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Article

Urban-Tree-Attribute Update Using Multisource Single-Tree Inventory

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Abstract: The requirements for up-to-date tree data in city parks and forests are increasing, and an important question is how to keep the digital databases current for various applications. Traditional map-updating procedures, such as visual interpretation of digital aerial images or field measurements using tachymeters, are either inaccurate or expensive. Recently, the development of laser-scanning technology has opened new opportunities for tree mapping and attributes updating. For a detailed measurement and attributes update of urban trees, we tested the use of a multisource single-tree inventory (MS-STI) for heterogeneous urban forest conditions. MS-STI requires an existing tree map as input information in addition to airborne laser-scanning (ALS) data. In our study, the tested input tree map was produced by terrestrial laser scanning (TLS) and by using a Global Navigation Satellite System (GNSS). Tree attributes were either measured from ALS or predicted by using metrics extracted from ALS data. Stem diameter-at-breast height (DBH) was predicted and compared to the field measures, and tree height and crown area were directly measured from ALS data at the two different urban-forest areas. The results indicate that MS-STI can be used for updating urban-forest attributes. The accuracies of DBH estimations were improved compared to the existing attribute information in the city of Helsinki's urban-tree register. In addition, important attributes, such as tree height and crown dimensions, were extracted from ALS and added as attributes to the urban-tree register.

Keywords: urban forest; remote sensing; LiDAR; Airborne laser scanning; GIS; forest inventory; forest mapping; city planning; land-use planning

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1. Introduction

Trees and woodlands are part of the urban environment, and they play an important role in urban areas [1]. Urban woodlands can improve people's quality of life, but they also improve the urban environment. Trees can reduce pollution effects [2] and improve air quality [3] in urban areas. In relation to this, urban forests can also store industrial carbon emissions [4], and when vegetation is sustained and maintenance practices are focused upon (e.g., energy conservation or producing long-term carbon storages), urban vegetation can be seen as a carbon sink [5].

Urban forests also offer recreational environment for citizens. However, use level, user composition, and the temporal distribution of activity types through commuting and recreation use may differ depending on the number and closeness of settlements, business areas and schools [6]. Urban forests can also be seen as a measure for strengthening social structures for interaction and for reducing social exclusiveness [7]. Urban forests and woodlands can provide multiple values and benefits (e.g., [8,9]) including education, economy, and urban biodiversity, in addition to the aspects mentioned above.

In Finland, the City of Helsinki's Street and Park Division maintains a digital tree register (approximately 40,000 trees) that includes trees that are situated at road sides and some of the trees in the parks. The tree-register data includes information on the species, height, diameter-at-breast height (DBH), and location. The tree-register data are used in city and environmental planning, in locating old trees that are hazardous (for citizens), and in biodiversity monitoring. Trees in the register have been located on city-planning maps. The City of Helsinki's Street and Park Division is also interested in expanding the register to include trees in the parks that are not yet registered. The requirements for up-to-date tree data in city parks and forests are increasing, and an important question is how to keep the digital databases current for the various applications. Traditional updating procedures, such as visual interpretation of digital aerial images or field measurements using tachymeters, are either inaccurate or expensive. Hence, the utilization of remote sensing data is appealing. Remote sensing data are in many cases collected automatically for other purposes and are therefore affordable for updating digital databases. As in many cities, this is also the situation in the City of Helsinki where aerial photographs and airborne laser scanning (ALS) data are collected for other urban planning purposes, such as mapping of buildings, roads, and other built objects. New opportunities for tree mapping and the updating of attributes have been opened because of the development of laser-scanning technology.

ALS is used in urban planning to create highly detailed digital surface models and eventually Digital City Models and virtual-city realities [10]. ALS has been used by forest companies and governmental organizations to acquire up-to-date information about forest resources. ALS provides a geo-referenced-point cloud, which enables the calculation of digital terrain models (DTMs) and, digital surface models (DSMs) that correspond to treetops and three-dimensional (3-D) models of an object (e.g., canopy-height model (CHM), normalized DSM), which are the main products used for laser-assisted forest measurements. The two main approaches to derive forest information from ALS data are the area-based approach (ABA) [11] and individual tree detection (ITD) [12]. With ALS it is possible to directly measure the forest structure, including canopy height (CH) and crown dimensions; hence, it is increasingly being used for forest inventories at different levels. It has been shown that ALS can be used for estimating a variety of forest attributes, including tree, plot, and stand-level estimates for tree height [12–15], stem volume [16–19], basal area (BA) [11,20–22] and tree species [23–27].

In recent years, the potential of terrestrial laser scanning (TSL) for measuring forest characteristics has been more understood. TLS data have been used for measuring forest parameters (e.g., [28–30]), tree-location accuracy (e.g., [31–33]), stem curve (e.g., [34,35]), stem reconstruction (e.g., [36]), stem mapping (e.g., [28,32,33]), and biomass (e.g., [37–42]).

Holopainen *et al.* (2013) [31] demonstrated that TLS and mobile laser scanning (MLS) can be used for producing accurate tree maps in urban forests. Based on the results presented in [31], ALS was selected as a means of updating Street and Park Division's tree register for the city of Helsinki [43]. In [43] an ALS-based mapping system was developed to be used for urban-tree mapping. On the basis of these studies, a conclusion can be drawn that urban-tree mapping will be done automatically in the near future. The next phase is to study how to measure and update automatically important tree attributes by using an existing tree map, which is a basic product in the urban-tree inventory. One especially interesting option is a combination of ALS and TLS data in which ALS can be used for measuring tree height and TLS is used for providing not only the accurate position of all trees but also detailed information about the quality of the tree stem. This method is useful for updating information of urban trees and also for developing precision forestry [44] in managed forests.

Here we tested the use of a multisource single-tree inventory (MS-STI) where ALS and TLS data were combined for mapping the trees and measuring tree variables. Our objectives were to investigate estimation accuracy of tree variables, estimate stem distributions, and asses the prediction accuracy while also producing completely new tree attribute such as crown size and update height for all trees in the city of Helsinki's urban tree register. Stem distribution can be used for urban-forest planning and for visualizing heterogeneous urban woodlands. In the future, 3D-virtual forests could be an essential part of urban planning, and stem distribution is an offset for creating these models.

2. Materials

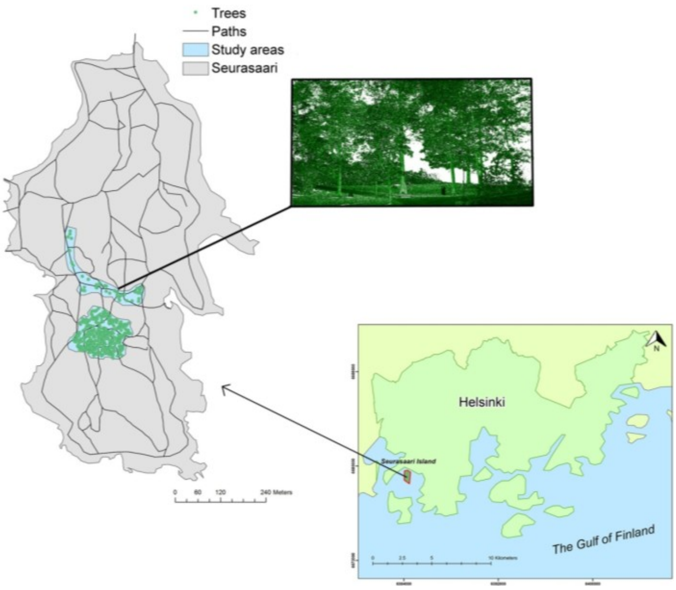
2.1. Study Area

The study area, Seurasaari (in Helsinki, Finland), is a popular outdoor recreation area located approximately 5 km from the Helsinki city center. It was made a public park in 1890 and quickly became a popular place for recreational activities. Seurasaari is a wooded island with rocks, hills, wetlands, and herb-rich forests covering about 46 ha. It receives hundreds of thousands of visitors per year. Our study area in Seurasaari comprised two parts, covering approximately 2.7 ha in total (Figure 1). The northern part is a well-managed urban park comprised mainly of widely separated old oaks and only grass as under-storey vegetation, while the southern part resembles more a natural unmanaged park forest with varying under-storey vegetation. The distribution of tree species was diverse and consisted of 11 different species (Table 1), which describes the heterogeneity of the research area. In the area, there is a dense network of artificially constructed outdoor paths that can also be used by vehicles.

Table 1. Relative tree-species distribution in the study area.

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

Figure 1. Study area.



2.2. Field Measurements

A predefined TLS tree map was used to identify each tree. The DBH was determined for 389 trees. Steel callipers were used for the DBH measurements. The average DBH for the entire study area was 268 mm and varied between 31 and 482 mm. Descriptive statistics were also calculated for two separate areas: the northern part, which is a well-managed urban park forest, and the southern part, which is denser, unmanaged forest with varying under-storey vegetation. The average DBH was 371 mm in the northern part and 261 mm in the southern part.

2.3. Airborne Laser Scanning

The ALS data were acquired in 2011 with an Optech 3100 laser scanner (Optech Inc., Vaughan, ON, Canada). The flying altitude was 400 m. The density of the pulses returned was approximately 10 points per m^2, and the return type was recorded (first-of-many, single, intermediate, last). The ALS data were first classified as ground and non-ground points according to the method developed by Axelsson (2000) [45]. Low-point classification was also used to improve the accuracy of the ground level. A DTM was developed from classified ground points, and laser heights above the ground (normalized height or canopy height) were calculated by subtracting the ground elevation from the laser measurements.

2.4. Terrestrial Laser Scanning

The TLS data were collected with a Leica HDS6100 TLS system (Leica Geosystems AG, Heerbrugg, Switzerland) 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 508,000 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 below (Table 2).

Table 2. Leica HDS6100 TLS system and specifications.

Leica HDS6100 System	Specifications
Field of View	310° × 360°
Range	79 m
Speed Points/s	508,000
Spot Size	3 mm + 0.22 mrad
Distance Measurement Accuracy at 25 m	±2 mm
Max Resolution	0.009° Hor × 0.009° Ver
Max Points 360°	40,000 Hor × 40,000 Ver
Laser Wavelength	690 nm
Laser Power	30 mW
Weight	14 kg
Operating Temperature	−10 to 45 °C

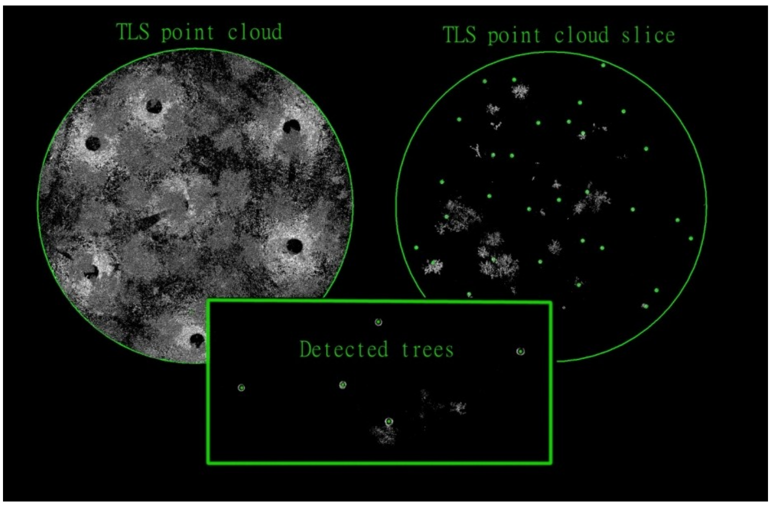
TLS measurements for the study area were collected in multi-scan mode. The park areas were scanned as-is. Pre-scan preparations, e.g., removal of low vegetation, were not done, since it was not permitted in the city forest. The objective of the measurements was to obtain good point coverage. The data were collected in five to seven scans per group; in total, 52 scans were performed to cover the entire study area. We positioned the center-scan station and at least one reference-target ball of each scan group using a GNSS virtual-reference station (VRS) and a tachymeter. The center scans were placed so that the canopy layer did not block the GNSS satellite visibility. Subsequently, we transformed the scans into global coordinates according to the scanner and sphere-target locations measured. The reference targets were placed on the forest ground for point-cloud registration. The TLS point clouds within each group were co-registered, using reference targets. Co-registration was done with Leica's Cyclone software (Leica Geosystems), in which the reported overlap root-mean-squared error (RMSE) of the scans ranged between 2.3 and 6.3 cm.

3. Multisource Single-Tree Inventory

3.1. TLS-Based Tree Map

Tree detection and location measurements were done manually in the present study using the 3D-environment of TerraScan (Terrassolid Ltd., Helsinki, Finland). Point clouds were processed in scan groups, and trees were searched within each group using visual interpretation. The process was performed through the following steps: (1) the point cloud of each scan group was imported into TerraScan by thinning the point cloud by 50%; (2) points from an approximately 1.3-m height (between 1.25 m and 1.35 m to be exact) were classified into a horizontal "slice" for identifying tree trunks; (3) tree trunks were detected and marked within the slice (see Figure 2); and (4) location and DBH information were recorded for all the trees.

Figure 2. Example of the tree-detection method from the TLS point clouds.



3.2. Extraction of Tree Height, Crown Area, and the Prediction Variables from the ALS Data

A raster canopy height model (CHM) was created from normalized ALS point-height data for tree-crown segmentation. The maximum ALS point height from first-of-many or single echoes was assigned to each CHM cell (resolution 0.5 m), and no-data cells were filled with the mean height value in the 3 × 3-neighborhood. Tree crowns were delineated using watershed segmentation described in [20,46,47].

Tree crown segments were linked to the field trees based on the TLS-measured location. If there were more than one tree within a segment, the segment was split equally. As segments from CHM represented tree crowns, areas for tree crowns were calculated as the area of each segment. Tree height was possible to update by using the maximum height of ALS points of each tree crown.

Statistical metrics describing tree crown density and tree height were calculated from the ALS point-data within the tree crown segment (Table 3). First, heights over 0.5 m were classified as coming from the vegetation (*i.e.*, tree), and a vegetation-density ratio (vege) was then calculated as a ratio between vegetation heights and all heights within a tree crown. The following were other extracted metrics: maximum (H_{max}), average (H_{mean}), standard deviation (H_{std}), and coefficient of variation of heights (CV); height at 10%–90% percentiles (h_{10}–h_{90}), and crown-cover density metrics as a proportion of heights below a certain relative tree height (p_{10}–p_{90}). Only the heights belonging to vegetation (that is, heights over 0.5 m) were used in the calculation of these metrics. The metrics were extracted from the ALS data using all returns.

Table 3. Statistics, such as minimum (min), maximum (max), range, mean, and standard deviation (Std) calculated from the extracted predictor variables.

Variable	**Forest**					**Park**				
	Min	**Max**	**Range**	**Mean**	**Std**	**Min**	**Max**	**Range**	**Mean**	**Std**
H_{max}	4.54	29.15	24.61	19.68	5.26	7.76	26.04	18.28	19.44	4.90
H_{mean}	3.14	22.95	19.81	12.99	4.19	4.84	23.09	18.25	12.73	4.44
H_{std}	0.64	9.11	8.47	4.30	1.50	1.43	6.82	5.38	4.47	1.33
Vege	0.25	1.00	0.75	0.71	0.15	0.35	0.94	0.58	0.65	0.13
CV	0.08	0.91	0.82	0.35	0.11	0.24	0.56	0.32	0.37	0.09
h_{10}	1.13	20.03	18.90	6.98	3.64	2.20	19.04	16.84	6.50	3.72
h_{20}	1.95	21.25	19.30	9.39	4.20	3.20	24.56	21.36	8.85	5.40
h_{30}	2.14	23.77	21.63	11.08	4.45	3.86	24.94	21.08	10.51	5.14
h_{40}	2.64	24.01	21.38	12.41	4.63	4.67	25.14	20.47	12.08	5.16
h_{50}	2.96	24.19	21.23	13.60	4.77	5.15	25.24	20.10	13.54	5.20
h_{60}	3.42	24.31	20.89	14.66	4.89	5.57	25.30	19.73	14.66	5.06
h_{70}	3.75	24.38	20.63	15.77	4.94	5.78	25.40	19.62	15.64	4.99
h_{80}	4.11	24.72	20.61	16.81	5.04	6.08	25.46	19.38	16.71	4.85
h_{90}	4.44	26.75	22.31	17.97	5.09	6.60	25.62	19.02	17.86	4.88
p_{10}	0.00	0.21	0.21	0.03	0.03	0.00	0.10	0.10	0.01	0.02
p_{20}	0.00	0.67	0.67	0.07	0.08	0.00	0.25	0.25	0.07	0.06
p_{30}	0.00	0.77	0.77	0.12	0.12	0.01	0.35	0.34	0.14	0.09
p_{40}	0.00	0.96	0.96	0.19	0.16	0.03	0.46	0.43	0.22	0.11
p_{50}	0.00	0.98	0.98	0.27	0.18	0.07	0.53	0.46	0.31	0.13
p_{60}	0.00	0.98	0.98	0.38	0.19	0.10	0.65	0.56	0.42	0.16
p_{70}	0.00	0.98	0.98	0.50	0.20	0.10	0.77	0.68	0.53	0.19
p_{80}	0.02	0.98	0.97	0.65	0.18	0.14	0.89	0.75	0.67	0.20
p_{90}	0.19	0.99	0.80	0.82	0.14	0.16	0.97	0.81	0.79	0.22

3.3. Estimation of the Tree Variables

Diameter-at-breast height (DBH) was predicted by means of ALS metrics using the nearest-neighbor (NN) approach. Tree variable measured in the field (*i.e.*, DBH) was used as target observations, and tree-specific metrics derived from ALS data were used as predictors. Random Forest (RF, [48]) was applied in the NN search. Based upon the quality of results and desirable statistical characteristics (*i.e.*, the capability to predict multiple response variables simultaneously, use a large number of predictors without the problem of over fitting, and evaluate accuracy with built-in functionality), the use of RF in NN estimation of forest variables is increasingly common (e.g., [19,47,49–51]). In [50] and [51] it was demonstrated that the RF method is more robust and flexible for forest variable prediction when compared to other NN distance measures, such as Euclidian distance, Mahalanobis distance, or Canonical Correlation Analysis. In the RF method, several regression trees are generated by drawing a replacement from two-thirds of the data for training and one-third for testing for each tree. The samples that are not included for training are called *out-of-bag samples*, and they can act as a testing set in the approach. The measure of nearness in RF is defined based on the observational probability of ending up in the same terminal node in classification. Predictor's importance can be assessed in RF by using the predictor's scaled-importance values. To measure the importance after the RF run, the values of the predictor are permuted among the training data, and the out-of-bag error is again computed on this blended data set. The importance score for the predictor is then computed by averaging the difference in the out-of-bag error before and after the permutation over all trees. The score is normalized by the standard deviation of these differences. The R statistical-computing environment [52] and yaImpute library [53] were applied in the RF predictions. The yaImpute library is tailored to NN forest-attribute estimation.

In the present study, 1200 regression trees were generated, and the square root of the number of predictor variables was picked randomly at the nodes of each regression tree. Randomness was taken into account by running the RF method 100 times. The final result was the average of these runs. The number of neighbors differed from 1 to 5.

Prior to the modeling, the RF was used to reduce the number of the predictor variables. A step-wise looping procedure was used to iterate RF, 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.

3.4. Accuracy Assessment at the Tree and Stand Level

In this study, predictors and target observations were available for all of the trees. Therefore, the accuracy of the predicted variables at the tree level was evaluated by calculating bias (Equation (1)) and RMSE (Equation (2)) using out-of-the-bag samples. The relative bias and RMSE were calculated according to the sampled mean of the variable in question. The accuracies of the tree-level measurements were evaluated by calculating the bias and RMSE:

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

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

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

Stem-diameter distributions were compiled from the tree-level predictions and compared to the field measurements for both parts of the study area separately. The predicted stem-diameter distributions were evaluated by the error index (EI) introduced in [54]:

$$EI = \sum_{i=1}^{k} w_i \left| f_i - \hat{f}_i \right| \tag{3}$$

where f_i and $\hat{f}_i$ are the numbers of stems in class i to be compared, k is the number of classes or bins, and w_i is the weight of class i.

In addition, an alternative error index was calculated following [55], who used relative frequencies:

$$e = \sum_{i=1}^{k} 0.5 \left| \frac{f_i}{N} - \frac{\hat{f}_i}{\hat{N}} \right| \tag{4}$$

where f_i is the true and $\hat{f}_i$ is the predicted stem number in class i, k is the number of classes or bins, and N is the true and $\hat{N}$ the predicted stem number of all diameter classes. A weight 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 for both error indices was 2 cm.

4. Results

4.1. Selecting Predictor Variables

Predictor variables that were used in further estimations were selected separately for forested (southern part) and park areas (northern part). There were in total 23 extracted features that were possible to be used in prediction. RMSEs were calculated for each predictor-variable combination, and a minimum number of predictors were chosen before the out-of-bag prediction accuracy started to increase notably. For the forested area (southern part), seven variables were selected as predictors, whereas for the park area (northern part), six variables were selected (Table 4). Depending on the used set of predictors, the relative-RMSE values varied between 25.0% and 33.8% in the forested area (Figure 3) and between 18.8% and 20.1% in the park area (Figure 4); thus, the prediction accuracy was not oversensitive to the number of predictor variables that were used.

Figure 3. Effect of number of predictors to DBH estimation accuracy in and selection of ALS features for the forested southern part of the study area.

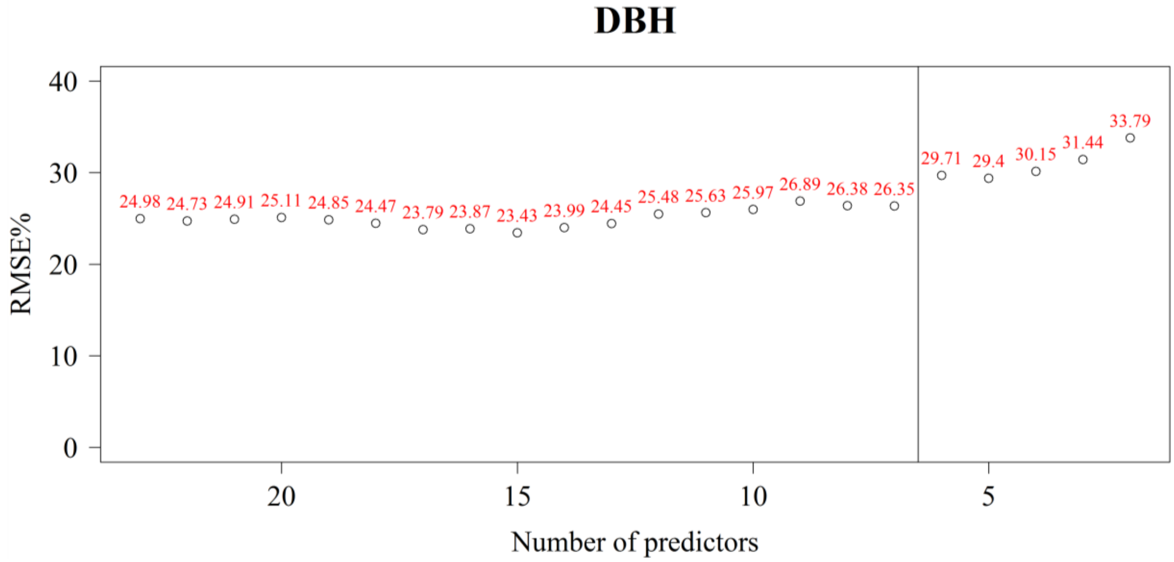
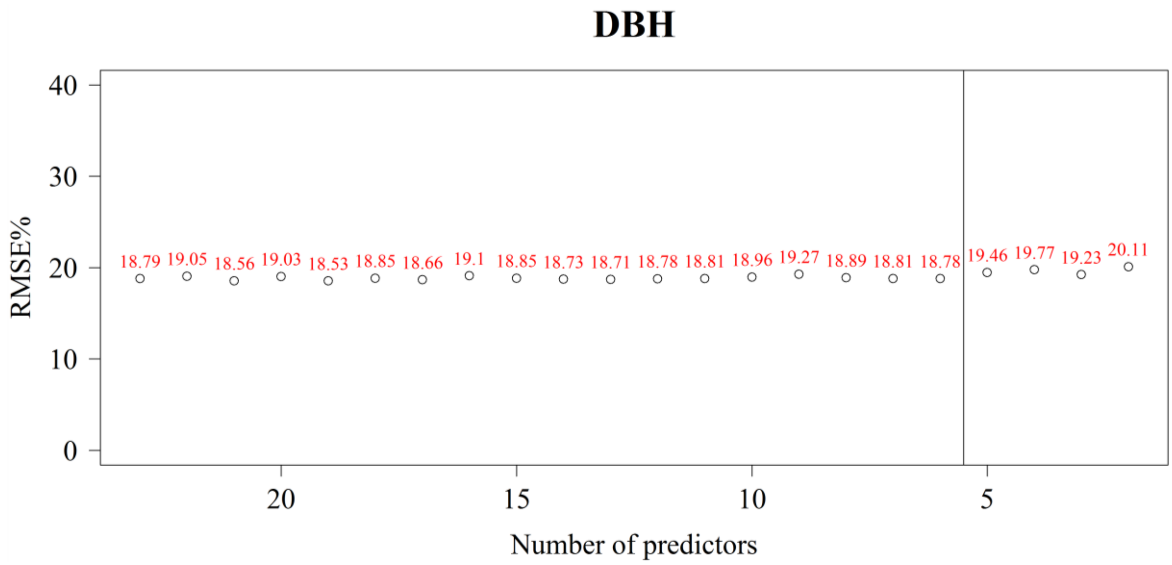


Table 4. Selected predictor variables for both parts of the study area in order of the predictor importance.

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

Figure 4. Effect of number of predictors to DBH estimation accuracy in and selection of ALS features for the park (northern part of the study area).



4.2. Prediction Accuracy of Diameter-at-Breast Height

Prediction accuracy for DBH varied between the southern (forest) and northern (park) parts of the study area. The increment of the number of *k* decreased the relative RMSEs in the forested area. For the park area, the relative RMSE increased when more than one neighbor were used. The relative RMSEs for the park area were smaller (from 10.7% to 19.1%) than for the forested area (from 26.3% to 29.1%) (Table 5). On the other hand, biases were bigger for the park area (from −4.2% to 1.8%) than they were for the forested area (from −2.5% to −0.4%).

The accuracy of the DBH measurements is highly affected by stem form, because tree stem form is not fully circular (Figure 5). Especially stem forms of urban trees can differ greatly from the circle form. This affects both the field measured and the predicted DBH accuracy.

Figure 5. Two examples of measured DBH from TLS-point clouds from two different directions.

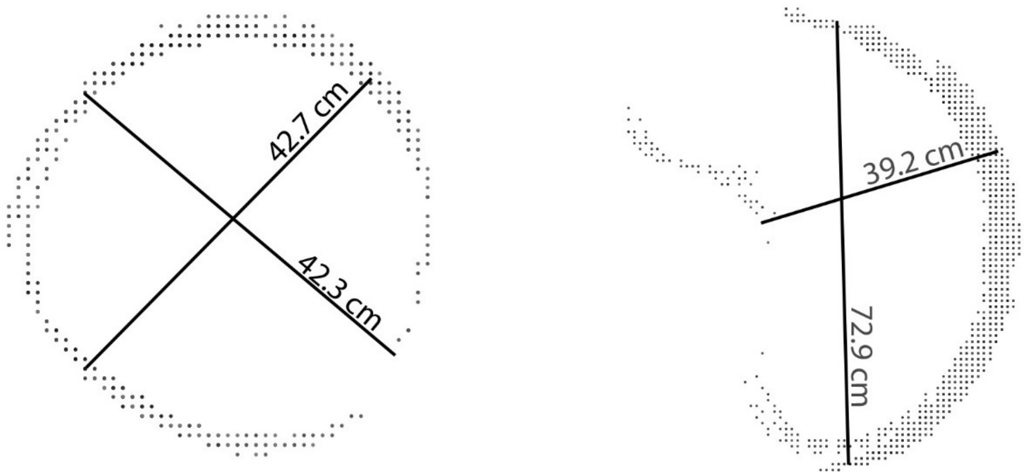


Table 5. Accuracy in DBH prediction.

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

4.3. Comparison of Stem-Distribution Series

Stem-diameter distributions were estimated separately for the northern (park area) and southern (forest area) parts of the study area. The main interest was in the forested area, since it could be better compared with results from managed forests. For both areas, the extreme bins of the DBH classes were omitted in the predicted stem-diameter distributions when the number of *k* increased (Figures 6 and 7). The number of trees in large DBH classes was especially difficult to predict. The Reynolds' error indices for the predicted stem-diameter distributions varied from 70 to 152 for the forested area (southern part) and from 6 to 26 for the park area (northern part) (Table 6). Reynolds' EI cannot be compared directly to other studies because they show the absolute value of the number of trees that do not match to the same DBH bins when comparing two distributions. The relative EI values showed better fit in the predicted stem-diameter distributions for the forested area than for the park area.

Figure 6. True stem-diameter distribution (**top left**) and predicted stem-diameter distributions with different *k* values for the forested southern part of the study area.

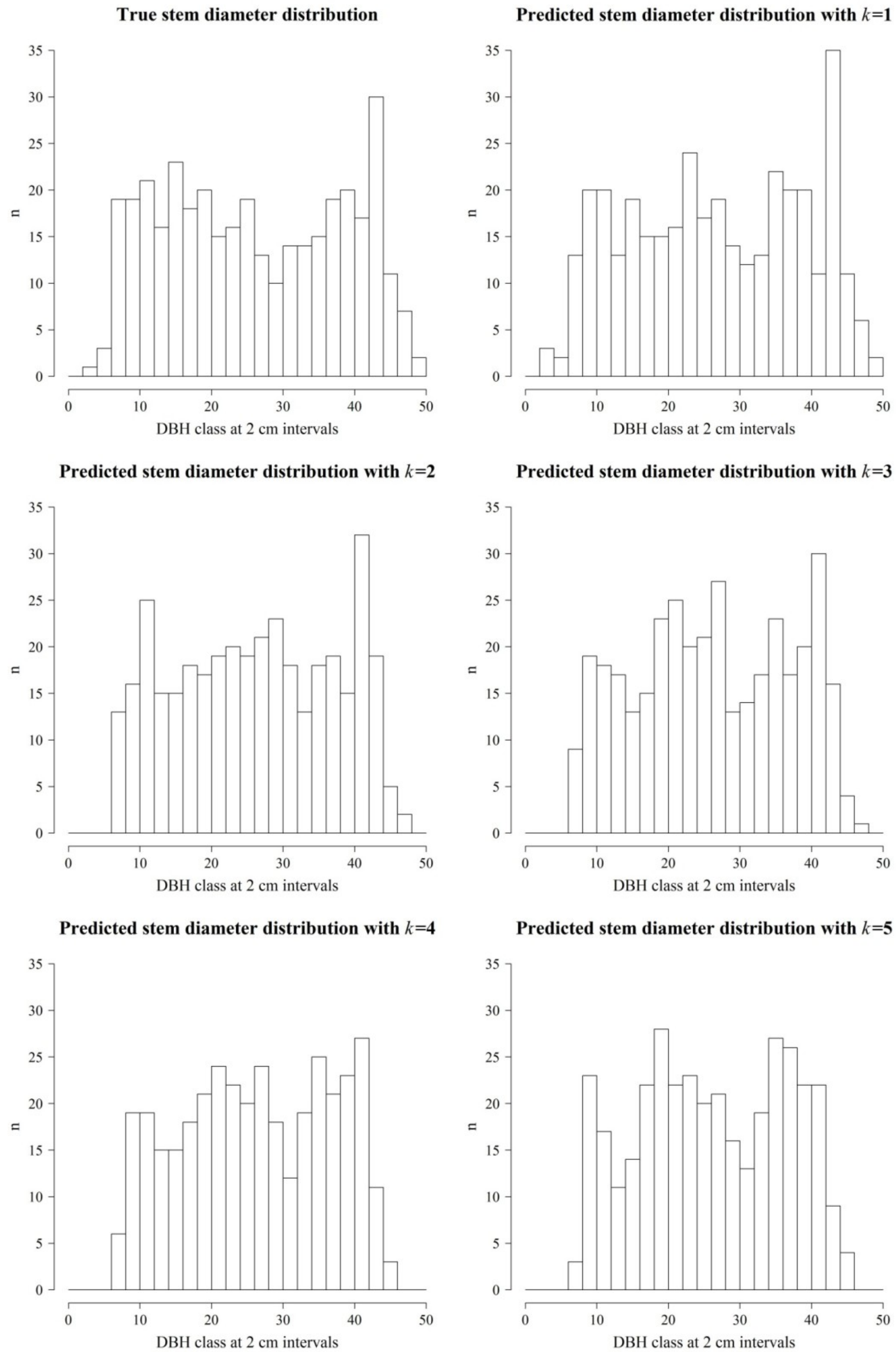


Figure 7. True stem-diameter distribution (**top left**) and predicted stem-diameter distributions with different *k* values for the park area (northern part of the study area).

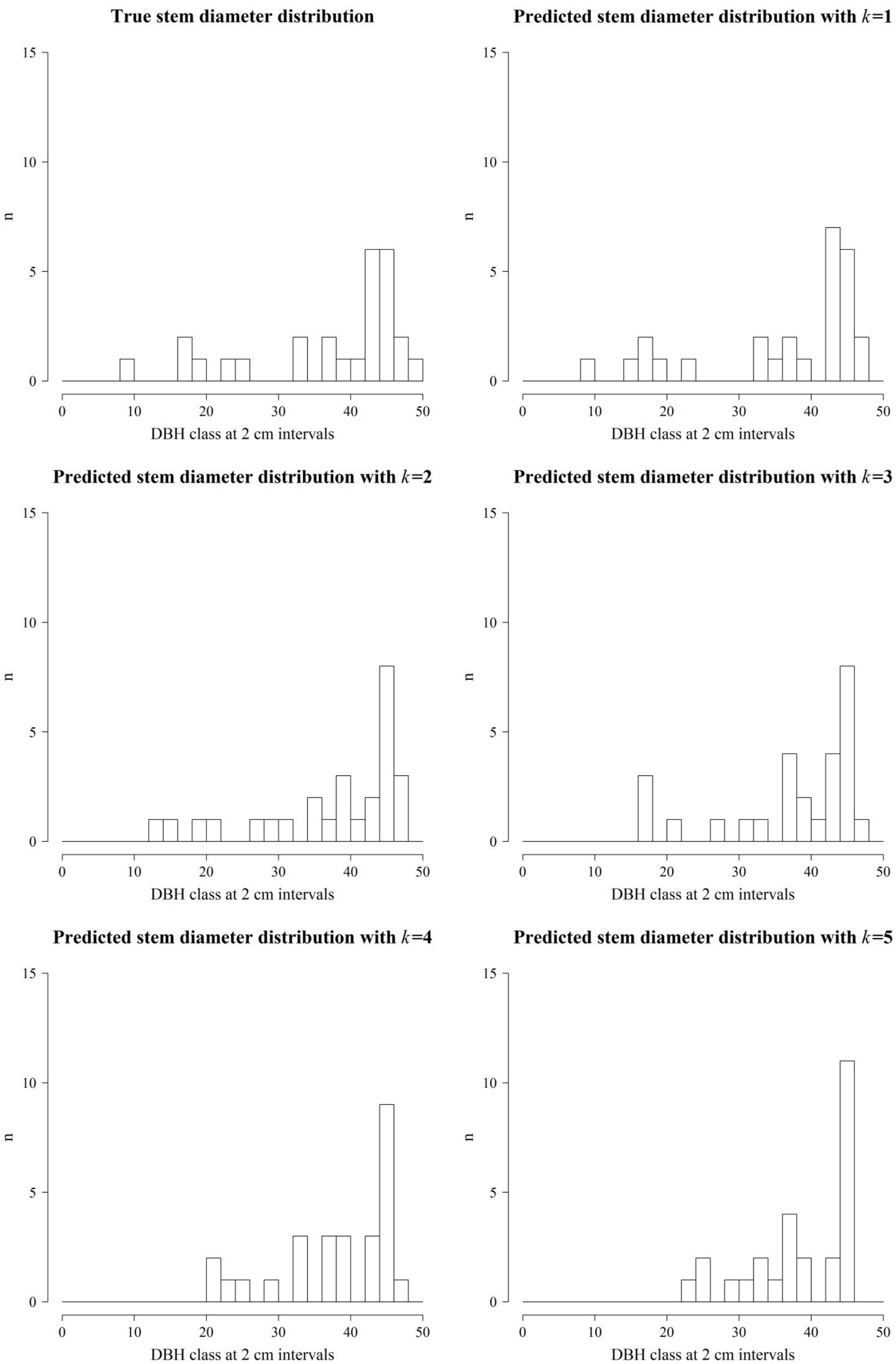


Table 6. Reynolds' error indices for the predicted stem-diameter distributions using a bin size of 2 cm.

Number of Neighbors	Forest		Park	
	Error Index	Error Index Using Relative Stem Frequency	Error Index	Error Index Using Relative Stem Frequency
$k = 1$	70	0.10	6	0.11
$k = 2$	110	0.15	26	0.48
$k = 3$	122	0.17	18	0.33
$k = 4$	132	0.18	20	0.37
$k = 5$	152	0.21	24	0.44

4.4. Extraction of Tree Height and Crown Area

It was possible to update the tree height by using the maximum height of ALS points of each tree crown. For the forested area (southern part of the study area), the tree height varied between 4.5 m and 29.2 m with a mean of 19.7 m and a standard deviation 5.3 m (Figure 8). The respective values for the park area (northern part of the study area) were 7.8 m, 26.0 m, 19.4 m, and 5.0 m (Figure 9). The tree crown area was computed from tree-crown segments and it varied between 1.1 m^2 and 86.5 m^2 in the forested area and between 2.5 m^2 and 95.2 m^2 for the park area. The mean and standard deviation for the forested area were 22.4 m^2 and 15.9 m^2, respectively. For the park area respective values were 34.3 m^2 and 23.2 m^2.

Figure 8. Tree-height distribution using maximum height of ALS points of tree crowns for the forested area (southern part of the study area).

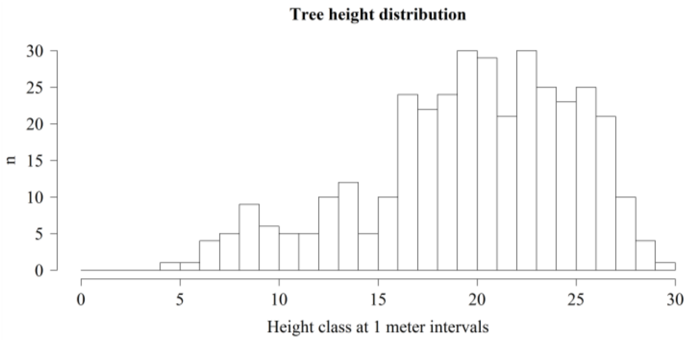
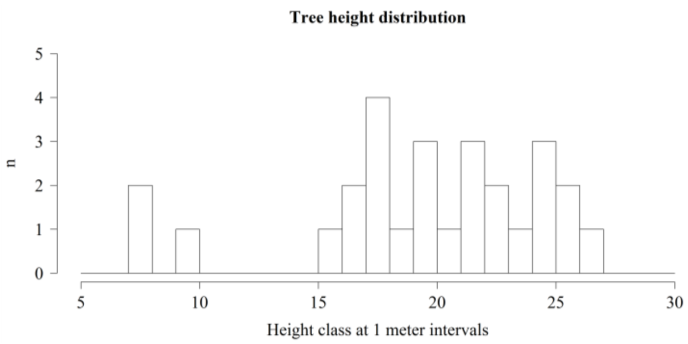


Figure 9. Tree-height distribution using maximum height of ALS points of tree crowns for the park area (northern part of the study area).



5. Discussion

Updating information of urban-tree characteristics has been challenging due to the high cost of traditional updating methods. ALS cost efficiently provides 3D information about urban trees, and this information can be used for planning urban-forest management practices and predicting the risk of forest damages. In this study, MS-STI was tested in two different urban-forest environments. In addition to ALS data, MS-STI requires an existing tree map as input information for a tree-attribute update.

Recent studies on single-tree inventory (e.g., [56–58]) have concentrated on managed forests, and the results have been promising due to conditions that are favorable for STI (mature stand, single-tree-species stand). Depending on forest conditions, the results of STI have varied considerably [47,59–61]). A tree map is a challenging prerequisite for the MS-STI analysis, but information from existing tree registers maintained by the city could be used as input for MS-STI. On the other hand, mobile mapping with imaging and laser sensors are also used more often for various surveying actions and could be used for tree mapping as well [31]. The tested-input tree map was produced by TLS and used GNSS with an expected accuracy of below 0.1 m. Similar location accuracies can be obtained using 2D- or 3D-laser scanning [31,33,62–67]. Detailed tree-level information could be used for optimizing management practices, spatial modeling of the growth, and localizing potentially hazardous trees for residents or infrastructure.

Predictors for tree-quality attributes were extracted from ALS data for mapped-tree locations. Stem distribution was compiled by summing single-tree measures. The accuracy of the MS-STI was validated using field measures (DBH). It should be noted that comparing results of this kind of study to other studies is only suggestive and highly data dependent. Forest conditions in this study were very heterogeneous and differed considerably from managed, one-tree-species forests; hence, results from other STI studies that have been conducted in managed forests are not fully comparable with our results. After this reminder, we can point out that our results are promising, and for the park area (northern part of the study area) they are on the same level as results obtained earlier using STI methods [47,56–58,68]. For the forested area (southern part of the study area) that was more heterogeneous than the northern part, the RMSEs were not as accurate as results obtained with earlier studies, but the difference was marginal. By enlarging the number of neighbors, RMSEs for the forested area did get lower, but for the park area, on the other hand, the RMSE increased. Also, enlarging the number of neighbors decreased the goodness of fit of the estimated stem-diameter distributions. In general, the obtained stem-diameter distributions for the forested area were similar to the ones in [55] and [69] in which a comparable error index was used. In [69] the STI technique and tree-list imputation method were used, and error indices varied from 0.33 to 0.40 for all the trees, and the species-specific error indices varied from 0.9 to 0.23. Error indices we obtained with MS-STI varied from 0.10 to 0.21 for the forested area and from 0.11 to 0.48 for the park area. In [55] ABA was used to predict species-specific stem-diameter distributions, and error indices varied from 0.21 to 0.34. Relative EI values for the forested area were notably lower than the ones obtained from the managed forest for all tree species reported in [69]. For the park area, on the other hand, the relative EI values were similar to those for all tree species reported in [69], with the exception of using only one neighbor when the EI was lower. With tree-species-specific EI values, Vauhkonen *et al.* (2013) [69] obtained better results.

Tree-height and crown-size information were extracted from the ALS data. Tree-height measurement accuracy from the ALS data is expected to be ±1 m [43,47,57,70,71] and that is close to the accuracy of clinometer measurements [72] traditionally used for measuring tree heights in the field. In Helsinki, the tree register does not contain tree-height information for park trees, because height measurements have been too laborious. In urban areas, tree-crown size is required for the planning and allocating of management practices. For example, this information can be used in locating trees that are interfering lamp posts, buildings, or drivers visibility at road junctions.

For urban tree-attribute updates MS-STI is an applicable method. Once the tree map is produced, there are various possibilities for updating the tree-attribute data. One intriguing application for MS-STI in green urban environments is a 3D-virtual forest, which can be used for visualizing the trees and modeling the effects of the alternative management options. This can be used to support decision making in green urban environments. In forthcoming studies, TLS- and MLS-based tree mapping and tree-species detection should be developed further with MS-STI. Required accuracy of the tree maps also requires further investigations.

6. Conclusions

This study showed the high potential of ALS and TLS measurements in very heterogeneous urban-forest environments. Here we tested a multisource single-tree inventory (MS-STI) method. In MS-STI, a tree map is produced by TLS and used as an input for ALS-based tree-attribute updating. We conclude that MS-STI is capable of providing realistic stem distributions and accurate tree-attribute update in an urban environment. Thus, the approach can be used for acquiring urban tree information and producing tree variables, such as tree height and crown size, for existing tree registers maintained by cities.

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Author Contributions

Ninni Saarinen was the main author of the article and conducted the analysis together with Mikko Vastaranta and Ville Kankare. Ville Kankare was responsible for the data collection. The article was improved by the contributions of all the co-authors at various stages of the analysis and writing process.

Conflicts of Interest

The authors declare no conflict of interest.

References

1. Tyrväinen, L.; Pauleit, S.; Seeland, K.; Vries, S. Benefits and uses of urban forests and trees. In *Urban Forests and Trees*; Konijnendijk, C., Nilsson, K., Randrup, T., Schipperijn, J., Eds.; Springer: Berlin/Heidelberg, Germany, 2005; pp. 81–114.
2. Beckett, K.P.; Freer-Smith, P.; Taylor, G. Urban woodlands: Their role in reducing the effects of particulate pollution. *Environ. Pollut.* **1998**, *99*, 347–360.
3. Nowak, D.J. Institutionalizing urban forestry as a "biotechnology" to improve environmental quality. *Urban For. Urban Green.* **2006**, *5*, 93–100.
4. Zhao, M.; Kong, Z.-H.; Escobedo, F.J.; Gao, J. Impacts of urban forests on offsetting carbon emissions from industrial energy use in Hangzhou, China. *J. Environ. Manag.* **2010**, *91*, 807–813.
5. Nowak, D.J.; Stevens, J.C.; Sisinni, S.M.; Luley, C.J. Effects of urban tree management and species selection on atmospheric carbon dioxide. *J. Arboric.* **2002**, *28*, 113–122.
6. Arnberger, A. Recreation use of urban forests: An inter-area comparison. *Urban For. Urban Green.* **2006**, *4*, 135–144.
7. Van Herzele, A.; De Clercq, E.M.; Wiedemann, T. Strategic planning for new woodlands in the urban periphery: Through the lens of social inclusiveness. *Urban For. Urban Green.* **2005**, *3*, 177–188.
8. Miller, R.W. *Urban Forestry: Planning and Managing Urban Greenspaces*; Prentice Hall: Upper Saddle River, NJ, USA, 1988.
9. Rydberg, D.; Falck, J. Urban forestry in Sweden from a silvicultural perspective: A review. *Landsc. Urban Plan.* **2000**, *47*, 1–18.
10. Zhou, G.; Song, C.; Simmers, J.; Cheng, P. Urban 3D GIS from LiDAR and digital aerial images. *Comput. Geosci.* **2004**, *30*, 345–353.
11. Næsset, E. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. *Remote Sens. Environ.* **2002**, *80*, 88–99.
12. Hyyppä, J.; Inkinen, M. Detecting and estimating attributes for single trees using laser scanner. *Photogramm. J. Finl.* **1999**, *16*, 27–42.
13. Falkowski, M.J.; Smith, A.M.; Gessler, P.E.; Hudak, A.T.; Vierling, L.A.; Evans, J.S. The influence of conifer forest canopy cover on the accuracy of two individual tree measurement algorithms using LiDAR data. *Can. J. Remote Sens.* **2008**, *34*, S338–S350.
14. Magnussen, S.; Eggermont, P.; LaRiccia, V.N. Recovering tree heights from airborne laser scanner data. *For. Sci.* **1999**, *45*, 407–422.
15. Maltamo, M.; Mustonen, K.; Hyyppä, J.; Pitkänen, J.; Yu, X. The accuracy of estimating individual tree variables with airborne laser scanning in a boreal nature reserve. *Can. J. For. Res.* **2004**, *34*, 1791–1801.
16. Hyyppa, J.; Kelle, O.; Lehikoinen, M.; Inkinen, M. A segmentation-based method to retrieve stem volume estimates from 3-D tree height models produced by laser scanners. *IEEE Trans. Geosci. Remote Sens.* **2001**, *39*, 969–975.
17. Naesset, E. Determination of mean tree height of forest stands using airborne laser scanner data. *ISPRS J. Photogramm. Remote Sens.* **1997**, *52*, 49–56.

18. Wallerman, J.; Holmgren, J. Estimating field-plot data of forest stands using airborne laser scanning and SPOT HRG data. *Remote Sens. Environ.* **2007**, *110*, 501–508.
19. Vastaranta, M.; Wulder, M.A.; White, J.C.; Pekkarinen, A.; Tuominen, S.; Ginzler, C.; Kankare, V.; Holopainen, M.; Hyyppä, J.; Hyyppä, H. Airborne laser scanning and digital stereo imagery measures of forest structure: Comparative results and implications to forest mapping and inventory update. *Can. J. Remote Sens.* **2013**, *39*, 1–14.
20. Kankare, V.; Vastaranta, M.; Holopainen, M.; Räty, M.; Yu, X.; Hyyppä, J.; Hyyppä, H.; Alho, P.; Viitala, R. Retrieval of forest aboveground biomass and stem volume with airborne scanning LiDAR. *Remote Sens.* **2013**, *5*, 2257–2274.
21. Lefsky, M.A.; Harding, D.; Cohen, W.; Parker, G.; Shugart, H. Surface LiDAR remote sensing of basal area and biomass in deciduous forests of eastern Maryland, USA. *Remote Sens. Environ.* **1999**, *67*, 83–98.
22. Means, J.E.; Acker, S.A.; Fitt, B.J.; Renslow, M.; Emerson, L.; Hendrix, C.J. Predicting forest stand characteristics with airborne scanning LiDAR. *Photogramm. Eng. Remote Sens.* **2000**, *66*, 1367–1372.
23. Brandtberg, T. Classifying individual tree species under leaf-off and leaf-on conditions using airborne LiDAR. *ISPRS J. Photogramm. Remote Sens.* **2007**, *61*, 325–340.
24. Holmgren, J.; Persson, Å. Identifying species of individual trees using airborne laser scanner. *Remote Sens. Environ.* **2004**, *90*, 415–423.
25. Korpela, I.; Ørka, H.O.; Maltamo, M.; Tokola, T.; Hyyppä, J. Tree species classification using airborne LiDAR—Effects of stand and tree parameters, downsizing of training set, intensity normalization, and sensor type. *Silva Fenn.* **2010**, *44*, 319–339.
26. Van Aardt, J.A.; Wynne, R.H.; Scrivani, J.A. LiDAR-based mapping of forest volume and biomass by taxonomic group using structurally homogenous segments. *Photogramm. Eng. Remote Sens.* **2008**, *74*, 1033–1044.
27. Vauhkonen, J.; Korpela, I.; Maltamo, M.; Tokola, T. Imputation of single-tree attributes using airborne laser scanning-based height, intensity, and alpha shape metrics. *Remote Sens. Environ.* **2010**, *114*, 1263–1276.
28. Maas, H.G.; Bienert, A.; Scheller, S.; Keane, E. Automatic forest inventory parameter determination from terrestrial laser scanner data. *Int. J. Remote Sens.* **2008**, *29*, 1579–1593.
29. Moskal, L.M.; Zheng, G. Retrieving forest inventory variables with Terrestrial Laser Scanning (TLS) in urban heterogeneous forest. *Remote Sens.* **2011**, *4*, 1–20.
30. Vastaranta, M.; Melkas, T.; Holopainen, M.; Kaartinen, H.; Hyyppä, J.; Hyyppä, H. Comparison of different laser-based methods to measure stem diameter. In Proceedings of the SilviLaser 2008, the 8th International Conference on LiDAR Applications in Forest Assessment and Inventory, Edinburgh, UK, 17–19 September 2008.
31. Holopainen, M.; Kankare, V.; Vastaranta, M.; Liang, X.; Lin, Y.; Vaaja, M.; Yu, X.; Hyyppä, J.; Hyyppä, H.; Kaartinen, H. Tree mapping using airborne, terrestrial and mobile laser scanning—A case study in a heterogeneous urban forest. *Urban For. Urban Green.* **2013**, *12*, 546–553.

32. Holopainen, M.; Vastaranta, M.; Kankare, V.; Hyyppä, J.; Liang, X.; Litkey, P.; Yu, X.; Kaartinen, H.; Kukko, A.; Kaasalainen, S. The use of ALS, TLS and VLS measurements in mapping and monitoring urban trees. In Proceedings of the 2011 Joint Urban Remote Sensing Event (JURSE), Munich, Germany, 11–13 April 2011; pp. 29–32.
33. Liang, X.; Litkey, P.; Hyyppä, J.; Kaartinen, H.; Vastaranta, M.; Holopainen, M. Automatic stem mapping using single-scan terrestrial laser scanning. *IEEE Trans. Geosci. Remote Sens.* **2012**, *50*, 661–670.
34. Liang, X.; Hyyppä, J.; Kankare, V.; Holopainen, M. Stem curve measurement using terrestrial laser scanning. In Proceedings of the 11th International Conference on LiDAR Applications for Assessing Forest Ecosystems, Hobart, Australia, 16–19 October, 2011; pp. 1–6.
35. Liang, X.; Kankare, V.; Yu, X.; Hyyppä, J.; Holopainen, M. Automated stem curve measurement using terrestrial laser scanning. *IEEE Trans. Geosci. Remote Sens.* **2013**, 52, 1739–1748.
36. Pfeifer, N.; Winterhalder, D. Modelling of tree cross sections from terrestrial laser scanning data with free-form curves. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2004**, *36*, part2/W2:76-81.
37. Hyyppa, J.; Jaakkola, A.; Hyyppa, H.; Kaartinen, H.; Kukko, A.; Holopainen, M.; Zhu, L.; Vastaranta, M.; Kaasalainen, S.; Krooks, A. Map updating and change detection using vehicle-based laser scanning. In Proceedings of the 2009 Joint Urban Remote Sensing Event, Shanghai, China, 20–22 May 2009; pp. 1–6.
38. Kaasalainen, S.; Hyyppä, J.; Karjalainen, M.; Krooks, A.; Lyytikäinen-Saarenmaa, P.; Holopainen, M.; Jaakkola, A. Comparison of terrestrial laser scanner and synthetic aperture radar data in the study of forest defoliation. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2010**, *38*, 82–87.
39. Kankare, V.; Holopainen, M.; Vastaranta, M.; Puttonen, E.; Yu, X.W.; Hyyppa, J.; Vaaja, M.; Hyyppa, H.; Alho, P. Individual tree biomass estimation using terrestrial laser scanning. *ISPRS J. Photogramm. Remote Sens.* **2013**, *75*, 64–75.
40. Yao, T.; Yang, X.; Zhao, F.; Wang, Z.; Zhang, Q.; Jupp, D.; Lovell, J.; Culvenor, D.; Newnham, G.; Ni-Meister, W. Measuring forest structure and biomass in New England forest stands using Echidna ground-based lidar. *Remote Sens. Environ.* **2011**, *115*, 2965–2974.
41. Yu, X.W.; Liang, X.L.; Hyyppa, J.; Kankare, V.; Vastaranta, M.; Holopainen, M. Stem biomass estimation based on stem reconstruction from terrestrial laser scanning point clouds. *Remote Sens. Lett.* **2013**, *4*, 344–353.
42. Zhao, F.; Yang, X.; Schull, M.A.; Román-Colón, M.O.; Yao, T.; Wang, Z.; Zhang, Q.; Jupp, D.L.; Lovell, J.L.; Culvenor, D.S. Measuring effective leaf area index, foliage profile, and stand height in New England forest stands using a full-waveform ground-based lidar. *Remote Sens. Environ.* **2011**, *115*, 2954–2964.
43. Tanhuanpää, T.V.; Vastaranta, M.; Kankare, V.; Holopainen, M.; Hyyppä, J.; Hyyppä, H.; Alho, P.; Raisio, J. Mapping of urban roadside trees—A case study in the tree register update process in helsinki city. *Urban For. Urban Green.* **2014**, *13*, doi:10.1016/j.ufug.2014.03.005.
44. Holopainen, M.H.; Hyyppä, J.; Vastaranta, M.; Hyyppä H. *Laserkeilaus Metsävarojen Hallinnassa*; University of Helsinki Department of Forest Sciences: Helsinki, Finland, 2013; Volume 5, p. 75.

45. Axelsson, P. DEM generation from laser scanner data using adaptive tin models. *Int. Arch. Photogramm. Remote Sens.* **2000**, *33*, 111–118.
46. Vastaranta, M.; Kankare, V.; Holopainen, M.; Yu, X.; Hyyppä, J.; Hyyppä, H. Combination of individual tree detection and area-based approach in imputation of forest variables using airborne laser data. *ISPRS J. Photogramm. Remote Sens.* **2012**, *67*, 73–79.
47. Yu, X.; Hyyppä, J.; Vastaranta, M.; Holopainen, M.; Viitala, R. Predicting individual tree attributes from airborne laser point clouds based on the random forests technique. *ISPRS J. Photogramm. Remote Sens.* **2011**, *66*, 28–37.
48. Breiman, L. Random forests. *Mach. Learn.* **2001**, *45*, 5–32.
49. Falkowski, M.J.; Hudak, A.T.; Crookston, N.L.; Gessler, P.E.; Uebler, E.H.; Smith, A.M. Landscape-scale parameterization of a tree-level forest growth model: A k-nearest neighbor imputation approach incorporating LiDAR data. *Can. J. For. Res.* **2010**, *40*, 184–199.
50. Hudak, A.T.; Crookston, N.L.; Evans, J.S.; Hall, D.E.; Falkowski, M.J. Nearest neighbor imputation of species-level, plot-scale forest structure attributes from LiDAR data. *Remote Sens. Environ.* **2008**, *112*, 2232–2245.
51. Latifi, H.; Nothdurft, A.; Koch, B. Non-parametric prediction and mapping of standing timber volume and biomass in a temperate forest: Application of multiple optical/LiDAR-derived predictors. *Forestry* **2010**, *83*, 395–407.
52. Team, R.D.C. *R: A Language and Environment for Statistical Computing*; R Foundation for Statistical Computing: Vienna, Austria, 2013. Available online: http://www.R-project.org (accessed on 2 December 2013).
53. Crookston, N.L.; Finley, A.O. Yaimpute: An R Package for kNN imputation. *J. Stat. Softw.* **2008**, *23*, 1–16.
54. Reynolds, M.R.; Burk, T.E.; Huang, W.-C. Goodness-of-fit tests and model selection procedures for diameter distribution models. *For. Sci.* **1988**, *34*, 373–399.
55. Packalén, P.; Maltamo, M. Estimation of species-specific diameter distributions using airborne laser scanning and aerial photographs. *Can. J. For. Res.* **2008**, *38*, 1750–1760.
56. Holmgren, J.; Barth, A.; Larsson, H.; Olsson, H. Prediction of stem attributes by combining airborne laser scanning and measurements from harvesters. *Silva Fenn.* **2012**, *46*, 227–239.
57. Maltamo, M.; Peuhkurinen, J.; Malinen, J.; Vauhkonen, J.; Packalén, P.; Tokola, T. Predicting tree attributes and quality characteristics of scots pine using airborne laser scanning data. *Silva Fenn.* **2009**, *43*, 507–521.
58. Peuhkurinen, J.; Maltamo, M.; Malinen, J.; Pitkanen, J.; Packalen, P. Preharvest measurement of marked stands using airborne laser scanning. *For. Sci.* **2007**, *53*, 653–661.
59. Kaartinen, H.; Hyyppä, J.; Yu, X.; Vastaranta, M.; Hyyppä, H.; Kukko, A.; Holopainen, M.; Heipke, C.; Hirschmugl, M.; Morsdorf, F. An international comparison of individual tree detection and extraction using airborne laser scanning. *Remote Sens.* **2012**, *4*, 950–974.
60. Pitkänen, J.; Maltamo, M.; Hyyppä, J.; Yu, X. Adaptive methods for individual tree detection on airborne laser based canopy height model. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.* **2004**, *36*, 187–191.

61. Vauhkonen, J.; Ene, L.; Gupta, S.; Heinzel, J.; Holmgren, J.; Pitkänen, J.; Solberg, S.; Wang, Y.; Weinacker, H.; Hauglin, K.M. Comparative testing of single-tree detection algorithms under different types of forest. *Forestry* **2012**, *85*, 27–40.
62. Forsman, P.; Halme, A. 3-D mapping of natural environments with trees by means of mobile perception. *IEEE Trans. Robot.* **2005**, *21*, 482–490.
63. Hellström, T.; Lärkeryd, P.; Nordfjell, T.; Ringdahl, O. Autonomous forest vehicles: Historic, envisioned, and state-of-the-art. *Int. J. For. Eng.* **2009**, *20*, 31–38.
64. Jutila, J.; Kannas, K.; Visala, A. Tree measurement in forest by 2D laser scanning. In Proceedings of the International Symposium on Computational Intelligence in Robotics and Automation, CIRA 2007, Jacksonville, FI, USA, 20–23 June 2007; pp. 491–496.
65. Miettinen, M.; Ohman, M.; Visala, A.; Forsman, P. Simultaneous localization and mapping for forest harvesters. In Proceedings of the 2007 IEEE International Conference on Robotics and Automation, Roma, Romania, 10–14 April 2007; pp. 517–522.
66. Ringdahl, O.; Hohnloser, P.; Hellström, T.; Holmgren, J.; Lindroos, O. Enhanced algorithms for estimating tree trunk diameter using 2D laser scanner. *Remote Sens.* **2013**, *5*, 4839–4856.
67. Öhman, M.; Miettinen, M.; Kannas, K.; Jutila, J.; Visala, A.; Forsman, P. Tree measurement and simultaneous localization and mapping system for forest harvesters. In *Field and Service Robotics*; Springer-Verlag: Berlin/Heidelberg, Germany, 2008; pp. 369–378.
68. Lindberg, E.; Holmgren, J.; Olofsson, K.; Olsson, H. Estimation of stem attributes using a combination of terrestrial and airborne laser scanning. *Eur. J. For. Res.* **2012**, *131*, 1917–1931.
69. Vauhkonen, J.; Packalen, P.; Malinen, J.; Pitkänen, J.; Maltamo, M. Airborne laser scanning based decision support for wood procurement planning. *Scand. J. For. Res.* **2013**, *28*, doi:10.1080/02827581.2013.813063.
70. Rönnholm, P.; Hyyppä, J.; Hyyppä, H.; Haggrén, H.; Yu, X.; Kaartinen, H. Calibration of laser-derived tree height estimates by means of photogrammetric techniques. *Scand. J. For. Res.* **2004**, *19*, 524–528.
71. Shrestha, R.; Wynne, R.H. Estimating biophysical parameters of individual trees in an urban environment using small footprint discrete-return imaging LiDAR. *Remote Sens.* **2012**, *4*, 484–508.
72. Vastaranta, M.; Melkas, T.; Holopainen, M.; Kaartinen, H.; Hyyppä, J.; Hyyppä, H. Laser-based field measurements in tree-level forest data acquisition. *Photogramm. J. Finl.* **2009**, *21*, 51–61.