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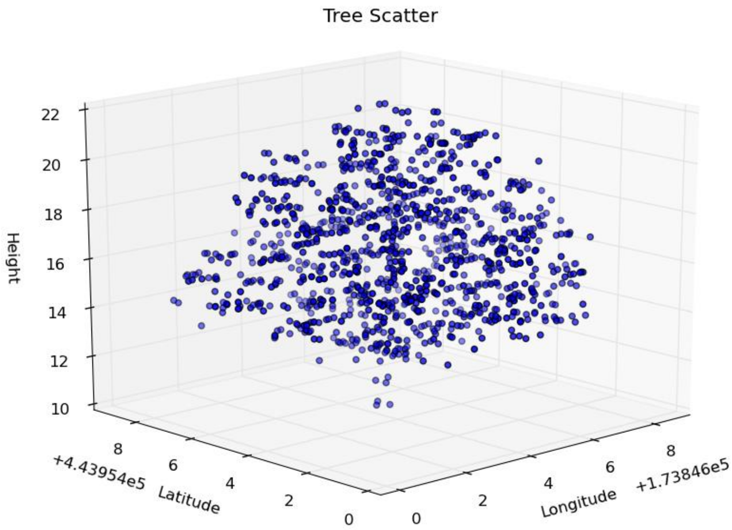
Comparison of 3D Tree Parameters

Minxue Chen



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Comparison of 3D Tree Parameters

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Summary

3D geo-information and airborne lidar techniques offer alternatives to measure trees. Tree parameters can be extracted from generated 3D models instead of measuring in the field. Some research have been done to predict tree parameters from airborne lidar data. However, most of them are studying forestry area by using regression methods. Trees in urban area are not suitable for applying regression approaches due to the variety of species and human impact.

This research first explored the approaches of deriving tree parameters from 3D tree models. Two types of models were generated and compared: raster based model and point cloud based model. These parameters include tree location, tree height, crown base height, crown width, diameter at breast height, crown volume and crown density. At the same time, these parameters were also measured through field measurements.

The core part of this research is comparing extracted parameters between two types of 3D models. The comparison showed that tree location, height, crown width and crown volume can be well extracted from both raster based model and point cloud based model. Crown base height and diameter at breast height had lower accuracy due to the low amount of lidar points describing tree stem. Crown density was found not suitable for compare since the 3D model results have different unit with field measurement results. Meanwhile, the possibility of using extracted parameters to determine *Quercus Robur*, *Fraxinus Excelsior* and *Acer Pseudoplatanus* was discussed. The comparison results illustrate that point cloud based model can provide better parameters accuracies and possibilities of species determination.

Keywords: airborne lidar, tree parameters, 3D tree models, parameter comparison

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List of abbreviations

ALS = Airborne laser scanning

CBH = Crown Base Height

CHM = Canopy Height Model

DBH = Diameter at Breast Height

DSM = Digital Surface Model

DTM = Digital Terrain Model

LOT = Level Of Tree-details

RMSE = Root Mean Square Error

SD = Standard Deviation

TIN = Triangulated Irregular Network

1 Introduction

1.1 State of art of 3D geo-information

3D geo-information technique is replacing 2D in many fields during the past few years and it is becoming a world trend. Although 2D GIS is still irreplaceable, 3D technique has already shown its great advantages. The capability of storing third dimension information expands the uses of GIS in urban planning, landscape management, ecosystem monitoring (Griffon et al., 2011, 2011).

3D objects have to be defined, detected and created. Within all the objects on a 2D map and dataset, trees are much more difficult to be represented in 3D than the other type of objects. Physical forms of trees diverse a lot due to the complex structures they have (Muhar, 2001, Tan et al., 2007). In addition, their physiological properties such as growing, seasonal change and their interactions with environment (wind, snow, human activities, etc.) have brought more challenges. In spite of these difficulties, trees play an irreplaceable role in purifying air, balancing temperature and humidity level in atmosphere, contributing greatly to human life and landscape forms (Müderrisoğlu et al., 2006). Studying 3D trees helps urban and rural planning, forestry, understanding of tree habitats and distinguish of tree species (Omasa et al., 2007). It is also a way to help understanding the influence on human perception, particularly for mental map mapping in urban areas (Müderrisoğlu et al., 2006).

Many researches have simulated or represented trees. Two main study scales have set (Muhar, 2001). The first one is the landscape scale, representing forest or woods from distance by adapting 3D texture mapping techniques, segmentation and regression techniques, etc. The second one is the object scale which simulates each tree model individually with details tree parameters. This level always has a aiming of recreating tree models. And it is widely used in urban area. This research has been done in the object scale.

Recently, Centre of Geo-information Wageningen (CGI) is building 3D tree models based on LOT theory. LOT is short to Level Of Tree-detail. It has four levels, ranging from zero to three (Fig.1).

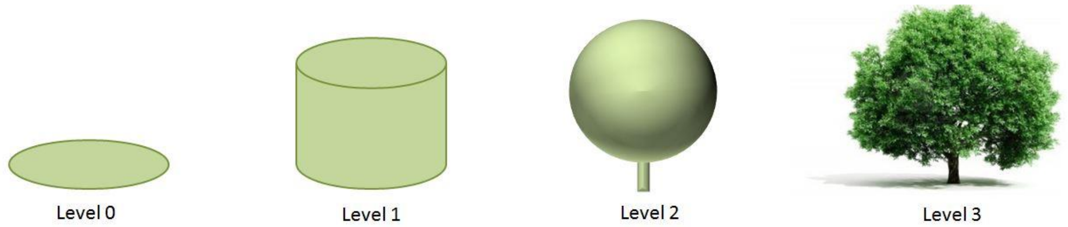


Figure 1: Example of LOT.

Level-0 is a 2D point with buffer. It gives information about tree location and expected crown projection. Level-1 is a cylinder that can also provide tree height value. Level-2 is a volumetric model based on location, DBH and crown shape.

Level-3 is a detail tree model with location, branches, crown shape and leave texture. These four levels can meet various requirements from different users. In this research, tree parameters were selected based on LOT theory.

1.2 Airborne lidar technique

A single 3D tree model can be generated by different means for example out of ground field measurement, lidar data, 2D images and related computer algorithms. Lidar technique is one of the most direct ways of representing trees compared to the use of some complex algorithms (e.g. AMAP, VRML, L-system, TREE system) which have been developed to simulate trees, requiring botanical models, expert knowledge and massive inventory data(Lim and Honjo, 2003).

Airborne lidar technique is an active method, having no limit to specific surface textures (except water) which is very suitable for measuring 3D objects on the ground (Omasa et al., 2007). The penetration property of laser beam is optimized for detecting the details of a tree under the canopy. The high sampling rate can describe tree canopy accurately (Vosselman et al., 2005). Apart from these, the short acquiring time can offer up-to-date tree information. The mechanism of this technique is using a laser scanner, located on airplane or helicopter, to send and receive laser pulses. Then the distance can be calculated by multiplying the time difference by light speed. The GPS on both the carrier and ground will give the accurate coordinates of objects' position.

The data is formed by huge amount of unstructured points in 3D, known as point cloud. These points only give basic geometric representation(Mallet and Bretar, 2009). To study a target object, in this case is a tree, the parameters should be further calculated based on these basic geometry and intensity(Hug and Wehr, 1997).

AHN2 data (Current Elevation Map of The Netherlands) was used in this research. AHN data is a product of a Dutch national project. The data was acquired by either airplane or helicopter. The first version of this data (AHN1) was made from 1996 to 2003 mainly designed for water management and flood risk management. Since 2008 until first quarter of 2012, AHN2 was made by newer techniques with higher resolution and (6-10 points/m2)(Zon, 2012).

1.3 Problem definition

There are two main processes to generate 3D tree model from airborne lidar data. The first one is point cloud or vector based approach by which Lidar data is classified first and next the tree model is extracted. The second approach is a raster based approach. It is also known as canopy height model (CHM), a raster surface model, which is generated by calculating the difference between digital surface model (DSM, also known as digital landscape model) and digital terrain model (DTM) (Lovell et al., 2005, Yu et al., 2004, Jenness, 2004) (Fig 2). DSM and DTM models are all generated from lidar data by interpolating the first return lidar points and last return lidar points respectively (Fig.2). DTM can also be done by interpolating contour lines (Gomes

Pereira and Janssen, 1999). Then the question is how to make a choice between these two approaches.

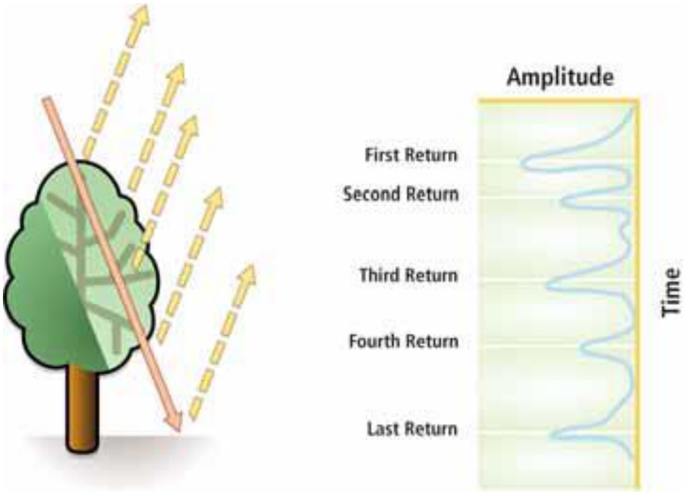


Figure 2: Airborne Lidar Return Points (ESRI, 2012).

From the aspect of calculation cost, point based approach is slower since it needs to process great amount of points. Raster based approach only takes the highest and lowest laser value within each pixel, reduced the processing speed and storage space.

Moreover, users might need different parameters from the trees which also mean different level of tree details (LOT). Thus, the accuracy of tree parameters can be interesting for stakeholders as well. Gomes Pereira and Janssen (1999) pointed out that the accuracy of lidar data is depend on the laser property, for example, laser wavelength and signal-to-noise ratio. And in addition, measuring process, such as viewing angle and errors of airplane (platform) and the condition of the weather can also effect on the modeling accuracy. These factors mentioned above are influencing both modeling approaches. When producing 3D tree models by point cloud based method, the choice of the point density and measuring season can make great different. In terms of raster based model (DSM), the resolution (pixel size) determines the detail level of trees while the choice of interpolation methods is influencing on the DTM(Vepakomma et al., 2008).

As a conclusion from most of the studies, the accuracy of tree height using lidar technique shows an overall underestimate trend(Anderson et al., 2006b). Researches have shown that airborne lidar can measure tree height more consistent than field measurement(Næsset and Økland, 2002) with error less than 1.0m for individual trees(Persson et al., 2002). However, an average underestimate of the height was also been found because of the pulses might miss the apex of trees (Andersen et al., 2006, Anderson et al., 2006a). Besides tree height, algorithms for extracting other tree parameters, such as crown width, have been developed (Solberg et al., 2006, Reitberger et al., 2009, Persson et al., 2002). These studies were concentrated on landscape scales. Regression methods were widely adapted in estimating DBH, crown volume (Riaño et al., 2004, Falkowski et al., 2010, Jung et al., 2011). However, the law of regression restrict these methods have to be used upon normal distributed data

(Faraway, 2002, Freedman, 2005). Trees in urban area are significantly influenced by human activities which can make the sample trees unrepresentative for population. The developed methodology is not completely suitable for generating tree parameters in urban area.

Nevertheless, no comparison has been made between a point cloud based model and a raster based model. But, looking for indications of how to choose a suitable model for purposes is necessary. Especially the accuracy, the most considered indicator, should be compared.

1.4 Research objective and research questions

Therefore, the main research objective of this study is to develop a methodology to compare tree parameters generated from 3D tree models.

This objective has then derived the following questions:

1. How to generate comparable 3D tree models based on the point cloud and raster based approaches?
2. What parameters should be extracted from field measurement and 3D models?
3. How to acquire those parameters from both field measurement and 3D models?
4. How to compare these two models and what's the comparison results?

1.5 Thesis structure

This thesis is composed by six chapters.

Chapter one gives the background, problems definition and research objective as what have been stated above.

Chapter two describes the methodology of field measurement, 3D models generation based on LOT, parameters extraction from two types of models and the comparisons between them. The parameters extraction parts are introducing the initial developed methods.

Chapter three illustrate the results of pre-processing, generated models and extracted tree parameters. This chapter also includes the update parameters extraction approaches.

Chapter four provide the parameters comparison results.

Discussion and recommendation corresponding to results are given in chapter five.

2 Methodology

2.1 Framework of methodology

A brief framework is shown as below. Field measurement was first carried out. Its results were treated as ground truth. Then point cloud based and raster based tree models were generated. Finally, tree parameters were extracted and compared with field measurement results and between two types of models. Refined methods will be described together with results in chapter three.

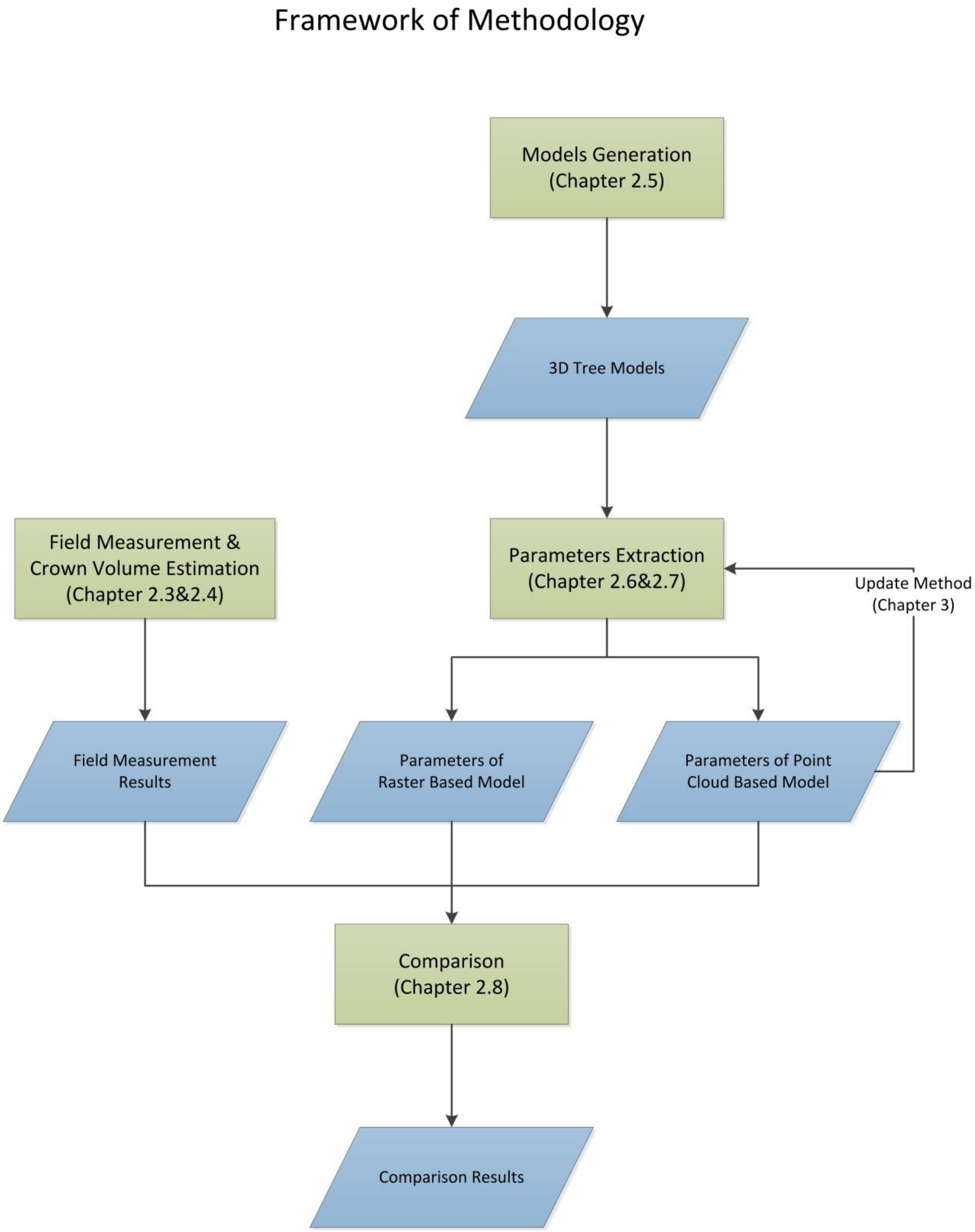


Figure 3: Framework of methodology.

2.2 Study area and materials

The study area is located in Wageningen, Netherlands. The study trees were picked close to Wageningen University campus (Fig.4). In total, 45 trees were selected as study sample. They are shown in appendix A1.

Airborne lidar datasets: AHN2, acquired in March, 2010.

Software been used: ArcGIS 10.1, LAStools, Python (MatLAB package).

Figure 4: Study area (Within red rectangle).

2.3 Field measurement

2.3.1 Parameters selection based on LOT

Before carrying out the field measurement, the study parameters need to be defined. The parameters which are expected to be obtained from each level are listed in Table.1. Location, height and crown width are essential parameters for describing the space which a tree is taking. DBH and CBH together with height and crown width can be used to calculate stem volume and crown volume. Density is influencing on human perception. In addition, all these parameters are the basic elements for recreating 3D tree models. Therefore, location, height, crown width, CBH, DBH and density were selected and measured. Explanation of some of these parameters is shown in fig.5.

Leaves texture and structure are not visible in both point cloud and raster models. Thus they were not measured in the field. Tree species is also invisible. However, it might be possible to determine species based on other parameters or other model properties. Therefore, species were recorded during the field measurement.

Table 1: Expected parameters of each LOT level.

Tree Parameters	LOT-0	LOT-1	LOT-2	LOT-3
Location	√	√	√	√
Height		√	√	√
Crown Width	√	√	√	√
CBH (Crown Base Height)			√	√
DBH(Diameter at Breast Height)			√	√
Density(Crown Volume)			√	√
Leaves Texture				√
Structure				√
Species				√

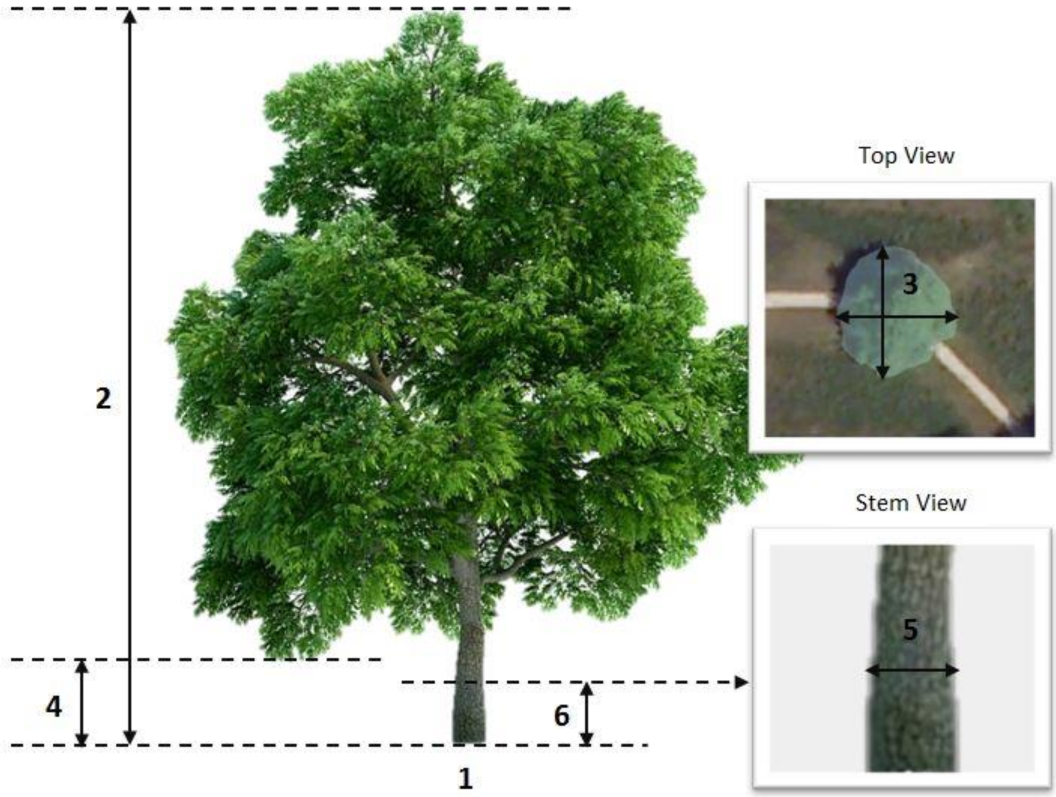


Figure 5: Explanation of some of the measured parameters. 1: Location. 2: Height. 3: Crown Width. 4: Crown Base Height (North-South and East-West). 5: Diameter at Breast Height. 6: Breast Height (1.3 meter).

2.3.2 Tree selection criteria

Several criteria were established to select study trees. First, trees that are commonly seen in the study area were first considered, because they have great impact on social life, urban planning and landscape management.

Second, solitary trees were given priorities. The tree crown of solitary tree won't interact with other trees. But some situations of interacting trees were also taken into this study.

At last, different species were selected in order to find if there is any indication of determination of species.

2.3.3 Field measurement process

The AHN-2 data was taken in early spring which there was no leaf on most. Laser beans were reflected by trunks which are representing the branch structures. Thus the field measurement was done in January, 2013. But another field work was taken in October, 2012 for the purpose of testing the seasonal influence on airborne lidar data. In total, 45 trees and more than 4 types of species were measured covering larger height variance.

Location of the tree can be easily acquired by GPS, but the accurate location of the middle point of the tree stem is rather hard to obtain. Because the location is covered by crown which can obstruct the GPS signal. Moreover, the GPS cannot be placed right on the middle point of the tree stem. Besides, the AHN2 data itself has a very high horizontal accuracy. An assessment shows that horizontal offsets are ranging from 2 cm to 34 cm (Sande et al., 2010). It means if the algorithm can extract the tree stem successfully, then the location of the tree stem is trustable. Thus, only the rough coordinate of each tree was obtained by GPS in order to locate them in lidar dataset.

Tree height was measured by FORESTOR VERTEX (version 4.1). It consists of two units: the hypsometer unit and the transponder (Fig.6). The transponder should be placed at 1.3 meters (breast height) above the ground and right at the projection of the top point of the tree. It is an equipment sending sound signal. The hypsometer should be pointed towards the transponder and stay as far as the user can see the tree top. By aiming to the transponder and tree top respectively, the hypsometer will automatically calculate the tree height.

Figure 6: Units of FORESTOR VERTEX, a hypsometer (left) and a transponder (right).

Crown width is the index representing crown cover. Crown width along north to south and east to west, two directions, were measured by a 50-meters tape. A compass was used to navigate the direction.

CBH was measured by the same equipment as measuring tree height. CBH is defined as the height where the lowest branch is located. Likewise, the transponder was placed right below the target branch.

DBH is defined as being taken at 4.5 feet above ground on tree. It was acquired by warping a diameter tape (D-tape) around the tree stem. When doing the field work, four situations have been seen (Fig.7). DBH was always taken on the uphill side of tree (S.P. D'Eon, 1994).

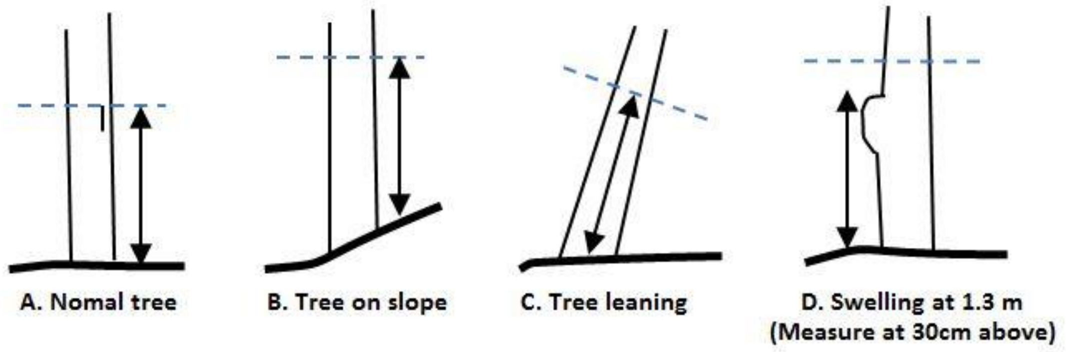


Figure 7: Where to measure DBH.

A spherical Densiometer was used to measure crown density. The way of using it is described as following:

- Take four densiometer readings while facing north, south, east and west.
- Average these four readings.
- Facing up stream, keep the instrument leveled (indicated by the gradienter).
- Hold the densiometer about half meter away).
- There are a total of 24, 1/8" * 1/8" squares in the grid. Each square represents an area of canopy opening (sky image or unfilled squares) or canopy cover (vegetation image or filled squares). Count the number of canopy opening squares. If there are squares that are only partially filled, these can be added to make a complete square. The uncovered area is determined by multiplying the number of squares by 4.17.
- Subtract this number from 100% to determine density in %. If more than half of the canopy area is open sky the counting process can be reversed.
- Count the filled square areas that are covered by the canopy.
- Multiply by 4.17 to obtain the estimated crown density directly in percent.

Besides, tree species were recorded, too. An image of each tree was taken by camera for further determinations of the crown shapes.

2.4 Crown volume estimation

Crown volume is calculated based on crown height, crown base height, crown width and crown shape.

The selection of an appropriate shape for a tree is a subjective issue. The Idealized solid geometric shape model (Coder, 2000) can make it objective. This model assumes that tree crowns have various shapes with bottoms in circles. It gives ten different pre-defined solid geometric shape models (Fig.8). The crown volume gradually decreases while shape numbers run from S1 to S10. The crown shape value is a formula multiplier where a right cylinder is 8/8 or 1.0, and the rest of the shape values are some fraction of a right cylinder. Crown volume formula uses crown diameter and crown thickness to calculate crown volumes. Crown shape name is a symbolic approximation for visualizing shape based upon solid geometric figures By looking at the pictures taken during field work, crown shapes were recorded.

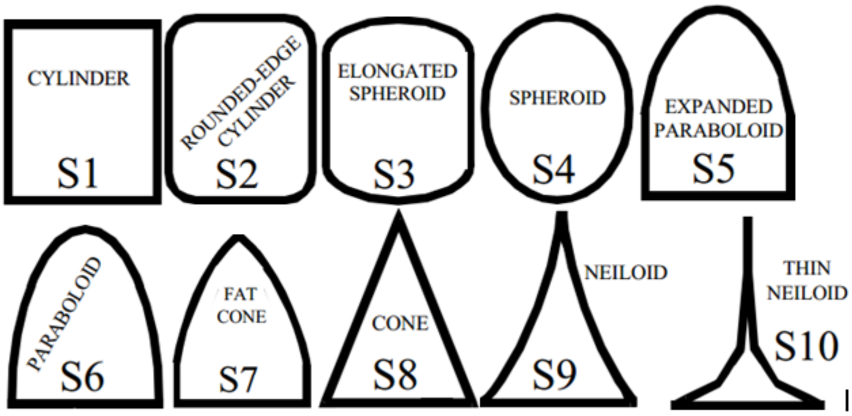


Figure 8: Tree crown volume estimates for different crown shape models (Coder, 2000).

After determining the crown shape, crown volumes were estimated by the following formulas (Table.2). The average crown width (aCW) and crown thickness (CT) were calculated based on previous field measurements results. Crown thickness equals tree height minus crown base height.

Table 2 Crown shape and crown volume formula (Coder, 2000).

Shape Number	Shape Value	Formula	Shape Name
S1	8/8 (1.0)	$(aCW)^2 * (CT) * (0.7854)$	CYLINDER
S2	7/8 (0.875)	$(aCW)^2 * (CT) * (0.6872)$	ROUNDED-EDGE CYLINDER
S3	3/4 (0.75)	$(aCW)^2 * (CT) * (0.5891)$	ELONGATED SPHEROID
S4	2/3 (0.667)	$(aCW)^2 * (CT) * (0.5236)$	SPHEROID
S5	5/8 (0.625)	$(aCW)^2 * (CT) * (0.4909)$	EXPANDED PARABOLOID
S6	1/2 (0.5)	$(aCW)^2 * (CT) * (0.3927)$	PARABOLOID
S7	3/8 (0.375)	$(aCW)^2 * (CT) * (0.2945)$	FAT CONE
S8	1/3 (0.333)	$(aCW)^2 * (CT) * (0.2619)$	CONE
S9	1/4 (0.25)	$(aCW)^2 * (CT) * (0.1964)$	NEILOID
S10	1/8 (0.125)	$(aCW)^2 * (CT) * (0.0982)$	THIN NEILOID

Explanation : aCW: average Crown Width, CD: Crown Thickness
CD = Tree Height – Crown Base Height

2.5 Three-dimensional tree models generation based on LOT

2.5.1 Lidar data classification

The AHN2 airborne lidar data had been pre-processed already, having information of return numbers, return time, coordinates, etc. Since the research targets are trees. So the points describing the trees should be filter out. The classification was done by tools from LAStools suite and modeling in ArcGIS (Fig.9).

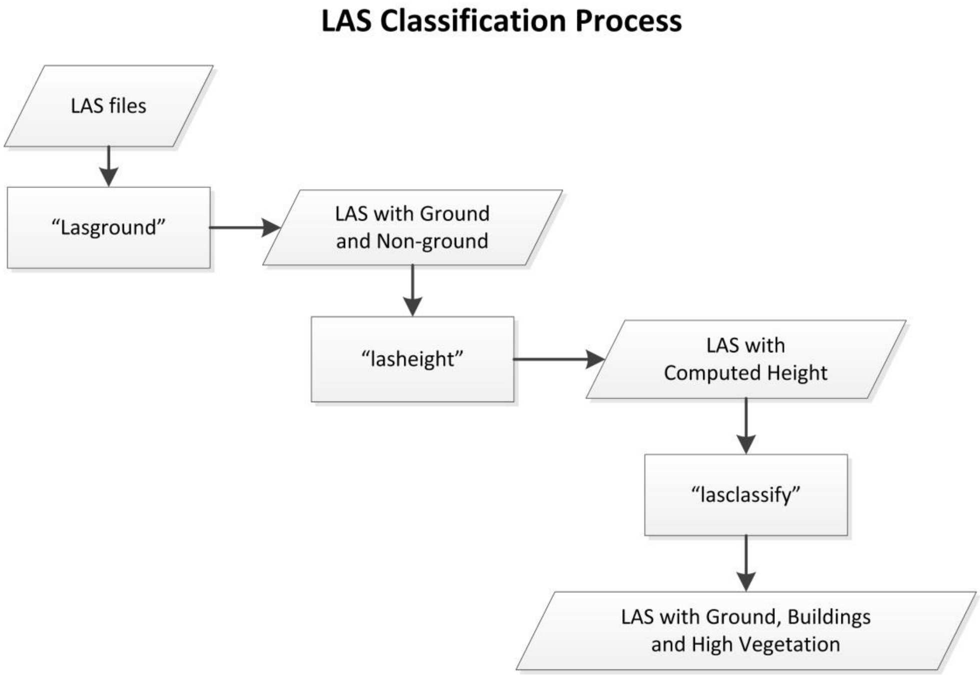


Figure 9: Classification process by using LAStools.

First, one of the LAStools, "lasground" was adapted. By using this tool, the original return points were classified into ground points (class=2) and non-ground points (class=1, also named as unassigned points) (LAStools, 2013).

Second, the height of the return points was derived by tool "lasheight". This tool triangulated the ground points (class=2) which were classified in the previous step into a TIN (Triangulated Irregular Network), and then computed the elevation of each point according to the TIN. Ground points will have an elevation of zero and other points will get their height above the ground TIN through calculation.

Finally, with the ground points and the height of each point above the ground, the tool "lasclassify" classified buildings and high vegetation (trees) by finding neighboring points two meters above the ground and form "planar=0.1" (roofs) and "ragged=0.4" (trees) regions. If the data is too noisy, the planar option can be adjusted to find the roof.

2.5.2 Raster based 3D tree models generation

Raster based 3D tree model is a three dimensional representation of canopy height model (CHM). CHM is calculated by equation 1 below:

$$CHM = DSM - DTM \qquad \text{Equation 1}$$

DSM is digital landscape model, presenting the ground surface, including all the objects like trees and buildings. On the contrast, DTM is digital terrain model, presenting the bare ground without any objects (Fig.10). Thus the result of using DSM minus DTM is the ground objects height model, in this case is canopy height model.

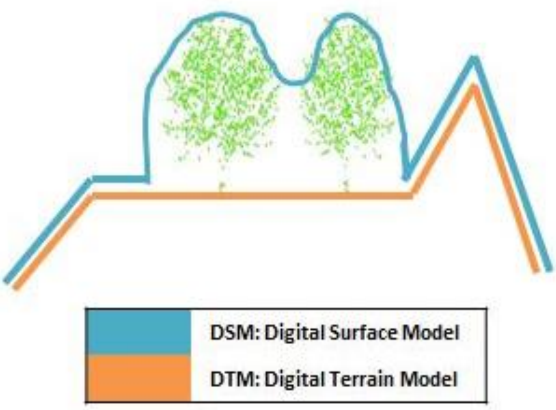


Figure 10: Illustration of DSM and DTM.

In order to get DSM and DTM, the lidar point clouds data need to be transformed to shape file first. ArcGIS 10.1 offers a tool “LAS To Multipoint” to fulfill this demand. The original LAS files have been processed by “lasheight” in the previous step. Before carrying out this step, these LAS files were put into “Point File Information” to get the average point spacing which is required in “LAS To Multipoint”. The average point spacing is an important symbol for checking lidar sampling error which means the point spacing value of each LAS file should be close to each in a same study area. Besides, this value gives an approximation for capturing point when converting LAS file to other formats. After knowing the average point spacing (in this case is 0.3m), the multipoint files were created.

Cell size is essential for the quality of DSM and DTM. It should neither be too big nor too small. If cell size is too small, many cells might only get one or zero return point. It can cause null value or no difference between DSM and DTM. If cell size is too large, it might lead the smoothing effect, losing ground details. In this study, the suitable cell size was four times of point spacing (point spacing: 1m×1m, cell size: 4×0.3m≈1m). So each cell has around four points. Then, DSM was generated by assigning the maximum z value (height value) of these points to each cell. In the contrast to DSM, DTM was calculated by assigning the minimum z value to each cell. Then DTM was easily derived by using minus tool.

Another option to generate CHM is using the classified lidar data. By only transforming points of trees to raster can also get CHM. But the program will automatically interpolate the lowest point with ground (height = 0 meter). Since the CHM would be used for studying crown volume, this approach was not chosen.

2.5.3 Watershed segmentation

For further analysis, the trees have to be extracted individually. Segmenting trees manually can create non-systematical error, especially when the target trees have overlapping canopies. It will further influence the accuracies of extracted tree parameters . Thus a watershed segmentation (Mei and Durrieu, 2004) was conducted. Watershed is generally refers to an area where surface water converge to. And ArcGIS offers a series of tools to locate watersheds. In this case, a reversed canopy area can be regard as a watershed. The produced CHM was used to help with this segmentation.

First, the CHM was reversed so that the raster is turned upside down. The cells used to be the peak of the tree became the depressions. The reversed raster was then used to create watershed. Curtis Edson (2011) named the watershed polygon “canopy basin”. Each canopy basin covers the area of one tree (Edson and Wing, 2011). The model of creating watershed is shown in appendix A2.

2.5.4 Point based 3D tree models generation

The classified LAS files were transformed into multipoint. During this conversion, only class5 was chosen. So the multipoint files were only containing high vegetation (trees). Then, multipoint was convert to single point, because each multipoint contains around 3500 single points. At last, by selecting the canopy basin polygon and clipping the multipoint, the single points of each study tree was derived. All the process above was done in ArcGIS by building models. The models are given in appendix A2.

2.6 Parameter extraction from point cloud based tree models

After generating the point based 3D tree models, the attributes table of each tree was exported into text file. Each file contains four columns: objectID, X-coordinate, Y-coordinate and height. All the generated text files are shown in appendix A3. The tree parameters were done by programming in Python. Therefore, the deliveries of this part were python scripts and excel files with extracted tree parameters. Python scripts are given in appendix A4.

2.6.1 Tree height

The attributes were firstly read into Python. The height of each tree is the maximum height within all the points. The build-in function in Python can directly derive the maximum value in height:

$$H_{Tree} = \mathrm{MAX}[H_i] \qquad (i=0,1\ldots n) \qquad \text{Equation 2}$$

Where H is the height and n is the total amount of points.

2.6.2 Crown base height

The crown base height is the height where the trunks start to grow (Fig.11). The point density above the crown base height is much higher than the density of below. One reason is the crown is much broader than stem. Another reason is that the airborne lidar couldn’t detect stem quite well because of the crown which is an obstacle for lidar beams. Thus, tree stem got few return points.

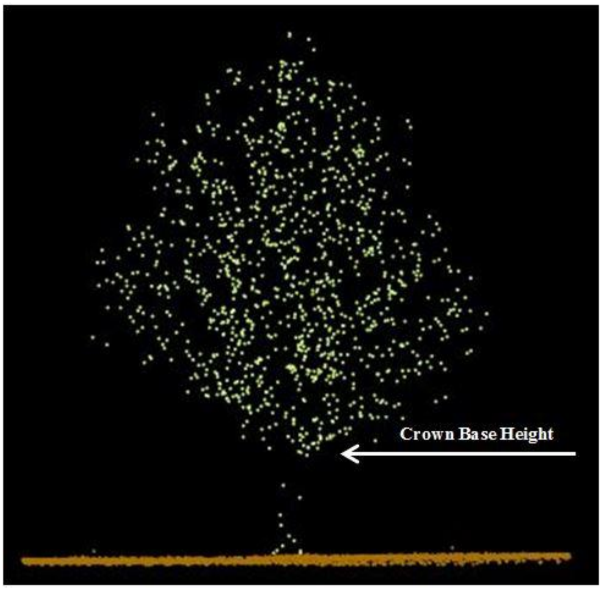


Figure 11: Illustration of crown base height.

Morsdorf(2004) assumed that 95% percentage of the height values belong to tree crown and the rest points are points on the stem (Morsdorf et al., 2004). This method is rather suitable for studying tree stands with large tree samples. In this case, a direct measuring approach was developed.

First, the amount of points in different height levels above ground needs to be calculated. However, the height values in lidar dataset have 15 decimal places. It is too detailed that they would hardly have two points with same height. So the decimal place was decreased to one so that there can be more than one points be counted in the height level above crown base height (Fig.12).

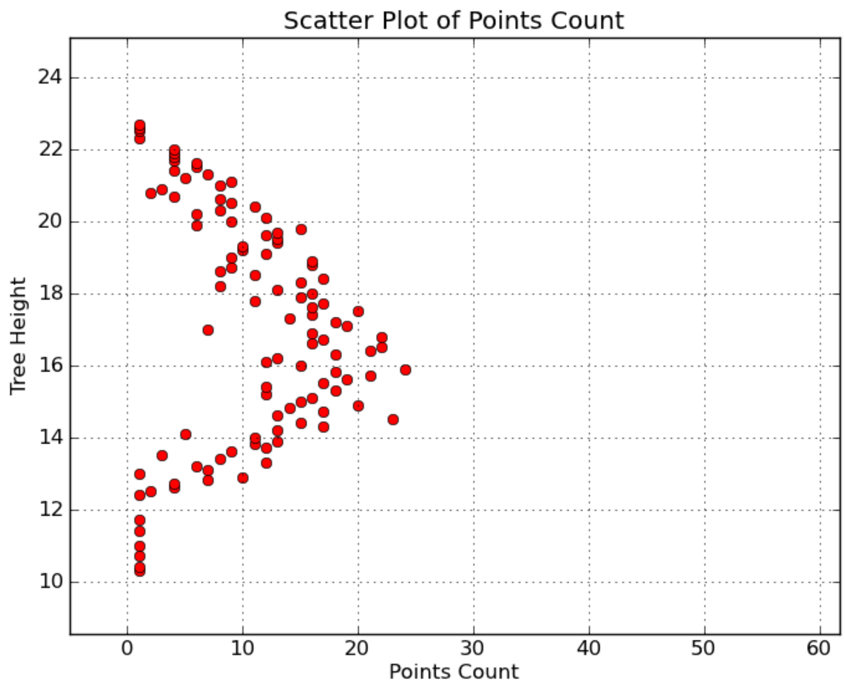


Figure 12: Example of scatter plot of amount of points been counted in each height.

Then, the vectors between each height were calculated:

$$V_i = (C_{i+1} - C_i, H_{i+1} - H_i) \qquad (i=1,2,3...n) \qquad \text{Equation 3}$$

Where V is the vector between each height level, C is points count value, H is tree height, and i is the number of height levels.

If the direction of the vector is negative, it means the amount of the points is decreasing. If it is zero, it means the amount doesn't change. Only when the vector is positive the amount of points is increasing and that is the height where trunks start to grow. Still, there could be a case that the amount of points increases within the stem. Although the chance is very low and even haven't been found in any study tree in this research, this situation should still be considered. Based on this consideration, the vector which is presenting the crown base height has to meet two criteria. The direction of the vector has to be positive and the following vector's direction has to be positive as well which ensure it is a gradually increasing other than an abnormal increasing:

$$\begin{cases} V_i > 0 \\ V_{i+1} > 0 \end{cases} \qquad \text{Equation 4}$$

Which equals to:

$$\begin{cases} (C_{i+1} - C_i) * (H_{i+1} - H_i) > 0 \\ (C_{i+2} - C_{i+1}) * (H_{i+2} - H_{i+1}) > 0 \end{cases} \qquad \text{Equation 5}$$

$$(i=1,2,3...n)$$

Where C is points count, H is tree height and i is the number of height levels.

2.6.3 Tree location

The center of the tree crown is not always the location of the tree, especially for deciduous trees (Fig.13). Instead, tree location is normally determined by tree stem position except some extreme declining stems. Since the crown base height has been found, the points belong to stem can be extracted. The center coordinates of these points is the tree location:

$$\begin{cases} X_{TreeLocation} = (\sum_{i=1}^{n} X_i)/n \\ Y_{TreeLocation} = (\sum_{i=1}^{n} Y_i)/n \end{cases} \qquad \text{Equation 6}$$

Where X is X-coordinate, Y is Y-coordinate and n is the amount of points found within stem.

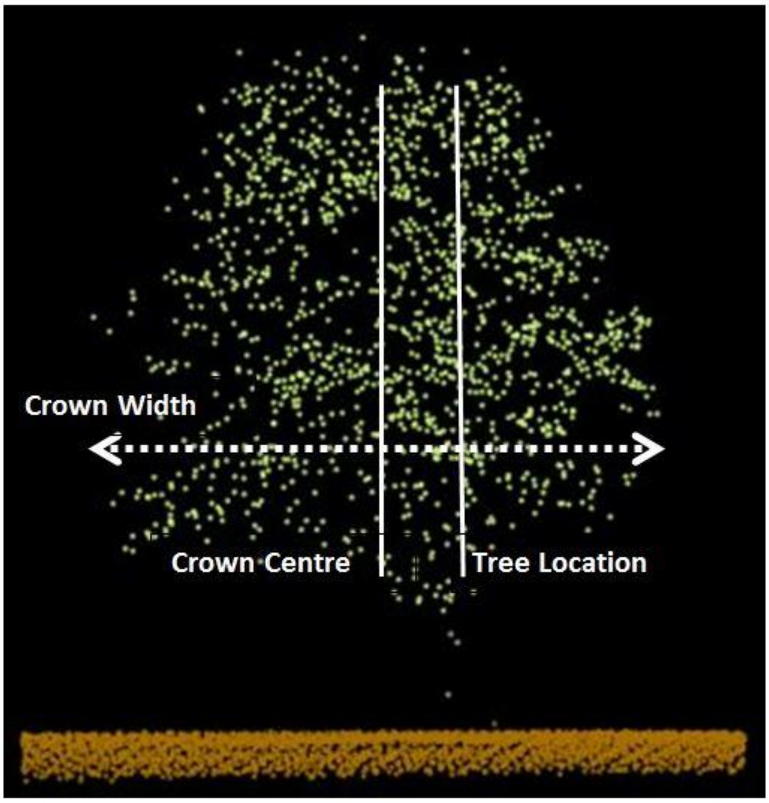


Figure 13: The location of the tree is not always the center of the crown.

2.6.4 Crown width

Crown widths have been measured during the field work in two directions which is north to south and east to west. Therefore, the crown widths in the same direction should be extracted. The most northern, most southern, most eastern and most western points of each tree were found (Fig.14).

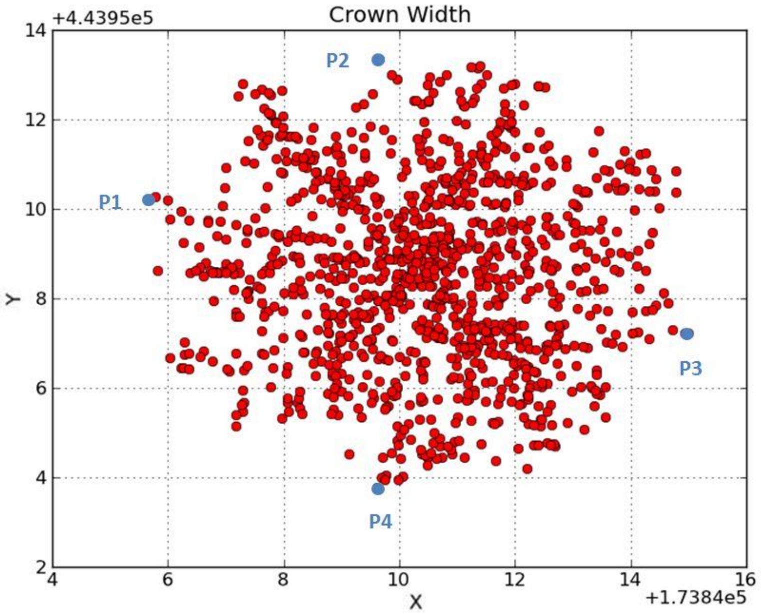


Figure 14: Example of point cloud tree crown (top view). P1, P2, P3, P4 are the most western, most northern, most eastern, most southern points, separately.

Then, the crown widths were calculated:

$$\begin{cases} CW_{N-S} = Y_{p2} - Y_{p4} \\ CW_{E-W} = X_{p3} - X_{p1} \end{cases}$$

&

Equation 7

$$\begin{cases} Y_{p2} = MAX[Y_i] \\ Y_{p4} = MIN[Y_i] \\ X_{p3} = MAX[X_i] \\ X_{p1} = MIN[X_i] \end{cases} \quad (i=1,2,3...n)$$

Where the CW is the crown width, X is X-coordinate, Y is Y-coordinate and n is the total amount of points.

2.6.5 Diameter at breast height

Diameter at breast height is the stem diameter been measured at the height of 1.3 meters above the ground. Three situations were considered.

Firstly, if there are no point or only one was measured on stem, the DBH cannot be generated.

Secondly, if there are only two points been measured or there are more than two points but they are on the same line(Fig.15), the DBH can be calculated as below:

$$DBH = MAX\left[\sqrt{\left(X_i - X_j\right)^2 + \left(Y_i - Y_j\right)^2}\right] \quad (i, j=1,2,3...n) \qquad \text{Equation 8}$$

where X is X-coordinate, Y is Y-coordinate and n is the amount of points which can be found at 1.3 meters.

Finally, if there more than three points been found and they are not on a same line, least square fitting method was adapted (Fig.16). The mechanism of least square fitting are presented by python scripts in appendix A4.

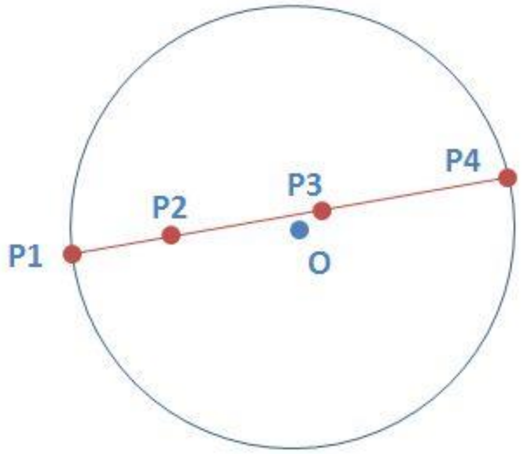


Figure 15: An example of points been found at 1.3 meters and all on a same line.

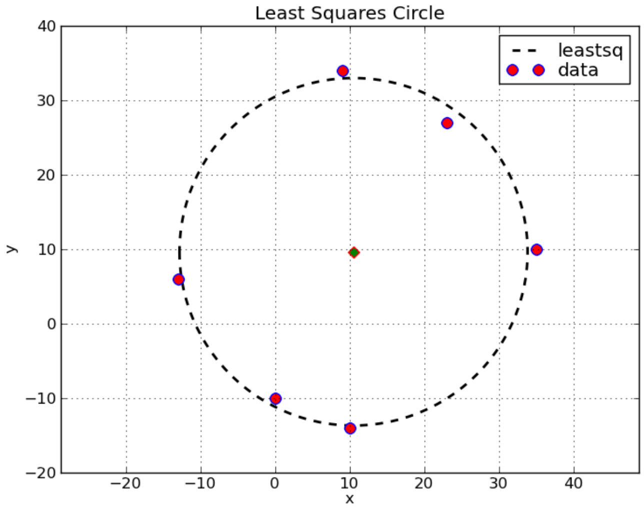


Figure 16: An example of point been found at 1.3 meters and not a same line.

2.6.6 Crown density and crown volume

Crown density in point cloud based tree model is determined by the amount of points and crown volume. The crown is the part of the tree above the crown base height and this height has been measured in the previous step. Thus, the amount of points in the crown can be calculated.

Three crown shape can be very irregular. It can't simply be regarded as a ball or a ellipsoid. There are a lot of studies have been done to calculate crown volume. For example, use "wrapping surface" to fit the crown surface and then the volume can be calculated by using calculus divergence theorem (Kato et al., 2009).

In this research, the shape of the tree was considered as a combination of several frustums and a cone on the top(Xiong et al., 2007). All the frustums have same height (Fig.17).

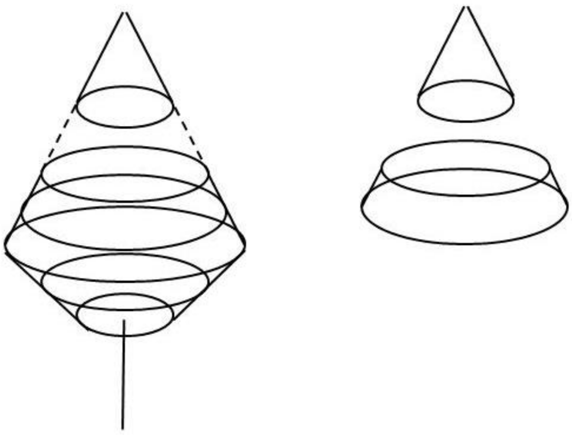


Figure 17: Combination of frustums and a cone.

The height of frustums affects the accuracy of the total volume. Normally, the smaller the height is defined, the higher accuracy of the volume will be. This is the same with the definition of the multiple integral. However, there are limited return points in the tree crown. If the height was set to too small, there might not be enough points to present each face of one frustum. The height should be neither too big nor too small. The original tree height has 15 decimal places (Fig.18). Base on the consideration above, the height decimal was set to one meter (Fig.19).

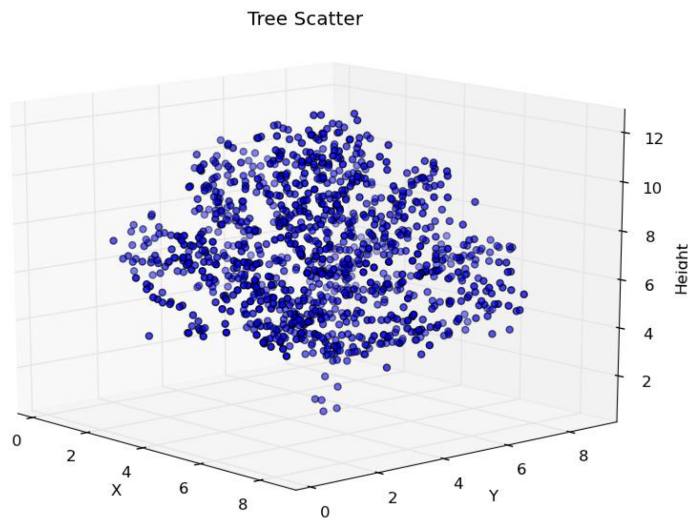


Figure 18: Original points 3D scatter plot.

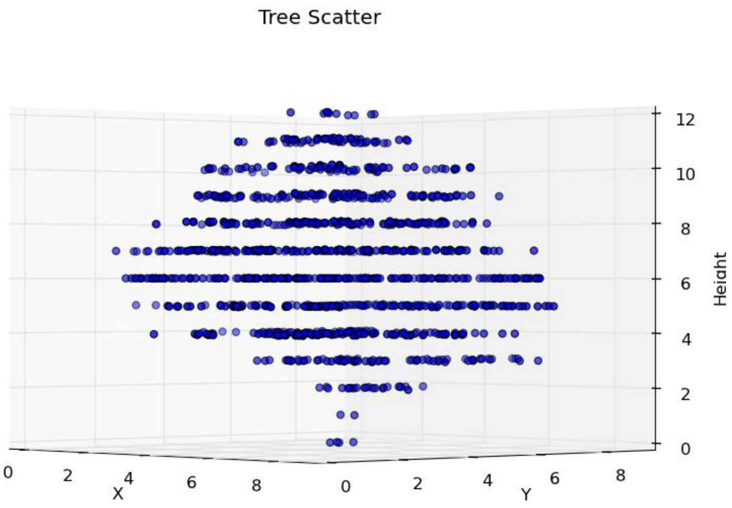


Figure 19: 3D points scatter plot after change decimal place of one meter.

The area of each face of a frustum should be calculated. Similar with calculating tree location, the center coordinate of each face was first extracted:

$$\begin{cases} X_{Center} = (\sum_{i=1}^{n} X_i)/n \\ Y_{Center} = (\sum_{i=1}^{n} Y_i)/n \end{cases} \quad \text{Equation 9}$$

Where X is X-coordinate and Y is Y-coordinate.

Then, the distances from the center location to each point in this face were calculated:

$$D_i = \sqrt{(X_i - X_{center})^2 + (Y_i - Y_{center})^2} \quad \text{Equation 10}$$

Where D is the distance, X is X-coordinate and Y is Y-coordinate.

In order to fit the outside circle of a face, the top five longest distances were taken to get an average value which will be used as radius. In another word, these five points were considered as the return points which are located on the outside circle. If there were less than five points in the face, the average distance was taken as the radius:

$$R = \sum D_{Top5} \quad \text{Equation 11}$$

Where R is the radius and D is the distance from point to center.

With all the radiuses, the volume of the tree except the cone on the top can be derived:

$$V = \sum_{i=1}^{n-1} [\pi * H * (R_i^2 + R_i * R_{i+1} + R_{i+1}^2)/3] \quad \text{Equation 12}$$

Where V is the crown volume, H is 1 meter, R is radius and n is the number of faces.

Since the assumption is that every tree has a cone as top. Therefore, the equation can be adapted as:

$$V = \sum_{i=1}^{n} [\pi * H * (R_i^2 + R_i * R_{i+1} + R_{i+1}^2)/3] \qquad \text{Equation 13}$$

2.7 Parameter extraction from raster based tree models

Tree parameters of the raster based model were generated from CHM in ArcGIS by constructing models. The models can be adapted to other data without changing any setting and the results will be automatically recorded into an excel file. Thus, the deliveries were an ArcGIS tool box and a excel file with extracted tree parameters. The models are given in appendix A2.

2.7.1 Tree height

Zonal statistics tool was implemented to get the maximum height which is also the tree height. The watershed segmentation results were used again here to indicate the zonal fields. This tool can then extract the maximum value in each canopy basin to a new raster dataset. After this, the maximum height values were extracted from raster to excel file.

2.7.2 Crown base height

Maltamo et(2006) and Popescu (2008) used regression methods to predict CBH(Maltamo et al., 2004, Popescu, 2007). However, the regression cannot be implemented to this case since the study area and study trees are all different. Therefore, a direct measuring method was tried out. Similar with extracting tree height, zonal statistics tool was used but to get the minimum height instead of the maximum value. The results were recorded for further comparison.

2.7.3 Crown width

There is no existing tool in ArcGIS to fulfill this measuring purpose. Python scripts were implemented into the ArcGIS models with build-in functions. This step is theoretically the same with extracting crown width from point based model. The four extreme points (the most north, south, east and west) were firstly located. Then, the differences were calculated by their coordinates.

2.7.4 Diameter at breast height

Raster tree model is also known as canopy model. It means the stem which is covered by tree crown is invisible. Thus it is impossible to extract this tree parameter directly.

Regression predicting models were widely applied in many researches (Kalliovirta and Tokola, 2005, Popescu et al., 2004, Popescu, 2007, Hyde et al., 2007). In those models, tree height and crown width were measured from lidar data and used as independent variables. And each model is suitable for a specific area with a specific species.

Although tree height and crown width can be extracted from raster based models, there are limit amount of study trees and variety of species. So, the regression methods cannot be implemented in this study. In summary, DBH could not be extracted from raster based tree models.

2.7.5 Tree location

Since tree stem is invisible in raster based tree models, the location of the tree cannot be determined by it. Kukko(2009) selected the highest points as tree stem location with an accuracy of 0.15m (Kukko and Hyyppa, 2009). But as what he mentioned in the article, tree stems are not always vertical which means the top of the tree might have displacement from the stem location. In this study, the geometric centers of trees crown were considered as stem location. Python scripts were implemented and the locations got recorded.

2.7.6 Crown density and crown volume

In order to get crown density, the amount of return points and crown volume are required.

To get the amount of return points of each tree, the point data set was split by each tree outline shape file. By using summary statistics tool, the total number of points gets counted.

There are several choices for calculating raster volume. First one is calculating it simply by using crown area times crown height (Riaño et al., 2003, Riaño et al., 2004, Goodwin et al., 2006). More precisely, a wrapped surface technique was developed. But is it actually a different raster based model which is different from this study. The surface return points was selected by convex hull and then wrapped by Radial Basis functions and an Iso-surface function(Kato et al., 2009). This is a method can be considered as a combination using of point based model and raster based model.

In this case, tree volume supposed to be generated directly from raster based model. The CHM can be considered as DEM of tiny hills. Then it became a problem to calculate the volume when the hills need to be removed. There are several tools exist in ArcGIS to accomplish this target. When carrying out these tools the base height where start to cut the "hills" should be specified. Therefore, the downsides of the crowns were treated as flat plains. Tools such as "surface volume" and "cut and fill" can only process them one by one because it require user to give the plain height manually which is not convenience. Alternatively, the CBH values were used to create these plain raster. By subtracting CHM raster and CBH raster, the difference of each cell was calculated. Then, the difference values were added up to get the total height difference of each tree. At last, by times the cell size, the volume of each tree crown was acquired.

Having the amount of the return points and the crown volume, crown density can be derived by dividing them.

2.8 Comparison of 3D tree parameters

2.8.1 Parameters comparisons

To evaluate the modeling accuracy, field measurements results were compared with raster based models and point cloud based models separately. All results, except tree location, were plotted by scatter-plot and box-plot.

In the scatter-plot, each tree parameter was plotted between field measurements results and model predicts results to fit a linear model. R2 and RMSE were conducted to assess prediction accuracy (Equation 14). R2 is referring to coefficient of determination, determining the degree of association between variables. RMSE is short of root mean square error, a frequent used estimator to indicate the error of prediction results, the residuals performed over the samples.

$$R^2 = 1 - \sum_{i=1}^{n}(y_i - f_i)^2 \,/\, \sum_{i=1}^{n}(y_i - \bar{y})^2$$

Equation 14

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - f_i)^2}$$

Where y_i is observed tree parameter, f_i is predicting parameter and $\bar{y}$ is mean value.

In order to check the statistical significance, P-value was calculated through T-test. The hypothesis of T-test is a null hypothesis which assumes that there is no difference between model prediction results and field measurements results and those differences are only caused by sampling error. P-value is the risk of rejecting this null hypothesis. Consequently, it indicates the statistical significance (Moore and McCabe, 2008). For example, if P-value is larger than 0.05, it means the null hypothesis could not be rejected (or the risk of rejecting this null hypothesis is too high). On the contrast, if P-value is smaller than 0.05, it proves that there is significant differences exists.

In addition, the differences between field measurement results and extracted parameters were calculated and standard deviation of the differences and average values of the differences were calculated as well. These statistical results of the differences will give indications of the models usability.

Box-plot gives five number-summaries: the sample minimum, lower quartile, median, upper quartile and sample maximum (Baayen, 2008) (Fig.20). It shows of the data variance and outliers. Moreover in this study boxplot might give an indication of the possibility to distinguish between difference species. All the plotting processes and statistical analysis were conducted by programming in Python (Appendix A5).

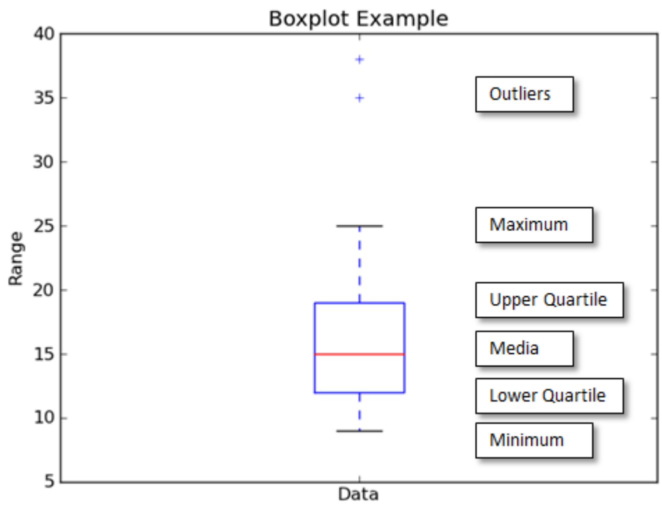


Figure 20: Illustration of boxplot.

Tree location results were first inputted into excel and then displayed as points in ArcGIS. They were overlaid with segmentation results and aerial imagery. If the points were overlapping with the trees in the imagery and inside the "Canopy Basin", they can describe the real tree location accurately.

2.8.2 Species comparisons

There were eight different species in the samples. *Quercus Robur* (Oak), Fraxinus Excelsior (Ash) and *Acer Pseudoplatanus* (Maple) were taking the majority numbers. Thus, the possibility of determination of these three tree species was discussed. Four parameters extracted form point cloud based models were used in this case. These parameters were number of points found on the stem, number of points found from 1 to 2.5 meters (close to DBH height), Crown Volume and Crown Density. Box-plot and scatter-plot were implemented again. If there were clear boundaries between each species in one or one combination of those parameters, we can assume that the species can be determined. The comparison python scripts and corresponding files are shown in appendix A6.

3 Parameter extraction results with update methods

Pre-processing and initial parameter extraction had been carried out and the results will be illustrated. By checking the initial results, CBH and DBH extracted from point cloud based model showed low accuracy. Therefore, some update methods were developed.

3.1 Results of generated 3D tree models

3.1.1 Lidar classification results

Lidar data was classified by “LAStools”. The “lasground” is the second conducted tool, resulted in the classification of ground and non-ground. The parameters of this tool can specify different terrain types and different above ground complexity. By default, this tool takes the last return points as ground points and earlier return points as non-ground points. By specifying terrain type and other options, it can also add classification criteria such as standard deviation and search radius.

The dataset locate to the north of the campus has a flat terrain with only cultivated land and tree lines. So the terrain type option was set to “forest and hills”. The other datasets are locating in the campus, having a lot of buildings. Thus the option was set to “towns and flats”.

In order to see the difference between those options, the field in North was changed to “towns and flats”. Then, lots of points on the ground were miss-classified into non-ground (Fig.21). Similarity for the dataset in the campus, terrain option was switched to “forest and hills”. It resulted in non-ground points being miss-classified into ground. In fig.22, the roof of the building has partly been classified into ground.

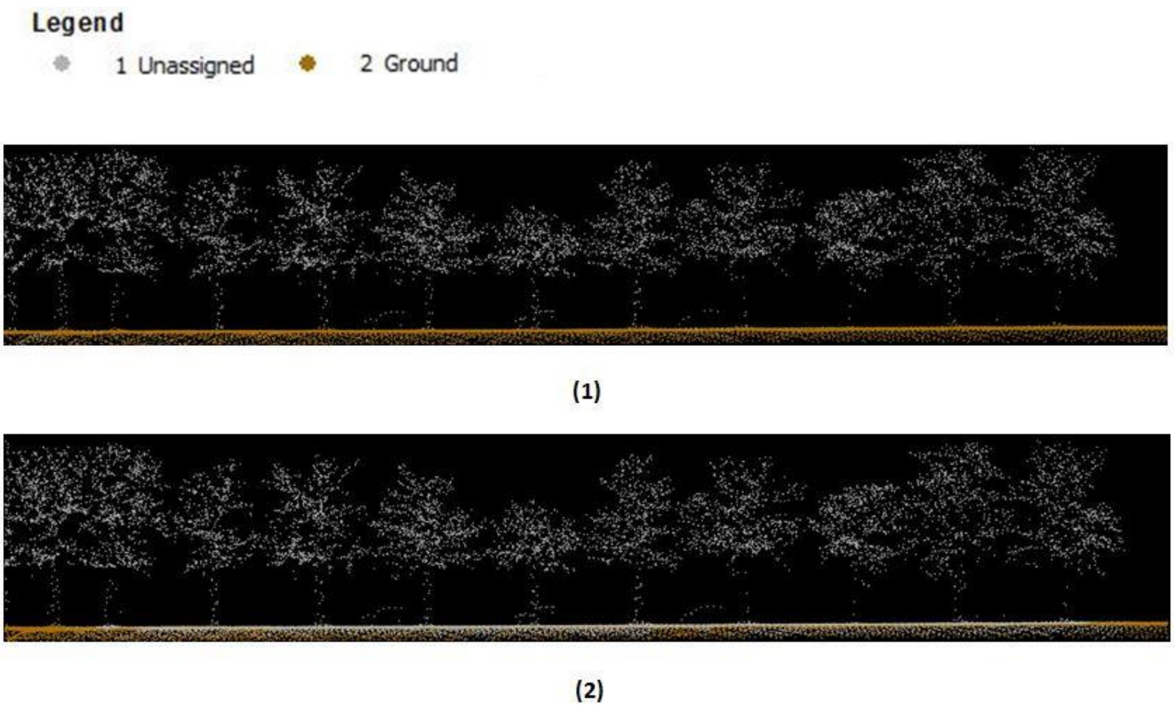


Figure 21: Results of different terrain type setting while using “lasground” classification. (1) terrain type = “forest and hills”, ground and non-ground was clearly distinguished. (2) terrain type = “town and flats”, part of the ground was classified into “non-ground”.

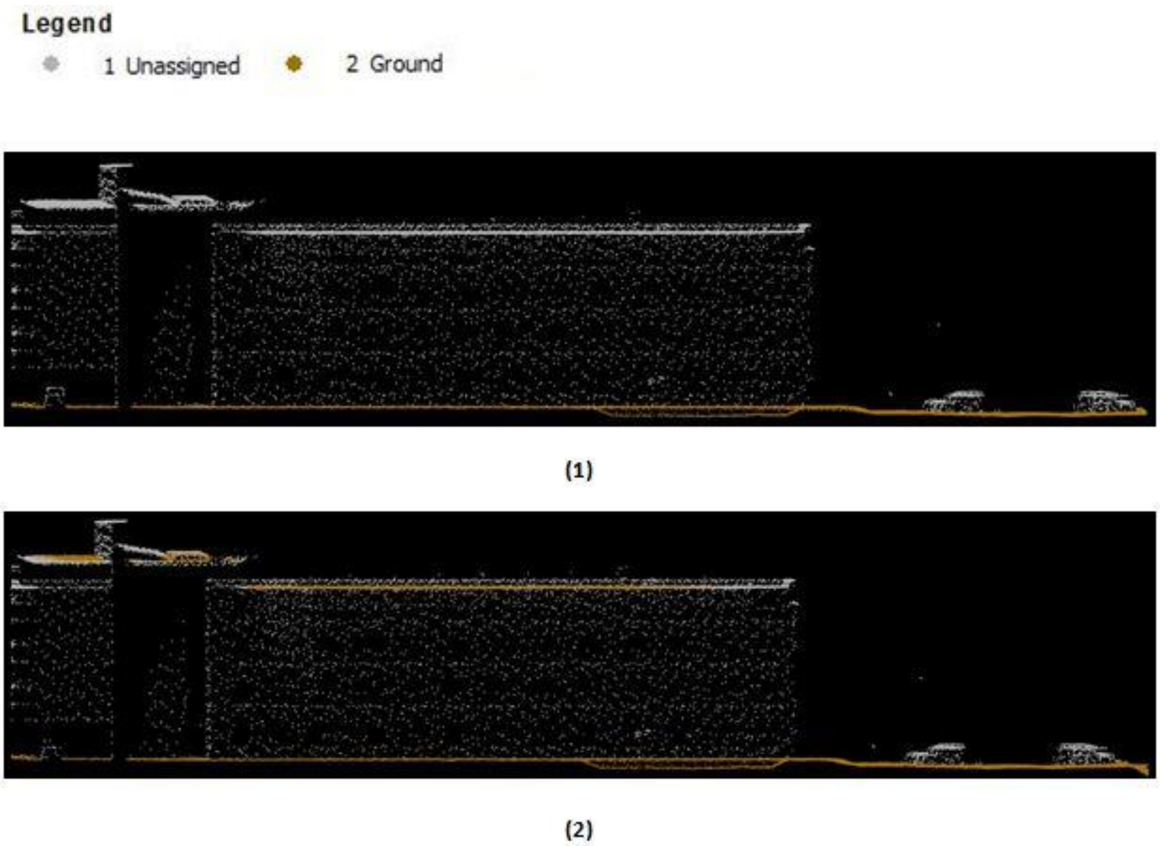


Figure 22: Results of different terrain type setting while using “lasground” classification. (1) terrain type = “town and flats”, ground and non-ground was clearly distinguished. (2) terrain type = “forest and hills”, part of the roof was classified into “ground”.

After using "lasclassify", the non-ground points (unassigned points) were assigned into "High Vegetation", "Buildings" and "Unassigned". The results are showing in Fig.23.

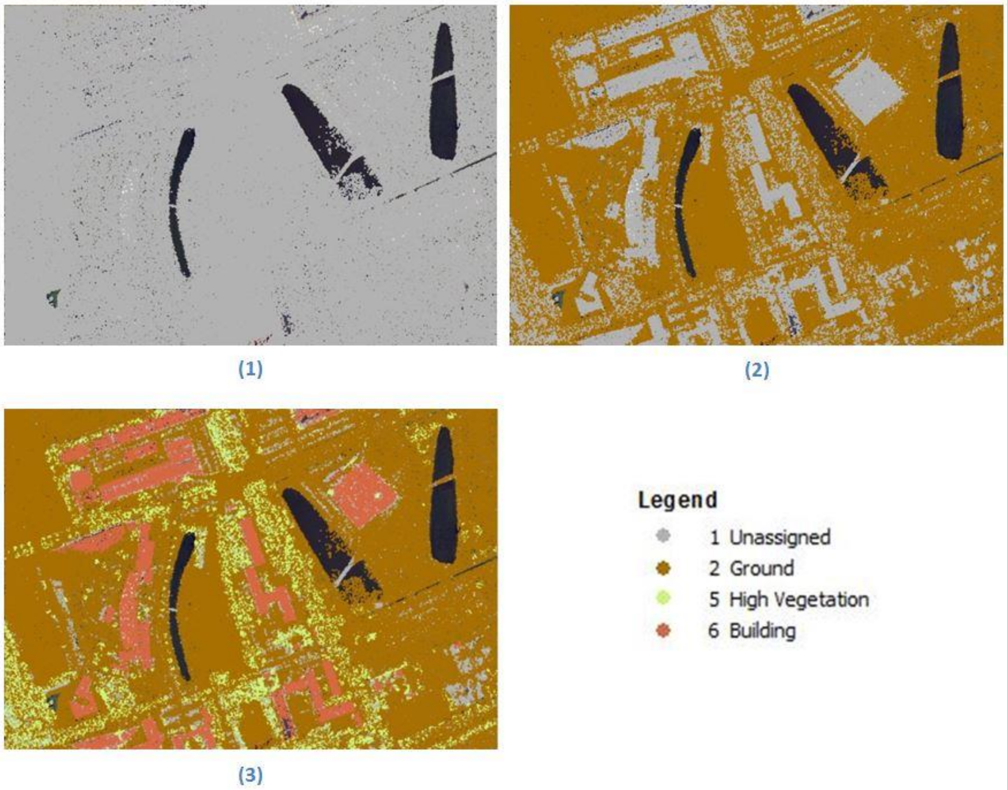


Figure 23: "LAStools" generated results, (1) Original class, (2) "lasground" result, (3) "lasclassify" result.

The classification result after using LAStools is not one hundred percent accurate. In fig.24, the stem of the tree has been partly miss-classified to class1 (unassigned) and class2 (ground). It is because the default setting has assigned the points higher than two meter to class5 (high vegetation). Apart from this reason, the tool was clustering points into different regions, so the points presenting the stem, closing to ground were classified to class2. The rest of points below two meters were assigned to class1. Those miss-classified points contain important information of tree stem. They can offer the values to extract crown base height (where the trunk starts to grow), DBH (Diameter at Breast Height) and tree location. To deal with this problem, changing the parameters in LAStools can bring more difficulties because of the complexity of different trees and ground truth. Since the segmentation has been done, each study tree was viewed by LAS profile tool in ArcGIS. And those miss-classified points were manually been selected and reclassified to high vegetation.

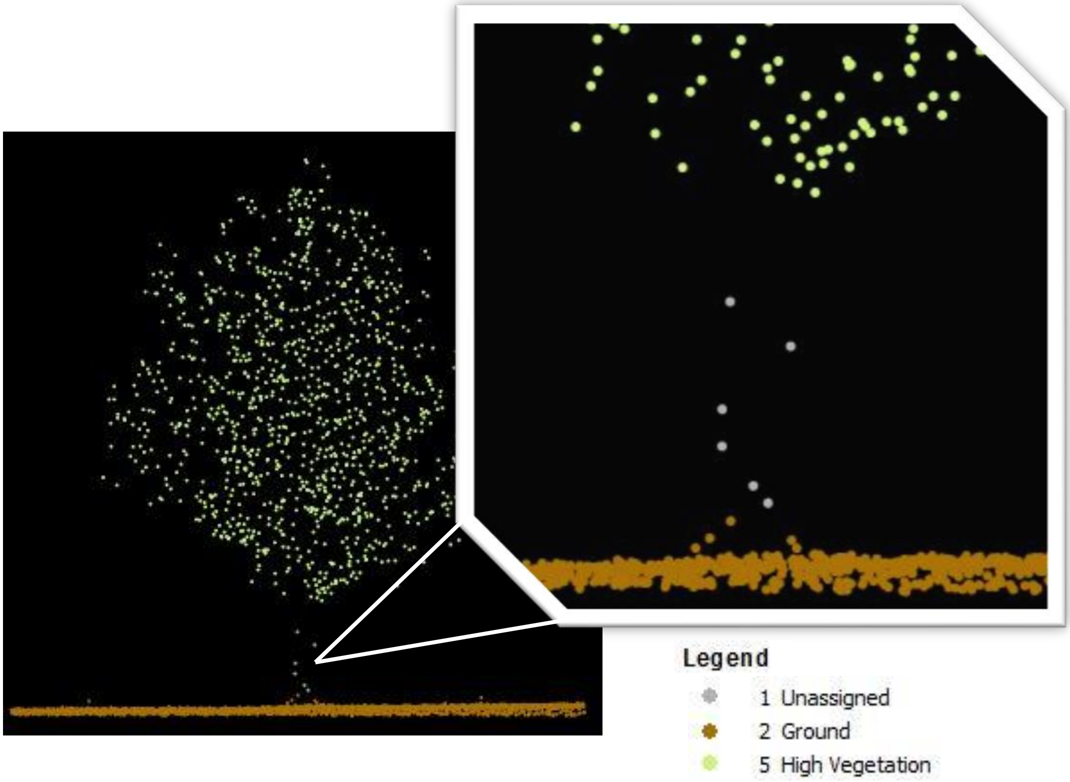


Figure 24: Miss-classification points after using LAStools.

However, when there are shrubs or climbing plants around the stem, it was hard to pick out the stem points (Fig.25). If this case was happen, no manual operation was conducted in order to avoid non-systematic errors.

Figure 25: Tree with shrubs around its stem.

Wrong classification results far away from the target trees were ignored. For example, the bridges which were classified into "unassigned" are ignored. However, some miss-classification results were found close to study trees. In Fig.26, the roof of a bike parking shelter was classified into vegetation. The reason is this roof has gradually height changes unlike the roofs which are flat. It will influence on the parameter extraction, because the segmentation polygon will extract part of the roofs as well. Thus, the roofs have to be taken out by manually reclassification.

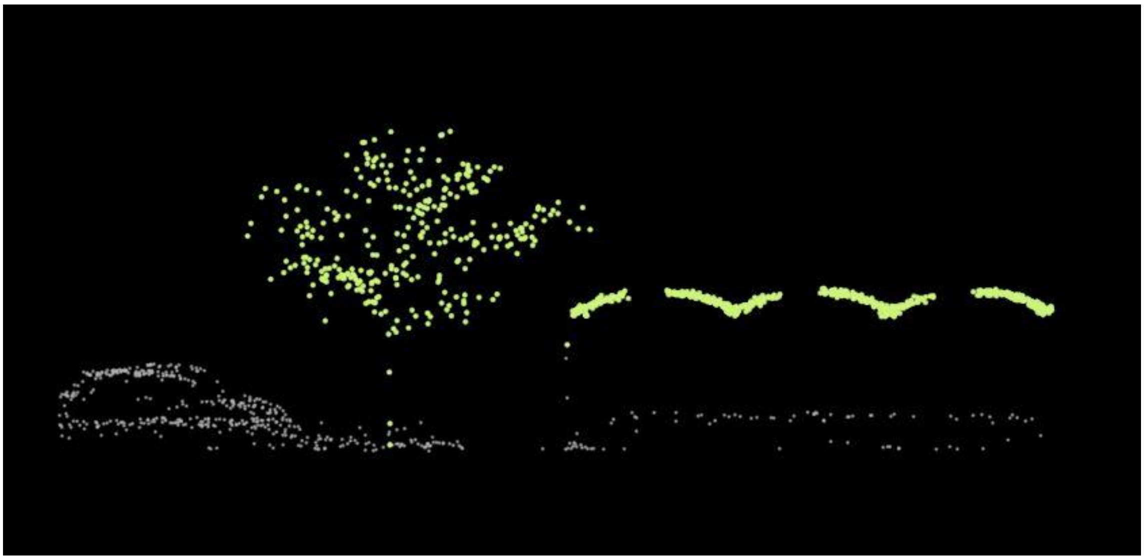


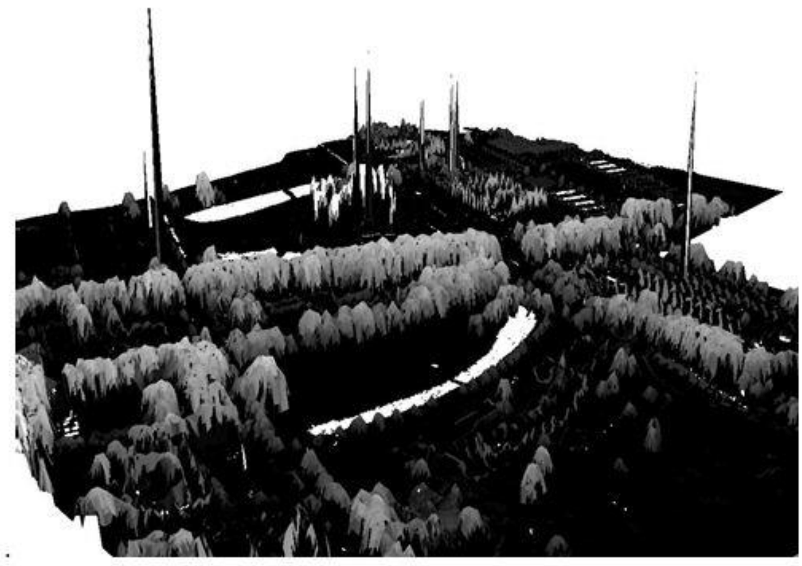
Figure 26: Roof been classified into vegetation.

3.1.2 Raster based 3D tree generation results

By viewing the results of CHM, some extreme high values were found (Table 3). A pre-processing of removing noise in the point cloud before starting the raster process is necessary. These noises can be caused by clouds, smoke, birds, etc. In the next step segmentation will be taken based on CHM, so a correction was necessary. Therefore, the points which are larger than 40 meters were simply deleted, since in this area there is no object is higher than 40 meters. The results are shown below in fig.27.

Table 3: Height level statistics based on CHM.

Height Level	0 – 19m	20 - 39m	40 - 400m
Cells Count	1061540	11401	147



(1)

(2)

Figure 27: (1) CHM with noise, (2) CHM after correction.

The generated CHM data was covering the whole study area, including both canopy and non-canopy area. Since the crown width will be measured, the data should only contain canopy area. CHM values for points classified as ground are ranging from 0 to 1which is much lower than canopy area (pixels values can reach 2 meters when they are on the edges of ditches). Therefore, non-canopy data was erased by setting a threshold of 2 meter. It is also possible to generate DTM and DSM without using ground points. However, the starting point of the generated CHM will be on the ground which cannot determine the crown base height.

After removing the non-canopy from raster tree models, outlines of buildings can be observed (Fig.28). They have been extracted into CHM. The reason to do so are the many return points on the vertical wall (Eysn et al., 2012). The lowest points on walls were assigned into DTM while the top points were assigned into DSM. Therefore, the differences of wall were reflected in CHM. On the contrast, roofs having little elevation difference were treated as normal ground. However, these building edges had no impact on the parameters extraction since the watershed segmentation had excluded them already.

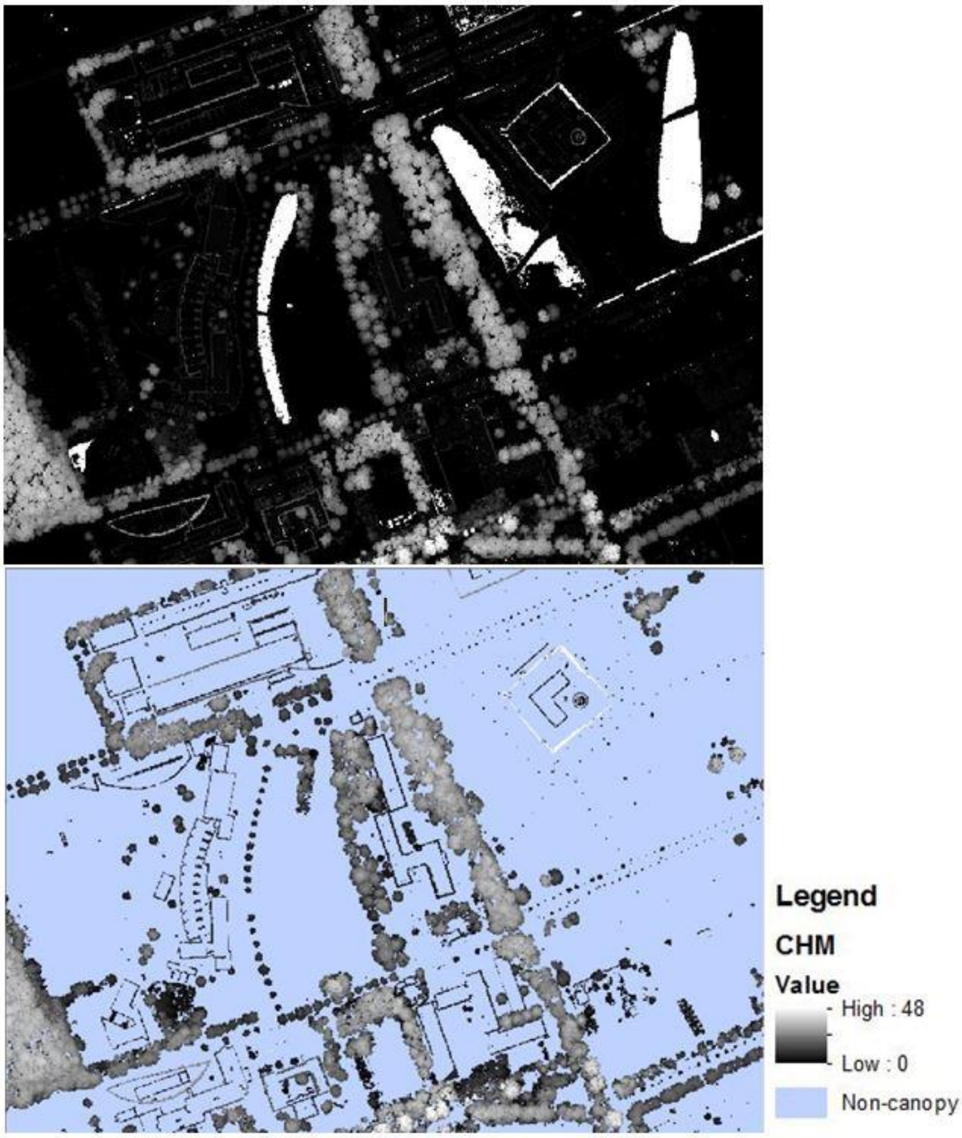


Figure 28: CHM before and after erase the non-canopy data.

3.1.3 Watershed segmentation results

Watershed segmentation was carried out and an example result is shown in fig.29. In the zoomed image in fig.29, an example tree was well segmented and located in a “canopy basin”. Several wrongly segmentation results are shown in fig.30. The picture on the left are two interacting trees where part of the left tree was segmented into the tree on the left. The picture one the right is showing one single solitary tree and the tree was divided into two by the canopy basins.

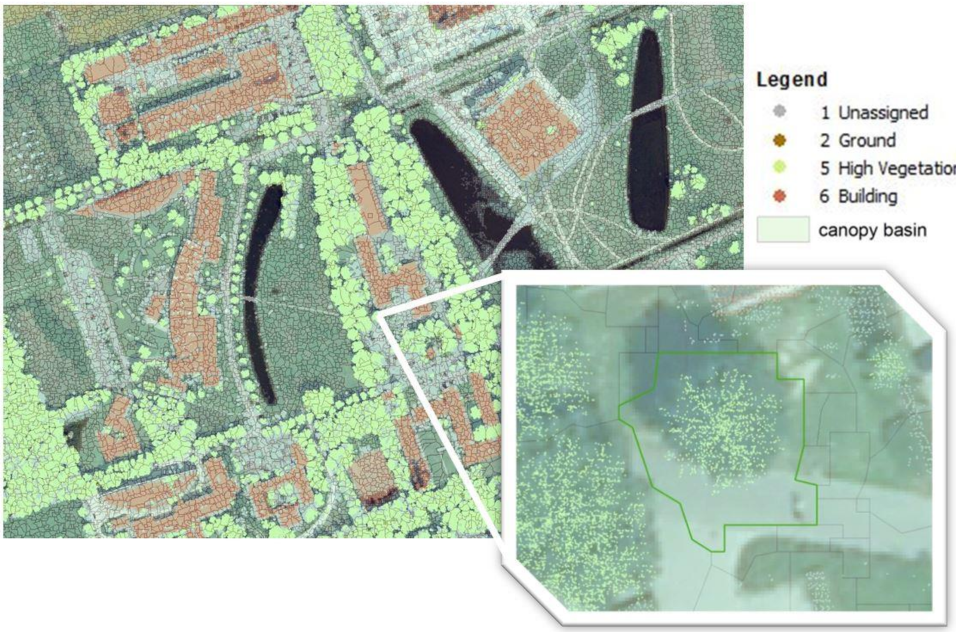


Figure 29: Watershed segmentation result (“canopy basin”).

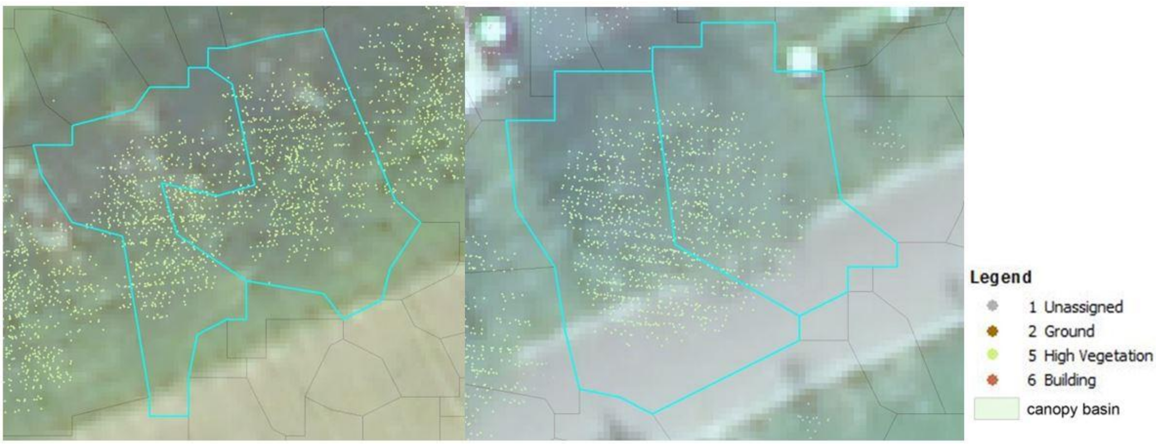


Figure 30: Segmentation errors.

3.1.4 Point based 3D tree generation results

The point based tree models after watershed segmentation are shown in fig.31. Segmentation quality were significantly influencing on the generated models. Solitary trees were easily and well segmented. However, some types of segmentation errors were found in interacting trees which will be showed and discussed later. In total, there are 18 interacting trees in the study area and 12 of them were found with segmentation errors.

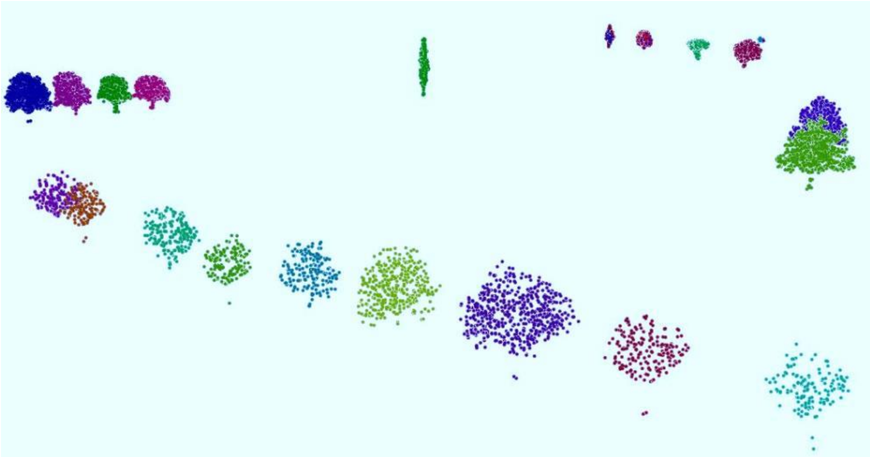


Figure 31: Point cloud tree models (each color represents one single tree).

3.2 Parameters extracted from point cloud based models

Parameters were first extracted from point cloud based tree models. After comparing with field measurements results, CBH and DBH had large differences (Table 4). Therefore, update methods were developed for them. Since tree location and crown density (crown volume) were calculated based on CBH, they were extracted again. Both first extracted results and update results are shown in Appendix B. Two study trees got two results since they are locating on the overlapping region of two lidar dataset, having different return points. Tree height, crown width and locations of all the study trees were successfully extracted. CBH of 2 trees and DBH of 9 trees were not found.

Table 4: Parameters (CBH and DBH) extracted from point cloud based models comparing with field measurements results.

Field Measurements	Average differences	
	CBH	DBH
Field Measurement 1	10.8 m	65.79 cm
Field Measurement 2	10.7 m	65.21 cm

3.2.1 Update CBH parameters extraction method

Many CBH values were found higher than field measurements results. It means lidar points from crown were miss-classified into stem. Based on the original method, crown base height was 3.2 meters where the points count start to increase continuously (Fig.32), but actually, at 3 meters, there are points from crown already (red points in Fig.33).

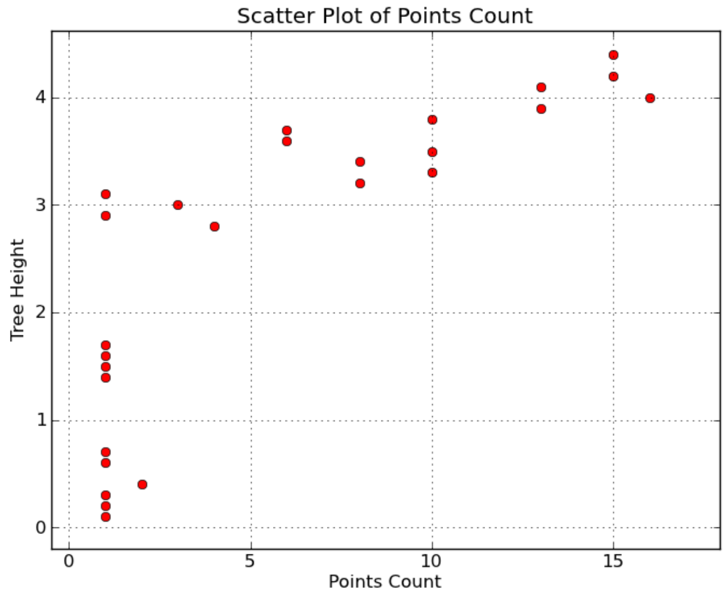


Figure 32: Points count on different height levels.

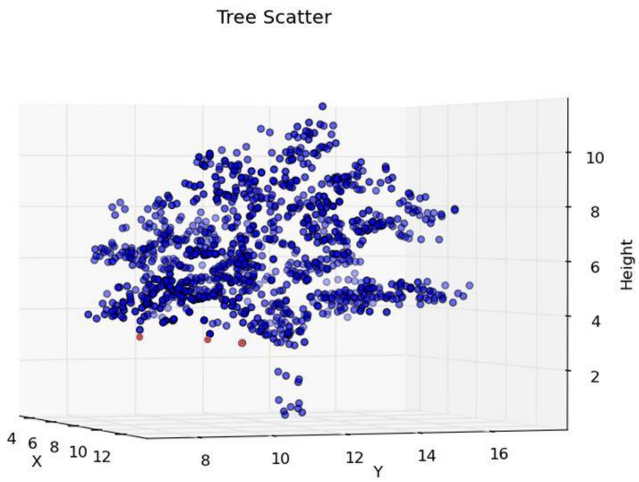


Figure 33: Tree in 3D with miss-classified points (in red).

These wrongly classified points were far from the stem but also met the initial criteria (see chapter 2.7.2). Therefore, a threshold of distance to stem could be added. However, before carrying out this step, the location of the tree stem couldn't be found, because without the information of CBH, the tree stem could not be identified. Thus the middle point of all lowest points was extracted. This reference point was referring to the stem location (assuming all the trees have return points on stem). After finding the location of the stem, the distance threshold should be decided. DBH in this study area normally won't exceed one meter. However, this point might locate on the edge of the stem since only one side of the stem got lidar return point. Apart from this situation, tree stem could be declining which means the reference point was not in the middle of the stem (fig.34). Besides, considering the diameter at height lower than breast could be larger, this threshold was set to 1.5 meter. Any points who have met the first criteria were tested by this threshold and unqualified points have to be reclassified. Generally, 20 miss-classified points were removed.

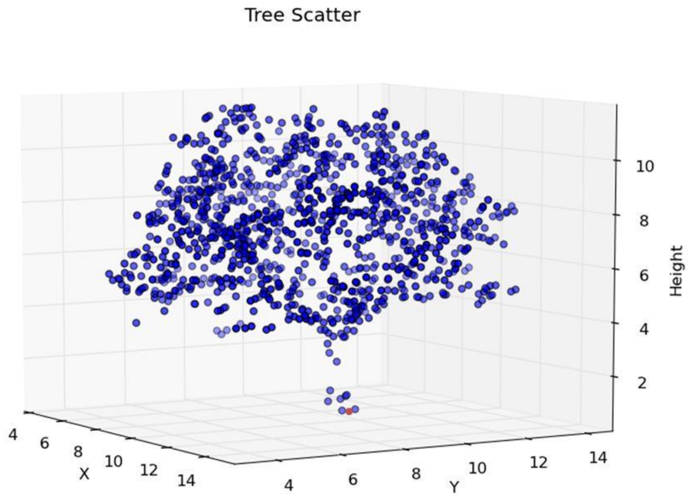


Figure 34: Middle point （in red）of the all lowest points.

3.2.2 Update DBH parameters extraction method

Based on the definition of DBH, points closed to 1.3 meters were extracted. However, almost no lidar return points can be found due to the property of the data. Therefore, the searching range was expanded. Points from 1 meter to 2.5 meters from the stem were extracted. The reason to expand the upper bound more than lower bound is the stem width change less while it goes up. After all, least square circle fit was used as the same. An example of the results is shown in fig.35. If less than three points were found in this range, all the points from the stem were calculated by least square fit method.

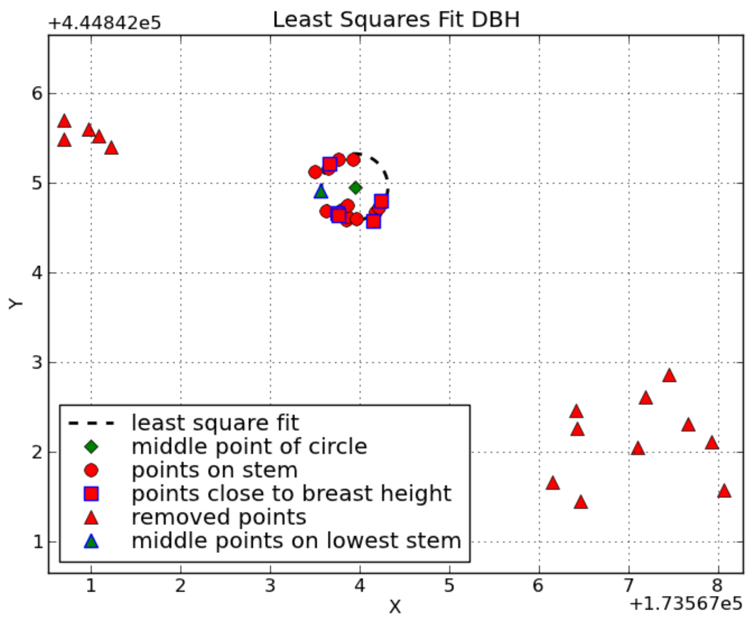


Figure 35: Least Square Fit DBH.

If only two points were found in the stem, all these two points were taken into equation 10

$$DBH = \sqrt{(X_1 - X_2)^2 + (Y_1 - Y_2)^2} \qquad \text{Equation 10}$$

where X is X-coordinate, Y is Y-coordinate.

Within the sampled trees data, sometimes data was not suitable for using least square fit, even when more than two points in the stem were measured (Fig.36). These points were not strictly in a line, but it resulted in a huge circle since they were regarded as points all on the circle and close to each other. Thus, in this case, if the result DBH was too large, the points were calculated by equation 11.

$$DBH = MAX\left[\sqrt{\left(X_i - X_j\right)^2 + \left(Y_i - Y_j\right)^2}\right] \quad \text{(i, j=1,2,3...n)} \qquad \text{Equation 11}$$

where X is X-coordinate, Y is Y-coordinate and n is the amount of points.

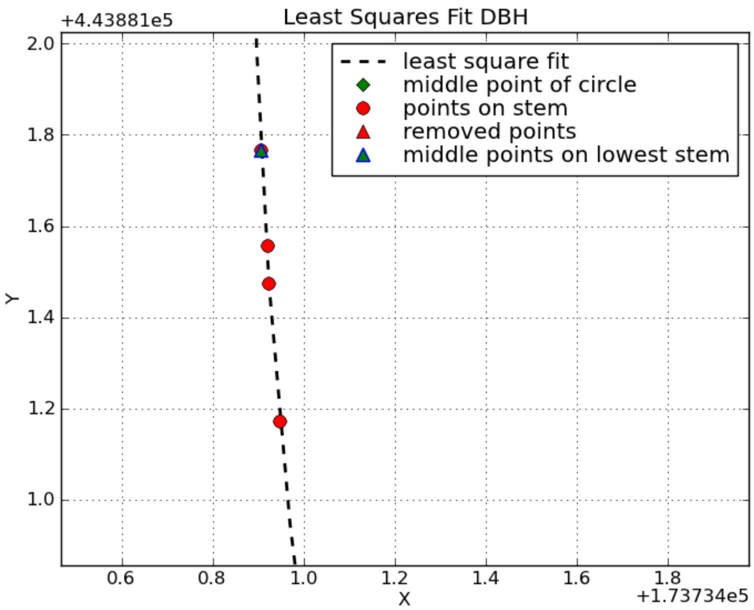


Figure 36: Least square fit DBH : huge fitted circle result.

3.2.3 Update tree location extraction method

Least square fit method was adapted to extract tree location. It is more accurate than simply calculate the middle point of all points from the stem. The points might not equally distribute on each side of the stem. By calculating the middle point, the location would bias to the side which has more points. But if only one point was found on the stem, this point was regarded as the tree location. However, there were two tree locations were extracted by calculating the middle point of the crown since there is no point on stem.

3.3 Parameters extracted from raster based models

In order to calculate crown width and tree location, python build-in functions were used. These build-in functions did only work for individual feature data type. Therefore, several pre-processing had to be done. First, the raster tree models were transformed into polygons. The tool "raster to polygon" took the height values as references to create polygons. Consequently, the results turned to be fragmented (Fig.37). In order to get complete tree outlines, dissolving polygons was necessary (Fig.38). At last, the dissolved polygons were split by canopy basin and exported to individual shape files.

Tree parameters extracted from raster based tree models are shown in appendix C.

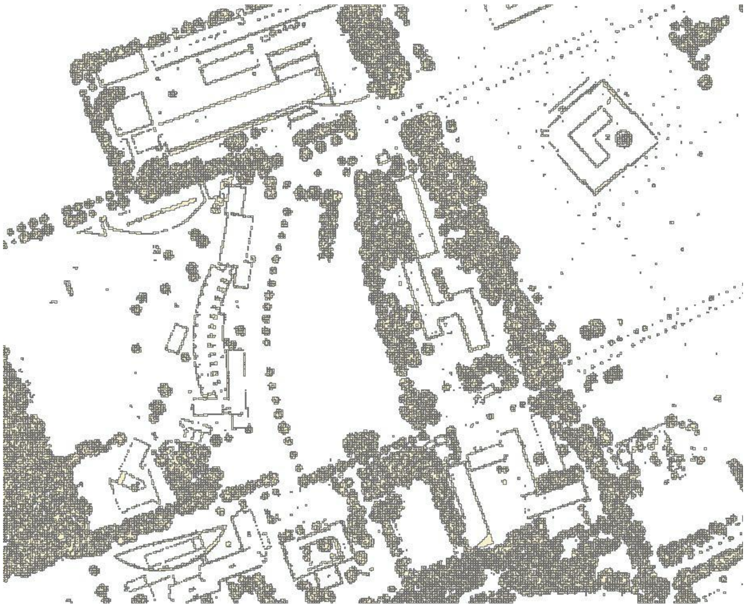


Figure 37: Fragmented tree polygons.

Figure 38: Dissolved tree polygons.

4 Parameters comparison results

3D tree parameters had been extracted. Combing with field measurements data, the comparison was done. This chapter will illustrate the parameters comparison results. First, the comparison between two models and field measurements results will be shown. Secondly, the possibility of species determination will be discussed.

4.1 Comparison between field measurements results and 3D tree models

Field measurement results are shown in appendix D, including estimate crown volume based on field measurements and shape values.

4.1.1 Tree location comparison

Generated tree locations were transformed into points using ArcGIS and displayed. All results were located inside the “Canopy Basin” and the trees in aerial imagery. Raster based models and point cloud based models locations were not overlapping and the differences can be clearly observed (Fig.39).

Figure 39: Illustration of overlaying location results from raster based and point based models with aerial imagery.

4.1.2 Tree height comparison

According with the statistic results (Table.5) (Fig.40), point cloud model and raster based model have R^2 larger than 0.8, which means that there is a good correspondence between the results from the models and the real heights. P-values are well below 0.05, indicating a strong statistical significance. RMSE are extremely small, comparing with real heights (ranging from 6.5m to 19.4m). Point cloud based model show larger R-square values, smaller P- and RMSE values than the raster based model. Furthermore, the predicted heights are corresponding better with field measurement 2, but the differences are relatively small. Moreover, the boxplot shows that the predicted heights are lower than the real heights.

Table 5: Tree height comparison statistical results.

Comparison Pairs	R-square	P-value	RMSE	SD	AD
F1 VS P	0.86	$5.53*10^{-14}$	0.0813	1.35	1.6
F2 VS P	0.88	$3.40*10^{-15}$	0.0756	1.47	1.8
F1 VS R	0.83	$1.26*10^{-12}$	0.0853	1.30	1.6
F2 VS R	0.85	$9.96*10^{-14}$	0.0829	1.47	1.8

F1: Field measurement 1, F2: Field measurement 2, P: Point cloud model, R: Raster based model, SD: Standard Deviation, AD: Average Difference

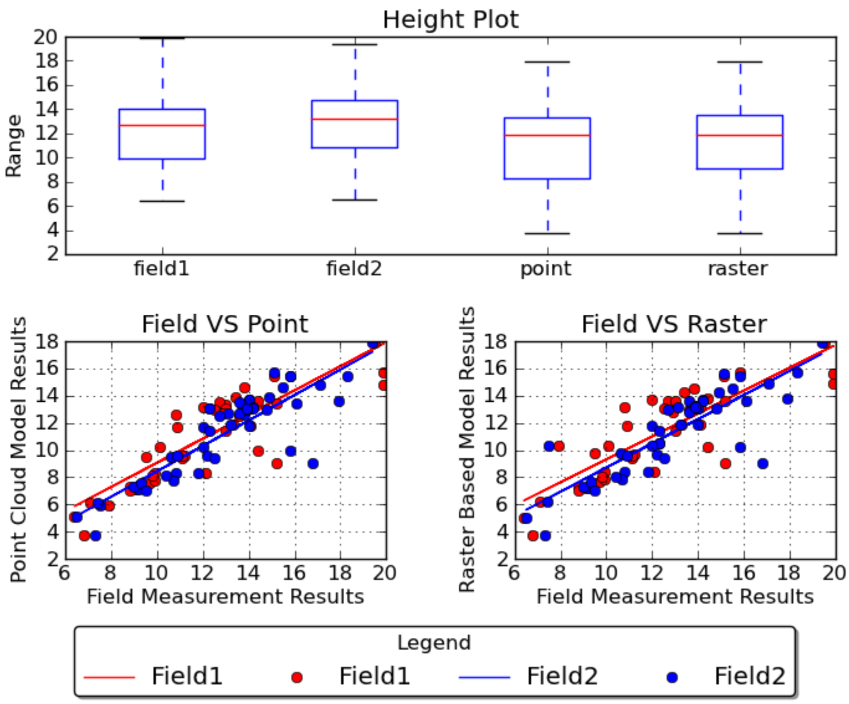


Figure 40: Boxplot and scatter plot of tree height.

4.1.3 CBH comparison

Predicted crown base height do not present a good correlation with the real value. The largest R-square is 0.3 with a P-value of 0.049 (Table 6). Boxplot shows that CBH results from point cloud based model and from raster based model are higher than field measurements results (Fig.41). After further calculations, we found that point cloud based model gives, in average, an over prediction of 0.8 meters while raster based model gives in average an 1.8 meters (when comparing to field measurement 2). This trend can be seen through the boxplot as well. By looking to the differences between point cloud model and field measurement 2, two of the studied trees (no.1 and no.33) show an extraordinary large difference (5 and 3.1 meters respectively).

Table 6: CHB comparison statistical results.

Comparison Pairs	R-square	P-value	RMSE	SD	AD
F1 VS P	0.30	0.0490	0.1950	0.85	0.9
F2 VS P	0.24	0.1214	0.2478	0.90	0.8
F1 VS R	0.29	0.0609	0.2194	1.33	1.6
F2 VS R	0.23	0.1405	0.2783	1.12	1.7

F1: Field measurement 1, F2: Field measurement 2, P: Point cloud model, R: Raster based model, SD: Standard Deviation, AD: Average Difference

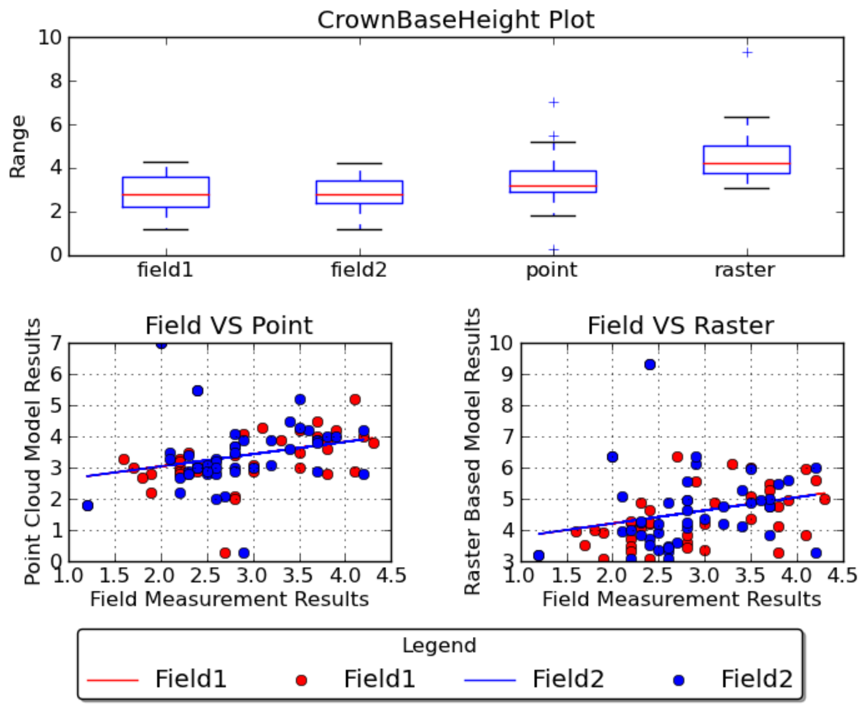


Figure 41: Boxplot and scatter plot of CBH. In the scatter plot, two lines are almost overlapped, having small differences.

4.1.4 Crown width comparison

Table 7 and fig.42 summarize the comparison results between field measurement and crown width. R-square values and P-values show that the both of the models can give promising crown width predictions. The results extracted from point cloud based model are slightly better than the ones from raster model. Additionally, the crown width from north-south direction is better predicted than for the east- west direction.

Table 7: Crown width comparison statistical results.

Comparison Pairs	R-square	P-value	RMSE	SD	AD
F1 VS P (N-S)	0.81	$2.27*10^{-11}$	0.0956	1.50	2.1
F2 VS P (N-S)	0.84	$7.70*10^{-13}$	0.0904	1.13	1.9
F1 VS R (N-S)	0.79	$1.23*10^{-10}$	0.1016	1.65	2.0
F2 VS R (N-S)	0.84	$6.79*10^{-13}$	0.0924	1.41	1.8
F1 VS P (E-W)	0.71	$3.92*10^{-8}$	0.1392	1.69	2.0
F2 VS P (E-W)	0.78	$2.09*10^{-10}$	0.1123	1.45	1.8
F1 VS R (E-W)	0.69	$1.57*10^{-7}$	0.1507	1.57	1.7
F2 VS R (E-W)	0.77	$5.84*10^{-10}$	0.1206	1.34	1.5

F1: Field measurement 1, F2: Field measurement 2, P: Point cloud model, R: Raster based model, SD: Standard Deviation, AD: Average Difference

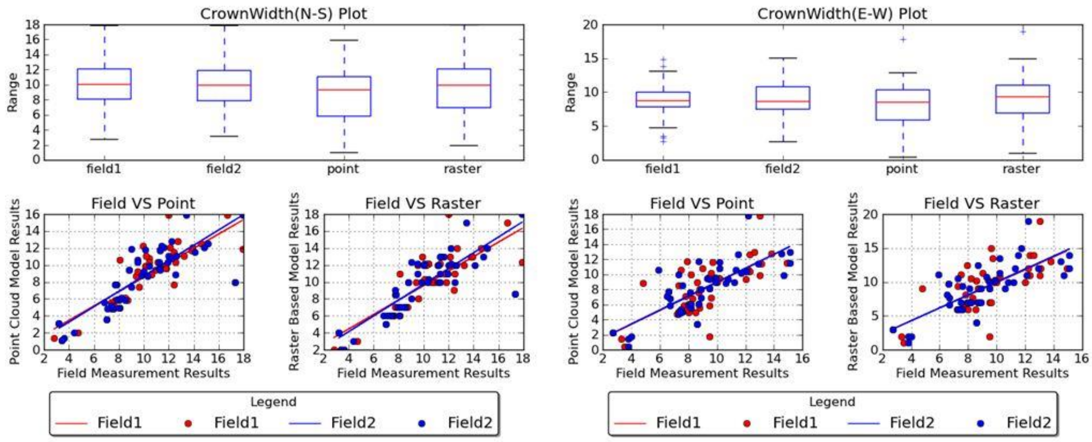


Figure 42: Boxplot and scatter plot of crown width.

4.1.5 DBH comparison

DBH was only extracted from point cloud based model. Therefore, comparisons were only conducted between point cloud based model and two field measurement results. However, the obtained DBH values show low accuracy (Table 8). After further calculation, average differences of 48.4 cm and 48.2 cm were got when comparing with two field measurements results.

Table 8: DBH comparison statistical results.

Comparison Pairs	R-square	P-value	RMSE	SD	AD
F1 VS P	-0.19	0.2588	0.7106	44.85	48.4
F2 VS P	-0.19	0.2682	0.7201	44.96	48.2

F1: Field measurement 1, F2: Field measurement 2, P: Point cloud model, SD: Standard Deviation, AD: Average Difference

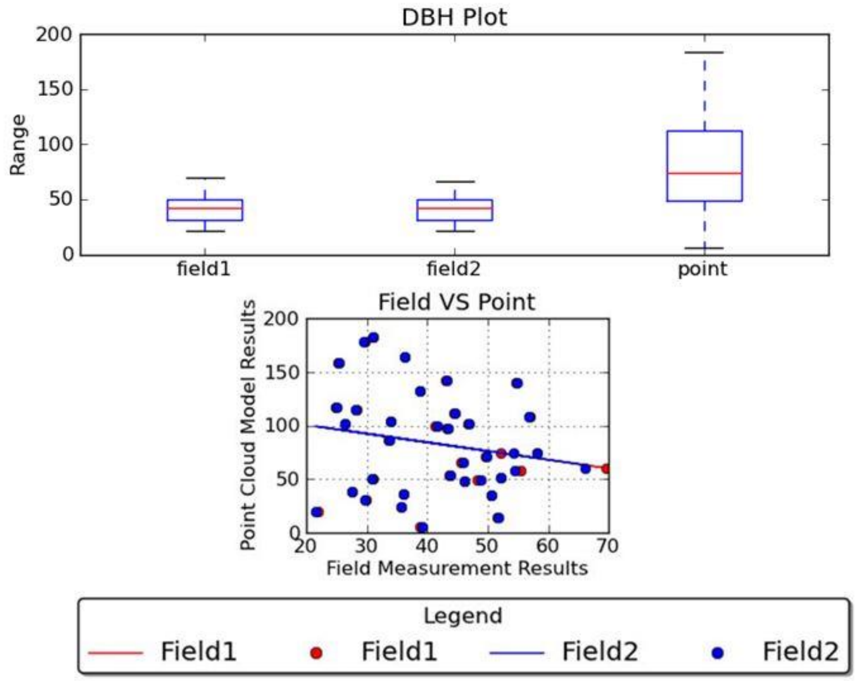


Figure 43: Boxplot and scatter plot of DBH. In the scatter plot, points and lines are almost overlapped, having small differences.

4.1.6 Crown density and crown volume comparison

The statistical results of crown density show that the 3D models prediction results are nearly or not correlated to the field measurement results (Table 9). Boxplots were done separately because the range of field measurement results and models generated results differs a lot: field measurement results are ranging from 40 to 100 while models prediction results are ranging from 0 to 12 (Fig.44). Moreover, comparing in between two types of 3D models, the density of point cloud based model is smaller than raster based model.

Crown volume comparison was analyzed. The statistical results indicate that the predicted volumes are corresponding very well with field measurement (Table 10), but the differences between the two field measurements can be clearly seen: both models are better correlated with field measurement 2. From fig.45, the following conclusions can be derived: crown volumes obtained from field measurement 1 are averagely larger than the ones from field measurement 2, and volume estimated from point cloud based model is larger than raster based model. After further calculations, we found that the volume extracted from point cloud based model is in average 167 m^3 larger than the one from raster based model.

Table 9:Crown density comparison statistical results.

Comparison Pairs	R-square	P-value	RMSE
F1 VS P	-0.3769	0.0139	0.0142
F2 VS P	-0.0885	0.5773	0.0135
F1 VS R	-0.2062	0.1901	0.0290
F2 VS R	-0.0097	0.9514	0.0262

F1: Field measurement 1, F2: Field measurement 2, P: Point cloud model, R: Raster based model

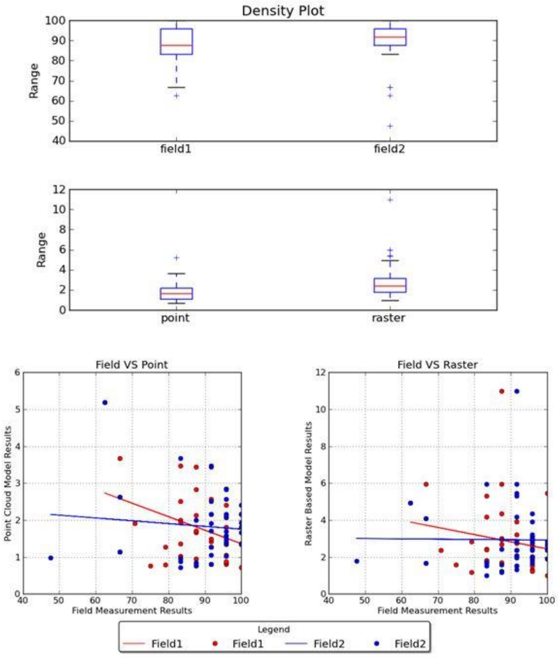


Figure 44: Boxplot and scatter plot of density.

Table 10: Crown volume comparison statistical results.

Comparison Pairs	R-square	P-value	RMSE	SD	AD
F1 VS P	0.52	0.0005	0.0927	443.29	473.7
F2 VS P	0.73	$5.1*10^{-8}$	0.1028	275.84	209.2
F1 VS R	0.53	0.0003	0.0625	503.63	502.1
F2 VS R	0.71	$1.33*10^{-7}$	0.0720	229.47	258.7

F1: Field measurement 1, F2: Field measurement 2, P: Point cloud model, R: Raster based model, SD: Standard Deviation, AD: Average Difference

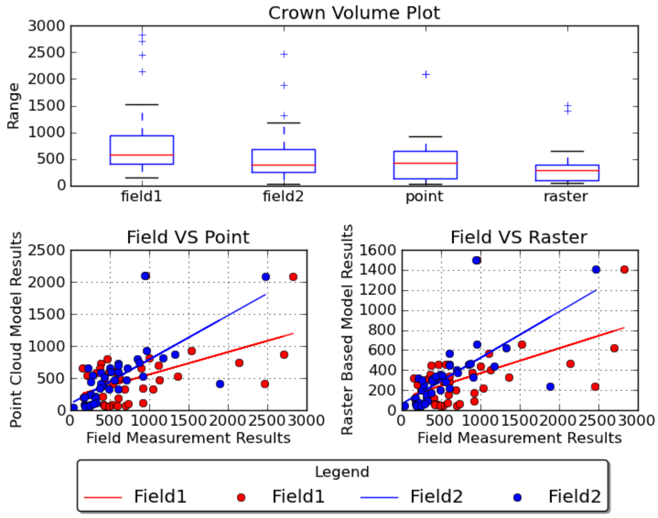


Figure 45: Boxplot and scatter plot of crown volume.

4.2 Tree species comparison

Comparing the target species from boxplots the following conclusions can be taken (Fig.46): first, *Acer Pseudoplatanus* has, in average, largest amount of return points on stem and on 1 to 2.5 meters range; secondly, *Fraxinus Excelsior* owns the lowest average crown volume but with many outliers; thirdly, crown density of these three species presents clear differences; finally, *Quercus Robur* has the lowest average crown density while *Acer Pseudoplatanus* has the largest and the average density of *Fraxinus Excelsior* is in between.

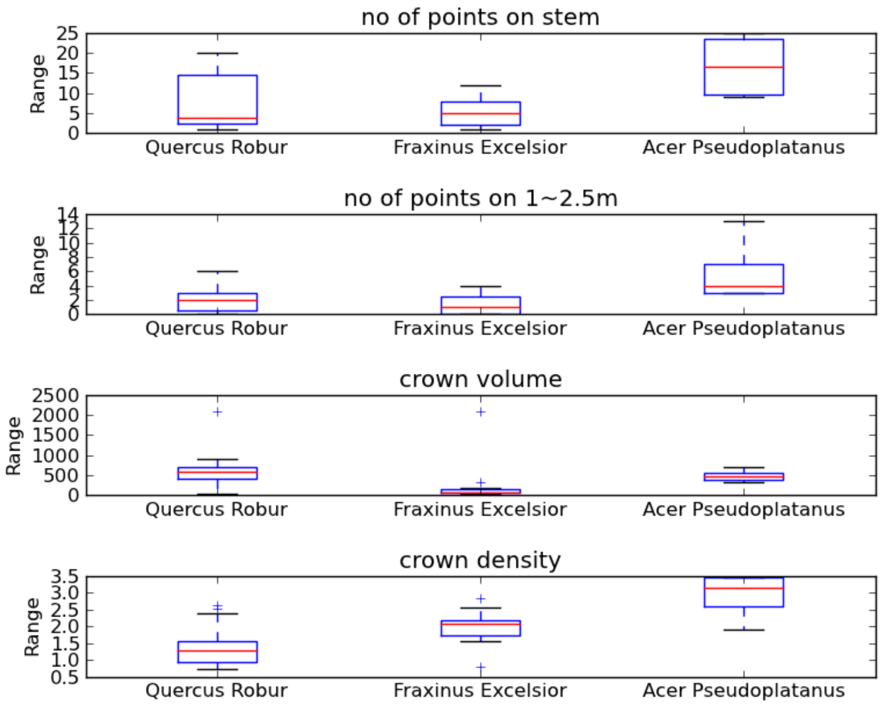


Figure 46: Boxplot of comparing three types of tree species. Four parameters were compared: number of points on stem, number of points on 1 meter to 2.5 meters, crown volume and crown density. In the titles of first two figures, "no" = "number".

Scatter plots of parameters pairs are shown in fig.47. Clustering boundary (in green) between *Quercus Robur* and *Fraxinus Excelsior* can be seen in P3 with one outlier. Density of *Fraxinus Excelsior* is mainly ranging from 1.5 to 3.0 with points on stem ranging from 1 to 12. *Quercus Robur* is clustering in two areas: density from 0 to 1.5 and points on stem from 1 to 8, density from 0.9 to 2.7 and points on stem from 13 to 20.

Similarly, boundaries between *Fraxinus Excelsior* and *Acer Pseudoplatanus* can be observed in P4 and P6.

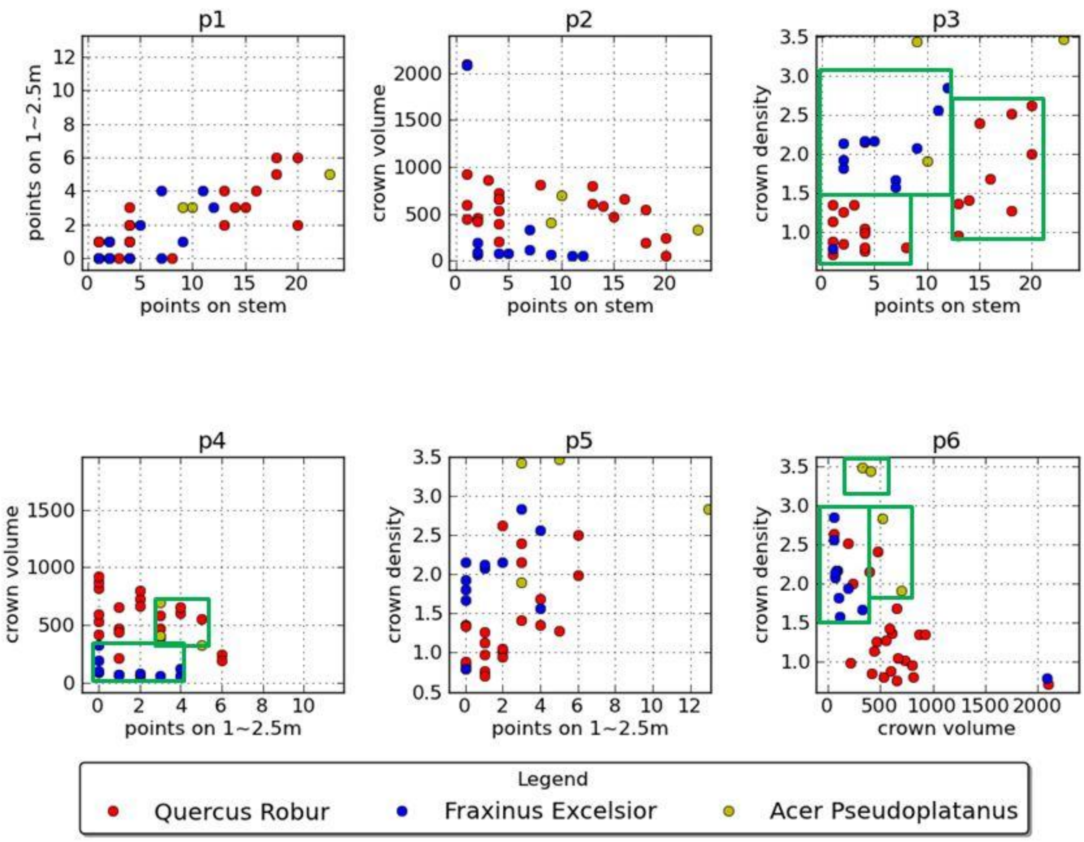


Figure 47: Scatter plot of parameters combination. P1: combination of number of points on 1 to 2.5 meters and number of points on stem. P2: combination of crown volume and number of points on stem. P3: combination of crown density and number of points on stem. P4: combination of crown volume and number of points on 1 to 2.5 meters. P5: combination of crown density and number of points on 1 to 2.5 meters. P6: combination of crown density and crown volume.

5 Discussion and recommendation

This study showed how to compare tree parameters extracted from point cloud based model and raster based model. Two types of 3D tree models were well generated through several pre-processing steps, such as classification and segmentation. Parameters used for comparison have been defined based on LOT and then extracted from generated models and field measurements. The comparison results demonstrate the quality of the two 3D tree models and point out the potential of further research.

5.1 Discussion

5.1.1 Segmentation errors

Few segmentation errors were found which might be caused by different reasons. In fig.48, a part of the tree was missing. This is because this tree has two tops and watershed segmentation treated them as two different trees. When conducting watershed segmentation, each top formed a canopy basin. As a result, this single tree was divided into two.

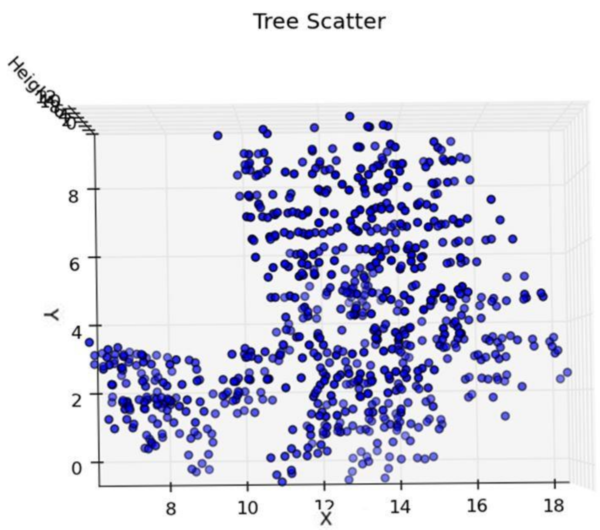


Figure 48: Segmentation error caused part of the tree missing.

Another possible reason to cause segmentation errors is when two trees are interacting with each other and have height differences (Fig.49). The taller tree is partly covering the other tree. They compose a smooth slope in the interacting side. When looking from above, only one top can be distinguished. Consequently, the segmentation method regarded them as one tree.

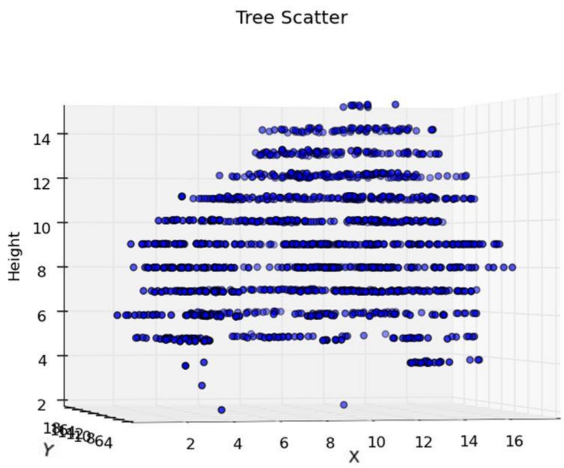


Figure 49: Segmentation error lead by smooth slope in the interacting side.

5.1.2 Selection close to dataset edges

In this research, the study area covered three datasets. The area of the two datasets overlap in certain areas. Trees located in this overlapping area perform differently in each dataset. Fig.50 shows two generated point cloud based models of one tree. In this figure, large difference can be observed. The model on the left was generated from dataset no.1 while the other model was generated from dataset no.2. This deviation is caused by the position of the tree and the building next to it (Fig.51). In addition, this tree is located on the edge of the dataset which make the scan angle rather small. The laser beams from flight position 1 were partly blocked by the building, leading the incomplete model. On the contrary, flight position 2 scanned the tree completely. Therefore, the point cloud model from dataset no.2 was selected.

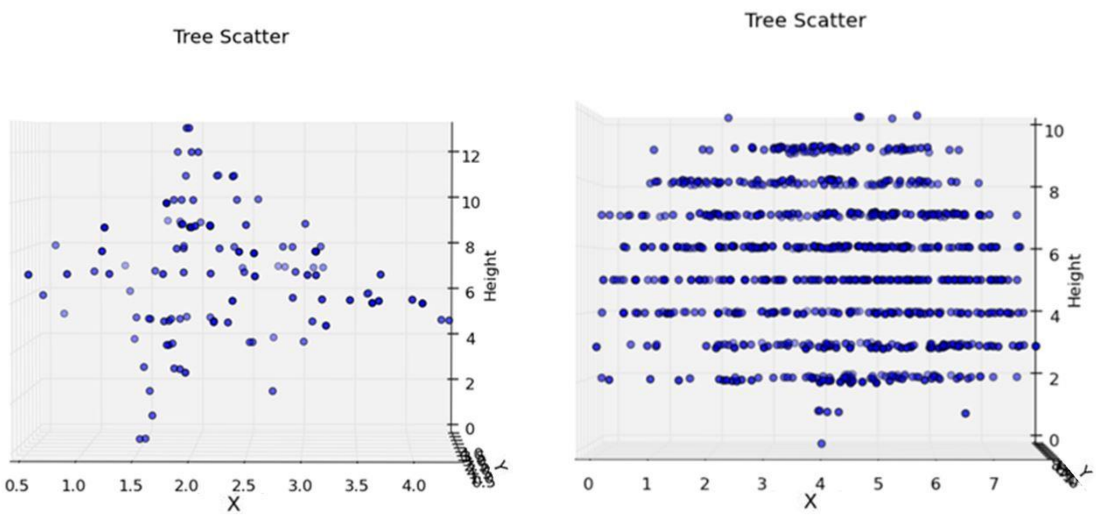


Figure 50: Different models of one tree.

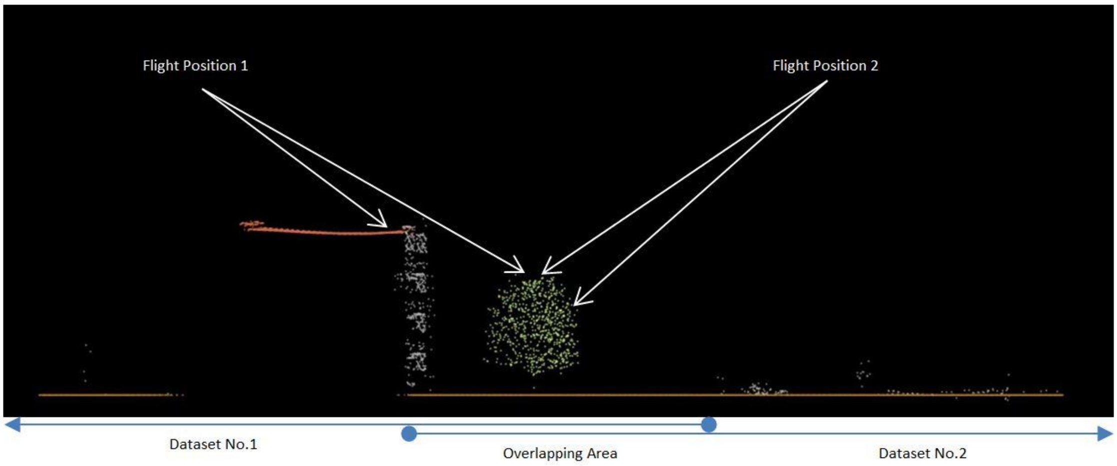


Figure 51: Illustration of two flight positions and datasets.

5.1.3 Parameter comparison

In this research multiple tree parameters were extracted. Tree location, tree height, crown width and crown volume can be predicted better than the other parameters. The remaining parameters, DBH, CBH and density, have low accuracy.

- Tree location results are corresponding to the real location accurately. The differences between the two types of models were caused by different calculation methods. Point cloud based model gave the location of the tree stem while the raster based model gave the location of the center tree crown. In addition, The pixel size of the raster based model also bring the differences.
- The correlation analysis shows that both models are capable of predicting the tree height correctly. Although, there is a trend of underestimating the values. This is because the lidar scans might have missed the tree top (Suárez et al., 2005, St-Onge and Achaichia, 2001). The AHN2 data has a resolution of 0.3 meters. Therefore, cone shaped tree crowns can be easily missed. Another possible reason is the growth of the study trees. Since the lidar data was acquired in 2010, the trees might have grown. The second field measurement results are better correlated with the two models. It is because in the winter the tree tops can be better observed and easier measured due to the fact that there is no leaf on the branches.
- Many researches have reported that the accuracy of CBH is not considered as good enough compared to other parameters extracted from the upper crown. An overestimation is usually reported (Vauhkonen, 2010) (Fig.52). This study shows also that extracted crown base height results have small R-square values. But the average difference between the point clouds based tree model and the field measured (0.8 meters) is acceptable if the growth of the tree is taken into account. On the contrary, raster based model gave a large average difference. It is caused by the mechanism of the generated CHM. The method is using DSM minus DTM. DSM is a raster model only containing the top surface of all the elements on the ground. Thus, the upper part of the crown surface is recorded while the downside part is missing (Fig.53). Consequently, the CBH

extracted from the raster based model is the height where the broadest crown width is. As mentioned in chapter 4.1.3, two of the study trees are showing extraordinary large difference. The common factor of these two trees is that both of them have a long narrow crown shapes. It makes the boundary between crown and stem fuzzy.

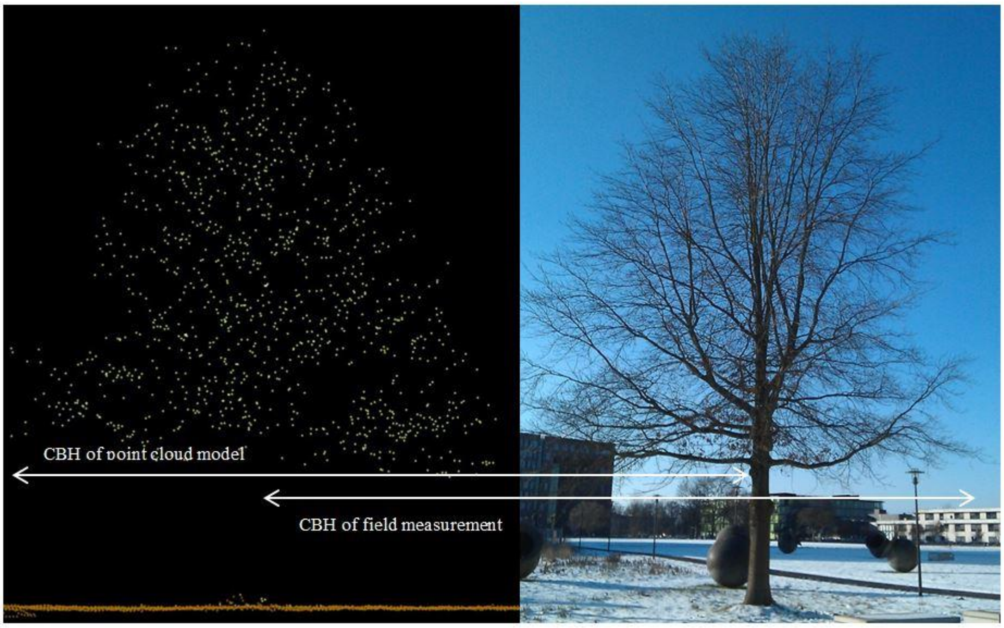


Figure 52: Overestimation of CBH.

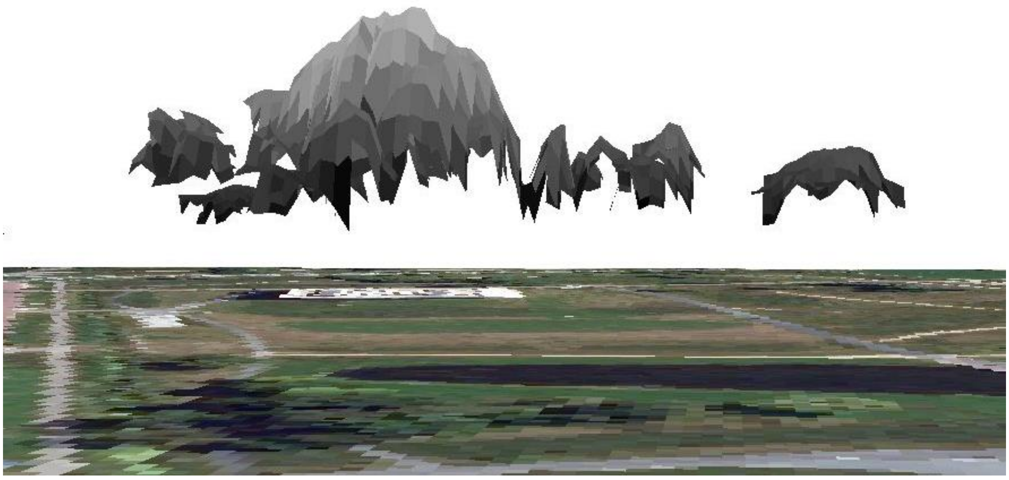


Figure 53: An example of raster based tree models。

- Crown widths obtained from both models are reliable and convincing. Cell size caused the difference between point cloud based model and raster based model. As mentioned in chapter 2.5.2, the resolution (cell size) of the raster based model was set to 1 meter caused smoothing effect.
- Comparison also shows that crown width of north to south was better predicted than east to west. It caused by the flight direction and scan direction. By exploring the lidar datasets, the flight direction can be known by looking at

"Scan Angle Rank" while scan direction can be found from "Scan Direction Flag" (ESRI, 2012). The flight direction is from north to south and scan direction is from left to right. Because of this, the side of the crown which is facing the flight direction can be recorded accurately. However, the opposite side of the crown was partially blocked. Therefore, crown width in north to south direction has better accuracy than crown width in east to west direction.

- DBH extracted from point cloud model has a poor accuracy. The low amount of return points on the stem is the main reason. All the study trees have an average of 10 points on the stem and 5 points from 1 meter to 2.5 meters. The amount of points is not sufficient enough to describe stem shape. Moreover, points were not distributing equally on the stem, caused by scan angle and blocking of the stem. Consequently, over- and underestimating DBH values were extracted.
- The statistical results of crown density show that the field measurements and 3D models are not comparable. The density from field measurement was obtained from the Spherical Densiometer. The results are hierarchically due the fact that this tool can only give 25 fixed values (ranging from 0 to 24). Besides, the results show the density of the trunk. In contrast, density extracted from 3D tree models is discrete and it is describes the density of lidar return points.
- Crown volume differences between two field measurements are caused by the different crown width and crown depth (tree height minus crown base height). As stated above, average crown volume extracted from raster based model is smaller than point cloud based model. It is because of the CBH extracted from raster based model is higher than point cloud based model. Therefore, the downside part of the crown volume is miscalculated. It also explains that why the average point density of raster based model is higher than point cloud based model.

In summary, point cloud based models showed a better accuracy than raster based models. Point cloud based model can predict tree parameters below the crown while raster based model couldn't due to its generating approach. Although point cloud based model predicted DBH and CBH with low accuracy in this research, it was caused by the poor quality of the airborne lidar data (low amount of points on stem) and not due to the methods. Based on the definition of LOT, raster based model is a level-1 model which can give good descriptions of upper crown. On the other hand, point cloud based model is a level-2 model which can represent both upper and downside crown. In spite of that raster based models can offer density information, as it is based on the points number from point cloud data. From the perspective of storage space, both of them were generated from large lidar point cloud dataset. From the perspective of processing speed, extracting tree parameters from point cloud based model is faster than extracting from raster based model. The previous one is easier generated while the second needs many more steps of pre-processing. In addition, point cloud based model also offers opportunities for determination of species. Above all, point cloud based model is definitely a better choice for all kinds of users and purposes.

5.1.4 Tree species determination

Although the average crown volume of *Fraxinus Excelsior* is the lowest of all species, the range of this index of this species is still overlapping with the others. Alike, it is not possible to distinguish *Acer Pseudoplatanus* from other species based on average return points on stem and points on 1 to 2.5 meters. Crown density is not suitable for species determination as well. All these average differences prove that the species influences the parameters of the point cloud based model.

However, the combinations of number of points on stem and crown volume can help to distinguish *Quercus Robur* and *Fraxinus Excelsior*. *Fraxinus Excelsior* and *Acer Pseudoplatanus* can be distinguished by following two combinations: combination of number of points on 1 to 2.5 meters with crown volume, combination of crown volume with crown density.

5.1.5 Problem of low amount of points on stems

The problem of the low amount of points on stem is the main reason that DBH can't be predicted accurately. To find the factor leading to this problem, average crown width was plotted with amount of points on stem (Fig.53). We can find the trend that the amount of points on the stem is increasing while the crown width is decreasing. As a conclusion, larger crown width will block more laser beams. CBH accuracy is also affected by the effect of crown blocking. Similar to CBH, laser beams that should reach the downside part of the crown, can be blocked. It explains why the CBH extracted from point cloud based model is averagely higher than the true value.

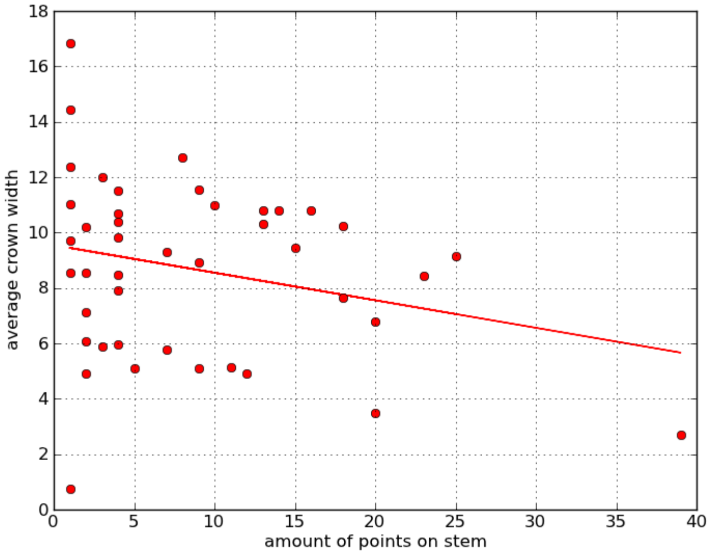


Figure 54: Relationship between average crown width and amount of points on stem.

5.2 Recommendation

This study provided a methodology of generating and comparing 3D tree parameters. The results show the qualities of two types of models and give an indication of choosing the point cloud based model will benefit in higher accuracy, faster processing speed and possibility of species determination. Although the methodology has solved the research questions and the results have reach the research objective, several shortages were found.

Point cloud based and raster based 3D tree models were successfully generated, but the quality of the watershed segmentation has a significant influence on the accuracy of both of the models. The use of extra segmentation methods, such as eCognition, might allow to increase the quality of the models (Yu et al., 2006, Bunting and Lucas, 2006).

Before generating the raster based model, the outliers from the CHM were simply removed by setting a threshold of 40 meters. This was based in the consideration that the trees in the study area are lower than 40 meters and there are no outliers located above the study trees. Other methods for correcting the outliers, such as zonal statistics, can be implemented for better results. If those outliers are locating right above target trees, the holes (null value) that are left after correction can be smoothed by taking the average values from its neighbors. Another possible approach is removing the noise from point cloud data before building DSM and DTM.

Approaches for extracting tree parameters from both models were developed. These approaches show very promising results for extracting tree location, height, crown width and crown volume, when comparing with field measurements results. However, the crown blocking effect reduces the accuracy. DBH could only be extracted from point cloud based model, but the low amount of points on the stem made the results coarse. An ideal way to solve this problem is by adding the terrestrial lidar technique, which is described to give a good description of the stem (Chasmer et al., 2006, Dassot et al., 2011). The scan angle and existence of buildings can cause blocking. This was not considered in the parameters validations. In addition, flight altitude also has impact on the amount of points on crown and stem (Goodwin et al., 2006). This perspective can be introduced in the further research.

Three species were discussed for the possibility of species determination. Density can be used as an index to distinguish between *Fraxinus Excelsior*, *Quercus Robur* and *Acer Pseudoplatanus*. Combination of crown volume with the amount of points on stem can help with the determination of *Quercus Robur* and *Fraxinus Excelsior*. Combinations of crown volume with crown density with the amount of points on 1 to 2.5 meters can help with the determination of *Fraxinus Excelsior* and *Acer Pseudoplatanus*. Tree age can be a potential parameter in determining species and it can be conducted in the further research.

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7 Appendices

Appendices include two parts. Some appendices are displayed here in the paper, others are stored in the attached DVD.

Appendix A. DVD catalog

- **A1. Photos of sample trees**
  - Path: DVD:\Appendix_A\A1_Pictures_Trees\...
  - Description: 45 photos of study trees took during field measurement.

- **A2. ArcGIS models**
  - Path: DVD:\Appendix_A\A2_ArcGIS_Models\...
  - Description: ArcGIS models were organized in an ArcGIS toolbox: “3Dtree.tbx”. It can be adapted by ArcGIS 10.1 (or higher version). It has included 5 toolsets (Table 11). Description of each model is given in “”

Table 11: Description of 5 toolsets.

Toolset Name	Description
IAa_RasterTreeModel&Segementation	Raster based model generation and segmentation.
IAb_PointCloudClassification	Airborne lidar data classification (Lastools has to be introduced again).
IBa_FieldMeasurementImport	Importing field measurement results into ArcGIS (from excel format to point shape format).
ICa_PointTreeModel	Point cloud based model generation (output modelsinto text files).
ICb_RasterTreeParameterExtraction	Raster based tree parameters extractions.

- **A3. Text files generated from point cloud model**
  - Path: DVD:\Appendix_A\A3_TextFiles\...
  - Description: 45 text files for study trees. Number 1 to 45 were simply used as trees names.

- **A4. Python scripts for tree parameters extraction**
  - Path: DVD:\Appendix_A\A4_PythonScrips_ParameterExtraction\...
  - Description: There 6 scripts with names of their calculating parameters.

- **A5: Python scripts for statistical comparison**
  - Path: DVD:\Appendix_A\A5_PythonScrips_SatisticalComparison\...
  - Description: There 8 scripts with names of their comparing parameters.

- **A6: Python scripts for species comparison and corresponding files**
  - Path: DVD:\Appendix_A\A6_PythonScrips_SpeciesComparison\...

- Description: This folder include two python scripts, one for scatter plot and one for boxplot. They are corresponding to 3 .csv files. Each file consists data for one species.

Appendix B: Parameter extraction results from point cloud based model (first extraction results and update results)

Table 12: Parameter extraction results from point cloud based model (first extraction results).

No	Height	CrownWidthEW (m)	CrownWidthNS (m)	CBH (m)	Pnumber (Stem)	LocationX	LocationY	DBH (m)	Pnumber (1-2.5m)	Volume (m^3)	PNumber (ExcludStem)	Density ($/m^3$)
1	13.8	3.863	3.957	8.3	20	174167.921650	444369.384650	0.134049	4	52.388308	104	1.985176
2	11.1	7.954	8.931	3.1	1	174178.968000	444348.967000		1	385.675077	816	2.115771
3	12	5.908	7.666	3.5	20	173541.685350	444833.787600	0.466299	10	218.659280	475	2.172329
4	12.4	9.541	11.082	4.0	22	173548.902636	444837.379000	0.596950	9	603.068800	823	1.364687
5	11.6	9.476	12.104	4.4	17	173556.225294	444840.445059	0.642587	6	614.662791	836	1.360095
6	8.9	7.573	7.700	3.7	21	173563.747810	444843.692238	0.559905	9	219.685714	493	2.244115
7	12.4	9.929	10.569	4.1	24	173570.839250	444846.957125	0.698951	11	529.316530	713	1.347020
8	12.2	10.793	12.243	4.6	4	173578.426000	444850.302000	0.494403	1	740.286961	745	1.006367
9	12.6	8.533	11.859	4.5	2	173585.797000	444853.419000	0.058034	1	486.741123	587	1.205980
10	13.2	11.752	9.885	3.3	14	173592.952429	444856.847214	0.654160	8	815.963296	764	0.936317
11	13.4	8.972	11.827	3.8	8	173600.215875	444860.260625	0.770806	2	596.235553	690	1.157261
12	13	12.634	12.810	5.0	17	173615.029706	444866.276941	1.582590	4	787.078683	653	0.829650
13	12	10.560	10.785	5.0	3	173622.245000	444869.899667	1.631130	2	567.005019	496	0.874772
14	14.4	9.335	10.321	5.0	4	173629.615000	444872.812500	0.585945	0	525.941081	429	0.815681
15	15.3	17.812	15.883	4.5	1	173651.029000	444882.363000		1	2025.603948	1487	0.734102
16	13.6	6.836	10.289	5.7	2	173658.278500	444885.879000	0.478553	0	389.464005	358	0.919212
17	12.9	11.642	10.374	4.0	1	173665.522000	444889.209000		1	624.965754	527	0.843246
18	10.4	7.142	8.711	3.9	9	173672.130667	444891.301889	1.531962	4	223.533318	208	0.930510
19	13	7.727	9.389	4.5	1	173679.654000	444895.387000		1	429.733319	501	1.165839
20	5.7	8.036	6.330	2.2	4	173865.474250	443927.413500	1.585324	2	103.363080	366	3.540916
21	12.7	9.346	9.586	2.5	12	173850.358917	443958.867667	0.604800	3	477.449313	1134	2.375121
22	11.5	10.563	11.067	3.6	10	173828.463100	443942.561500	0.659976	4	631.933123	1109	1.754933
23	7.2	6.661	5.213	3.2	2	173744.128000	443860.354000	0.134462	1	61.077245	159	2.603261
24	7.2	5.000	5.231		0	173739.5281	443871.7086	1.16893	1	65.886034	135	2.048993

25	7.5	6.061	5.878	3.5	3	173734.916000	443882.599667	18160.137579	0	94.405448	185	1.959633
26	9.3	8.973	9.621	3.3	6	173731.229000	443893.742000	0.559507	4	324.419121	545	1.679926
27	9.1	6.859	7.425	3.4	2	173727.254500	443905.043500	0.236038	2	182.304339	371	2.035059
28	8	5.347	4.885	3.9	9	173725.251889	443916.004667	1.782272	5	71.424409	166	2.324135
29	6.8	4.751	5.547	3.0	11	173721.545364	443928.408364	1.451375	10	59.037747	147	2.489932
30	8.1	5.605	5.970	4.9	6	173720.268667	443940.162000	0.897028	6	116.545721	183	1.570199
31	7.5	4.921	4.911	4.5	13	173717.715538	443963.808769	7.467197	9	69.709456	147	2.108753
32	7.7	6.053	6.083	5.2	8	173717.023000	443973.292750	1.001257	8	107.083937	178	1.662247
33	17.6	2.288	3.087	5.2	39	173875.202590	444130.971564	0.466421	7	42.608341	220	5.163308
34	11	10.406	11.541	2.1	8	173749.441250	444119.302375	1.515947	7	668.650130	1332	1.992073
35	10.7	8.891	9.419	2.6	20	173762.766900	444125.619300	0.975986	18	520.167969	1458	2.802941
36	9.4	8.056	8.847	1.8	12	173775.290083	444131.077750	0.703648	1	328.376462	1138	3.465535
37	8.4	9.911	7.931	1.2	12	173787.403167	444136.335000	0.935781	0	435.796880	1403	3.219390
38	11.7	11.416	11.699	2.8	9	174079.495778	444179.694778	0.604703	3	750.606992	1103	1.469477
39	9.8	10.154	9.280	5.7	9	174112.828444	444241.396444	1.516383	4	331.796240	567	1.708880
40	5.8	2.522	1.392		0				0	1.858383	24	12.914452
41	4.5	0.432	1.077		0				0		8	
42	15.5	11.469	12.513	4.3	3	174312.525000	444198.918667	0.141618	0	838.793481	1175	1.400822
43	13.8	12.712	12.074	4.6	1	174326.243000	444172.519000		0	954.850509	1239	1.297585
44	16.4	12.963	15.928	5.5	2	174360.886000	444191.858000	1.482228	2	2121.632748	1651	0.778174
45	6.2	1.788	2.043		0				0		21	

Table 13: Parameter extraction results from point cloud based model (update results).

No	Height (m)	CrownWidthEW (m)	CrownWidthNS (m)	CBH (m)	Pnumber (Stem)	LocationX	LocationY	DBH (m)	Pnumber (1-2.5m)	Volume (m^3)	PNumber (ExcludStem)	Density ($/m^3$)
1	13.7	3.431	3.575	7.0	20	174168.109540	444369.813914	1.832960	2	50.878648	106	2.629072
2	13.1	8.168	8.802	1.8	4	174178.972000	444348.828750	0.743712	3	389.611936	816	2.156606
3	12.7	5.908	7.666	3.9	20	173541.742215	444833.795417	0.356083	6	239.014075	477	1.995698
4	13.3	9.541	11.082	3.6	13	173548.980120	444837.049209	0.515637	4	606.377265	824	1.358890
5	12.5	9.476	12.104	4.0	14	173556.298852	444840.362924	0.708160	3	587.425853	832	1.416349
6	9.5	7.573	7.700	4.5	18	173563.786457	444843.599523	0.534681	6	195.482238	491	2.511737
7	13.2	9.929	10.569	4.2	18	173570.944500	444846.956385	0.742361	5	548.055541	700	1.277243
8	13.5	10.793	12.243	3.9	4	173578.286596	444850.225235	0.494403	2	729.411042	745	1.021372
9	13.0	8.533	11.859	3.0	2	173585.797000	444853.419000	0.058034	1	464.419271	587	1.263944
10	13.6	11.752	9.885	3.5	13	173593.218461	444858.643774	0.351446	2	803.153033	764	0.951251
11	14.6	8.972	11.827	3.9	4	173600.376913	444860.295435	1.018606	2	660.016882	690	1.045428
12	13.4	12.634	12.810	4.0	8	173615.669008	444866.570529	1.399404	0	816.832040	655	0.801878
13	12.6	10.560	10.785	3.8	4	173622.119441	444869.818962	1.112956	1	655.339384	498	0.759912
14	15.7	9.335	10.321	5.2	4	173629.378379	444872.836728	0.585945	0	531.511822	429	0.807132
15	15.4	17.812	15.883	2.9	1	173651.029000	444882.363000		1	2093.790109	1487	0.710195
16	13.9	6.836	10.289	4.2	2	173658.278500	444885.879000	0.478553	0	421.022105	358	0.850312
17	13.1	11.642	10.374	4.1	1	173665.522000	444889.209000		0	597.379997	527	0.882186
18	10.2	7.142	8.711	4.3	4	173672.694644	444891.089522	1.152774	1	210.411136	207	0.983788
19	13.0	7.727	9.389	3.7	1	173679.654000	444895.387000		1	441.671776	501	1.134327
20	5.9	5.910	5.831	2.2	3	173863.651825	443926.814177	0.200180	1	83.199552	305	3.665885
21	12.7	9.346	9.586	2.8	15	173850.084841	443959.344009	1.327301	3	472.310269	1134	2.400964
22	11.7	10.563	11.067	3.0	16	173828.382473	443942.502844	0.659976	4	656.901215	1109	1.688229
23	7.1	4.959	4.878	3.3	12	173743.810931	443859.905629	1.589387	3	54.893575	156	2.841863
24	7.3	5.000	5.231	3.2	9	173739.528087	443871.708601	1.168930	1	65.060674	135	2.074986
25	7.6	6.061	5.878	3.0	4	173734.924000	443882.493000	0.386091	0	85.025859	184	2.164048
26	9.6	8.973	9.621	2.9	7	173731.672126	443893.828493	0.992327	0	326.689215	545	1.668252

27	9.4	6.859	7.425	3.1	2	173727.254500	443905.043500	0.236038	0	192.569641	372	1.931769
28	8.3	5.347	4.885	3.5	5	173725.218557	443915.714679	1.782272	2	77.295227	167	2.160547
29	7.0	4.751	5.547	3.0	11	173721.462260	443928.910519	1.021010	4	57.303726	147	2.565278
30	8.3	5.605	5.970	3.3	7	173720.623404	443939.837300	1.646014	4	117.069657	184	1.571714
31	7.8	4.921	4.911	2.9	2	173717.698500	443963.924500	0.309429	1	68.849794	147	2.135083
32	8.1	6.053	6.083	2.7	2	173716.975500	443973.501500	0.503359	0	96.016616	174	1.812186
33	17.9	2.288	3.087	5.5	39	173875.434963	444131.047155	1.043894	2	42.476642	220	5.179317
34	11.9	10.406	11.541	2.8	10	173749.460257	444119.436857	1.421278	3	698.226277	1332	1.907691
35	11.4	8.891	9.419	3.1	25	173762.789215	444125.606830	0.861033	13	514.627901	1459	2.835058
36	10.0	8.056	8.847	2.8	23	173775.404355	444130.856584	0.974200	5	327.138367	1137	3.475594
37	9.0	9.911	7.931	2.1	9	173787.343395	444136.796999	1.086201	3	407.748120	1400	3.433492
38	11.8	11.416	11.699	2.8	9	174079.504247	444179.692823	0.604703	2	740.196252	1103	1.490145
39	9.6	10.154	9.280	0.3	1	174113.621000	444240.780000		0	341.063727	580	1.700562
40	5.1	1.438	1.392		0	174272.390625	444338.500000		0		25	
41	3.7	0.432	1.077	3.0	1	174279.026000	444340.827000		0		8	
42	14.8	11.469	12.513	3.4	3	174312.536558	444198.889237	0.141618	0	867.718378	1175	1.354126
43	13.1	12.712	12.074	2.9	1	174326.243000	444172.519000		0	921.748807	1239	1.344184
44	15.4	12.963	15.928	2.0	1	174361.627000	444191.871000		0	2086.326786	1651	0.791343
45	6.1	1.788	2.043		0	174060.500000	444041.000000		0		21	

Appendix C: Parameter extraction results from raster based model

Table 14: Parameters extraction results from raster based model.

No	Height (m)	CrownWidthEW (m)	CrownWidthNS (m)	CBH (m)	LocationX	LocationY	Volume (m^3)	Pnumber	Density ($/m^3$)
1	13.1	4.000	5.000	6.3	174168.390625	444369.000000	46.776985	191	4.083205
2	10.5	9.000	10.000	3.2	174178.890625	444349.500000	290.858978	1585	5.449376
3	13.2	6.618	8.500	4.8	173541.812500	444833.250000	204.199005	494	2.419209
4	13.3	10.252	12.000	4.1	173548.625000	444836.500000	460.244049	839	1.822946
5	13.0	10.799	13.000	5.5	173556.906250	444841.000000	308.178009	849	2.754901
6	9.8	8.982	9.000	5.3	173564.000000	444844.000000	123.115013	512	4.158713
7	13.7	10.539	11.000	6.0	173569.984375	444847.000000	255.034042	724	2.838837
8	13.6	11.320	13.000	4.8	173579.156250	444850.000000	448.937012	749	1.668385
9	13.0	9.408	12.310	4.3	173586.203125	444854.656250	285.864014	589	2.060420
10	13.8	12.408	10.329	5.1	173592.296875	444856.343750	455.095978	771	1.694148
11	14.6	10.166	12.107	6.1	173600.421875	444860.437500	354.684998	698	1.967943
12	13.6	14.000	14.000	5.6	173616.500000	444866.500000	436.608978	666	1.525392
13	13.2	11.098	12.187	5.0	173625.046875	444869.406250	317.340057	498	1.569294
14	15.7	10.000	11.000	6.0	173630.500000	444872.000000	332.209991	433	1.303392
15	15.7	19.000	17.000	3.9	173649.000000	444882.000000	1503.831787	1487	0.988807
16	14.3	7.670	12.170	5.0	173659.671875	444885.406250	295.796997	360	1.217051
17	13.6	13.494	12.000	5.6	173665.750000	444888.500000	347.474945	528	1.519534
18	10.3	8.129	10.000	4.9	173671.718750	444892.500000	119.751999	212	1.770325
19	13.2	9.726	10.000	5.0	173679.234375	444893.500000	300.631989	502	1.669816
20	10.3	7.000	7.000	3.1	173866.000000	443927.000000	61.945976	369	5.956803
21	12.8	10.000	10.000	3.9	173850.500000	443958.500000	404.963013	1145	2.827419
22	11.8	12.000	12.000	3.7	173828.500000	443942.500000	372.270996	1119	3.005875
23	7.2	6.000	6.000	3.5	173744.500000	443860.500000	51.767986	160	3.090713
24	7.3	6.000	6.000	3.3	173739.500000	443871.500000	57.480991	139	2.418191

25	7.7	7.000	7.000	4.6	173735.000000	443883.000000	48.020023	188	3.915033
26	9.7	10.000	11.000	4.2	173731.500000	443894.000000	202.979019	547	2.694860
27	9.4	7.000	8.000	4.2	173727.000000	443905.500000	154.989975	373	2.406607
28	8.4	7.000	6.000	4.1	173725.000000	443916.500000	72.547012	171	2.357092
29	7.1	6.000	6.000	3.5	173721.500000	443928.500000	46.037010	148	3.214805
30	8.4	7.000	7.000	4.0	173720.000000	443940.000000	91.668983	184	2.007222
31	7.8	6.000	6.000	4.2	173717.500000	443964.500000	50.023003	148	2.958639
32	8.1	7.000	7.000	4.0	173717.000000	443974.000000	68.487999	178	2.598995
33	17.9	3.000	4.000	9.3	173875.000000	444131.500000	45.578003	225	4.936592
34	11.9	11.000	12.000	3.3	173750.000000	444119.500000	565.328064	1333	2.357923
35	11.4	9.000	10.000	4.2	173762.000000	444125.500000	336.649017	1460	4.336861
36	10.2	9.000	10.000	4.3	173775.000000	444131.500000	215.755966	1148	5.320826
37	9.1	11.000	8.618	3.6	173787.000000	444135.812500	237.508942	1414	5.953460
38	11.9	12.000	13.000	4.9	174079.500000	444179.000000	467.108063	1110	2.376324
39	9.6	15.000	12.000	6.4	174115.000000	444241.500000	172.362000	1893	10.982699
40	5.1	2.000	2.000	3.8	174272.390625	444338.500000	2.279999	25	10.964918
41	3.7	1.000	2.000	3.1	174278.890625	444341.500000	0.668999	8	11.958169
42	14.8	12.000	14.000	3.8	174312.390625	444199.500000	623.596069	1178	1.889043
43	13.1	13.000	13.000	3.4	174325.890625	444173.000000	653.910950	1240	1.896283
44	15.5	14.000	18.000	3.4	174361.390625	444190.500000	1404.831177	1652	1.175942
45	6.2	2.000	3.000	3.6	174060.500000	444041.000000	4.581001	21	4.584151

Appendix D: Two field measurements results, including estimated crown volume based on field measurements and shape values

Table 15: Results of field measurement 1.

No	Species	DBH (cm)	Height (m)	CBH (m)	CrownWidthEW (m)	CrownWidthNS (m)	Density	CalculateDensity	Shape	ShapeIndex	Volume (m^3)
1	*Betula Pendula*	31.0	14.0	2.0	8.6	7.0	8	66.64	8	0.2619	191.2080
2	*Quercus Robur*	58.2	12.3	1.2	9.5	9.8	0	100.00	6	0.3927	405.9182
3	*Quercus Robur*	36.1	12.7	4.2	7.7	7.7	4	83.32	5	0.4909	247.3964
4	*Quercus Robur*	52.1	13.0	4.0	9.4	13.2	4	83.32	5	0.4909	564.1472
5	*Quercus Robur*	49.6	13.6	3.7	10.2	12.1	2	91.66	6	0.3927	329.4462
6	*Quercus Robur*	43.6	9.5	4.2	8.7	12.4	4	83.32	6	0.3927	161.3900
7	*Quercus Robur*	52.1	12.0	3.5	8.2	8.1	5	79.15	6	0.3927	206.7526
8	*Quercus Robur*	48.2	12.7	3.7	9.0	9.9	4	83.32	4	0.5236	378.5235
9	*Quercus Robur*	38.8	12.5	3.9	7.3	17.9	2	91.66	2	0.6872	606.8897
10	*Quercus Robur*	50.6	14.4	4.5	7.9	10.1	3	87.49	3	0.5891	469.7748
11	*Quercus Robur*	46.8	13.8	4.2	8.6	11.3	1	95.83	6	0.3927	367.6049
12	*Quercus Robur*	54.6	15.2	5.6	12.3	12.7	2	91.66	2	0.6872	1001.9376
13	*Quercus Robur*	44.4	10.8	4.3	7.5	10.4	6	74.98	8	0.2619	156.1693
14	*Quercus Robur*	55.5	19.9	5.0	9.8	12.5	1	95.83	2	0.6872	1358.5989
15	*Quercus Robur*	56.2	15.8	4.1	13.0	16.7	0	100.00	6	0.3927	955.2153
16	*Quercus Robur*	46.2	13.4	4.5	8.3	10.4	1	95.83	4	0.5236	529.3922
17	*Quercus Robur*	44.5	13.0	4.0	9.7	11.1	1	95.83	6	0.3927	490.7022
18	*Quercus Robur*	28.4	10.1	3.1	7.8	9.4	4	83.32	4	0.5236	406.6173
19	*Quercus Robur*	46.0	13.9	2.8	6.6	8.8	8	66.64	6	0.3927	429.6201
20	*Others*	21.9	7.9	1.9	9.5	8.7	8	66.64	4	0.5236	421.6813
21	*Quercus Robur*	38.7	12.9	1.9	12.0	11.8	1	95.83	4	0.5236	1130.8975
22	*Quercus Robur*	45.6	10.9	2.0	12.2	10.2	3	87.49	4	0.5236	892.4909
23	*Fraxinus Excelsior*	25.2	9.1	1.6	8.0	7.4	1	95.83	4	0.5236	468.6875
24	*Fraxinus Excelsior*	24.9	8.8	1.8	7.3	7.6	1	95.83	4	0.5236	427.3348

25	*Fraxinus Excelsior*	27.6	9.7	2.0	8.0	7.7	2	91.66	4	0.5236	522.2085
26	*Fraxinus Excelsior*	41.3	11.2	2.2	10.0	11.7	3	87.49	6	0.3927	690.2488
27	*Fraxinus Excelsior*	35.6	11.1	2.4	9.6	9.6	4	83.32	6	0.3927	600.2090
28	*Fraxinus Excelsior*	29.7	9.9	1.8	7.9	7.6	2	91.66	4	0.5236	589.9984
29	*Fraxinus Excelsior*	26.4	8.8	1.7	7.2	7.4	2	91.66	4	0.5236	491.2012
30	*Fraxinus Excelsior*	36.2	12.1	1.6	8.8	8.5	1	95.83	4	0.5236	922.5858
31	*Fraxinus Excelsior*	29.8	9.9	1.8	8.5	8.1	3	87.49	4	0.5236	695.2322
32	*Fraxinus Excelsior*	31.0	9.8	1.8	8.7	8.5	1	95.83	4	0.5236	733.0819
33	*Others*	34.0	19.5	2.4	2.7	3.2	9	62.47	8	0.2619	235.8261
34	*Acer Pseudoplatanus*	43.0	13.3	3.4	12.3	12.4	7	70.81	6	0.3927	1111.5117
35	*Acer Pseudoplatanus*	33.5	13.0	3.0	4.8	10.9	3	87.49	6	0.3927	613.4563
36	*Acer Pseudoplatanus*	43.3	14.4	2.2	8.8	10.6	4	83.32	6	0.3927	1040.9754
37	*Acer Pseudoplatanus*	56.9	15.2	2.8	13.0	17.3	3	87.49	4	0.5236	2459.0874
38	*Salix alba*	69.5	14.1	2.2	13.1	13.8	2	91.66	4	0.5236	2141.2126
39	*Others*	62.2	11.1	1.0	9.6	9.5	3	87.49	6	0.3927	920.4324
40	*Quercus Robur*	10.4	6.4	3.4	3.3	2.8	2	91.66	4	0.5236	103.7239
41	*Quercus Robur*	11.4	6.8	2.4	3.5	3.4	1	95.83	4	0.5236	176.8485
42	*Quercus Robur*	51.6	19.9	3.5	14.9	14.6	0	100.00	6	0.3927	2702.5830
43	*Quercus rubra*	54.4	14.1	4.2	13.8	13.9	1	95.83	6	0.3927	1529.1997
44	*Fraxinus Excelsior*	66.4	15.1	3.3	12.6	12.0	5	79.15	2	0.6872	2822.6479
45	*Others*	19.6	7.1	1.8	9.5	4.7	1	95.83	4	0.5236	536.9086

Table 16: Results of field measurement 2.

No	Species	DBH (cm)	Height (m)	CBH (m)	CrownWidthEW (m)	CrownWidthNS (m)	Density	CalculateDensity	shape	ShapeIndex	Volume (m^3)
1	*Betula Pendula*	31.0	14.0	2.0	8.6	7.0	8	66.64	8	0.2619	191.2080
2	*Quercus Robur*	58.2	12.3	1.2	9.5	9.8	2	91.66	6	0.3927	405.9182
3	*Quercus Robur*	36.0	13.1	3.2	6.7	7.8	3	87.49	5	0.4909	255.4490
4	*Quercus Robur*	52.2	13.7	3.4	9.9	12.0	1	95.83	5	0.4909	606.2594
5	*Quercus Robur*	49.8	12.7	3.8	9.3	11.6	1	95.83	6	0.3927	381.6660
6	*Quercus Robur*	43.8	10.6	3.4	8.1	7.7	2	91.66	6	0.3927	176.4605
7	*Quercus Robur*	54.3	14.2	4.2	7.3	9.5	2	91.66	6	0.3927	277.0891
8	*Quercus Robur*	48.8	13.6	3.7	10.2	11.4	1	95.83	4	0.5236	604.6198
9	*Quercus Robur*	39.1	14.8	3.0	7.6	9.0	2	91.66	2	0.6872	558.6263
10	*Quercus Robur*	50.5	17.9	2.1	8.7	10.4	4	83.32	3	0.5891	848.8928
11	*Quercus Robur*	46.9	15.5	2.9	9.9	10.1	2	91.66	6	0.3927	494.8020
12	*Quercus Robur*	54.9	16.1	3.9	11.5	12.2	2	91.66	2	0.6872	1177.2798
13	*Quercus Robur*	44.6	13.8	3.7	5.9	12.2	3	87.49	8	0.2619	216.6477
14	*Quercus Robur*	54.5	15.1	3.5	9.5	11.9	2	91.66	2	0.6872	912.6593
15	*Quercus Robur*	57.0	18.3	3.7	12.2	13.4	4	83.32	6	0.3927	939.3635
16	*Quercus Robur*	46.1	14.9	3.6	6.7	9.5	3	87.49	4	0.5236	388.1934
17	*Quercus Robur*	44.6	14.2	2.8	10.2	11.2	4	83.32	6	0.3927	512.5465
18	*Quercus Robur*	28.1	12.0	3.5	6.5	10.3	14	41.62	4	0.5236	314.0343
19	*Quercus Robur*	46.0	13.9	2.8	6.6	8.8	8	66.64	6	0.3927	258.4433
20	*Others*	21.5	7.5	2.2	8.0	8.0	4	83.32	4	0.5236	177.6051
21	*Quercus Robur*	38.7	13.6	2.5	10.8	11.2	0	100.00	4	0.5236	703.2472
22	*Quercus Robur*	46.0	12.0	2.4	11.3	12.6	1	95.83	4	0.5236	717.8053
23	*Fraxinus Excelsior*	25.5	9.2	2.6	7.5	7.5	1	95.83	4	0.5236	194.3865
24	*Fraxinus Excelsior*	25.1	9.0	2.6	7.6	7.4	1	95.83	4	0.5236	188.4960
25	*Fraxinus Excelsior*	27.5	9.3	2.8	8.7	8.5	1	95.83	4	0.5236	251.7155
26	*Fraxinus Excelsior*	41.6	12.2	2.3	11.2	11.3	0	100.00	6	0.3927	492.0408

27	*Fraxinus Excelsior*	35.6	12.5	2.5	8.9	9.0	0	100.00	6	0.3927	314.5625
28	*Fraxinus Excelsior*	29.5	10.8	2.8	7.5	7.1	0	100.00	4	0.5236	223.2212
29	*Fraxinus Excelsior*	26.3	9.5	2.4	7.3	6.8	1	95.83	4	0.5236	184.7720
30	*Fraxinus Excelsior*	36.2	11.8	2.1	8.2	7.9	1	95.83	4	0.5236	329.1267
31	*Fraxinus Excelsior*	29.7	10.7	2.8	7.5	8.0	1	95.83	4	0.5236	248.4449
32	*Fraxinus Excelsior*	30.8	10.4	2.2	8.2	8.2	0	100.00	4	0.5236	288.6963
33	*Others*	34.0	19.4	2.4	2.7	3.2	9	62.47	8	0.2619	38.7461
34	*Acer Pseudoplatanus*	43.3	13.2	4.2	12.1	14.1	2	91.66	6	0.3927	606.5212
35	*Acer Pseudoplatanus*	33.7	12.3	3.2	10.6	11.3	1	95.83	6	0.3927	428.4800
36	*Acer Pseudoplatanus*	43.4	15.8	2.3	8.9	12.5	2	91.66	6	0.3927	606.9630
37	*Acer Pseudoplatanus*	56.8	16.8	2.7	14.7	17.3	2	91.66	4	0.5236	1889.9866
38	*Salix alba*	66.0	14.0	2.6	12.9	11.3	1	95.83	4	0.5236	873.9271
39	*Others*	76.6	10.9	2.9	11.7	10.0	2	91.66	6	0.3927	369.8370
40	*Quercus Robur*	10.7	6.5	2.5	3.8	3.6	4	83.32	4	0.5236	28.6723
41	*Quercus Robur*	11.4	7.3	2.6	3.8	3.4	1	95.83	4	0.5236	31.8935
42	*Quercus Robur*	51.7	17.1	2.3	15.1	15.1	0	100.00	6	0.3927	1325.1850
43	*Quercus rubra*	54.0	13.9	2.5	14.5	14.8	0	100.00	6	0.3927	960.8177
44	*Fraxinus Excelsior*	67.0	15.8	2.6	15.1	17.9	3	87.49	2	0.6872	2469.5906
45	*Others*	19.7	7.4	2.1	4.0	4.4	1	95.83	4	0.5236	48.9524