. 2012) have used CHM for finding the local height maxima representing tree tops and delineating the crown. Persson et al. (2002) were able to link 71% of the crowns delineated by CHM to reference trees. The accuracy of finding all the trees depends on the measurement density to ensure returns from tree tops and the entire crown (e.g. Lefsky et al. 2002), thus larger measurement density (preferably 5–6 points per m^2) has traditionally been required. However, when comparing several techniques, Kaartinen and Hyyppä (2008) found no significant differences between detection accuracies and point densities. When comparing different methods, Kaartinen and Hyyppä (2008) and Vauhkonen et al. (2012) discovered that the accuracy of detecting single trees also depends on forest structure and how well suppressed trees can be identified. One of the drawbacks of applying CHM in tree detection is that only trees contributing to the CHM can be detected (Kaartinen and Hyyppä, 2008). Thus, surface models from other return types could also be generated for detecting suppressed trees more accurately. Hyyppä et al. (2012) demonstrated the applicability of last returns in improving the detection accuracy by 6%. Maltamo et al. (2004a) predicted Weibull distribution parameters to detect suppressed trees and were able to decrease the relative RMSE from 74.4% to 49.2% for the stem number when comparing with trees detected using CHM-based segmentation. Other methods have applied a 3D point cloud (Morsdorf et al. 2004; Wang et al. 2008) to better discriminate nearby and suppressed trees, although the results are similar (Gupta et al. 2010; Vauhkonen et al. 2012) to those applying CHM. Tanhuanpää et al. (2014) developed a system for mapping roadside trees in the City of Helsinki, Finland and adding height information based on ALS data to the tree register. They were able to map 89% of all the trees automatically. Holopainen et al. (2013) applied ALS, TLS, and MLS for locating urban trees and concluded that TLS and ALS provided accuracies acceptable for operational urban tree mapping (from 65.5% to 73.3%), although manual tree detection from MLS point clouds gained similar results with TLS (79.2% and 73.3%, respectively). However, it should be noted that these results are not fully comparable because canopy and forest structure as well as the acquisition specifications of laser scanning varied between different studies.

Predicting forest inventory attributes

ALS is already becoming a standard technique for mapping forest resources, especially for the purpose of forest management planning particularly in Nordic countries (Maltamo and Packalén, 2014; Næsset, 2014). The so-called area-based approach (ABA) has increasingly been used in practical forest inventory for forest management planning when predicting species-specific forest inventory attributes, such as basal area-weighted mean diameter (D_g) and height (H_g) (i.e. Lorey's height), mean basal area per hectare, mean stem volume per hectare, and number of stems, based on stand-level ALS data. In ABA, forest inventory attributes are predicted based on statistical dependency between metrics derived from ALS data and response variables measured from field plots. The approach provides wall-to-wall predictions for the attributes of interest. Most studies apply either regression (e.g. Means et al. 2000; Næsset, 2002; Holmgren, 2004; Næsset et al. 2005) or non-parametric (e.g. Maltamo et al. 2006; Hollaus et al. 2007; Packalén and Maltamo, 2007; Hudak et al. 2008; Latifi et al. 2010) models when predicting forest inventory attributes with ALS, and selected ALS metrics are utilized as predictors in these models. Several imputation approaches have been developed, and Hudak et al. (2008) concluded that Random Forest was the most robust and flexible method when predicting forest inventory attributes compared to other imputation approaches (i.e. Euclidean distance, Mahalanobis distance, Independent Component Analysis, Most Similar Neighbor, or Gradient Nearest Neighbor), which has been supported by the results by Latifi et al. (2010). Regression modeling has also been applied in mapping riverine vegetation where ALS provided the predictor variables for estimating spatial distributions of forest vegetation density as well as vegetation height and the density of herbaceous vegetation (Straatsma and Baptist, 2008).

One of the main interests related to the precision and accuracy of estimated forest/vegetation attributes has been in examining measurement density. Research has shown that the required measurement density for appropriate estimations of grid-level forest inventory attributes (e.g. 265 m^2) is 0.5 points per square meter, and increasing the point density will not improve results considerably (Hyyppä et al. 2001b; Næsset, 2002; Holmgren, 2004; Næsset, 2004b; Treitz et al. 2012). Tree height estimations vary more based on leaf-off data (Næsset, 2005), especially in deciduous stands (Wasser et al. 2013). Tree height based on ALS data is reportedly an underestimation (Rönnholm et al. 2004; Vauhkonen et al. 2012), because the laser pulse does not necessarily hit the tree top and/or the used elevation model is higher due to undergrowth vegetation. However, White et al. (2015a) compared leaf-on and leaf-off ALS data in modeling forest inventory attributes and concluded that leaf-off data can also be applied in estimating forest attributes for both coniferous and deciduous forests.

Forest inventory attributes can also be predicted based on single-tree methods where individual trees are first detected and the metrics are extracted to predict tree-level attributes that are then compiled into plot- or stand-level predictions, similarly as in traditional field-plot measurements. Methods applying single trees as sampling units merely utilize metrics from a surface model (i.e. CHM) because it is also developed for detecting the trees. Greater point densities have enabled the extraction of more metrics (e.g. height percentiles of the canopy height distribution, mean height, standard deviation, and coefficient of height variation) (Yu et al. 2010) and utilization of geometrical features, representing the volume, shape, and structure of a crown (Chauve et al. 2009; Vauhkonen et al. 2010), that could be applied in improving tree attribute estimations. In addition, with techniques producing greater point densities the nearest neighbor (NN) approaches can also be applied to the single-tree level when predicting tree attributes: NN approaches improve single-tree attributes estimation (Maltamo et al. 2009; Vauhkonen et al. 2010; Yu et al. 2011). Most studies using individual trees as a sample unit (e.g. Friedlaender and Koch, 2000; Lefsky et al. 2002; Persson et al. 2002; Kaartinen and Hyyppä, 2008; Vauhkonen et al. 2012) have concentrated on detecting trees and estimating tree-level attributes (DBH, height, and volume of individual trees) but plot- or stand-level estimates are still scarce, thus comparison between different studies and methods is challenging. Results are also reported in various ways, which makes comparison even more difficult. One comparison of the accuracy of forest inventory attribute estimations based on ABA has been compiled by Næsset et al. (2004), where standard error (SE) or RMSE varied between 8.4% and 16.6% for stand-level stem volume, between 2.5% and 6.4% for mean tree height, and between 8.6% and 13.2% for basal area. Table 1 combines the assessment of traditional forest inventory attribute estimates from several studies utilizing different methods. It should be noted that results are very dependent on the data and methodology applied, thus not fully comparable. Hence international benchmarking studies on the same area are becoming increasingly important (Kaartinen, 2012b). After this reminder, it can be pointed out that although estimate accuracies vary between studies the variation is not considerable, especially when methods with different sampling units (i.e. grid vs. individual tree) are compared (Table 1). One of the biggest issues causing uncertainty in the estimations of forest inventory attributes when applying individual trees as sample units is the tree detection rate, i.e. plot- or stand-level estimates for volume or basal area are underestimations if not all trees in a plot or a stand can be detected (Hyyppä and Inkinen, 1999). As for ABA, one critical point is the inaccuracy in georeferencing the field plots (Gobakken and Næsset, 2009;

Frazer et al. 2011). The effect of a possible error in co-registration of the positioned field plots and ALS metrics can be decreased with larger plot size (Gobakken and Næsset, 2009, Frazer et al. 2011), thus larger plots are typically used in estimating forest inventory attributes when applying ABA (e.g. Næsset et al. 2004; Packalén and Maltamo, 2007; Woods et al. 2011; White et al. 2013).

Above-ground biomass (AGB), on the other hand, is associated with international conventions related to climate change as it can be converted into carbon storage. The main aim of the international programs (e.g. UN Collaborative Programme on Reducing Emission from Deforestation and Forest Degradation in developing Countries, REDD) is to reduce global carbon emissions, and a need exists for measuring and monitoring (forest) biomass effectively and accurately. Thus, several studies have concentrated on applying ALS for estimating AGB mainly in managed forests on the single-tree level (Bortolot and Wynne, 2005; Popescu, 2007; Zhao et al. 2009; Allouis et al. 2013; Kankare et al. 2013b), and plot level (Jochem et al. 2011; Popescu et al. 2004), and on a grid-level by applying ABA (Næsset, 2004a; Latifi et al. 2010; Kankare et al.2013c). Studies have also been carried out in urban environments estimating urban green volume (i.e. the sum of individual tree and grassland object volumes) (Hecht et al. 2008; Huang et al. 2013b). Not all results from abovementioned studies are comparable because they are not presented in a similar way, but Kankare et al. (2013c) and Latifi et al. (2010) applied analogous non-parametric approaches and Kankare et al. (2013c) gained a smaller relative RMSE (24.9%) than Latifi et al. (2010) (47.5%). Popescu (2007) reported the coefficient of determination (R^2) varying between 0.58 and 0.95 for several regression models estimating biomass. Allouis et al. (2013) included waveform metrics in estimating AGB and perceived improvement in the estimates (mean percentage error from -15% to -4%). Kankare et al. (2013b) developed linear models to estimate single tree biomass with predictor variables extracted from ALS data, but they first estimated DBH and height based on ALS data and used these estimates in existing biomass models. Results suggest that single-tree biomass is more accurately estimated when predictors are derived directly from ALS data. Jochem et al. (2011) introduced canopy transparency parameters to estimate AGB and resulted in R^2 between 0.64 and 0.71 whereas results by Popescu et al. (2004) demonstrated a better fit to a model for estimating AGB for pines (R^2=0.82) than for deciduous trees (R^2=0.33).

Predicting biodiversity

Biodiversity is commonly used to describe species diversity or species richness, which in ecological environments includes plants, animals, and other organisms. Biodiversity is an important feature in both urban and managed forests, and many species are dependent on dead wood (i.e. coarse woody debris, CWD), thus decaying wood is one of the key factors for biodiversity (e.g. Franklin et al. 1987; Siitonen et al. 2000) and it has been used as a measure for biodiversity. As other vegetation characteristic, ALS has also been applied in measuring woody debris and canopy gaps that are formed in old-growth forests after the death of an individual tree or a group of trees (Kuuluvainen, 1994; Siitonen et al. 2000). Woody debris has therefore been mapped in forested areas on a plot level (Pesonen et al. 2008), canopy-gap level (Vehmas et al. 2011), and single-tree level by applying object-based image analysis (Blanchard et al. 2011), surface models (Mücke et al. 2013; Nyström et al. 2014), or point clouds (Lindberg et al. 2013). Each method has proved to be appropriate for detecting CWD. The results obtained by Pesonen et al. (2008) affirm the applicability of ALS in CWD estimations as the model with ALS predictors only produced lower RMSEs (51.6% for downed and 78.8% for standing dead wood) than the model with field-measured predictors (RMSE 85.7%). Vehmas et al. (2011) concluded that a difference in ALS height structure can be applied in identifying canopy gaps from semi-natural and managed forests, hence in assessing the amount of CWD. Nyström et al. (2014) applied a surface model generated from only or last returns in identifying downed windblown trees in managed forests.

Table 1. Assessment of estimates for forest inventory attributes with different techniques. D_g = basal area-weighted mean diameter, H_g = basal area-weighted mean height (Means et al. 2000 used term "mean height" which might not be basal area-weighted). ITD = individual-tree detection (i.e. sample unit is an individual tree), ABA = area-based approach (i.e. sample unit is a grid cell). Estimation is performed either at plot or stand level. SE = standard error, STD = standard deviation, RMSE = root mean square error. (Percentages are presented in brackets).

Study	***D_g, cm***	***H_g, m***	***Basal area, m^2/ha***	***Volume, m^3/ha***	***Method***	***Unit***
Hyyppä and Inkinen (1999)		SE: 2.3 (13.6%) Bias: -2.5	SE: 1.9 (9.6%) Bias: 9.7	SE: 16.5 (9.5%) Bias: -65.0	ITD	Stand
Means et al. (2000)		RMSE: 1.7	RMSE: 5.4	RMSE: 73.0	ABA	Stand
Hyyppä et al. (2001a)		SE: 1.8 (9.9%) Bias: -0.9	SE: 2.0 (10.2%) Bias: -3.9	SE: 18.5 (10.5%) Bias: -48.3	ITD	Stand
Næsset (2002)	STD: 1.4–1.6 Bias: -1.0–-0.7	STD: 0.6–1.2 Bias: -0.4–0.1	STD: 2.3–2.5 (8.6–11.7%) Bias: -0.7–0.9	STD: 18.3–31.9 (11.4–14.2%) Bias: -8.2–-0.3	ABA	Stand
Popescu et al. (2003)				RMSE: 47.9	ITD	Plot
Hollaus et al. (2007)				RMSE: 90.9 (21.4%)	ABA	Plot
Holmgren (2004)		RMSE: 0.6–1.0 (3–5%)	RMSE: 2.7–4.2 (10–15%)	RMSE: 31–50 (11–19%)	ABA	Stand
Næsset et al. (2005)	STD: (5.5–15.8%) Bias: (-7.9–0.2%)	STD: (3.1–7.3%) Bias: (-4.7–5.5%)	STD: (7.1–13.6%) Bias: (-8.4–7.3%)	STD: (8.3–14.9%) Bias: (-10.1–3.9%)	ABA	Plot
Packalén and Maltamo (2007)	RMSE: 2.6–3.4 (20.2–25.3%) Bias: -0.2–0.1	RMSE: 1.4–2.3 (8.5–18.4%) Bias: -0.3–0.1	RMSE: 1.6-3.3 (27.1–52.5%) Bias: -0.3–0.3	RMSE: 13.7–27.7 (28.1–62.3%) Bias: -2.1–2.5	ABA	Stand
	RMSE: 4.4–5.3 (23.1–45.9%) Bias: -0.1–0.7	RMSE: 2.6 - 4.1 (16.0–32.2%) Bias: -0.1–0.4	RMSE: 2.6 -5.6 (46.6–87.8%) Bias: -0.2–0.2	RMSE: 22.4 -50.3 (51.6–102.8%) Bias: -1.1–2.2	ABA	Plot
Breidenbach et al. (2010)				RMSE: 41.7 (20.6%) Bias: 4.4 (2.2%)	ABA	Plot
				RMSE: 34.6–42.1 (17.1–20.8%) Bias: 1.1–13.0 (0.5–6.4%)	ITD	Plot
Latifi et al. (2010)				RMSE: 61.2–121.3 (23.3–46.1%) Bias: (-2.9–3.1%)	ABA	Plot
Yu et al. (2010)	RMSE: (10.3%)	RMSE: (6.4%)		RMSE: (20.9%)	ABA	Plot
	RMSE: (7.2–12.1%)	RMSE: (4.4–9.3%)		RMSE: (15.4–56.5%)	ITD	Plot
Peuhkurinen et al. (2011)	RMSE: (13.0%) Bias: (1.1%)	RMSE: (2.3%) Bias: (0.4%)	RMSE: (15.0%) Bias: (-0.4%)	RMSE: (13.5%) Bias: (-1.2%)	ABA	Plot
	RMSE: (15.7–19.5%) Bias: (-14.8–-10.8%)	RMSE: (8.0–9.5%) Bias: (-3.1–-2.9%)	RMSE: (11.4–14.7%) Bias: (2.9–6.7%)	RMSE: (13.6–16.3%) Bias: (-8.2–-3.5%)	ITD	Plot
Valbuena et al. (2014)			RMSE: 0.1 (10.9%) Bias: -0.00 (-3.2%)		ABA	Plot
			RMSE: 0.2 (23.1%) Bias:-0.00 (-19.1%)		ITD	Plot

TLS and MLS in predicting vegetation characteristics

The applicability of TLS and MLS in operational use for predicting vegetation characteristics is still studied but the vision is to apply TLS and/or MLS in the acquisition of reference data for large area vegetation mapping (Holopainen et al. 2014). TLS has been applied in detecting individual trees in urban environments (Holopainen et al. 2013) and managed forests (Maas et al. 2008; Liang et al. 2012b), where the detection accuracy of individual trees from TLS varied from 73% to 97.5%. TLS has been applied in predicting tree characteristics such as DBH, height, and height of crown base in managed forests (Hopkinson et al. 2004; Pfeifer and Winterhalder, 2004; Maas et al. 2008; Lindberg et al. 2012), AGB (e.g. Yao et al. 2011; Kankare et al. 2013a; Calders et al. 2015), but also canopy-related characteristics (Moorthy et al. 2008; Jung et al. 2011). Previous studies have showed that tree height is underestimated by TLS data, as the highest point is usually not visible to the scanner; underestimates have varied between 0.64 m and 1.5 m (e.g. Hopkinson et al. 2004; Maas et al. 2008; Liang and Hyyppä, 2013). No such trend has been observed with DBH estimations but the RMSE has varied between 0.74 cm and 3.8 cm (Hopkinson et al. 2004; Pfeifer and Winterhalder, 2004; Maas et al. 2008; Lindberg et al. 2012; Liang and Hyyppä, 2013). TLS-based estimations for AGB have been reported to correlate very well with reference data, between 0.90 and 0.98 with individual trees (Kankare et al. 2013a; Calders et al. 2015) and between 0.85 and 0.98 at the plot and stand levels (Yao et al. 2001). Danson et al. (2007) applied TLS for estimating gap fractions and reported RMSEs between 5% and 11% demonstrating the high potential of TLS in estimating LAI. In urban environments traditional tree attributes such as DBH, height, basal area, and volume were estimated based on TLS data and results showed that with TLS-based metrics most of the variation in DBH (91.2%) can be explained, but only 18% of the total volume can be captured due to occlusion (Moskal and Zheng, 2012). Vonderach et al. (2012) applied TLS in estimating the volume of urban trees and the relative difference varies between -5.1% and 14.3% compared to field measurements. Dassot et al. (2012), on the other hand, reported a relative difference of ±10% between TLS-based tree volume estimations and manual destructive field measurements in the forest environment.

Stem form and the number of branches affect wood quality and are thus interesting attributes regarding the decision-making of private forest owners and forest industry. Identification of big branches in urban areas could also be interesting as they can hinder drivers’ visibility or interfere with lamp posts. Predictions of stem curve based on TLS have been studied to feasibly model the stem form and volume (Pfeifer and Winterhalder, 2004; Thies et al. 2004; Liang et al. 2012b; Liang et al. 2014b). These studies have shown promising results in reconstructing stem curve accurately, which is important information for optimizing harvest operations. Kretschmer et al. (2013) used TLS data in measuring bark scars and branched knots of beech trees that affect wood quality. They demonstrated that in 58% of cases the differences in heights of branched knots between reference and TLS measurements were less than 1.0 cm. Raumonen et al (2013) presented a method for modeling tree stem and branches automatically from the TLS point cloud as Krooks et al. (2014) estimated branch size distribution from TLS data and concluded that tree height could be used in predicting branch size distribution for trees with similar growing conditions and topography. Branch size distribution has an effect on wood quality, but it is also used as bioenergy when information on branch amount and size are required. This is also true regarding stump-root systems used for energy production. Liski et al. (2014) used TLS data in modeling the 3D structure of uprooted stump-root systems for estimating indirect emissions (i.e. energy production emissions from stumps and roots that do not become a part of soil organic carbon because they are used as energy).

As TLS has become a widely studied technique for retrieving tree-level attributes, applications for estimating vegetation characteristics with MLS are still scarce. The capability of MLS in mapping individual trees has been studied by Jaakkola et al. (2010), Lehtomäki et al. (2010), Rutzinger et al. (2010), and Holopainen et al. (2013), and the detection rates varied from 69.7% to 90%. Many MLS studies have concentrated on identifying trees in urban environments: Rutzinger et al. (2011) applied MLS in an urban environment and were able to detect 86% of the trees, whereas Pu et al. (2011) obtained a 63.5% detection rate for roadside trees. Puttonen et al. (2011) studied tree species recognition in urban environments with a combination of MLS and hyperspectral data and obtained 95.8% classification accuracy for separating coniferous and deciduous species. Wu et al. (2013) applied a voxel-based method for identifying trees in urban environments and estimating DBH, height, crown diameter, and crown base height with MLS data. They were able to detect over 98% of the trees correctly with an R^2 over 0.9 for height and crown diameter and over 0.8 for DBH and crown base height when compared to reference data. However, MLS has also been evaluated in estimating single-tree-level biomass (Lin et al. 2010) and DBH in managed forest (Liang et al. 2014a). Lin et al. (2010) compared MLS-based estimated to TLS and reported an R^2 of 0.61 between these two estimates. Liang et al. (2014b) reported an RMSE of 2.36 cm, which is similar to results obtained with TLS (Hopkinson et al. 2004; Pfeifer and Winterhalder, 2004; Maas et al. 2008; Lindberg et al. 2012; Liang and Hyyppä, 2013).

Alternative 3D techniques

High-resolution aerial imagery can also provide 3D information when aerial images are applied in generating 3D point clouds which can then be transformed into DSM (St-Onge et al. 2004; St-Onge et al. 2008; Leberl et al. 2010; Honkavaara et al. 2012; Vastaranta et al. 2013; White et al. 2015b). In generating 3D point clouds from optical stereo imagery, an object needs to been viewed from at least two images with slightly different viewing angle. St-Onge et al. (2008) combined digital stereo imagery (DSI) and ALS to the developed CHM: DSM was generated from DSI and ALS was applied in providing DTM, which was then subtracted from DSM to gain CHM. They concluded that DSI-based CHM provides similar height values but is lacking in accuracy and resolution when compared to ALS-based CHM. Vastaranta et al. (2013) discovered that DSI-based CHM does not provide as much variation in canopy height, which suggests that ALS is more capable in penetrating the canopy and describing vegetation density. Generating 3D point clouds from aerial images collected by unmanned aerial vehicles (UAVs) has been studied in several environmental applications (Lelong et al. 2008; Hunt et al. 2010; Flener et al. 2013; Honkavaara et al. 2014; Näsi et al. 2015). Flener et al. (2013) applied UAV in generating a bathymetry model with an accuracy of less than 10 cm to generate a seamless wet-dry DTM for a riverine environment. Honkavaara et al. (2014) demonstrated the use of hyperspectral UAV photogrammetry for a forest inventory purpose and provided a hyperspectral point cloud that could be further applied in generating CHM. Hunt et al. (2010), as well as Lelong et al. (2008), applied UAV-imagery in an agricultural environment to monitor wheat farming and found a correlation between LAI and the green normalized difference vegetation index (GNDVI), and LAI and NDVI, respectively.

An example of new and emerging 3D generating techniques from passive remote sensing, i.e. photographs, is to combine structure from motion (SfM) algorithms with photogrammetric principles. In SfM optical stereo imagery can be utilized in extracting 3D point clouds automatically. SfM algorithms do not require accurate positioning and inertial measurements of a camera, but enable 3D point cloud generation with overlapping but otherwise unordered images (Snavely et al. 2008). Puliti et al. (2015) utilized SfM technique for estimating plot-level forest inventory attributes and reported relative RMSE equal or smaller than 15.4% for Hg, dominant height, basal area, and stem volume (m^3/ha). Lisein et al. (2013) utilized CHM generated from SfM-based 3D point cloud and received a relative RMSE of 8.5% (corresponding to absolute RMSE of 1.7 m) for plot-level dominant height and relative RMSE of 4.7% (absolute RMSE of 1.0 m) for tree-level heights. Rahlf et al. (2015) compared ITD and ABA in estimating forest inventory attributes and obtained similar relative RMSEs for stem volume (30%) and basal area (25% with ITD and 26% with ABA) with both methods. SfM was also applied in developing a DTM for a river channel by Javernick et al. (2014) who reported vertical surface error of 0.1 m in non-vegetated areas.

Spaceborn remote sensing data have traditionally been applied in large-scale inventory, which can also provide 3D information. Synthetic aperture radar (SAR) images in particular have been used in deriving 3D data based on stereoscopic measurements (i.e. radargrammetry) (La Prade, 1963; Raggam et al. 2010), which is similar to stereo photogrammetry where the 3D coordinates of an object can be measured from two images taken from different positions. Another possibility is to apply interferometry, which utilizes the phase difference of two SAR images. SAR images have been applied in estimating growing stock volume and AGB as a comparison with other remote sensing data sets such as ALS (Hyde et al. 2007; Nelson et al. 2007; Holopainen et al. 2010a; Vastaranta et al. 2014a). The results of these studies indicate a higher prediction accuracy of ALS. The radar satellites offer data at short time intervals and are thus suitable for change detection although their spatial resolution is not comparable to ALS. Thus, they are not adequate in retrieving detailed forest resource information, but their best features are in monitoring.

Table 2. Digital terrain model accuracies used in change detection studies reported as root-mean-square error (RMSE).

Study	Data source	Smallest RMSE (m)	Largest RMSE (m)
Thoma et al. (2005)	ALS	0.061	0.067
Rosso et al. (2006)	ALS	0.020	0.043
Vaaja et al. (2011a)	MLS	0.023	0.076
Flener et al. (2013)	MLS	0.015	0.018
Blasone et al. (2014)	TLS	0.036	0.080

Remote sensing in change detection

Remote sensing provides a tool for inventorying large areas and performing repetition during data collection in a more affordable manner than traditional field measurements. In addition, requirements for monitoring vegetation and its changes have improved the accuracy of remote sensing data and increased multi-temporal 3D remote sensing data sets, i.e. the spatial and temporal resolutions of remote sensing data have increased. Landsat satellite images provide the highest temporal resolution of space-based Earth observation programs and they have been applied in mapping and monitoring vegetation characteristics especially after the data became accessible free of charge in 2008 (e.g. Borak et al. 2000; Wulder et al. 2008; Wulder et al. 2010; Banskota et al. 2014; White et al. 2014; Hermosilla et al. 2015). Banskota et al. (2014) reviewed the utilization of Landsat satellite images in forestry applications and concluded that two main approaches exist for detecting changes: classification and trajectory analysis, although methods in between have also been proposed (e.g. Lambin and Strahler, 1994a, b; Varjo and Folving, 1997; Häme et al. 1998). In classification analysis two or more images are classified and then compared to identify changes, whereas the variation in a single spectral value is analyzed in trajectory-based methods to detect changes in vegetation. The uncertainty of cloud-free products and the coarse spatial resolution are challenges faced when using optical 2D images.

Bi- or multi-temporal laser scanning data sets have been used in detecting changes in varying environments and changes have been estimated directly or based on differences between the estimations from two or several time points. In urban recreational forest, bi-temporal ALS data were applied in creating a difference raster to map the downed woody debris on the single-tree, canopy-gap, and stand levels (Tanhuanpää et al. 2015). First, trees were delineated from both years and changes in the difference raster were detected, as they were expected to indicate new canopy gaps, i.e. fallen trees that were possible to detect with 97.8% accuracy. Hyyppä et al. (2009) applied MLS in urban environments for predicting changes in biomass at the single-tree level, and they concluded that by comparing the total number of laser points from different time points it would be possible to determine changes in the biomass of an individual tree, although the method requires further studies and development.

Multi-temporal ALS data sets have been applied to observe erosion or deposition on shorelines, based on changes in DTM (White and Wang, 2003; Thoma et al. 2005) or in 3D profiles (Stockdonf et al. 2002; Shrestha et al. 2005). Alterations in riverbanks have also been investigated using TLS- (Blasone et al. 2014) or MLS-based (Vaaja et al. 2011a; Flener et al. 2013) multi-temporal DTMs, where changes have been detected by identifying differences between the DTMs from different time points. The accuracy of change detection is a result of the accuracy of the produced DTMs, thus these studies merely reported the DTM accuracies that seem to be similar to each other (Table 2). However, Vaaja et al. (2011a) reported a standard deviation (STD) of 3.4 cm in the error for change detection while RMSEs for DTMs varied between 0.023 m and 0.076 m after removing systematic error. Vegetation changes along water systems have been monitored using ALS-based DSMs from different years by subtracting them from each other and creating a difference raster (Rosso et al. 2006).

This type of analysis based on difference rasters has also been applied in predicting forest growth (Yu et al. 2006; Yu et al. 2008), detecting harvested trees (Yu et al. 2004), mapping snow-induced disturbance (Vastaranta et al. 2012b), as well as estimating change in the AGB (Hudak et al. 2012) of managed forests using ALS. Yu et al. (2008) also presented several methods for estimating plot-level forest growth and concluded that differencing individual tree tops from point clouds obtained from different years provided most accurate results for mean height growth estimations (an R^2 value of 0.86 and an STD of residuals of 0.15 m). For volume growth, on the other hand, a difference raster produced the best results: the R^2 value was 0.58 and the STD of residuals was 8.39 m^3/ha (35.7%). Yu et al. (2004) were able to detect 73.5% of harvested trees correctly whereas, Vastaranta et al. (2012b) identified 66.3% of damaged trees accurately with a difference raster. One of the challenges related to single-tree-level change detection (Yu et al. 2004; 2006; 2008; Vastaranta et al. 2012b) is the uncertainty in matching the trees from different data sets. However, Yu et al. (2006) concluded that ALS-based location and tree heights together are adequate for tree-to-tree matching. Hudak et al. (2012) predicted the AGB for two separate time points and created biomass maps as well as a difference image to produce change predictions. Based on stand-level validation, the RMSEs of estimated AGB for 2003 and 2009 were 45.1 Mg/ha and 57.1 Mg/ha, respectively.

Another way of distinguishing alterations is to predict attributes of interest for several years based on multi-temporal ALS. Huang et al. (2013a) used large footprint ALS data to predict AGB for 2003 and 2009 and to obtain change predictions. They concluded that a plot size of 1.0 ha produced the most accurate results for AGB with RMSE varying between 22.4 Mg/ha (15.6%) and 23.1 Mg/ha (16.1%). Andersen et al. (2014) monitored selective logging with bi-temporal ALS data through AGB predictions. They reported a change of -9.1 Mg/ha and demonstrated an increase of roads, skid trails, and large tree gaps as a result of logging activities. Using model-based (MB) statistical approach Andersen et al. (2014) were able to assess the uncertainty of the change, which was reported to be 1.9 Mg/ha. Magnussen et al. 2015) compared model-assisted (MA) and MB estimations in assessing AGB changes with ALS and concluded that results were similar for both: the relative STD for the change estimate using MA was 2.5 Mg/ha (93.1%) and 2.6 Mg/ha (96.7%) using MB. Næsset et al. (2013) and Skowronski et al. (2014) compared direct estimates of changes in AGB (i.e. a change in ALS metrics was applied) to the change estimates of AGB based on different regression models from various years. Both studies gained better results when change was estimated directly compared to separate estimates for different years that are then differenced to obtain change: standard error (SE) decreased from 3.7 Mg/ha to 1.6 Mg/ha in Næsset et al. (2013) and from 1.6 Mg/ha to 0.1 Mg/ha in Skowronski et al. (2014). Kaasalainen et al. (2014) applied TLS in a laboratory environment to detect detailed changes in branches and gained underestimations for TLS-based volume and length. Liang et al. (2012a), on the other hand, tested the applicability of TLS in distinguishing harvested trees and obtained 90% accuracy in mapping removed stems. Srinivasan et al. (2014) used TLS in estimating tree-level changes in AGB and obtained best results when estimating change directly, although an R^2 value of only 0.5 was obtained corresponding to an RMSE of 10.09 kg.

Natural disturbances have traditionally been considered a risk for forest ecosystems and yield value, although they could be perceived as introducing biodiversity. Even without multi-temporal data, it has been possible to predict snow accumulation and ablation (Varhola et al. 2010), and fire severity (Montealegre et al. 2014) using ALS. Varhola et al. (2010) concluded that an ALS-derived variable of forest cover was the most significant explanatory variable resulting in R^2 values of 0.70 and 0.59 with snow accumulation and snow ablation, respectively. Motealegre et al. (2014) used logistic regression modeling and were able to obtain 85.5% accuracy when estimating fire severity. On the other hand, Honkavaara et al. (2013) applied surface models based on both ALS and digital aerial imagery to automatically detect wind-blown trees by distinguishing differences between the two surface models obtained before and after a storm. They were able to automatically map clearly damaged (more than 10 fallen trees per ha) and undamaged forest stands with an accuracy of 100%, whereas the accuracies for minor damage (1–5 fallen trees per ha) and low damage (6–10 fallen trees per ha) were 52% and 36%, respectively. Näsi et al. (2015) further advanced the method developed by Honkavaara et al. (2014) for mapping bark beetle damage in urban forests and were able to detect single trees with an accuracy of 74.7% from which the best overall accuracy of 90% was obtained when trees were classified as healthy or dead. A combination of ALS and satellite images can be utilized for monitoring large-scale disturbances (Wulder et al. 2007).

One of the challenges in monitoring any types of changes lies in the registration of several data sets relative to each other. Different remote sensing data acquisition systems may result in imprecisions when data from different times are compared. The accuracy in observing changes thus decreases and may cause biased changes (e.g. Næsset, 2009), although ALS data accuracy is very high. Næsset and Gobakken (2005) used bi-temporal ALS and concluded that a two-year period is not enough for accurately predicting forest growth as sensor-specific acquisition specification may affect the metrics applied in predictions. To avoid this, a reported flight trajectory should be repeated when data acquisition for monitoring purposes is planned, especially when a widely applied differencing technique is concerned (Yu, 2007). One possibility, suggested by Hopkinson (2007), is to develop calibration models that could include the variation of different survey settings.

Study objectives

There is a need for accurate and up-to-date vegetation information for deciding on appropriate management activities or mitigating the possible effects of disturbances. Current systems for collecting information on vegetation (e.g. forest data systems) are inflexible for reacting to rapid changes in vegetation characteristics, thus new methods for updating this information are needed. Updated and improved knowledge of vegetation characteristics can be employed in observing changes in vegetation, for which increased temporal resolution of laser scanning data sets are required. Moreover, up-to-date materials are then available for decision-makers whether for preventing accidents in urban areas because of hazardous trees, providing protection against floods and erosion in riverine environments, or answering the objectives of private forest owners by means of forest management planning. Multi-temporal laser scanning data sets enable the development of accurate updating procedures for various environmental applications.

Information on occurred changes can be expected to be required annually, depending on the nature of the change. The type of information needed also varies between changes, e.g. when a disturbance event occurs, location and extent as well as effects (e.g. amount of damaged timber) of the event would be reported as soon as possible whereas improvement in the amount and quality of key habitats would be interesting when monitoring biodiversity during a certain time period. A real-time database for forest resource information would be an ideal situation where updated information could be stored. Compared to managed forests, the growth of urban trees and forests is not updated or predicted using statistical models, i.e. frequent inventories are required and cost efficient methods are needed. Knowledge of riverine vegetation is required to better understand fluvial hydrodynamics, geomorphology, bank erosion, and channel migration for improving flood risk mapping. Mapping and modeling disturbance events, especially wind, which has been the main cause of losses in forest yield values, is important to better understand and quantify drivers of wind damage risk.

The main aim of this dissertation was to develop techniques for predicting vegetation characteristics in varying environments (Figure 4). In more detail, substudy I aimed to develop a method for updating urban tree attributes. In substudy II, we developed a boat-based MLS method for mapping and monitoring vegetation changes in riverine environments. To advance methods for providing for changes in forests due to natural disturbances, we generated a risk map for wind damage in substudy III with open access ALS and multi-source NFI data sets to identify areas that are liable to wind-induced disturbance. The specific objectives of studies I–III were:

I To test a method called multisource single-tree inventory (MS-STI) in an urban environment for updating tree attributes. In our demonstration a TLS-based stem map is combined with an ALS data set that is further used in improving the accuracy of existing and in producing new tree attributes.

II To investigate the capability of MLS in developing an approach for mapping riverbank vegetation and applying the developed method for monitoring changes in vegetation.

III To analyze the applicability of open access ALS data especially for mapping the predisposition to wind disturbance in forests. The main emphasis was to investigate variables derived from ALS data that explain the probability of wind-induced forest disturbances.

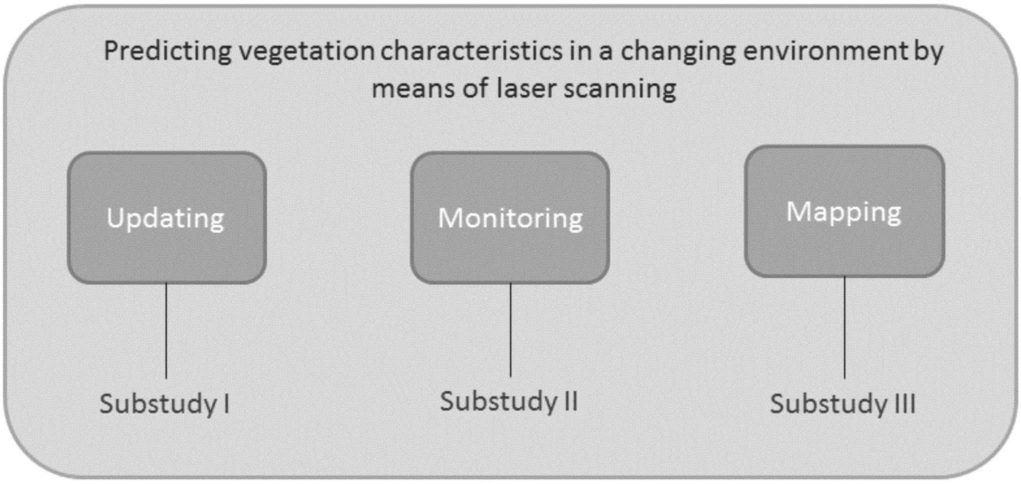

Figure 4. Different vegetation characteristics can be predicted using laser scanning on various platforms. However, predictions can be interpreted in various ways: i) ALS-based predictors were used and predictions provided updated tree attributes for urban green environments; ii) a vegetation class for riversides was predicted with MLS data for several years to enable the monitoring of occurred changes; and iii) mapping areas susceptible to wind disturbance was enabled with predictions based on ALS data.

MATERIALS

Study areas

Data for this thesis were acquired from three separate study areas (Figure 5). The study areas included a recreational urban park Seurasaari in Helsinki (I), Pulmanki River on the border of Finland and Norway (II), and an area of mainly managed forest in southwestern Finland near Huittinen (III). The study areas and data collected from these areas are presented here.

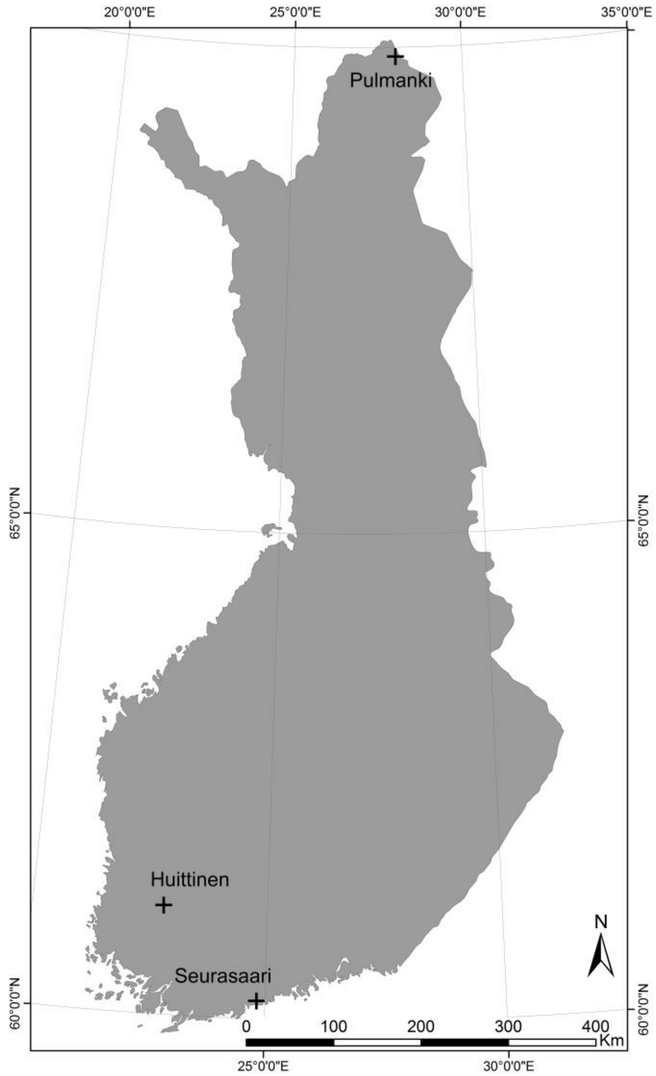

Figure 5. Locations of the three separate study areas used in this thesis.

Seurasaari

Seurasaari is a wooded island with rocks, hills, wetlands, and herb-rich forests covering ca. 46 ha, located approximately five kilometers from the Helsinki city center in Finland. The Seurasaari study area was used in substudy III. Seurasaari is a popular outdoor recreation area: it was made a public park in 1890, quickly became a popular place for recreational activities, and currently receives hundreds of thousands of visitors per year. Our study area in Seurasaari comprised of two parts, covering approximately 2.7 ha in total.The northern part is a well-managed urban park comprised mainly of sparsely situated old oaks with grass as the only understory vegetation, while the southern part more resembles a natural unmanaged forest park with varying understory vegetation. The distribution of tree species was diverse and consisted of 11 different species (Table 3), which describes the heterogeneity of the research area. The area has a dense network of artificially constructed outdoor paths that can also be used by vehicles.

Pulmanki

Pulmanki River is a 58-km tributary of the subarctic River Tenojoki (Tana) and flows across the border of Finland and Norway at a latitude of 69.95 °N and a longitude of 28.10 °E, where Lake Pulmanki divides the river into two parts. A study area of 3.5 km along the Pulmanki River was used in substudy II. The river has eroded a channel 30 m deep and 20–50 m wide. The river is characterized by steep banks, is highly sensitive to erosion, and has large point bars. Snowmelt causes spring floods, whereas the water level is lowest and point bars are maximally exposed in late summer. During snowmelt and the spring flood period, the water level can be several meters higher than during low-flow periods in summer and autumn. Flooding causes remarkable sediment transport, including heavy erosion and deposition along the riverbanks and point bars.

Huittinen

The study area of substudy III is located in southwestern Finland with center coordinates 61°4′33″N, 22°52′3″E and covers approximately 173 km^2 (Figure 5). The area is comprised primarily of managed boreal forests and agricultural fields. The main tree species are Scots pine, Norway spruce, and silver and downy birches. The area has a flat topography with a terrain height range of approximately 50 m to 111 m above sea level (STD 12 m). On 26th and 27th December 2011, the area was subjected to a heavy winter storm. The storm caused extensive damage to the study area, with the most damaging west and northwest winds blowing on the morning of December 26th 2011 at an average speed of 18.3 m/s and a maximum speed of 28.7 m/s.

Reference data

Seurasaari

Steel calipers were used to measure the DBH of 389 trees. The average DBH for the entire study area was 268 mm and varied between 31 and 482 mm. Because the two detached areas differed from each other, the mean DBH was determined for both areas separately: DBH was 371 mm in the park and 261 mm in the forest. The number of trees was 27 in the park and 362 in the forest. More specific statistics on DBH are presented in Table 4.

Table 3. Relative tree species distribution in the study area of Seurasaari.

Species	***%***
Acer platanoides	2.64
Alnus sp.	9.13
Betula sp.	7.30
Picea abies	25.96
Pinus sylvestris	19.88
Populus tremula	9.94
Quercus robur	6.69
Salix caprea	0.81
Sorbus aucuparia	14.60
Tilia cordata	2.43
Ulmus sp.	0.61

Pulmanki

In substudy II aerial images were applied as reference data and they were acquired using an unmanned aerial vehicle (UAV) helicopter to provide additional information on vegetation. The images were taken in 2012 at the same time as MLS data were acquired. The images were taken with a Samsung NX1000 micro-DSLR camera equipped with a 16- mm F2.4 lens mounted onboard a T-Rex 700E RC helicopter. As the UAV helicopter was controlled manually, the flying altitude varied, with most of the images taken between 20 and 70 m above ground level, and with an average flying altitude of 47 m. A total of 1687 images from six flights were used in the production of the orthophoto, which was generated using the Agisoft PhotoScan software. The images were geo-referenced with 84 signals or spherical targets placed around the target area, and the accuracy of the bundle adjustment was 7.3 cm.

Huittinen

Aerial images were also used as ground truth in substudy III. They were acquired using a Microsoft UltraCamXp (Microsoft UltraCam 2013) large-format mapping camera after a wind damage event on January 8th 2012. The average flying height was 5370 m above ground level, which provided a ground sample distance of 32 cm. The images were taken in a block structure, with 16 image strips and approximately 30 images per strip; the forward overlap of the images was 65%, whereas the side overlap was 30%; the distances of the image strips were approximately 3900 m. The atmosphere was clear, and the solar elevation was as low as 5° to 7°. The data were collected between 11:56 am and 2:11 pm local time (UTC +2). The first snow had fallen prior to the collection of the aerial images, so there was approximately 10 to 20 cm of snow cover on the ground. It is likely that there was also some snow on the trees, but the visual evaluation of the images indicated that snow levels were tolerable for delivering accurate data of the study area.

Laser scanning data

Airborne laser scanning

ALS data were used in substudies I and III. For substudy I an Optech 3100 laser scanner (Optech Inc., Vaughan, ON, Canada) was used with a flying altitude of 400 m. The measurement density was at least 20 points per m^2 (the pulse density was approximately 20 pulses per m^2), and the return type was recorded (first-of-many, single, intermediate, last). The dense ALS data for substudy I were acquired in May 2011. The ALS data set used in substudy III was open access data obtained from the NLS. The specifications for the data collections provided by the NLS include a flying altitude of 2000 m, a maximum scan angle of ± 20° and a footprint of 50 cm; preferential collection occurred during the bare-ground season or during spring time, when trees have small leaves. The minimum measurement density of the NLS ALS data is half a point per square meter and the elevation accuracy of the pulses in well-defined surfaces is 15 cm with a horizontal accuracy of 60 cm. The ALS data used in substudy III were collected in the spring of 2008.

Table 4. DBH statistics (presented in cm) calculated from the field measurements.

	Park	**Forest**
Minimum	8.6	3.1
Maximum	48.2	48.1
Mean	37.1	26.1
Standard deviation	11.0	12.5

Terrestrial laser scanning

The TLS data for substudy I were collected with a Leica HDS6100 TLS system (Leica Geosystems AG, Heerbrugg, Switzerland) from the Seurasaari study area (I) in September 2010. The HDS6100 is a 690-nm phase-based continuous-wave laser scanner with a 360° × 310° field of view (FOV) upward, and its data acquisition rate is 508000 points per second. The distance measurement accuracy is ±2 mm at a distance of 25 m. The circular-beam diameter at the exit and the beam divergence are 3 mm and 0.22 mrad, respectively. The point spacing is 6.3 mm at 10 m. Further detailed specifications are presented in Table 5.

TLS measurements in Seurasaari were collected in multi-scan mode. The park areas were scanned as-is. Pre-scan preparations, e.g., removal of low vegetation, were not performed, as this is not permitted in the city forests of Helsinki. The measurement objective was to obtain good point coverage. The data were collected in five to seven scans per group; a total of 52 scans were performed to cover the entire study area. The center scan station and at least one reference target (sphere) of each scan group using a GNSS virtual reference station and a tachymeter to ensure accurate co-registration. The center scans were placed so that the canopy layer did not block GNSS satellite visibility. We subsequently transformed the scans into global coordinates (ETRS-35TMFIN) using reference target locations and scanning locations.

Mobile laser scanning

MLS data were used in substudy II and were acquired to measure riverine topography and characterize vegetation at the Pulmanki River study area. The data were acquired in late summer (late August to early September) in 2009, 2010, 2011, and 2012. The ROAMER -mobile mapping system (MMS) was employed and it was mounted on an inflatable boat with a motor. The ROAMER MMS utilizes the FARO Photon 120 (for data acquisition in 2009 the FARO Photon 80 for a previous ROAMER version was used) terrestrial laser scanner to acquire 3D measurements (Alho et al. 2009; Kukko et al. 2007). The FARO Photon 120 achieves a maximum mapping range of 120 m, a measurement rate of 120–976 kHz, a FOV of 320°, and a beam divergence of 0.16 mrad. The system parameters used each year are summarized in Table 6. The navigation solution for the MMS is generated by the NovAtel Synchronized Position Attitude Navigation (SPAN) technology, which integrates a Global Positioning System (GPS) and inertial data for applications that require greater functionality and reliability than traditional stand-alone GPS is capable of offering. The SPAN system also operates in real-time kinematic mode with an internet-based application (Kukko et al. 2007). The GPS receiver is a NovAtel DL-4plus containing an OEMG2 engine and a GPS-702 antenna that offers access to the GPS L1 and L2 frequencies. The IMU is a tactical-grade, ring-laser gyro-based unit manufactured by Honeywell. The laser-acquired point data were geo-referenced during post-processing using raw laser scanning data, laser scanning trajectory data, and synchronization data. Waypoint Inertial Explorer software was used to compute the laser scanning trajectory, combining IMU and GPS data logged by the SPAN and data logged at the GPS reference station on the site. Under good conditions the elevation accuracy of the ROAMER point cloud is better than 3.5 cm up to a range of 35 m, and the planimetric accuracy is better than 5 cm with a range of 45 m (Kaartinen et al. 2012a).

Table 5. Leica HDS6100 TLS system and specifications.

	Leica HDS6100
Field of view	310◦ × 360◦
Range	79 m
Speed points/s	508000
Spot size	3 mm + 0.22 mrad
Distance measurement accuracy at 25 m	±2 mm
Max resolution Hor × Ver	0.009◦ × 0.009◦
Max points 360◦ Hor × Ver	40 000 × 40 000
Laser wavelength	690 nm
Laser power	30 mW
Weight	14 kg
Operating temperature	−10 to 45 ◦C

Multisource national forest inventory data

We did not use field data as such in substudy III, but openly accessible forest attribute data provided by the Natural Resources Institute Finland based on multisource NFI. Data from Finnish 11th NFI were utilized to obtain information of tree species-specific stem volumes and biomasses (per hectare). The field plot measurements for the 11th NFI were conducted during five years, starting in the summer of 2009 (VMI11, 2009). Sample plots (492 m^2), utilized in the multisource NFI, are arranged into clusters, and the distance between clusters is 6 × 6 km in the southernmost part of Finland where the study area of Huittinen is located. In addition to field measurements, Landsat TM satellite images were utilized in multi-source NFI to predict forest attributes using a k-nearest neighbor approach (Tomppo et al. 2008). The results are presented as thematic maps (a resolution of 20 m x 20 m) picturing site type, canopy cover, age, mean DBH and height, basal area, as well as species-specific stem volume and biomass per hectare. The expected accuracy of the estimated forest attributes at the sample plot level varies between 50–80% (RMSE) in stem volume, height, and basal-area (Tuominen and Haakana, 2005). Information from the thematic maps of site type, species-specific volume, and biomass were used in this study. In Finland, site types are classified based on soil fertility and identified by means of surface vegetation by adopting indicator species (e.g. *Vaccinium myrtillus*) which are also applied when naming the site types.

Table 6. System parameters for the mobile laser scanning acquisitions at different time points (f_s = scanning frequency, f_p = point measurement frequency, h_s = sensor altitude from the water surface, and r_a = angular resolution).

Date	f_s (Hz)	f_p (kHz)	h_s (m)	r_a (°)
2009 September 3	30	120	2.5	0.090
2010 August 31	49	244	2.5	0.072
2011 September 8	49	244	2.5	0.072
2012 September 13	49	488	2.5	0.036

METHODOLOGY

Methods used in several substudies

Generating terrain, surface, and canopy height models

Laser scanning provides 3D point clouds that are used to generate surface models for various purposes. One laser pulse can produce several echoes and these echoes and their differences are utilized in surface model generation. The last returns are assumed to come from the ground, and thus these returns are used in generating DTM. On the other hand, the first recorded returns are applied in generating DSM to develop CHM. ALS data were used in substudies I and III in generating DTM, whereas DTM was generated from MLS data in substudy II. The method developed by Axelsson (2000) was applied to classify as ground and non-ground laser points. The method creates a sparse triangulated irregular network (TIN) from seed points that are confident hits from the ground. The seed points form the initial DTM and laser points are then added one at a time if they fit within specified constrains (i.e. maximum distance and maximum angle between a point and the triangle plane, projection of a point on the triangle plane, and closest triangle vertex). The iteration continues until no points are left below the thresholds. Above-ground point heights (normalized height or canopy height) were then calculated by subtracting the ground elevation heights from the maximum point heights. A CHM with a resolution of 0.5 m (I) and 1 m (III) was then created from normalized ALS point-height data by assigning the maximum ALS point height from first-of-many or single echoes to each CHM cell. Cells with no data were filled with the mean height value from a window of 3 x 3 neighboring cells. MLS data based on phase-shift measurements in riverine environments include false points in the air and below ground that are mainly reflections from the water surface and have to be filtered out before further processing. Typically these noise points have relatively low intensity values, thus points with less intensity than a specified threshold can be removed. Noise points in the air can be removed by detecting isolated points, i.e. points with empty space around them within a certain radius. The appropriate thresholds for intensity and density values were determined in substudy II based on test samples of points from each year. The intensity threshold used in substudy II for the filtering varied from 500 to 700 between years, whereas the threshold for the density-based method varied between 10 and 15 points within a spherical radius of 30–50 cm for different years.

Extracting metrics from laser scanning data

Metrics for predicting vegetation characteristics can be extracted from created surface models, usually from CHM, or from normalized point clouds. The unit for extracting metrics can vary depending on the method used and the objectives of the study. The most common units are a grid cell, tree crown segment, or micro stand. In this study, a grid cell of different sizes and tree crown segments were used as units for the metrics extraction. In individual-tree detection CHM is segmented in a way that allows individual tree crowns to be delineated from each other. Micro stands are produced automatically or semi-automatically from CHM, producing continuous and homogenous areas that correspond with the natural boundaries of a stand. Information on CHM height and density can be used when micro stands are segmented. Tree crowns were delineated in substudy I with watershed segmentation, where the local maxima of CHM are detected and segments describing tree crowns are considered as basins (Kankare et al. 2013c; Vastaranta et al. 2012a; Yu et al. 2011). In the grid-based approach, metrics from laser scanning data are usually extracted from normalized point clouds (Næsset, 2002; Woods et al. 2011) because they are as close to the original data as possible. Several tools exist for extracting metrics, but Fusion software was applied in substudy II to derive metrics from MLS point clouds. The height values were normalized to above-ground height using DTM generated from the MLS data. Metrics are usually extracted for grid cells with size corresponding to the size of the field plots used as a reference (Magnussen and Boudewyn, 1998; Næsset, 2002). In substudy II, the grid cell size was 2 m x 2 m to incorporate small-scale variability of vegetation, whereas in substudy III the grid cell size was 16 m x 16 m, corresponding the resolution used in ALS-based forest inventory information in Finland. In substudy II, the reference data covered the entire study area and all vegetation classes were included in the reference data set.

Nowadays, as the ALS pulse frequency has increased, similar metrics can be extracted for a grid cell and crown segment, and thus the extracted metrics of different substudies were also similar. The metrics extracted from CHM in substudies I and III included maximum, minimum, and mean values, as well as STD and the coefficient of variance. The metrics in substudy II included minimum, maximum, mean, and STD of point heights as well as the 1st, 5th, 10th, …., 90th, 95th, and 99th percentiles of laser heights. In addition, in substudy I heights at various percentiles (from the 10th to the 90th) from the height distribution of CHM and crown-cover density metrics as a proportion of heights below a certain relative tree height were calculated. To ensure the predicative power of the developed models, the relationship between the attributes of interest and laser scanning metrics is expected to be as strong as possible. In forestry applications, this relationship relies on the ALS data and how well the characteristics from canopy height and density can be derived from it (Næsset, 2011). As a result, research has shown (Nilsson, 1996; Nyström et al. 2012) that a threshold height could be used to separate canopy and non-canopy returns to ensure the predicative power of the models. Two meters has been a widely applied value for the threshold (Nilsson, 1996; Næsset, 2002; Packalén and Maltamo, 2008; Latifi et al. 2010; Frazer et al. 2011; Maltamo et al. 2011; Hyyppä et al. 2012; Bouvier et al. 2015), i.e. returns below that threshold, which were not classified as ground returns, were excluded from the point cloud metric calculations. This idea was thus also applied in substudies I and III: in substudy I the heights within a tree segment above 0.5 m were classified as originating from the vegetation (i.e. tree) and therefore included in the analysis, whereas a threshold value of 2 meters was applied in substudy III; heights below the thresholds were left out from further analyses. Vegetation density ratio was a metrics used to describe vegetation density, and it was calculated as a ratio between vegetation heights (i.e. heights above 0.5 m) and all heights within a tree crown, in substudy I. In substudy III, vertical canopy cover was expected to represent forest density and it was derived from CHM by including all points higher than 2 meters (CHM > 2 m).

Selection of predictor variables and prediction of vegetation characteristics

Attributes of interest are predicted for the same units where the metrics were extracted from. One of the most used methods in predicting forest or tree attributes is the nearest neighbor (NN) approach, where variables measured from the field (substudy I) or from other references (substudy II) are used as target observations and metrics extracted from remote sensing data are used as predictors. In recent years, the Random Forest approach (Crookston and Finley, 2008) has been applied widely in NN predictions of forest variables (Hudak et al. 2008; Yu et al. 2011) and it has proved more robust and flexible than other NN approaches such as Euclidian distance, Mahalanobis distance, or canonical correlation analysis (Hudak et al. 2008). It was therefore also used in substudies I and II.

In the Random Forest method, several regression or classification trees are generated by drawing a replacement of two-thirds of the data for training and one-third for testing each tree (i.e. out-of-the-bag samples). A regression tree is a sequence of rules that splits the metrics space into partitions that have values similar to the response variable. The measurement of nearness in a random forest is defined based on observations of the probability of ending up in the same terminal node during classification. The output is the percentage increase in the misclassification rate as compared to that of the out-of-bag rate (with all variables intact).

Usually the amount of metrics extracted from remote sensing data is large, thus the number of predictors is decreased before further modeling the attributes of interest. Haapanen (2014) presented that an automatically selected subset of all features resulted in better estimates for forest inventory attributes and smaller estimation error compared to including all possible features. This is due to a reduction of noisy features and dimensions. In substudy I, random forest was also used to reduce the number of predictor variables, discarding the least important of the candidate variables after each iteration based on the importance of the variable, until only one predictor variable remained. RMSEs for each predictor-variable combination were calculated, and a minimum number of predictors were selected before the out-of-the-bag estimation accuracy (i.e. RMSE) increased notably. In substudy II, on the other hand, predictor variables were chosen based on biological relevance and previous experience, thus predictors that were sensitive to single errors were left out. The selection process in substudy III began with stepwise logistic regression, but the final selection included analyses of the data, correlations, and on preliminary modeling results, i.e. the predictors were chosen on the basis of biological plausibility as well as statistical significance. The methods used in different substudies are described in more detail in the following chapters.

More detailed descriptions of methods used in different substudies

Multisource single-tree inventory (I)

MS-STI is a method where tree mapping on the ground and above the canopy are combined, i.e. species-specific stem map and remote sensing data are conjoined in predicting tree attributes. This stem map can be either produced by traditional tachymeter measurements or it can be a tree register from urban trees, the important aspect is that tree locations are known. Remote sensing data from ALS or aerial images then provide predictor variables for modeling. The principle of MS-STI is presented in Figure 6, where reference data are envisioned to be produced by TLS or MLS, not only through traditional field measurements using calipers and a clinometer. Compared to other methods identifying individual trees, MS-STI attempts to avoid two major bottlenecks of the current ALS-based single-tree-level inventory, namely tree detection and tree species recognition.

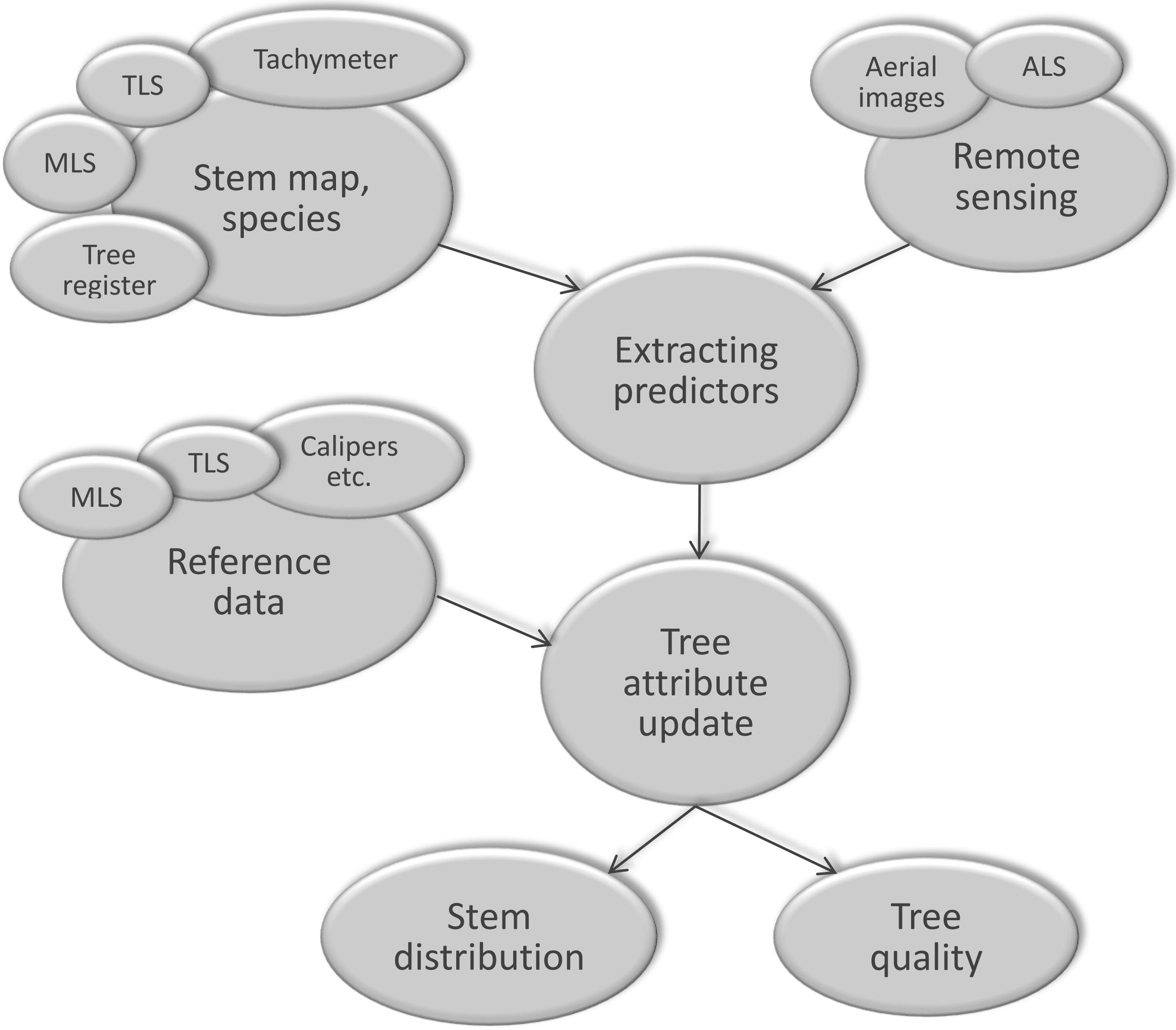

Figure 6. Overview of multisource single-tree inventory.

A stem map was created from TLS data in substudy I: tree detection was performed manually from processed TLS point clouds using visual interpretation. The tree detection from TLS data was performed through the following steps: (1) the point cloud of each scan group was imported into TerraScan and thinned by 50%; (2) points at a height of approximately 1.3 meter were separated from the remainder of the point cloud as a horizontal “slice”; (3) tree stems were identified and marked within the slice (see Figure 7); and (4) location and DBH information were recorded for all the identified trees.

CHM segments presenting tree crowns were linked to the trees in the stem map and predictor variables (i.e. statistical metrics) describing tree crown density and tree height from the ALS data were extracted to these segments. Random forest was applied in selecting nearest neighbors for predicting DBH, 1200 regression trees were generated in substudy I, and the square root of the number of predictor variables was randomly picked at the nodes of each regression tree. Randomness was taken into account by running the random rorest method 100 times. The final result was the average of these runs. The number of neighbors varied between 1 and 5. Prior to the modeling, random forest was used to reduce the number of predictor variables. A step-wise looping procedure was used to iterate random rorest, discarding the least important of the candidate variables at each iteration, based on the variable importance, until only a single predictor variable remained. RMSEs were calculated for each predictor variable combination and analyzed before the final modeling. As the study area in substudy I consisted of two very different parts (urban park and semi-natural forest) ALS-derived predictors were selected and results calculated separately for both parts.

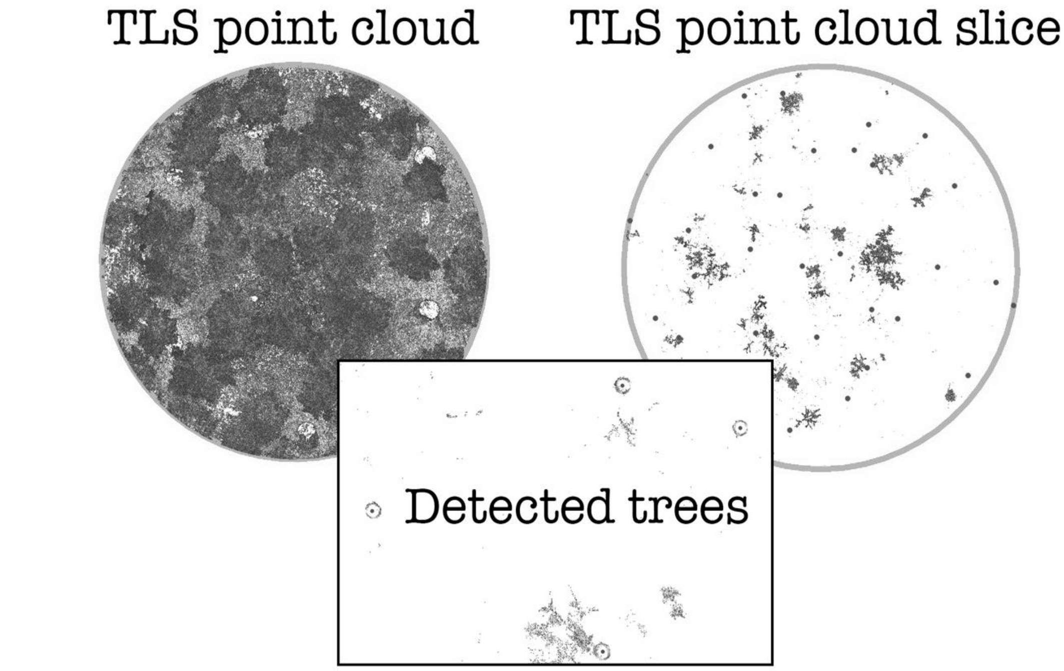

Figure 7. Example of the tree detection method (substudy I) from the TLS point clouds. © MDPI.

Area-based approach in mapping and monitoring riverine vegetation (II)

To map riverine vegetation four vegetation classes were defined according to a common woodland sequence structure found in Finnish forests. Areas with no vegetation were called bare ground. The field layer was composed of grasses, ferns, and low-growing shrubs, (e.g. blueberry (*Vaccinium myrtillus*) and heather (*Calluna vulgaris*)), whereas the shrub layer contained small trees and larger shrubs. The dominant tree canopy was determined as the canopy layer. Vegetation class was determined for 230 training grid cells using the visual interpretation of aerial images. Training cells were selected systematically over the study area to include approximately equal samples from each vegetation class.

The area-based prediction of vegetation was based on a statistical dependency between the vegetation classes defined from the aerial photos and predictor metrics extracted from MLS point clouds acquired in 2012. A total of twenty metrics were extracted from MLS data, three of which were chosen for further predictions. The selected metrics were: mean height, height at 95th percentile, and standard deviation of height. The selected metrics characterized vegetation height and density, but were not oversensitive to single erroneous points. The random forest method was used where the number of nearest neighbors (parameter *k*) was defined as five based on previous knowledge concerning the optimal number of *k* in regards to reducing relative RMSE (Vastaranta et al. 2014a). A total of 1000 regression trees were used in each run to increase the consistency. The model developed with the random forest method was trained with the data from 2012; the same model was also used to predict vegetation classes in 2009, 2010, and 2011.

Logistic regression in mapping and modeling wind damage risk (III)

Before wind damage probability could be modeled the damaged areas were mapped based on aerial imagery. Altogether 500 sample grid cells (16 m x 16 m) were selected and verified visually, from which 70 were deleted because they were located somewhere else than a forest (i.e. on an agricultural field, a road) or they were adjunct to a field, road, house, or other infrastructure. After visual inspection 430 sample grid cells remained: 196 were classified as damaged and 234 as undamaged. Predictor variables for logistic regression were extracted for these sample cells from ALS and multisource NFI data. Variables related to topography and elevation, such as slope and aspect, as well as general statistics (i.e. minimum, maximum, mean, and STD) of the elevation values were derived from the DTM. Mean elevation (also mean value of DTM), slope, and aspect as well as mean value of CHM were extracted for each sample unit (16 m x 16 m grid cell), but also for a window of nine 16 m x 16 m grid cells centered by the sample cell, to take in more information of conditions surrounding the sample cells. Furthermore, aspect was calculated as a categorical variable corresponding to half-cardinal points (i.e. northeast, southeast, southwest, and northwest) to correspond to the direction of the destructive winds, namely northeast. CHM was also applied in extracting geographical variables describing distance and proximity of the sample unit to the closest open area. Open areas were identified as areas with no canopy cover based on information from the CHM, and contiguous areas were larger than 1 ha. Distance was determined as the shortest distance from each sample cell to an adjacent open area. Conversely, proximity was a categorical variable characterizing whether a sample cell was located next to an open area or not. A total of 31 continuous and four categorical predictor variables were extracted.

Logistic regression is used in estimating binary dependent variables, thus, the discrete dependent variable (i.e. damage, no damage) in substudy III was-well suited for applying logistic regression for modeling the probability of a wind damage event. Logistic regression calculates changes in the logit variable, not in the dependent variable itself (Hosmer and Lemeshow, 2000) and thus logistic regression is not subjected to many of the restrictive assumptions of ordinary least squares regression (OLS) (i.e. normal distribution of the dependent variable and error terms, homogeneity of variance, interval or unbounded independent variables) (Press and Wilson, 1978; Rice, 1994). The logistic regression coefficients (β_0, β_1, etc.) are presented in logarithmic scale, which means they can be interpreted as a change in the probability of the event in interest (wind damage) when the predictor variable changes by one unit.

Logistic regression was applied to form two separate models, one with predictors only from ALS data (LR_{ALS}) and another where ALS derived predictors were combined with multi-source NFI variables ($LR_{ALS+NFI}$). Thus, the effect of including information of tree species could be assessed. Potential predictor variables were assessed by using logistic regression analysis in R (v. 3.1.1, R Core Team, 2007), with stepwise elimination of variables where both forward and backward elimination was applied. The maximum number of steps to be considered was set to be 1000. The final predictors for the models were selected based on previous studies (Peltola et al. 1999; Jalkanen and Mattila, 2000; Hanewinkel et al. 2008), by analyzing the sample, correlations, and on preliminary modeling results. Preliminary models were also compared separately using Akaike's information criterion, AIC (Akaike, 1974).

Final models were applied to generate maps indicating predisposition to wind disturbance. These maps allowed the identification of areas with a high probability of susceptibility to disturbance caused by wind across the study area. A cell size of 16 m x 16 m was used in the maps to correspond to the cell size of the sample cells.

Accuracy assessments and model validation

Predictors and target observations were available for all trees in substudy I. The accuracy of the predicted variables, namely DBH, at the tree level were therefore evaluated by calculating RMSE (Eq. 1) and bias (Eq. 2) using out-of-the-bag samples. The relative bias and RMSE were calculated according to the sampled mean of the DBH.

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

$$BIAS = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n} \tag{2}$$

where n is the number of observations, y_i the true value from the field data for observation i, and $\hat{\boldsymbol{y}}_{\boldsymbol{i}}$ the estimated value for observation i.

Stem diameter distributions were compiled from the tree-level estimations and compared to the field measurements in substudy I. The estimated stem diameter distributions were evaluated by the error index (EI) introduced by Packalén and Maltamo (2008):

$$e = \sum_{i=1}^{k} 0.5 \left| \frac{f_i}{N} - \frac{\hat{f}_i}{\hat{N}} \right| \tag{3}$$

where f_i is the true and $\hat{f}_i$ is the estimated stem number in class i, k is the number of classes or bins, and N is the true and $\hat{N}$ the estimated stem number of all diameter classes. The error index is modified from the one suggested by Reynolds et al. (1988). A weight of 0.5 was used to scale the error index between 0 and 1, where 0 means a perfect fit and 1 means that distributions do not overlap at all. The used bin size was 2 cm for DBH.

To evaluate the accuracy of vegetation mapping in substudy II, an independent testing set of 212 grid cells was selected: vegetation class was determined for this testing set again using the visual interpretation of aerial images. Aerial images were only available for the year 2012, thus this kind of evaluation was only possible to perform with the MLS data from 2012. Cohen's kappa values (Cohen, 1960) were calculated (Eq. 4) in addition to classifying the accuracy as a percent. As the acquisition parameters varied from year to year, a random sample (n = 27) from unchanged grid cells was chosen to validate the effect of the parameters on classification accuracy in 2009-2011.

$$K = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \tag{4}$$

where $\Pr(a)$ is the overall agreement among raters, and $\Pr(e)$ is the expected chance agreement (if agreement occurs by chance only). If the raters are in complete agreement then k = 1. If there is no agreement among the raters other than what would be expected by chance (as defined by $\Pr(e)$), K = 0.

Model validation in substudy III was performed by calculating the overall prediction accuracy and fit statistics: Nagelkerke's R^2 was applied to evaluate the goodness of fit of the logistic regression models; Wald z-statistics and their associated p-values were applied when validating the significance of each predictor variable for the model (p-values for the selected variables were set to have a maximum value of 0.01 to be sufficiently strong); and a likelihood ratio test (LRT) was employed to measure the overall significance of the model.

To assess the accuracy of produced risk maps, the risk maps produced with the two final models (LR_{ALS} and $LR_{ALS+NFI}$) in substudy III were compared to the reference acquired by visual interpretation of aerial images. If the predicted risk probability for a sample cell was over 0.5, the cell was interpreted as damaged and two-scheme classification accuracy percentage and Cohen's kappa values (Eq. 4) were calculated for the produced risk maps.

RESULTS

Multisource single-tree inventory in updating tree attributes (I)

When the relative RMSE was calculated for each predictor-variable combination, the minimum number of predictors was chosen before the out-of-bag prediction accuracy began increasing notably. However, the relative RMSE values varied between 18.8% and 20.1% in the park and between 25.0% and 33.8% in the forest; the estimation accuracy was thus not oversensitive to the number of used predictor variables. Eventually, six and seven predictors were selected for further modeling the park and forest, respectively, and they are presents in Table 7.

Although study area in substudy I was highly heterogeneous and forest conditions varied considerably, relatively reliable accuracies for the DBH estimations were obtained, particularly for the park, although the biases were, in general, smaller for the forested part (Table 8). Greater variation was observed in the forested part of the study area, which may be one reason for the larger relative RMSEs. Despite the forest conditions being somewhat different compared to the managed forest, and not fully comparable with previous research, the results were promising, particularly from the park as they are similar to the results obtained earlier (Peuhkurinen et al. 2007; Maltamo et al. 2009; Yu et al. 2011; Holmgren et al. 2012; Lindberg et al. 2012). It was additionally possible to produce more attributes for the existing tree register such as height and crown size. Moreover, more detailed information on DBH was produced as the existent tree register only included approximated DBH class estimation for each tree. Consequently, with the developed MS-STI method it was possible to update several attributes for all the trees and the estimated size distributions were close to the actual ones: relative error indices varied between 0.1 and 0.21 in the forested part (0 is a perfect fit). The goodness of fit between the actual and estimated diameter distribution decreased when the number of neighbors was more than one, in part because the extreme bins of the DBH classes were omitted when the number of neighbors increased. Nevertheless, the results were superior compared to previous studies (Packalén and Maltamo, 2008; Vauhkonen et al. 2013).

Table 7. Selected predictor variables for both arts of the study area in Seurasaari (substudy I) in order of importance. h_i = height percentile, p_i = proportion of heights below a certain relative tree height.

Park	Forest
h_{90}	h_{50}
p_{80}	h_{mean}
h_{70}	h_{60}
h_{60}	h_{70}
p_{90}	h_{40}
h_{max}	h_{20}
	p_{10}

Table 8. DBH estimation accuracy with different number of neighbors in substudy I.

Number of neighbors	Forest				Park			
	BIAS, cm	BIAS %	RMSE, cm	RMSE %	BIAS, cm	BIAS %	RMSE, cm	RMSE %
k = 1	−0.66	−2.53	7.58	29.11	0.67	1.81	3.97	10.70
k = 2	−0.17	−0.64	7.15	27.45	−0.15	−0.41	5.63	15.18
k = 3	−0.22	−0.85	7.06	27.08	−0.39	−1.05	6.63	17.90
k = 4	−0.15	−0.58	6.93	26.62	−1.06	−2.86	6.77	18.27
k = 5	−0.11	−0.41	6.85	26.29	−1.56	−4.21	7.09	19.12

Mapping and monitoring riverine vegetation (II)

Riverine environments are vulnerable to floods and erosion, and vegetation plays an important role in preventing or at least hindering their effects. MLS was used to map riverbank vegetation and detect changes in them. MLS data were combined with reference measurements in developing predicative models for vegetation classes at a resolution of 4 m^2. The predictor variables selected for the classification, namely mean height (H_{mean}), standard deviation of heights (H_{std}), and 95th height percentile (H_{95}), differed between the four vegetation classes within the grid cells used to train the random forest classification derived from the 2012 data. This result indicated that vegetation classes could be separated using the selected MLS metrics. The differences between vegetation classes for the mean values of H_{mean}, H_{std}, and H_{95}, were all statistically significant using the Student's t-test ($p < 0.001$). For bare ground, H_{mean} was 0.01 m on average. The respective mean values for field layer, shrub layer, and canopy layer were 0.7, 0.52, and 2.52 m, whereas the mean values for H_{std} were 0.01, 0.07, 0.40, and 1.90 m, and H_{95} were 0.02, 0.20, 1.19, and 5.59 m for the respective vegetation classes.

With a separate test set (n = 212) it was possible to classify vegetation cover with an overall classification accuracy of 72.6% by using the nearest neighbor approach based on MLS data from 2012. Classification accuracies for vegetation classes varied between 35.0% and 100.0%, where the field layer was most inaccurately classified whereas correctly classifying the canopy layer was possible (Table 9). Bare ground was misclassified as vegetated areas in 20.5% of occasions and vegetated areas were misclassified as bare ground in 0.7% of the instances. It was not possible to verify the accuracy of vegetation mapping for 2009–2011 since no ground truth data were available. Nevertheless, the random sample from unchanged grid cells (n = 27) attested the robustness assumption of classification and further that the selected metrics were not overly sensitive to variation in MLS acquisition parameters. The classification of vegetation was additionally rather simple. It can thus be assumed that the classification accuracy for 2009–2011 and through that the reliability of change detection was similar to the classification accuracy obtained with the 2012 data. Vegetation class was predicted to each year using the selected predictors and the random forest model based on data from 2012 and vegetation map for each year was produced. A vegetation map for each year was produced based on these predictions (Figure 8). Changes between data acquisition years were detected by subtracting the predicted vegetation maps from each other. Some variations were observed in the amount of change from year to year: from 2009 to 2010 changes occurred in 25.0% of the study area, whereas the respective figures from 2010 to 2011 and from 2011 to 2012 were 25.2% and 21.2%. Changes were detected all the way through the study area, not only on banks but also in meander bends and straight channel sections.

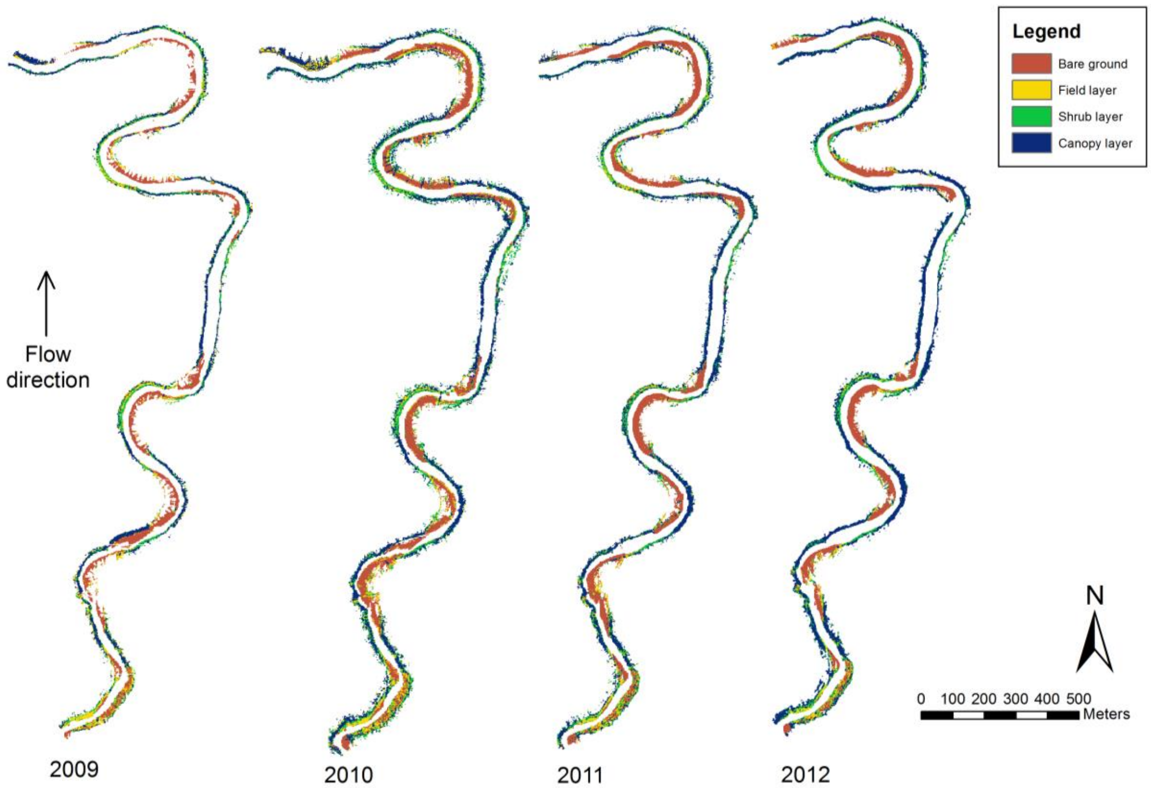

Figure 8. Predicted vegetation maps based on MLS data and random forest modelling for Pulmanki River in substudy II. © MDPI.

Modeling wind damage risk with multi-source data sets (III)

There is growing interest in utilizing openly accessible data sets especially in forest and environmental applications to increase data value and to develop new potential applications utilizing open access data from different sources. The Finnish NLS provides nationwide ALS data sets for public use. Natural Resources Institute Finland, on the other hand, produced forest attribute data for the entire country based on multisource NFI. These data sets were applied in predicting the predisposition to wind disturbance using logistic regression.

Scots pine and Norway spruce dominated the entire study area and 82.1% of the sample was dominated by conifers. Wind damage occurred in 45.6% of the sample, 94.4% of which was conifer-dominated. The mean volume per hectare was larger in damaged sample cells than in undamaged ones. CHM_{mean} and CHM_{max} were also higher in damaged plots, and it can thus be expected that mature conifer stands are most exposed to wind damage.

The mean CHM value from nine grid cells (including the sample cell) produced better results than the mean CHM value within the sample cells alone, and therefore CHM_{buf} was used over CHM_{mean} when predicting wind disturbance probability. The selected predictor variables included mean elevation (DTM_{mean}) and mean height of the surrounding forest (CHM_{buf}) when only ALS-derived variables were used in the logistic regression (LR_{ALS}). When adding information from the multi-source NFI in the modeling, the selected variables included pine and spruce stem volume (VOL_{pine}, VOL_{spruce}) in addition to DTM_{mean} and CHM_{buf}. Based on the Wald test, the significance level of 0.01 was reached in both models with the selected predictors. The model with a combination of ALS- and multisource NFI-derived variables ($LR_{ALS+NFI}$) was discovered to explain 52% of the variation related to wind damage; hence it was best suited to address the probability of wind disturbance. A prediction accuracy of 73% was obtained with the LR_{ALS} whereas the $LR_{ALS+NFI}$ produced an accuracy of 81%. Per unit change resulted in an increase in the odds ratios (damage probability) in any parameter (Table 10).

The output from the logistic regression is the probability of wind damage occurring and we used that to produce a continuous probability surface to present the likelihood that any given grid cell has wind damage. These surfaces can also be interpreted as maps indicating each cell's susceptibility to wind disturbance (Figure 9). For our results to be useful to forest practitioners, at resolution of 16 m was selected because this is the commonly used grid cell resolution for providing forest resource information from privately owned forests in Finland. The resulting maps could also be included in the forest management plans to assist in the decision-making of forest owners. In addition, forest managers could also incorporate the knowledge concerning forest predisposition to wind damage into their strategic and operative planning when allocating management activities for preserving biodiversity and maintaining the sustainable use of ecosystem services. This approach is most appropriate for mapping and modelling disturbance events associated with drivers related to topography as well as forest height and density because these attributes can easily be obtained from ALS data.

Table 9. Accuracy of vegetation classification into four vegetation classes in substudy II.

	Training Accuracy (%)	**Testing Accuracy (%)**	**Kappa Training**	**Kappa Testing**
Bare Ground	100.00	79.45	0.99	0.82
Field Layer	88.00	35.00	0.91	0.39
Shrub Layer	97.83	45.16	0.93	0.29
Canopy Layer	97.40	100.00	0.98	0.72
Average	97.39	72.64	0.96	0.61

Table 10. Parameters and fit statistics for the logistic regression models with DTM_{mean} and CHM_{buf} (LR_{ALS}), and combination of these two with pine and spruce stem volume per hectare ($LR_{ALS+NFI}$) developed in substudy III.

Predictors for LR_{ALS}	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**e^{β}**	**% change in odds**	**Wald**	**Wald sig.**
Intercept	-6.974414	0.923	-7.559	0.000			57.1	0.000
DTM_{mean}	0.051753	0.010	5.326	0.000	1.053	5.31	28.4	0.000
CHM_{buf}	0.358002	0.042	8.611	0.000	1.431	43.05	74.2	0.000
Predictors for $LR_{ALS+NFI}$	**Estimate**	**Std. Error**	**z value**	**Pr(>|z|)**	**e^{β}**	**% change in odds**	**Wald**	**Wald sig.**
Intercept	-7.567191	1.091	-6.935	0.000			48.1	0.000
VOL_{pine}	0.021675	0.003	6.548	0.000	1.022	2.19	42.9	0.000
VOL_{spruce}	0.011135	0.002	5.631	0.000	1.011	1.12	31.7	0.000
DTM_{mean}	0.049585	0.011	4.352	0.000	1.050	5.08	18.9	0.000
CHM_{buf}	0.194245	0.048	4.024	0.000	1.2144	21.44	16.2	0.000

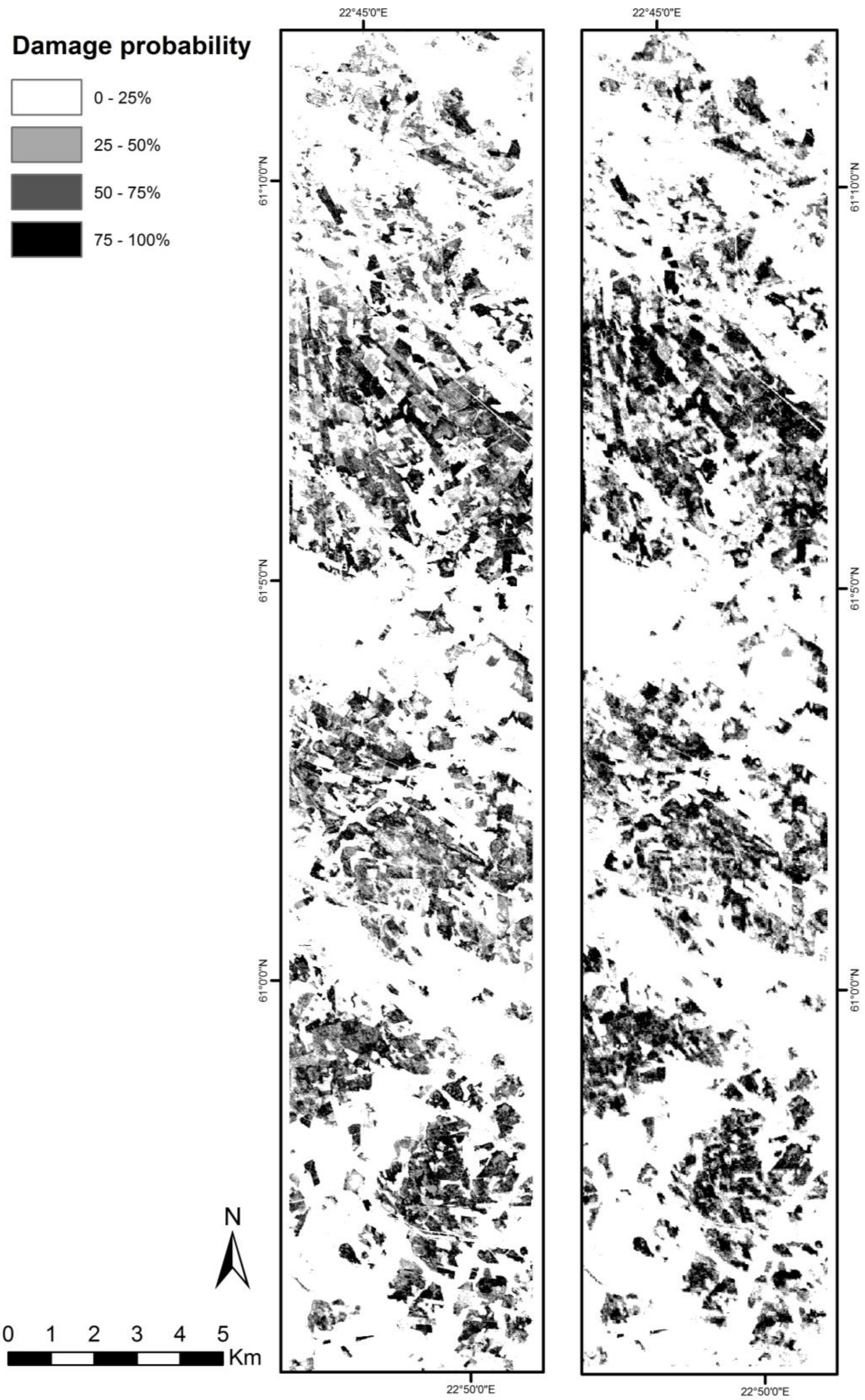

Figure 9. Maps indicating predisposition to wind disturbance derived from two models developed in substudy III. LR_{ALS} on the left-hand side panel (using only DTM_{mean} and CHM_{buf}) and $LR_{ALS+NFI}$ on the right-hand side (combined model with DTM_{mean}, CHM_{buf}, VOL_{pine}, and VOL_{spruce}). © Taylor & Francis.

DISCUSSION AND CONCLUSIONS

Vegetation plays an important role in upholding different ecosystem services: it hinders the effects of pollution in urban environments and the erosion of steep slopes and river bends, offers recreational possibilities, and provides raw materials for forest industry, but also berries and other goods for personal/private use, to name a few functions. Decision-making related to managing natural resources requires updated and accurate information of vegetation characteristics, whether deciding on the removal of an individual roadside tree or on the management activities for larger forest areas. The development of 3D remote sensing has brought new methods for collecting accurate information on vegetation characteristics at varying scales. Laser scanning has increased data dimensionality and improved spatial resolution. Especially laser scanning has proved an accurate technique for mapping vegetation from terrestrial, mobile, and airborne platforms. Increasing demand will exist in the future for detailed vegetation monitoring, which will require improved temporal resolution in addition to spatial resolution.

The aim of this thesis was to develop laser scanning -based methods for updating vegetation characteristics, monitoring vegetation changes, and modeling the probability of a disturbance event. Results demonstrate the applicability of airborne and mobile laser scanning (ALS and MLS) in predicting divergent vegetation characteristics in varying environments. Although the methods developed in this dissertation are in their early stage, they proved to be applicable despite additional ground-measured validation data being potentially useful for gaining solid verification. Before transferring the developed methods to operational use, validation in larger practical tests are required to further develop the methods and ensure their working capability.

Changes occur constantly in urban areas and these changes also affect green environments and vegetation characteristics. More efficient and accurate methods for updating information concerning urban vegetation are therefore required. The aim of substudy I was to tackle this challenge by developing a method called MS-STI, where several data sources could be used and the sampling unit was an individual tree. Substudy I was conducted to test the method and gain experiences on this detailed forest-inventory process of attribute updating in urban parks and recreational forests. TLS was used in producing a stem map in substudy I with an expected location accuracy less than 0.1 m. Others have obtained similar location accuracies with 2D or 3D laser scanners (Forsman and Halme, 2005; Öhman et al. 2008; Hellström et al. 2009; Liang et al. 2012b; Holopainen et al. 2013; Ringdahl et al. 2013). The stem map enabled the identification of all trees in the study area and ALS data were employed in updating tree attributes. Most studies concentrated on predicting tree attributes on the single-tree level also including the detection of trees, whereas MS-STI implicitly deals with this, although obtaining an accurate stem map is one of the challenges of MS-STI. The comparison between results from substudy I and other studies is not straightforward because the study was conducted in very heterogeneous conditions that differ considerably from managed, single-species forests. However, the results were promising: DBH estimation accuracies were similar for the park and only marginally lower in a very heterogeneous forest when compared to other studies (Peuhkurinen et al. 2007; Maltamo et al. 2009; Yu et al. 2011; Holmgren et al. 2012; Lindberg et al. 2012). The study also demonstrated the generation of new attributes: it was possible to produce accurate height and crown size predictions for urban tree registers as ALS-based height estimations have proved close to field-measured height data (Rönnholm et al. 2004; Maltamo et al. 2009; Yu et al. 2011; Shrestha and Wynne, 2012; Tanhuanpää et al. 2014). The developed method proved suitable for updating purposes in urban environments. When trees are accurately located, MS-STI can be applied for updating tree attributes over time with new remote sensing data (ALS or digital stereo images). Although a species-specific stem map is a demanding prerequisite, existing tree registers could be a means for overcoming this by providing information of individual trees especially in urban environments. MS-STI could thus initially be applied for updating roadside and park tree attributes, where tree registers exist. The method has also been tested in managed forests (Vastaranta et al. 2014b), but the production of cost-efficient detailed stem maps still requires more research before the method would be applicable in large forest areas. The development of TLS and MLS methods in tree recognition in particular, and through that stem-map production, are needed for MS-STI to be applicable in managed forests. However, further investigations concerning the capabilities of the developed method are needed in both urban and managed forests. Other applications apart from updating, where MS-STI could provide detailed tree-level information for both urban and managed forests include optimizing management activities, spatial growth modeling, and identifying potentially hazardous trees for citizens or infrastructure.

As vegetation can prevent soil erosion, it is anticipated that future riverine models could include vegetation information. When vegetation classes and changes in vegetation are known, a variable for erosion rates can be incorporated into the models, which would improve the prediction of river dynamics and flood risks. MLS data from a boat were used in substudy II for mapping riverine vegetation. The main focus in studying riverine environments has traditionally been measuring flow velocity, depth, and fluvial geomorphology, i.e. river-related characteristics and not vegetation. However, studies applying ALS in mapping the characteristics of floodplain vegetation cover do exist (Farid et al. 2006; Zlinszky et al. 2012). Farid et al. (2006) were able to obtain an overall accuracy of 78% for classifying three age classes of riparian vegetation, whereas Zlinszky et al. (2012) reported an accuracy of 82.5%

when classifying wetland vegetation with ALS. However, extensive field data were collected for these studies, while we obtained 72.6% overall classification accuracy without a need for field reference. The results of substudy II show that vegetated areas could be detected with very high accuracy: only 0.7% of the vegetated areas were classified as bare ground. This is in line with a previous study that used TLS in classifying vegetated areas on riverbanks (Brodu and Lague, 2012). Even though the accuracy of MSL-based DTM is better on non-vegetated point bars (Vaaja et al. 2011a; Lotsari et al. 2014) compared to ALS-based DTM in riverine environments (French, 2003; Thoma et al. 2005), the errors in DTM may affect the accuracy of vegetation classification as a results of the survey angle and close range. MLS is very well-suited for riverine mapping due to the close range of the interest area, which is limited by the riverbed and occlusion does not hinder mapping. With the developed classification model and multi-temporal MLS data sets, it was possible to map changes in the vegetation of riverbanks and bend bars. The acquisition parameters for MLS data varied from year to year, which may have affected the classification. However, robust classification metrics (mean, standard deviation, and 95th percentile) were selected to minimize this effect. Based on the STD of these metrics in four vegetation classes from a random sample of unchanged grid cells, we assumed that selected metrics were not overly sensitive to the variation of MLS acquisition parameters. However, temporal variation caused by different months of collection and yearly weather variations might have played a role in change analysis. With appropriate reference data this could have been addressed. The aim of substudy II was to apply multi-temporal MLS data sets when monitoring changes in riverbank vegetation. Although MLS has mainly been applied in object-based analysis (Lehtomäki et al. 2010; Holopainen et al. 2013), the results proved that it could also be applied in mapping vegetation on a raster level, which is a commonly used sampling unit for retrieving forest resource information. The results of substudy II provided new information regarding how MLS data can be used for mapping and especially monitoring riverbank vegetation. Stream habitat analysis could benefit from this kind of research as it might provide a bridge between conservation-based policies of riverbank management. In environmental management, vegetation monitoring is of increased interest. New and emerging 3D techniques, such as SfM, could serve a role there as the cost of optical stereo imagery is lower compared to laser scanning data, especially in small areas. Therefore SfM is an interesting option for updating riparian information where remote sensing data sets with high spatial and temporal resolution are required. In addition, e.g. UAVs can be utilized even under cloud cover because the flying altitude can be less than 150 m (Jaakkola et al. 2010). However, optical stereo imagery does not provide as large height variation as laser scanning, especially the lack of ground points can be a limiting factor (Niethammer et al. 2012). In the substudy II, mapping distance of MLS system varied between 2.5 m and 32.6 m depending highly on terrain topography, system trajectory, and vegetation. With stereo imagery acquired with UAV it is possible to obtain continuous coverage of the area of interest. However, steep river banks cause shadowing and occlusion and therefore observations from the ground, especially below vegetation, can be challenging to acquire (Niethammer et al. 2012).

There is a growing need to develop methods for identifying areas susceptible to various natural disturbances that are becoming more frequent (e.g. Westerling et al. 2006; Seidl et al. 2011, 2014). Therefore, especially connections between vegetation characteristics and different kinds of disturbance events need to be better understood and predisposition to these events quantified. Many vegetation characteristics that have been used to predict the wind damage risk of forests such as tree height, crown size, stem density, and topography (Lohmander and Helles, 1987; Wright and Quine, 1993; Peltola et al. 1999; Jalkanen and Mattila, 2000) can be derived from ALS data. Drivers to wind predisposition were studied in substudy III by utilizing openly accessible ALS and multisource NFI data sets for developing a risk model to identify areas liable to wind disturbance. Topography was not find to be a major contributor to the wind risk models, but the study area was not comprised of wide topographic variations. However, the approach should be tested in a more complex terrain and environment to assess the wide applicability of the approach in producing wind risk maps. Then these risk maps could be of interest of forest practitioners and forest owners especially if the maps are included in the forest attribute information database provided by the Finnish Forest Centre. Forest managers could then incorporate this knowledge of wind damage susceptibility into their strategic planning when assessing the operational environment and determining which management practices should be used to preserve biodiversity and maintain the sustainable use of the ecosystem services provided by the forests. Compared to other studies related to forest disturbance modeling (Stadelmann et al. 2013; Thom et al. 2013; Pasztor et al. 2014) our approach provides detailed 3D information concerning topography and forest structure, but also the spatial resolution of our model output (16 m) is advantageous. Furthermore, the use of ALS enables the inclusion of predictor variables characterizing forest structure, such as mean height and vertical canopy cover that act as drivers of wind disturbance (Fridman and Valinger, 1998; Peltola et al. 1999; Jalkanen and Mattila, 2000; Hanewinkel et al. 2008). Other possible drivers, for instance forest health, may also be related to wind damage susceptibility, but are difficult to objectively quantify and are not often available over large areas.

One of the implications of this thesis is the added value of laser scanning data, although it was not the purpose of the studies as such. Despite the fact that the research questions were there, the data of each substudy were also acquired for other purposes besides the studies included in this thesis. However, this is most probably the real-life situation as well. In urban environments, laser scanning and other remote sensing data are acquired for other urban planning purposes and the results of the substudies showed that such data are also suitable for updating tree attributes. The MLS data could be used in accurate analyses processes of the river channel, especially regarding geomorphology and hydrology producing information for flood-risk modeling purposes. However, the multi-temporal MLS data sets proved capable of distinguishing different vegetation classes and detecting changes over the years. The Finnish NLS has provided open access ALS data for public use since 2012 and the purpose of the data have been to improve DTM accuracy. As demonstrated in substudy III, these data are also suitable for predicting vegetation characteristics in relation to mapping and modeling forested areas susceptible to wind disturbance. Another application for ALS could be forest conservation planning as it produces more accurate information than openly accessible multisource NFI data (Lehtomäki et al. 2015). Consequently, these studies provide additional beneficial applications for these data sets and through that increase the value of the data.

Vegetation characteristics in urban and managed forests are quite similar (e.g. DBH, height, volume) but the scale has traditionally been different, which is also one reason why techniques concentrating on individual trees could first be applied in urban environments at the operational level. Another reason is that techniques developed for predicting forest inventory attributes in managed forests may not be suitable for urban environments. Although the area-based approach could be applied in urban forests for predicting forest inventory attributes, as cities tend to have ALS data, the main objective of urban forests is not in wood production because management activities are aimed at maintaining recreational possibilities for citizens. Therefore more detailed and updated information of forests are merely needed for locating and removing hazardous trees. The relative value of an individual tree is bigger in an urban environment because of their planting and maintenance costs, thus the interest in individual trees has traditionally been higher in urban areas. However, interest for individual-tree level information is also increasing in relation to managed forests to improve estimations of stem-diameter distribution as well as stem form and quality. Compared to traditional field measurements, where DBH is the easiest attribute to measure, tree height and crown diameter are easier to obtain from ALS data (e.g Maltamo et al. 2004b). Allometric models (Kalliovirta and Tokola, 2005) have therefore been used in DBH predictions (e.g. Tanhuanpää et al. 2015). A need therefore exists for new models incorporating predictor variables that are easily extracted from laser scanning data to fully utilize the potentials of 3D remote sensing data.

Although the temporal resolution of laser scanning data sets is increasing and they are more and more applied in environmental mapping and monitoring applications, the temporal resolution can be a limiting factor when applying the developed methods in practice. In urban environments ALS data are most probably acquired for various purposes once a year, which would enable the utilization of MS-STI for tree-attribute update with an accurate tree register. Monitoring of riverine environments by means of laser scanning has not been regular, but the utilization of boat-mounted MLS could provide a feasible means of mapping rivers after floods, at least those of high importance. Compared to traditional techniques of mapping river channel, MLS additionally affords improvement in spatial and temporal resolution. Our method would then offer the possibility of also monitoring vegetation changes. Most managed forested areas are already covered by ALS data, whereas high temporal resolution would be required to map sudden changes such as wind or snow damage. If ALS or digital stereo imagery -based surface models are only available in cycles of five or more years these data sets could merely be applied in risk modeling rather than change mapping.

This thesis developed new methods for predicting vegetation characteristics in divergent environments, with specific emphasis on various changes. With laser scanning data sets it was possible to update urban tree attributes using remote sensing data (I), detect changes in riverbank vegetation (II), and produce risk maps for forested areas vulnerable to wind-induced damage (III). Different application environments offered varied test beds for developing these methods and focus on future research can be directed to assess the accuracy in operational applications. As a result, this thesis provides more knowledge concerning the applicability of laser scanning on different platforms for various environmental applications.

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