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Opportunities for LIDAR to improve and validate tree data sets in the Netherlands

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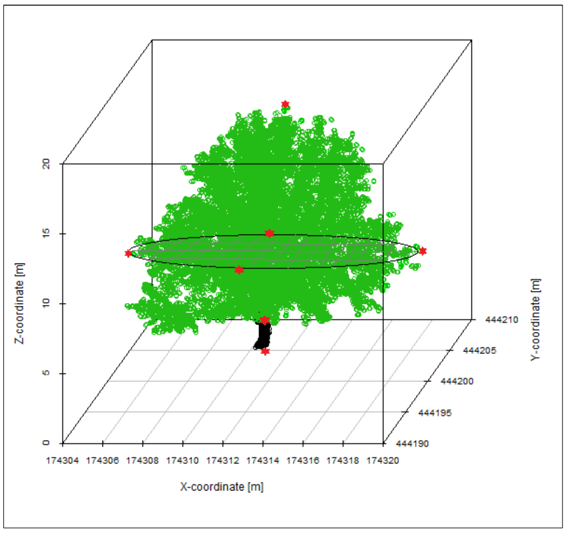

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Opportunities for LIDAR to improve and validate tree data sets in the Netherlands

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Abstract

Light detection and ranging (LiDAR), an active remote sensing (RS) technique, is able to describe tree structural attributes by measuring responses of emitted laser pulses from a tree. Alterra in cooperation with Geodan and NEO created a tree database which was based on raster airborne laser scanning (ALS) LiDAR data and included information about tree locations, tree crown projection perimeters, and several tree shape parameters according to SILVI-STAR method. SILVI-STAR method was designed to save tree attributes as a parameterized, 3D model.

The aim of the study was to find a new way of delineating trees and deriving their parameters using terrestrial laser scanning (TLS) and ALS LiDAR point data, which can improve the existing method of tree parameter extraction and to assess the quality of the existing method.

The delineation essence was in extraction of aggregated and classified as high vegetation TLS points. Individual TLS and ALS tree point clouds were processed in R to derive tree parameters. Visual assessment showed that tree height, peripheral height and peripheral points extracted from TLS point data were accurate in more than 90% of cases, while the same parameters extracted from ALS point data were correct only in 46-77% of the cases. Meanwhile, only in 60.41% of cases the height of the first living fork and in 63.07% of cases the DBH and tree location have been correctly computed, thus the method of tree parameter extraction from point data needs improvements. The suggested enhancements are the separation of solitary trees from the aggregation of trees and creation of a better technique for noise removal.

The quality of tree parameters derived from ALS raster and point data was assessed using parameters derived from TLS point data. Based on the results of validation, the tree location calculation from ALS raster data was not as precise as urban tree managers may be requiring, producer's accuracy was 0.23 and user's accuracy was 0.15. However, this result is not very much reliable, as only in 63.07% of cases tree locations derived from TLS point data were correct. In addition, height parameters retrieval from ALS data were reliable only for tree heights extracted from ALS point data (R^2 = 0.71 and RMSE = 3.89). This could be explained by the fact that the accuracy of ALS raster data is much lower, which is caused by the low density of points and averaging these points during the transformation of point data into 0.5m×0.5m raster cells. The extraction of periphery points from ALS point, as well as raster, data was perfect (R^2 was no smaller than 0.9). In general validation showed that extraction of parameters using ALS point data rather than ALS raster data gives more precise result.

Undoubtedly, extraction of tree parameters from TLS point data is more precise compared to ALS data. However, taking into account the fact that acquiring TLS data in comparison with ALS data for the same area takes more time and requires more labour, the perspective of using ALS point data to derive tree parameters seems more realistic.

Keywords: Terrestrial Laser Scanning, Airborne Laser Scanning, LiDAR, SILVI-STAR tree parameters

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Nomenclature

AHN – Actueel Hoogtebestand Nederland, the precise height dataset of the Netherlands

LiDAR – Light Detecting and Ranging

DEM – Digital Elevation Model

DTM – Digital Terrain Model

DSM – Digital Surface Models

ALS – Airborne Laser Scanning

TLS – Terrestrial Laser Scanning

TP – True positive

FP – False positive

FN – False negative

CP – Canopy Projections

TCPE – Tree Canopy Perimeter Extraction

TLSref – Terrestrial Laser Scanning reference

DBH – Diameter at breast height (1.3 m above the ground)

PCTPE – point cloud tree parameters extraction

ALStpe – Aerial Laser Scanning tree parameter extraction

R^2 – coefficient of determination

RMSE – root-mean-square error

RS – remote sensing

1. Introduction

1.1. Background

The trees in the cities are highly important, as they perform many useful functions (Sander et al. 2010). However, tree maintenance is necessary to keep them healthy and to prevent the occurrence of events that could have negative consequences for inhabitants of a city. For successful urban tree management a database, which includes information about tree locations and their attributes, is needed (Benthem 2013).

In order to explore the possibilities of creating an open tree dataset for the Netherlands, in 2012 a Public-Private Partnership has been set up between Wageningen UR-Alterra and two private-sector companies: Geodan (IT) and Neo (Remote Sensing) (Rip and Bulens 2013). On the base of the “AHN2” national digital elevation dataset Alterra has developed a method of canopy perimeter extraction (Rip and Bulens 2013). Actueel Hoogtebestand Nederland (AHN) is the official governmental dataset, the precise height dataset of the Netherlands, seized through airborne LiDAR. AHN2, the new version of AHN, is more accurate and has a higher point density compared to the previous version, was being acquired from 2007 (Rafiee et al. 2013). The method of canopy perimeter extraction is still under development. In addition, Alterra has created a procedure to compute the values of several tree shape parameters according to SILVI-STAR method (Koop 1989). The derived parameters have been used to produce 3D visualizations of trees in urban environment. Urban tree managers are interested in the produced result, as it could help them to have a better overview of the trees with less labor.

According to a field test the tree canopy perimeters derived by Alterra are captured with about 60% completeness (Rip and Bulens 2013). Further assessment of the quality of the tree canopy perimeter dataset and of the SILVI-STAR parameter values derived from this dataset, showed that an improvement of the extraction method is needed. This research is focused on improvement of the tree parameters extraction from the AHN2 data, using the raw terrestrial and airborne LiDAR point cloud data, validation of the results of the tree canopy perimeter extraction method and validation of derived SILVI-STAR parameter values.

1.2. Research overview

Problem definition

Trees are very important in urban areas. They protect from soil erosion, provide the habitat for wildlife, improve the quality of air, mitigate urban heat island effect, help to save energy through building shading and insulation, and reduce stormwater runoff. There are also cultural benefits, which urban tree cover provides. Trees in an urban environment improve the quality of urban life as they may refine the scenic quality of a neighbourhood, provide privacy, reduce stress, etc (Sander et al. 2010).

As Europe realizes this value, its policy is directed to increase the number of green area and at once to decrease agricultural area, because there is an excess in agricultural production. This policy should encourage the increase of biodiversity through the presence of small landscape elements such as bushes, hedges, trees (Rip and Bulens 2013).

The owners of the trees in the Netherlands have public responsibility to keep them healthy in order to prevent falling of branches or a tree itself to public space. This obliges tree owners to keep record of individual tree conditions. However, this information is not uniform and it is not collected with the purpose to make one database. Such a database should contain information about locations and properties of all non-forest trees of different owners, such as private and public organizations and private owners. The absence of the database limits the effectiveness of tree maintenance, pests and diseases management (Rip and Bulens 2013).

The database might be useful for urban tree managers who take care of large amount of trees. Despite they are the main inspirers of the database creation; the main focus of this research is not an investigation of their needs and desires concerning the database. This research is concentrated on technical part of tree parameters acquisition for creation of the dataset.

To derive all the necessary information about the trees location and their main attributes there are traditional methods, such as field measurements. However, they are very labor-intensive and time consuming (Chang et al. 2013). Therefore remote sensing has a potential to supplement or even replace field measurements (Homolova et al. 2013).

The main action to derive single tree information from any kind of remote sensing data is to find and delineate individual trees. To delineate separate trees using multispectral imaginary several methods have been used: multiple scale edge segmentation (Brandtberg and Walter 1998), valley-following method (Gougeon 1995), template matching (Pollock 1996), watershed segmentation (Schardt et al. 2002), local maxima filtering (Dralle and Rudemo 1996). However, the spatial resolution of the imaginary has to be higher than the area of tree crowns, otherwise tree crown will not be recognizable as discrete objects (Kwak et al. 2007).

With the appearance of LiDAR and its wide introduction into remote sensing, the number of studies on individual tree detection started to increase (Jakubowski et al. 2013). LiDAR is based on measurements of laser range to acquire *x*, *y* and *z* coordinates of reflecting objects. This provides a modern and powerful tool to derive individual tree data (Chang et al. 2013). To detect single trees and get their main attributes different algorithms like k-means clustering (Morsdorf et al. 2004), region-growing algorithm (Koch et al. 2006), morphological analyses (Kwak et al. 2007), spatial wavelet analysis (Falkowski et al. 2008), and a combination of variable windows size filtering (Popescu and Wynne 2004) were used (Jakubowski et al. 2013).

Latter studies focus on operating with point cloud data and not transforming the LiDAR data into a raster. An adaptive clustering algorithm implemented by Lee et al. (Lee et al. 2010) is similar to watershed segmentation. However, the method was applied to the 3D LiDAR points. The algorithm in this method bases on training data to perform segmentation relied on supervised learning. However, there is an individual tree segmentation approach, where training data are not necessary. The algorithm implemented by Li et al. (Li et al. 2012) uses the distance between the tops of the trees to identify and group points into a single tree based on rules of proximity and likely tree shape (Jakubowski et al. 2013).

The method of tree crown perimeter extraction (TCPE), created by Alterra employee Jan Clement (Clement 2013), uses the AHN-2 Digital elevation model (DEM) covering the Netherlands which was acquired during the period 2007-2012. LiDAR point clouds, Digital Terrain Models (DTMs) and Digital Surface Models (DSMs) are available AHN-2 products. On average the point cloud has 8 points per m^2. DTM and DSM are raster data with a resolution of 0.5 m and vertical accuracy of 5 cm. The tree crown extraction algorithm uses DTM and DSM. A normalized height raster, called delta_h_raster, is gained by subtracting the DTM from the DSM. Moreover, to decrease the search area of the algorithm, two exclusion masks were created. One of them, called nodata_top10, made on the base of the topographic Top10smart raster, excludes buildings from the search area. Additionally, this mask contains no data areas of the DTM. Another one, called STD_notrees, made by applying a standard deviation filter on the DSM, serves to remove areas with low standard deviation, i.e. no tree areas, which based on Jan Clement's observation that in the AHN2 DTM vegetation shows a relatively high, more than 1.5 m, standard deviation in grid cell values[1]. After applying masks and defining the search area, the

[1] Source: personal communication with Frans Rip

final extraction of the tree crowns is made on the basis of the delta_h_raster. The extraction algorithm also records the attributes of the extracted tree crowns (Table **1**).

Table 1. The attributes of the tree crown extractions

Attribute name	**Description**
BLAD_ID	Map number of the corresponding AHN-2 sheet
BOOM_ID	Unique tree crown number
BM_X	X coordinate of the crown centroid
BM_Y	Y coordinate of the crown centroid
GEM_MV	Average ground elevation beneath crown (AHN-2 DTM)
BOOM_HOOGT	Maximum normalized height (delta_h_raster) with crown projection
GEM_HOOGTE	Average normalized height (delta_h_raster) with crown projection
SHAPE_AREA	Area of crown projection in m^2

There are several versions of the algorithm. The base of the canopy extraction algorithm is almost the same; however, there are some minor differences between the versions. The differences consist in modification of the filtering of the output, masking of buildings and filling of no data. The method is still under improvement.

From the result, produced by the TCPE algorithm, an additional set of parameters was derived in accordance with the SILVI-STAR tree model (Koop 1989). This model is designed to save tree attributes as a parameterized, 3D model. SILVI-STAR describes the trees using *x, y* and *z* coordinated of 8 points: stem base (B), height of first bifurcation (F), top of the tree crown (T), base of the tree crown (C), and four peripheral points of the crown circumference (P1, P2, P3, P4). The 3D model of the tree is shown in Figure 1. The horizontal projection of the tree crown is indicated by a combination of quarter of ellipses, sketched up by peripheral points, which are extremities of the tree crown in x- and y-direction (Figure 2).

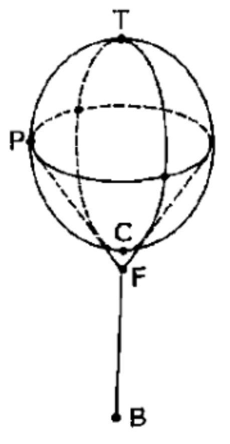

Figure 1. The 3D tree model, where B-stem base, F-height of the first bifurcation, T-top of the tree crown, C-base of the tree crown, P-periphery point. "Source: Koop 1989"

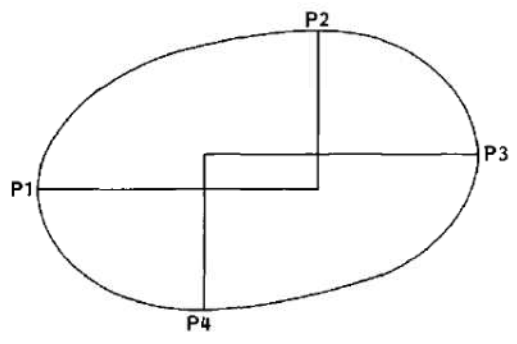

Figure 2. Horizontal projection of the tree crown. Peripheral points P1, P2, P3, P4 are connected to each other with quarters of ellipses. "Source: Koop 1989"

The vertical projection is approximated with ellipse equations, where the ellipses are used to connect both the top of the tree crown and the base of the tree crown with each of the peripheral points. As different species of the trees have different forms of the crowns, the ellipse equations are adjusted to allow convex or concave crown curves (Benthem 2013).

The dataset, created by version 9.2 of the TCPE method, is referred to as the Canopy Projections (CP) dataset. Several validations were made to find out how good the CP dataset is. An early field test in 2011 for a limited area was made (Schouten 2012). It indicated that around 60% of the tree canopies were captured (Rip and Bulens 2013). Validation of the tree extraction algorithm made in 2013 by Rik van Benthem, intern at NEO, was focused on (1) checking the algorithm's ability to find individual tree locations, (2) comparing extracted crown projections with actual crown areas, and (3) verifying the correctness of the extracted height parameters. Validation of the algorithm was based on comparing the extracted tree crown projections with the ground truth database. The basis of this database was the municipal tree database of Amersfoort; it was improved using the available aerial images. The validation indicated that the extraction algorithm misses 30 to 50% of the municipal and private trees in the urban study area. The accuracy values for the crown areas are higher than for tree locations; the algorithm misses 25 to 38% of the urban tree crown area. There are no large differences between the heights calculated by the algorithm and the extracted heights (Benthem 2013). In 2013 another validation was made by Frans Rip (Meijer 2014). The tree crown perimeters, which served as reference model, were derived by digitizing tree canopies from the aerial photographs for the part of WUR campus. There were two types of trees distinguished within the model: solitary trees (SolitaryVegetationObjects) and groups of neighboring trees with adjoining canopies (PlantCover). The validation was made for two versions of the tree canopy extraction algorithm: V5 and V9.2. The validation was made by finding True Positives (TP), False Positives (FP), False Negatives (FN) and then by calculating the value of Quality, which is Quality=TP/(TP+FN+FP). The closer the Quality value to 1, the better the quality of the result of TCPE method. As a result of validation, the Quality value of PlantCover looking at area in m^2 is 0.78 for V5 and 0.83 for V9.2; the Quality value of SolitaryVegetationObjects looking at the number of canopies is 0.44 for V5 and 0.48 for V9.2 (Meijer 2014).

There are several versions of the tree crown extraction algorithm and each of them has limitations. In V5 and V6 the algorithm extracts trees with a height of more than 1 m and crown area of more than 1 m^2; in V7 the algorithm only extracts trees with height of more than 4 m and crown area more than 5 m^2.

There are some drawbacks in the used method, which reduces the accuracy of the tree crown extraction. The extraction algorithm uses raster data as input. In order to derive the raster ALS points were resampled in favour of the highest values to a grid, where possible values for the underside of the canopy and the stem got lost. Thus there is no possibility to derive the point representing the base of the tree crown and the point of the first bifurcation. Moreover, the location of the tree stem is based on calculating the centroid of the crown projection, so it can be not accurate.

There are also some problem cases with the form of the trees themselves. First of all, its shape may not be ideal; trees are not totally symmetric. Further, there can be several trees, which stand close by and their crowns intersect. Thirdly, the trunk of the tree can split on the base of the tree, so such a tree has two crowns, a stem can be bent and the crown will be not above the stem or a tree can be totally without crown, e.g. freshly cut pollard-willows. This makes it difficult to distinguish and extract individual trees from aerial imaginary.

The TCPE method is still under development and improvement. Further validation of the results of the method and the correctness of the derived SILVI-STAR parameters is necessary. To derive better accuracy of the tree canopy extraction method, cope with drawbacks of the method and with problems with tree shapes indicated above the improvement of the method appears necessary.

Research objectives

The main objective of this research is to find a new way of delineating individual trees and deriving their parameters, which can improve the existing method of tree canopy extraction.

In order to achieve the main objective of the research the following questions have to be answered:

1. Is it possible to improve the extraction of tree parameters, using the raw point cloud terrestrial and airborne LiDAR data, instead of the top-of-canopy raster datasets?

2. How good is the CP dataset for use by municipal tree managers?

3. How good are the SILIVI-STAR parameter values, as derived from ALS point data and ALS raster data for use by municipal tree managers?

2. Methodology

2.1. Study area

The area selected for this research is the North-Eastern part of Wageningen University and Research centre campus (Figure 3). It is located in Wageningen city in the Netherlands. The size of the area is around 122 740 m^2.

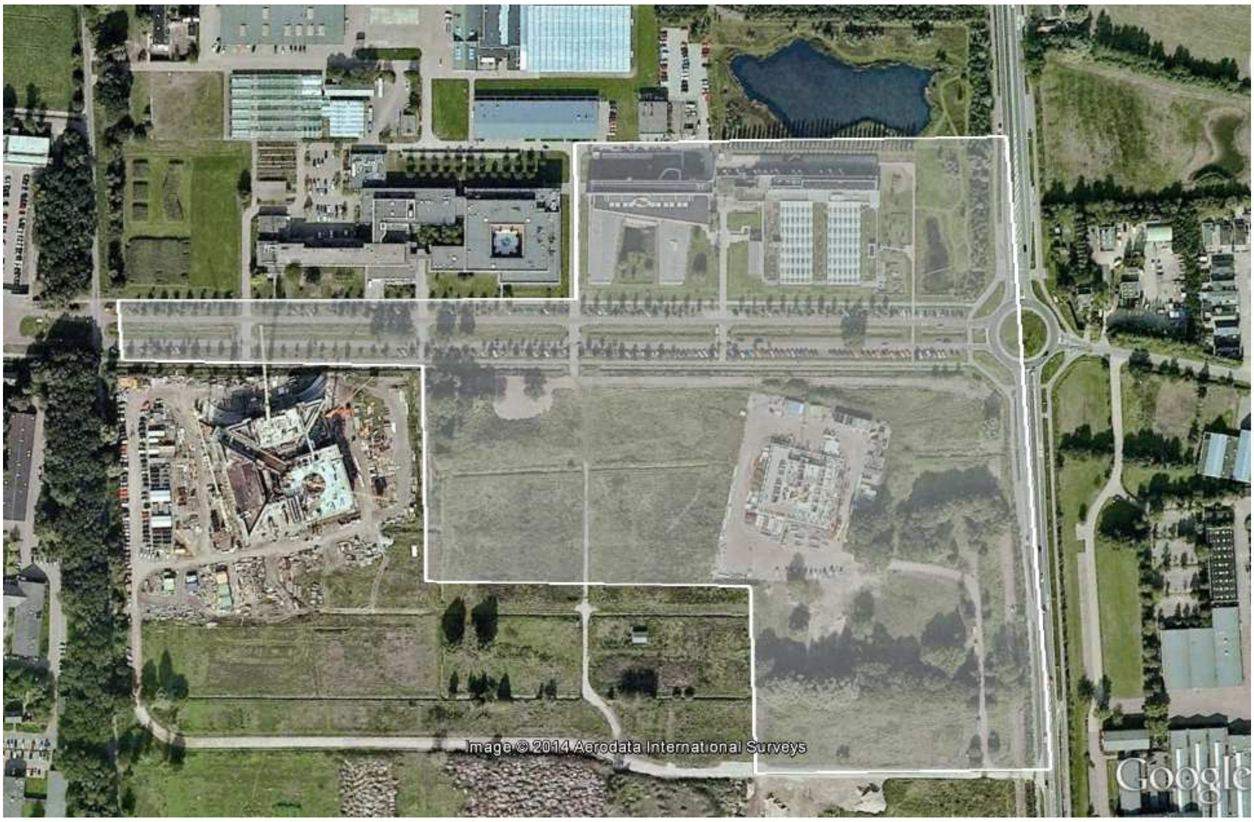

Figure 3. Study area (part of Wageningen UR campus)

2.2. Data

To improve the method and to make validation of the latest version (V9.2) of the CP dataset, created by Jan Clement, both terrestrial and aerial LiDAR point cloud data were used.

Terrestrial Laser Scanning

Terrestrial laser scanning (TLS) is an active sensor technology which uses a LiDAR scanner fixed on a tripod on the ground and is capable to record spatial distribution of the tree in the three dimensions. TLS gives a possibility to describe vertical tree properties more accurate compared with any other RS techniques, as it has high resolution characteristics and stands at below-canopy level. A terrestrial laser scanner Reigl VZ-400 was provided by Wageningen University in order to acquire TLS data for the study area.

Airborne Laser Scanning

Airborne laser scanning (ALS) is an active sensor technology which uses a LiDAR scanner mounted on aircraft. It is also able to record spatial distribution of the tree in the three dimensions and has quite high spatial resolution. The advantage of ALS is in its ability to cover areas with larger extent as the scanner is orbiting at higher altitudes. However, as it scans from above the surface, vertical tree properties are described worse than by TLS.

Aerial LiDAR point cloud dataset, the Actueel Hoogtebestand Nederland 2 (Actual Height model of the Netherlands 2, AHN2), was provided by Wageningen University. The AHN 2 product consists of precise and detailed LiDAR database covering the whole Netherlands. The density of the points in the AHN data used in this research is approximately 2-3 pts./16 m^2. The data were acquired in 2010. There were 8 ALS tiles which covered the study area. Figure 4 shows ALS data for the study area.

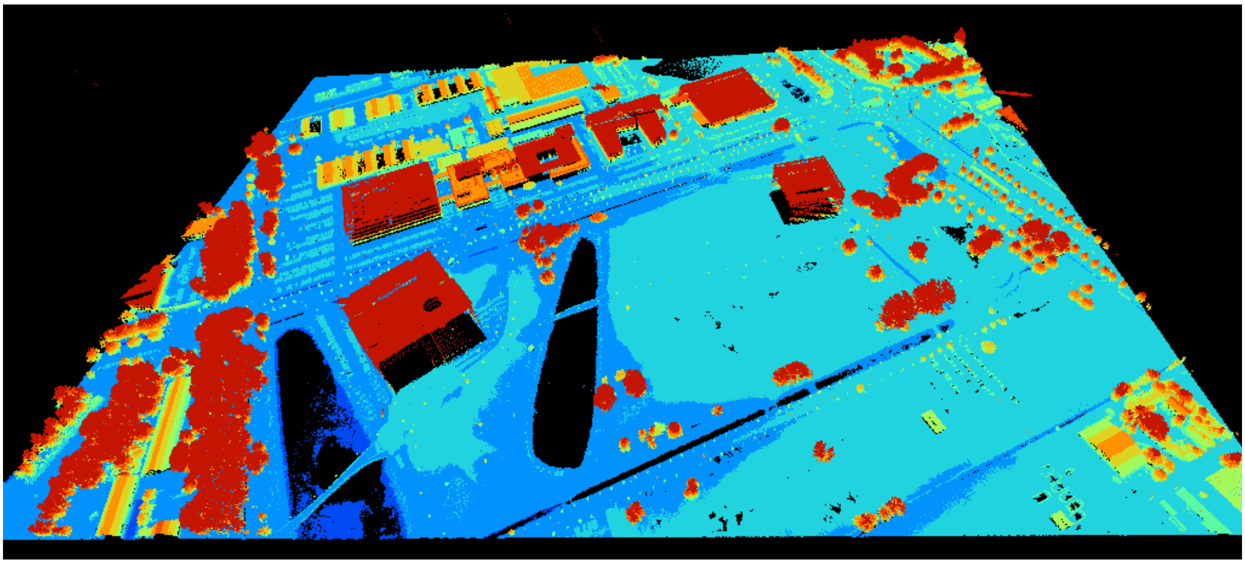

Figure 4. ALS data for the study area

2.3. Used software

To process the data the following software was used: R 3.0.2., RiSCAN pro v1.7.9., ArcGIS 10.1, LasTools[2] v.131105. R is a free software environment for statistical computing and graphics. The following packages were used: rgl[3], colorspace[4], raster[5], fields[6], sp[7],

[2] Martin Isenburg, LAStools - efficient tools for LiDAR processing. version 131105, http://lastools.org.
[3] Daniel Adler, Duncan Murdoch and others (2014). rgl: 3D visualization device system (OpenGL). R package version 0.93.996. http://CRAN.R-project.org/package=rgl
[4] Ross Ihaka, Paul Murrell, Kurt Hornik, Jason C. Fisher, Achim Zeileis (2013). colorspace: Color Space Manipulation. R package version 1.2-4. URL http://CRAN.R-project.org/package=colorspace
[5] Robert J. Hijmans & Jacob van Etten (2013). raster: raster: Geographic data analysis and modeling. R package version 2.1-16. http://CRAN.Rproject.org/package=raster

spatstat[8], gstat[9], scatterplot3d[10], hexbin[11], hydroGOF[12], rgeos[13], circular[14], ggplot2[15]. RiScan PRO is the accompanying software for RIEGL Terrestrial 3D Laser Scanner Systems. It gives opportunity to visualise data right after acquisition and provides a multiplicity of functions for data processing. ArcGIS is powerful GIS software for working with geographic information. Used functions are: “Create Las dataset”, “Multipoint to single point”, “Aggregate”, “Split by attributes”, “Calculate geometry”. LAStools is a collection of tools which are able to process LAS, LAZ, BIN, SHP and ASCII file formats. The following tools were used: “lasclip”, “lasmerge”, “lasground”, “lasclassify”, “las2las”, “las2txt”.

2.4. Research methodology

This section is dedicated to give an overview about the content of the research. According to the research objective and the research questions, two main stages could be identified. In the first stage (Figure 5) the requirements for the tree dataset and the usability of the research were investigated, TLS point data were acquired and pre-processed, individual trees were delineated and the tree parameters, which were necessary for the 3D modelling of trees, were acquired from terrestrial and airborne LiDAR point cloud data. The main purpose of the first stage was to improve the TCPE method, to find a new way of delineating trees and deriving tree parameters. The second stage (Figure 6) was focused on comparing and validating the tree parameters from

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Roger S. Bivand, Edzer J. Pebesma, Virgilio Gomez-Rubio, 2008. Applied spatial data analysis with R. Springer, NY. http://www.asdar-book.org/

[8] Adrian Baddeley, Rolf Turner (2005). spatstat: An R Package for Analyzing Spatial Point Patterns. Journal of Statistical Software 12(6), 1-42. URL http://www.jstatsoft.org/v12/i06/.

[9] Pebesma, E.J., 2004. Multivariable geostatistics in S: the gstat package. Computers & Geosciences, 30: 683-691.

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[11] Dan Carr, ported by Nicholas Lewin-Koh and Martin Maechler (2013). hexbin: Hexagonal Binning Routines. R package version 1.26.3. http://CRAN.R-project.org/package=hexbin

[12] Mauricio Zambrano-Bigiarini (2014). hydroGOF: Goodness-of-fit functions for comparison of simulated and observed hydrological time series. R package version 0.3-8. http://CRAN.R-project.org/package=hydroGOF

[13] Roger Bivand and Colin Rundel (2013). rgeos: Interface to Geometry Engine - Open Source (GEOS). R package version 0.2-16. http://CRAN.R-project.org/package=rgeos

[14] C. Agostinelli and U. Lund (2013). R package 'circular': Circular Statistics (version 0.4-7). URL https://r-forge.r-project.org/projects/circular/

[15] H. Wickham. ggplot2: elegant graphics for data analysis. Springer New York, 2009.

the CP dataset and tree parameters, acquired from ALS point cloud data, with the help of tree parameters, acquired from the TLS point cloud data.

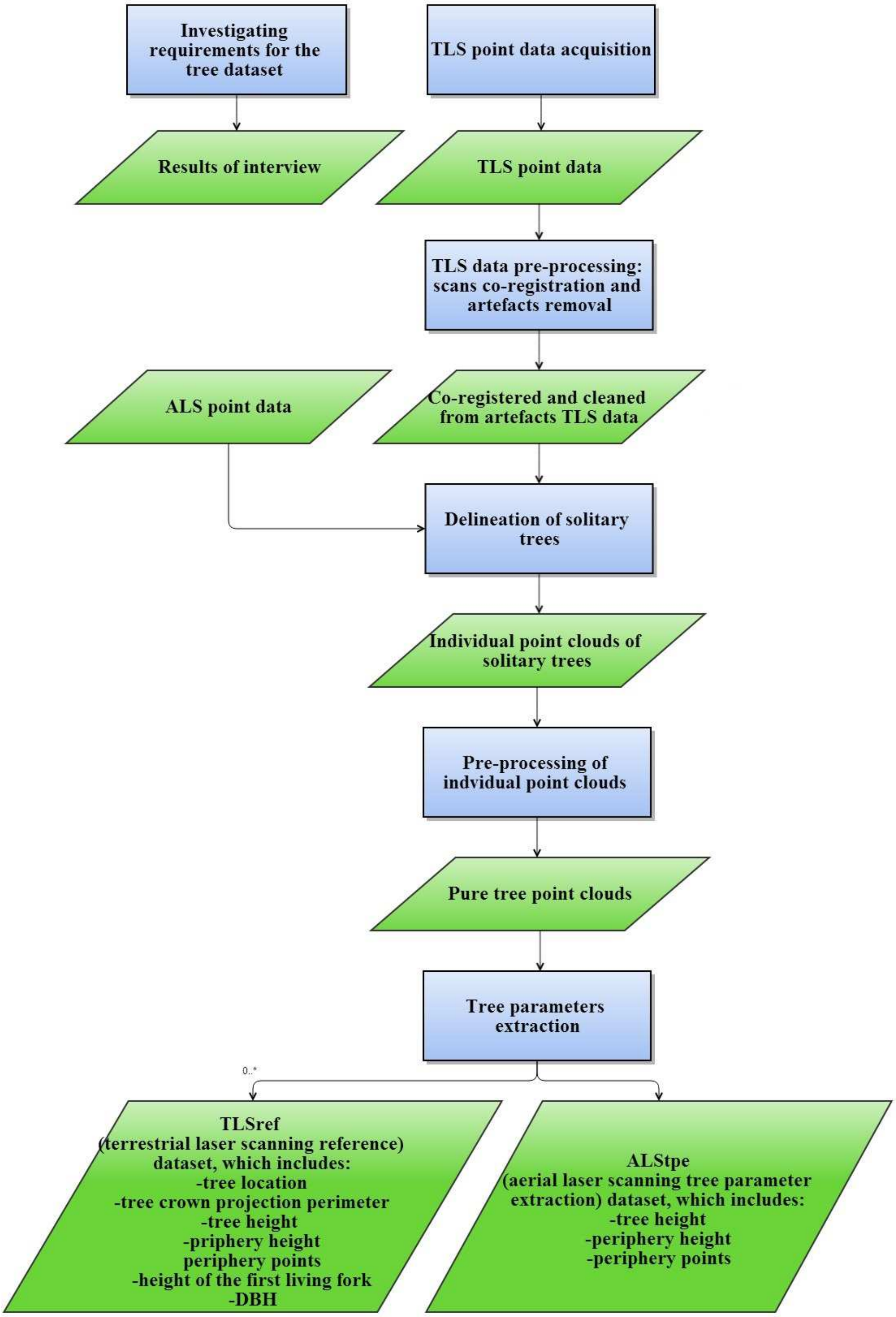


Figure 5. Methodology flowchart (stage 1)

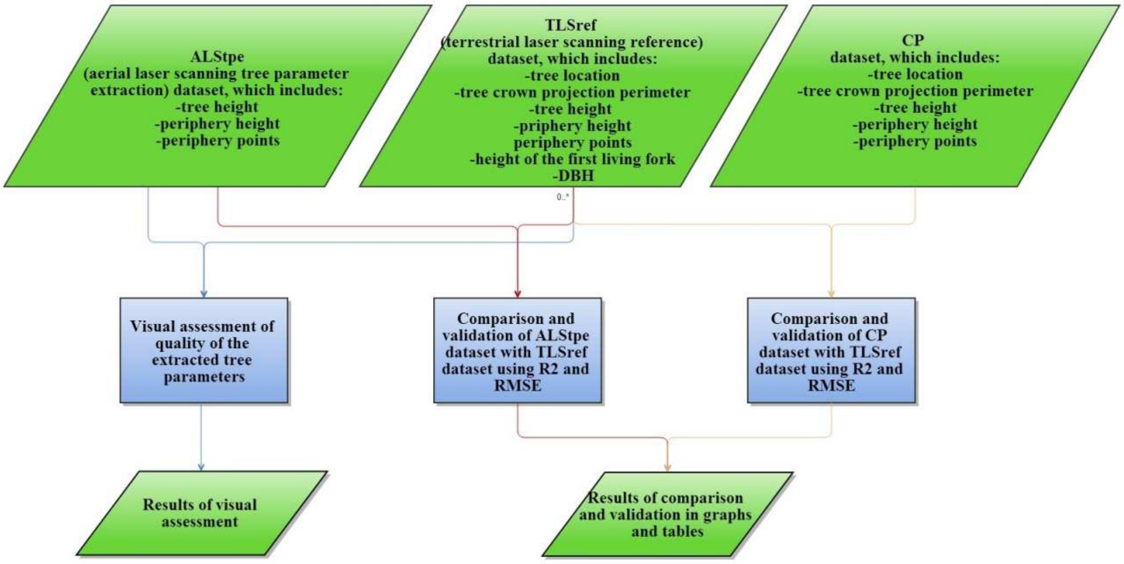


Figure 6. Methodology flowchart (stage 2)

2.4.1. Usability and requirements for the tree dataset

In order to investigate which parameters are essential to know for urban tree managers, which geometrical accuracies tree parameters should have and to assess the usability aspect of the research a questionnaire for interviewing urban tree managers was designed. The questionnaire is presented in Appendix 1.

2.4.2. Data acquisition and pre-processing

Two rules had to be fulfilled during data acquisition process. All the trees in the study area had to be covered by terrestrial laser scanner from 2-3 scan positions. Scans had to be derived on reasonable distance, around 50 meters from each other.

Data pre-processing included scans co-registration and artefacts removal.

Scans co-registration

The origin of each scan refers to the specific position of the scanner. First, in order to have all TLS scans in the same coordinate system, they were co-registered together. Reflectors, which were already present in the scanned environment, were used as tie-points. The co-registration of the scans was based on the locations of tie-points. It was accomplished in RiSCAN PRO v1.7.9. software. The settings which were used to find reflectors are presented in Table 2.

Table 2. Reflector extraction parameters

Search radius	0.05 m
Maximum diameter	0.8 m
Minimum points	2
Maximum reflectors	1000
Maximum deviation	0
Minimum reflectance	5 dB

The parameters which were used to find corresponding points in two scans were the following: tolerance was equal to 0.1 m, minimal number of corresponding points was set to 15.

Artefacts removal

The scans contained mistake points mainly because the signal of the scanner reflected from the windows of the buildings and from water surface. In order to get rid of the artefacts the scans were filtered by visually selecting and manually deleting them. The examples of point cloud with noise and point cloud filtered from noise are presented in Figure 7 and Figure 8.

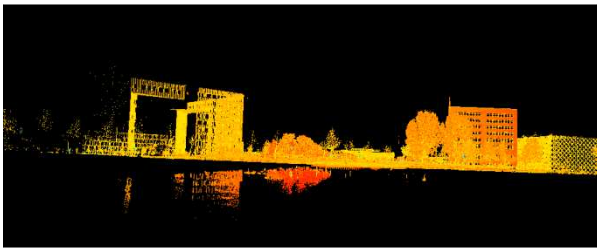


Figure 7. An example of TLS point cloud with noise

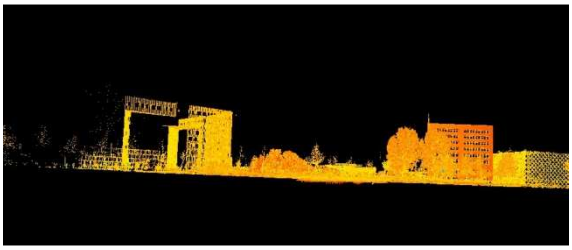


Figure 8. An example of filtered TLS point cloud

ALS data was already co-registered and without noise, thus co-registration and filtering were not applied to ALS data.

In order to combine points from different scans of the derived data, the LAStools function lasmerge was applied to TLS scans, as well as to ALS scans. Both TLS and ALS data were clipped by the study area with the help of lasclip function in LAStools in order to exclude unnecessary points.

2.4.3. Point cloud tree parameters extraction (PCTPE) method

This section is dedicated to describe the procedures, which were followed, to delineate trees and to derive tree parameters using aerial and terrestrial LiDAR point cloud data. Tree delineation and each single tree parameter extraction are treated in each corresponding subsection, where the undertaken methodology approaches are described.

The following tree parameters were derived from the collected data:

1. Location of tree (L)
2. Perimeter of tree canopy projection (A)
3. Tree height (crown top) (T)

4. Four periphery points (P1,P2,P3,P4)
5. Periphery height (height of the greatest width of the crown) (P)
6. Diameter at Breast Height (DBH)
7. The height of first bifurcation (F)

Two of the SILVI-STAR parameters, described in Koop's work (Koop 1989), namely height of the crown base and height of first bifurcation, were not derived by the TCPE method. One of these parameters, the height of first bifurcation and additionally DBH were used only for improvement of this research. The crown base parameter was not possible to derive from the existing point data, as both TLS and ALS data were derived in the period of year, when there were no leaves on the trees. Another SILVI-STAR parameter, namely the relative height of the tree base to the ground level, was not derived as 3D models of trees are usually placed directly to existing DTM[16]. All other parameters listed above were used both for the extraction method improvement and for validation of the existing dataset.

There was an existing R script (Source: Harm Bartholomeus) which removed the noise from individual tree point cloud and calculated such parameters of pure solitary tree point cloud as tree height, tree location, height of the first bifurcation of the tree, DBH. The script was improved in order to be able to derive parameters as periphery height, periphery points' coordinates, perimeter of the tree crown projection and to process the point clouds of all individual trees automatically, store the extracted parameters and validate the CP dataset. The improved script it presented in Appendix 4.1. It was applied to point clouds of solitary trees.

Extracted parameters were stored in one dataset, called Terrestrial Laser Scanning reference (TLSref) dataset. The extraction method, which was used to complete the dataset, was referred to as the Point Cloud Tree Parameters Extraction (PCTPE) method.

The PCTPE method was developed in order to apply it to terrestrial LiDAR point cloud data. However, it seemed interesting to check how aerial LiDAR point cloud data could improve the extraction of tree parameters. Not all the parameters, which were derived from TLS dataset, could be derived from aerial LiDAR point cloud data by applying the method. Thus the PCTPE method was applied to aerial LiDAR point cloud data to extract only part of the parameters: tree height, periphery points' coordinates and periphery height. The dataset, where the extracted parameters were stored, was called Aerial Laser Scanning tree parameter extraction (ALStpe) dataset.

[16] Source: personal communication with Henk Kramer

The TLSref dataset was used for assessing the quality of the tree parameters from the CP dataset and ALStpe dataset.

3.4.3.1. *Delineation of trees*

The study area is situated in urban environment. There could be human made objects, which could be recognized as trees. To exclude non-vegetation objects in was necessary to create a non-vegetation mask.

Three LAStools functions (lasground, lasclassification, and las2las) were applied to terrestrial LiDAR point cloud data to separate vegetation points from non-vegetation. Lasground classified LiDAR points into ground points and non-ground points. As the tool was designed for airborne LiDAR, for processing of the TLS data the “not airborne” option was used. Settings of the tool were adjusted taking into account the fact, that large buildings are situated in the territory of the study area and the landscape is mostly flat. The step size was set to 50 meters; granularity was set to “fine”. In order to skip using lasheight, the height above the ground for each point was computed directly in lasground and elevation value of each point was replaced by this calculated value. Function lasclassify was applied in order to classify points into “ground”, “building”, “high vegetation” and “unassigned” classes. The default settings of the tool were changed. As TLS data has high density of points, search area size was set to 1 meter instead of 2 meters. By default the algorithm intends to find neighboring points that are at least 2 meters above the ground and form “planar 0.1” or “rugged 0.4”, which correspond with buildings and trees, regions. The city of Amsterdam consider a tree as a tree, if the stem is present at DBH and stem diameter is more than or equal to 0.1 meter[17]. Relying on this information the ground offset (the height from which neighboring points were being searched) was set to breast height, 1.3 meters. The threshold value corresponds with standard deviation that neighboring points can have from the region they share. The “building planarity” and “forest ruggedness” was set after set of experiments aimed at finding appropriate threshold for more precise classification of points. Figure 9 shows an example of classification.

[17] http://www.bomenstichtingamsterdam.nl/ visited April 2013

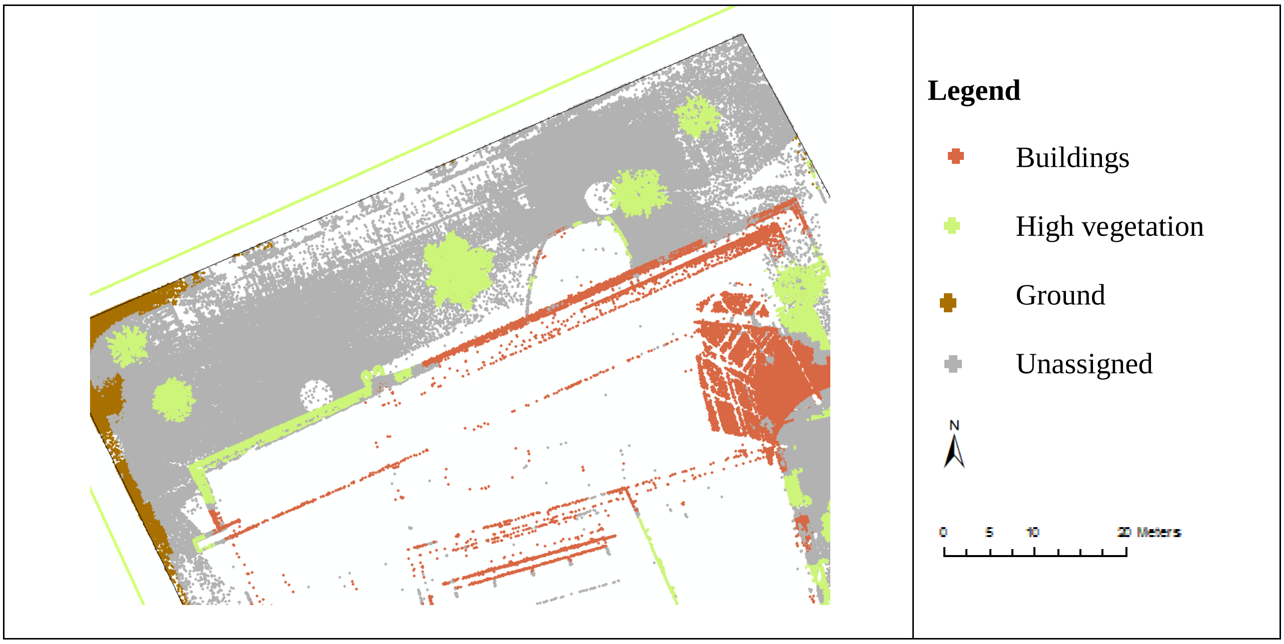


Figure 9. An example of classification of the point cloud for the part of study area

With the help of las2las function points, which belong to “high vegetation” class were selected using “keep classification 5” option. In ArcGIS the LAS files, which were storing high vegetation class points were transformed to Multipoint objects using “LAS to Multipoint” function (point spacing 0.001). Eventually, applying to the points ArcGIS “Aggregation” function with aggregation distance of 0.3 meters the map of vegetation was produced. Because of the time constraints, it was decided not to delineate individual tree crown projections from the aggregation of trees and process only solitary trees. The trees were chosen by visually assessing if their projections had specific shape of tree crown projection. A tree was considered as solitary if its crown projection didn’t touch the boundary of neighboring tree crown projection. An example of vegetation mask is presented in Figure 10.

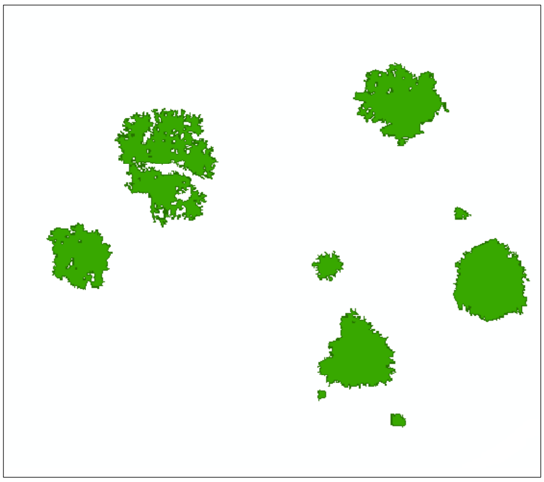


Figure 10. An example of vegetation mask

Crown projections of solitary trees were selected and exported as individual shape files. These shape files were applied to raw point cloud TLS and ALS data in order to clip point clouds of individual trees.

2.4.3.1. *Pre-processing of individual tree point clouds*

The aim of pre-processing of individual tree point clouds was in deleting from them all the points, which didn't belong to trees and were considered as noise. Noise removal consisted on two steps. First, solitary outlier points were removed from the individual tree point cloud. Second, understory and ground points were deleted from individual tree point cloud.

Removal of solitary outlier points

In the point clouds of individual trees besides the points, which belong to the tree or to the ground there were solitary outlier points. In order to remove them filtering was made. To remove the outliers, the distance from each point to its nearest neighbour in the point cloud was calculated, and threshold, which was investigated by experiments, was set to 10 cm. All points, which were further than 10 cm away from their nearest neighbour, were deleted. Figure 11 presents an example of outlier points' removal.

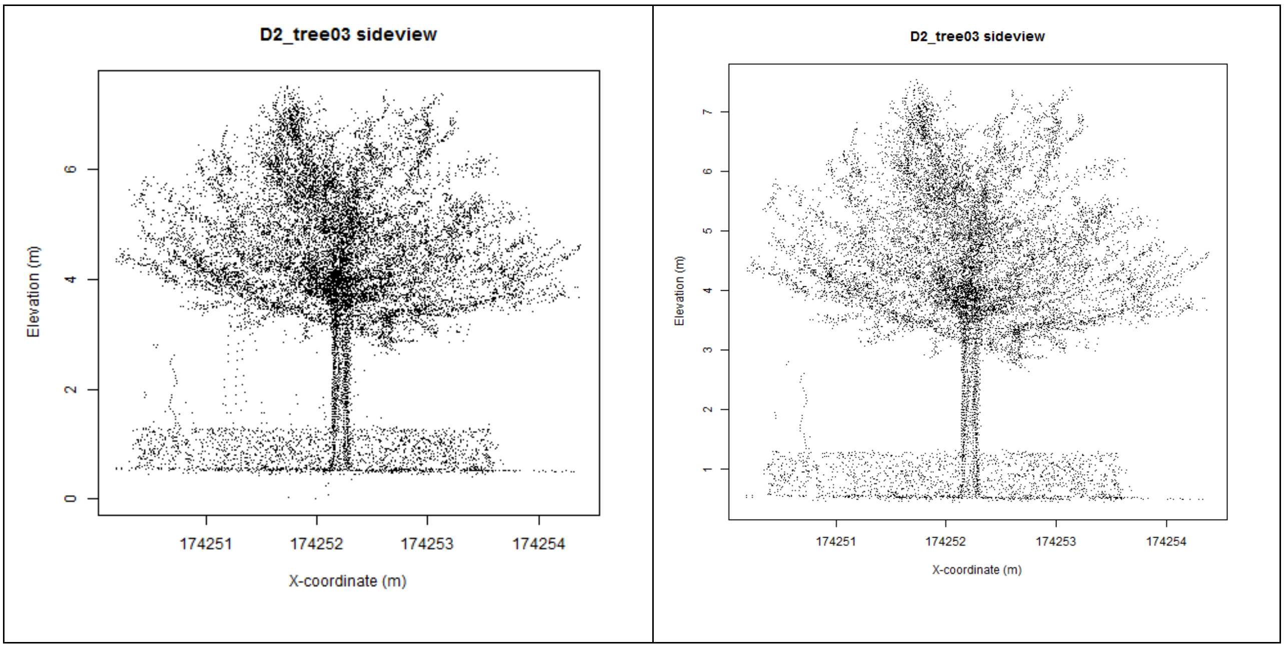


Figure 11. An example of solitary outlier points' removal. Tree point cloud before (left) and after (right) outliers removal

Removal of understory and ground points

DEM

Point clouds of individual trees were extracted from the raw data, so all the heights were absolute, not relative to the ground level. It order to find heights of all points relative to the ground level, first, it was necessary to find the ground points. The procedure of finding them was: making a ground raster, deleting all infinite values from it, and dividing all the objects in the raster into two classes ground and non-ground depending on their height. If they were less than mean height value of the ground raster, they were considered as ground. After that the DEM was interpolated. An example of interpolated DEM is presented in Figure 12. For further calculations interpolated ground raster was transformed to tree-dimensional point pattern.

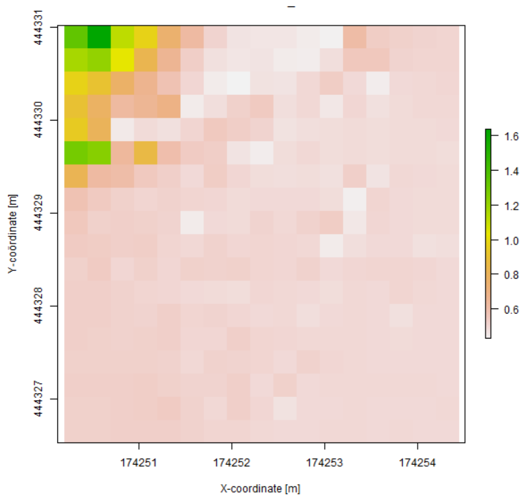
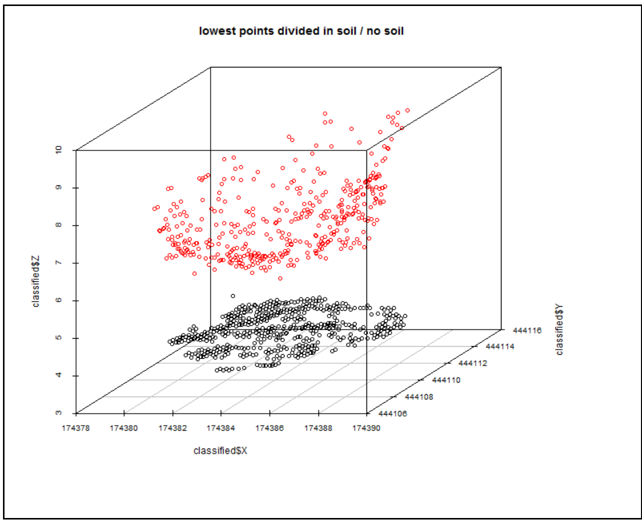


Figure 12. An example of interpolated raster DEM for a solitary tree

Individual pure tree point clouds

In order to reduce the number of errors in calculations of tree parameters from individual tree point clouds, it was decided to delete all unnecessary points, namely points, which belong to the ground and understory of a tree. Using the DEM tree-dimensional point pattern the minimal distance from the original filtered point clouds' points to ground points was calculated. These distances were stored in the individual tree point cloud data frame. First, the points which were closer than 1.3 m to the ground were assigned as ground points; other points were classified as tree points. Figure 13 shows an example of initial separation of the TLS points to the ground and tree points.



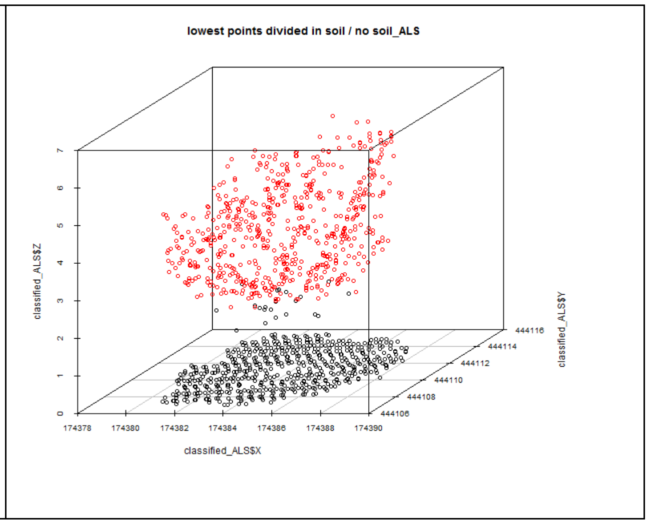


Figure 13. An example of initial separation of TLS point cloud into ground and tree points

Figure 14. An example of separation of ALS point cloud into ground and tree points

However, for TLS data such separation made the tree 1.3 m shorter, so some stem points should have been returned to the tree. The density raster was calculated from the filtered raw data and the cell in that raster with the highest number of returns was designated as the tree stem. An example of density raster is presented in Figure 15.

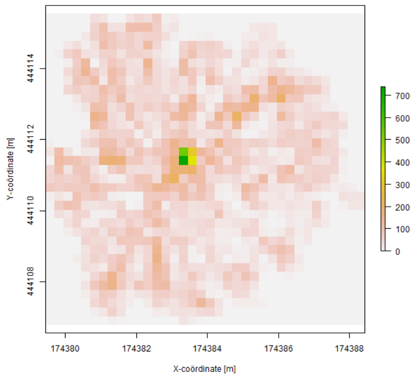
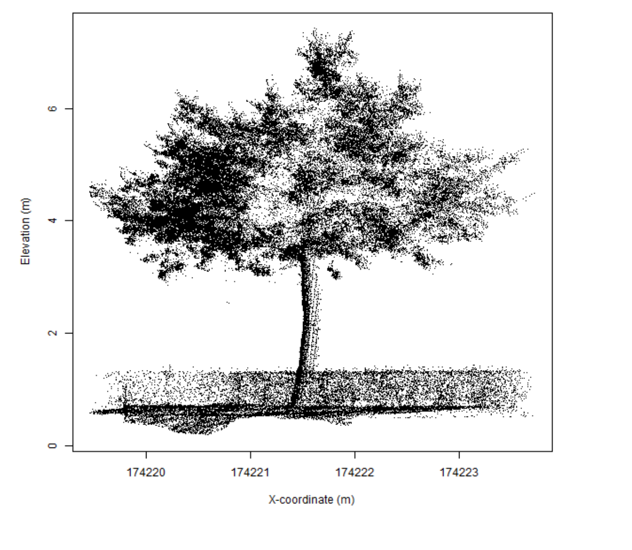


Figure 15. An example of density raster of a tree. Dark green raster cell is the cell with the highest number of returns (stem position)

A buffer of 0.3 m was made around the stem cell. This buffer was applied to ground points. All points from the ground points, which fell into this buffer, were returned to tree points. An example of tree points with understory and ground points is presented in Figure 16, while an example of pure tree points is presented in Figure 17.



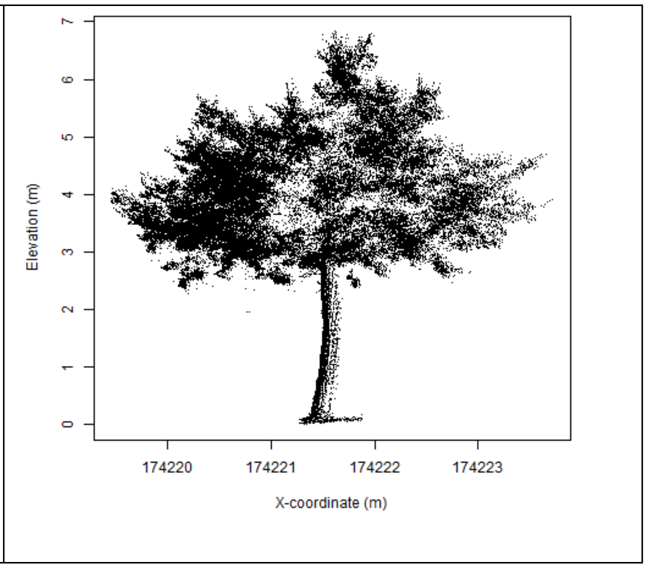


Figure 16. An example of TLS tree points with understory and ground points

Figure 17. An example of pure TLS tree points

ALS data consisted mostly from points which belong either to the tree crown, either to the ground. It didn't have any solitary outlier points. In order to extract solitary pure tree point clouds, tree points and ground points were separated depending on their height. If they were less than mean height value of the point cloud, they were considered as ground, if they were more – as a tree. Figure 14 shows an example of separation of a point cloud into ground and tree points. The height value was replaced by calculated shortest distance from the tree points towards the ground points.

2.4.3.2. Tree parameters extraction

Tree location

In order to derive tree location, first, the cross-section of the point cloud of individual tree was done at breast height (1.3 m), which thickness was 10 cm (1.25 m – 1.35 m). After the subsection was done, a stem of a tree was represented as a set of points resembling the circular geometry of circumference. Second, tree stem was detected by circle fitting using "lsfit.circle" function in R software. The assumption was made, that the centre of each circumference represents the location of a tree.

Tree crown projection perimeter

Crown projections of solitary trees, which were extracted using vegetation mask and stored as shape files were used in order to derive tree crown projection perimeters. Perimeter of each tree crown object was calculated in ArcGIS using "Calculate geometry" function.

Tree height

As height values of raw point cloud data of each solitary tree was in absolute heights, first, the z-coordinate was corrected for ground level value. The tree height parameter was calculated as maximum height value (maximum of corrected z-coordinate) of the point cloud.

Periphery points

In the TCPE dataset there were only *x* and *y* coordinates of periphery points, however in PCTPE method also z-coordinate of the peripheral points was calculated, in order to use it for computing the periphery height. First, the minimum and maximum *x* and *y* coordinates of tree crown projections, made to horizontal plane, were found. These minimum and maximum *x* and *y* coordinates represented the coordinates of four points of the boundary box of the tree crown projection. On the other side, each of these coordinates was either x or y coordinate of one of the periphery points. Afterwards, using alternately each of these coordinates corresponding *y* and *z* coordinates or *x* and *z* coordinates were found.

Periphery height

The peripheral height is the height of the maximum width of the crown. In other words, the periphery height is the height, where the periphery points are situated. The 3D tree model is geometrically correct and symmetric; all the periphery points are situated at the same height. However, in reality it is not always the case. So the periphery height was found by averaging the *z* coordinates of four periphery points, calculation of which is described in Section ”Periphery points”.

DBH

The DBH parameter was computed with the identical approach described in the tree location calculation section, in which the location of a tree was retrieved by finding the centre of the circle, which was fitted to the cross-section of the point cloud made on breast height. The DBH parameter was calculated as diameter of fitted circumference.

The height of the first bifurcation

Vertical tree profile slices were made by every 5 cm and the number of returns was calculated for each slice. An example of graph, representing number of returns computed per slice of vertical tree profile, is presented in Figure 18.

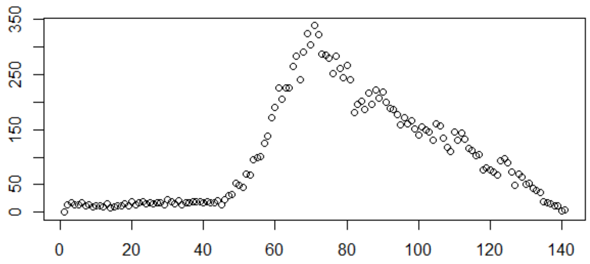


Figure 18. An example of graph, representing number of returns computed per slice of vertical tree profile

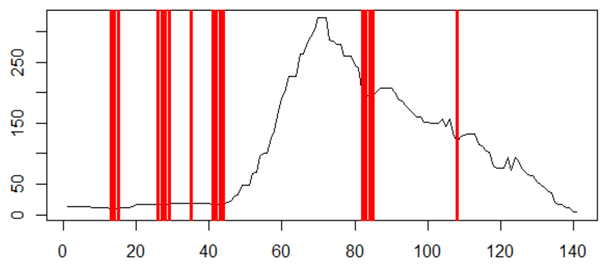


Figure 19. An example of inflection points of fitted line

Afterwards a line was fitted through the plot of the number of the returns at the different slices. Inflection points of the fitted line were found. An example of inflection points of fitted line is presented in Figure 19. Distances between all inflection points were computed. The inflection point after which the largest increase was detected was considered as a point, where the first branch of the tree starts.

2.4.4. Assessment of quality of SILVI-STAR parameters from TLSref and ALStpe datasets

Quality of SILVI-STAR tree parameters, which were extracted from TLS and ALS point cloud data using PCTPE method, was assessed visually by comparing side views, top views and cross-sections of tree point clouds with derived parameters. The number of parameters extracted accurate was found and divided to the number of processed trees point clouds in order to calculate percent of cases when parameters were computed correctly.

2.4.5. Validation of CP and ALStpe datasets

Based on previous research ((Watt et al. 2003), (Hopkinson et al. 2004), (Henning and Radtke 2006)) the assumption that TLS parameters retrieval is as good as derivation of them by field measurements was made. Thus the assessment of quality of the CP and the ALStpe datasets were made by comparing them with TLSref dataset.

The assessment of quality of the CP dataset consisted of several parts: 1) assessing the TCPE algorithm ability to find individual tree locations, 2) validating tree crown projection perimeters and 3) validating extracted SILVI-STAR parameters (tree height, periphery height, periphery points). The assessment of quality of the ALStpe dataset consisted on validating extracted SILVI-STAR parameters (tree height, peripheral height and peripheral points).

2.4.5.1. Assessing the algorithms ability to find tree locations

In order to investigate how well the algorithm finds trees, tree location extracted from CP dataset was compared with the ground truth stem locations from TLSref dataset. The distance between two corresponding points was calculated and a threshold value was set according to results of interviews with urban tree managers. There were three possibilities defined as a result of comparison:

1) True Positive (TP): when the distance between ground truth stem location and extracted from CP dataset was not more than threshold value (what was both in CP and TLSref datasets).
2) False Negative (FN): when there were no trees from the CP dataset within the threshold value distance from the ground truth stem locations (what was missing in CP dataset compared to TLSref dataset).
3) False Positive (FP): when there were no ground truth trees within the threshold value distance from the tree locations, extracted from CP dataset (what is more in CP dataset compared to TLSref dataset).

Calculations of quality aspects were made based on (Xiao et al. 2012). Both producer's and user's accuracy were calculated with the use of TP, FN and FP. Producer's accuracy (completeness) was calculated as TP/(TP+FN). User's accuracy (correctness) was calculated as TP/(TP+FP). The quality was calculated as TP/(TP+FN+FP). Producer's accuracy, user's accuracy and quality approach 1.

2.4.5.2. *Assessing the quality of tree crown projection perimeters*

Both CP and ALStpe datasets were validated with TLSref dataset. Validation was done, by comparing tree crown projection perimeters from the CP dataset with corresponding tree crown projection perimeters from the TLSref dataset. For assessing the quality of tree crown projection perimeters such type of statistics as coefficient of determination (R^2) and root-mean-square error (RMSE) were used. R^2 is used to show the goodness of fit between the model and reality. Coefficient of determination ranges between 0 and 1, where 0 means no fit and 1 means a perfect fit.

2.4.5.3. *Assessing the quality of the SILVI-STAR parameters*

The SILVI-STAR parameters from CP and ALStpe datasets which were validated were: tree height, periphery height of a tree and locations of periphery points. Validation of these SILVI-STAR attributes from CP and ALStpe datasets was made by comparing them with the corresponding attributes from the TLSref dataset. For assessing the quality of these parameters the coefficient of determination (R^2) and root-mean-square error (RMSE) were used.

3. Results

3.1. Usability aspect and requirements to the tree dataset

Using the questionnaire two urban tree manages were interviewed in order to investigate which parameters of trees are necessary to know for them, which geometrical accuracies of this parameters they accept and how important are the tree dataset and 3D visualizations in urban tree management. Interviewed persons were municipal tree manager of Arnhem city Codi Duyster and tree manager of WUR campus Pieter Goedhart. The results of interview were almost opposite, most probably this was caused by the amount of trees each of them is managing.

About 1200 campus trees are managed by Pieter Goedhart. From the interview with him it was found that he assesses the conditions of all campus trees visually, doesn't measure any parameters of trees and it is possible to make visual observation of all campus trees easily. Thus neither a tree database with tree parameters nor 3D visualizations of trees were interesting to him.

The results of an interview with Codi Duyster were quite different. He manages large amount of trees. As he mentioned there are 40 000 solitary trees in Arnhem city, which he manages, and about 1.5-2 million aggregated trees in parks and forests in the municipality of Arnhem.

Answers of Codi Duyster to the part of questionnaire are presented in Table 3.

Table 3. Answers of Codi Duyster to questions 3-5 of the questionnaire

Parameter	Which parameters of the trees are important for urban tree managers?	How important is the accuracy of each parameter?	What is the required accuracy for the important parameters?
Tree location	Essential	Essential	0.2-0.5m
Tree crown projection perimeter	Neutral	Essential	0.2-0.5m
Tree height	Essential	Essential	0.5m
Height of the first bifurcation	Important	Essential	0.5m
Height of crown base	Neutral	Neutral	0.3m
Periphery height	Neutral	Neutral	1m
Periphery points	Minor importance	Important	0.3m
Diameter at breast height (DBH)	Important	Essential	few cm

He told that exact position of the tree is one of the essential tree parameters to know. The required accuracy for it is around 0.2-0.5 m. It should be quite precise, because in an urban environment all the territory is divided and has its owner. Knowing the exact location of the tree will improve urban planning.

He also mentioned that by themselves, without knowing parameters of the tree crowns, the locations of the trees are not such important. He noted that height of the first bifurcation is especially important in urban tree management as there is a law, according to which all the trees which are growing near the road have to be maintained in a special way, namely depending on the class of the road, branches of a tree should start growing at certain height and not lower. If the crown will start growing too low it can impede the traffic movement. The point of the first bifurcation is also important to know in order to assess the stability of the tree; the lower this point is, the better the stability of the tree. Tree height is important for nursery. The higher the tree the more time is required for its maintenance. If the exact height of a tree is known it is easier to estimate the amount of time, labor and money, which are necessary for maintenance of a tree. Codi Duyster mentioned that by law, if DBH of the tree is more than 25 cm, even if it is private tree, it is not possible to cut it down without permission, because each tree costs money for the municipality.

In general, he is convinced that it will be cheaper to have a tree database with information about essential parameters of the trees, because tree maintainers will not be obliged to go outside and measure it, thus it will save time and money.

Codi Duyster is further convinced that 3D visualizations of trees could be useful for urban tree managers. He thinks they may help in many cases, for instance, in prediction of how diseases will spread by wind from one tree to another. During the diseases the tree crown is getting smaller – so the quality of the tree is getting worse and it can be shown by use of 3D models.

The database and 3D models are necessary to have to know the reality outside. They are also useful in order to know what kind of investment is necessary to make, which economic value of the trees is in the city. Codi Duyster concluded that the quality of the trees in the cities is decreasing. Having 3D visualizations of them will serve to show visually the problems or the current situation and will help in creating better more persuasive reports to the local government.

Another reason to support the idea that a tree database is useful for tree managers is given by a commercial party. Started in the second half of 2013, the firm Cobra (director Joost Verhagen is a recognized European Tree Technician) has the commercial lead for marketing web services based on the CP dataset. The basic CP dataset will be made available as Open Data through http://www.Boomregister.nl in 2014[18].

[18] Source: personal communication with Frans Rip

3.2. Results of data acquisition and pre-processing

The terrestrial LiDAR point cloud data were collected during fieldwork on the 17th of December 2013 with a Riegl VZ-400 terrestrial laser scanner. The angle between the points was 0.06 degrees.

Terrestrial Laser Scanning data consisted of fifty-five scans at different locations of the study area. Each scan was made approximately in 5 minutes: about 2-3 minutes of scanning and about 2 minutes to move the tripod with the scanner to scan position. The data volume of 55 scans was equal to 10.3 Gb. The map, which presents the actual scan positions, is presented in Figure 20. TLS scan positions The study area was completely covered by the scans, thus there were no white spots in the data.

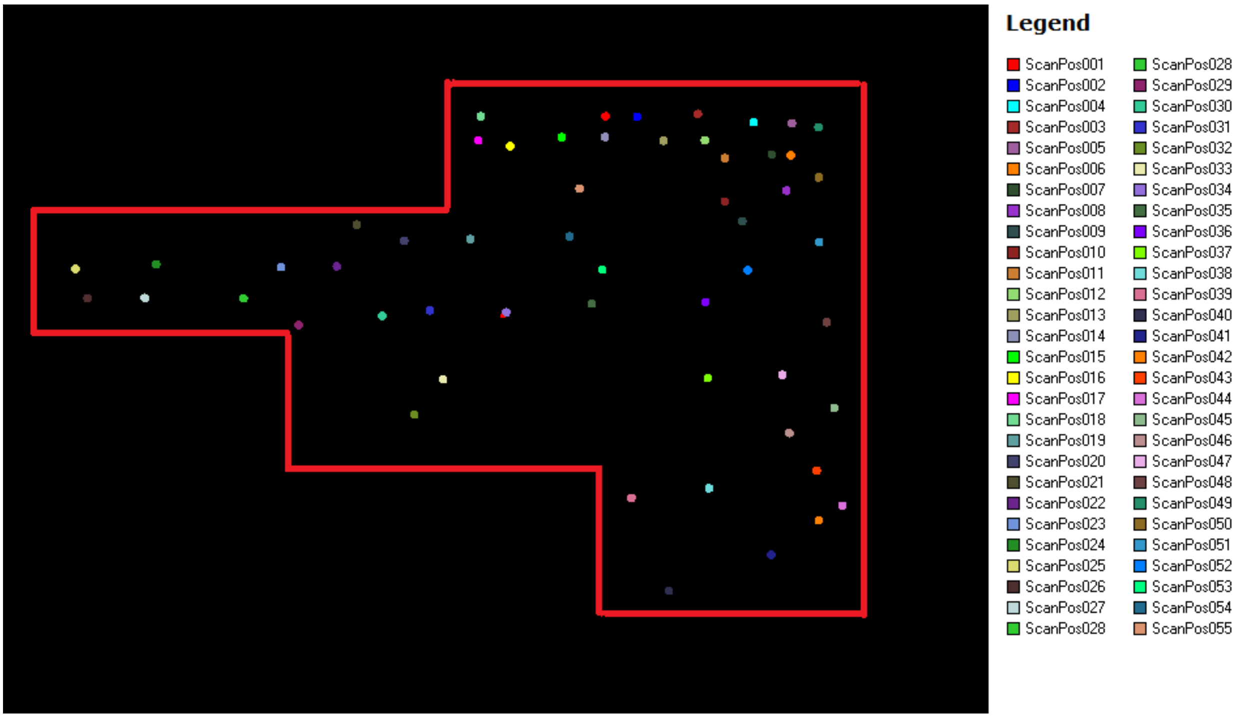


Figure 20. TLS scan positions

Pre-processing of the collected data included co-registering of all the scans and removal of artefacts. Figure 21 shows co-registered and filtered from artefacts TLS data.

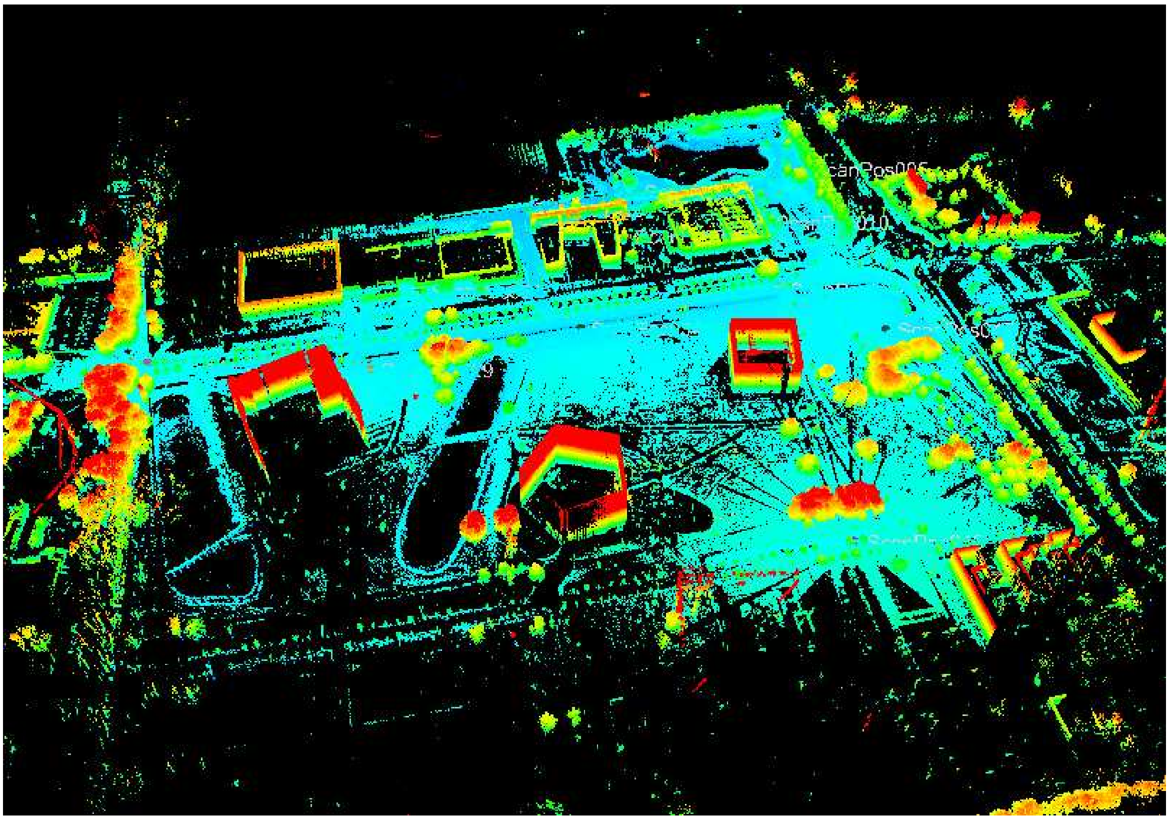


Figure 21. Co-registered and filtered from artefacts TLS scans (combination of 10 scans is presented in the image)

ALS data was already co-registered and without artefacts, thus co-registration and filtering were not applied to ALS data.

In order to combine all the point data, which were stored in different scans TLS and ALS scans and clip the data by the boundaries of the study area lasmerge and lasclip function was applied to the data. Merged and clipped TLS and ALS data are presented Figure 22.

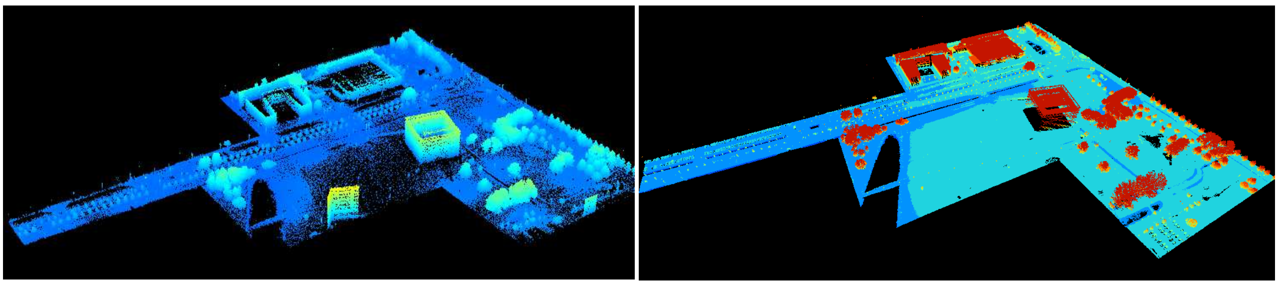


Figure 22. Merged and clipped TLS (left) and ALS (right) data

3.3. Results of data processing using PCTPE method

3.3.1. Delineation of trees

Using lasclassify function of LAStools TLS points were classified. Set of experiments was accomplished in order to investigate, which standard deviation threshold gives more precise separation of high vegetation and buildings points. The “building planarity” was set to 0.8, the "forest ruggedness" to 0.81. The high threshold was chosen because the walls of the buildings in the study area were quite rugged. The result of the point classification is presented in Figure 23.

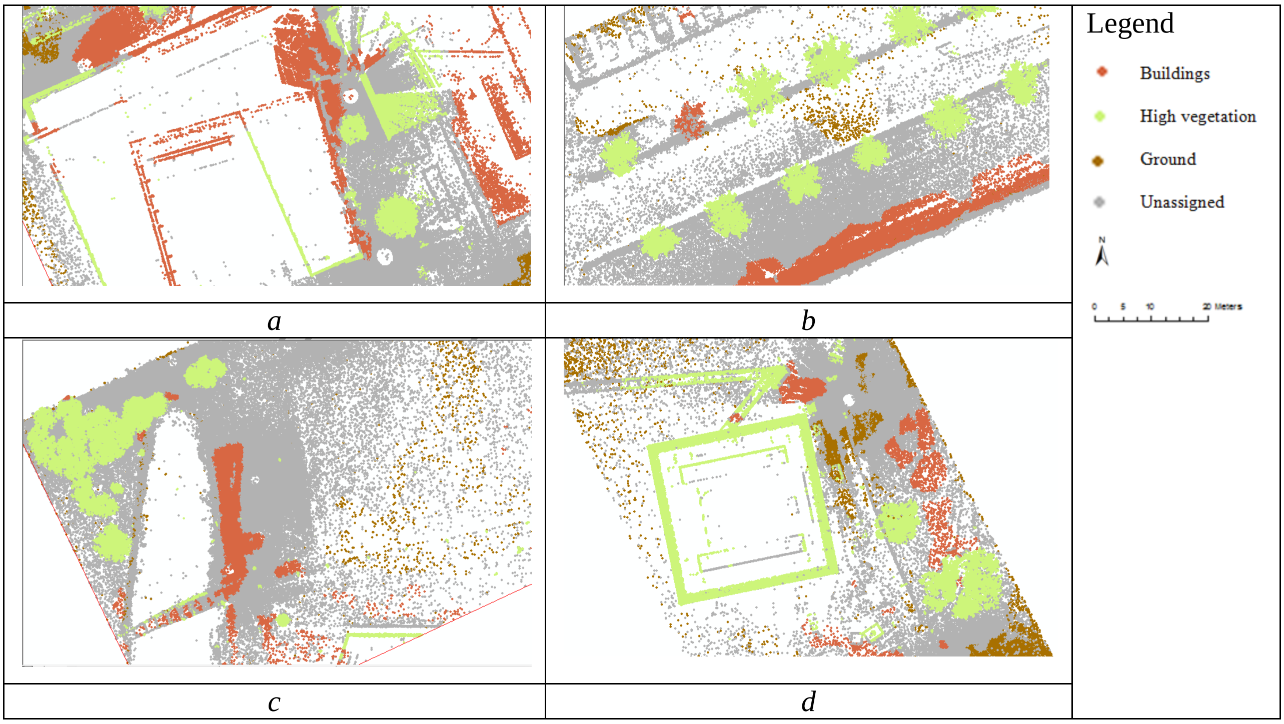


Figure 23. The result of point classification for different parts of the study area

Points, which were classified as high vegetation, were selected using las2las function. Selected high vegetation points are presented in Figure 24.

Figure 24. Points, which belong to "high vegetation" class

Initial vegetation mask was produced by making aggregation of the selected points in ArcGIS. It included solitary trees, aggregations of trees and objects which were incorrectly classified as trees. Thereafter only solitary trees were selected.

Figure 25 shows vegetation mask with aggregation of trees and noise and vegetation mask, which consists only on solitary trees. The total amount of identified solitary trees was 240.

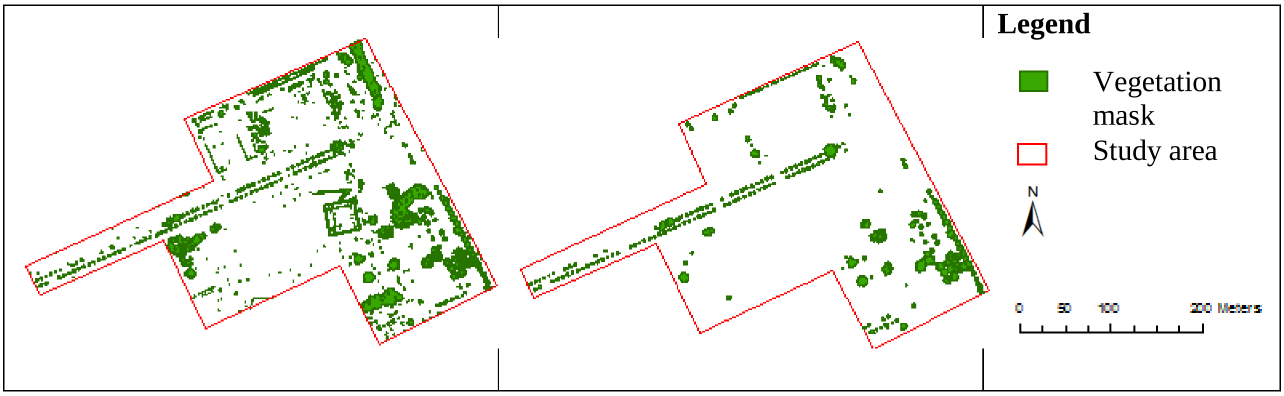
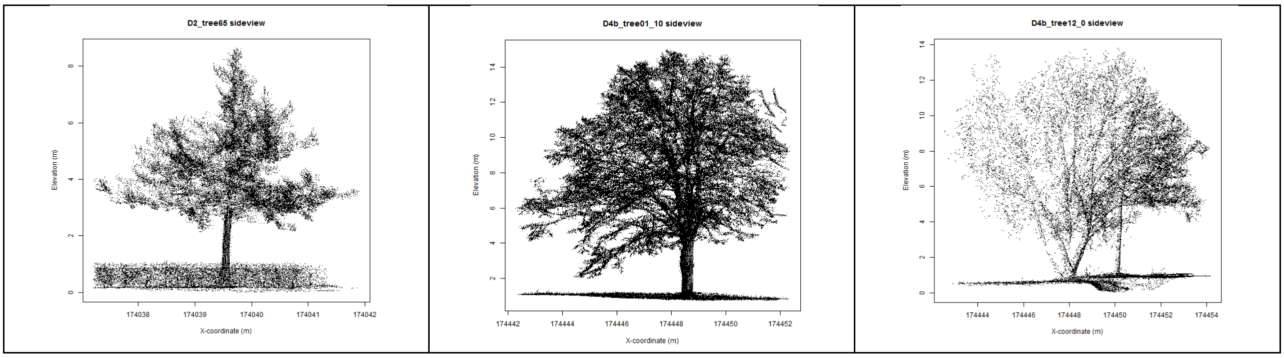


Figure 25. Vegetation mask with aggregation of trees and noise (left) and vegetation mask consisting only on solitary trees (right)

3.3.2. Pre-processing of individual tree point clouds

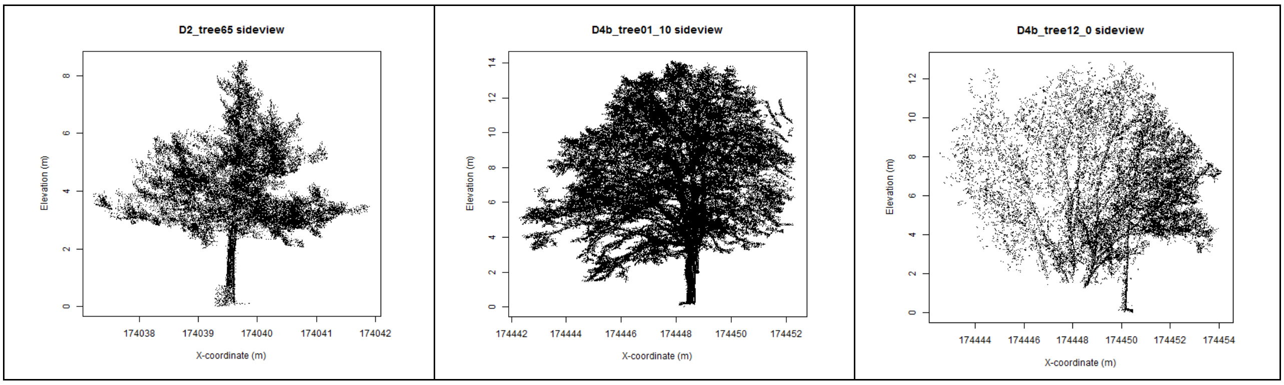
Pre-processing of individual tree point clouds included removal of solitary outlier points and removal of ground points and understory. Solitary outlier points, which were present in individual trees point clouds, were filtered. Side views of filtered individual trees point clouds are presented in Appendix 4.2. Figure 26 shows filtered from solitary outlier points trees.



a b c

Figure 26. Tree point clouds filtered from solitary outlier points

Thereafter the understory and ground points were removed from individual tree point clouds, thus only pure tree points remain. Pure tree TLS and ALS points are presented in Appendix 4.3. Figure 27 shows pure tree point clouds, which were produced after filtering understory and ground points. These TLS and ALS point clouds, which included only tree points, were processed in order to extract tree parameters.



a *b* *c*

Figure 27. Tree point clouds filtered from understory and ground points

3.3.3. Result of extraction and assessment of tree parameters

The result of the processing of pure tree point clouds extracted from TLS and ALS data with R script were tree parameters, which were stored in corresponding datasets. Table 4 shows parameters which were extracted and stored in each dataset.

Table 4. Parameters stored in the datasets

Dataset	CP dataset	TLSref dataset	ALStpe dataset
Data from which the parameters were extracted	AHN raster, ALS LiDAR data	Point cloud, TLS LiDAR data	Point cloud, ALS LiDAR data
Tree location	+	+	
Tree crown projection perimeter	+	+	
Tree height	+	+	+
Periphery height	+	+	+
Periphery points	+	+	+
Height of the first bifurcation		+	
DBH		+	

Not all of the parameters from Table 4 could be extracted from ALS data using PCTPE method, mostly because it had fewer points. Figure 28 shows side views of tree extracted from TLS data and from ALS data, where the differences between TLS and ALS data can be well noticed.

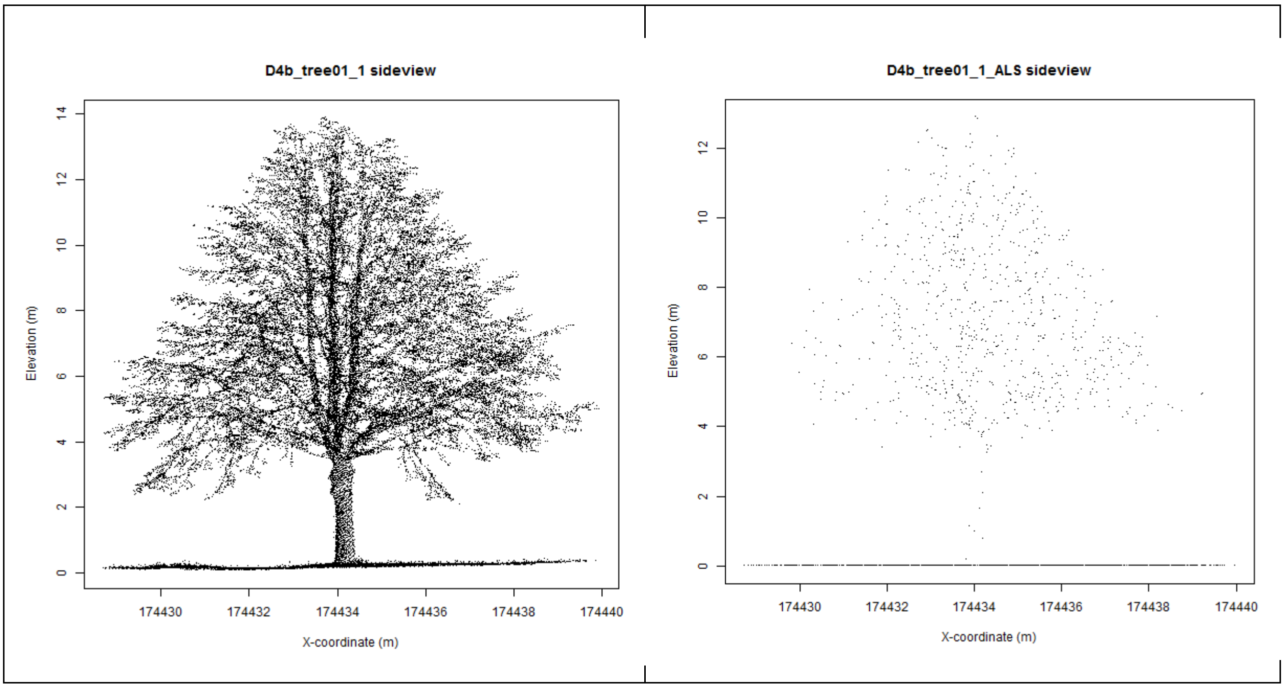


Figure 28. Side view of a tree, extracted from TLS data (left) and from ALS data (right)

There were a few stem points or no stem point at all in tree point clouds, extracted from ALS data. This made it impossible to extract DBH and the height of the first bifurcation of the tree from the ALS data with the created method. As in the PCTPE method tree location was derived from the circle fitted on the stem cross-section made on breast height, it wasn't possible to derive this parameter from ALS point data. Tree crown projection perimeter was calculated for the tree crown projection shape files, with which both TLS and ALS data was clipped in order to extract individual trees point clouds. Thus if it would be extracted the values of this parameter would be the same in TLSref and ALStpe datasets. It wasn't worthwhile to add this parameter to ALStpe dataset and validate it.

Height of the first living fork

The height of the first living fork was extracted from TLS data and stored in TLSref dataset. For all of the trees graphs with side view of a tree and a line representing the height of the first bifurcation were produced. These graphs are presented in Appendix 4.4.

In Figure 29 and Figure 30 side views of the different shape trees, where the height of the first living fork is shown, are presented.

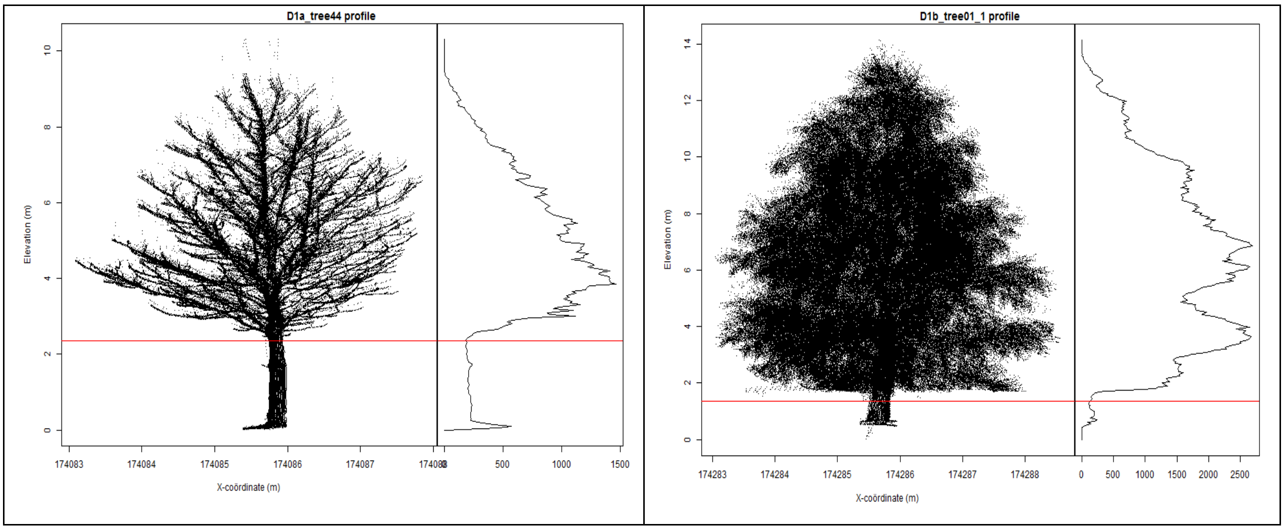


Figure 29. Examples of trees' side views with vertical profile and the red line, which represents the height of the first living fork

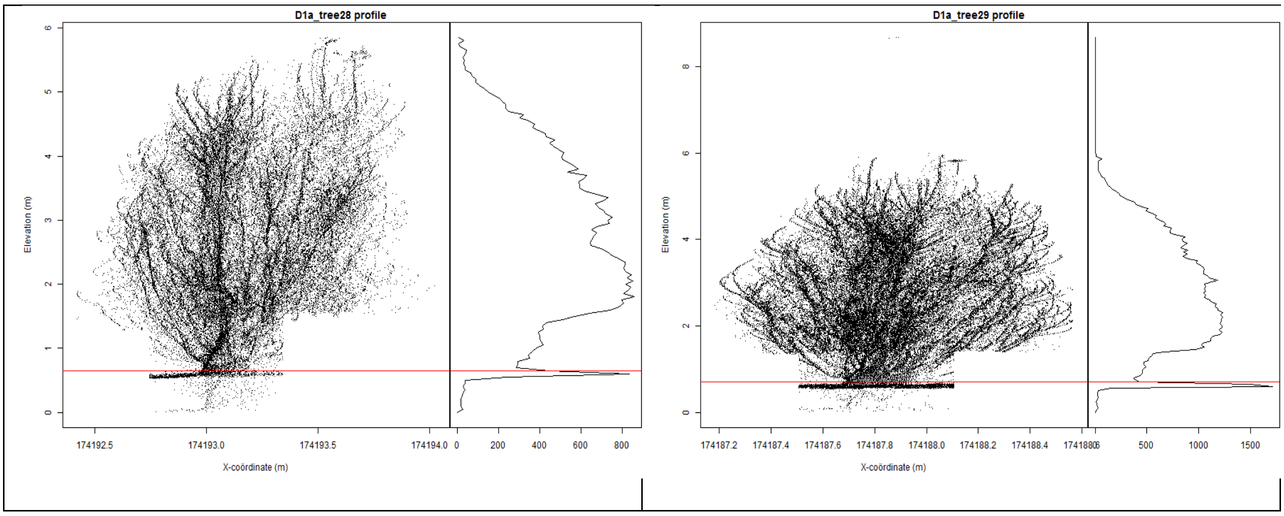


Figure 30. Cut pollard-willows, which first branch heights were detected correctly

According to visual analysis of the side view graphs of the trees with the red line, which represents the height, where the first living fork starts to grow, in 60.41% of cases the parameter was calculated correctly, like it shown in Figure 29 and Figure 30.

Tree side views, where the height of the first living fork was not detected correct due to different reasons are presented in Figure 31, Figure 32 and Figure 33.

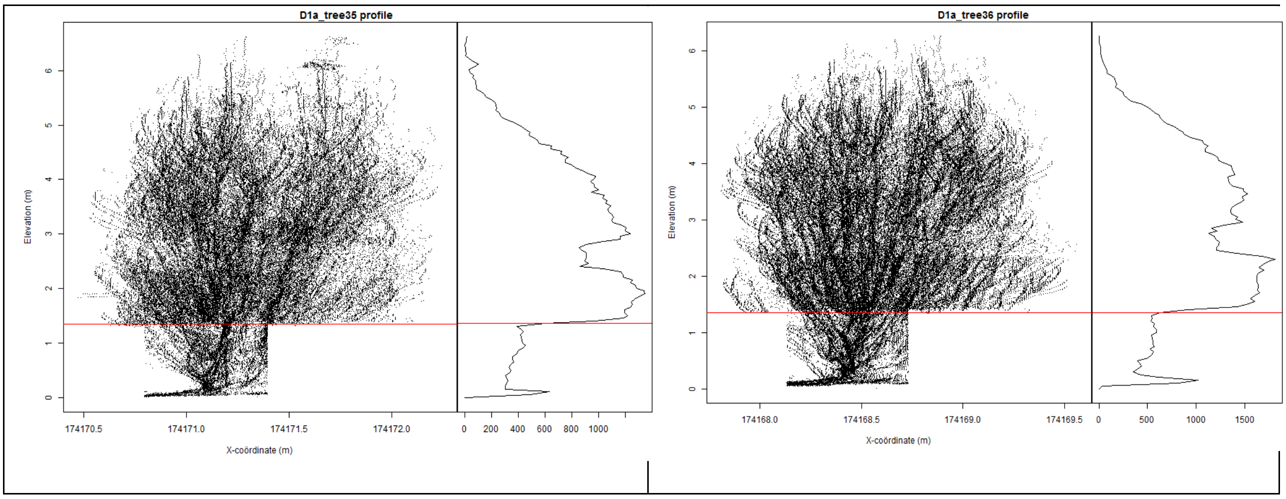


Figure 31. First branch detection on cut pollard-willows, which branches start growing from the bottom of stem

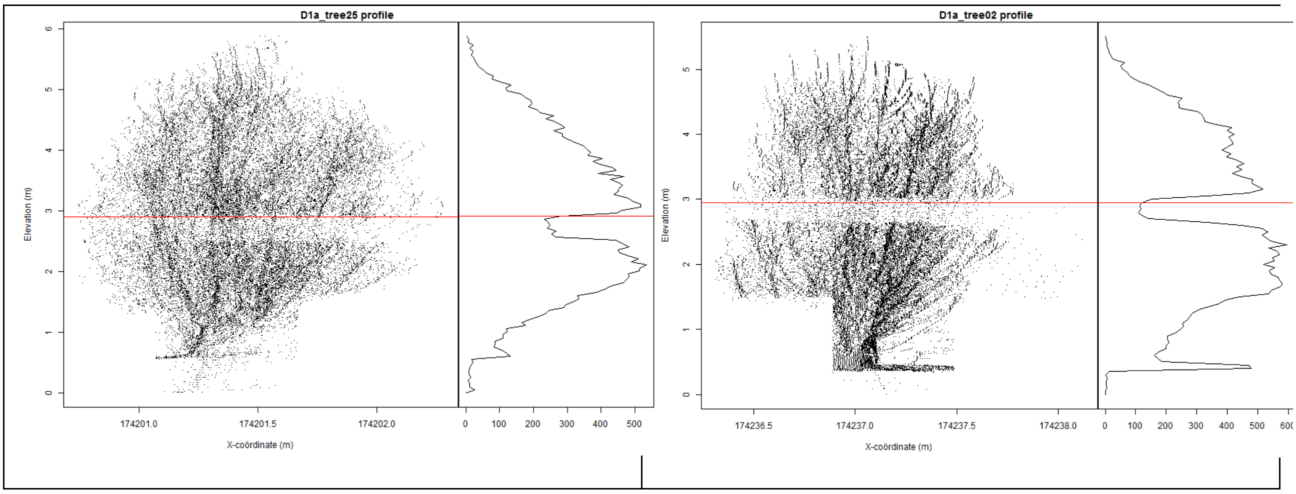
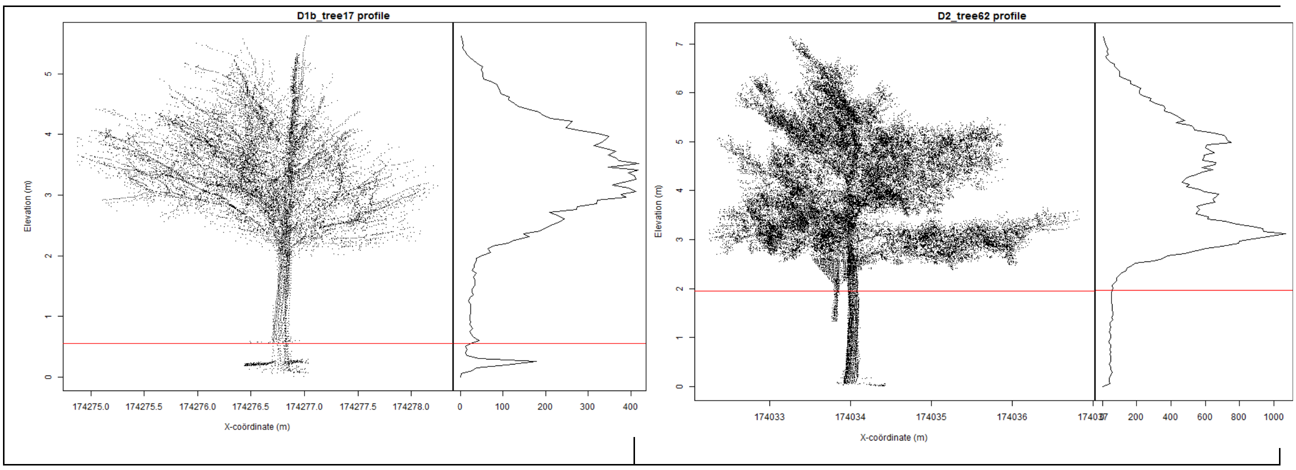


Figure 32. Low amount of tree points on certain height caused by obstruction during scanning.



a *b*

Figure 33. Examples of tree point clouds with noise, which caused errors in detection of first branch

Difference in detection of height of first branch for trees with upwardly directed secondary branches and downwardly directed secondary branches is presented in Figure 34.

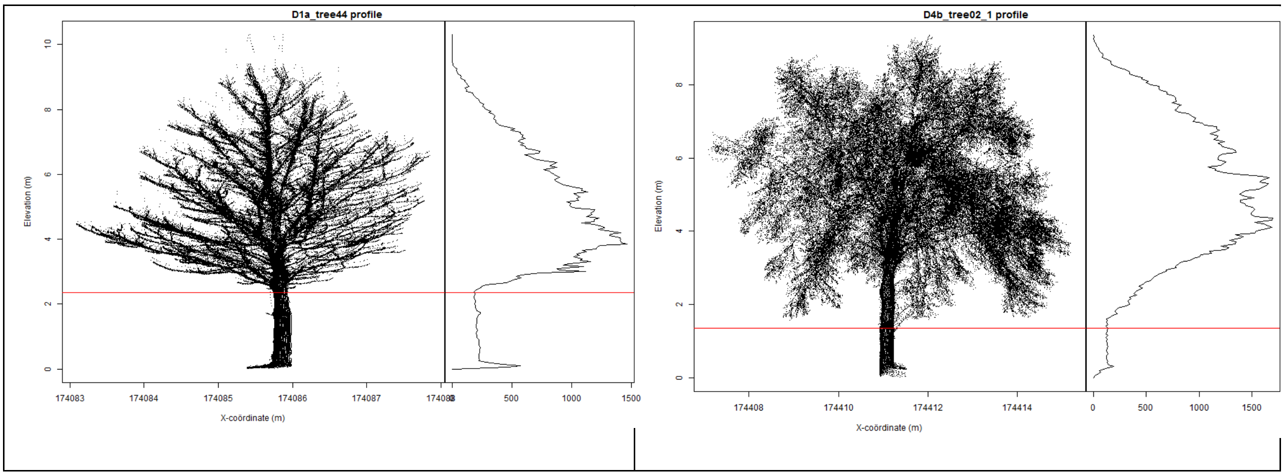


Figure 34. Detection of first branch height on trees with upwardly directed secondary branches(right) and downwardly directed secondary branches(left)

DBH

Diameter at breast height values were calculated and stored in TLSref dataset. For all of the trees graphs with cross-sections of tree point cloud at breast height and circles fitted through them were produced. The graphs are shown in Appendix 4.5.

Examples of circles fitted through the cross-sections of trees point clouds correctly are presented in Figure 35.

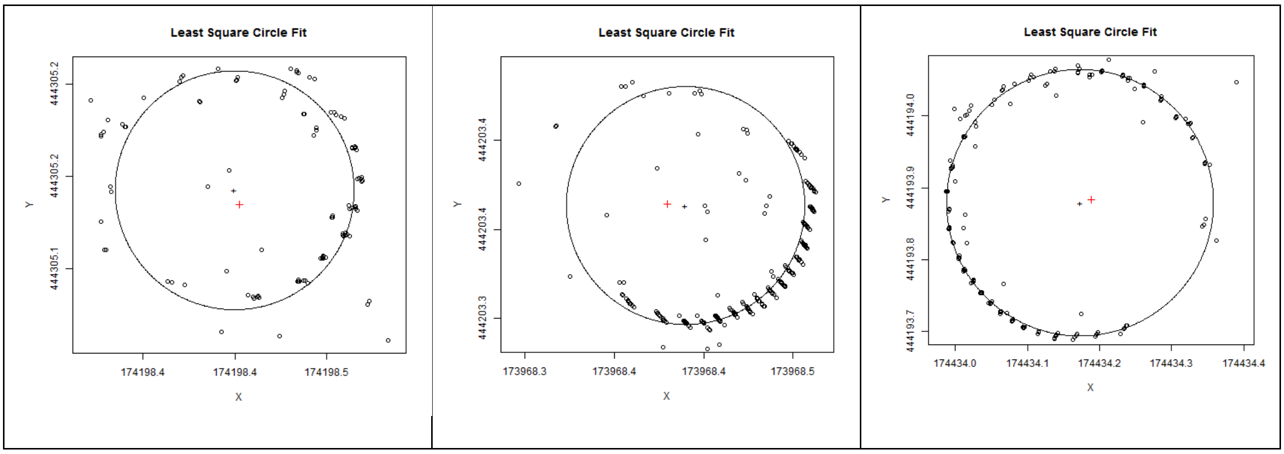


Figure 35. Examples of circles fitted through tree cross-sections made on breast height correctly

According to visual analysis of the graphs of fitting circle to the tree cross sections about 63.07% of circles were fitted correct. This allows assuming that at least 63.07% of DBH values were calculated correctly, like it presented in Figure 35.

Figure 36 and Figure 37 show errors in fitting circle through cross-sections of tree point clouds, made on breast height.

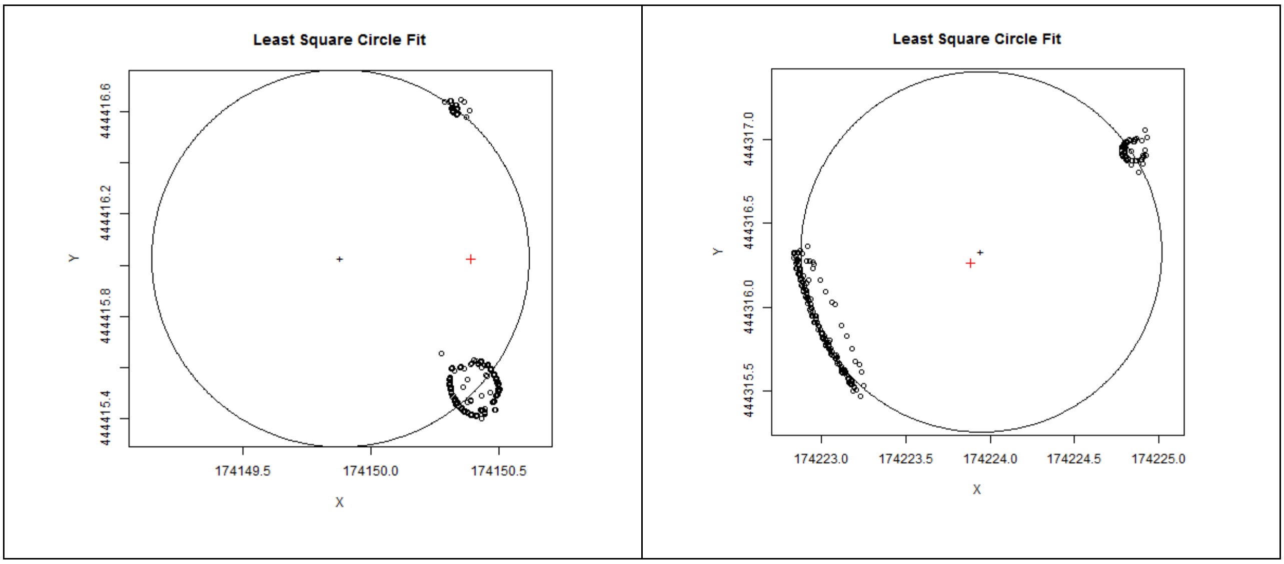


Figure 36. Not correct circle fitting through cross-sections of trees caused by appearance of foreign objects and noise points

Visual assessment showed that situations than circles were fitted incorrectly, like it presented in Figure 36, happened quire rare, only in 8.71% of cases.

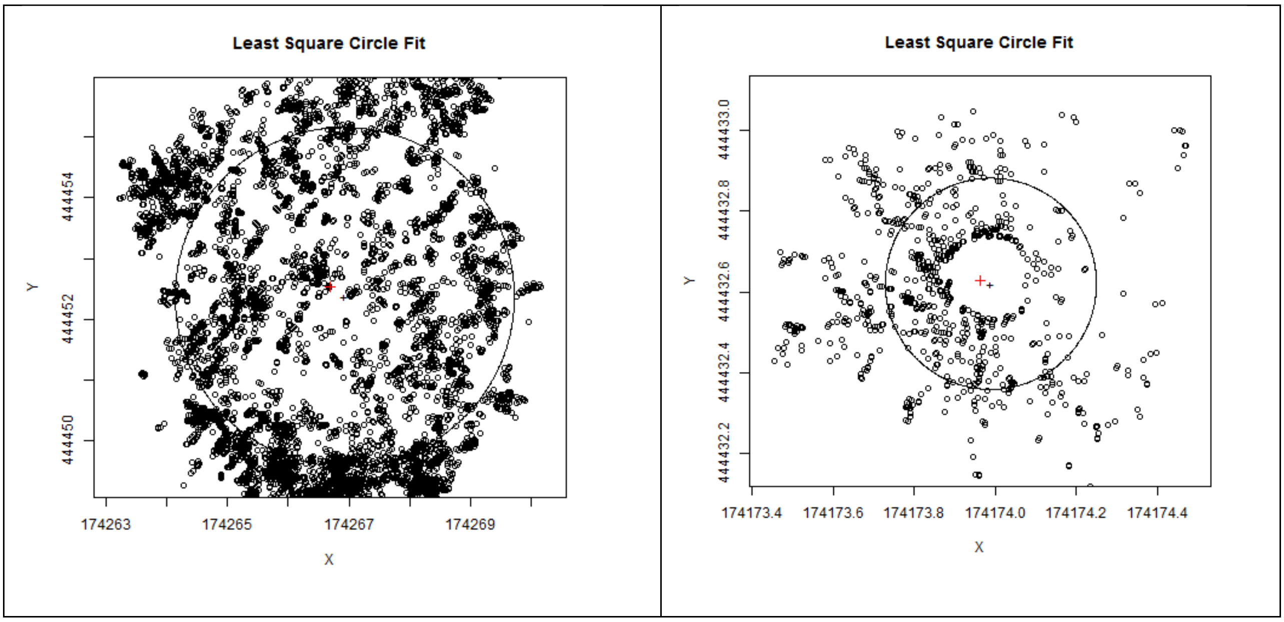


Figure 37. Not correct circle fitting through cross-sections of trees caused by appearance of branches on the breast height level

According to visual assessment, situations, when circle was fitted in the way in presented in Figure 37 occurred in 28.21% of cases.

Tree location

Tree locations extracted with TCPE method were compared with locations extracted with PCTPE method, which was used as a reference (Figure 38).

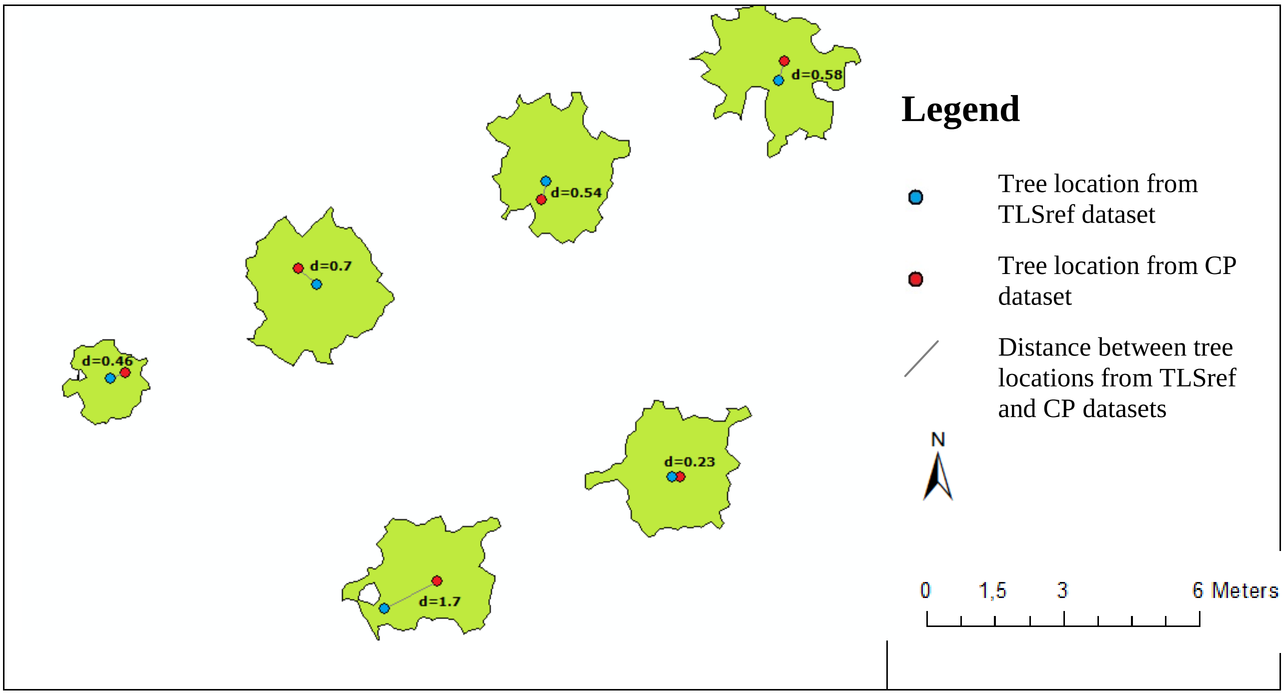


Figure 38. Distances between tree locations from TLSref and CP datasets (part of the study area).

There were 240 trees in the TLSref dataset and 364 trees in CP dataset. In order to assess the retrieval of trees location, the spatial distances between tree locations from CP dataset and corresponding tree locations from TLSref dataset were computed. The result of the comparison is presented in Table 5.

Table 5. Result of the comparison of tree locations from the datasets

True Positives (TP)	55
False Negatives (FN)	186
False Positives (FP)	309

The comparison showed that 55 trees were found in both datasets, 186 trees were missing in CP dataset compared to TLSref dataset, and 309 trees were more in CP dataset compared to TLSref dataset. Figure 39 shows the map of True Positives, False Negatives and False Positives.

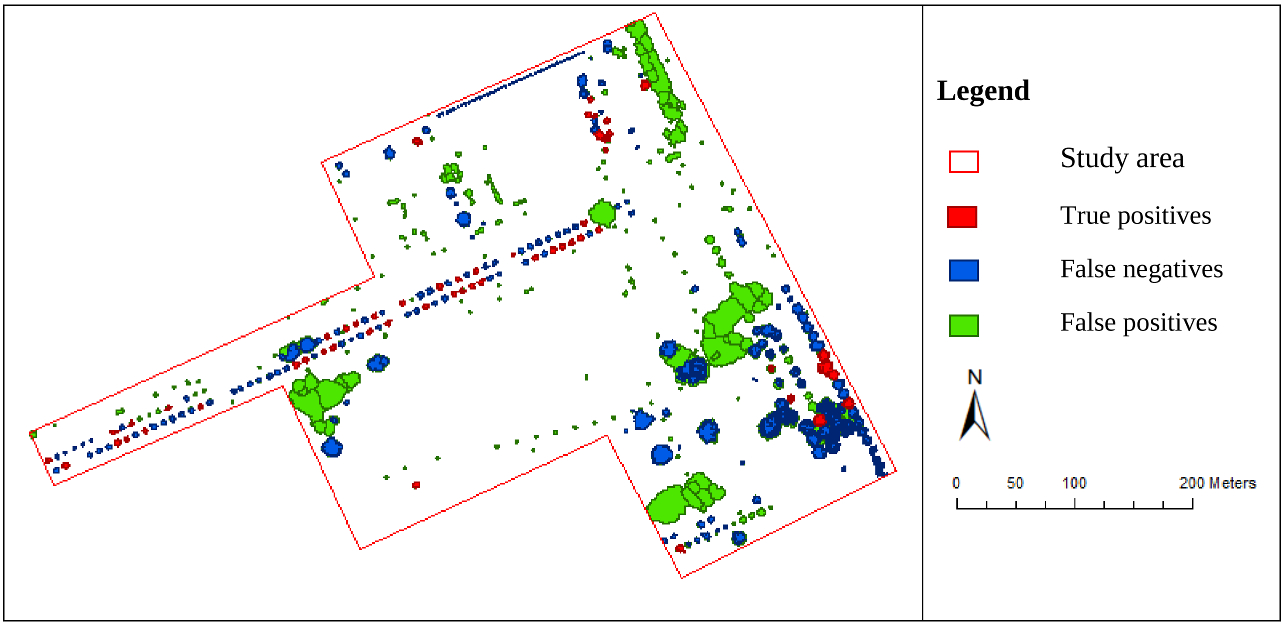


Figure 39. Map presenting TP, FN and FP

Comparison of percentage of trees with certain height and crown projection perimeter for TP, FN and FP trees is presented in Figure 40 and Figure 41.

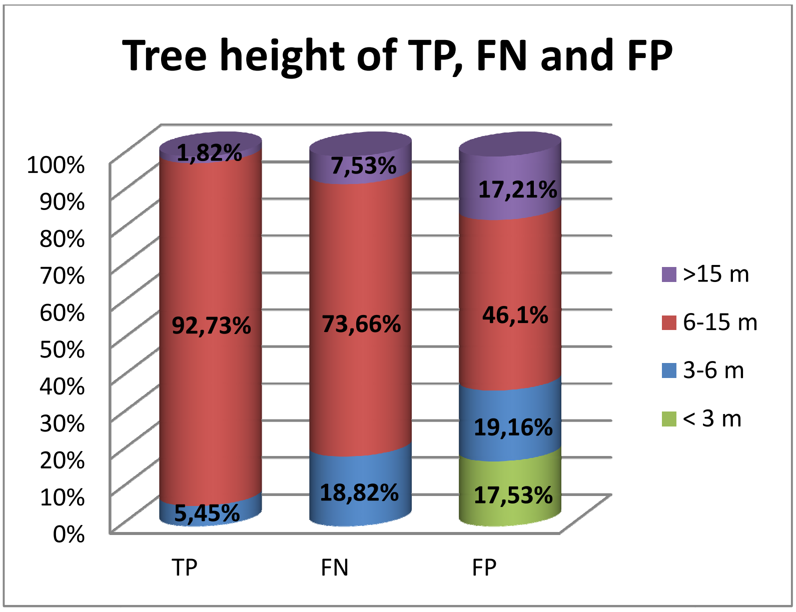


Figure 40. Comparison of tree heights distribution in TP, FN and FP

In FP around 17.53% of the all trees were very small trees (less than 3 m), approximately the same percent were very high trees (more than 15 m). Small trees from the CP dataset seem to be infrastructure object, because of the identical shape and regularity in spatial distribution. There were no small trees (less than 3 m) in TLSref dataset. Very high trees from the CP dataset are mostly trees separated from aggregations of trees.

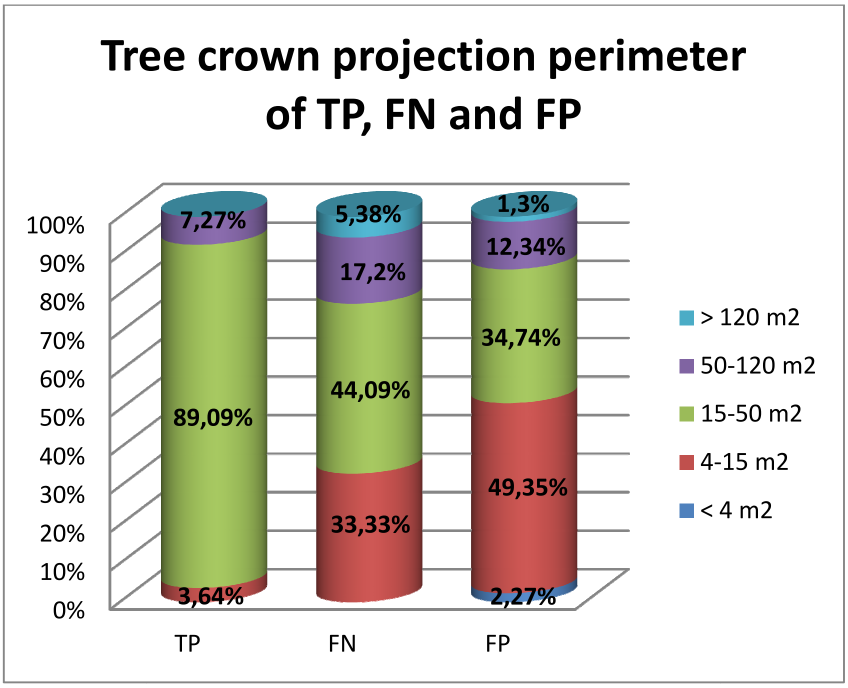


Figure 41. Comparison of tree crown projection perimeters distribution in TP, FN and FP

Producer's accuracy which determines the ability of the algorithm to extract all trees in the study area was equal to 0.23. User's accuracy which defines the probability of a tree extraction being a tree in reality was equal to 0.15. The quality was equal to 0.1.

Tree crown projection perimeter

Tree crown projections were extracted and stored in the TLSref dataset. Fragment of the study area with tree crown projections from the CP dataset and the TLSref dataset are presented in Figure 42.

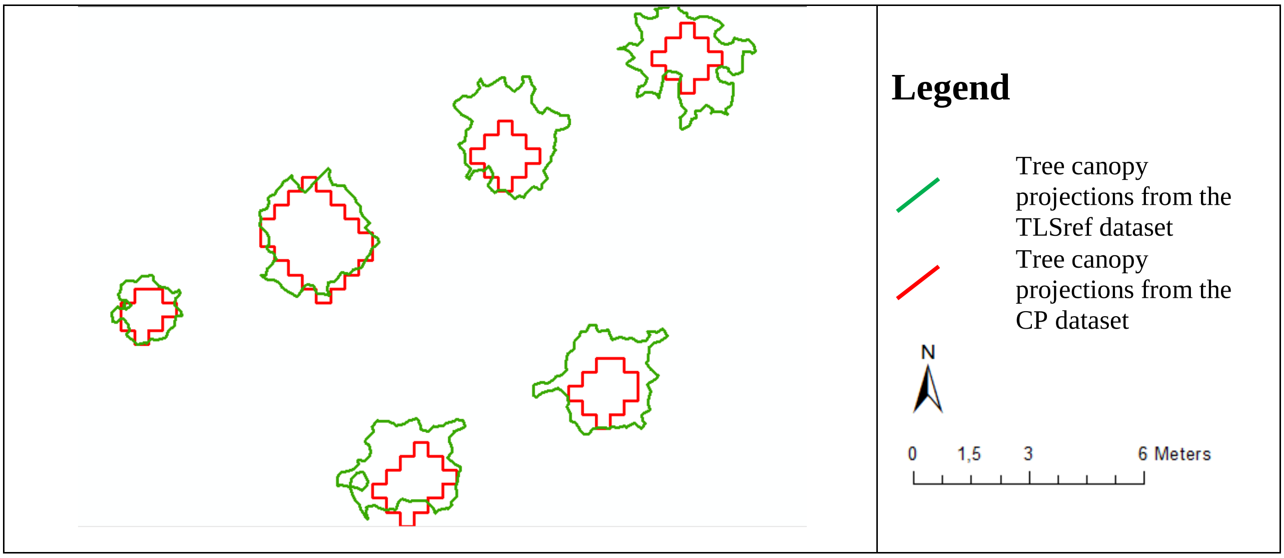


Figure 42. Tree crown projections from TLSref and CP datasets (part of the study area)

The quality of this parameter was assessed by means of R^2 and RMSE, which serve to show the goodness of fit between the tree crowns projection perimeters extracted with PCTPE and TCPE methods. The coefficient of determination is equal to 0.62. Root mean square error is equal to 26.64 m^2. Figure 43 shows scatter plot of tree crown projection perimeter from TLSref dataset and tree crown projection perimeter from CP dataset.

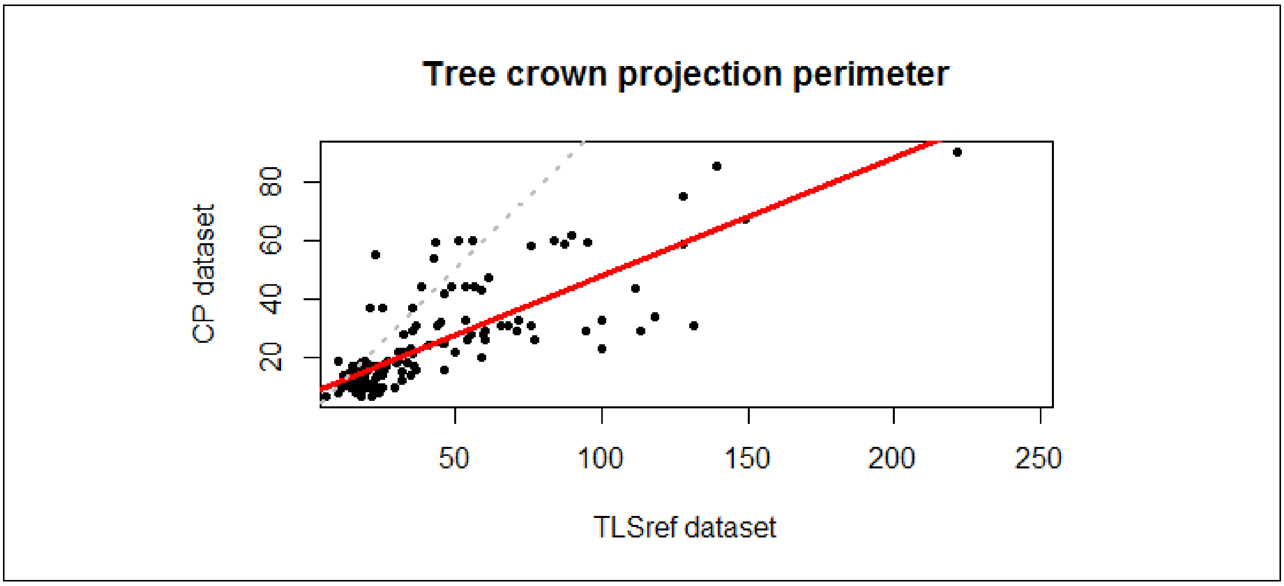


Figure 43. Scatter plot which shows goodness of fit between tree crown projection perimeter from TLSref dataset (x-axis) and tree crown projection perimeter from CP dataset (y-axis). The trend line is plotted in red. The 1:1 line is plotted in grey

Tree Height

Tree heights were found both from TLS and ALS data and stored correspondently to TLSref and ALStpe datasets.

The graphs of tree side views of all the trees, extracted from TLS and ALS point data, with height plotted on them as red line are presented in Appendix 4.6.

According to visual assessment of graphs of trees side views with the red line, which represents the height of the tree from TLSref dataset, 93.62% of tree heights were calculated correctly. Examples of trees, extracted from TLS point data which heights were calculated correctly are shown in Figure 44.

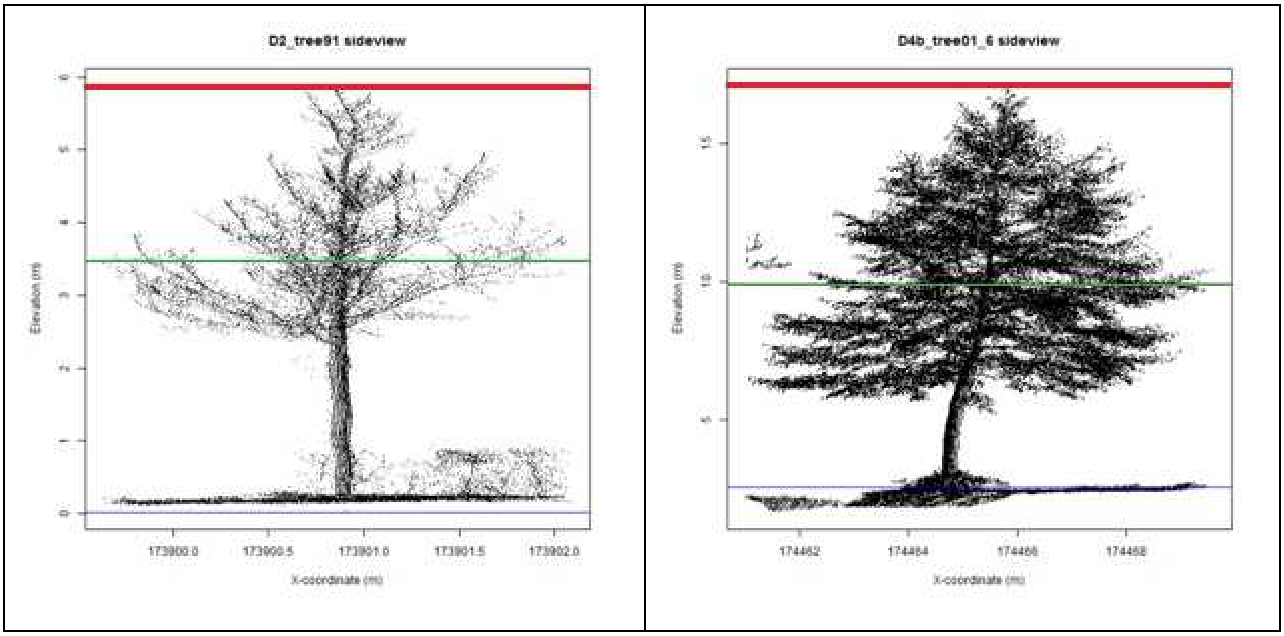
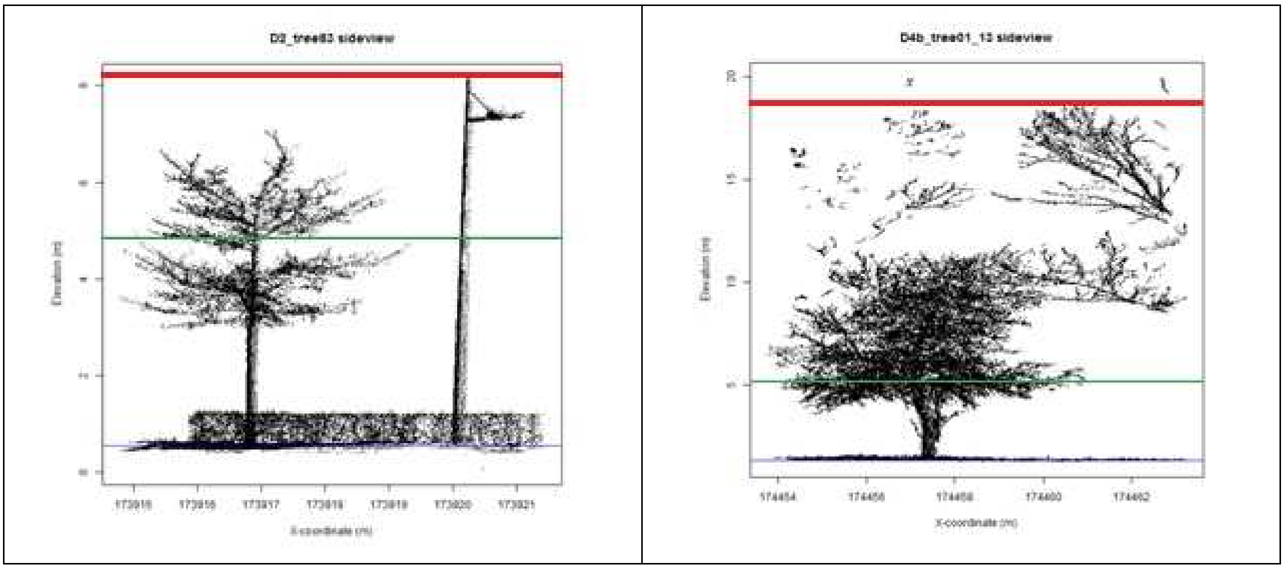


Figure 44. Extracted from TLS data trees side views, which tree height parameters were calculated correctly. Red line represents calculated height of a tree.

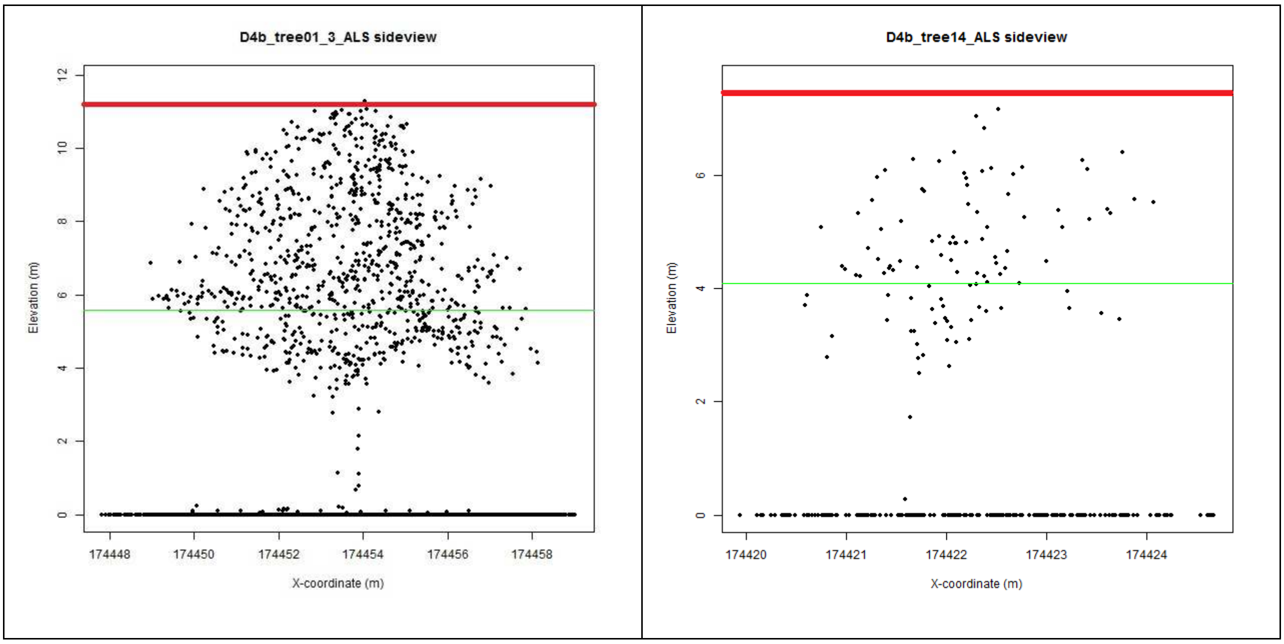
Figure 45 shows tree side views, extracted from TLS point data, which heights were miscalculated.



a *b*

Figure 45. Extracted from TLS data, trees side views, which tree height parameters were calculated incorrectly because of noise in data. Red line represents calculated height of a tree.

According to visual assessment of graphs of trees side views with the red line, which represents the height of the tree from ALStpe dataset, 45.99% of tree heights were calculated correctly. Examples of trees, extracted from ALS point data which heights were calculated correctly are shown in Figure 46.



a *b*

Figure 46. Extracted from ALS data trees side views, which tree height parameters were calculated correctly. Red line represents calculated height of a tree.

Figure 47 and Figure 48 show ALS tree point clouds' separation into ground points and tree points. The separation in Figure 47 was perfect, thus shortest distance from tree points towards ground points was calculated correctly. For the tree presented in Figure 48 tree height was miscalculated because of wrong separation.

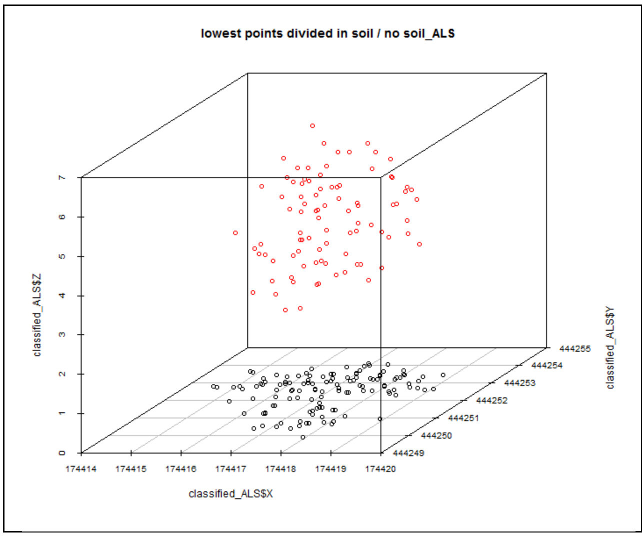


Figure 47. ALS tree point clouds, where points are divided to tree points and ground points and the separation of points is perfect

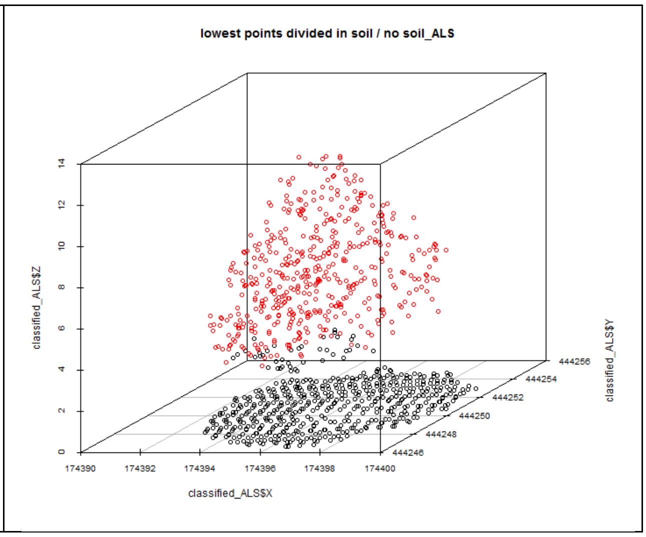
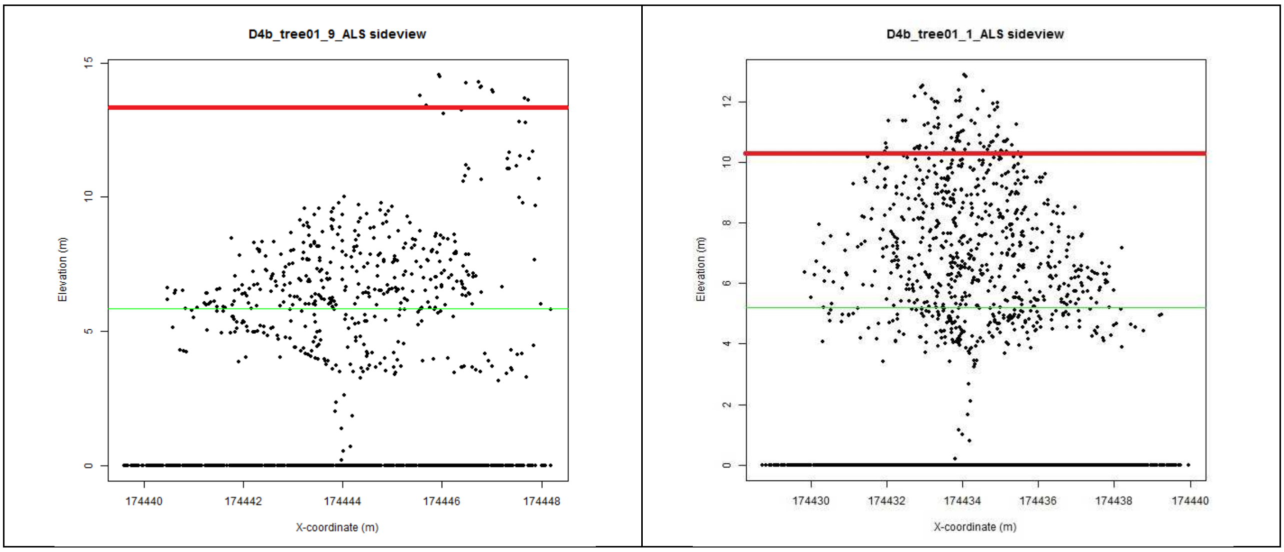


Figure 48. ALS tree point clouds, where points are divided to tree points and ground points and some tree points are misclassified as ground points

Figure 49 shows tree side views, extracted from ALS point data, which heights were overestimated or underestimated.



a *b*

Figure 49. Extracted from ALS data, trees side views, which tree height parameters were overestimated (a) because of noise in data or underestimated (b) because of incorrect calculation of shortest distance to the ground. Red line represents calculated height of a tree.

The quality of tree height parameter was assessed for CP dataset and for ALStpe dataset. The R^2 and RMSE of are shown in Table 6.

Table 6. Result of the assessment of tree height

	R2	RMSE, m
CP dataset vs. TLSref dataset	0.20	5.41
ALStpe dataset vs. TLSref dataset	0.71	3.89

Figure 50 and Figure 51 show scatter plots of TLSref tree height (x-axis) and corresponding CP tree heights/ALStpe tree heights (y-axis).

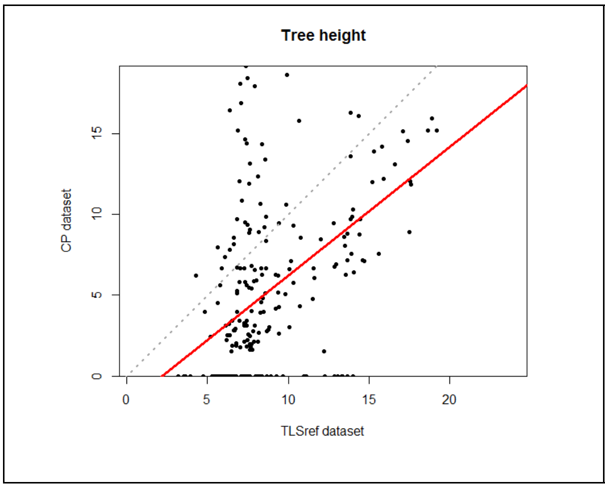


Figure 50. Scatter plot which shows goodness of fit between tree height from TLSref dataset (x-axis) and tree height from CP dataset (y-axis). The trend line is plotted in red. The 1:1 line is plotted in grey

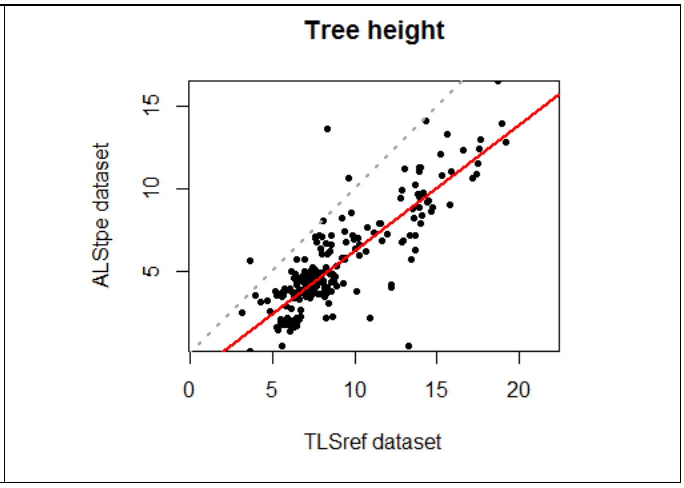


Figure 51. Scatter plot which shows goodness of fit between tree height from TLSref dataset (x-axis) and tree height from ALStpe dataset (y-axis). The trend line is plotted in red. The 1:1 line is plotted in grey

Periphery height

Tree periphery heights were calculated both from TLS and ALS data and stored correspondently to TLSref and ALStpe datasets.

The graphs of tree side views of all the trees, extracted from TLS and ALS point data, with periphery height plotted on them as green line are presented in Appendix 4.6. According to visual assessment of graphs of trees side views with the green line, which represents the periphery height of the tree from TLSref dataset, 93.19% of tree periphery heights were calculated correctly.

Examples of trees, extracted from TLS point data with correctly calculated periphery height are shown in Figure 52.

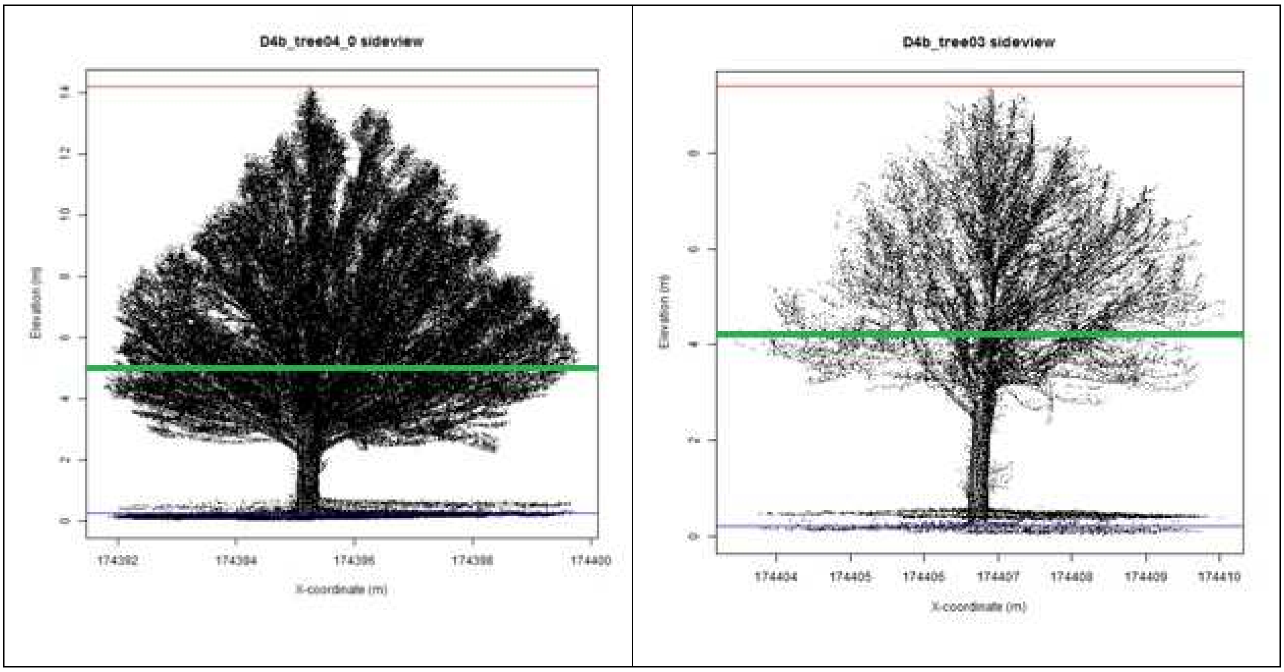


Figure 52. Extracted from TLS data tree side views, which periphery height calculated by PCTPE method are correct. Periphery height is presented by green line.

Examples of incorrectly computed periphery heights from TLSref dataset are presented in Figure 53.

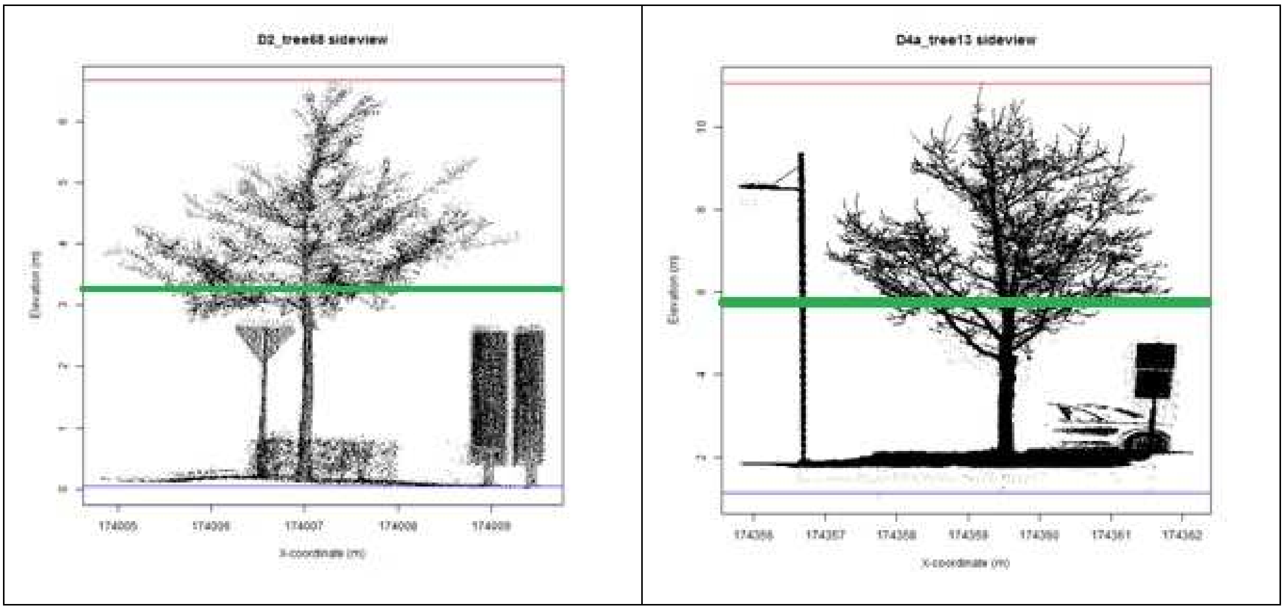


Figure 53. Extracted from TLS data tree side views, which periphery height calculated by PCTPE method are incorrect. Periphery height is presented as green line.

According to visual assessment of graphs of trees side views with the green line, which represents the periphery height of the tree from ALStpe dataset, 77.22% of tree periphery heights were calculated correctly.

Examples of trees, extracted from ALS data, which periphery heights were calculated correctly are presented in Figure 54.

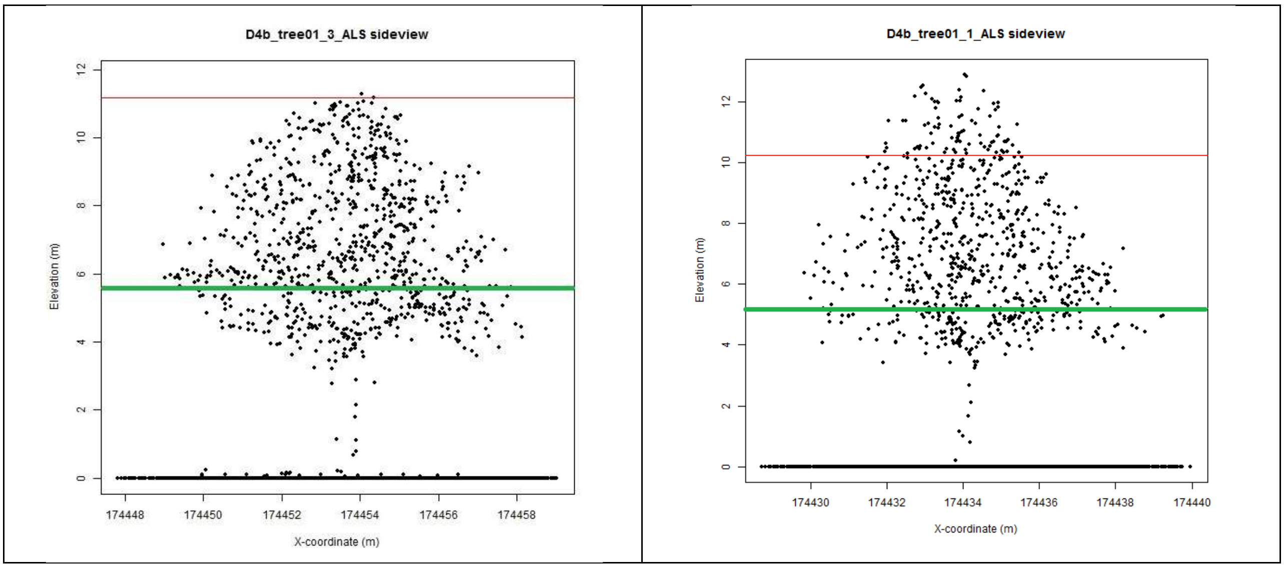


Figure 54. Extracted from ALS data tree side views, which periphery height calculated by PCTPE method are correct. Periphery height is presented as green line.

Examples of trees, extracted from ALS data, which periphery heights were calculated incorrectly are presented in Figure 55.

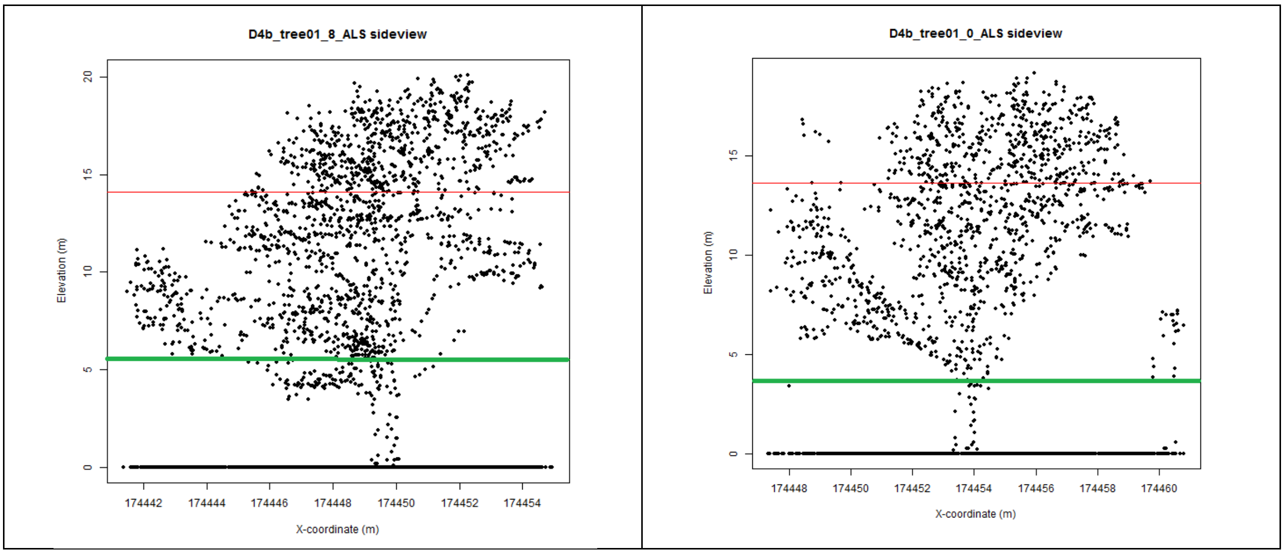


Figure 55. Extracted from ALS data tree side views, which periphery height calculated by PCTPE method, are incorrect. Periphery height is presented as green line.

The quality of tree periphery height parameter was assessed for CP dataset and for ALStpe dataset. The R^2 and RMSE of are shown in Table 7.

Table 7. Result of the assessment of periphery height

	R2	RMSE, m
CP dataset vs. TLSref dataset	0.23	5.95
ALStpe dataset vs. TLSref dataset	0.36	1.69

Figure 56 and Figure 57 show scatter plots of TLSref tree periphery height (x-axis) and corresponding CP tree heights/ALStpe tree heights (y-axis).

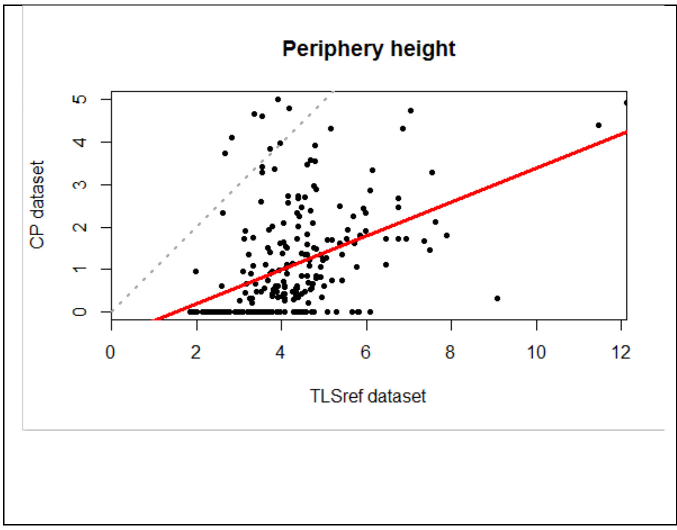


Figure 56. Scatter plot which shows goodness of fit between tree periphery height from TLSref dataset (x-axis) and tree height from CP dataset (y-axis). The trend line is plotted in red. The 1:1 line is plotted in grey

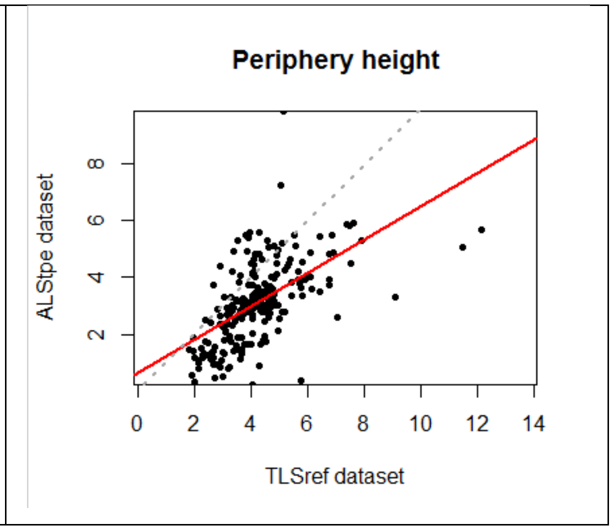


Figure 57. Scatter plot which shows goodness of fit between tree periphery height from TLSref dataset (x-axis) and tree height from ALStpe dataset (y-axis). The trend line is plotted in red. The 1:1 line is plotted in grey

Periphery points

Tree periphery point's coordinates were calculated both from TLS and ALS data and stored correspondently to TLSref and ALStpe datasets.

The graphs of tree top views of all the trees, extracted from TLS and ALS point data with periphery points plotted on them as red dots are presented in Appendix 4.7. According to visual assessment of graphs of trees top views with four red points, which represents the periphery points of the tree crown from TLSref dataset, for 90,21% of the trees periphery point locations were calculated correctly

Figure 58 shows top views of trees, extracted from TLSref dataset, with marked four correctly calculated periphery points on them.

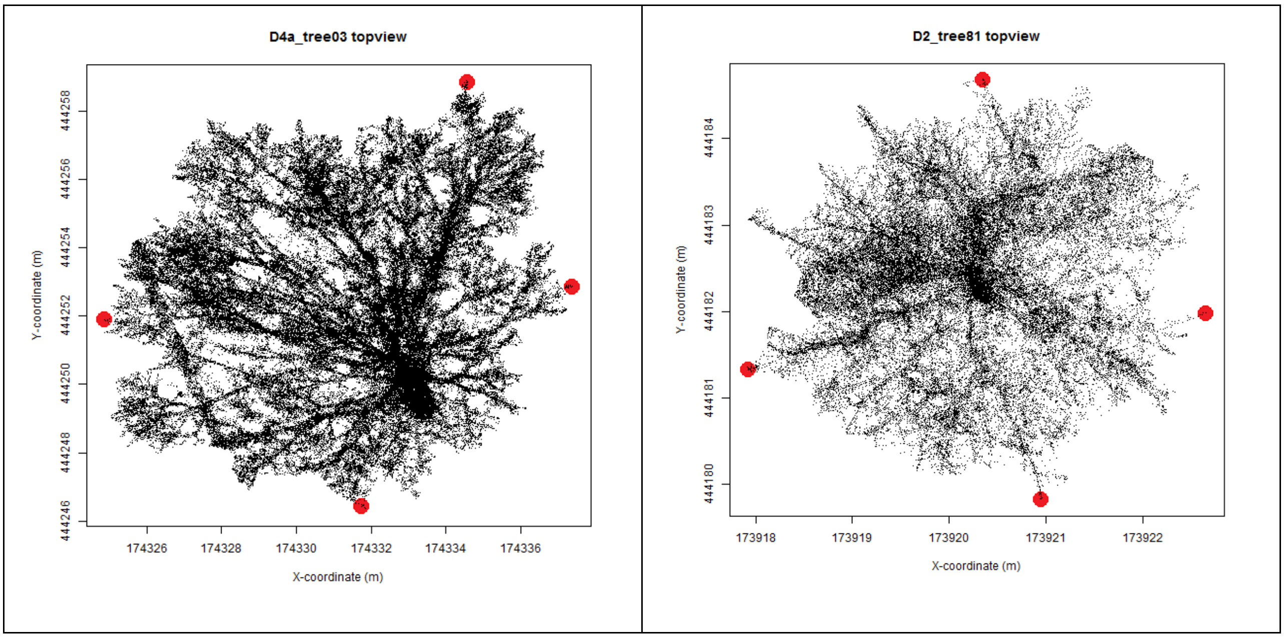


Figure 58. Examples of tree top view, extracted from TLS, and four periphery points (red dots) calculated correctly

Figure 59 shows examples of tree top views, extracted from ALStpe dataset with incorrectly calculated periphery points.

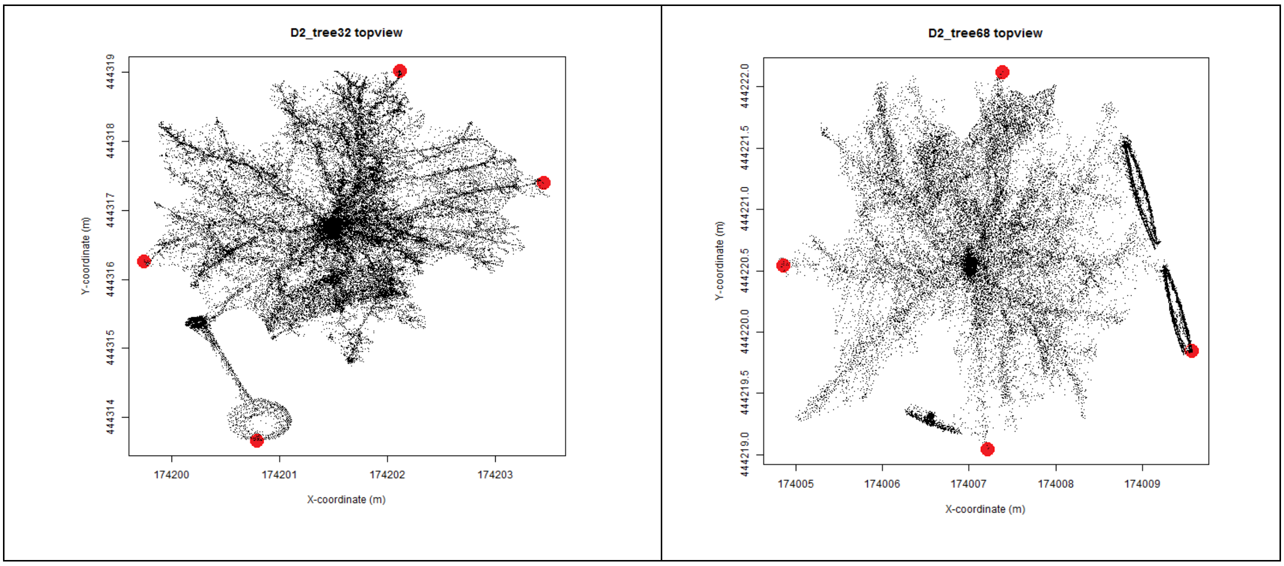


Figure 59.Examples of tree top view, extracted from TLS and four periphery points (red dots) calculated incorrectly

According to visual assessment of graphs of trees top views with four red points, which represents the periphery points of the tree crown from ALStpe dataset, for 65.4% of the trees periphery point locations were calculated correctly.

Figure 60 shows top views of trees, extracted from ALSref dataset, with marked four correctly calculated periphery points on them.

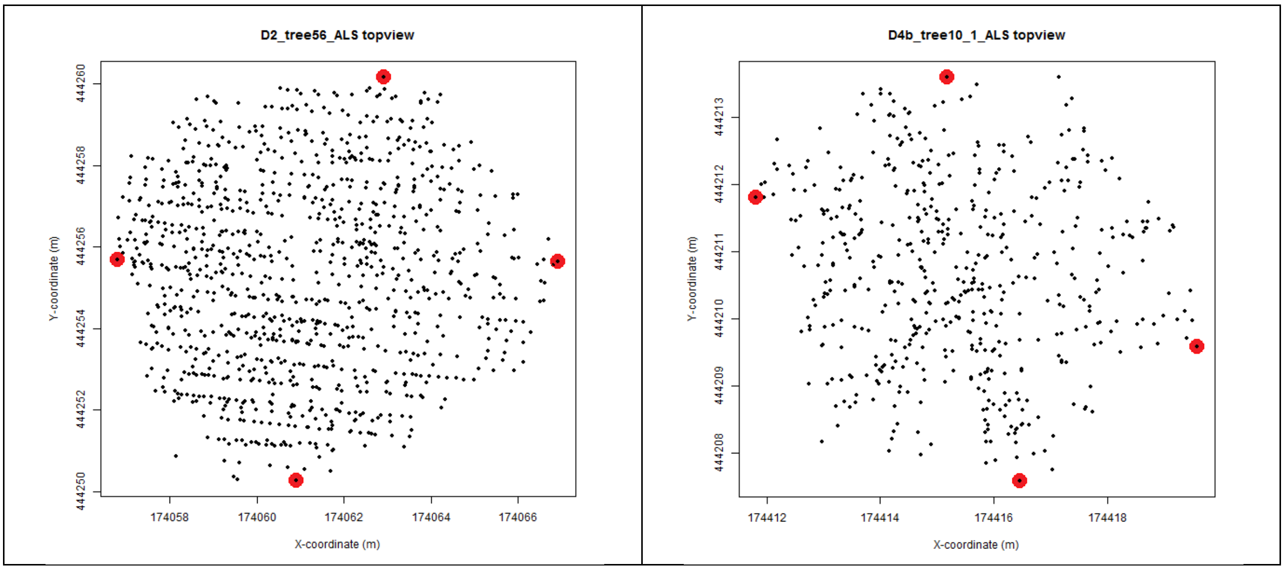


Figure 60. Examples of tree top view, extracted from ALS, and four periphery points (red dots) calculated correctly

Figure 61 shows examples of tree top views, extracted from ALStpe dataset with incorrectly calculated periphery points.

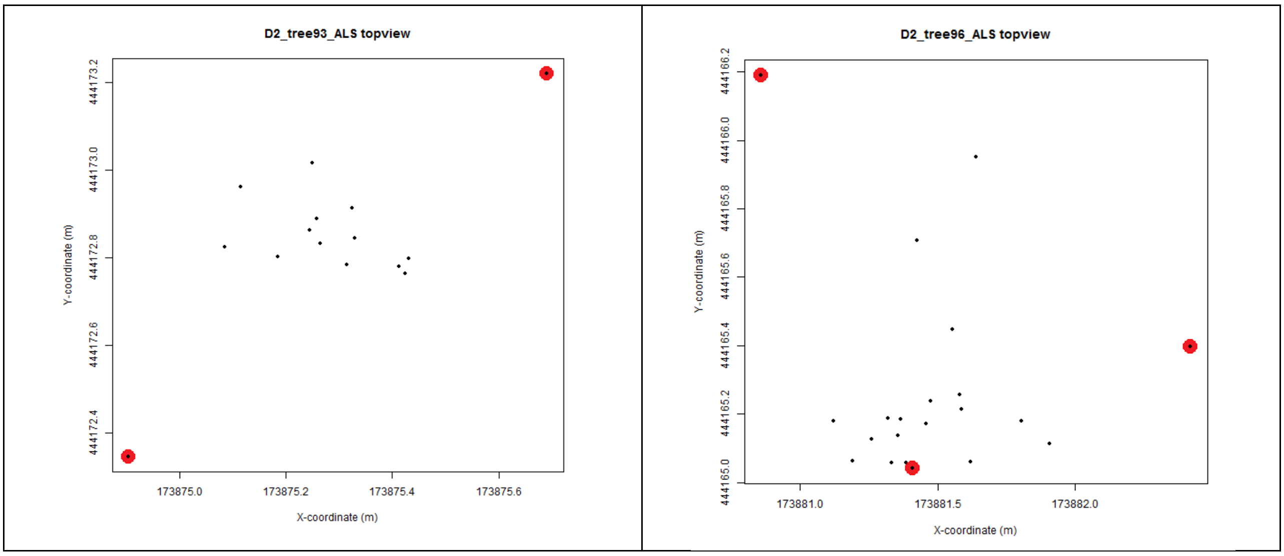


Figure 61. Examples of tree top view, extracted from ALS, and periphery points (red dots) calculated incorrectly

The quality of each coordinate of periphery points was assessed for CP dataset and for ALStpe dataset. The R^2 and RMSE of are shown in Table 8 and Table 9.

Table 8. Result of comparison of periphery points from TLSref and CP datasets

Periphery point	R^2	RMSE, m
P1x	0.9957	11.1754
P1y	0.9063	27.0693
P2x	0.9951	11.9899
P2y	0.9134	25.8219
P3x	0.9950	12.2233
P3y	0.9088	26.5452
P4x	0.9948	12.3760
P4y	0.9054	27.2265

Table 9. Result of comparison of periphery points from TLSref and ALStpe datasets

Periphery point	R^2	RMSE, m
P1x	0.9915	15.0238
P1y	0.9469	24.3271
P2x	0.9915	14.9665
P2y	0.9476	24.1311
P3x	0.9915	15.0547
P3y	0.9470	24.3031
P4x	0.9915	15.0285
P4y	0.9460	24.6314

Scatter plots of TLSref periphery points (x-axis) and corresponding CP periphery points from CP dataset (y-axis) are presented in Appendix 2. Scatter plots of TLSref periphery points (x-axis) and corresponding periphery points from ALStpe dataset (y-axis) are presented in Appendix 3.

4. Discussion and recommendations

This section is dedicated to discussion of the results of the tree parameters extraction from point cloud TLS and ALS data using PCTPE method and discussion of the results of validation of CP dataset and ALStpe dataset by TLSref dataset, as well as discussion of results of interview and data used in the research. The main focus lies on the causes of errors and inaccuracies of the extraction algorithms. This chapter also provides recommendations for improvement of tree parameters extraction.

4.1. Discussion of usability and requirements

The interviews with urban tree managers were not aiming at investigation of the opinion of all tree managers in the Netherlands about the tree dataset. The purpose of it was in defining potential need in 3D visualisations of trees, potential necessity of tree database and requirements, which it should satisfy. With the help of the interviews in was found that tree locations, three height, first living fork and DBH parameters are essential to know in urban tree management. However, 3D visualisations are also have potential use in urban tree management, consequently, all SILVI-STAR or other tree parameters which could be used to produce 3D models of trees, are important to know. Requirements to geometrical accuracy of the tree parameters were used during visual assessment of extracted tree parameters.

4.2. Discussion of data

Three different data sources, namely raster ALS point ALS and point TLS data were used to delineate trees and extract their parameters. The data specifications were different from each other. According to previous research extraction of tree parameters from TLS data gives more accurate result. TLS gives opportunity to derive information on below canopy level. This information can be hardly acquired with ALS, because of the occlusion by the upper parts of the crown (Hilker et al. 2010). However, ALS data scans above the ground and covers larger area and TLS in comparison with it is less suitable to investigate trees structure (Hilker et al. 2012). There is also one source of LiDAR data, which was not used in the research. It is mobile LiDAR data. The advantage of this technique is in ability of catch vertical structure of trees like TLS and in possibility to collect data on the same area faster, than TLS (Rutzinger et al. 2010). Hence this data could be a good alternative to TLS data.

4.3. Discussion of tree delineation

Initial non-vegetation mask, which was produced by aggregation points, classified as high vegetation, included a lot of foreign objects, which did not belong to high vegetation class. This happened, because classification of points was not perfect. The classification algorithm was checking if the standard deviation of the points which are 1.3 meter above the ground is below 0.8 (buildings) or above (high vegetation) the standard deviation threshold. Despite the threshold of planarity/ruggedness was quite high (0.8), points which in reality were belonging to edges of buildings, to bike shed, lamp posts, statues were classified as high vegetation, which is presented in Figure 23. The result of point classification for different parts of the study area This could be explained by roughness of building walls, which require higher standard deviation values for being classified as 'buildings'. Meanwhile some points, which actually belong to a tree, were classified as buildings, like in shown in Figure 23b. This occurred because the threshold for ruggedness was too high for separating points of some trees. Recommendations for the classification of points using lasclassify tool is to make test classification first in order to find appropriate parameters.

Solitary trees were extracted from the vegetation mask by visual assessment of objects' shapes. This approach was time-consuming. First recommendation is to additionally introduce reflectance values of the data in order avoid the occurrence of foreign objects in vegetation mask. Second recommendation is to find a way to automatically detect solitary trees and separate them from aggregation of trees. This could be done, for instance, by creating top view density graphs for aggregations of trees to find stems positions, making a buffer of certain width around found stems and clipping aggregation of trees points using the buffer. LiDAR based methods, which are were used by other researchers for individual tree delineation could be used to solve the problem. The most popular method of tree crown boundaries delineation in 2D data have been watershed segmentation (Lee et al. 2010). Marker-controlled watershed separation (Chen et al. 2006) gave absolute accuracy of trees delineation of 64.1%. The region-growing algorithm gave similar quite result, it was able to detect two third of non-suppressed trees (Solberg et al. 2006). While the overall accuracy of the crown delineation based on Optimized object recognition, Treetop identification, and Hill-climbing (COTH) method was 72.5% (Gleason and Im 2012). There are also methods of 3D delineation of trees, presented in works of (Li et al. 2012) and (Lee et al. 2010). In the research of Lee et al. a new method which was similar to watershed segmentation however applicable to raw LiDAR point data was presented. The overall tree detection accuracy of this method was 95.1%. An algorithm developed by Li et al. gave the overall accuracy of 94%.

4.4. Discussion of pre-processing of individual trees point clouds

Pre-processing of individual tree point cloud was aiming at noise removal. However, in some tree point clouds not all the noise was removed. Mostly it concerned foreign objects, which were present in the point cloud, like it presented in Figure 33b and grass near tree stem, like it shown in Figure 27a. In some cases, as shown in Figure 27b and c, a part of a stem or the whole stem was cut. The removal of the whole stem means that there was a foreign object, like lamp post, in a point cloud and due to this stem location, which was derived from density top view raster, was calculated in the position, where a foreign object was situated. Therefore, instead of stem points, part of the foreign object was returned to the pure tree point cloud. In case, when only part of the stem is deleted, the buffer which is taken around the stem position should be enlarged, that will solve the problem.

Foreign objects in tree point clouds lead to problems in calculation of tree parameters, hence they should be recognized by the algorithm and the method should be adjusted to process such point clouds. Filtering of foreign objects could be in individual tree point clouds implemented by using intensity information of LiDAR data.

4.5. Discussion of the results of the improvement of tree parameters extraction

One of the aims of the research was in making improvements in extracting parameters of the trees. Parameters, which were extracted using TLS point cloud data and PCTPE method, were expected to be more precise, were considered as ground truth and were used to validate parameters from ALStpe and CP datasets.

4.5.1. Height of the first living fork of the tree

Problems with extraction of first branch height appeared mostly during the processing of bushes, which had no stem or trees, which braches, because of human maintenance, started growing near the ground. Such human maintained cut pollard-willows are presented in Figure 31.

In this case the error in calculation of the parameter happened, because during the cleaning of the tree point clouds from noise, understory and ground points, part of a point cloud, which was lower and 1.3 m was classified as non-tree points and afterwards, in order to return stem points to a tree, non-tree points which were within a buffer of 0.3 m from stem location were added to tree points again. This algorithm worked well for trees, which had standard shape, however, for trees which had a lot of low branches, it happened, that a part of tree was cut. This caused sharp jump on the vertical profile of a tree on 1.3 m height and, eventually, the first branch was detected on this height.

Another problem was detected during the extraction of first branch height parameter from cut pollard-willows. Trees were obstructed by metal frame of bike shed on the approximate height 2-3 m during their scanning from one side. This caused low amount of points in tree point clouds and detection of the first branch at this height (Figure 32).

However, some of these of trees didn't have the problems, discussed above, and first branch detection was successful for them. Examples of such trees are presented in Figure 30.

The most precise detection of the first branch height was observed for more or less standard shape trees with upwardly directed branches. Detection of first branch height on trees with upwardly directed secondary branches and downwardly directed secondary branches is presented in Figure 34. For the trees with downwardly directed secondary branches, the first branch was detected lower than it starts in reality. In case if the secondary or even the branches of the first order were directed downwards and their ends were situated lower than real first branch, the high number of returns on vertical profile of a tree occurred right on the height, where downwards directed branches were finished. This height was detected by algorithm as a height of first branch.

In some cases not all the noise points were filtered from the tree point cloud, which caused errors in detection of first branch height (Figure 33).

In order to reduce errors described above, several procedures are suggested to accomplish. First, after the separation of initial tree point cloud into tree/non-tree points, during the procedure of retrieving stem points back to a tree, it is necessary to expand the buffer, which is made around tree location. Second, if it is possible scan trees in such a way that minimal amount of objects will obstruct it.

4.5.2. Diameter at breast height

Problems with fitting circle in the tree cross-section at breast height occurred because of the noise or some foreign objects were not deleted after the filtering process. As they were not removed, circle was fitted both through points, which belong to stem and through noise points (Figure 36). These situations lead to overestimation of DBH, however they happened quite rare.

Problems were also observed for trees, which had branches at this certain height of 1.3 meters (Figure 37). The branches points were not filtered, and the circle was fitted taking them into account. These situations occurred more often in comparison with the previous one; however errors in DBH calculation and stem location estimation seem to be smaller.

Recommendation which can be given in order to avoid errors in fitting circle through cross sections is to filter out all foreign objects, which exist in the point cloud.

4.5.3. Tree location

The correctness of tree locations, extracted with PCTPE method is very much dependent on how good the circle was fitted through the cross sections of the trees made on breast height. Thus, if the circle fitting will be improved as it described in previous section, the tree location extraction will be also improved. According to visual assessment circles were fitted correct in 63.07% of cases, consequently, tree locations were computed correct at least for 63.07% of the trees.

The aggregations of trees were not splitted to solitary trees and tree locations were not calculated for aggregation of trees.

The recommendations which could be given concern the improvement of PCTPE algorithm. First, separation of solitary trees from aggregation of trees will make it possible to derive tree locations for more trees and therefore will decrease the number of false positives.

Second, the location of the tree in PCTPE method was calculated as a centre of a circle fitted through points at breast height, while it would be more natural to extract it from a cross-section of the stem near the ground, because tree stem were not always straight, sometimes they were leaning.

4.5.4. Tree crown projection perimeter

The tree crown canopy projection perimeter TLSref dataset is very precise, as canopy projections were made by aggregating points, which were quite accurate classified as high vegetation. The aggregation of classified trees was made with very small aggregation distance, thus the shape of the crown projection was very detailed.

4.5.5. Tree height

In general according to visual assessment of side view graphs of the trees, tree height in TLSref dataset was calculated very precise. Examples are shown in Figure 44. However, there were issues, which caused errors in estimation of tree height.

First, problems appeared, when tree was situated near the ditch or near water object. In this case points under the actual ground level appeared and were considered as ground points, thus distance from the tree points towards ground points was overestimated. An example of such error is presented in Figure 45 a.

Second, if there was not filtered noise above the tree, as branches of neighboring trees or streetlights, errors in tree height calculation appeared (Figure 45 b). However, both situations, described above appeared very rare.

Visual assessment of tree side views, extracted from ALS point data, was quite often difficult due to small amount of points representing a tree. According to visual assessment only for less than half of the trees tree height was calculated correct, like it shown in Figure 46. Extracted from ALS data trees side views, which tree height parameters were calculated correctly. Red line represents calculated height of a tree.In many cases the height of tree was underestimated (Figure 49b), in some of them overestimated (Figure 49a). Visual comparison of trees side views, extracted from ALS and TLS point clouds, showed that, except the fact that ALS data has less points, height of the trees is quite often underestimated. Especially this was the case for smaller trees. Another issue which caused underestimation of tree heights extracted from ALS point cloud data was in calculation of the shortest distance towards the ground. During the separation of the point cloud into tree points and ground points, some tree points were misclassified as ground points. Figure 48 illustrates such a situation. Thus errors occurred when the shortest distance towards these misclassified ground points was calculated and accepted as an actual height of the crown points towards ground. This error could be avoided if the threshold of separation into tree points and ground points will be changed. Overestimation of tree height in ALStpe occurred because of not filtered noise above the tree.

4.5.6. Peripheral height and peripheral points

Visual comparison of tree side views and top view of trees and the coordinates of peripheral points and periphery height (the height of the greatest width of the crown) showed that coordinates of periphery points of trees and periphery height in TLSref dataset are very precise, for at least 90% of the trees periphery points and for at least 93% of the trees periphery height were computed correct. Examples are shown in Figure 52 and Figure 58.

There could be several points in the coordinate, where crown of a tree touches the boundary box surrounding the tree crown projection. This means that for x or y coordinate of one periphery point there could be several x, y or z values. This is the reason, why in the PCTPE method mean of all found x, y or z coordinates was taken for each peripheral point. However, as visual assessment showed it didn’t have negative consequence in periphery height estimation.

In order to get the peripheral height of a tree height the mean height of its four peripheral points is taken. The one who will make visual assessment of this parameter should keep in mind that peripheral height will not be exactly in the height of the greatest width of the crown, it will be averaged.

Errors which appeared in calculation of these parameters were caused by noise in tree point clouds.

Visual assessment of side views and top views of the trees, extracted from ALS point data with the periphery height and periphery points from ALStpe dataset showed that the calculation of these parameters was satisfactory, at least for 65% of the trees periphery points and at least for 77% of the trees periphery height were calculated correct. Periphery height and periphery points in some cases was not possible to find and as well as visually assess due to small amount of points in an ALS tree point cloud. Sometimes there were less than 4 points which belong to a tree crown, thus it was not possible to extract four periphery points. Underestimation of periphery height from ALStpe dataset occurred due to wrong separation of a point cloud into tree and ground points, which caused misclassification of shortest distances from tree crown points to ground points.

4.6. Discussion of the validation results

Assessment of quality of CP and ALStpe datasets was made using TLSref dataset as ground truth. As it was shown in Section 4.5 tree parameters in TLSref dataset were not as correct as they are in real world. According to visual assessment only 63.07% of circles were fitted through cross sections of trees at breast height this implies that validation of tree location from CP dataset with TLSref dataset was not very reliable. The evaluation of tree height, periphery height and periphery points from CP and ALStpe datasets using TLSref dataset was more reliable, as visual assessment of these parameters from TLSref dataset showed , that in not less than 90% of cases they were calculated correct.

4.6.1. Tree location

In CP dataset calculation of trees locations were based on simple centroid calculation of 50x50 cm raster canopy projections. In TLSref dataset tree locations were found as centres of circles fitted through cross-sections of stems at breast height. Thus tree locations from TLSref were expected to be more precise, even taking into account the fact that not for all trees circle was fitted perfectly.

Table 5 shows that the number of FP and FN is very high. Producer's accuracy, user's accuracy and quality, which were derived as a result of assessing TCPE algorithm's ability to find individual tree locations, are very low, as in ideal situation these values are equal to 1. Such a middling result is caused by several factors.

First, the threshold which was set to compare two datasets was very small (0.5 m). If the threshold would be set to 1 m the number of TP increases to 119.

Second, in general, ALS data in comparison with TLS data have fewer point density, and the raster made on the base of the ALS data is even less precise. As raster ALS data were used during the delineation of the trees in TCPE method, crowns of trees were underestimated or lost completely. In Figure 39 it is well seen that a lot of small trees were set as False Negatives. As it was investigated during validation of CP dataset, made by Frans Rip the TCPE method has problems with capturing small trees (Meijer 2014). Thus high number of false negatives mostly occurred because small trees were not captured by TCPE algorithm.

Third, according to previous validations of CP dataset ((Meijer 2014), (Benthem 2013)) lamp posts and road signs were quite often classified as trees. This caused an increase in false positives.

Forth, important difference lies in the fact that aggregations of trees were not separated into solitary trees and processed in PCTPE method, while in TCPE method the trees were delineated from aggregations and processed, what lead to increase in FP.

Fifth, the difference in date of data acquisition should be taken into account. TLS data was collected in 2013, while ALS data was obtained in 2010. Apparent errors could have happened due to the fact that the landscape of study area has changed; some trees were cut down, what also increased the number of FP.

Analyzing Figure 40 and 41, among the True Positives there were mostly trees of medium height (6-15 m) and medium tree crown projection perimeter (15-50 m^2). This could be explained by the fact that in comparison with very high and low trees the likeliness for medium trees to have stem position in the centre of the crown is bigger. For big trees there is more deviation in tree location, as tree crown is larger, while for very small trees tree location is restricted by sever pixels of the tree crown, which could be underestimated.

The recommendation which can improve the extraction of tree location from raster ALS data is to calculate the location of the tree using density raster made on horizontal plane instead of calculating the centroid of crown projection.

4.6.2. Tree crown projection perimeter

R^2 and RMSE were calculated in order to show how well individual tree crowns were delineated by the TCPE method. As it shown in scatterplot (Figure 43. Scatter plot which shows goodness of fit between tree crown projection perimeter from TLSref dataset (x-axis) and tree crown projection perimeter from CP dataset (y-axis). The trend line is plotted in red. The 1:1 line is plotted in grey) tree crown projection perimeter is underestimated. The coefficient of determination is satisfactory, but still quite low, which means that fit between the crown projection perimeters from TLSref and CP datasets is not bad, but not very good. The fact, that fit is not perfect could be explained by two main reasons.

First, in general, ALS data in comparison with TLS data have fewer points. As ALS data was used during the delineation of the trees in TCPE method, crowns of trees were underestimated. Second, the tree crown projections in CP dataset are raster based, what makes the shape of the crown projection more different from reality and causes overestimation or underestimation of tree crown projections.

4.6.3. Tree height

Table 6 shows that coefficient of determination is very low for validation of CP dataset and quite good for validation of ALStpe dataset. Such low R^2 for validation of CP dataset can be explained by the fact that tree height is extracted from ALS raster data as a difference between digital surface model and digital terrain model, where the raster cell is 0.5x0.5m and point height values were averaged.

The situations, which caused underestimation of tree height from point cloud ALS data, described in section 4.5.5, resulted in not perfect fit between the tree height extracted from ALS and TLS point clouds.

Whereas R-squared is a relative measure of fit, RMSE is an absolute measure of fit. The smaller the difference between crown projection perimeters from two datasets, the smaller RMSE should be. It is useful in comparing the results of different models. As it is shown in Table 6 ALStpe has lower RMSE, this means that that the difference between ALStpe tree heights and TLSref tree heights is smaller than difference between CP tree heights and TLSref tree heights.

Previous research (Jung et al. 2011) showed that tree height estimation using ALS data can be very precise. Thus if the PCTPE method would be improved, more accurate height values would be derived.

4.6.4. Peripheral height

Table 7, Figure 56 and Figure 57 show that coefficient of determination is very low and the validated data doesn't fit good to data from TLSref. The reasons of this are the same as for tree height. In the case when periphery height from CP dataset was validated by corresponding parameters from TLSref dataset, this could be explained by the fact, that periphery heights were extracted from raster and heights were averaged. For the case, when ALStpe dataset was validated by TLSref, low coefficient of determination is explained by underestimation of height in ALStpe and low point density in ALS data.

4.6.5. Periphery points

Very high coefficients of determination were obtained during the validation of coordinates of peripheral points from both CP and ALStpe datasets by corresponding parameters from TLSref dataset (Table 8 and Table 9) and scatter plots (Appendix 2 and Appendix 3) show very good fit between the data. This indicated that extraction of peripheral points from ALS data with TCPE method and PCTPE method are both very reliable techniques.

5. Conclusions

In this research the potential of TLS and ALS point data in extraction of tree parameters, which could be useful in urban tree management was analysed. Structural tree attributes were derived from TLS and ALS point clouds as an improvement of the existing method, which received these attributes using ALS raster data. Results confirm that extraction of tree parameters using TLS point data have remarkable advantage in accuracy comparing to ALS point and raster data, mostly due to higher TLS point density. The extraction of parameters from ALS point data also gave satisfactory result. Taking into account the fact that acquiring TLS data in comparison with ALS data for the same area takes more time and requires more labour, the perspective of using ALS point data to derive tree parameters seems more realistic.

Regarding the specific research questions and recalling the thesis objective the following conclusions can be drawn.

Research question 1: Is it possible to improve the extraction of tree parameters, using the raw point cloud terrestrial and airborne LiDAR data, instead of the top-of-canopy raster datasets?

Raw point cloud TLS and ALS data were used to extract tree parameters. Most of the tree parameters extracted from TLS data, such as tree height, periphery height, periphery points and tree crown projection perimeter were calculated very precise. The improvement was also in calculating tree parameters, which were not included in CP dataset, such as height of the first living fork and DBH from TLS data. Although results of visual assessment of correctness of these two parameters and tree location parameter were quite good, the PCTPE algorithm needs improvements in calculating them. Only a few parameters were extracted from ALS data with the created method: tree height, periphery height and periphery points. Further research is needed to investigate the ways of extracting more parameters, such as relative height of the tree base to the ground level, tree location and tree crown projection perimeter.

Research question 2: How good is the CP dataset for use by municipal tree managers?

The ability of TCPE algorithm to find individual tree locations and the quality of tree crown projections from CP dataset were assessed. The validation was made by comparing the tree locations and trees crown projection perimeters from CP dataset with corresponding parameters from TLSref dataset.

Based on the results of validation, the tree location calculation is not as precise as urban tree managers may be requiring (according to interview with Codi Duyster the accuracy should be not less than 0.5 m).

Validation showed that tree crown perimeter extraction with TCPE method is satisfactory. It could be improved if delineation of tree crowns was made by using ALS point cloud data instead of ALS raster data.

Research question 3: How good are the SILVI-STAR parameter values, as derived from ALS point data and ALS raster data for use by municipal tree managers?

The quality of the SILVI-STAR parameter values, derived from raster ALS data and point ALS data was assessed by comparing them with corresponding parameter values derived from TLS point data.

Validation showed that the extraction of all height parameters, such as tree height, periphery height and relative height of the tree base to the ground level, calculated from raster ALS data using TCPE method is not satisfactory. The same result, except for the tree height, got from validation of height parameters, extracted from point ALS data. ALS point data was quite good to extract tree height parameter. The conclusion which was drawn, is that ALS point data is acceptable to extract tree height parameter.

In extraction of periphery points both extraction of this parameter from raster ALS data and from point ALS data, performed very good. Thus they are reliable techniques to extract periphery points for use by municipal tree managers.

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Appendices

Part of the appendices are presented in the paper, others are stored in the attached DVD.

Appendix 1

Questionnaire for urban tree managers

1. What is the usefulness of Canopy Projection dataset, which stores data about the location of trees and perimeters of tree crowns?

2. Are 3D models of trees are important now or will be potentially useful for urban tree managers in future?
If yes, how is it useful or will be useful to have 3D models of trees?

3. Which parameters of the trees are important for urban tree managers?

Parameter	Description	Ranking of importance
Tree location	The location of a tree (x and y coordinates)	- Essential - Important - Neutral - Minor importance - Unnecessary
Tree crown projection perimeter	The perimeter of tree crown projection	- Essential - Important - Neutral - Minor importance - Unnecessary
Tree height	Crown top	- Essential - Important - Neutral - Minor importance - Unnecessary
Height of the first bifurcation	Height of the first living fork	- Essential - Important - Neutral - Minor importance - Unnecessary
Height of crown base	Height of the base of the crown	- Essential - Important - Neutral - Minor importance - Unnecessary

Periphery height	(height of the greatest width of the crown)	- Essential - Important - Neutral - Minor importance - Unnecessary
Periphery points	4 points on crown circumference on peripheral height	- Essential - Important - Neutral - Minor importance - Unnecessary
DBH	Diameter of the tree stem on the breast height	- Essential - Important - Neutral - Minor importance - Unnecessary

4. How important is the accuracy of each parameter?

Parameter	Description	Ranking of importance
Tree location	The location of a tree (x and y coordinates)	- Essential - Important - Neutral - Minor importance - Unnecessary
Tree crown projection perimeter	The perimeter of tree crown projection	- Essential - Important - Neutral - Minor importance - Unnecessary
Tree height	Crown top	- Essential - Important - Neutral - Minor importance - Unnecessary
Height of the first bifurcation	Height of the first living fork	- Essential - Important - Neutral - Minor importance

		- Unnecessary
Height of crown base	Height of the base of the crown	- Essential - Important - Neutral - Minor importance - Unnecessary
Periphery height	(height of the greatest width of the crown)	- Essential - Important - Neutral - Minor importance - Unnecessary
Periphery points	4 points on crown circumference on peripheral height	- Essential - Important - Neutral - Minor importance - Unnecessary
DBH	Diameter of the tree stem on the breast height	- Essential - Important - Neutral - Minor importance - Unnecessary

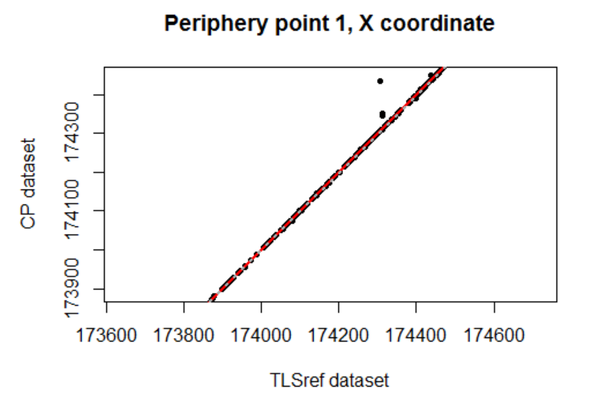
5. What is the required accuracy for the important parameters?

Parameter	Description	Required accuracy
Tree location	The location of a tree (x and y coordinates)	- Millimeters - Centimeters - Meters
Tree crown projection perimeter	The perimeter of tree crown projection	- Millimeters - Centimeters - Meters
Tree height	Crown top	- Millimeters - Centimeters - Meters
Height of the	Height of the first living fork	

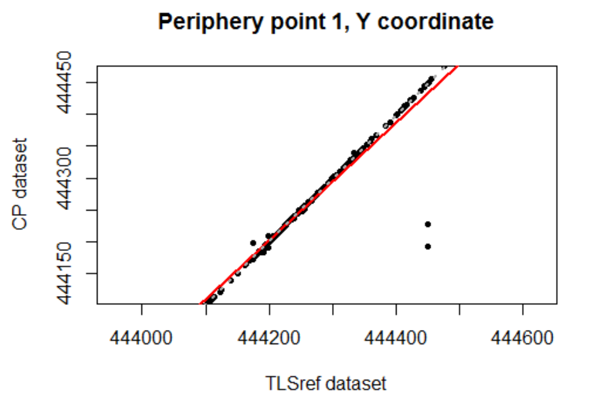
first bifurcation		- Millimeters - Centimeters - Meters
Height of crown base	Height of the base of the crown	- Millimeters - Centimeters - Meters
Periphery height	(height of the greatest width of the crown)	- Millimeters - Centimeters - Meters
Periphery points	4 points on crown circumference on peripheral height	- Millimeters - Centimeters - Meters
DBH	Diameter of the tree stem on the breast height	- Millimeters - Centimeters - Meters

Appendix 2

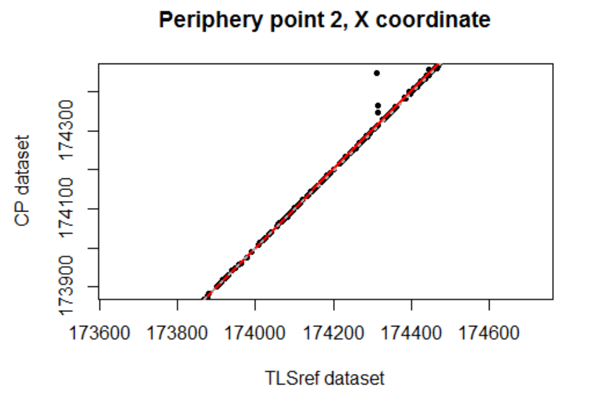
Scatter plots which show goodness of fit between periphery points from TLSref dataset (x-axis) and tree height from CP dataset (y-axis). The trend line is plotted in red. The 1:1 line is plotted in grey dash.



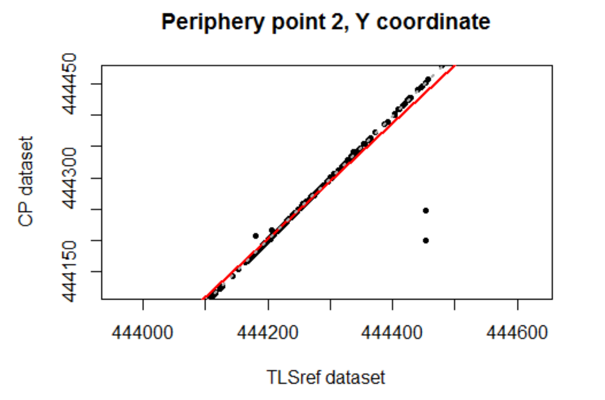
P1x



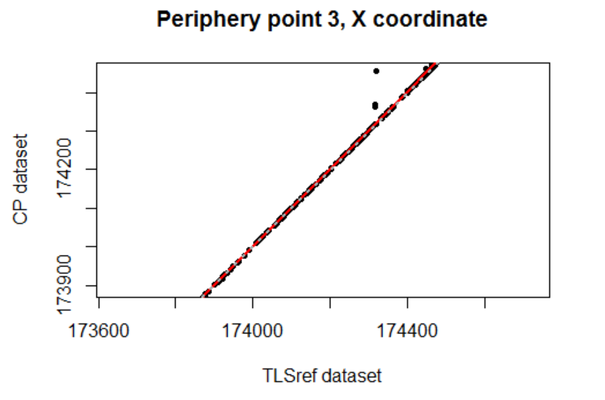
P1y



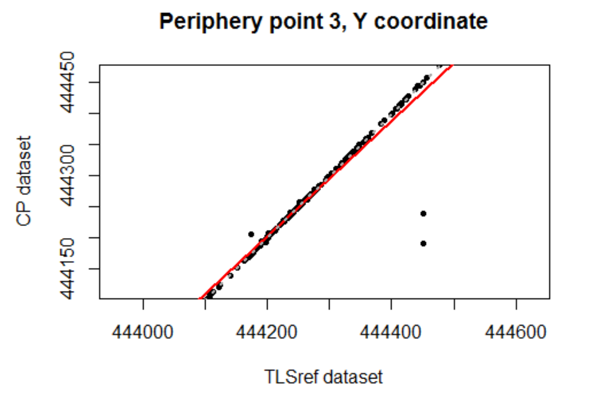
P2x



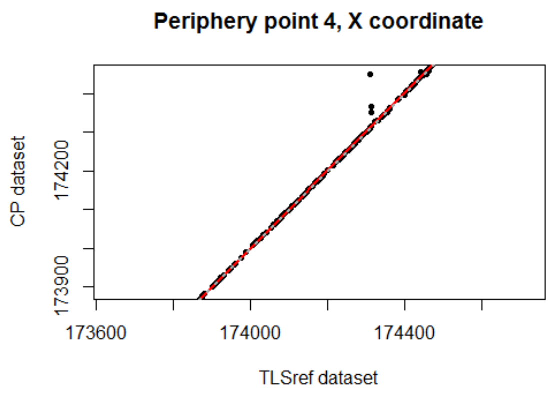
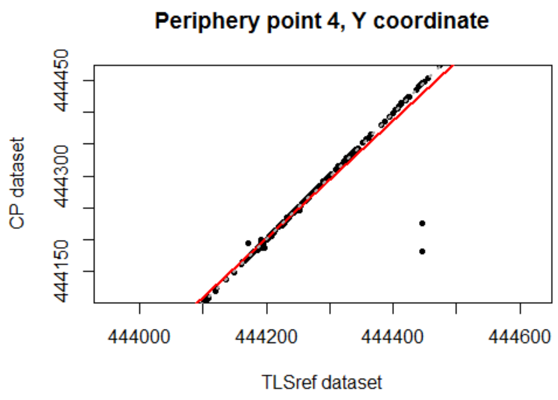
P2y



P3x

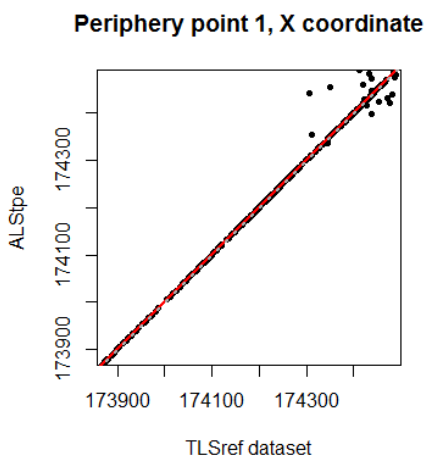


P3y

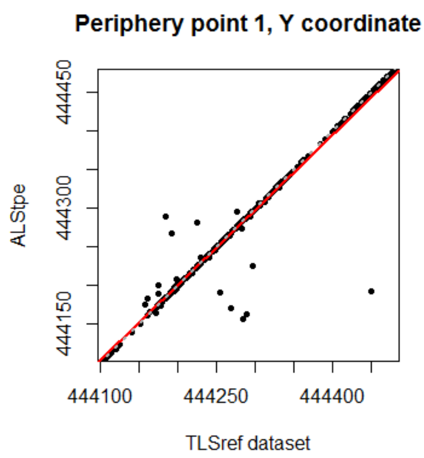
Periphery point 4, X coordinate CP dataset 173900 174200 173600 174000 174400 TLSref dataset	Periphery point 4, Y coordinate CP dataset 444150 444300 444450 444000 444200 444400 444600 TLSref dataset
P4x	*P4y*

Appendix 3

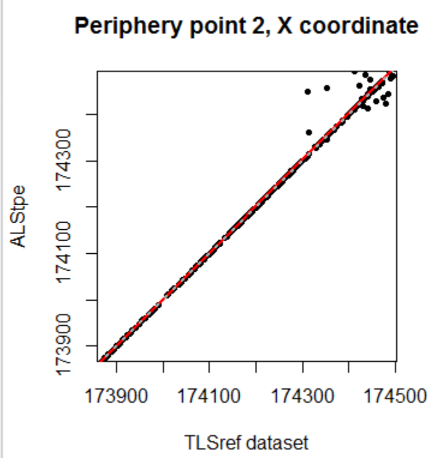
Scatter plots which show goodness of fit between periphery points from TLSref dataset (x-axis) and tree height from ALStpe dataset (y-axis). The trend line is plotted in red. The 1:1 line is plotted in grey.



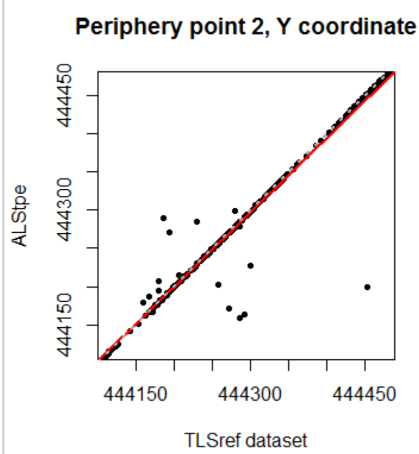
P1x



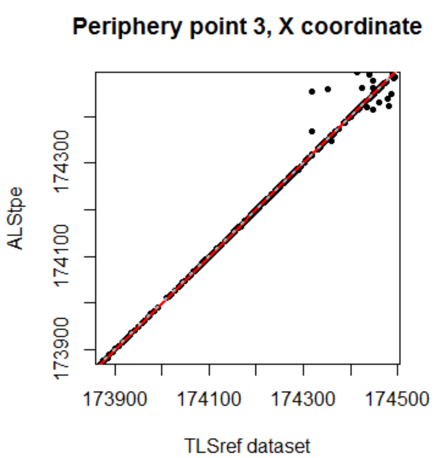
P1y



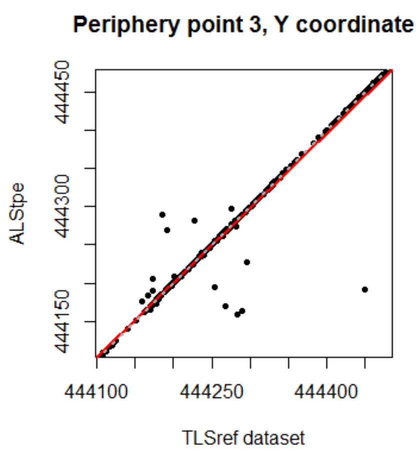
P2x



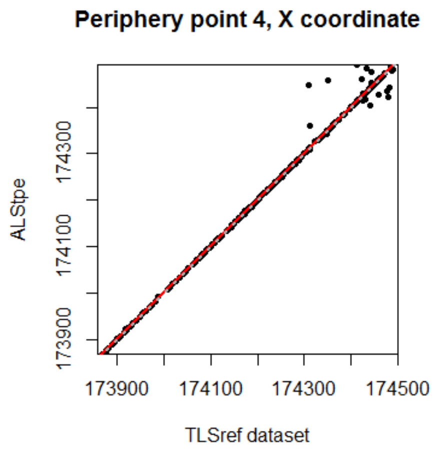
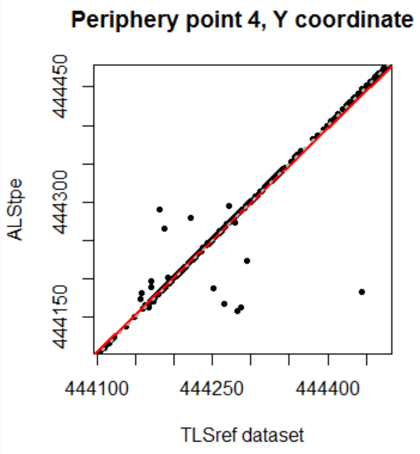
P2y



P3x



P3y

Periphery point 4, X coordinate ALStpe 173900 174100 174300 174500 TLSref dataset	Periphery point 4, Y coordinate ALStpe 444150 444300 444450 444100 444250 444400 TLSref dataset
P4x	*P4y*

Appendix 4

Appendix4 is DVD catalog

4.1. Script for tree parameter extraction

Path: DVD:\4.1. Script for tree parameter extraction
Description: script (source: Harm Bartholomeus) used in PCTPE method to extract tree parameters and to validate CP and ALStpe datasets

4.2. Tree side views

Path: DVD:\4.2. Tree side views
Description: Side views of the trees (extracted from TLS and ALS point data) cleaned from solitary point outliers.

4.3. Side views of pure tree points

Path: DVD:\4.3. Sideviews of pure tree points
Description: Side views of all trees (extracted from TLS and ALS point data) which represent only pure tree points without ground and understory points.

4.4. Height of the first bifurcation

Path: DVD:\4.4. Height of the first bifurcation
Description: Side views of all trees (extracted from TLS point data) with the red line representing the height of the first bifurcation from TLSref dataset.

4.5. DBH

Path: DVD:\4.5. DBH
Description: Cross-sections of all the trees (extracted from TLS point data) with a circle fitted through points

4.6. Tree height and periphery height

Path: DVD:\4.6. Tree height and periphery height
Description: Side views of all trees (extracted from TLS and ALS point data) with the red line representing the height of the tree and green line representing periphery height.

4.7. Periphery points

Path: DVD:\4.7. Periphery points
Description: Top views of all trees (extracted from TLS and ALS point data) with the red dots representing the periphery points of the tree.