A new method for individual tree measurement from airborne LiDAR

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Abstract

This paper presents a new method for individual tree measurement from Airborne LiDAR data. This method involves 3 steps; 1) individual tree crown delineation based on density of high points (DHP), 2) tree filtering, and 3) measurement of tree trunk diameter at breast height (DBH). In the second step, a special tree filtering algorithm is introduced which combines a histogram analysis and region growing (RG) segmentation method. In forest area, undergrowth vegetation is considered as noise and it should be removed to ease the DBH measurement process of trees. The DBH measurement on point cloud is done based on two steps; 1) three-dimensional line fitted on points of tree trunk, and 2) histogram analysis of distances between points and the line. It shows that more than 60% trees are successfully filtered and compared to the actual DBH measurement in the field the DBH estimations on point cloud have the root mean square error of 0.18 m.

Keywords: LiDAR, individual tree measurement, diameter at breast height (DBH), tree filtering, crown delineation

1. Introduction

Airborne LiDAR data has been used quite extensively in forest mensuration (Hyyppä et al., 2004). Studies on utilizing LiDAR data to assess forest conditions have moved from an average forest stand scale to individual tree level (Roberts et al., 2005). This is clearly encouraged by the fact that improvements in LiDAR technology have led to higher pulse rates and increased LiDAR posting densities. Therefore, the semiautomatic mapping of single tree crowns (delineation and estimation of tree parameters), has become a key approach in forestry inventory research (Heurich, 2008). Measuring forest attributes at fine scales is necessary to manage terrestrial resources, in which natural ecological condition could be replicated much closer (Zimble et al., 2003). Moreover, forest information derived in a fine scale can be easily translated into coarser scales depending on the requirement of certain applications. For example, if the tree measurement is too detailed, then it can be aggregated to mean values per stand of hectare (Brandtberg et al., 2003). However, only few studies have focused on individual tree level (Popescu, 2007). The main challenge of this field is result validation for individual trees variable measurements, where detailed field data is required. The field data should be collected at a fine scale, and this introduces positioning problem when dealing with dense tree canopy cover that would interrupt the GPS signal.

In previous studies, most of individual tree variable measurements, for example diameter at breast height (DBH) measurement are based on low density LiDAR data (Heurich, 2008; Hyyppä et al., 2001; Maltamo et al., 2004; Persson et al., 2002; Popescu, 2007; Tomoaki et al., 2005). In this case, it requires a relationship between crown dimension, tree height and DBH to be established. The problem is this relationship might be dependent on tree species and site. In consequence, regression model with low regression coefficient value will introduce error in tree variable estimations. It was shown that direct measurements of tree variables on point clouds are dominated by the ground based scanning LiDAR (Hopkinson et al., 2004; Thies et al., 2004; Watt and Donoghue, 2005). Though the ground based LiDAR capable of delivering detailed measurement of tree variable but this method becomes less effective for large area.

The laser beam of airborne LiDAR with specific settings could penetrate deep inside the forest especially during leaf-off condition (Brandtberg et al., 2003). For example FLI-MAP 400 data that has a capability of scanning in three directions (forward, downward and backward) can deliver massive amount of point clouds over forest area. The high density LiDAR data clearly reveals the structure of individual trees, thus giving better opportunity for more accurate forest variable measurements. It was shown by previous studies (Rahman and Gorte, 2009*a*; Rahman and Gorte, 2008*b*; Reitberger et al., 2007) that high density LiDAR can be used to delineate the whole structure of individual tree which opens to an opportunity of direct measurement of tree variables on the point clouds. However, direct measurement of tree DBH on point clouds is not a straightforward process and it has several challenges as follow:

a. Individual tree crown delineation is not perfect. The individual tree crown delineation still contains errors, in which a single tree segment might contain points from neighbouring trees
b. The lower part of the tree in several cases covered by undergrowth vegetation. The undergrowth vegetation is considered as noise and it should be removed prior to tree DBH measurement.
c. Data density of Airborne is less compared to terrestrial laser scanner, thus suitable method are required in estimating tree DBH.

In this study we introduce a method for individual measurement that consists of 3 processing steps; 1) individual tree crown delineation based on density of high points (DHP), 2) tree filtering, and 3) measurement of tree DBH.

2. Methodology

2.1 Study area

The study site is in forest area of the Duursche Waarden floodplain, the Netherlands (see Figure 1). This floodplain is located along the IJssel River, the smallest tributary of the Rhine River in the Netherlands. The area is partly covered by meadow and arable land and a large part of the areas has become nature.

2.2 LiDAR data

The LiDAR data were captured using a FLI-MAP 400 system. The FLI-MAP 400 is a helicopter mounted LiDAR system designed to capture highly detailed terrain features with high accuracy. It is claimed that the absolute accuracy of FLI-MAP 400 data measured over hard and level surfaces is 2.5 to 3.0 cm. The system is capable of scanning in three directions (forward, downward and backward) and this increases the amount of reflected pulses from the ground even in a quite densely vegetated area. The FLI-MAP 400 data records a maximum of four partial reflections from a single pulse if the distance difference between the reflections is at least 0.9 m.

This enables optimal interpretation of a detailed terrain model even in vegetated areas. The Airborne LiDAR of FLIMAP-400 data with a density of 70 points per meter square were acquired in 2007. The leaf-off LiDAR data allows better penetration through canopy and thus the vertical structure of tree could be more easily revealed. In this study, two different areas are selected (see Figure 1).

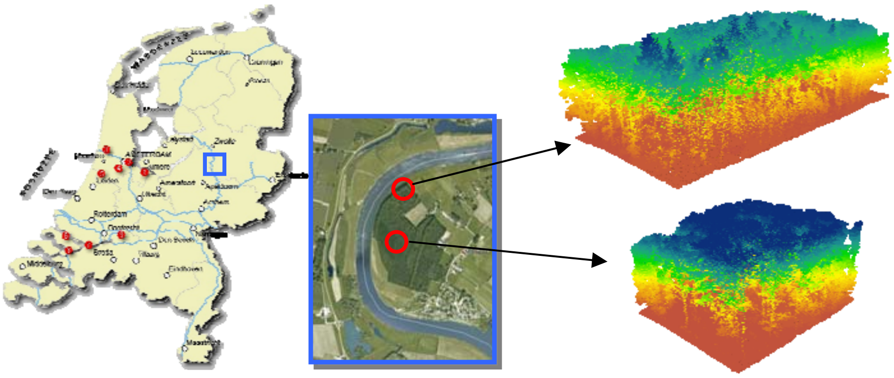

Figure 1: Study area at the Duursche Waarden floodplain, the Netherlands and the LiDAR dataset are taken at two different areas

2.3 Individual tree delineation

Individual tree delineation consists of three main steps, namely 1) extraction of digital terrain model (DTM) and normalization of point clouds, 2) individual tree crown delineation, and 3) tree filtering.

2.3.1 DTM extraction and normalization of point clouds

In order to reduce the effect of undulating terrain, the datasets are normalized based on DTM. In this study, the ground points are collected using an adaptive triangulation irregular network (TIN) model (Axelsson, 2000). The ground points are interpolated using TIN approach. The normalization step is quite important since the tree filtering algorithm needs to define a reference height for further processing (see Figure 3).

2.3.2 Individual tree crown delineation

Individual tree crown delineation is based on the DHP method introduced by Rahman and Gorte (2009a). The main concept of the DHP method is the density of laser pulses from tree branches above a certain reference height is highest at the centre of a tree crown and decreases towards the edge of crown. This is due to the fact that the total volume of tree branches is higher in the centre part of the tree crown and becomes less towards the edge of the crown (see Figure 2). Tree crown delineation on the DHP surface is done using the Inverse Watershed segmentation algorithm. The individual tree crown segmentation based on DHP method produces two types of output, 1) individual tree locations, and 2) individual tree crown segments. The tree location is placed at the centre of the tree with the highest DHP value in each tree segment. The main input required by the delineation algorithm are point buffer, cell size of raster data, minimum and maximum crown radius. The tree crown segments are used to assign the point clouds to their corresponding tree segments. The segmented point clouds and the tree locations are then used as input for tree filtering routine.

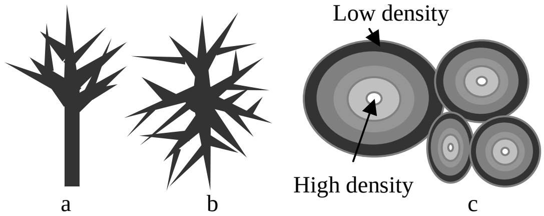

Figure 2: Side view of a tree (a), aerial view of a tree (b) and the distribution of DHP for tree crowns (c)

2.3.3 Tree filtering

In this study, a tree filtering algorithm aims at separating dominant trees and undergrowth vegetation. This algorithm requires three input parameters; 1) maximum growing distance for tree crown, 2) maximum growing distance for tree trunk, and 3) average tree trunk diameter. This algorithm is basically inspired by the fact that a tree would have distinct parts in the histogram that represent tree crown, tree trunk, ground surface, and undergrowth vegetation. It was shown by Straatsma and Middelkoop (2006) that the shape of height distribution of point clouds for a tree during winter season has a high frequency of laser pulses from the crown and the ground surface. However, in the case where the lower part of tree covered by undergrowth vegetation, instead of ground surface, most of the reflected pulses are coming from the undergrowth vegetation. The reflected laser pulse from the trunk has lower frequency. In the tree filtering phase, the point clouds of each tree segment are processed separately. The filtering algorithm can be divided into two main phases; 1) region growing (RG) segmentation of tree crown, and 2) RG segmentation of tree trunk.

The whole LiDAR dataset is segmented according to tree crown segments and each tree is attached with a single seed point obtained from the individual tree crown segmentation step (see part 2.3.2). The results are referred here as tree segments. Histogram of vertical distribution of point cloud is created for each tree segment and the reference height is defined based on the shape of the histogram (refer Figure 3). In order to define the reference height, the histogram is filtered with a one-dimensional (1D) Gaussian filter to produce a smoother histogram. The first part of the filtered histogram is fitted with a Gaussian function and the reference height is defined as a value of 3-sigma from the mean value. The RG segmentation of tree crown starts from the seed point until the reference level. It should be noted that the individual tree crown delineation is not perfect and individual tree segment might contain points from tree crown of neighbouring trees. Further step is introduced to remove these points from the tree of interest. The DHP approach has a potential to constraint the RG segmentation of tree crown from spreading to the tree crown points of neighbouring trees. The whole concept of RG segmentation in this research is illustrated in Figure 4. According to the DHP approach the growing distance value for points of tree crown are assigned based on their density, in which points close to the crown centre have higher growing distance than points at the edge of the crown. The normalized point density (from 0.0 to 1.0) is linearly converted to growing distance and in this case we need to define the minimum (the minimum is set 0.1 meter) and the maximum growing distance. The seed points for RG segmentation of tree trunk are selected from the points of tree crown located near to the reference height.

RG segmentation of tree trunk starts from the reference level until the ground surface. The segmentation is done based on constant value of growing distance and this process is repeated from 0.1 meter to maximum growing distance of tree trunk. The main reason behind this strategy is to collect as much as possible points for tree trunk which referred here as candidate points of tree trunk. As more points are selected as candidate points a histogram is created to represent its vertical distribution and the 1D Gaussian filter is used to produce smoother histogram surface. The candidate points are assigned to tree trunk if only they meet two conditions; 1) they frequency of the candidate points should be at least similar to the average frequency of tree trunk and, 2) average distance of each candidate points should be at least similar to the pre-specified average tree trunk diameter. At each height, number of points added to tree trunk is evaluated. In the case of no points are added to tree trunk the RG segmentation of tree trunk will stop and the RG segmentation of tree crown is done all over again with different growing distance values (minimum and maximum growing distances). This continues until the segmentation of tree trunk reaches the ground surface.

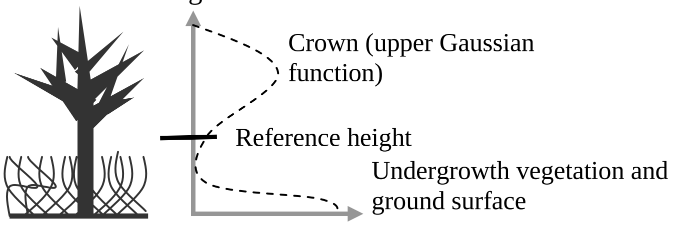

Figure 3: Reference height

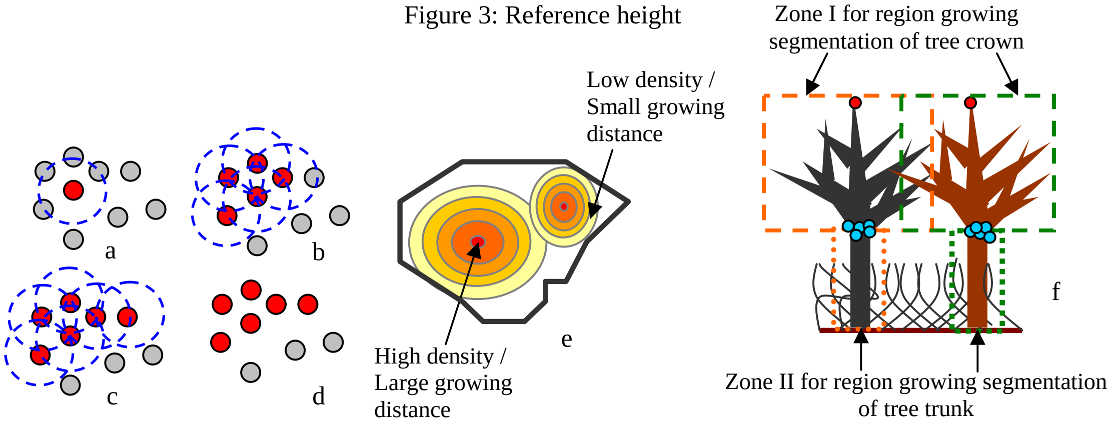

Figure 4: RG segmentation steps of tree crown and trunk (*a*, *b*, *c* and *d*). The growing process starts with a seed point (*a*), and points within a specified growing distance are used as seed points for the next growing process (*b* and *c*). The growing stops when there is no other point within the growing distance of all seed points (*d*). For zone I (*f*) the RG process starts from a seed point (red point) and the growing is based on the based on DHP concept where each point has a unique growing distance depending on its density (*e*). Instead on that, for zone II (*f*) the RG segmentation of tree trunk is starts from the seeds points (blue points) based on a fixed growing distance.

Finally, for the condition where the RG segmentation of tree trunk fails to reach the ground surface, additional points for tree trunk are collected based on a vertical line fitted on tree trunk points. Candidate points are selected based their distance to this line and their frequency. The distance and frequency should be at least similar to the growing distance and average frequency of tree trunk respectively. The line is stretched until it reaches the ground surface. Detailed explanation on the tree delineation method can be found in Rahman and Gorte (2008b)

2.4 Method for DBH measurement on point clouds

The DBH measurement on point clouds basically similar to method of Bucksch et al.(2009) which was based on two steps; 1) skeletonization of single trees with a modified method of Bucksch and Lindenbergh (2007), and 2) histogram analysis of the point distances to the skeleton. However instead of creating a tree skeleton the points belong to tree trunk are fitted with a 3D line. In this study, the tree DBH measurement is carried out based on three steps; 1) removing noise from tree trunk, 2) fit a 3D line on the filtered points and, 3) histogram analysis for tree DBH estimation.

2.4.1 Removing noise from tree trunk

Point clouds of tree trunk still contain points considered as “noise” which were mainly reflected by tree branches. The noise is removed based on histogram of distance between the points to a 3D line created using Random Sample Consensus (RANSAC) algorithm. RANSAC is an iterative method to estimate parameters of a mathematical model from a set of observed data which contains outliers (Foley, 1981). At first, the histogram represents the distances is filtered with a 1D Gaussian filter to produce smoother histogram. The noises are then removed by ignoring points with distance more than the specified distance. The threshold distance is defined based on method in Figure 4 (a), where the left-side of the histogram represents points belong to tree trunk while the right-side represents reflected pulses from tree branches.

2.4.2 Fitting a 3D line and tree DBH estimation on point clouds

In this step, the filtered points are fitted with a least-square 3D line fitting approach. This is crucial to ensure that the 3D line is nicely fitted to the tree trunk with less interference from noise. The distances between the original points and the 3D line are calculated and the frequency of each distance is represented by a histogram. The histogram is filtered with a 1D Gaussian filter and finally the tree trunk radius is estimated based at 4 different location of the histogram (see Figure 5(b)). In this study, the tree DBH is estimated by two times tree trunk radius and the DBH is estimated at four different points; 1) at the beginning of the first Gaussian shape of the histogram which marks the underestimation of tree DBH (DBH1), 2) peak of the first Gaussian shape (DBH2), 3) end of the first Gaussian shape that represents the overestimation (DBH3), and 4) the average of DBH1 and DBH3 (DBH4).

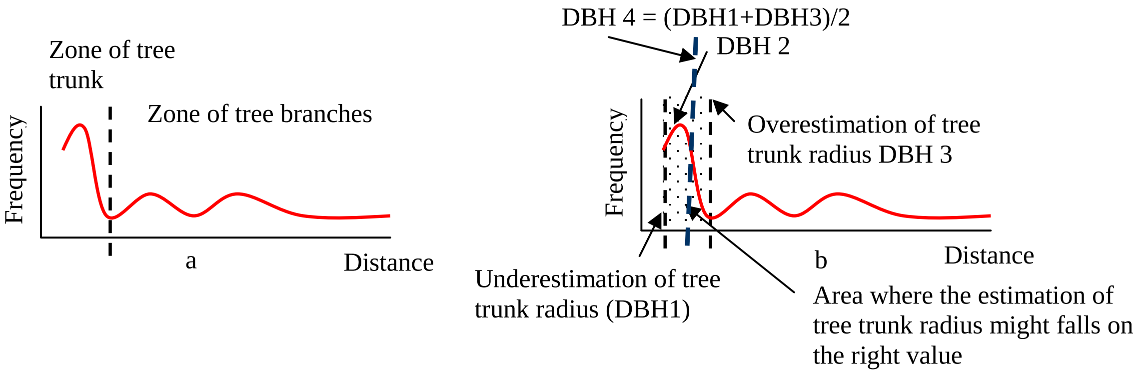

Figure 5: Histogram of distance between points to 3D line created based on RANSAC (*a*) which is only points at the zone of tree trunk are used to fit the next 3D line (based on least-square), and histogram for distance between points to 3D line created based on least-square (*b*)

3. Results and discussion

3.1 Tree crown delineation

The individual tree crown delineation has successfully identified 76 trees and 38 trees in dataset 1 and dataset 2 respectively (see Figures 6(a) and 6(b)). The fieldwork has been done only at the area of dataset 1. It was found that the tree crown delineation process somehow has only identified 72 trees from the total 114 trees in the study area (63 % accuracy), with 4 % of commission error, and 36 % omission error. This area contains quite significant number of young trees with DBH less than 0.2 meter and less. In most cases, these young trees are omitted during the tree crown delineation process. Table 1 shows the parameters used in the individual tree crown delineation process. The corresponding tree segments are shown in Figures 6(c) and 6(d). However, it is observed that for a single tree segment it still contains points especially from the neighbouring trees.

Table 1: Parameters used in individual tree crown delineation based on DHP

Dataset	Point buffer (m)	Cell size (m)	Minimum crown radius (m)	Maximum crown radius (m)
1	2.0	0.3	1.2	5.5
2	2.0	0.3	1.5	4.5

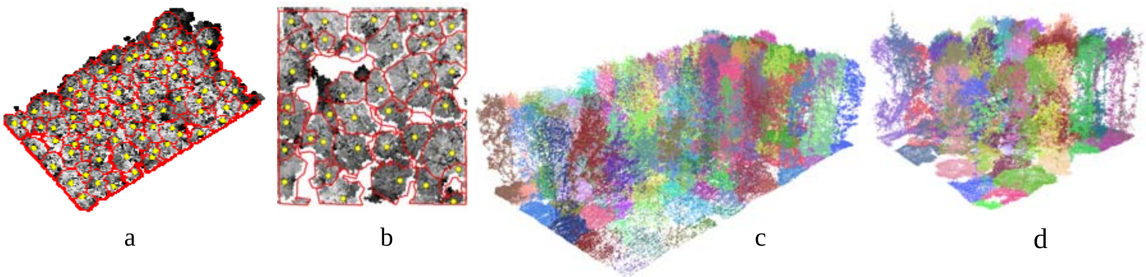

Figure 6: Individual tree crown segments (*a* and *b*), and individual tree segments (*c* and *d*)

3.2 Tree filtering

In the tree filtering step, the maximum growing distances of tree crown and tree trunk are set to 2.0 meter. The average tree trunk diameter is set to 1.5 meter for all trees. The tree filtering algorithm has successfully filtered about 63% and 71% from the total trees found in dataset 1 and dataset 2 respectively (see Figure 7). It is observed that, the filtering algorithm needs at least a small space of tree trunk, especially in the area just below the tree crown. This space allows precise points for tree trunk to be collected until the filtering routine reaches the ground surface (see Figure 4). On the other hand, the crown of dominant tree should be distinguishable from the undergrowth vegetation, or otherwise the RG for tree crown would not be able to filter out the points of undergrowth vegetation. Due to forest interception on LiDAR signal, there are situations where the LiDAR data failed to reflect a complete structure of a dominant tree and undergrowth vegetation and this has raised another problem to the filtering algorithm. The filtering method still needs to be optimized in order to select proper values for the required parameters automatically or semi-automatically.

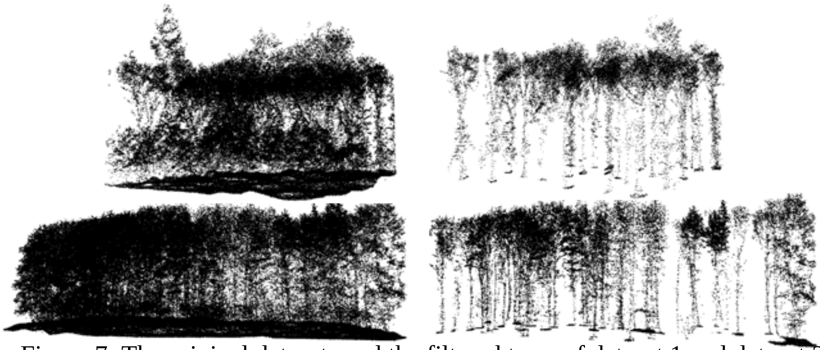

Figure 7: The original datasets and the filtered trees of dataset 1 and dataset 2

3.3 Results for DBH measurement of dominant trees

The 3D line is fitted nicely on the tree trunk points (see Appendix B), though the field tree DBHs were measured at 1.3 meter from the bottom of tree, the measurements of DBH on point cloud requires all point clouds until 8.0 meter. This is necessary since very less points available at 1.3 meter and more points are required to get the best fitting of 3D line along the tree trunk. The resultant tree DBH estimations are compared to the DBH measurements of 36 trees in the field. It is shown (see Appendix A) that the field measured DBHs still fall between the underestimation (DBH1) and overestimation (DBH3) of tree DBH measurements. Besides, in most cases the field measured DBHs agree with the DBH estimation obtained at the peak of the first Gaussian shape in the histogram (DBH2) with the root mean squared error (RMSE) of 0.18 meter and correlation of 0.41 (see Table 2).

Table 2: Root mean squared error and correlation between field measured DBH and estimated DBHs

DBH	RMSE	Correlation
DBH 1	0.33	-0.08
DBH 2	0.18	0.41
DBH 3	0.92	0.11
DBH 4	0.43	0.16

4.0 Conclusion and outlook

It is shown that high density Airborne LiDAR acquired during winter season capable of delivering detailed measurement of forest variable, for instance DBH. The measurement is done directly on the point cloud thus reducing chances of error produces by a conventional method of forest mensuration based on regression models. The DBH estimations directly on point cloud show quite promising results. However future works are still required to reduce processing time by further optimize the tree filtering method using widely available optimization approaches. Furthermore the applicability of this method on different LiDAR data quality, for instance point density needs to be investigated further.

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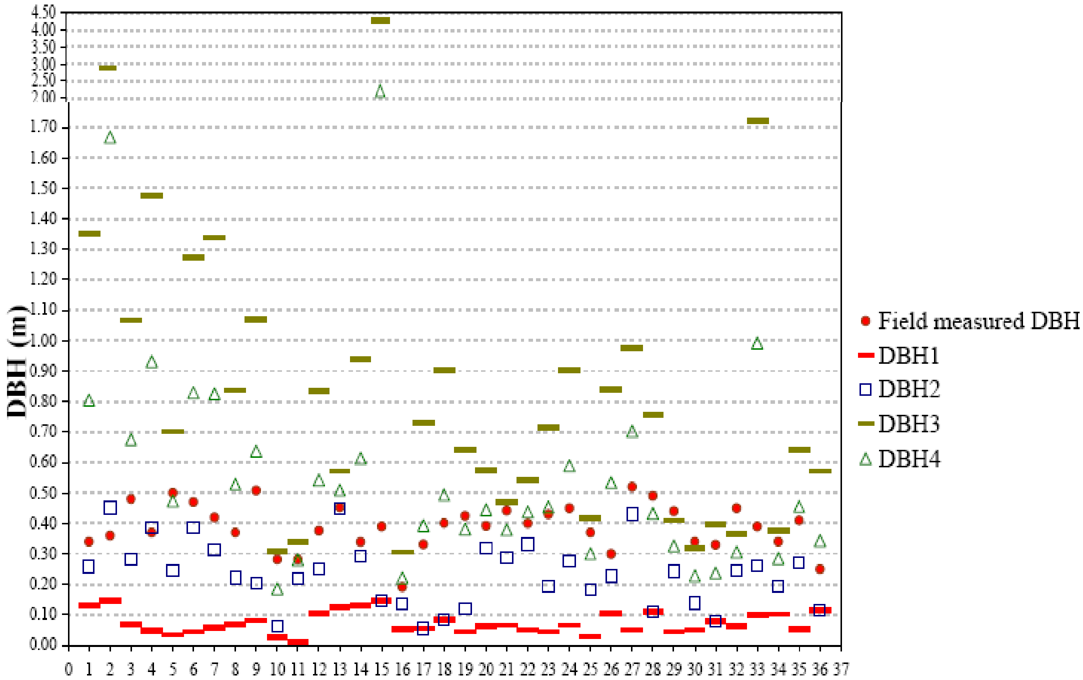
Appendix A: DBH 1, DBH 2, DBH 3, DBH 4, and field measured DBH



Appendix B: Example of 3D line fitted on point of tree trunk from tree bottom until 8.0 meter height