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February, 2015

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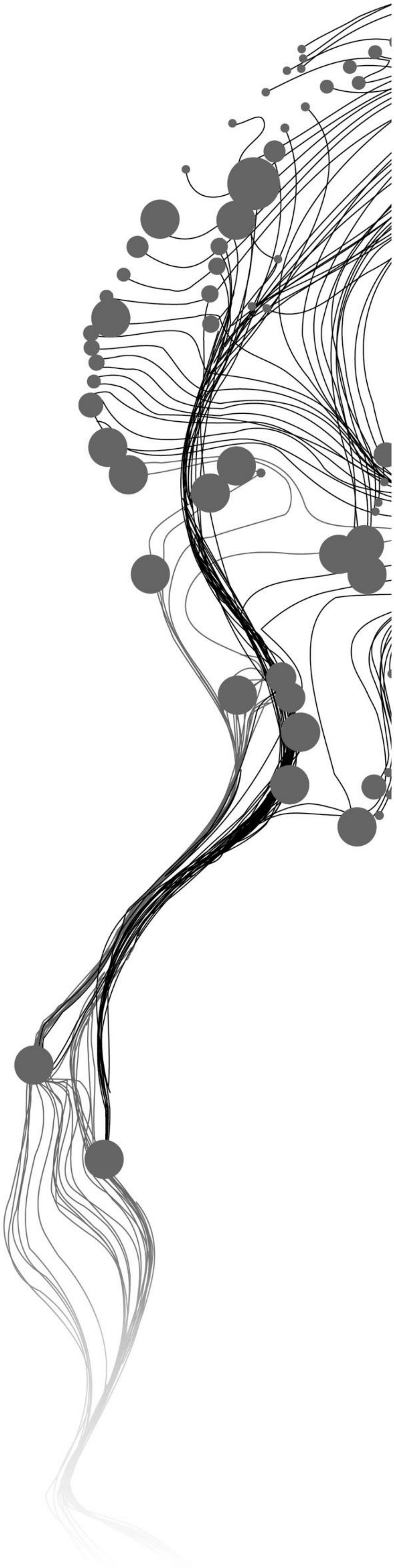

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Zemeron Mehari Ghebremichael

Enschede, The Netherlands, February, 2016

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
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ABSTRACT

Tropical rain forests are one of the main terrestrial ecosystems that are playing an important role in the mitigation of global climate change through carbon sequestration. In recent years the application of airborne LiDAR (Light Detection and Ranging) and Terrestrial Laser Scanner (TLS) has been increasing in the measurement and extraction of forest biophysical parameters and characteristics and, estimation of aboveground biomass (AGB) and carbon stock. so far few studies have been done on the use of Terrestrial Laser Scanner (TLS) in a tropical rain forest ecosystem. Thus the main objective of this study is to assess how the Terrestrial Laser Scanner and airborne LiDAR perform in tropical rain forest in the estimation of aboveground biomass and carbon stock.

A Canopy Height Model (CHM) was generated from the airborne LiDAR data by subtracting Digital Terrain Model (DTM) from the Digital Surface Model (DSM). Using a multi-resolution segmentation the CHM of airborne LiDAR was segmented. Manual delineation of the upper tree crowns and segmentation accuracy assessment of was done by the measure of D "measure of goodness of fit" approach and an accuracy of 68.6% was obtained.

Using Terrestrial Laser Scanner (TLS) point cloud data was collected through multiple scan positions. After registration of the point cloud data (with error of 0.016m) out of 779 trees 627 trees (80.5%) were extracted and 152 trees (19.5%) were missed. Tree parameters, Diameter at Breast Height (DBH) and Height were derived from the extracted tree and a correlation analysis was done with the corresponding field measured parameters and also with the height derived from airborne LiDAR.

The coefficient of determination (R^2) for the field measured DBH and TLS derived DBH was 0.98. field measured height and TLS derived height was 0.70, which is a reasonably good relationship especially in the case of DBH measurement. Also the relationships between the heights derived from the airborne LiDAR and heights from the field and TLS were calculated with R^2 of 0.65 and 0.87 respectively however, a regression analyses was done between the delineated Canopy Project Area (CPA) of the delineated trees and with field measured DBH the result of the R^2 was 0.3 which shows a poor relationship between these parameters.

Thus, in this study the Terrestrial Laser Scanner (TLS) was able to estimate DBH and height in a reasonable accuracy in a tropical rain forest. However, in the case of height there was a slight underestimation due to occlusions of the overlaying tree canopies. Airborne LiDAR was able to measure the tree heights only of the upper canopy layers with good accurately, but the lower layers could not be detected. Generally this study reveals that Terrestrial Laser Scanner and airborne LiDAR are very promising in the estimation of above ground biomass and carbon stock in tropical rainforest ecosystems.

Keywords: Terrestrial Laser Scanner (TLS), Air borne LiDAR (ALS), multiple scans, Point cloud Data, Canopy Height Model (CHM), Segmentation, Canopy Project Area (CPA), DBH, Allometric equation, Aboveground Biomass (AGB)

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Zemeron Mehari Ghebremichael

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February, 2015

Dedicated to my grandfather Abrha Abay Desu and my grandmother
Mihret Weldeghebriel Ghebresilasie
"The ultimate source of inspiration"

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF EQUATIONS

LIST OF APPENDIXES

1. INTRODUCTION

1.1. Background

Global climate change is mainly caused by the increase of greenhouse gases (GHGs) specifically the emission of carbon dioxide (CO_2) in the atmosphere. Terrestrial forest ecosystems are playing a crucial role in the sequestration and storage of carbon(Gibbs et al., 2007). Carbon which is stored in the forest can be released in to the atmosphere in the form of CO_2. In tropical forests deforestation and forest degradation is the main source of CO^2 emissions after burning of fossil fuels (Zhang et al., 2003). According Malhi et al., (2000) tropical forest comprises approximately 50% of the total global forest area. Annually about 1- 2 billion tons of carbon was released from tropical deforestation in the 1990s, which is about 15-25% of the annual global Greenhouse Gases (GHGs) emission. (Malhi & Grace, 2000; Fearnside, 2000) .

The United Nations Frame work Convention on Climate Change (UNFCCC) was established in 1992 to reduce the emission of greenhouse gases (GHGs). On December 1997 the United Nations adopted the Kyoto protocol (KP) in Japan, and set a target to reduce the greenhouse emissions by 5% of the level of 1990 in the period of 2008 to 2012. Moreover, it set binding quantitative obligations to all parties to meet the target of emission reduction (UNFCCC, 1998). According to this protocol countries are obliged to report regularly on the amount of carbon emitted and sequestered from their forest areas on national level using more effective and feasible mechanisms and methods(Gupta et al., 2003). In 2012 an amendment was made to the Kyoto protocol in Doha, Qatar. Accordingly, parties committed to reduce the level of greenhouse gases (GHGs) emission by 18% below the 1990 levels, in the period from 2013 to 2020 (GOV.UK, 2015).

The Bali action plan, which was adopted in the year of 2007, came with the impressive idea to support and give financial incentives to the developing countries to stimulate in the reduction of carbon emission from deforestation and forest degradation so called REDD(UN-REDD, 2008; REDD+ Cookbook, (2012).

After the fifteenth conference of the parties in the year 2009, the "REDD" was expanded in to "REDD-plus"/REDD-plus (kanninen et al., 2009). The REDD –plus comprised a mechanisms for conservation, sustainable management of forest and enhancement of the carbon stock of forests. Developing countries are expected to estimate their forest carbon stock. Therefore if there is an increase in the carbon stock they can expect a financial incentives or carbon credits from REDD (Dhital, 2009).

Above ground biomass (AGB) refers to the total amount of biomass above the ground. Approximately about 47-50% of the total biomass of forest is assumed to be carbon stock (Malhi & Grace, 2000). The best approach of estimating of woody forest biomass is by measuring the biophysical parameters of the tree such as height, diameter at breast height (DBH), tree volume and wood density and calculating the biomass using algometric equations.

Remote sensing technology plays an important role in forest's carbon stock estimation; forest monitoring and can play a vital role in forest biomass estimation and forest management (Nilsson, 1994). According to Gibbs, (2007) the different approaches and methods of remote sensing for the estimation of above ground carbon stock resulted with different uncertainties from high to medium and low. Basically this depends on the type of remotely sensed data and optical remote sensors. He explains that a combination of remotely sensed data with the ground measurements can result in a relatively high accuracy of carbon stock estimation. Light Detecting and Ranging (LiDAR) is one of the remote sensing techniques that has a good potential and capability in the forest carbon stock estimation as it can provide 3D perspective of the forest structures and accurate measurement of the tree parameters, specially height (Montaghi et al., 2013; Patenaude et al., 2004).

1.2. Problem statement and justification

Accurate estimation of forest carbon stock in a sustainably managed forest ecosystem in the countries committed to the REDD + is one of the main concerns of REDD-plus programs before the financial incentives are issued (REDD+Cookbook1, 2012). The UNFCCC emphasized the necessity of measuring, reporting and verification (MRV) of forest carbon stock, and in COP15 it adopted a scientific approach with the application of remote sensing data and field data(UN-REDD,2008; REDD+Cookbook1, 2012; Vaglio Laurin et al., 2014).
Although different approaches and methods for estimation of the carbon stock in the tropical forest are used or applied (Gibbs et al., 2007). it still remains a challenge to find the most feasible and accurate method of estimating forest biomass in tropical rain forests (Steininger, 2010) According to Lu, (2006), Luther et al., (2006), and Lu et al., (2012) different optical remote sensing data with different spatial resolution ,have been used in estimation of biomass. However their studies reveal that optical remote sensing data are unable to extract the forest parameters and forest structures directly (Lu et al., 2014). Also Lu, (2006) mentioned that the cloud and atmospheric conditions in most areas and especially in the tropical forests limits the acquisition of good data from optical sensors. Second problem of optical remote sensing especial in tropical rain forests, where there is high biomass density and complex structures, is data saturation (He et al., 2013; Lu, 2006).
Airborne LiDAR data has been used to estimate the above ground biomass of different geographical and ecological forest systems (Lovell et al., 2003; García et al., 2010; Hilker et al., 2010). Unlike the optical remote sensing systems, LiDAR has a capability of detecting the individual trees and provide three dimensional (3D) measurement (vertical and horizontal) of the essential - forest structures (Lovell et al., 2003; St-Onge et al., 2008). Tree canopy can be extracted from airborne LiDAR which is also considered as an advantage over satellite and aerial images as it is based on height information. Tree height is an important parameter in estimation of aboveground biomass and carbon stock. However, in tropical forest tree height measurement in the field is not easy due to dense understories, tall canopies and overlapping canopies (Hunter, et al., 2013). Airborne LiDAR (ALS) which has higher accuracy could be a solution (Hilker et al., 2010). However, it is not known how it will perform for canopy areas, especially in tropical forest. solve this problem of height.(O'Beirne, 2012; Sexton, et al., 2009; C. Wang, etal., 2008).

Terrestrial laser scanner (TLS), relatively a new technology, has been used to extract the forest parameters with high accuracy though observations from the ground. This technology has a potential to replace the traditional time consuming and costly way of collecting forest inventory parameters(Hopkinson et al., 2004). However, most of the previous studies which have been conducted with this instrument were in the temperate forests and wood lands (Hopkinson et al., 2004; Watt et al., 2005; García et al., 2010) it is still unknown how this instrument will perform in the tropical forest with its complex structure and intermingling crowns.
Therefore, this study is aims to assess how airborne LiDAR and Terrestrial Laser scanner will perform in in assessing AGB in the tropical rain forest ecosystem.

1.3. Research Objectives

General Objective

The general objective of this research is to assess the performance of Airborne LiDAR and Terrestrial laser scanner for the assessment of above ground biomass/carbon stocks in Tropical Rain Forest Reserve of Ayer Hitam, Malaysia.

Specific objective

1. To assess the relationship between height and DBH derived from TLS and the manually measured height and DBH in the field.
2. To assess the relationship between heights derived from LiDAR with TLS measured height.
3. To assess the relationship between heights derived from LiDAR with field measured height.
4. To assess the accuracy of detecting and measuring individual tree crowns based on airborne LiDAR in Tropical rain forest.
5. To assess accuracy of airborne LiDAR for estimating DBH, as compared to field measured DBH.
6. To estimate aboveground biomass/carbon stock using TLS and LiDAR derived parameters.

Research Questions

1. Is there a significant difference between Heights derived from TLS with the manually field measured height?
2. Is there a significant difference between DBH derived from TLS with the manually field measured DBH?
3. Is there a significant difference between height derived from Airborne LiDAR and TLS derived height?
4. Is there a significant difference between height derived from Airborne LiDAR and field measured height?
5. How accurately can tree crowns of a tropical rain forest be identified and measured from airborne LiDAR data?
6. How accurately can DBH be estimated from airborne LiDAR?
7. Is there a significant difference between the aboveground biomass/carbon stock estimated from TLS and airborne LiDAR?

Research Hypotheses

1. Ho: There is no significant difference between Heights derived from TLS with the manually field measured height.
Ha: There is significant difference between Height derived from TLS with the manually field measured height.

2. Ho: There is no significant difference between DBH derived from TLS with the manually field measured DBH.
Ha: There is significant difference between DBH derived from TLS with the manually field measured DBH.

3. Ho: There is no significant difference between Heights derived from Airborne LiDAR and TLS derived heights.
Ha: There is a significant difference between Heights derived from Airborne LiDAR and TLS derived from TLS.

4. Ho: There is no significant difference between Height derived from Airborne LiDAR and field measured height.
Ha: There is significant difference between Height derived from Airborne LiDAR and field measured height.

5. Ho: The CPA derived from Airborne LiDAR of a tropical rain forest cannot be segmented with an accuracy of >70%
Ha: The CPA derived from a tropical rain forest can be segmented with an accuracy of > 70%.

6. Ho: There is no significant difference between DBH measured in field and DBH estimated from airborne LiDAR.
Ha: There is significant difference between DBH measured in field and DBH estimated from airborne LiDAR.

2. LITERATURE REVIEW

2.1. Concepts and Definitions

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This section includes on the working principle of the airborne LiDAR and the terrestrial Laser Scanner (TL) in the field of forestry and the extraction of tree parameters. Moreover, estimation of aboveground biomass and the use of the allometric equation with its main parameters for the assessment of carbon stock are addressed.

2.1.1. Biomass and Carbon

Biomass refers to the mass of living or dead biological material in a unit area (Janetos et al., 2009). According Gschwantner et al., (2009) tree biomass can broadly be categorized as aboveground biomass(AGB) which includes the stem, branches , leaves , bark, foliage and seeds; and below ground biomass which is mainly the root below the ground (Figure1). Estimation of above ground biomass is very important as it affects the different climate variables and plays a crucial role in the climate changes (Janetos et al., 2009). Out of the total biomass approximately 50 % is estimated to be carbon.

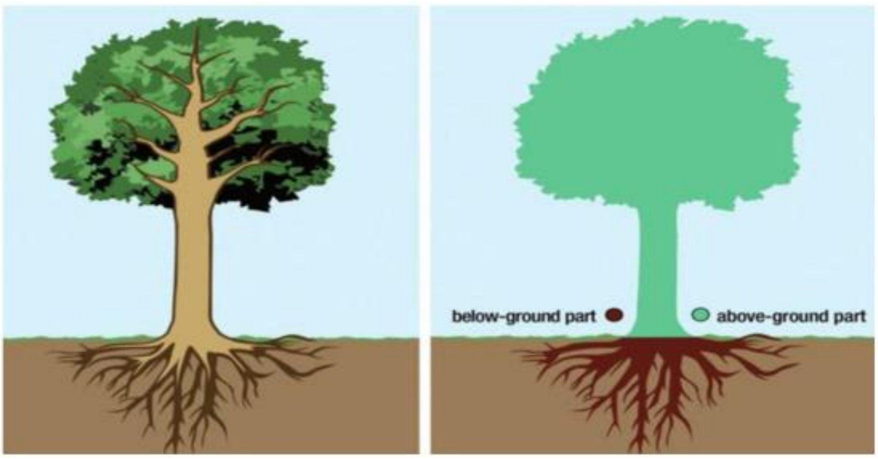


Figure 1: Above ground and below ground biomass

2.1.2. Allometric Equations

Allometric equations are equations which are developed by the relationships of the biophysical parameters of a tree to accurately estimate above ground biomass(AGB) (Beets et al., 2012; Picard, 2012; Ketterings et al., 2001). They are the common and widely approach and method of estimating above-ground biomass in which diameter at Breast height (DBH) and height of a tree are the main input parameters (Ketterings et al., 2001). Allometric equations are expressed as a function of diameter at breast height (DBH), height and wood density (equation 1). Allometric could be generic equation or local one. In the former it can be applicable in many areas where the forests are the same type. While the second it is used to only forests within the same land scape or species. However in forest ecosystems like the tropical rain forests it is difficult to use species-specific allometric equations `as the numbers of species per unit may be as many as 300 many species. Therefore to solve this IPCC adopted a generic equation based on the ecological and forest types of different regions (Chave et al., 2005; Aalde et al., 2006).

Biomass = [V×WD] ……………………………………………….. Equation 1

Where V is volume stand volume (m^3) and WD wood density (kg/m^3)

2.2. Overview of Above ground biomass estimation methods and remote sensing techniques

Considering the forest ecosystem as the main carbon sink through sequestration and carbon source due to deforestation and degradation in the terrestrial biosphere, it is very important to measure the changes in carbon stock and flux of these forest ecosystems (Gibbs et al., 2007; Zhang et al., 2003).
Among the different methods and approaches for estimating of above ground biomass the destructive (harvesting) method is most accurate as it weights the dried carbon stock (Woods and Hole, 2001). However this method is very destructive and time consuming and is generally applied in a very small area.
Over the past years a number of studies using different remote sensing techniques in estimation of carbon stock have been done (DeFries et al., 2007; Drake et al., 2013; Lu, 2006) however the issue of accurately estimation of aboveground carbon stock is still there. In a structurally complex ecosystem of tropical forests, the saturation of the signals (eg. In Synthetic aperture radar) tends to saturate approximately at 50 – 100 t C/ha; which affects the accuracy of the carbon stock estimation (Gibbs et al., 2007). Lu et al., (2012); and Foody et al., (2003) also explains that the statistical relationship of the optical satellites data's and the ground measurements underestimate the aboveground biomass. This was due to incapability and limitation of the optical sensors in dense canopy structures.
LiDAR (Light Detecting and Ranging), an active, sensor unlike the optical sensors has an advantage of the detecting the tree parameters in 3D which improves the accuracy of biomass estimation(Drake et al., 2003). Hilker et al., (2010) worked on comparing canopy metrics derived from airborne laser scanning (ALS) and TLS in a Douglas-fir dominated forest stand. Accordingly both (ALS) and TLS were able to determine the height with change of height<2.5m. Moreover he recommended that multiple TLS scanning could improve estimation of below canopy carbon stock. In a multiple- scan position a tree is scanned from different direction and can be represented in 3D. Antonarakis, (2011) evaluated the forest biometric measurements obtained from TLS in the Riparian forest, and he noted that the diameter at breast height (DBH) derived from TLS were almost similar to field measured parameters (with a mean biases of 0.3-0.4cm). However for the tree heights due to the limitation of the scan to detect the top edges of the trees the mean bias was around 2m. As it is previously explained, measurement of tree height parameter is important for estimation of aboveground biomass and is an input for the allometric equation.

2.3. Overview of Laser Scanning

LiDAR is a comparatively recent active remote sensing technology (Patenaude et al., 2004) which uses laser light pulses to detect target objects or features (Jamie et al., 2012). This emerging technology has the ability of measuring accurately the three- dimensional forest structures and is contributing much to the forest carbon stock estimation. The height or distance of a target object is obtained by taking half of the time elapsed for the laser pulse from the sensor and back to the sensor and multiplying by the speed of light (Lefsky et al., 2002). LiDAR sensors work in the near infrared of the electromagnetic spectrum ranging from 900nm to 1064nm, where there is high reflectance of vegetation. LiDAR can be categorized discrete – return and waveform based on the type or form of returning pulse signals (Figure2). The former measures either one (single-return system) or a number (multiple-return system), usually 1- 5, of heights from the return signals with peak returns. Whereas the waveform recording device records the complete waveform of the returning pulses and produce multiple returns between the first and last returns. Hence its main application is designed particularly for vegetation studies (Lefsky et al., 2002; Mallet and Bretar, 2009).

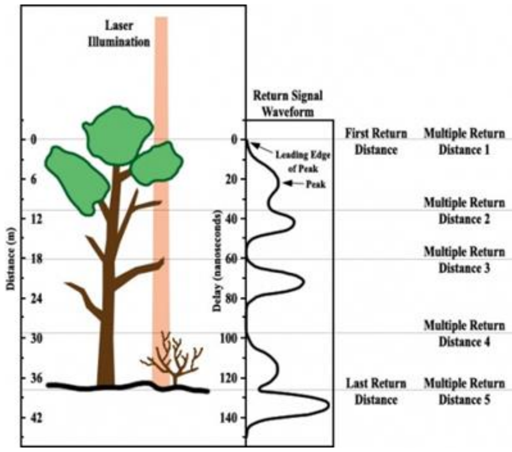


Figure 2: Illustration of the conceptual difference between discrete-return and waveform recording devices

2.4. Overview of Terrestrial laser Scanner

Terrestrial laser scanners are a ground based laser scanning instruments which enables a rapid collection of forest inventory measurement parameters and precise three dimensional (3D) point clouds data composed of millions of points which represent the surface of a scanned tree (Dassot et al., 2011).The device is mounted on a tripod and takes a hemispherical scanning by rotating a complete horizontal rotation and the rotating mirror scanning in the vertical plane (Figure3) (Dassot et al., 2011). In some terrestrial laser scanners a digital single-lens reflex cameras (DSLR) is mounted on top. This camera provides colored images which helps to display the point cloud data in RGB colors (RIEGL, 2014). A mid-range terrestrial laser scanner can measure a range from 2m to 800m (Kankare et al., 2013)

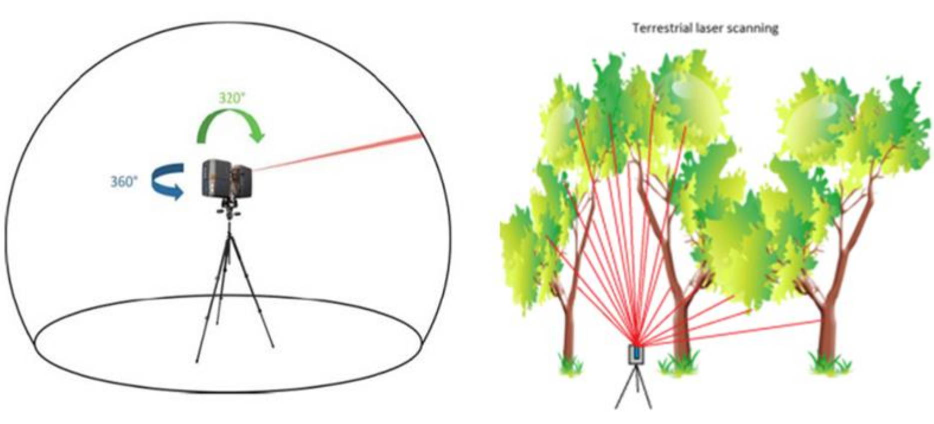


Figure 3: Working principles of TLS(source: Dassot et al., 2011)

In Terrestrial Laser scanners (TLS) two methods or mechanisms of scanning can be applied: single scanning or multiple scanning. In a single scanning method the scanner is placed in a single place as a result only one dimension or side of the tree or an object can be scanned, however in multi scanning method the scanning can be done from different positions (3 or 4) positions (Figure4). Hence, this method gives a chance for a single tree to be scanned in all directions (Dassot et al., 2011).

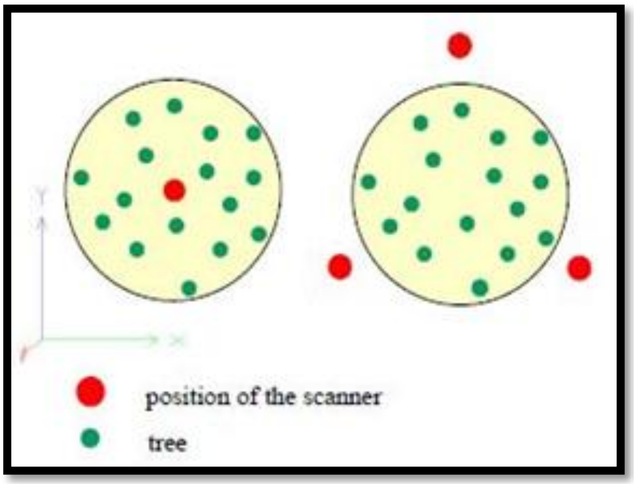


Figure 4: Single and multiple scanning method

Source: (Bienert et al., 2006)

In this study Riegl VZ-400, was the type of the terrestrial laser scanner that is used (Figure4). This scanner records a multiple returns (up to four per emitted pulse) (Calders et al., 2013) and has a high accuracy capability and measuring a long range measurements more up to 600m.This accuracy is based on RIEGL,s exceptional full wave and the online processing. Moreover the camera on this type of scanner which can be fixed on the top of the instrument enabled the instrument to acquire images in RGB (RIEGL, 2014). The photos of the camera enables for coloring the point cloud data and result photorealistic 3D data. Some of the basic specification of the RIEGL VZ-400 terrestrial laser scanner is mentioned in Table 1.

Table 1 Specification of RIEGL VZ- 400 Terrestrial Scanner

Description	**Terrestrial Laser scanner Type**
	Riegl VZ-400
Max. Range	600
Scan Angle (vertical and horizontal)	Vertical(+60°/-40°)=100° and Horizontal 360°
Accuracy(mm)	5
Beam divergence (mrad)	0.3
Min. range	1.5
Wave type/ wavelength(nm)	Near-infrared(1,550)
Weight(kg)	9.6

3. STUDY AREA, MATERIALS AND METHODS

3.1. Study Area

The study was carried out in Malaysia in the state of Selangor in the tropical rain forest of Ayer Hitam Forest Reserve (AHFR) with a geographical location between 2° 56' to 3°16' north latitude, and 101°30' to 101°46' eastern longitude (Figure 5). The topography of the forest area is undulating between 15 to 157m above mean see level. It is about 20km from University of Putra Malaysia(UPM) and 45 km from city of Kuala Lumpur(I et al., 2008). It has an area of about 1248 hectares. Initially the total area was about 3500 hectares, however due to socioeconomic developments, infrastructures, oil palm plantation, housing projects and other developments it has lost its area. As a consequent of this many animal species including large mammals have disappeared or reduced in number (Ehsan, 1999).

3.1.1. Climate

The climate of the study area is a tropical monsoon climate with annual rain fall of 2178mm, maximum and minimum temperature of 27.7°C and 22.9°C respectively and a relative humidity (77.4%-97.8%) (Ehsan, 1999) The area is 202.5 above sea level with a maximum elevation of 233m (I et al., 2008).

3.1.2. Vegetation

This tropical rain forest of the study area is classified as a rich lowland *Dipterocap* forest of *Kempas – kedondong*. This forest area is a secondary forest as it has been logged in 1930s (Ainuddi, 1999). According Hanum et al., (1999) and Ehsan, (1999), about 430 different plant species, out of these 177 are tree species, have been identified. The dominant tree species are *Dipterocarpaceae*. More over from field observation there are also considerable under growing palm trees and climbers (Liana) in the study area.

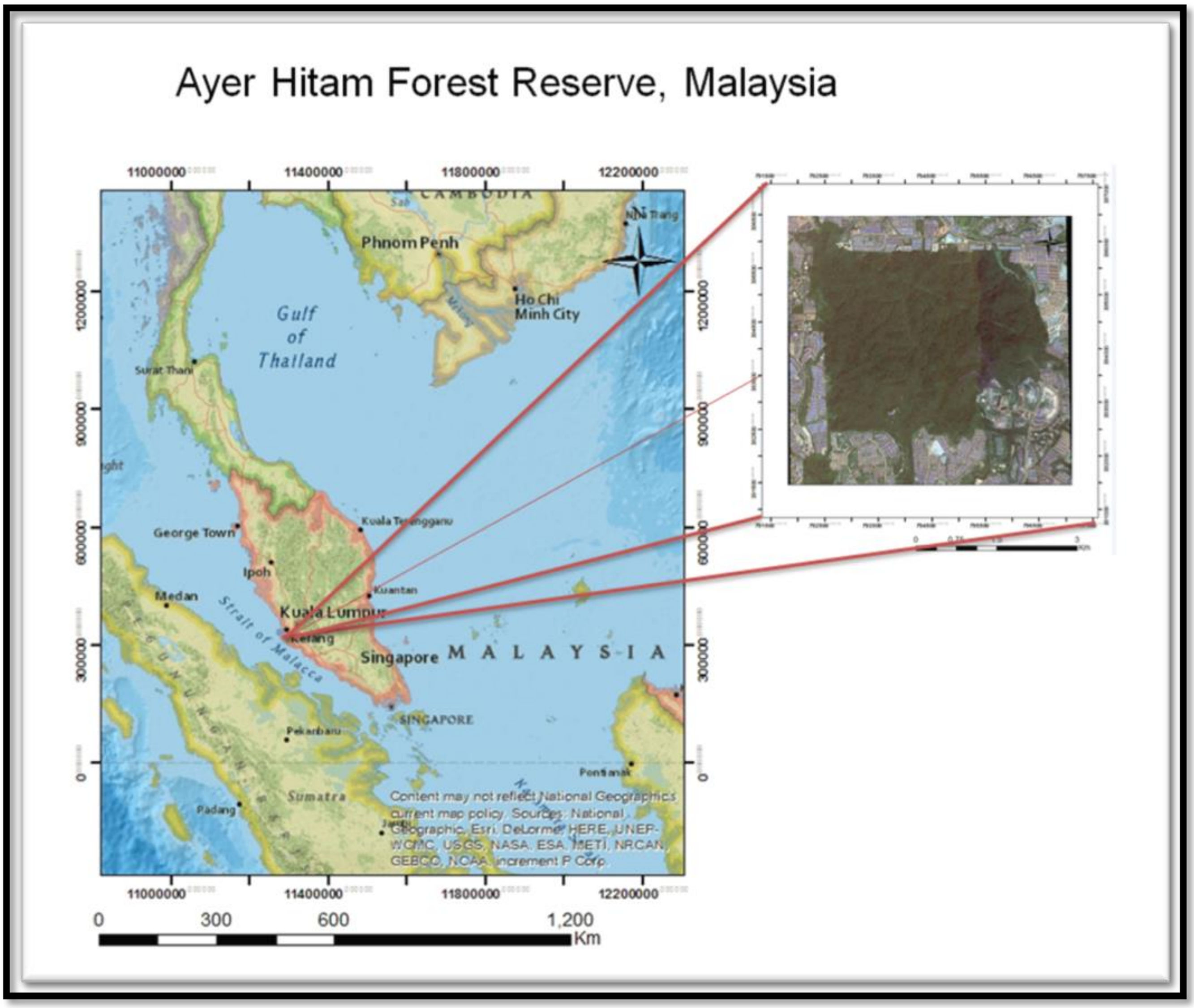


Figure 5: Location map of the study area.

3.2. Materials

3.2.1. Field instruments and data used for the study

The field instruments listed below in table 2 were used during the field work. These different field instruments have been used for navigating sample plots, measuring and collecting of tree parameters.

Table 2: List of instruments used in the field

Sn	Type of instrument	Used for
1	Terrestrial Laser Scanner	Scanning Trees (Point cloud data)
2	Measuring tape (30)	Measuring plot diameter
3	Diameter tape(5m)	Measuring tree diameter
4	Suunto Clinometer	Measuring Slope
5	Suunto Compass	Measuring bearing
6	iPAQ	For navigation (Couldn't function properly)
7	GPS	Coordinates (Couldn't function properly)
8	I pad	Navigation
9	Field work data sheet	Recording field data
10	Densitometer	Measuring canopy density
11	Chalk	Marking DBH
12	Pencils and eraser	Writing the field data

3.2.1.1. Data set used

Airborne LiDAR data which was acquired on 23 July, 2013 and a Terrestrial Laser scanner point cloud data that was obtained from the field using a Riegl VZ-400 scanner are the data used in this study. Table 3 shows the airborne laser scanning information.

Table 3: Characteristics of the LiteMapper 5600 system

Pulse rate	Range between 70 kHZ and 240Khz (normal 70kHz)
Scan angle	60^0
Scan pattern	Regular
Effective rate	46,667Hz
Beam divergence	0.5mrad
Line/sec	Max 160
A/c ground speed	90Kts
Target reflectivity	Min 20% max 60% (vegetation 30%, cliff 60%)
Flying height	700m -1000m
Laser point/m^2	0.9 to 1.2 points with swath width 808m to 1155m
Spot diameter (laser)	0.35 to 0.50m
Max (above ground level)	1040 m (3411ft)

3.2.1.2. Software used

The research used different software according to their specific purpose and use. Table 4 below shows the list of software used.

Table 4: Software used in this research

Software	Purpose
RiSCAN PRO v 2.1	Registration (coarse registration and Multi-station Adjustment, MSA), visualization with different viewer modes, tree extracting and manual measurements.
Arc Map 10.2	GIS analysis
Erdas Imagine 2013	Image processing
LAS tools	ALS data processing
eCognition	Segmentation of tree crowns
R studio, SPSS and Microsoft excel	Statistical analysis
MS Office 2010	Thesis writing and presentation

3.3. Methods

In this research four main processing parts can be described. These parts include the processing of the Airborne LiDAR data, Terrestrial Laser Scanner (TLS), field measured data and statistical analysis. Accordingly in the field biometric parameters of the trees such as DBH, tree height, and crown density (at plot level) have been recorded and also multiple scans of 26 plots using TLS have been carried out. Finally a statistical analysis was done to analyze the relationship between the dependent and independent parameters different measurements. The detailed research methodology and processes is shown in flow chart in Figure 6, and following sections.

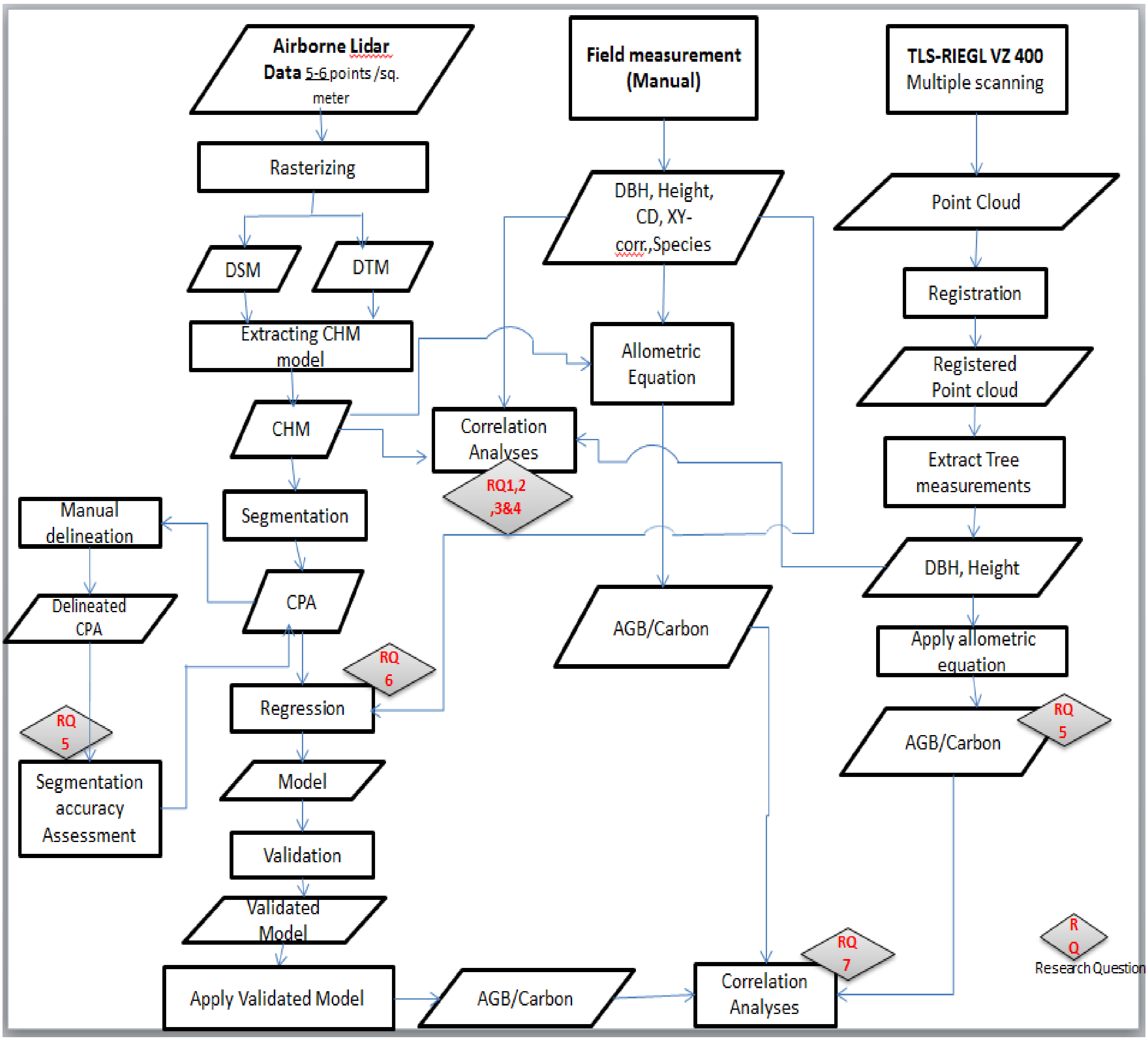


Figure 6: Flowchart of research methodology.

3.3.1. Pre-field work

Prior to field work a number of preparatory tasks had been done;

- Field data collection sheet was prepared (recording sheet.) (Appendix 1).
- Different field instruments, including the TLS, were collected from ITC and their condition was checked.
- Preparing map of the study area from worldview_2 image and uploaded in to iPAQ, for navigating in the forest to sample plots.

3.3.2. Sampling design and Determination of sampling plot

In this study a purposive sampling approach was used. Purposive sampling method is a none probability method where samples are chosen from a population based on the judgment of the researcher. Therefore, in this study, considering the terrain of the study area and the weight of the Terrestrial Laser Scanner (TLS) also limited time available a purposive sampling method was used. Circular plot with a radius of 12.62 m (500m²) was used as sampling unit. The use of this circular plot is very advantageous in forest areas as it makes measuring the dimension more accurate and has minimum perimeter as compared to a rectangular or square shaped of the same area. This can minimize the number of trees on edges (Lackmann, 2011). Moreover, 500m² – 600m² is the maximum sample plot size in estimating forest structure attributes using LiDAR point cloud (Ruiz, et al. 2014). In slopping areas (greater than 5%), a slope correction of the plot radius was done according the correction factor using the slope correction table (Appendix 2). Note that, sample points were common for all the team members and worked in team.

3.3.3. Field Data Collection

3.3.3.1. Biometric Data

After delineation of plot biometric measurements of all the trees with in the plot was taken, that is tree height, DBH, species and canopy density of the plot. Trees only with DBH of greater than 10cm were measure according to Brown, (2002) trees with a DBH less than 10 cm have insignificant contribution to the total above ground biomass(AGB)/carbon stock. Trees were tagged with unique tree numbers and accordingly their heights were measured using a laser distance meter and DBH at 1.3 m using a diameter measuring tape. Moreover the canopy density of plots was measured using a densitometer.

3.3.3.2. TLS scanning

In a process of scanning of trees by the TLS, it is advisable to avoid movement of people. This helps to reduce unwanted point cloud data (noise) and occlusion of trees. However, since the scanning of a plot (four different scan positions) required more time than the manual measurement, TLS scanning and manual measurements was done simultaneously. The following steps were followed for TLS scanning.

Determination of center of plot and tree numbering

After identifying a sample plot the center of the plot was selected in such a way that tree stems and undergrowth will not cause occlusion or at least minimize its effect. Trees or other undergrowth very close to the scanner can create a large area shadow behind (Liang et al., 2012) the center point and the other three outer scans of all the plots were identified with ocular judgments. Then after identifying the plot center and plot radius trees within this radius were tagged with tree numbers (Figure7). Later in the process the extraction of trees from the point cloud data of each plot was done with help of these numbers.

Figure 7: Tree numbering

Setting of the TLS

The Terrestrial Laser scanner (TLS) used in this study was the one that works being mounted in tripod set. This helps the scanner to be fixed firmly at a certain height from the ground and have a good view (vertical and horizontal) of the plot. Therefore after fixing the scanner on the tripod and setting the instrument the pitch, roll and yaw angles of the TLS was adjusted to a minimum values using the tripod legs.

Scan Position set up

In this study multiple scan positions method was used. Accordingly each plot was scanned one from the center of the plot and other three scans from outside of the plot at 120 degree apart from each other (Figure8). Though its time consuming multiple scan position can with a good 3D representation of all the trees in the plot that's why it was chosen. In a single scan position, mostly from the center of a plot, only one side of tree scanning can be scanned.

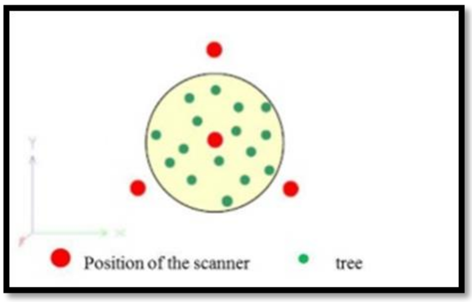


Figure 8: Multiple scan position
(Anne Bienert, 2006)

Setting tie points

To be able to co registrer the multiple scans after field work tie points were used. In this study a total of 15 tie points (reflectors), 12 cylindrical and 3 circular reflectors were used in a plot (Figure9). The cylindrical ones are 3-dimention with 10 cm length and 10 cm diameters. The circular reflectors are 2 dimensional reflectors which were pinned on the stem of the trees whereas the cylindrical were positioned on top of a stick with height of 1 – 1.5 m at a distance of 2 – 3 m from each of the three outer scan positions these reflectors should be seen clearly from the scan positions.

(a) (b)

Figure 9: Cylindrical (a) and circular (b) reflectors from in the field

3.3.4. Post fieldwork

3.3.4.1. Preprocessing of point cloud data

Registration is a process of merging all the scans in to single point cloud. The software used for the registration and preprocessing of the point cloud data was RiSCAN PRO v 2.1 software which was provided by RIEGL. In registration process the multiple scans, the tree outer scans, are registered to a common scan position that is to the center scan position. Therefore for every registration of one outer scan position (2, 3 or 4) with a central scan position a five (5) tie points were used. In Figure10, registration of scan position one with scan position two of plot 7 is shown. Corresponding tie point, shown in red color, were identified in both scan positions and numbered with the same number. After manual registration, also called course registration, using these tie points, a Multi Station Adjustment (MSA), was done. MSA is a powerful tool which allows multiple scans to bring in one scan position. In Figure 11, a registered sample plot is shown where four different colors from four scan positions form a complete 3D visualization of a tee.

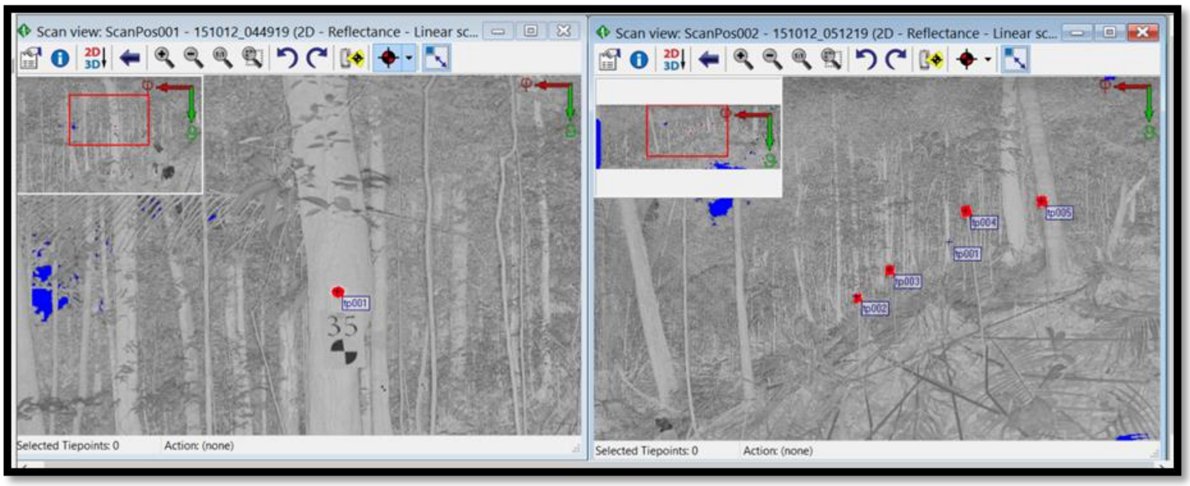


Figure 10: Registration of scans with tie points, circular reflector (left) and cylindrical reflectors (right), in RiSCANPRO software

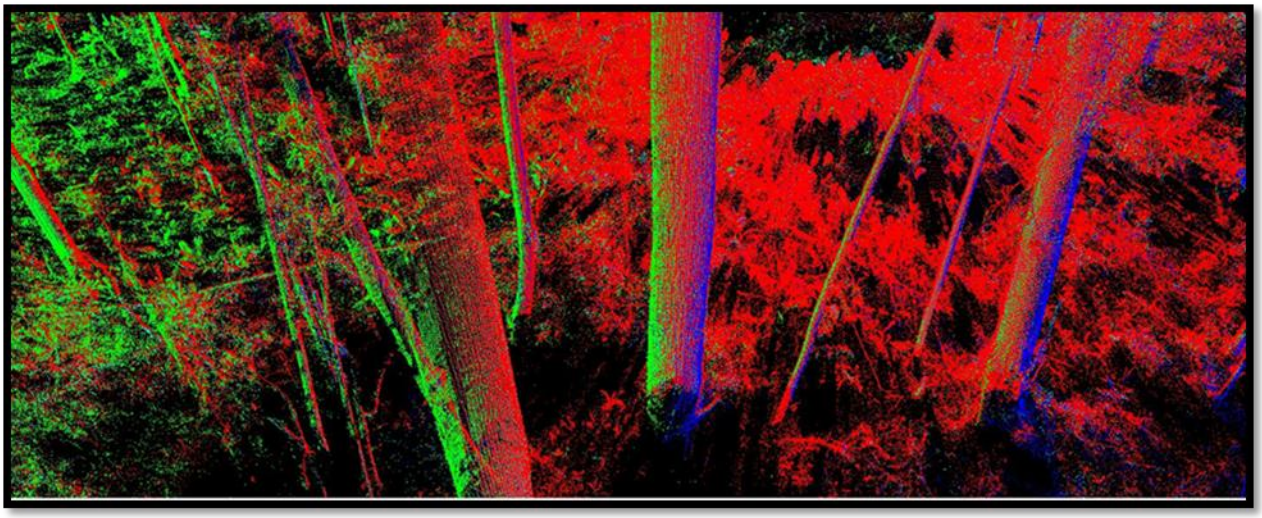


Figure 11: A sample of registered plot (Four different colours representing four scan potions)

3.3.4.2. Extraction of Plot

The next step after registration of the multiple scans is extraction of plots with radius of 12.62m from the center scan position. During scanning in the field point clouds from outside the mentioned radius or plot were involuntarily collected, therefore filtering of these unwanted point clouds was done in a RiSCAN PRO using the range function.

3.3.4.3. Extraction of Individual Trees

In the field, all measured trees (DBH> 10cm) were tagged with a unique identifying number. Therefore, with the help of these tree numbers the extraction of trees was done using the 'selection tool', in RiSCAN PRO software. All point cloud data associating to a single tree, with maximum crown diameter and maximum height, were selected. Figure 12 is an example of how an extracted tree looks like.

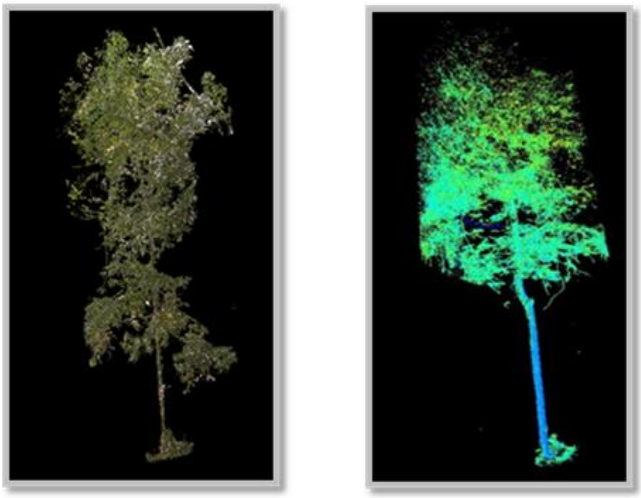
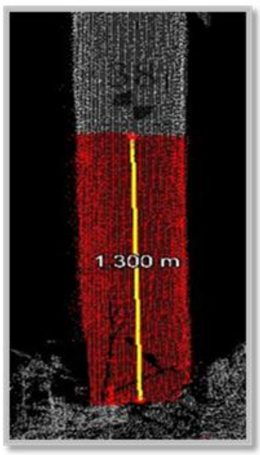


Figure 12: Sample of Extracted trees from point cloud data

3.3.4.4. Measurement of Tree Height and DBH

The measurement of tree height and Diameter at Breast Height (DBH) was determined in RiSCAN PRO. DBH is measured at a height of 1.3m on the stem of the tree from the ground. Likewise height was measured from the lowest point of the stem on the ground to the highest top of the tree. Figure 13 shows how tree height and DBH measurement was done.



. (a) (b)

Figure 13: Tree height (a) and DBH (b) measurement

3.3.5. Generating Pit free Canopy Height Model (CHM)

The creating of tree canopy height model (CHM) was done by computing the difference between digitals surface model (DSM) and the digital terrain model (DTM). In the a LiDAR point cloud data there are 5 returns per point, the first and the last returns are used to generate the DSM and DTM in Las tool software. Therefore raster calculator in ArcGIS was used to subtract the DTM from DSM and get the CHM. In this process pits which are created due to penetrating of LiDAR beams down the lower canopies before creating first return, were removed (Figure14) using an algorithm developed by (Anahita, et al., (2014). The methodology diagram of the pit-free algorithm is presented in appendix 3.

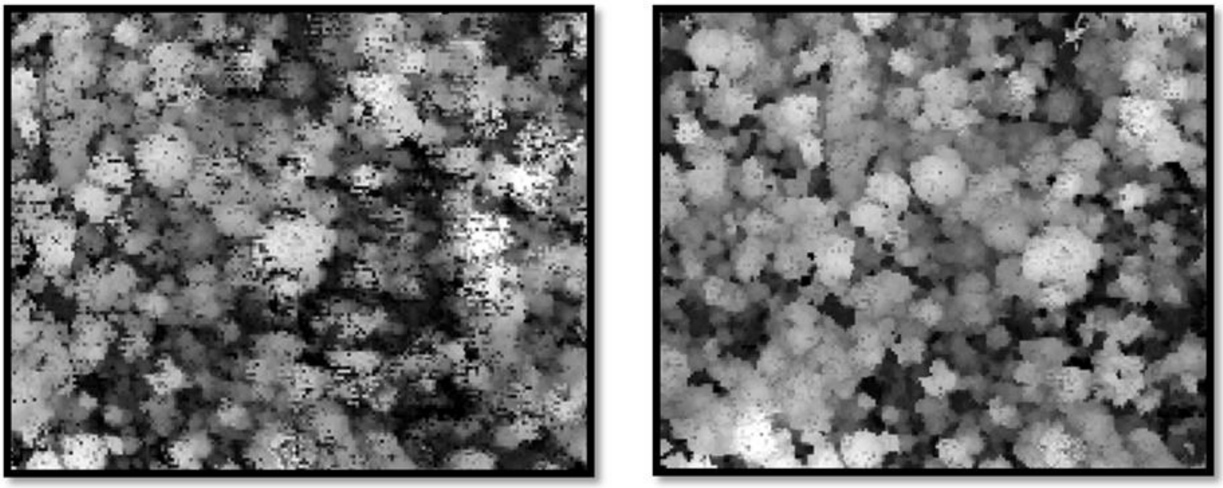


Figure 14: Canopy Height Model (CHM) with pits (a) and without pits (b)

3.3.6. Segmentation

The term image segmentation is the name given to the process of segmenting and partitioning of an image in to meaningful homogeneous units or objects based on the color, shape, texture, size, compactness and context of the image (Ryherd & Woodcock, 1996; Clinton, et al; 2010). In the process of object image segmentation, shape and size form the main blocks for further processes. Segmentation can be done using two approaches or techniques namely bottom-up or top-down techniques. In the bottom up algorism smaller object primitive merges to get larger image objects. Where as in the top-down large objects, or the entire images, are divided in to smaller objects. Chessboard and quad tree segmentation are examples of top down approach.

3.3.6.1. Multi-resolution Segmentation

Multi-resolution Segmentation is a segmentation technique offered by eCognition software which is based on bottom-up technique and is region-based algorithm (Saha, 2008). In the algorism each pixel is considered as a single and separate image object. Subsequently, according to user- defined thresholds; it begins to merge the surrounding small units based on local homogeneity. Accordingly the entire image can be segmented in to large image objects having less heterogeneity (Figure15).

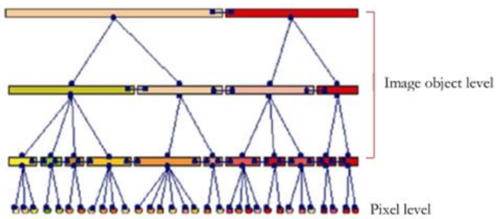


Figure 15: An Illustration of multi-resolution structure in eCognition. Source :(Benz et al., 2004)

3.3.6.2. Segmentation Parameters

Scale parameters determine the size of image objects by modifying their values. It limits the maximum heterogeneity of a segmented image object. In a heterogeneous data a smaller values of scale parameters are used as compared to a homogeneous data. In smaller scale values fewer pixels are merged. Thus, as result small image objects are produced (Saha, 2008). The homogeneity of an object defined by criterion color which refers to the spectral response the object, and shape which is divided in two equally exclusive properties: smoothness and compactness (Figure 16).The values of these parameters ranges from 0 - 1. Decreasing the value of color increases the value of shape (color +shape = 1) the same for the criteria smoothness and compactness. In this study the values used for color and shape are 0.7 and 0.3 respectively.

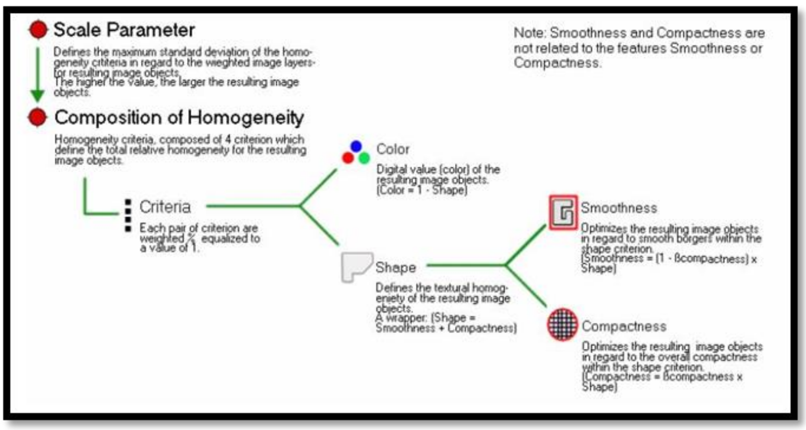


Figure 16: Multi-resolution Concept flow diagram

(Definiens, 2007)

3.3.6.3. Estimation of scale Parameters (ESP tool)

ESP tool which enables to estimate suitable scale parameters in the Definiens software for a multi-resolution segmentation (Drăguţ et al., 2010). ESP tool is based on the local variance (LV) of an image at multiple scales. It segments the data and calculates the local Variance (LV) of the image objects obtained through segmentation. Therefore the rate of change of local variance from one object level or scale to another indicates the level or scale at which the object can be segmented in a more meaningful and appropriate manner. In the ESP graph (Figure 17) the peaks of the ROC between the segmented objects specifies the suitable level at which an image can be segmented.

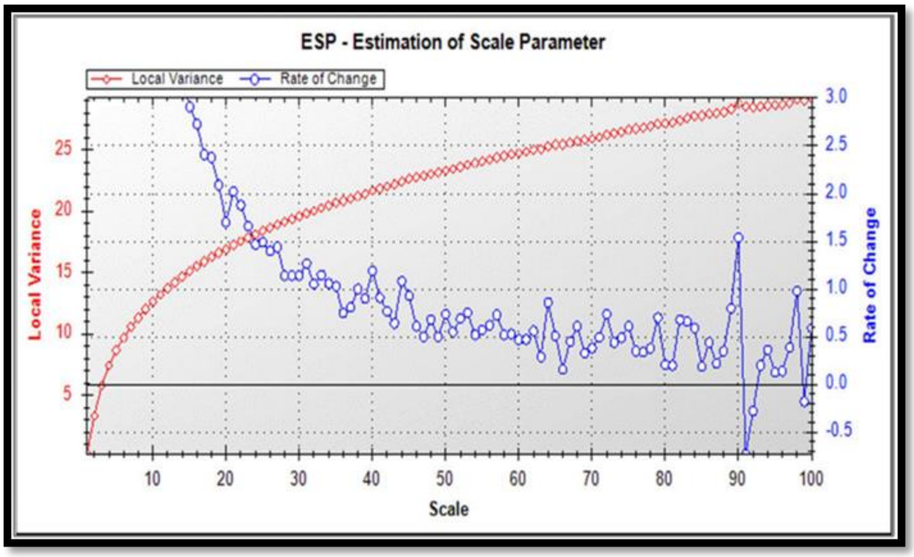


Figure 17: ESP graph for estimating scale parameter

(Definiens, 2007)

3.3.6.4. Watershed Transformation

Watershed transformation is an algorism which is used to separate image objects. In tropical rain forests, where there is intermingling of tree canopies, this algorithm is widely used to separate the individual tree crowns. Field measured tree crowns and expert knowledge are the bases for setting thresholds of splitting. In this algorism the study area is considered to be an inverted topographic surface where tree tops are valleys and gaps between trees are the peaks. (Figure18). In an inverted image the local maxima are those local minima in the original image and vice versa (Definiens, 2007). The Inverted image resembles to a watershed catchment. The minima are gradually flooded by increasing the water level. The image objects are split where water basin, touch each other.

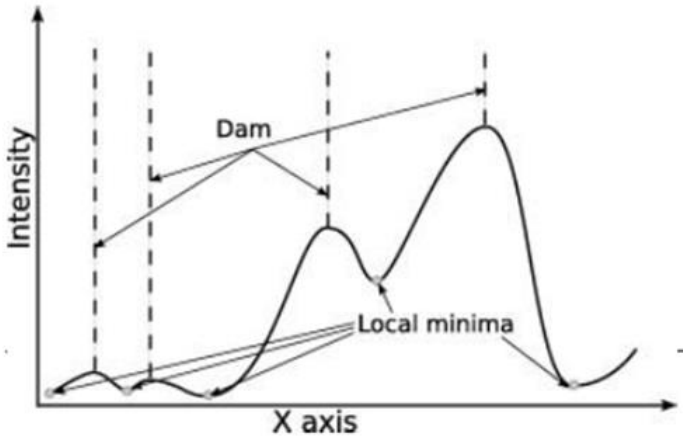


Figure 18: Watershed transformation illustration (Beucher, 1992)

3.3.6.5. Morphology

Morphology is a pixel based operation used for smoothing of image objects. This processing step has two operations namely opening and closing image objects. In an open image object process pixels are removed to have a smoother surface where as in close image object pixels are added to it to fill the gaps (Definiens, 2007). In this study tree crown is the main image object, therefore a close image object was used.

3.3.7 Validation and accuracy of Segmentation

Validation of the digitally segmented tree crowns was done to assess and evaluate how these segmented tree crowns fit compared to known objects. According Möller et al. (2007) the quality of segmentation has a direct relation with the type and quality of data (e.g., noise, spectral and spatial resolution) and also the optimal customization of parameters. Validation of segmentation can be done in various methods. However, in object- based segmentation the geometric and topological relationship should be considered.

A segmentation accuracy assessment approach developed by Clinton et al., (2010) is based geometrical accuracy of the segmented tree crowns compared with the manually delineated tree crowns. Accordingly the over segmentation and under segmentation is calculated using Eqs.1 and Eqs.2 respectively, and "D" value "goodness of fit" Eqs.3 where its value ranges from 0 to 1. Values close to 0 indicates high matching whereas values close to 1 indicates minimum match.

$$Over\ segmentation = 1 - \frac{area\,(xi \cap yj}{area\,(xi)}\ , yi \in Yi'$$ ……………………………………………..Equation 2

$$Under\ segmentation = 1 - \frac{area\,(xi \cap yj}{area\,(yi)}\ , yi \in Yi'$$ …………………………………………….. Equation 3

Where: xi reference object (manually digitized) and yj its corresponding segmented object.

$$D_{ij} = \sqrt{\frac{Oversegmentation_{ij}^2 + Undersegmentation_{ij}^2}{2}}$$ ……………………………………………...Equation 4

3.3.7. Comparison of DBH and height from field, TLS and Airborne LiDAR (ALS)

The correlation analysis of the tree parameters (DBH, height and CPA) both from the field measured and TLS derived measurements was done. To test the significances between these parameters derived from the field, TLS and airborne LiDAR measurements a paired t-test was performed. A test between DBH and Heights from TLS and field, and between airborne LiDAR derived height with field and TLS heights. Moreover a normality test of the TLS observation, Airborne LiDAR height and field height was done.

3.3.8. Allometric equation for estimation Above Ground biomass and Carbon Stock Calculation

Allometric equations are equations used to estimate the aboveground biomass (AGB) and carbon stock. A number of allometric equations for the estimation of above-ground biomass in tropical rainforest are available. Therefore choosing an appropriate allometric equation is very important to generate more reliable estimation of above-ground biomass. In this research an allometric equation which is developed by Chave et al. (2005) is applied for the estimation of AGB. This equation (equation 5) is recommended by IPCC guidelines for estimation of above-ground biomass and carbon stock (Equation6) in tropical rainforests.

$$AGB = 0.0509 \times \rho D^2 H \quad \text{......} \quad \text{Equation 5}$$

Where:
AGB: Above-ground biomass (Kg)
ρ: Specific wood density (g/cm^3)
D^2: Diameter at breast height (DBH) (cm)
H: Height of tree (m)

For Calculating the carbon stock the AGB can be multiplied by a conversion factor (CF) of 0.47 (IPCC, 2007). Therefor carbon stock is calculated using:

$$C = AGB \times CF \quad \text{......} \quad \text{Equation 6}$$

Where,
C: Carbon stock (Mg C)
AGB: Above ground biomass
CF: Fraction of above ground biomass (0.47)

4. RESULTS

4.1. Descriptive statistics

Throughout all the plots six different species, which were occurring more than twenty times were identified. Tree species of *Streblus elongate (26%), Syzygium* spp *(20%)* were the dominant species in terms of species whereas as family Dipterocarpaceace family where the dominant trees family in the study area. The occurrence of the species is presented graphically in Figure 19.

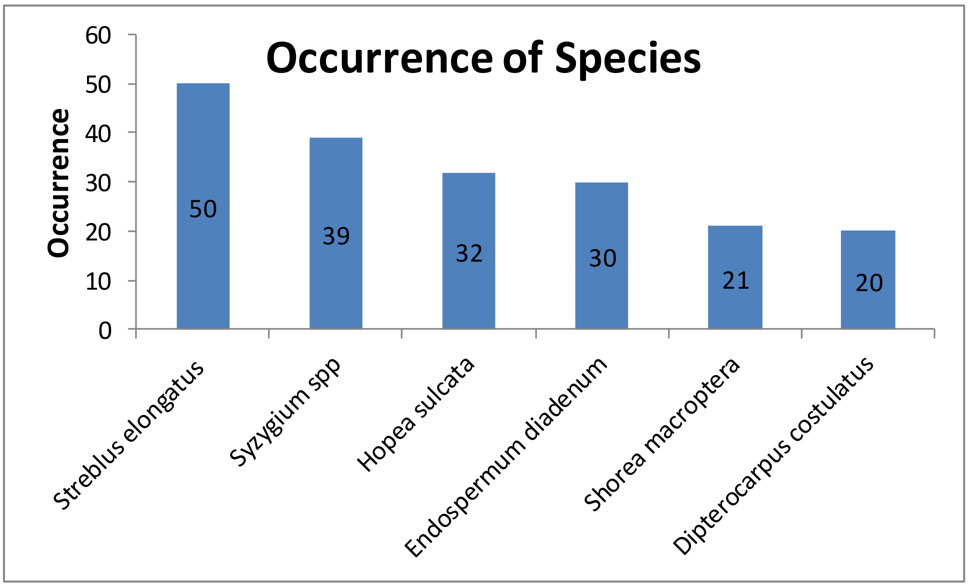


Figure 19: Species occurrence in the study area

In the field a total of 26 plots were sampled and a manual field measurements and a multiple scanning by TLS was done. Out of all 627 trees 228 trees, which could be easily identified both on the point cloud data of the TLS and the airborne LiDAR data were used for further analysis. The descriptive statistics of the stand parameters (DBH and tree height) of the field, TLS and ALS measurements are presented in Table5. Also box plot of field DBH and TLS DBH is shown in Figure20 (a) and box plot of heights from field, TLS and ALS in Figure21 (b).

Table 5: Summary descriptive statistics of measurements

Tree Parameter	Min.	Max.	Mean	Standard Deviation	Standard Error	Skewness	Kurtosis
Field DBH	10	150	30.72	16.51	1.09	2.2	11.3
TLS DBH	10	108	30.64	15.4	1.02	1.25	2.68
Field Height	6	42	17.05	5.89	0.39	0.85	1.64
TLS Height	7.61	38	20.22	6.10	0.40	0.43	0.25
ALS Height	8.43	38.4	22.39	6.37	0.42	0.26	-0.297

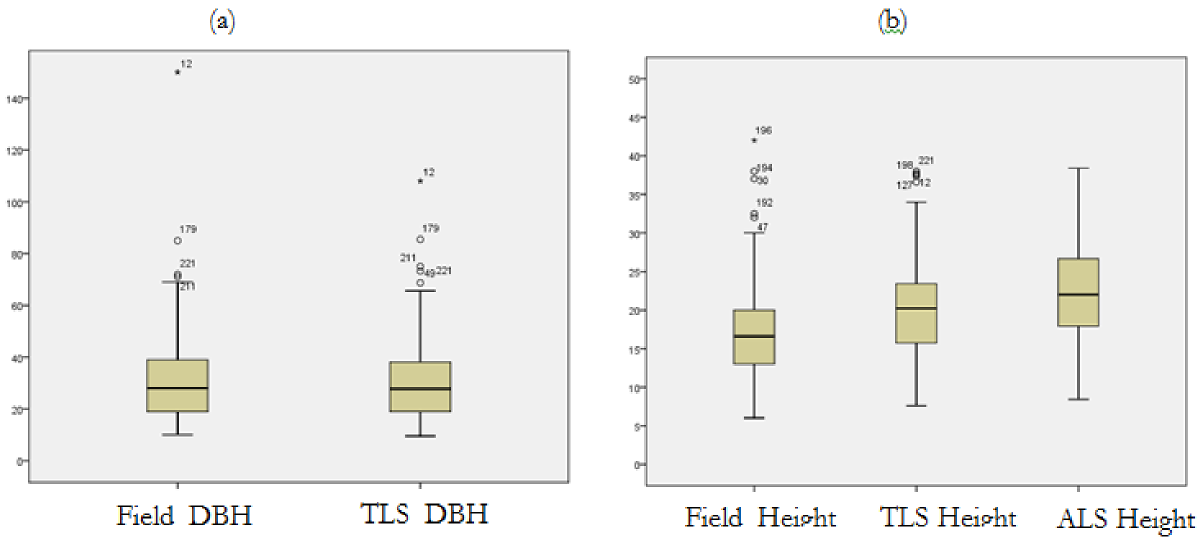


Figure 20: Box plot of DBH of field and TLS (a) Box plot of heights from Field, TLS and ALS (b)

The descriptive statistic summary shows that the measurement values from the field and TLS scanner seems to be more in agreement (Table 5). Calculation of the Root Mean Square Error (RMSE) of the field and TLS was done to see how these measurements deviate. For the DBH measurement the RMSE was 1.7cm. While in the height measurement the RMSE was 3.01m. Likewise the RMSE of the height measurement of TLS and airborne LiDAR (ALS) was 2.15m.Which shows underestimation of tree heights measurements by TLS as compared to ALS.

Normality test of the data was evaluated in SPSS statistics software. Accordingly the measurements of DBH and Height from TLS were not normally distributed, the value of ShapiroWilk (p _value) is smaller than 0.005 (Table 6). The distribution pattern of the TLS measurements of DBH, is highly skewed to the right (positively skewed) whereas TLS height is less skewed (Figure 21).

For the Field observations (DBH and Height) and Height from ALS it is provided in Appendix 4.

Table 6: Normality test of TLS Observation

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistics	df	Sig.	Statistics	df	Sig
TLS_DBH	.088	228	.000	.918	228	.000
TLS_Height	.054	228	.000	.980	228	.000

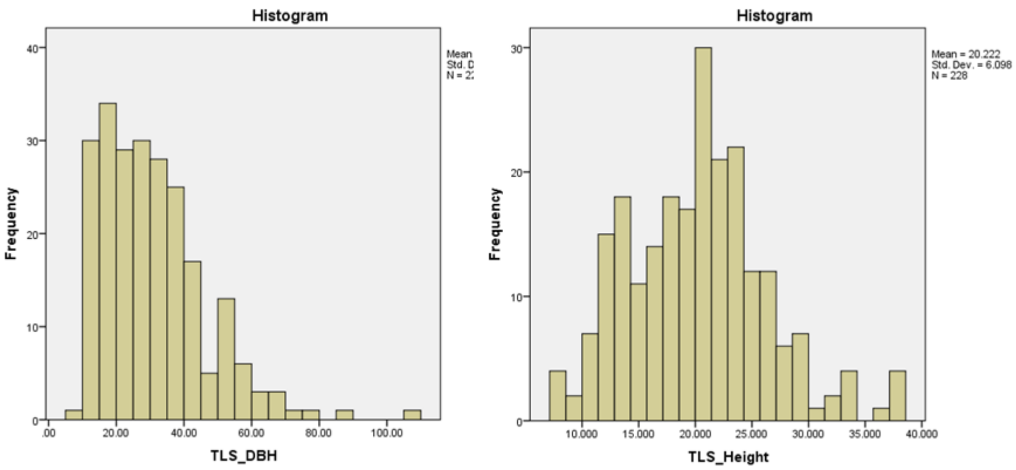


Figure 21: Distribution of DBH and Height measurements from TLS

4.2. Registration

All the multiple scan positions of all the plots were registered to the corresponding centre scan position. Figure 23 shows sample of a registered tree stem represented by different colours of the different scan positions. The standard deviation error of registration of all the multiple scans of twenty six plots ranges between 0.0127m – 0.0206m, with average of 0.016m see Table7. Also a reader can refer Appendix5 to see an example for the result of Multi-station Adjustment of sample plot 19.

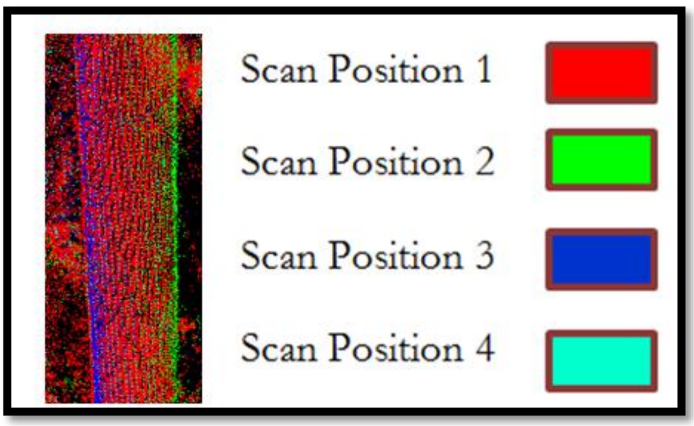


Figure 22: Sample of registered tree stem from four different scan positions

Table 7: Standard deviation, (Error) in meters of multiple-scan registration of all the plots

Plot	1	2	3	4	5	6	7	8	9	10	11	12	13
Error(m)	0.0185	0.0162	0.02	0.0153	0.016	0.0138	0.0149	0.014	0.0201	0.0149	0.0127	0.0146	0.0163
Plot	14	15	16	17	18	19	20	21	22	23	24	25	26
Error(m)	0.0157	0.0206	0.0177	0.0224	0.0155	0.0179	0.0195	0.0206	0.0158	0.0184	0.0148	0.0169	0.0158

4.3. Individual Tree identification and Extraction

Identification of trees was done by detecting point clouds belonging to a single tree stem (Liang, et al., 2011). A tree trunk is assumed to form concentrated enclosed circular point cloud that continues to a certain height. After identifying the individual trees, manual extraction of individual trees was done in RiSCAN PRO software with the help of tree tags. From twenty six plots a total of 779 trees were measured in the field. And out of this 627 trees were in the point cloud data of the TLS and (152) trees were missed. The number of missed trees differs from plot to plot. The total number of extracted trees and missed trees and their percentage is shown in Table 6. The extraction of trees is a time consuming process, hence the TLS data was shared among other two team mates for the extraction of all the mentioned number of trees.

Table 8: Number of tree measured in the field and extracted trees from the point cloud of TLS

Plot No	Field Measured	TLS DERIVED	TLS Derived (%)	Missing Trees	Plot No	Field Measured	TLS Derived	TLS Derived (%)	Missing Tree
1	17	16	94	1	14	35	16	45.7	19
2	25	23	92	2	15	38	20	52.6	18
3	30	27	90	3	16	30	17	56.7	13
4	25	24	96	1	17	36	22	61	14
5	23	21	91	2	18	37	37	100	0
6	26	26	100	0	19	35	29	82.9	6
7	29	26	89.7	3	20	25	22	88	3
8	26	25	96	1	21	45	43	95.6	2
9	31	28	90.3	3	22	41	39	95	2
10	25	12	48	13	23	31	17	54.8	14
11	29	20	69	9	24	26	26	100	0
12	36	18	50	18	25	25	23	92	2
13	25	23	52	12	26	28	27	96.1	1
TOTAL	Plots	Field Measured	TLS Derived	Missed trees	TLS Derived (%)			MISSED TREES (%)	
	26	779	627	152	80.5			19.5	

4.4. Plot-wise comparison of Field and TLS measured DBH

In order to have a good image on the individual sample plots and see the variation between the fields measured DBH and the TLS derived DBH of all the 26 plots a plot wise assessment of these measurements was done (Table9). The result shows a very high correlation between these two DBH measurements. Figure 23, shows sample plots with high R^2. On the other hand plots 14 and 15 (Figure 24) have R^2 of 0.85 and 0.91 which is relatively lower value. The main cause for this value is plots 14 and 15 had too much understory which affected to the accuracy of DBH measurement. The scatter plots of the remaining plots are Appendix 6.

Table 9: Summary of relationship between field measured DBH and TLS derived DBH

Plot	1	2	3	4	5	6	7	8	9	10	11	12	13
R^2	0.99	0.97	0.97	0.99	0.99	0.99	0.99	0.99	0.99	0.98	0.97	0.98	0.98
RMSE	0.57	8.05	1.94	0.06	1.4	0.06	0.04	0.14	0.13	0.27	0.59	0.22	0.50
Plot	14	15	16	17	18	19	20	21	22	23	24	25	26
R^2	0.91	0.85	0.91	0.98	0.99	0.98	0.99	0.99	0.98	0.99	0.99	0.99	0.99
RMSE	2.10	0.96	1.17	0.14	0.43	0.73	0.28	0.24	0.29	0.25	0.58	0.37	0.26

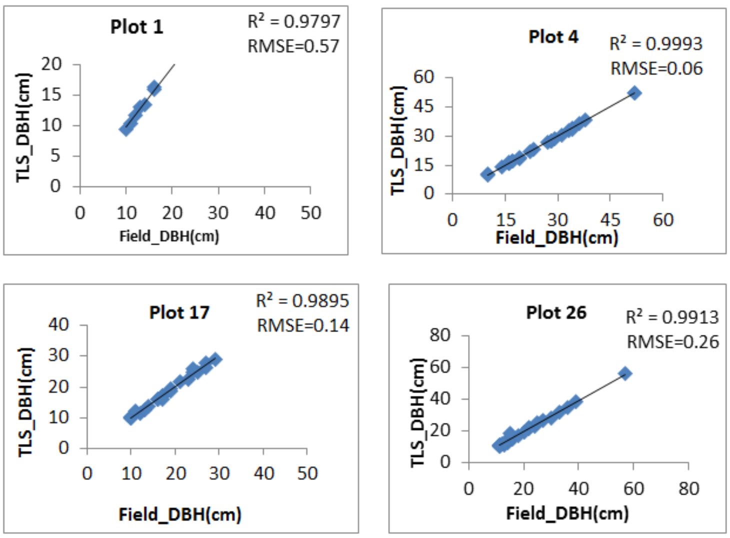


Figure 23: Sample Plots having high values of R^2 in comparison of the field measured DBH and TLS derived DBH

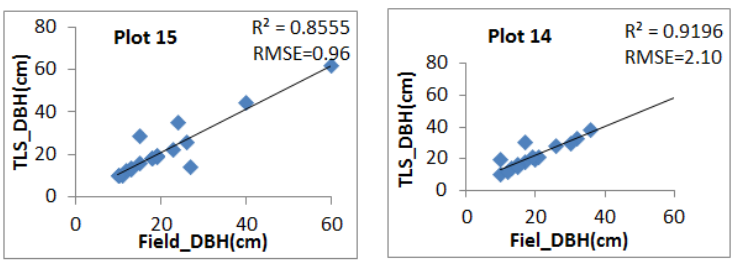


Figure 24: Sample plots with lower R^2 value due to much understory coverage in the plots

4.5. Plot-wise comparison of Field and TLS measured Height

Pot wise assessment of the field measured tree heights and the TLS derived heights was also done to see the variations and relationship of these measurements among the plots. Table 10, shows the result values for R^2 and RMSE of all the sample plots. Plots 8, 10, 16 and 26 are sample plots with higher R^2 values of 0.82, 0.7, 0.97 and 0.82 (Figure 25). However in plots 1, 4, 17, 19, 22 and 24 (Figure 26) the relationship between these heights is not strong which is mainly caused due to the overlapping of tree crown and high density undergrowth in the plots. The scatter plots of all the remaining plots are presented in Appendix 7.

Table 10: Summary of relationship between field measured Height and TLS derived Heights

Plot	1	2	3	4	5	6	7	8	9	10	11	12	13
R^2	0.32	0.69	0.75	0.45	0.64	0.52	0.91	0.82	0.74	0.77	0.55	0.73	0.53
RMSE	2.93	3.73	2.37	2.77	3.7	2.66	1.12	4.1	2.6	1.97	2.56	2.06	2.04
Plot	14	15	16	17	18	19	20	21	22	23	24	25	26
R^2	0.74	0.69	0.97	0.25	0.44	0.31	0.63	0.73	0.04	0.74	0.12	0.82	0.82
RMSE	1.2	1.68	0.75	1.17	2.23	1.57	2.1	1.49	2.5	2.3	1.57	3.19	1.03

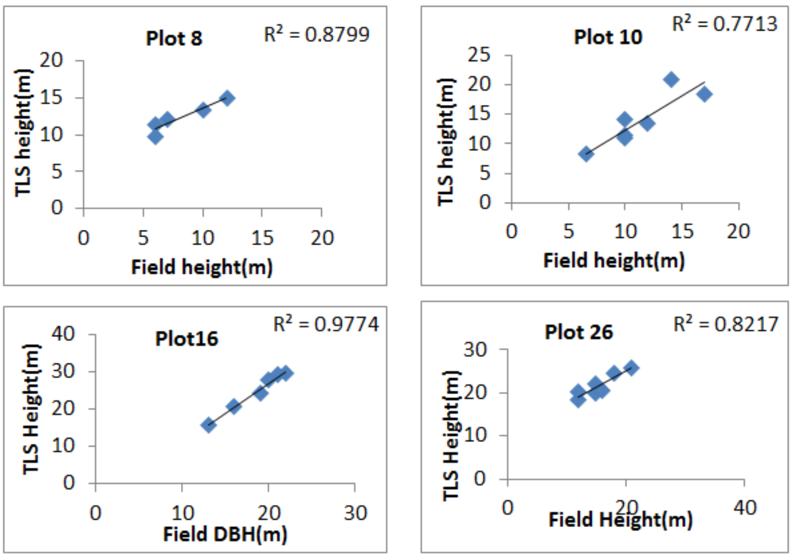


Figure 25: Sample plots having relatively higher R^2 value of the comparison in the field and TLS height

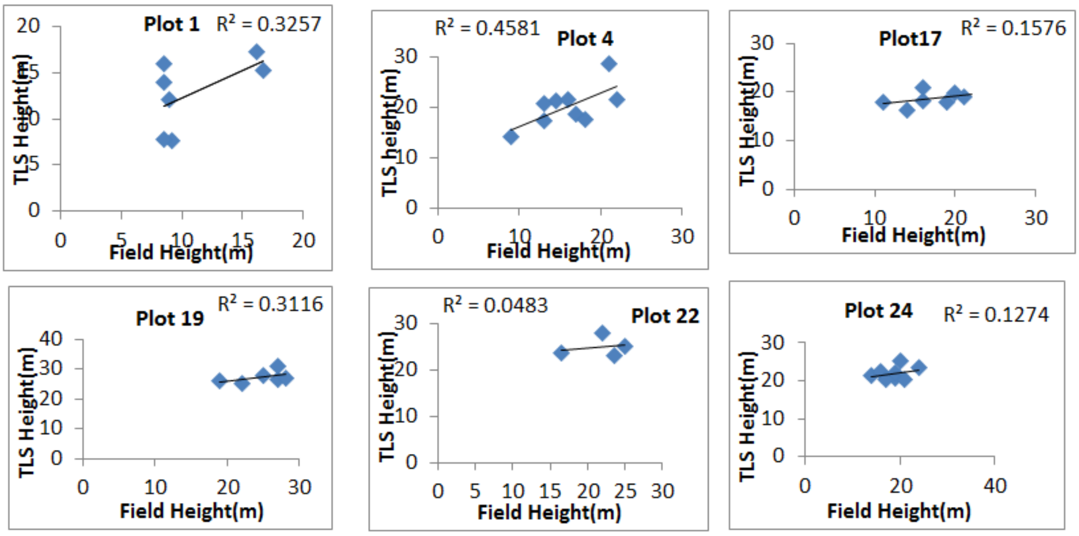
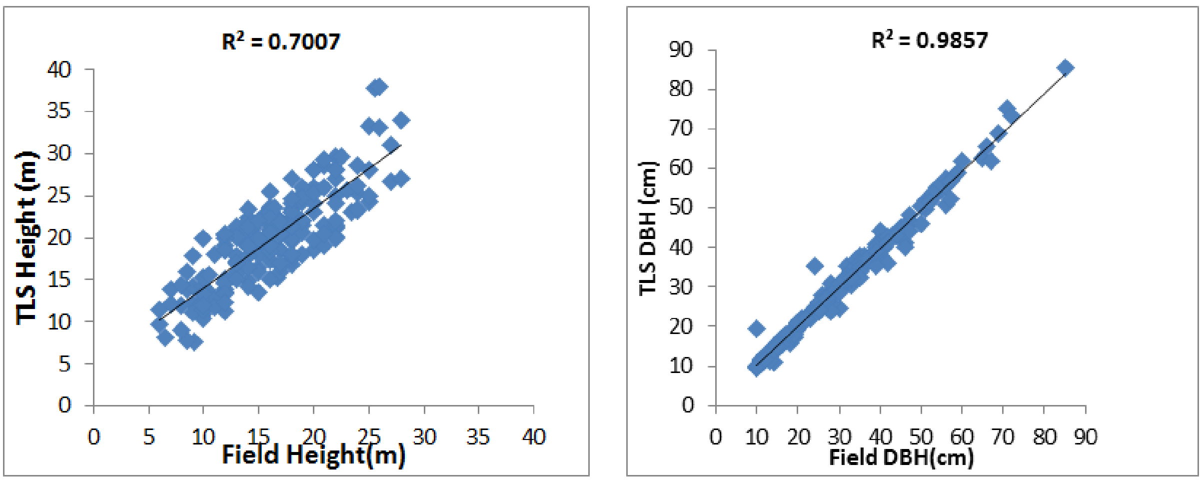


Figure 26: Sample plots having low R2 value in the comparison of the field and TLS Height

4.6. Relationship between field and TLS measurements of DBH and Heights of individual Trees

The relationship between the DBH and height measured from the field and the corresponding measurements of DBH and height derived from the point cloud data of the TLS was done by plotting the data in excel (Figure 10). The relationship of the height and DBH, from the field and TLS, measurements was a linear positive relationship. Accordingly for DBH and height measurements values of R^2 0.986 and 0.70 and RMSE of 1.7cm and 3.01m was recorded respectively. (Figure 27). Therefore from this result the relationship between the field DBH and TLS DBH is a stronger linear positive relation as compared to the height measurement of field and TLS. TLS was measuring slightly higher than field. A reader can notice that in the case of DBH (Figure 26), the line goes almost through the origin indicating that the intercept is almost zero and slope approximately one, which shows a good relation between the two variables.



(a) (b)

Figure 27: Scatter plot of field and TLS DBH (a) and field and TLS Height(b)

4.7. Paired t-test for the means of DBH and Height from the field and TLS.

According to research questions of one and two a paired T-test analysis was done at 95% (α= 0.05) of significant level to see the significance of the relationship between field and TLS measurements of DBH and Height. Accordingly the result of the t-test shows that there is no significant difference between the field measured DBH and heights from the TLS. Therefore the null hypothesis stating that there is no significant difference between field and TLS derived measurements of DBH and Height is accepted as t-calculate is greater than t- critical. (Table 11)

Table 11: Summary statistics of paired t- Test for the field and TLS measured DBH and Height

	Field DBH	TLS DBH	Field Height	TLS Height
Observations	228	228	228	228
Mean	30.7	30.6	17.05	20.22
df	227	227	227	227
t Stat	0.27087		9.4705	
P(T<=t) two-tail	0.7867		3.8E-18	
t Critical two-tail	1.9704		1.9704	

4.8. Canopy Height Model (CHM) and Pit Removal

In order to be able to answer research question three, a Canopy Height Model with a spatial resolution of 1 metre was created by subtracting the DTM from DSM (Figure 27). In this process all points less than 1m and also all points greater than 50 m were removed, assuming that any point cloud above that can't be a tree. According the field height measurements the maximum measured tree was 42 m. Pits in Canopy Height Model (CHM) can negatively affect in the identification of individual trees (crowns). Hence decreases the accuracy of tree detection. A portion of the CHM is shown with pits and pit- free Figure28).

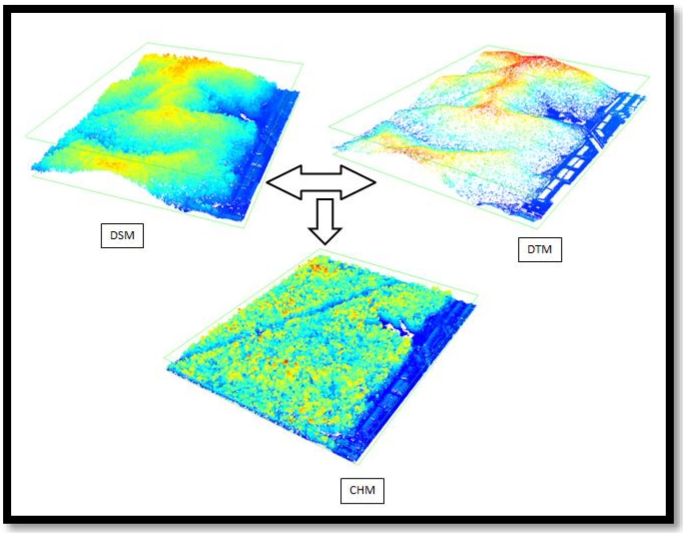
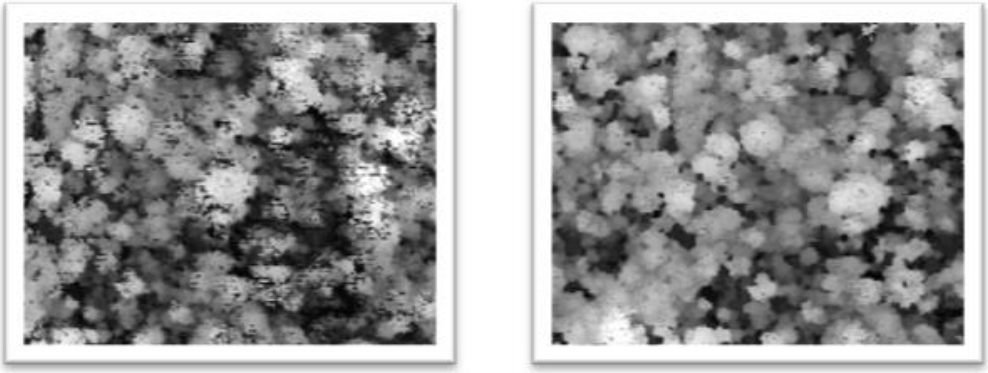


Figure 28: Sample of CHM generating



(a) (b)

Figure 29: CHM with pits (a) and without pits (b)

4.9. Relationship between LiDAR dirived heights and TLS heights

To address research question three of this study, an assessment on the relationship between the heights derived from CHM of LiDAR of the 228 manually delineated tree crowns and the corresponding height measured from the TLS scanner was done by plotting these two variables. The relation was a positive linear relationship with R^2 of 0.87 and RMSE of 2.15m (Figure 30).

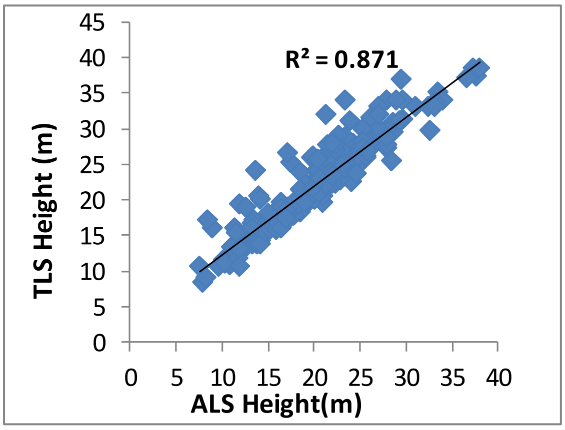


Figure 30: Scatter plot of ALS and TLS Height

To test the significance of the relashionship between these measurements a paired T-test was done. Result of the t-test shows that is no significant difference between these measurements. The t-calculated was greater than t-critical. Therefore the null hypothesis stating there is no significant difference between heights derived from CHM of LiDAR and TLS derived heights is accepted. Table 12 is showing the result of t-test between heights derived from ALS and TLS.

Table 12: Summary statistics of paired t- Test for the ALS and TLS Heights

	ALS_Height	TLS_Height
Observations	228	228
df	227	227
t Stat	11.52	
P(T<=t) two-tail	1.7E-24	
t Critical two-tail	1.9704	

4.10. Relationship between Airborne LiDAR (ALS) derived heights and Field measured heights

In this regard, based on the research question number four, tree heights derived from LiDAR (ALS) and field measured heights were taken and analyzed their relationship by plotting these two variables (Figure 31).The R^2 value and RMSE were calculated as **0.65 and 3.5m** respectively. This relationship revealed that there is not strong relation. Normality test was done for both data measurements (Appendix 8). LiDAR heights were normally distributed whereas the field measurements were not. However, to test the significance of the two measurements a paired t-test was done at 95% of confidence interval, assuming the variance of these variables equal. Table13 shows result of t-test and the t-calculated was found to be greater than the t- critical, therefore there is significant difference between these two measurements. Thus, the null hypothesis is not rejected and there is no significant difference between these two measurements.

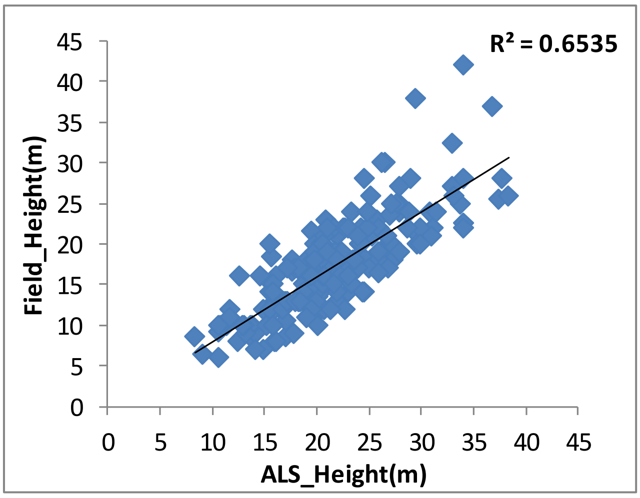


Figure 31: Scatter plot of ALS and Field Height

Table 13: Summary statistics of paired t- Test for the field height and ALS height

	Field Height	ALS Height
Observations	228	228
df	227	227
t Stat	14.96	
P(T<=t) two-tail	1.109	
t Critical two-tail	1.97	

4.11. Image Segmentation

Digital (automatic) image segmentation of the LiDAR derived Canopy Height Model (CHM) was done using multi-resolution segmentation algorithm.
Estimation of Scale parameter (ESP), which is embedded in the eCognition software, was used to identify the most appropriate scale parameter for segmentation (Figure 32).

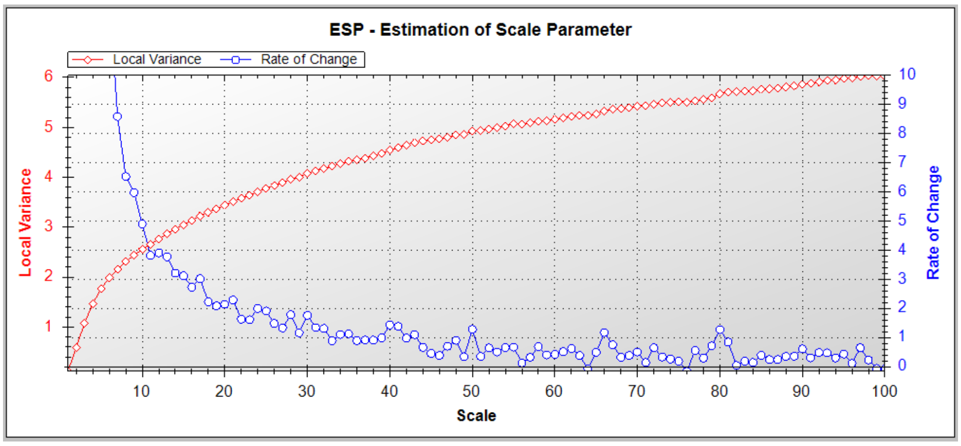


Figure 32: ESP tool of CHM of the Airborne LiDAR.

Therefore a multi-resolution segmentation with a scale parameters obtained from ESP was used for the segmentation. Firstly scale parameter 17 was tried however it resulted on under segmentation of the tree crowns. Scale parameter 12 gave a reasonable segmentation result therefor; finally this value was used for the multi-resolution segmentation with 0.3 and 0.6 values for shape and compactness respectively. After segmentation it appeared that only the top crowns were properly segmented, the lower canopy is partially hidden and covered by the upper canopies which lead to smaller crowns than the reality. This scale parameter result a reasonable over and under segmentation of the upper canopy crowns (Figure 33).

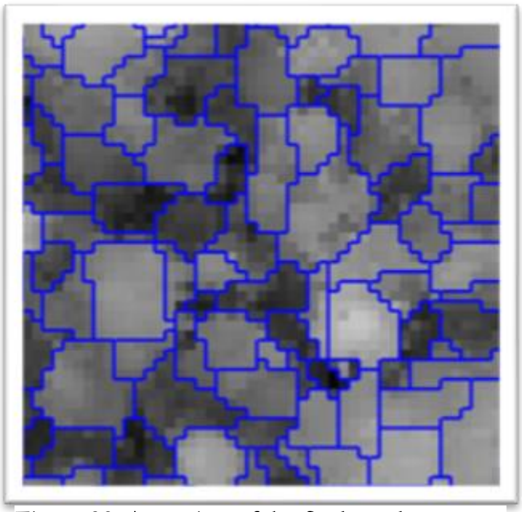


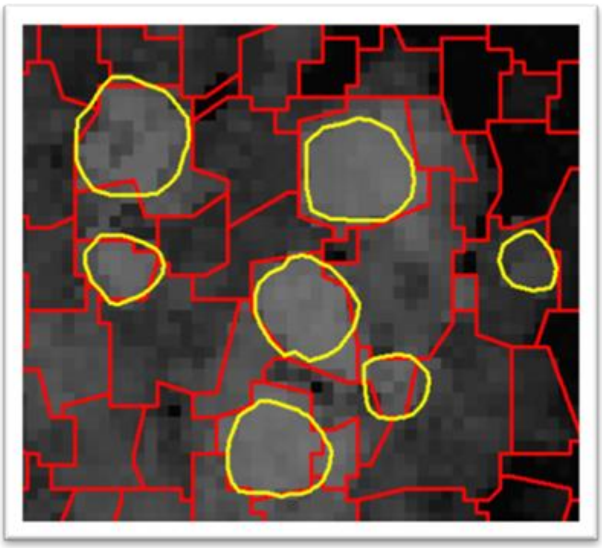
Figure 33: A portion of the final result segmentation CHM

4.12. Validation of Segmentation CPA

Tree crown validation was done to address research question number five, using accuracy assessment measures of D using manually delineated tree crowns as a reference tree crowns. (Figure34). As the D-value "measure of goodness" was done the over and under segmentation values for the scale parameter of 12 are 0.11 and 0.42 respectively. The D value was 0.314. Therefore the total accuracy of the crown delineation was 68.6%, which means a segmentation error of 31.4%.

Table 14: Segmentation accuracy

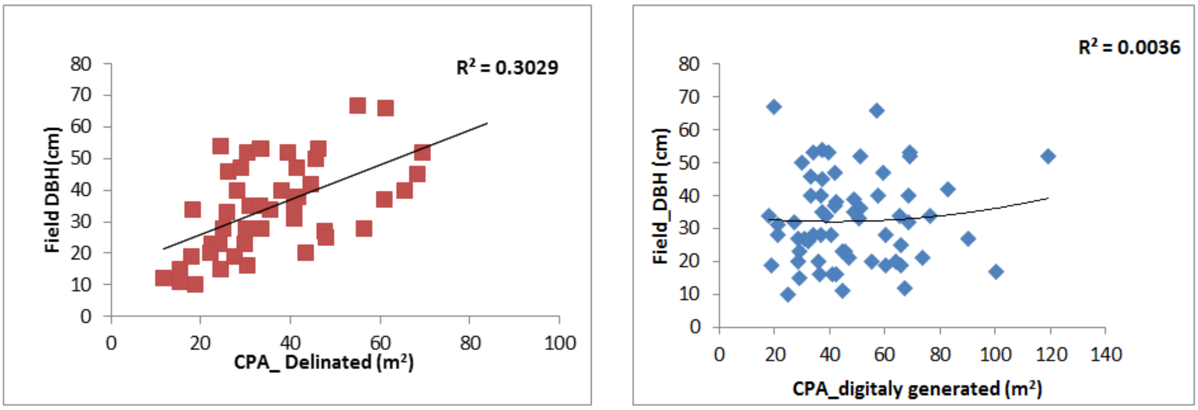
	Oversegmentation	Undersegmentation	D_value
Goodness of fit	0.11	0.42	0.314
Total accuracy			**68.6%**



4.13. Relationship between Canopy Projection Area (CPA) and DBH

According to research question six, assessment of a relationship between the DBH, estimated based on the manually delineated CPA of the segmented tree crowns and diameter at breast height (DBH) from the field was performed. Hence, to see how accurately the DBH can be estimated from the CPA of the trees from the CHM of LiDAR, a regression analysis was performed. However, the result of the relationship between these two variables was very low with R^2 of 0.303.

In addition to that another regression analysis was done using the automatic (digitally) generated polygons from eCognition Developer software (Appendix 9a and 9b), but still the relationship was very poor with R^2 of 0.0036 (Figure 35b). The result of the regression analysis of the field DBH and CPA (both manually delineated and digitally derived) is presented in Figure35 (a) and (b) respectively. Note that a reader can see in Appendix 10 toFigure 34: Reference polygons (yellow lines) and digital segmented polygons (red lines)



(a) (b)

Figure 35: Scatter plot of a relationship between field DBH and CPA of manually segmented (a) and CPA of digitally segmented.

4.14. Above ground biomass (AGB) and Carbon Estimation

In this research the AGB was computed based on TLS derived parameters and also using the field measured DBH and height from CHM of airborne (ALS). Hereafter AGB_ALS refers to AGB estimated from a combination of ALS and DBH field measurements. Therefore applying an allometric equation given in (Equation4) of Chave et al., (2005) and a conversion factor given in Equation 5, AGB and carbon stock were calculated respectively. To assess the relationship between the AGB estimated from TLS and ALS combined with field DBH scatter plot was made (Figure36) and the R^2 and RMSE were 0.96 and 190.6kg (22.9% of the mean AGB) respectively.

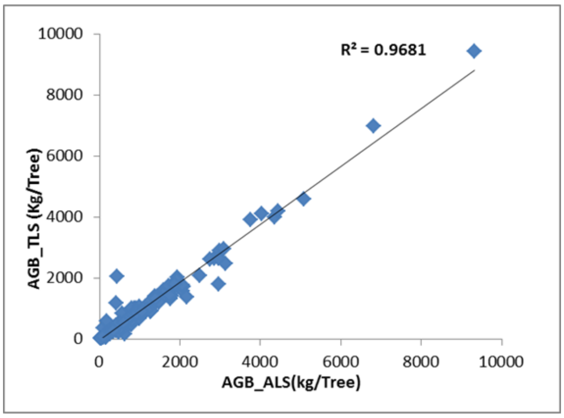


Figure 36: Scatter plot of a relationship between AGB estimated from ALS and TLS

Based on the research question of number 6, a t-test was done to see the significance of AGB derived from TLS and AGB estimated from ALS (Table 11). Based on the result there was no a significance difference between these two AGB so both approaches are equally accurate. Thus the null hypothesis was accepted since the t-calculated is greater than t-critical.

Table 15: Paired t-test of AGB estimated from ALS and TLS

	AGB_ALS	AGB_TLS
Observations	228	228
df	227	227
Mean	831.06	769.00
t Stat	4.69	
P(T<=t) two-tail	2.26E-06	
t Critical two-tail	1.9704	

In order to have a good visualization of the difference between the estimated amount of aboveground biomass (AGB) and Carbon stock from Air borne LiDAR and Terrestrial Laser scanner (TLS) a graphical representation is presented in Figure37 and Figure 38. Almost in all the plots the estimated above ground biomass (AGB) by ALS is slightly higher than the AGB estimated by the TLS. This difference could be due to underestimation of height measurements by the TLS.

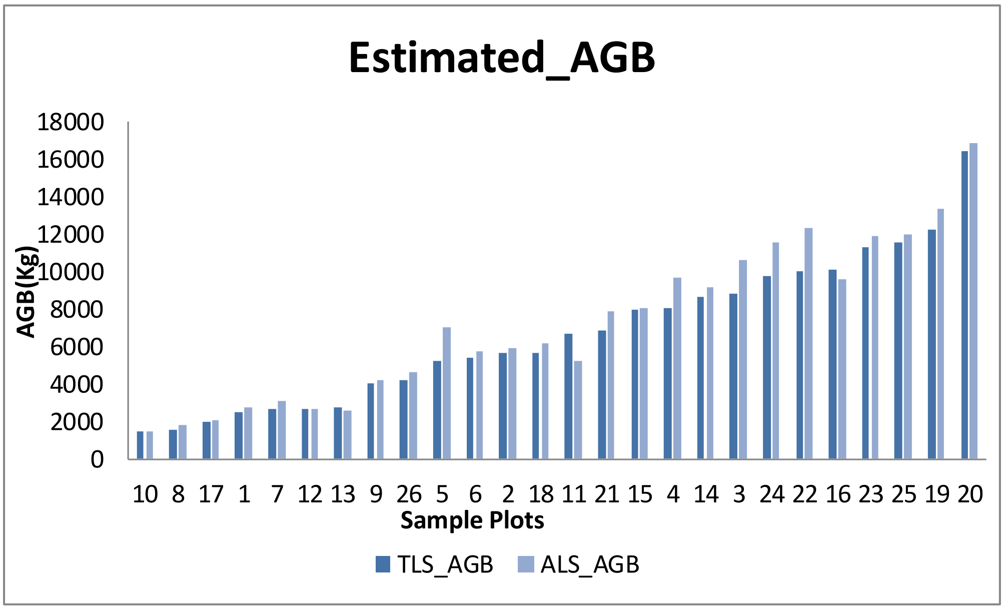


Figure 37: Comparison of AGB (of the most top trees) estimated from ALS and TLS

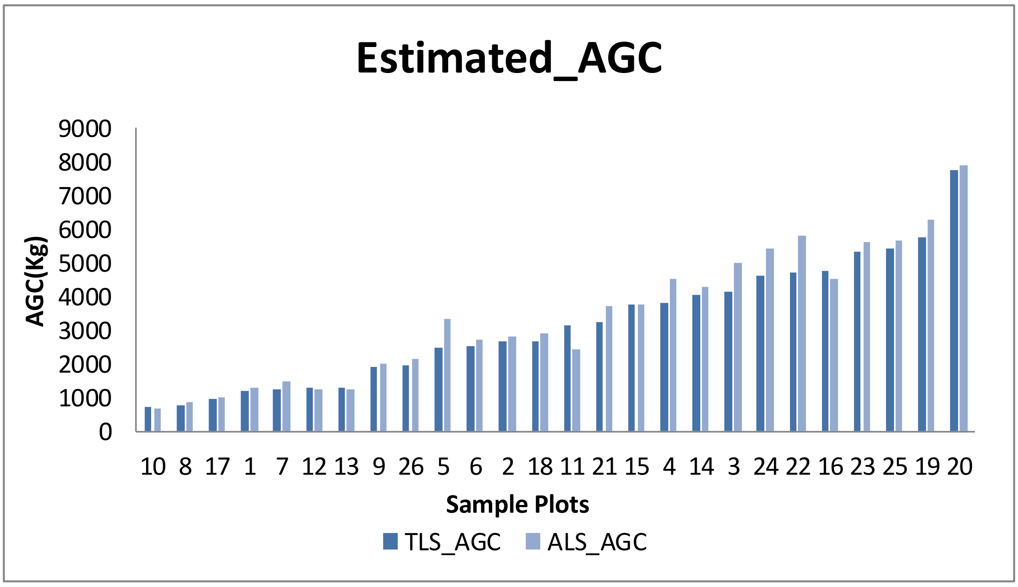


Figure 38: Comparison of AGC (of the most top trees) estimated from ALS and TLS

5. DISCUSSION

5.1. Individual Tree Identification and Extraction

The extraction of individual trees from the point cloud of all the plots of 779 trees 627 trees that is 80.5% were extracted (Figure39) and 152 trees (19.5%) were missed. This extracting of tree varied from plot to plot depending on the amount of undergrowth and density of tree trunks and leafy material of the plots. Plots 10 and 16 are some of the plots where lowest rate of tree detection and extraction occurred because of the dense undergrowth (Figure39). This study was conducted in a tropical rain forest where much undergrowth and overlapping of trees occurs. In previous study done by Antonarakis (2011) all 166 (100%) trees were detected in the natural riparian forest along the Garonne River (France), were there is little undergrowth using a ground scanner.
Some of the reasons for missing trees were due to occlusion and blocking of tree numbers and density of point cloud data. The farthest the tree the lower the detection percentage of the tree (Antonarakis, 2011; Liang, et al., 2011).

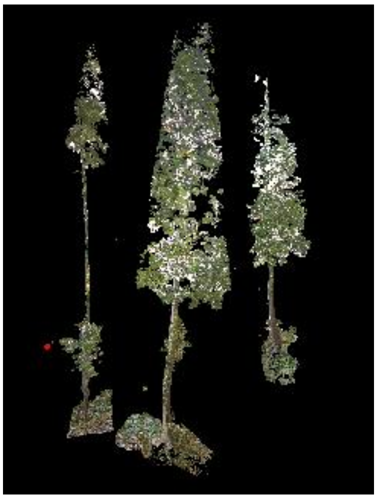


Figure 39: Sample of Extracted trees (Plot 18, trees 20, 7 and 14

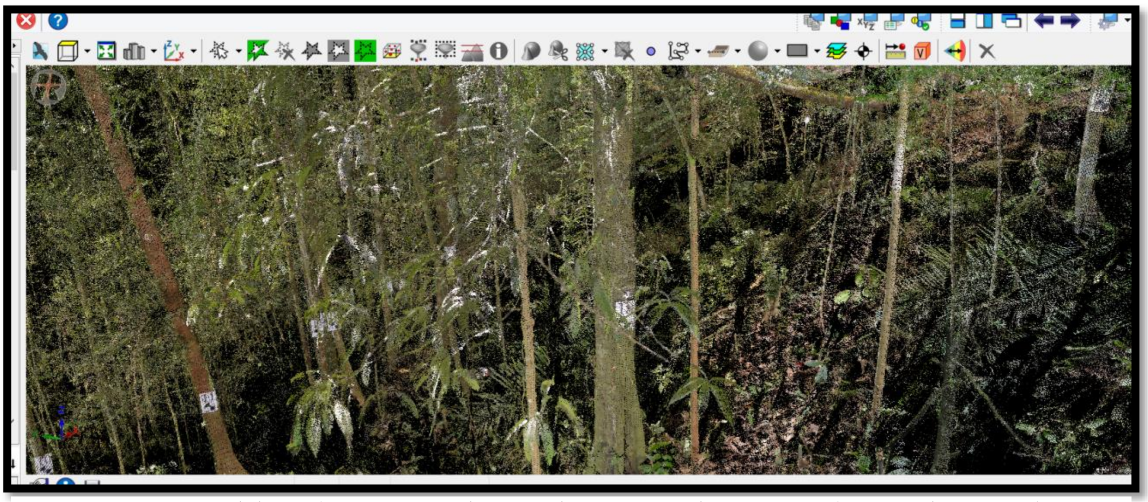


Figure 40: Point cloud data of Plot 10 with dense undergrowth and occlusion of trees and tree numbers

5.2. TLS Tree Parameters

The data distribution of the tree measurements of Diameter at breast Height (DBH), at 1.3m, derived from TLS was skewed the right (positively) while for the height measurement it's approximately normally distributed (Figure 21). In statistics skewness measures the asymmetry of the distribution of a data. It can be skewed to the right (positive) or to the left (negative) (Figure41). The main reason for the skewness of the DBH measurements to the right or positively skewed is because all the measurements where taken a DBH of 10cm and above.

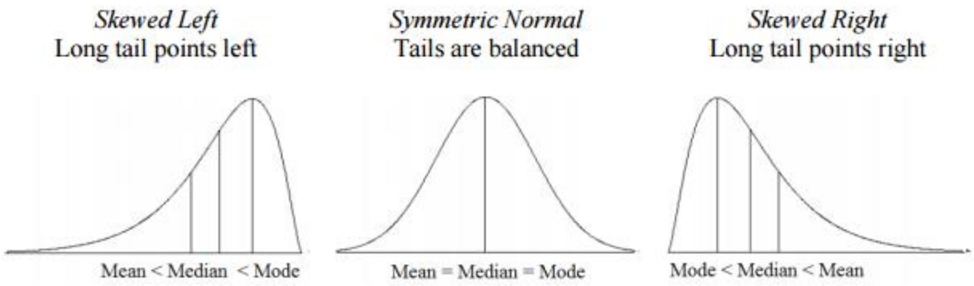


Figure 41: Sketches showing the distribution of a data (skewness) (Doane et al., 2011)

5.3. Plot-wise comparison of Field and TLS measured DBH and Height

Initially this study intended to carry out a plot based assessment. However, after initial analyses it became clear that due to occlusions and overlapping of the canopies and understory (Figure43) all trees within a plot couldn't be found both in airborne LiDAR and TLS. Top canopy tree can be seen on ALS whereas lower canopy trees can only be seen on TLS. Further analyses were done on those trees which were visible clearly on both the ALS and the TLS. Figure 42 shows an illustration about tropical rain forest structure and how TLS and ALS perform.

In the plot wise comparison plot number 14, 15 and 16 have a relatively low value of R^2 0.91, 0.85 and 0.91 while in the rest of the plots R^2 was minimum of 0.97 for the DBH measurements. In regard to the height comparison, plots 1, 4, 17, 19, 22 and 24 were among the plots in which R^2 of 0.32, 0.45, 025, 0.31, 0.31 and 0.12 values were respectively obtained. The main reason for this was these plots had much of undergrowth and understory especially the palm trees and the Lianas (climbers) (Figure 42). Some climbers were really difficult to remove and where problematic as they grew in the tree canopies and send their roots to the ground.

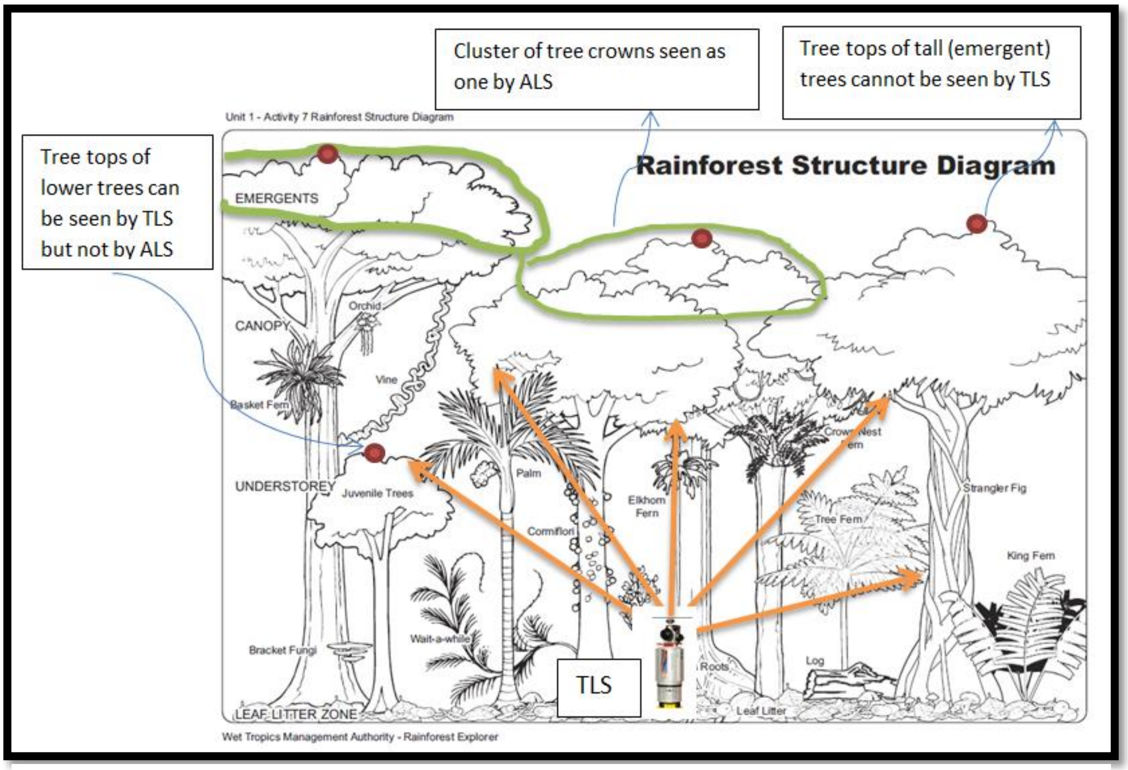


Figure 42: Illustration of a tropical rain forest structure with understory and overlapping of canopies. (http://www.wettropics.gov.au/rainforest-structure)

(a) (b)

Figure 43: Overlapping of tree crowns of the study area (a) and Undergrowth plant and climbers affecting tree detection and DBH measurements (b)

5.4. Relationship between Field and TLS measurements of DBH and Height

As mentioned in the above section further analysis was based on the 228 tree which could be identified clearly both in ALS and TLS. Accordingly a regression analysis and a statistical t-test of paired two sample for mean of the tree heights and DBH as well as heights from ALS was performed to see and asses their significance diffferences.

5.4.1. Tree Height measurments

In airborne LiDAR, tree heights can be estimated more accurately as it scans from above and tree tops can be easily detected and the LiDAR also penetrates to the ground so the full height of a tree can be detected. In this study heights measured by ALS are assumed to be the correct measurements (O'Beirne, 2012). Other studies also show that an airborne LiDAR (ALS) can describe the top canopy in more details as compared to the TLS (Hilker et al., 2010). Hodgson & Bresnahan, (2004) did an accuracy of airborne LiDAR derived heights on evergreen forests and deciduous forests in which they got a RMSE of 17 to 19 cm and 26cm respectively. Tree height measurement by TLS a result of coefficient of determination (R^2) and RMSE were **0.87 and 2.15m** (**9.6%** of the average tree height of ALS) respectively. Hilker et al. (2010) compared the heights of old coniferous forest in Canada from TLS and ALS and obtained R^2 of 0.86 which is almost the same to the result obtained in this study.
A study done by Hopkinson et al. (2004) explains an error of 1.5m(7% of the mean). This result is less than the result obtained in this study. This difference could be due to the different forest characteristics as Hopkinson et al. (2004) did his study in a matured red pine and multitier mixed deciduous tree, with no understories in southern Ontario and forest which is different from this study. Nevertheless in both cases tree height were underestimated by TLS. The underestimation of tree heights by TLS is mainly due to the overlapping and intermingling of tree canopies in the study area. TLS does upward shooting from the ground therefore the pulses get obscured and intercepted by the underneath canopies and foliage. In such forests it is difficult to determine the top of the trees. This was also the case in the study area in Malaysia. The underestimation of tree heights by TLS is due to much understory and overlapping of canopies. In most cases of the tall trees their top part was not scanned properly due to shadowing or overlapping (Figure 33) with other tree canopies. This caused a very low density of point cloud data or totally blockage of pulse and ultimately underestimation in the height measurement (Figure 44

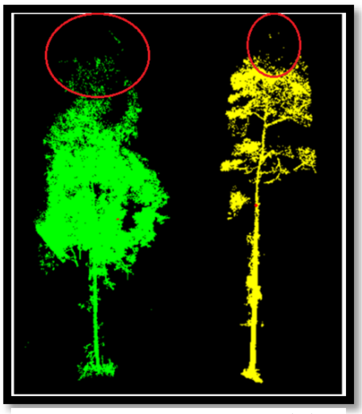


Figure 44: Less point cloud data density on the top of trees affecting tree height accuracy

The variation in the manual field height measurements could be attributed due to the random error in the field measurements. This error can be higher due to the nature of the forest area, especially in tropical rain forests where it is difficult to determine the most top of trees. Secondly tree heights derived from TLS could be underestimated due to upward shooting from the ground and obstruction of the pulse reflection by the foliage.

In the field, trees that have large crown and are tall are difficult to point out exactly their true top from the ground. Therefore, this leads to a measurement of tree heights at larger angle which will measure false overestimated tree heights. Some errors were also occurring due to the intervening foliage blocking of the view of the bottom and top of the trees which possibly can cause underestimation of the tree heights. Also some errors were due to misreading of the actual tree heights of tilted trees (Figure45).
In estimation of the above Ground biomass and carbon stock in sample plots of 3, 4, 5, 24 and 25 there was high underestimation of tree heights plots due to canopy overlapping which resulted in underestimation of aboveground biomass by the TLS as compared to other plots.

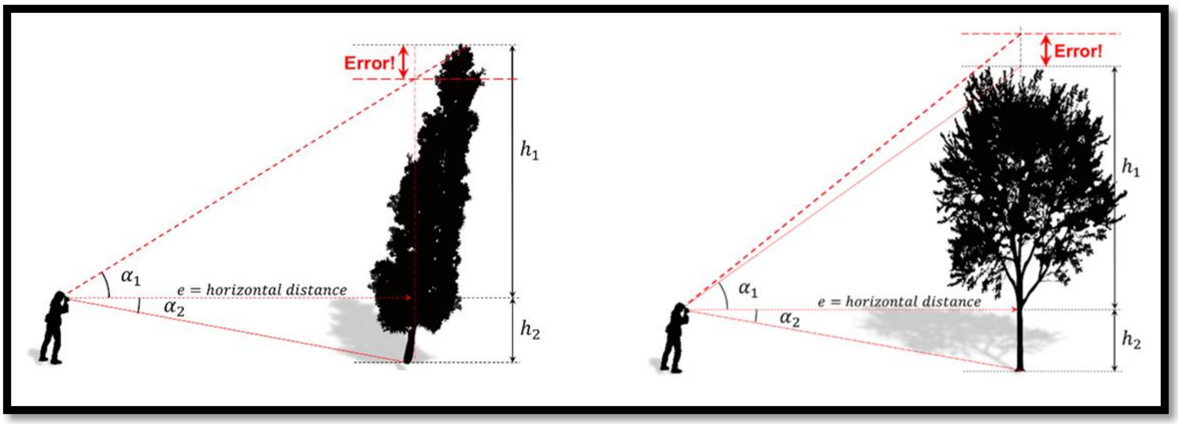


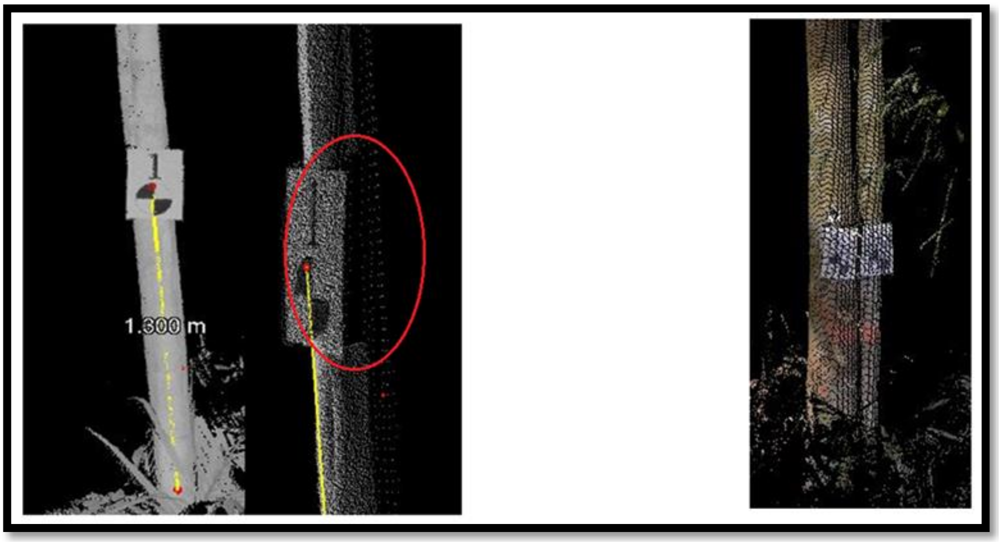
Figure 45: Figure45: Errors in tree height measurements

(Source: http://wiki.awf.forst.uni-goettingen.de/wiki/index.php/Tree_height)

5.4.2. DBH measurments

Measurement of tree Diameter at Breast Height (DBH) is very important in above ground biomass and carbon stock estimation. According to Brown, (2002). About 94% Variation in above ground biomass of trees can be explained by DBH. The correlation analysis between the field measured DBH and DBH from TLS resulted a very high relationship with coefficient of determination (R^2) of 0.985 and RMSE of 1.7cm were obtained. A study done by Maas et al. (2008) got a R^2 of 0.975 and RMSE of 1.8cm with a multiple scan data. Similarly Simonse et al. (2003) also compared DBH from field and TLS and got an error of 1.7cm. Watt & Donoghue, (2005) reported a variance of 1.5cm with R^2 of 0.92. The multi- scan mode and the low error in point cloud registration (Table 5) in this study can be one of the reasons for high agreement between the measurement of the field and the TLS DBH. Moreover, Maas et al. (2008) got a low RMSE of DBH as he compared accuracy of the DBH of trees from three plots which were scanned with single scan-set up and another plot scanned with multi-scan set up. The number of scan positions has an effect on the accuracy of DBH measurements (Figure 48).
Measuring DBH exactly at a height of 1.3m from the tree base in the field is not simple and practical. Different people determine breast height at different heights according to their own height. In addition to that the base of the trees is not always levelled, therefore because of these reasons the DBH of the trees

could be measured at height of more or less than 1.3m. Therefore in this study to avoid this differences a stick with a length exactly 1.3 m was used to mark the trees from their base in the sample plots. During extracting of DBH measurements from the point cloud data unfortunately in some plots tree numbers were paced exactly where the 1.3 measurement is (Figure46). This led to a low density of point cloud data



at that section of the tree which ultimately affected to the accuracy of DBH measurements. Moreover, some trees were too close together so it was difficult to measure their DBH more accurately (Figure 47).

(a) (b)

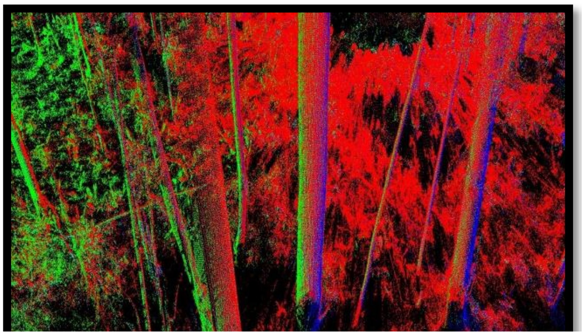


Figure 46: Tree number causing less point cloud density (a) and too close trees affecting DBH measurements (b).

Figure 47: Sample -Multiple scanned trees, increasing the accuracy of DBH measurement. (Each colour representing scans from different positions).

5.5. Delineation of Tree Crowns and Segmentation Accuracy

In this study, multi- resolution segmentation was used. This approach gives a meaningful image objects, especially from high resolution imagery (Baatz, 2000). Moreover according Lamonaca et al., (2008) a multi-resolution segmentation is the most applicable method in a heterogeneous and complex forest structures specifically with high resolution data. This is due to the capably of multi-resolution segmentation to segment scale dependent patterns of a heterogeneity of a forest structure. The accuracy of segmentation obtained in this study using the goodness of fit approach was 68.6% with 0.314 D value. This result is based only on the upper canopy crowns. This is because trees under the top canopy were not included because they were not fully visible. Airborne LiDAR do not have any spectral information, it is just point cloud hanging in the air based on the height with black and white, and do not give further detailed visualization of the forest.

The segmentation accuracy was based on the relative intersection area between the manually delineated trees , as a reference, and the digitally segmented tree crowns (Möller et al., 2007). An accuracy result obtained by Kwak, et al. (2007) was 67.4% which is almost the same to the result obtained in this study The result is less than the accuracy of 74.4% and 75.6% obtained by Karna et al. (2015) and Wang et al. (2004) respectively. The accuracy obtained by Wang et al. (2004) was in a white spruce (*Picera glauca*) and Douglas fir (*Pseudotsuga menziesii*) However these results were from integration of airborne LiDAR and satellite imagery and a high- spatial resolution aerial imagery (Figure49). Holmgren, et al. (2008) obtained an improvement of 8% in tree crown segmentation based on LiDAR data and optical satellite imagery data.

Figure 48: High- spatial resolution aerial imagery

Identification of individual trees (crowns) using airborne LiDAR data in a tropical rain forest is not easy due to the overlapping of the top tree canopies over the underneath canopies. Based on heights of the Canopy Height Model (CHM) eCognition was able to separate the tree crowns especially the upper trees, based on height information, however the under canopies were partly hidden and couldn't be separated properly. (Figure50). The manual delineation of crowns was also done on those upper tree crowns that seen clearly.

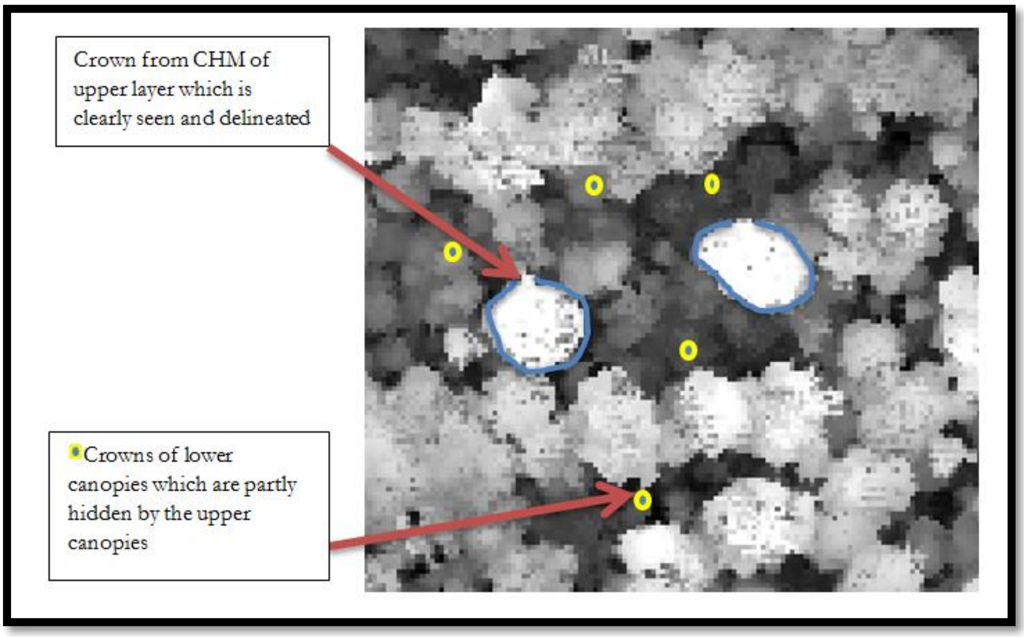
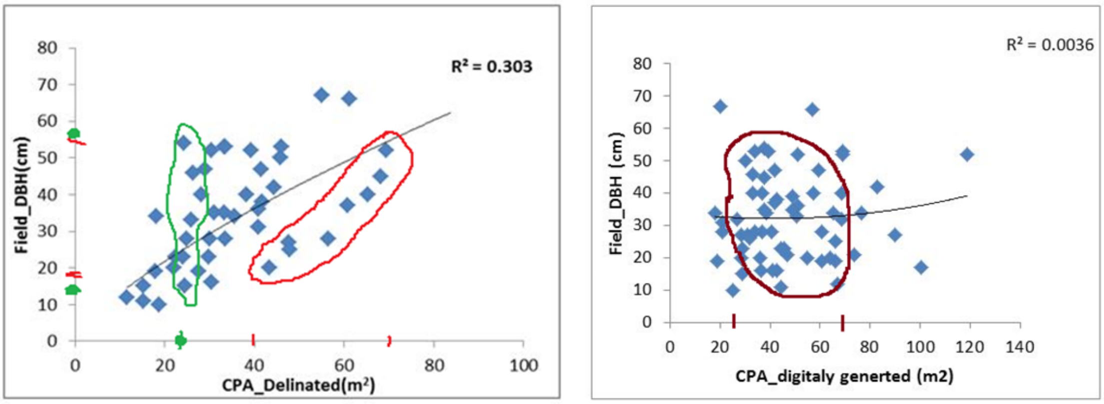


Figure 49: CHM: with clearly seen upper canopy trees (circled with blue line) and lower canopy trees (yellow dots)

Figure 50: eCognition segmented upper crowns

5.6. Modelling the Relationship between Crown project Area (CPA) and DBH

According to the objective number five (5) of this study, a relationship between the segmented tree crowns and the field measured DBH was to be developed. Therefore a regression model was developed (section 4.13) based on the 228 manually delineated trees and digitally segmented ones. Nevertheless, the relationship (nonlinear relationship) was poor with coefficient of determination (R^2) of 0.3 and 0.003 for the manually delineated and digitally segmented polygons respectively which couldn't estimate the DBH accurately. In some tree with different DBH measurements have same size of crowns (Figure51a). Also in some observations trees with different DBH measurement (from15cm to 54cm) are having the same crown size of 24m² labelled in green colours. In the case of the relationship between digitally segmented (eCognition) and DBH, the observations are clustered in the CPA range of 25m² and 60m². There is no pattern within any ranges of CPA. To assess the effect and role of species diversity in this poor relationship most frequent occurring species *Shorea* was taken (Figure 52) the result was R^2 of 0.4 which still poor relationship. The possible reason for this poor relationship between these parameters (CPA and DBH) in both cases could be due to the number of species. In this study as it's a tropical rain forest 100 plus tree species were recorded in the field. Different trees and tree species have different growth rate, canopy structure, and different tropisms to ward resources. Had the relation been done per species the result would probably have been better. Moreover in certain plots some trees with big trunk were having small tree crowns and vice versa. In a previous study done by Ali et al. (2010) a linear relationship between CPA and DBH was obtained with R^2 of 0.63, 0.69 and 0.74 was obtained for the tree species of *Schima wallichii*, Shorea robsta and *Terminalia alata,* respectively. However, the study used a very high resolution Geoeye satellite images.



(a) (b)

Figure 51: Relationship between Field DBH and manually delineated CPA (a) and between Field DBH and digitally segmented CPA(b)

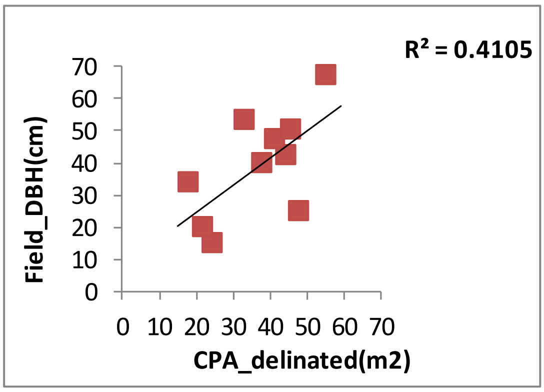


Figure 52: Relationship between Field DBH and manually delinated CPA of Shorea species

6. CONCLUSION AND RECOMMENDATION

The main objective of is study was to evaluate and assess the performance of the airborne LiDAR and the Terrestrial laser Scanner (TLS) in the assessment of the above ground biomass in the tropical rainforest of Ayer Hitam forest reserve (AHFR). To achieve this regression and correlation analysis among the tree parameters of Diameter at Breast Height (DBH), tree height and Canopy Project Area (CPA) derived from field measurements, TLS and airborne LiDAR. According to the research objective and research questions the following conclusions were made:

1. **Is there a significant difference between Heights derived from TLS with the manually field measured height?**

The relationship between tree height derived from TLS and manually measured in the field was with R^2 of 0.70. The statistical analyses of a paired t- test was conducted and the result reveals that at a confidence interval of 95% significance level there is no significant deference between the two tree height means from field and TLS derived one. Thus the null hypothesis was accepted as the t- calculated was less than t-critical.

2. **Is there a significant difference between DBH derived from TLS with the manually field measured DBH?**

Measurement of DBH Derived from TLS and the field measured DBH are highly correlated with R^2 of 0.98. According the result of significance test, there is no significant difference between these two DBHs measurements. Therefore the null hypothesis was not rejected.

3. Is there a significant difference between height derived from Airborne LiDAR and TLS derived height?

Airborne LiDAR (ALS) and TLS derived tree heights were relatively highly correlated with coefficient of determination (R^2) of 0.87. Based on the result of the t-test, the null hypothesis was accepted. as the t-calculated was less than t-critical. Therefore, there is no significant difference between the means of these height measurements at 95%e level of significance.

4. Is there a significant difference between height derived from Airborne LiDAR and field measured height?

The relationship between the manually field measured height and height derived from Airborne LiDAR was assessed with R^2 of 0.65. And the result of the statistics showed a significance relationship. The null hypothesis was accepted as t-calculated was greater than t-critical.

5. How accurately can tree crowns of a tropical rain forest be identified and measured from airborne LiDAR data?

Accuracy of delineated tree crowns was assessed trough measure of goodness of fit (D-value). The result was 68.6%. This result is generally in agreement as compared to previous studies considering that only airborne LiDAR is used in this study.

6. How accurately can DBH be estimated from CPA of airborne LiDAR?

In this study the regression model of the CPA of LiDAR and field measured DBH was weak. Thus the DBH estimated from the crown of airborne LiDAR was significantly different from the field measured DBH. The null hypothesis was not rejected since t-calculated was greater than t- critical. Therefore, the estimated DBH was not enough good to estimate the above ground biomass.

7. Is there a significant difference between the aboveground biomass/carbon stock estimated from TLS and airborne LiDAR (ALS)?

The above ground biomass (AGB) estimated from ALS and TLS were highly correlated with coefficient of determination (R^2) of 0.968. The t-calculated was greater than the t- critical therefore the null hypothesis was accepted.

In general conclusion tree parameters (DBH and Height), derived from the Terrestrial Laser Scanner (TLS) are highly correlated especially in terms of DBH with the field measured ones. Thus, the aboveground biomass (AGB) and carbon Stock (AGC) can be estimated in a reasonably accuracy in tropical rain forest using Terrestrial Laser Scanner (TLS) and Airborne LiDAR (ALS). In the case of airborne LiDAR the CPA of the LiDAR was not adequate enough to predict the DBH accurately. Moreover, from this study it can be conclude that identification of individual tree crowns is not easy in such tropical rain forest using only Airborne LiDAR data.

Recommendation

1. The application of Terrestrial Laser Scanner (TLS) in a tropical rain forest is not fully discovered, therefore a further studies in a similar forest structures landscapes should be done to see the results of this study and for additional new discovers.
2. Multiple scanning, especially in a tropical rainforest with high tree density and undergrowth is more recommended to improve the rate of tree identification and extraction.
3. To minimize error in the measurement of DBH it is more advisable to tie a tree at exactly 1.3 meter with a reflecting ribbon which can be easily detected and safe time while measuring DBH from the point cloud in RiSCAN PRO software.
4. Considering the weight of TLS instrument is that it is a little bit heavy instrument to carry it in undulating and sloppy landscape forest areas, like Ayer Hitam Forest. So it would have been easy to carry it if the weight was less.

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LIST OF APPENDICES

Appendix 1: Field data collection sheet used in the study area

DATA COLLECTION SHEET (AYER HITAM TROPICAL RAIN FOREST RESERVE, MALAYSIA

Name of recorder...**Date**...

Sample Plot No.	GPS Coordinates	X:	Grid cell No.	Slope (%)	Undergrowth		Crown Cover (%)
		Y:		Bearing (Scan Position):	Y	N	

Tree No.	Species	DBH (cm)	Hgt 1 (Leica)	Hgt 2 (Haga)	Hgt 3 (TruPulse)	Crown diam.(m)
1						
2						
3						
4						
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						
16						
17						
18						
19						
20						
21						
22						
23						
24						
25						
26						
27						

Appendix 2: Slope Correction Table

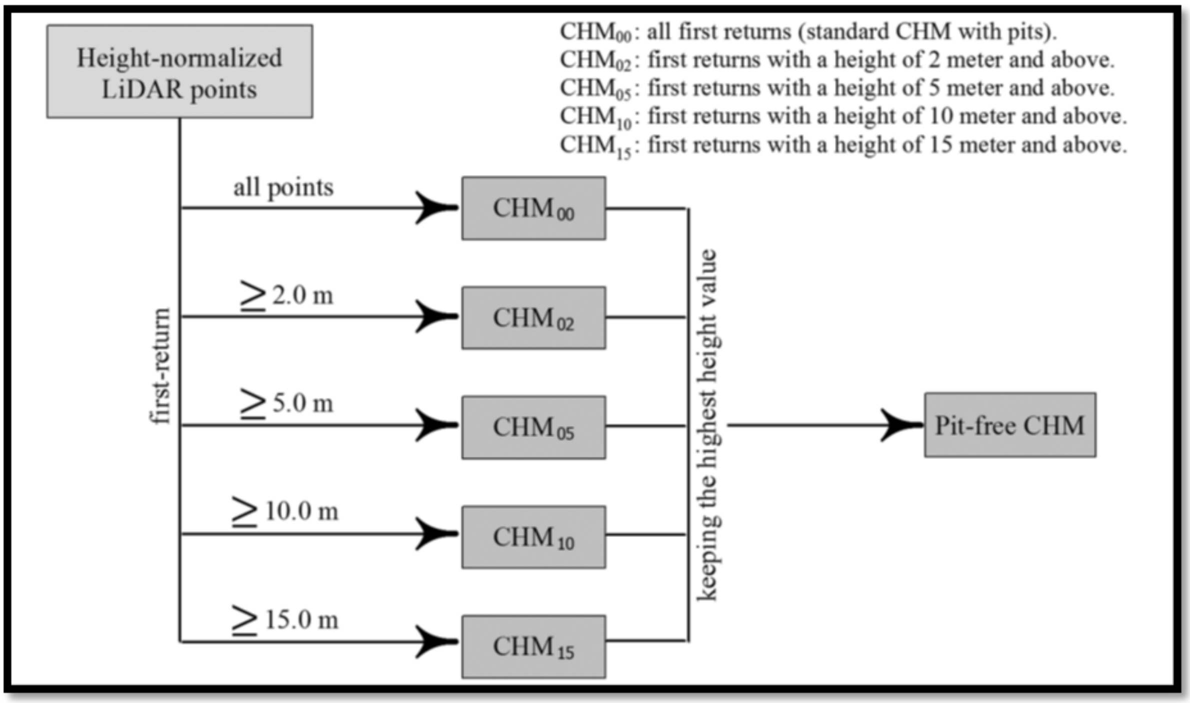
Slope correction table

Plot size 500 m^2

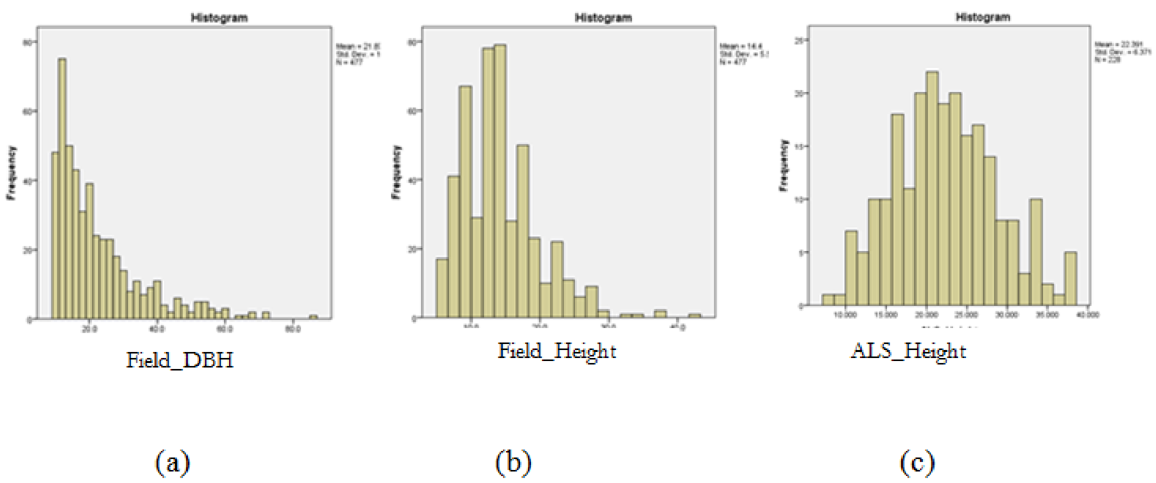
Slope%	Radius(m)	Slope%	Radius(m)	Slope%	Radius(m)
0	12.62				
1	12.62	36	13.01	71	13.97
2	12.62	37	13.03	72	14.00
3	12.62	38	13.05	73	14.04
4	12.62	39	13.07	74	14.07
5	12.62	40	13.09	75	14.10
6	12.63	41	13.12	76	14.14
7	12.63	42	13.14	77	14.17
8	12.64	43	13.16	78	14.21
9	12.64	44	13.19	79	14.24
10	12.65	45	13.21	80	14.28
11	12.65	46	13.24	81	14.31
12	12.66	47	13.26	82	14.35
13	12.67	48	13.29	83	14.38
14	12.68	49	13.31	84	14.42
15	12.69	50	13.34	85	14.45
16	12.70	51	13.37	86	14.49
17	12.71	52	13.39	87	14.52
18	12.72	53	13.42	88	14.56
19	12.73	54	13.45	89	14.60
20	12.74	55	13.48	90	14.63
21	12.75	56	13.51	91	14.67
22	12.77	57	13.53	92	14.71
23	12.78	58	13.56	93	14.74
24	12.79	59	13.59	94	14.78
25	12.81	60	13.62	95	14.82
26	12.82	61	13.65	96	14.85
27	12.84	62	13.68	97	14.89
28	12.86	63	13.72	98	14.93
29	12.87	64	13.75	99	14.97
30	12.89	65	13.78	100	15.00
31	12.91	66	13.81	101	15.04
32	12.93	67	13.84	102	15.08
33	12.95	68	13.87	103	15.12
34	12.97	69	13.91	104	15.15
35	12.99	70	13.94	105	15.19

A. de Gier - 2000

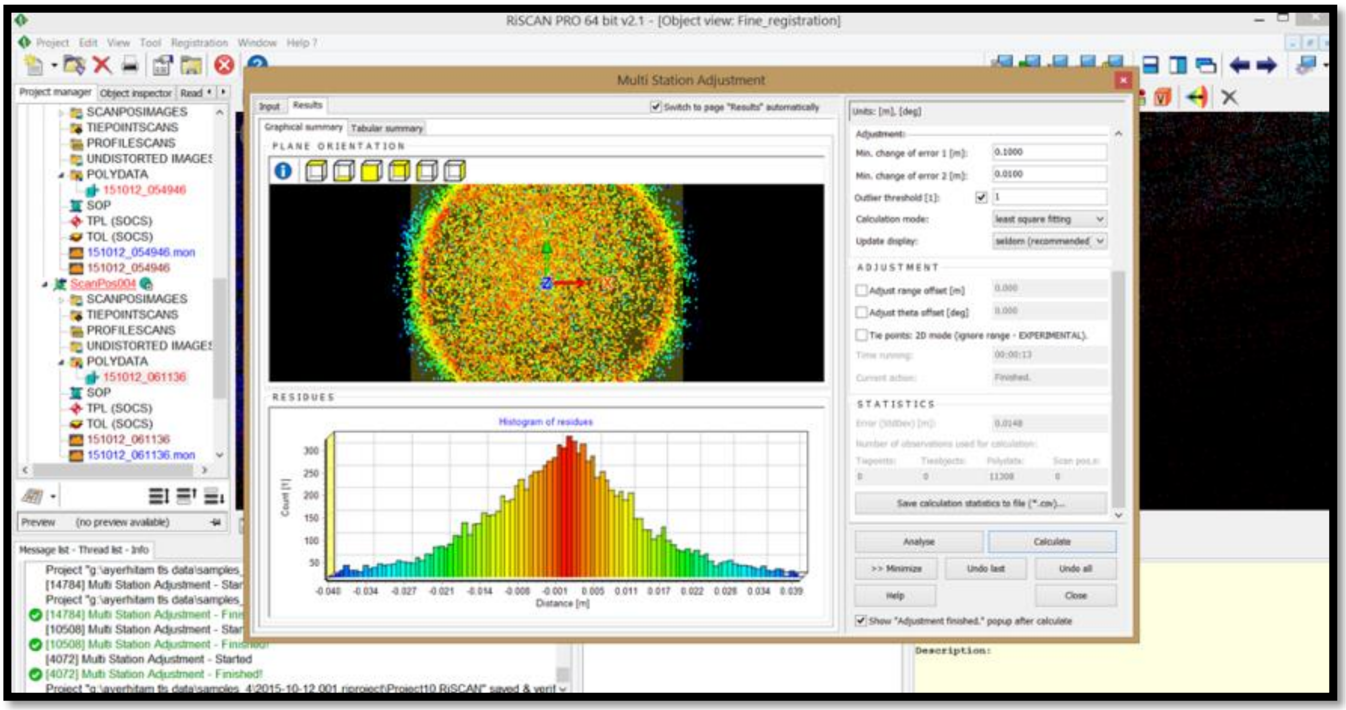
Appendix 3: Methodology diagram of the pit-free algorithm



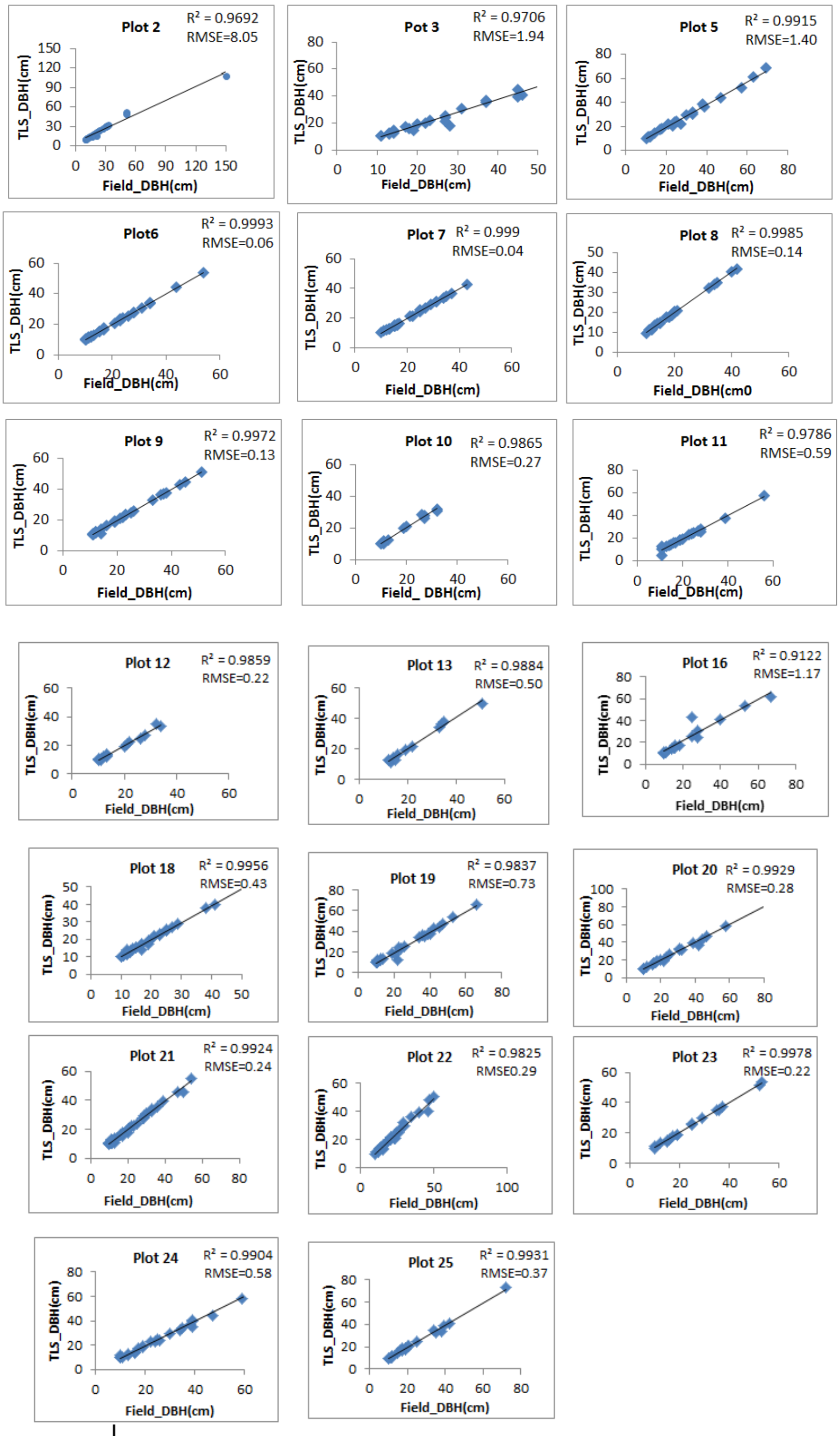
Appendix 4: Distribution DBH (a) and Height (b) from Field, and Height from ALS.



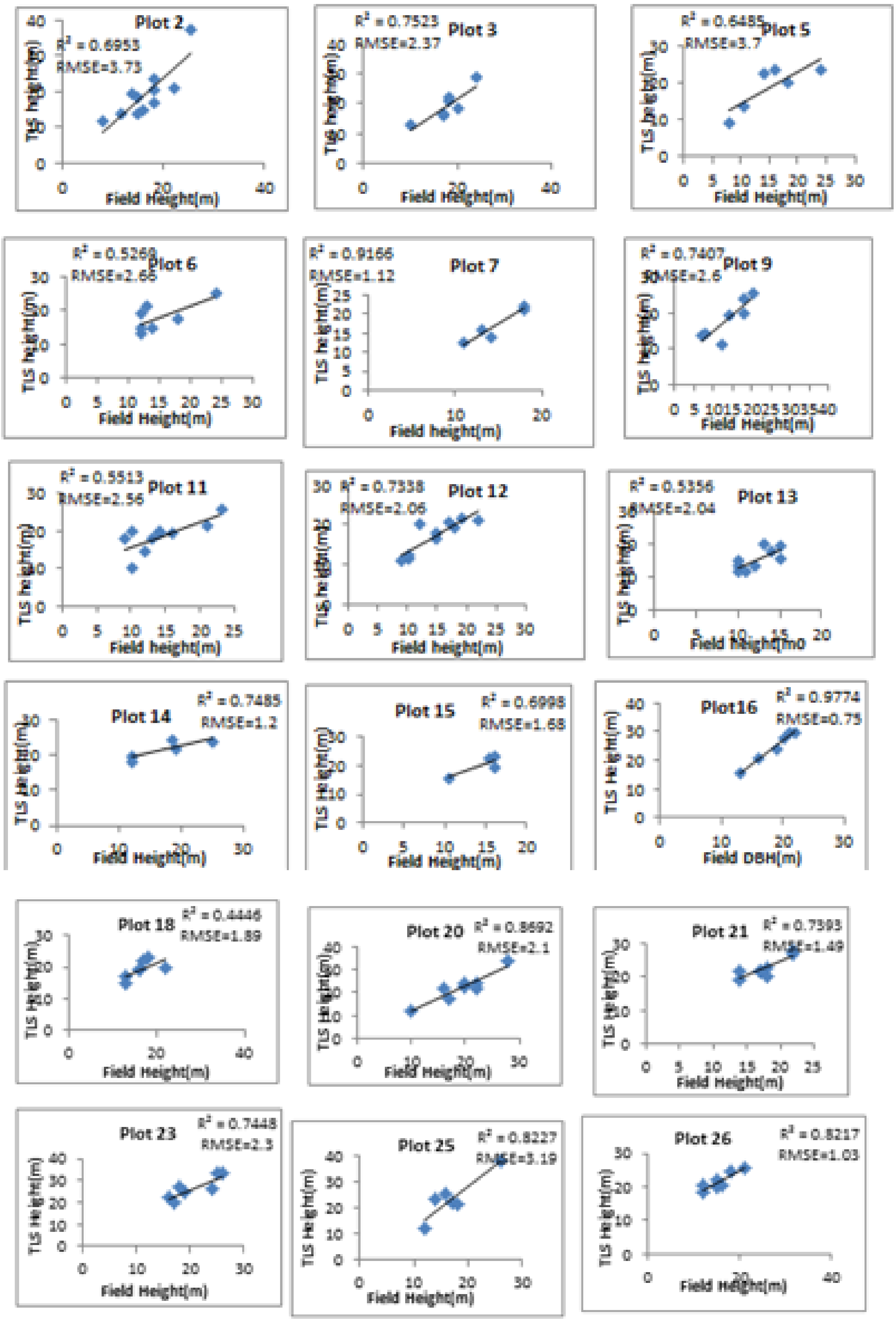
Appendix 5: Sample result of Multi-station Adjustment of plot 19 in RiSCAN PRO



Appendix 6: Scatter plot of Field measured DBH and TLS derived DBH comparing relationship



Appendix 7: Scatter plot of plots heights measured from the field and derived from TLS



Appendix 8: Normality Test for the Field measured heights and ALS derived heights

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Field_Height	.094	228	.000	.959	228	.000
ALS_Height	.043	228	.200*	.989	228	.084

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Appendix 9: (a) Regression analysis of the Field DBH and manually delineated CPA and automatically generated CPA (b)

(a)

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.550
R Square	0.303
Adjusted R Square	0.287
Standard Error	12.411
Observations	46.000

ANOVA

	df	*SS*	*MS*	*F*	*ignificance F*
Regression	1	2944.7	2944.7	19.11605	7.42E-05
Residual	44	6777.908	154.0434		
Total	45	9722.609			

	Coefficients	*andard Erro*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	14.99	4.89	3.06	0.00	5.13	24.85	5.13	24.85
X Variable 1	0.55	0.13	4.37	0.00	0.30	0.81	0.30	0.81

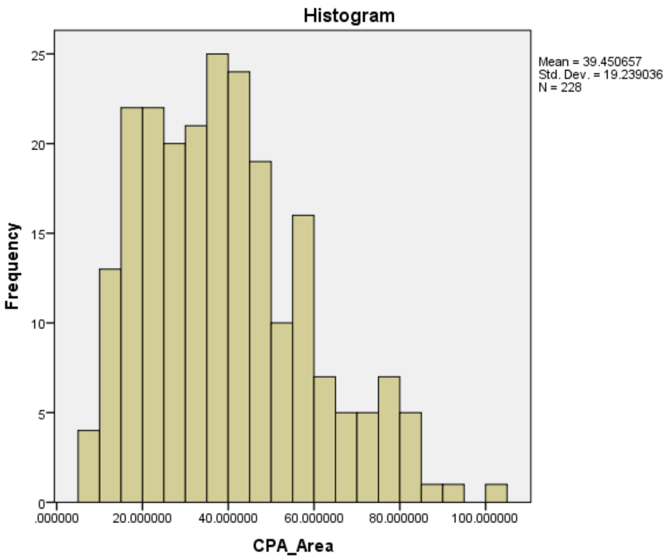
(b)

SUMMARY OUTPUT	
Regression Statistics	
Multiple R	0.060
R Square	0.004
Adjusted R	-0.013
Standard E	13.667
Observatic	63.000

ANOVA					
	df	*SS*	*MS*	*F*	*ignificance F*
Regressior	1	40.935	40.935	0.219	0.641
Residual	61	11393.668	186.781		
Total	62	11434.603			

	Coefficients	*tandard Erroi*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	30.727	4.423	6.947	0.000	21.882	39.572	21.882	39.572
X Variable	0.040	0.085	0.468	0.641	-0.131	0.211	-0.131	0.211

Appendix 10: Histogram of a manually delineated CPA



Appendix 11: Field work and study area Photos