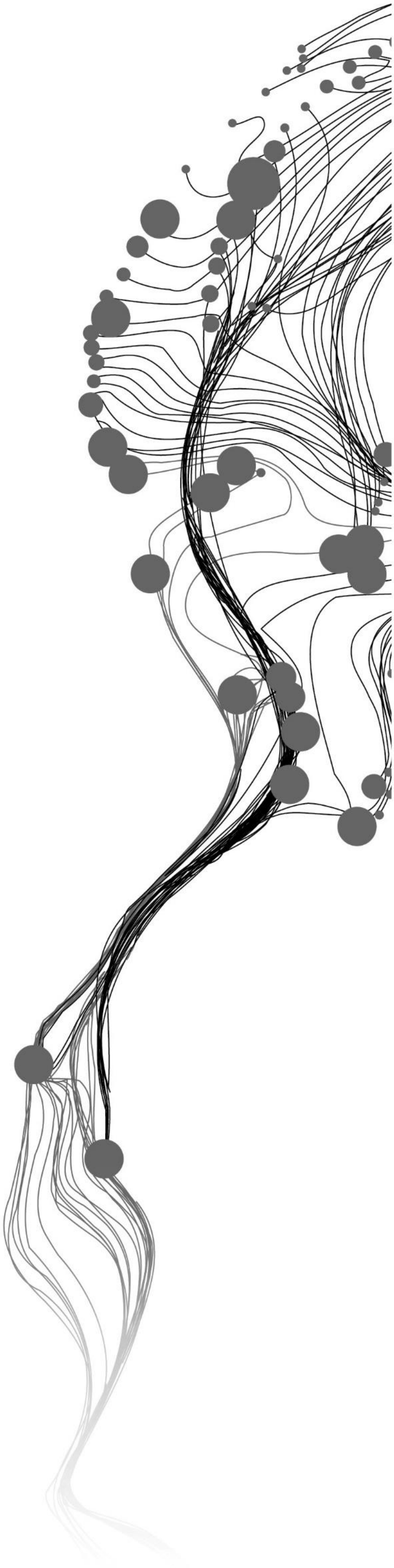
EFFECT OF FOREST STAND DENSITY ON THE ESTIMATION OF ABOVE GROUND BIOMASS/CARBON STOCK USING AIRBORNE AND TERRESTRIAL LIDAR DERIVED PARAMETERS IN BERKELAH TROPICAL RAIN FOREST, MALAYSIA

AGERIE NEGA WASSIHUN
February 2018

SUPERVISORS:
Dr. Yousif A. Hussin
Ir.L.M.Van Leeuwen

ADVISOR:
Dr. Zulkiflee Abd Latif



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AGERIE NEGA WASSIHUN
Enschede, The Netherlands, February, 2018

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.
Specialization: Natural Resource Management

SUPERVISORS:
Dr. Yousif A. Hussin
Ir.L.M.Van Leeuwen

ADVISOR:
Dr. Zulkiflee Abd Latif

THESIS ASSESSMENT BOARD:
Prof. Dr. A.D. Nelson (Chair)
Dr. Tuomo Kauranne (External Examiner, Lappeenranta University of Technology, Finland)
Dr. Yousif A. Hussin (1st Supervisor)
Ir.L.M.Van Leeuwen (2nd Supervisor)

ABSTRACT

Tropical rainforests have an important and an exceptional function in mitigating global warming caused by the increase in atmospheric CO_2 since they are the highest terrestrial carbon reservoir. Forest stand density in tropical rainforests is crucial functional and structural variable of forest ecosystems in which above ground biomass can be obtained. Currently, there is a growing demand for airborne and terrestrial LIDAR in measuring forest trees parameters (e.g., DBH and height) for accurate assessment of forest biomass/carbon stock to meet the requirements of UN-REDD+ program. Although several studies have been conducted on above ground biomass/carbon stock in tropical rainforest using forest inventory parameters derived from airborne and terrestrial LIDAR, no research is conducted on how the estimation of above ground biomass/carbon stock using airborne and terrestrial LIDAR derived parameters is affected by forest stand density in a tropical rainforest. Therefore, this study aims to analyze and investigate the effect of forest stand density on the estimation of AGB/carbon stock using airborne and terrestrial LIDAR derived trees parameters in Berkelah tropical rainforest.

Purposive sampling approach was adopted for the selection of the unit of analysis. Results are based on data collected from 32 sample plots measured and scanned in the field. Airborne LIDAR was used to derive upper canopy trees height, while terrestrial LIDAR was used to derive the height of lower canopy trees and DBH of all scanned trees in all sampled plots. DBH measured in the field was used to validate the DBH manually derived from Terrestrial Laser Scanner (TLS) point cloud data, and it was also used to compute the stand basal area of field measured trees and extracted from TLS point cloud data. The DBH manually derived from TLS point cloud data was used to estimate AGB of the sampled plots for both upper and lower canopy trees. Descriptive statistics, linear regression and correlation analysis were used to answer the research questions of this study.

The coefficient of determination R^2 and RMSE of the DBH manually derived from TLS point cloud data validated by field measured DBH were 0.99 and 1.37cm respectively. This result revealed the existence of almost one to one relationship and based on the statistical test undertaken; there is no statistically significant difference between the two DBH measurements. Out of 1033 trees measured and scanned in the field, 855 trees (82.7%) were extracted from TLS point cloud data and 178 trees (17.3%) were missed. The Pearson correlation coefficient(r) between a total number of trees measured and scanned in the field and the total number of trees extracted from TLS point cloud was 0.95. R^2 of 0.89 and 0.15 was found to explain the relationship between number of missed trees per plot against a number of trees measured in the field and number of missed trees against forest stand density respectively per plot regardless of the size of missed trees. On the other hand, R^2 of 0.912 and 0.179 were found for above ground biomass against forest stand density and above ground biomass against number of trees per plot respectively.

Furthermore, for AGB sensitivity analysis, when TLS tree height was validated by corresponding trees height from airborne LIDAR, 0.72 and 2.42m were found for R^2 and RMSE respectively, and AGB was not sensitive to TLS tree height measurement variation. Finally, based on the findings, forest stand density significantly affect the estimation of above ground biomass at Alpha equal to 0.01 significance level.

Keywords: Tropical rainforest, ALS, TLS, AGB, Point cloud data, Stand basal area, Missed trees, Forest stand density, Number of trees, REDD+, Sensitivity analysis, DBH, Carbon stock, Plot

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LIST OF ACRONYMS

AGB	Above ground biomass
AGC	Above ground carbon
ALS	Airborne Laser scanner
CF	Conversion Factor
CHM	Canopy height model
DBH	Diameter at breast height
DSM	Digital surface model
DTM	Digital terrain model
GPS	Global positioning system
Ha	Hectare
IMU	Inertial measurement unit
IPCC	Intergovernmental Panel on Climate Change
LIDAR	Light Detection and Ranging
LIDAR	Light Detection and Ranging
Mg	Megagram
MRV	Measurement, reporting, and verification
REDD+	Reducing emission from deforestation and forest degradation
RMSE	Residual Mean Squared Error
SOCS	Scanner Own Coordinate System
TLS	Terrestrial laser scanner
UiTM	University Technology MARA
UNFCCC	United Nations Framework Conventions on Climate Change

1. INTRODUCTION

1.1. Background of the Study

In the past few centuries, the concentration of carbon dioxide, as part of greenhouse gases in the atmosphere, has increased mainly due to anthropogenic activities and natural events (Jayakumar et al., 2012; Zaki et al., 2016). Forests play an important role in mitigating global warming and climate change. They sequester and store more carbon than any other terrestrial ecosystem. The carbon stored in forests is released in the form of carbon dioxide when forests are cleared or degraded (Gibbs et al., 2007).

Forest above ground biomass(AGB) is a very important parameter used for forest productivity and carbon balance assessment (Nie et al., 2017). Forests have an important and an exceptional function in mitigating global warming caused by the increase in atmospheric CO_2 since they contain 86 % of terrestrial plant carbon on Earth. With or without disturbances from humans or nature, forests can absorb or release enormous amounts of carbon. Therefore, for a better understanding of the terrestrial carbon cycle as well as improving the decision making process in forest management, monitoring the dynamics of forest carbon storage at various spatial scales is very important (Wang et al., 2013).

Tropical rainforests are rich ecosystems in biological diversity, and it is the highest terrestrial carbon reservoir (Drake et al., 2002). These rainforests play a crucial role in maintaining about 70% of the world biodiversity and numerous species of wildlife due to their habitat diversity (Zakaria, 2013). But now a day, tropical rainforests are undergoing degradation and deforestation in alarming rate (Palace et al., 2015). One of the major causes of forest degradation is selective logging, which is a major economic activity in moist tropics (Neba et al., 2014). As explained by Putz et al. (2008) in tropics despite improvement in forest management practices, still there are destructions during timber harvesting because most logging operations are still carried out by untrained and unsupervised tree fellers. This traditional logging practice aggravates the forest degradation in tropics, and it leads to low forest stand density.

Forest stand density is a quantitative measure of tree cover per unit area or space. More specifically it is a measure of the degree of how crowded trees are in a stand or within a specified area. Forest stand density can be measured in two ways. These are number of trees per unit area (tree density) and basal area per unit area. In some literature, forest stand density and stocking are considered as synonyms. However, there is a slight difference. Stocking is related to carrying capacity of the given area or fixed resources in relation to the available variable resources. Therefore, it is related to the issue that can be considered to be optimum or standard for a certain objective. For the forest, a subjective indication of the stocking is comparing number of trees to the desired number considered to be optimum for a particular area for a certain objective to get best results. Accordingly, stands can be understocked, fully stocked, or overstocked. When the forest is even-age forest, in which all the trees almost have similar DBH and height, then the number of trees per unit area can reasonably represent forest stand density. However, in a natural forest such as tropical rainforest, it is difficult to use the number of trees as a measure of forest stand density because it doesn't consider the variation in the size of the tree. In this case, the sum of the basal area for all trees in the stand per unit area (i.e., ha) provides the total stand basal area per unit area can be used as a measure of forest stand density (Brack, 2012; Density, 1982; Elledge & Barlow, 2012). The stand basal area is the cross-sectional (circular) area of a stem measured at the breast height (i.e., 130 cm) from the ground (Brack, 2012; Elledge & Barlow, 2012).

The forest of the study (Berkelah tropical rainforest) is natural forest, hence stand basal area for all trees per plot is used as a measure of forest stand density. Forest stand density is crucial functional and structural variable of forest ecosystems. Above ground biomass/carbon stock and timber volume can be obtained from forest stand density. In this study, different densities have been considered since different densities can be related to the different degree of degradation.

In developing countries, deforestation and forest degradation take the lion's share of greenhouse gas emissions accounting for approximately 11–13% of all global CO_2 emissions during the last decade (Kaisa et al., 2017). To overcome this problem, the United Nations Framework Convention on Climate Change (UNFCCC) designed a climate change mitigation action by reducing emissions from deforestation and forest degradation in its REDD+ program (Eckert et al., 2011).

As one of the central elements of the REDD+ program, United Nations Framework Convention on Climate Change (UNFCCC) has proposed a mechanism of Measurement, Reporting, and Verification (MRV) of carbon to assess carbon stock accurately. Accordingly, the REDD+ program focused not only on emission reduction from deforestation and degradation but also on the conservation of forest carbon stocks, sustainable management of forest and enhancement of forest carbon stocks which are expected to be undertaken by countries and implementation bodies. Therefore, Measurement, Reporting, and Verification of carbon stocks have been one of the mechanisms used to mitigate climate change (Lyster et al., 2013). Countries and implementing bodies can receive financial compensation from REDD+ activities up on the implementation of a reliable measuring, verification and reporting mechanism (Ene et al., 2016; Willem et al., 2013).

Forest biomass/carbon stock must be first estimated at the national or sub-national level. For this purpose, under the United Nations Framework Convention on Climate Change (UNFCCC), the use of remote sensing technologies is proposed. As a result, optical sensors having high resolution, UAV, Synthetic Aperture Radar(SAR) and Light Detection and Ranging(LIDAR) images are recommended. The choice of the platform depends on forest area, forest type, forest density and level of degradation (REDD, 2012).

Currently, there is a growing demand for accurate and operational techniques for assessing forest biomass/carbon stocks to meet the requirements of UN-REDD program (Prasad et al., 2016). However, so far accurate estimation of the forest above ground biomass remains a bottleneck. Above ground biomass can be estimated using either destructive (harvest) or nondestructive method. The destructive method (i.e., cutting down trees and weighing their parts) is very accurate to estimate biomass. However, it needs much time and labor, it is very expensive, sometimes it is illegal, it is not feasible for large-scale analysis, and often it is not environmentally friendly. To overcome, the limitations of the destructive approach, a nondestructive method is used using biophysical parameters of trees mainly tree height and DBH which are the most common inputs for large scale above ground biomass and carbon assessment through allometric models (Andersen et al., 2006; Ketterings et al., 2001). These parameters can be derived either directly or indirectly. But the direct measurement is very expensive because it needs much time, cost, labors and not applicable in large areas.

The specific function obtained by relating two or more forest parameters for biomass/carbon estimation is called an allometric equation (Jayakumar et al., 2012; Rahman et al., 2017). For developing an allometric equation to be applied for biomass estimation on a larger-scale, a destructive method is very important (Jayakumar et al., 2012; Yuen et al., 2016). The allometric equation can be species specific or generic. The species specific allometric equation can be used for forests of the same species. While the generic allometric equation can be applied to different locations given the same type of forests, but it is less accurate.

1.2. Statement of the Problem

For accurate estimates of carbon stock, accurate above ground biomass assessments are required. Remote sensing tools play a crucial role for accurate measurement of forest inventory parameters for above ground biomass and carbon stock estimation in a relatively large area. Even though remote sensing techniques are useful, the use of optical remote sensing technologies in tropical rainforests for above ground biomass estimation is not optimal because of the complexity of the forest structure (Drake et al., 2002). LIDAR is one of the recently developed remote sensing sensor systems using the laser beam for its measurement. In recent years, highly accurate measurements of individual tree heights over large areas of forest are derived from airborne LIDAR also called Airborne Laser Scanner remote sensing, which works very efficiently and its accuracy ranges from 0.02 ± 0.73 m (Andersen et al., 2006). Moreover, the demand for terrestrial laser scanning (TLS) also called Terrestrial LIDAR for forest biomass assessment increases in recent years. Basic forest inventory parameters such as number and position of trees, DBH, tree height and crown shape parameters can be derived from TLS automatically and efficiently (Bienert et al., 2006). A study conducted by Henning & Radtke (2006) revealed that DBH and height are derived from TLS at the reasonable accuracy. In their finding, they revealed DBH could be derived with errors not exceeding 1 cm, and the tree height also can be derived with errors between the range of 2cm up to 13m. However, the problem of TLS is that it is plot based only.

Moreover, in dense, complex forest structure like a tropical rainforest, accurate measurement of these tree parameters is not an easy task particularly tree height. Tree height from the ground can be measured directly using a handheld instrument like hypsometers, clinometer, and Laser Ranger like Leica Disto D510. However, there is uncertainty in height measurements using these instruments since the terrain is not homogenous and there is variation in the height of trees, canopy densities and crown width. As pointed out by Larjavaara & Muller-Landau (2013) using Leica DISTO D510 which is a laser-based instrument in tropical rainforest, for tree height measurement it provides a biased result since it is difficult to see the top of the tree because the view is blocked by shorter undergrowth trees. But Williams et al. (1994) confirmed that the Leica DISTO D510 is more accurate in measuring tree height compared to other ground height measurement instruments.

Remote sensing technologies have been used to measure and assess trees height to quantify above ground biomass quickly, efficiently and effectively in a nondestructive way. Tree height and DBH can be derived from active remote sensing technologies like Airborne and Terrestrial LIDAR (Lucas et al., 2008; Molto et al., 2013). According to Clark et al. (2004) height under a wide range of canopy conditions can be derived from Airborne LIDAR (ALS). On the other hand, the gap between conventional inventory techniques and Airborne Laser Scanning data processing schemes can be filled by using Terrestrial LIDAR (Srinivasan et al., 2015). Yu et al. (2004) explained that accuracy of tree height estimation by ALS is affected by pulse density and footprint diameter while selection of locations to be surveyed, the number of points or plots to be surveyed, the skill level of individuals conducting the survey, type of equipment used determine the accuracy of DBH and height derived from TLS (Prasad et al., 2016). A study conducted by Van Leeuwen et al. (2011) revealed that airborne and terrestrial LIDAR have their inherent strength and weakness. Due to the top-down perspective, airborne LIDAR focuses on the upper part of the canopy. Thus, it has limitations to characterize vegetation structure in the lower canopy. While TLS returns typically focuses on lower parts of the canopy. As a result, it is difficult to assess the upper crown structure and tree heights.

Consequently, accurate trees height measurement of the upper canopy can be obtained using Airborne LIDAR and accurate DBH for all trees and lower canopy trees height can be measured by Terrestrial LIDAR. However, the effect of forest stand density on the estimation of above ground biomass using airborne and terrestrial LIDAR derived parameters in the tropical rainforest is not tested so far.

Even though several studies (Drake et al., 2002; Gibbs et al., 2007; Prasad et al., 2016; Rahman et al., 2017) have been conducted on above ground biomass/carbon using forest inventory parameters derived from Airborne and Terrestrial LIDAR in tropical rainforest, according to the literature review, no research is conducted on how the estimation of above ground biomass/carbon stock using airborne and terrestrial LIDAR derived parameters is affected by forest stand density in tropical rainforest.

Therefore, this study aims to assess the effect of forest stand density on the estimation of above ground biomass/carbon stock using airborne and terrestrial LIDAR derived parameters in Berkelah Tropical Rain Forest, Malaysia.

1.3. Objectives of the Study

1.3.1. General Objective

The main objective of this study is to assess the effect of forest stand density on the estimation of above ground biomass/carbon stock using airborne and terrestrial LIDAR derived forest trees parameters in Berkelah Tropical Rain Forest, Malaysia.

1.3.2. Specific Objectives

1. To investigate the accuracy of DBH derived from TLS as compared with field measured DBH
2. To assess the effect of number of trees per plot on occlusion using TLS scanning at plot level
3. To assess the effect of forest stand density on the estimation of AGB/Carbon stock using ALS and TLS derived parameters at plot level
4. To investigate the effect of TLS tree height inaccuracy on the estimation of AGB for selected trees

1.4. Research Questions

1. Is there a significant difference between DBH derived from TLS as compared with field measured DBH?
2. A. Is there a significant difference between total number of trees extracted from TLS point cloud as compared with the total number of trees measured in the field?
   B. Is there a direct relationship between number of trees per plot and missed trees per plot from TLS point cloud data due to occlusion?
   C. Is there a direct relationship between forest stand density per plot and missed trees per plot from TLS point cloud data due to occlusion?
3. A. Is there a direct relationship between forest stand density and amount of AGB/carbon stock estimation?
   B. Is there a direct relationship between number of trees per plot and amount of AGB/carbon stock estimation?
4. What is the effect of TLS tree height inaccuracy on the estimation of AGB for selected trees?

1.5. Research Hypothesis

1. **Ho**: There is no significant difference between DBH derived from TLS and measured in the field.

   Ha: There is a significant difference between DBH derived from TLS and measured in the field.

2. **A. Ho:** There is no significant difference between total number of trees extracted from TLS as compared with the total number of trees measured in the field.

   Ha: There is a significant difference between total number of trees extracted from TLS as compared with the total number of trees measured in the field.

   B. Ho: There is no direct relationship between number of trees per plot and missed trees per plot from TLS point cloud data due to occlusion.

   Ha: There is a direct relationship between number of trees per plot and missed trees per plot from TLS point cloud data due to occlusion.

   C. Ho: There is no direct relationship between forest stand density per plot and missed trees per plot from TLS point cloud data due to occlusion.

   Ha: There is a direct relationship between forest stand density per plot and missed trees per plot from TLS point cloud data due to occlusion.

3. **A. Ho:** There is no significant relationship between forest stand density and amount of AGB estimation at $\alpha = 0.01$.

   Ha: There is a significant relationship between forest stand density and amount of AGB estimation at $\alpha = 0.01$.

   B. Ho: There is no direct relationship between number of trees per plot and amount of AGB/carbon stock estimation.

   Ha: There is a direct relationship between number of trees per plot and amount of AGB/carbon stock estimation.

4. **Ho**: There is no significant effect of TLS height inaccuracy on biomass estimation at $\alpha = 0.05$.

   Ha: There is a significant effect of TLS height inaccuracy on biomass estimation at $\alpha = 0.05$.

1.6. Conceptual Diagram

For this study, the conceptual diagram is developed after the problem of the study is defined. The significant systems and subsystems for the study within the boundary of the study area are identified. Moreover, the role of each system and subsystems and their interaction within the boundary is identified. Figure 1 shows the conceptual diagram used for this study.

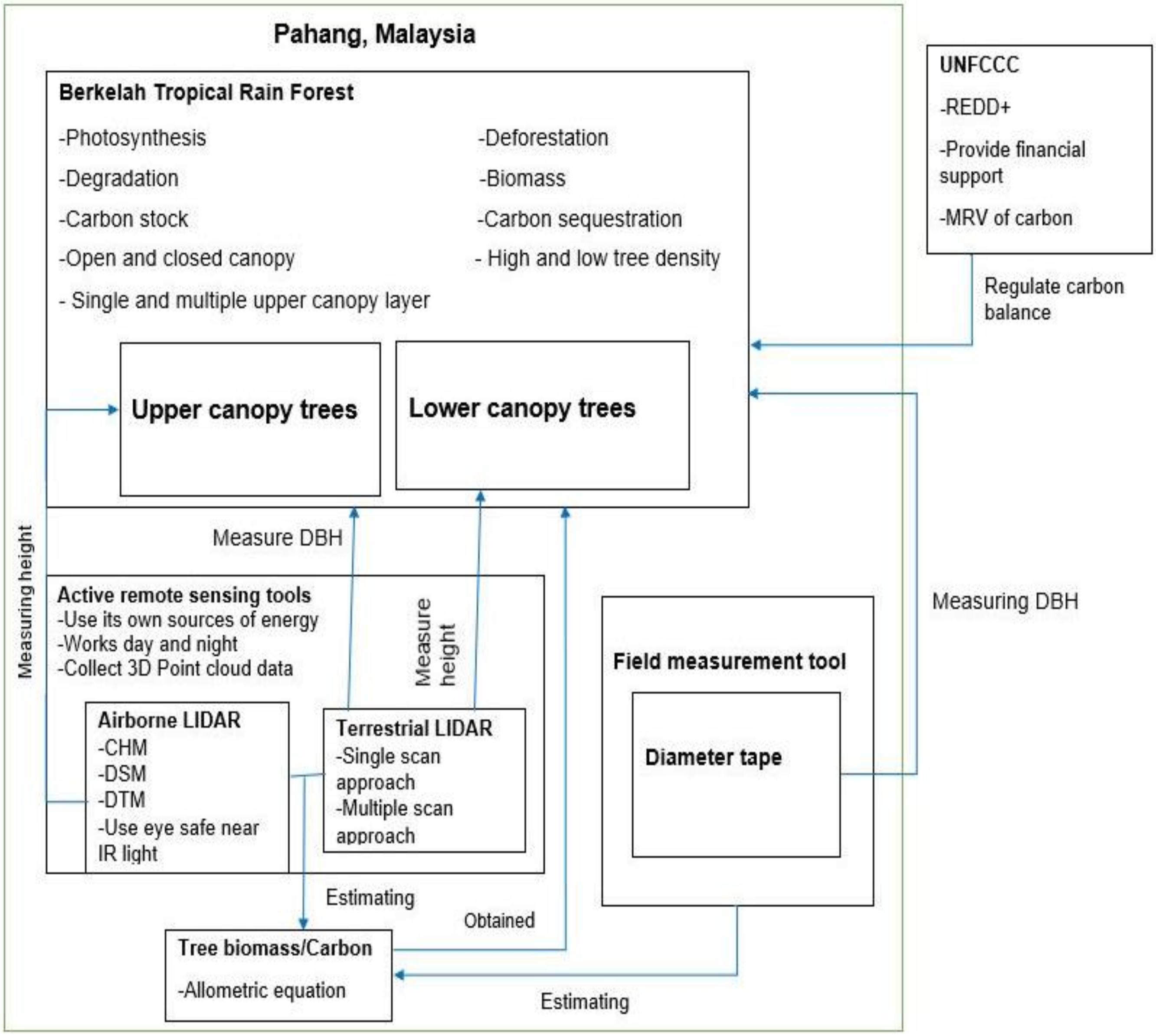


Figure 1: Conceptual diagram for the study in Berkelah tropical rainforest.

2. CONCEPTS AND DEFINITIONS

In this section, the basic concepts of airborne LIDAR and Terrestrial Laser Scanner (TLS) and its application in the field of forestry for the extraction of tree parameters example DBH and height are explored. Moreover, the concepts of above ground biomass and the different methods used to estimate AGB is addressed.

2.1. Biomass and Carbon

Above Ground Biomass refers to the total amount of oven dried biological material available above the soil surface in a given area at a given time (Drake et al., 2003). Carbon is derived from above ground biomass, and it is assumed that approximately 50% of dry biomass is carbon (Basuki et al., 2009; Drake et al., 2003). There are five carbon pools recognized by Intergovernmental Panel on Climate Change (IPCC). These are: above ground biomass, belowground biomass, deadwood, litter, and soil organic carbon (Jayakumar et al., 2012). 46% of the world's living terrestrial and 11% of soil carbon pools are stored by tropical rainforest. Therefore, tropical forests are crucial terrestrial ecosystems which play an important role in the global carbon cycle (Brown & Lugo, 1982). However, the largest carbon pool in the tropical forest ecosystem is mainly above ground biomass, and it is affected by degradation and deforestation. Therefore, above ground biomass estimation is an important step in quantifying carbon stock from tropical forests (Gibbs et al., 2007). Also, it provides up to date information about the monitoring of the forest resource and sequestration potential (Jayakumar et al., 2012).

2.2. Allometric Equation

There are two methods for tree biomass estimation. These are a destructive method and nondestructive method. The destructive method includes harvesting of all the trees in the known area and measuring oven dried weight of the different components of the harvested tree. Using the destructive method it is okay to cut 100-150 trees for developing biomass equation to be applied for biomass estimation on a larger-scale, this method is very important (Jayakumar et al., 2012; Yuen et al., 2016). However, the destructive method is not appropriate for degraded forests containing threatened species (Montès et al., 2000). To overcome the problems of the destructive method, the nondestructive method is used. The nondestructive method is used to estimate the biomass of forests without harvesting by using allometric equations. Allometric equations are developed based on the relationship of the biophysical parameters of trees mainly DBH and tree height is used as the main input parameters (Ketterings et al., 2001). It is simply using DBH and height and developing a statistical regression model to estimate AGB/carbon stock. Above ground biomass can be estimated using either species specific or generic allometric equation. For forests of the same species, species specific allometric equation is used. While for the same type of forests generic allometric equation can be applied even the location of the forest is not the same. However, in tropical rainforest applying species specific allometric equation is very difficult hence there are numerous species. Therefore, the generic allometric equation is used for the tropical rain forests (Basuki et al., 2009; Chave et al., 2005; Ketterings et al., 2001). But applying allometric equations outside of the geographical locations where they were developed without considering environmental conditions and vegetation characteristics is a key source of uncertainty in above ground biomass/carbon stock estimation(Yuen et al., 2016).

2.3. Airborne LIDAR and its Application in the Field of Forestry

Airborne LIDAR which stands for Light Detection and Ranging also called airborne laser scanning(ALS) is one of the active remote sensing technology. LIDAR sensors are operating from 900nm to 1064nm of the near infrared range of the electromagnetic spectrum where there is high vegetation reflectance. This active remote sensing technology is relatively recent, and it uses laser light pulses to detect target objects or features.

Half of the time taken for the laser pulse from the sensor and back to the sensor multiplying by the speed of light provides height or distance of a target object (Gallay, 2013; Lefsky et al., 2002). Airborne LIDAR can measure three-dimensional forest structures accurately. It plays a crucial role in directly assessing vegetation characteristics and deriving forest biomass at multiple scales because of its characteristics of high sampling intensity, extensive area coverage, ability to penetrate the top layer of the canopy, accurate ranging measurements and precise geolocation (Popescu, 2007). Airborne LIDAR operates from airborne platform backed up with instruments; LIDAR sensor which sends the pulse of laser light to the target and records the laser travel time and energy scattered from the target; Inertial measurement unit(IMU) used to measure the orientations of roll, pitch, and yaw of the aircraft and angle encoders for the orientation of the scanning mirror; Differential GPS used to obtain accurate XYZ positions of sensor relative to GPS base station at ground (Gallay, 2013; Lefsky et al., 2002). Figure 2 presents an example of the Airborne LIDAR Scanning system.

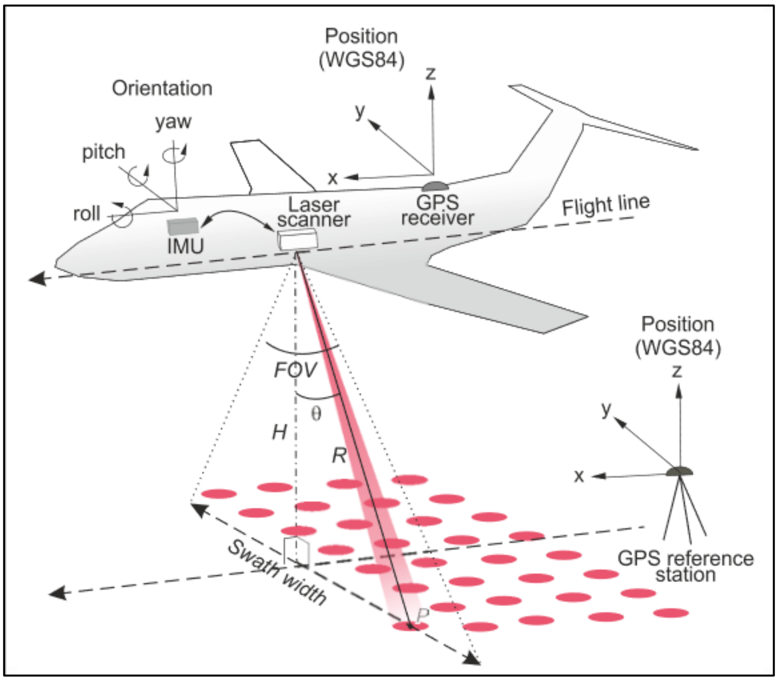


Figure 2: Typical operation of an Airborne LIDAR scanning system. Source: (Gallay, 2013).

Airborne LIDAR has no saturation problem at high biomass level (Patenaude et al., 2005). However, a study conducted by Yu et al. (2004) revealed that accurate and precise products of LIDAR data depend on its pulse density. The number of laser returns per unit area is referred to as point cloud density for airborne LIDAR. It can be considered as analogous to resolution for passive imaging sensors. Moreover, they also explained in their study that the footprint diameter determines the estimation and the accuracy of tree height from the airborne LIDAR system.

LIDAR system can be categorized based on a recording of return signals and size of the foot print. Further based on the record of return signals classified into the discrete return and full wave form. Discrete return LIDAR system records single or multiple returns for each pulse. In this system, limited information is recorded about the returned waveform which may be only the first and last significant returned signal. However, full wave form LIDAR system records the complete waveform of the returning pulses and produce multiple returns between the first and last returns. As a result, it gives detailed information on the vertical structure of forests. (Lefsky et al., 2002). Based on the foot print size LIDAR can be divided into the small and large footprint. Small footprint records footprint up to a diameter of 100 cm. Due to high frequency, it produces very high measurement density. This is a good example of the airborne LIDAR because the altitude of the platform is not so high 40—500meters.

While large foot print system records footprint up to a diameter range of 10-100 meter. Since they have lower repetition rates, few footprints are recorded in each scan line. This type of system is a good example of a satellite LIDAR sensor because the altitude of the platform is very high up to 700Km similar with the IceGlas satellite LIDAR system (Heritage et al., (2009). Figure 3 shows an example of airborne LIDAR discrete-return and full waveform returning pulse signals.

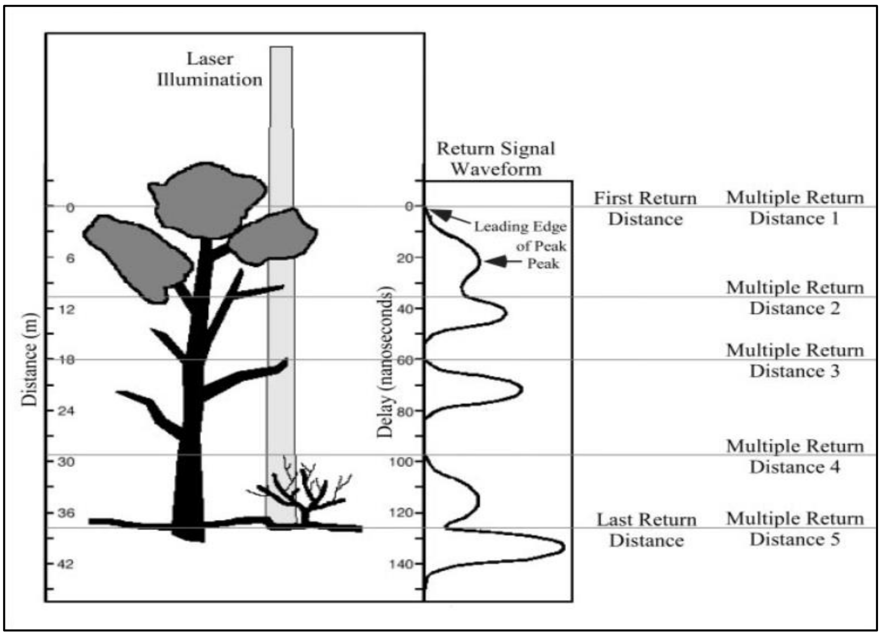


Figure 3: Airborne LIDAR discrete-return and full waveform returning pulse signals. Source: (Lefsky et al., 2002).

2.4. Terrestrial LIDAR and its Application in the Field of Forestry

Terrestrial laser scanning (TLS) also called terrestrial LIDAR is an active remote sensing measurement technology. This technology enables a rapid collection of forest inventory parameters from 3D point clouds data which is composed of millions of points representing the surfaces of the scanned trees (Dassot et al., 2011). Basic forest inventory parameters such as number and position of trees, DBH, tree height and crown shape parameters can be derived from TLS automatically and efficiently (Bienert et al., 2006). The device (laser beam) is mounted on a vertical plane backed up with rotating mirror scans, and the complete rotation of the device allows hemispherical scanning (Dassot et al., 2011). A digital single-lens reflex camera (DSLR) is mounted on top of terrestrial laser scanners to display the point cloud data in RGB colors. Figure 4 shows the operating principle of a terrestrial LIDAR.

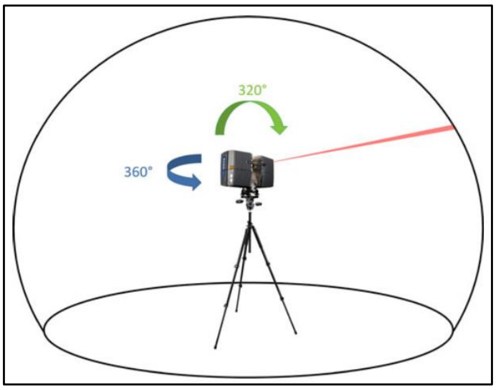


Figure 4: Operating principle of a terrestrial LIDAR. Source: (Dassot et al., 2011).

In terrestrial laser scanner two scanning protocols can be applied: single scanning or multiple scanning. In the single scan method, the laser scanner is placed at a single location which is placed in the center of the plot. Even though this is the quickest scanning approach, only one side of the objects or trees can be scanned and represented in the point cloud. However, in multiple scanning methods, the scanning of the objects or trees can be done at the different positions mainly at three or four positions inside and outside of the plot (Figure 5). Despite that this method provides the complete 3D description of the objects, it increases the time needed for field measurement, which depends on the number of scanning positions and processing steps which also depends on the number of targets and the method used to detect the point cloud which means automatic or manual detection (Bienert et al., 2006; Dassot et al., 2011). Table 1 and Figure 6 show a close up look at the RIEGL VZ-400 Terrestrial laser scanner and list its specification.

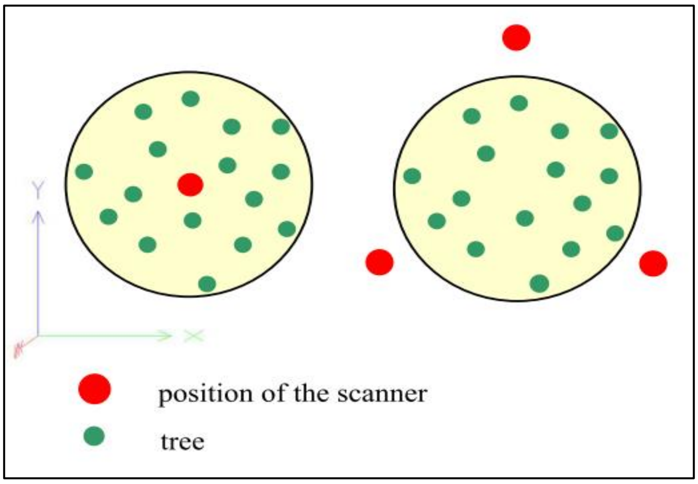


Figure 5: Single and multiple scanning methods. Source: (Bienert et al., 2006).

Table 1: Specification of RIEGL VZ-400 Terrestrial laser scanner.

Description	Performance
Maximum range (m)	600
Horizontal field of view	0-360 deg
Vertical field of view	100 (30-130) deg
Minimum range (m)	1.5
Precision (mm)	3
Accuracy (mm)	5
Beam divergence (mrad)	0.35
Weight(Kg)	9.6
Wave type/ wavelength	Near infrared (1550nm)

Figure 6: Terrestrial laser scanner (RIEGL VZ-400) without and with the camera. Source: (RIEGL, 2017).

3. STUDY AREA, MATERIALS, AND METHODS

3.1. Description of the Study Area

This study was conducted at Berkelah tropical rainforest, Malaysia. Berkelah Forest Reserve is located in the Pahang province of Malaysia roughly at latitude 3°46'1"N and longitude 103°1'1"E. The forest is found at 234 km to the North-East of Kuala Lumpur and 218 km to the North-East of Forest Research Institute Malaysia (Zakaria, 2013). At the very beginning, Malaysia was selected for this study because of the reason that Malaysia is one of the tropical country implementing REDD+ programs. For this reason, the government of Malaysia is interested the MRV of carbon to be studied in their country. Particularly Berkelah forest was selected based on accessibility and availability of data. University Technology Mara, Malaysia collaborated the research teams of University of Twente (ITC), the Netherlands in the field data collection and by providing the airborne LIDAR data of the study area.

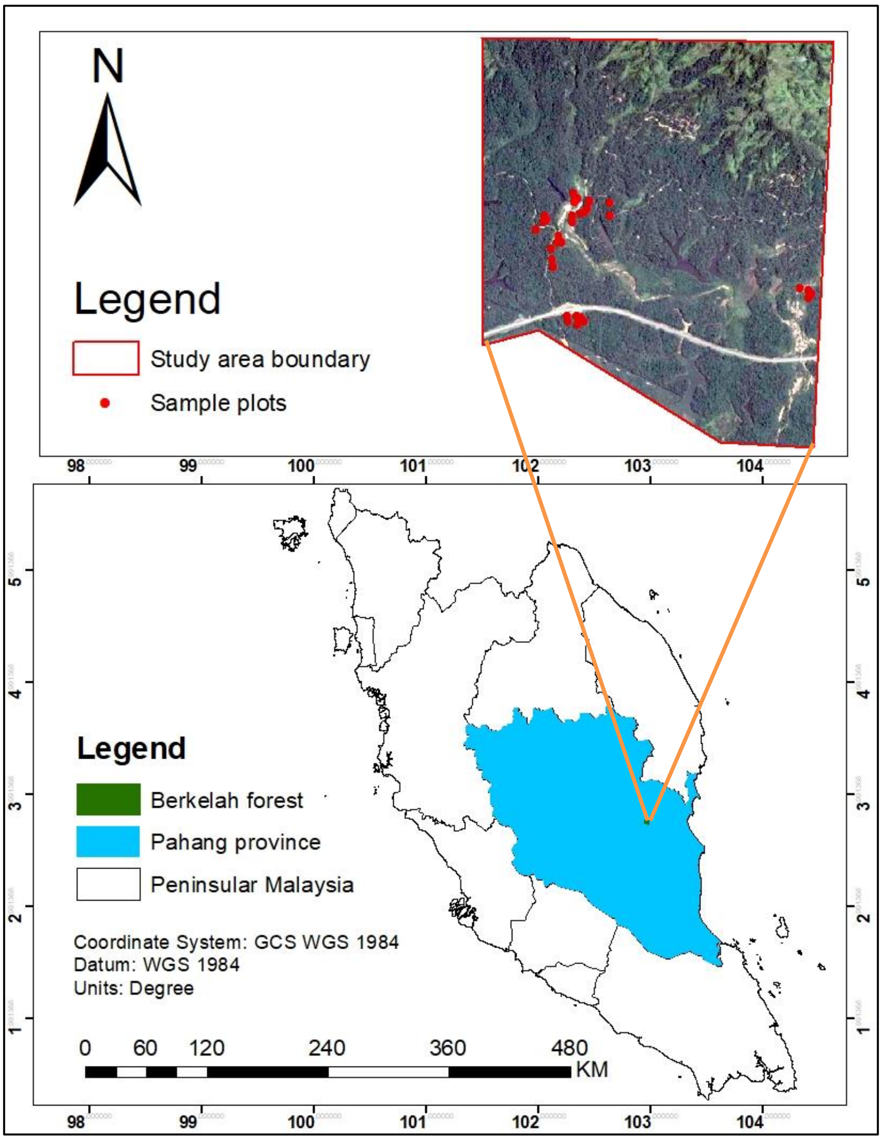


Figure 7: Location map of Berkelah forest reserve, Pahang, Malaysia.

3.1.1. Climate

The climate of Peninsular Malaysia is characterized by high and uniform temperatures, high humidity and abundant year-round rainfall. The average temperatures are 32°C and 28°C during the day and night times respectively. The mean annual rainfall of Peninsular reaches 2,540 mm while the maximum rainfall is 5893 mm (Barizan et al., 1997).

3.1.2. Vegetation

Berkelah tropical forest reserve has been recognized as a red Meranti forest. The forest is characterized by a high proportion Shorea species which is categorized under red meranti group. In 1986-1987 the area was tractor-logged once. After that, the vegetation of Berkelah forest reserve can be classified as a mixed hill dipterocarp forest dominated by Dipterocarpaceae which is the dominant timber producing tree family (Barizan et al.,1997).

3.2. Materials

3.2.1. Datasets

In this study, Airborne LIDAR point cloud, Terrestrial Laser Scanner (TLS)point cloud and field based datasets were used. The Airborne LIDAR data which was provided by University Technology Mara (UiTM) was collected on 12 November 2014 while the terrestrial laser scanner and field based parameter data sets were collected during the last part of September to mid-October of 2017. The Airborne LIDAR data was used to generate canopy height model (CHM) from Digital Surface model (DSM) and Digital Terrain Model (DTM) which is used to derive height of upper canopy trees. The TLS data was used to generate 3D point clouds to derive DBH for all trees and height for lower canopy trees. Moreover, DBH, XY coordinates of the plot center and individual trees were collected from the field.

3.2.2. Field Instruments

The following list of instruments was used for field data collection for different purposes.

Table 2: Field instruments and their purposes.

S.N.	Field Instrument	Specific Purpose
1	RIEGL VZ-400	TLS for point cloud data acquisition
2	Measuring tape (50 m)	Measuring plot layout
3	Diameter tape(5m)	Measuring tree diameter
4	Field data recording sheet	Recording field measurements
5	Chalk	Marking DBH and plot boundary
6	Plastic laminated paper with numbers	Tagging trees for measurement
7	Pencils and eraser	Writing the field data
8	Tablet	Plot and tree location coordinate record and Navigation

3.2.3. Software

In this study, several software packages were used to process, analyze and present ALS, TLS and field data sets.

Table 3: Software used for the study.

S.N.	Name of Software	Specific Purpose
1	ArcGIS 10.5.1	Data processing, Mapping, Visualization
2	RiSCAN PRO	TLS data processing
3	eCognition	Tree crown delineation
4	ERDAS IMAGINE 2016	Image processing
5	SPSS	Statistical analysis
6	Microsoft Excel	Data processing and analysis
7	Mendeley	Citation and reference writing
8	Click Charts V 2.12	Flowchart drawing
9	Microsoft Word	Thesis writing
10	Microsoft power point	Presentation of thesis

3.3. Methods

To achieve the objectives of this study, mainly four methods were employed. The first part was collecting tree parameters using field instruments. Mainly DBH measurement was collected using diameter tape in the field for validation of DBH derived from TLS point cloud data.

In the second part, all trees in all sample plots were scanned using TLS and point cloud data was acquired. From the point cloud data, DBH for all sampled trees and lower canopy tree height were manually extracted. The DBH derived from TLS was validated using DBH measured in the field.

In the third part, the upper canopy trees height was extracted from the Airborne LIDAR CHM which was obtained by subtracting Digital Terrain Model (DTM) from Digital Surface Model (DSM). These models were acquired after the LIDAR point cloud data rasterized and interpolated. To extract height of individual trees and identify upper canopy from lower canopy trees, multi resolution segmentation was undertaken.

Finally, the effect of forest stand density was assessed on the estimated AGB/carbon stock from DBH and tree height measured using ALS and TLS at the plot level. Moreover, the sensitivity of AGB due to Terrestrial laser scanner derived tree height inaccuracy was assessed. The details of the methods followed in this study is shown in Figure 8.

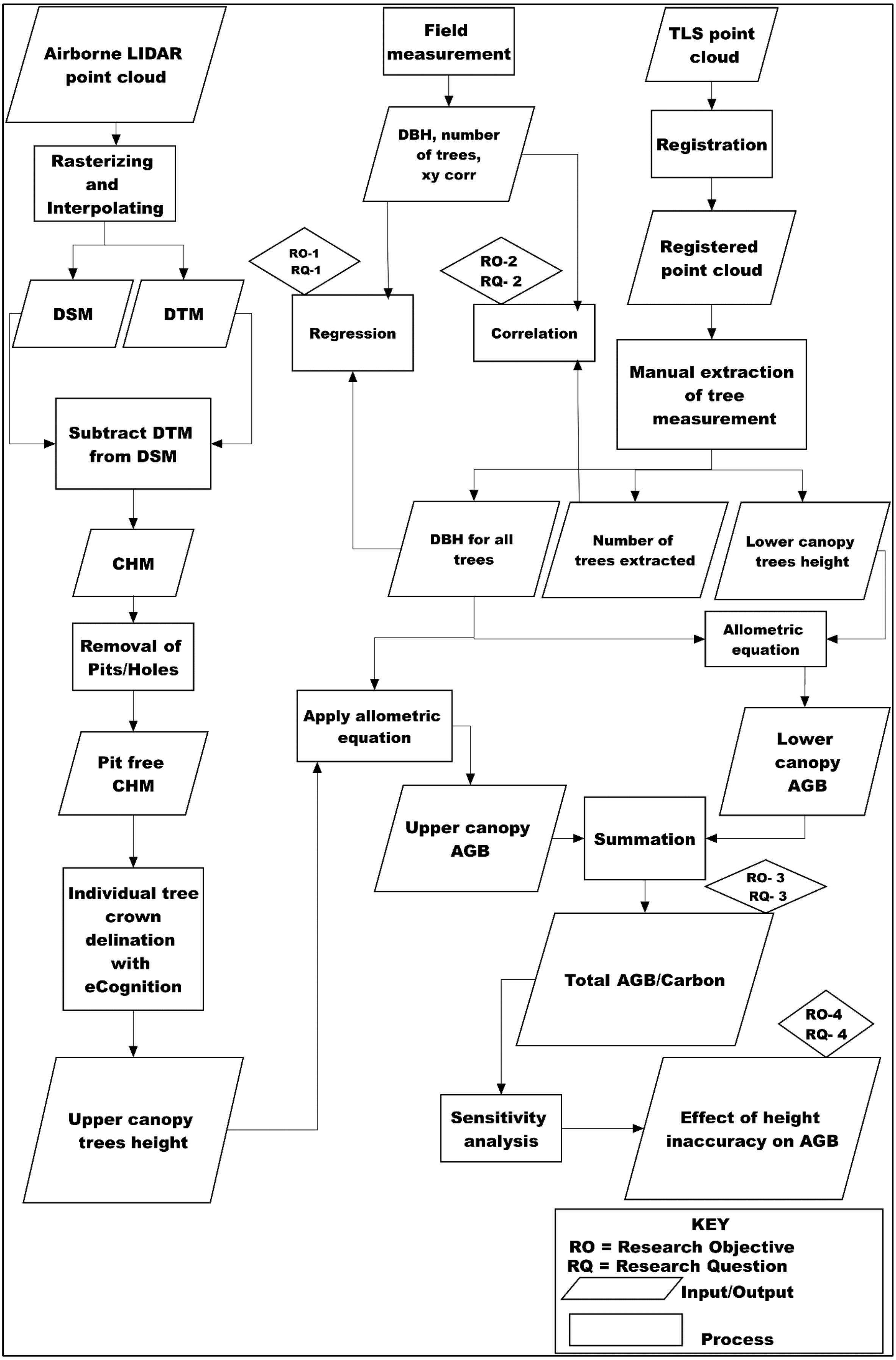


Figure 8: Flowchart of the study method implemented in Berkelah tropical rainforest.

3.3.1. Pre-field work

Before actual field data collection, activities like preparation of field data recording sheet, collecting, checking and practicing different field instruments, identification of data needed for the study, sampling design and preparation of study area map were undertaken.

3.3.2. Sampling Design and Determination of Sample Plot

In this study, purposive sampling approach was adopted to select the unit of analysis. Purposive sampling is a nonprobability sampling technique in which all elements in the population do not have an equal chance of being selected as a sample. Therefore, in this study to select the unit of analysis (plots), the terrain/slope of the area, time availability, weight of TLS, thickness of undergrowth, the density of the forest, proximity to the road were considered. A total of 32 circular plots with a radius of 12.62metre equivalent to 500meter square were taken as the unit of analysis considering the variation in tree densities. According to Ruiz et al. (2014) plot size of the 500-600 meter square is recommended for biomass estimation because larger plot sizes increase the cost of fieldwork but do not significantly increase the accuracy of the result. For TLS multiple scan position, the circular plot is more preferred than rectangular or square shaped plot of the same size. Lackmann (2011) pointed out since the boundary of the plot is smaller in relation to the area, and thus the number of trees on edge is less, circular plots are less vulnerable to errors than square plots.

3.4. Field Data Collection

3.4.1. Biometric Data Collection

The field work for this study was done from 21st September to 14 October of 2017. After delineation of plots, DBH were measured for all tree with their DBH ≥10cm within the plot. As pointed out by Brown (2002) trees with DBH less than 10cm have an insignificant contribution to biomass/carbon stock. DBH was measured using diameter tape at 1.3meter height from the ground. To be consistent with DBH measurement, 1.3meter measured stick was used. In case of the buttress and fork trees, DBH was recorded above the buttress while fork trees were considered as two trees if the fork is below 1.3meters and as one tree if the fork is above 1.3 meters. The data sheet used to collect the biometric data during the field work is shown in Appendix 6.

3.4.2. Plot Preparation and TLS Position set up

There are two types of TLS scanning approaches. These are single and multiple scan modes (Bienert et al., 2006). For this study, a multiple scan mode with four scanning positions was undertaken. The center of the plot was selected in the way it avoids or minimizes occlusion from the stem of the trees and undergrowth. According to Liang et al.(2012) trees or other undergrowth very close to the scanner can create a large area shadow behind. The outer three scanning positions of the plot were carried out at an angle of 120° determined using the TLS tripod stands at the center position backed up with visual judgment. Figure 9 shows the TLS scan position used for the study.

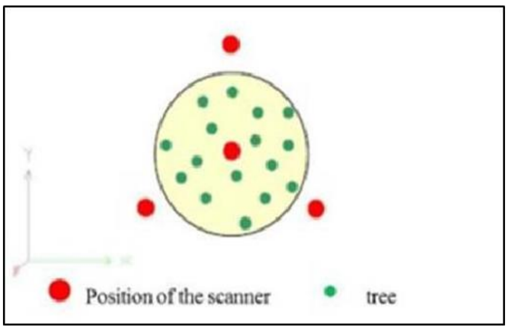


Figure 9: TLS scan positions used for the study. Source: (Bienert et al., 2006).

3.4.3. Setting of Retro Reflectors and Tree Numbering within the Sample plot

After the plot preparation is completed, trees within the plot with their DBH equal or greater than 10cm were tagged with laminated tree numbers which helped later for the extraction of tree parameters from the point cloud data (Figure 10). Point cloud data generated from the four scanning positions were used to get the 3D structure of the plot and individual trees. Individual tree height for lower canopy trees and DBH of all upper and lower canopy trees were manually extracted from the TLS point cloud data.

Figure 10: Tree numbering (Plot 29).

In order to register and georeferencing of the multiple scan positions with the home(reference) position, tie points were used during scanning of each plot in the field (Bienert et al., 2006). For this study, a total of 18 reflectors (tie points), 12 cylindrical and 6 circular were used in each plot. Cylindrical retro-reflectors were placed on top of a stick near to the three outer scanning positions on the way to be observable to the scanner at different scanning positions. Circular retro-reflectors which were pinned on selected tree stems facing towards the center scanning position. Figure 11 shows both the cylindrical and circular reflectors used for TLS plot scanning in the field.

Figure 11: Setting of circular (yellow color) and cylindrical (red color) reflectors in sample plots.

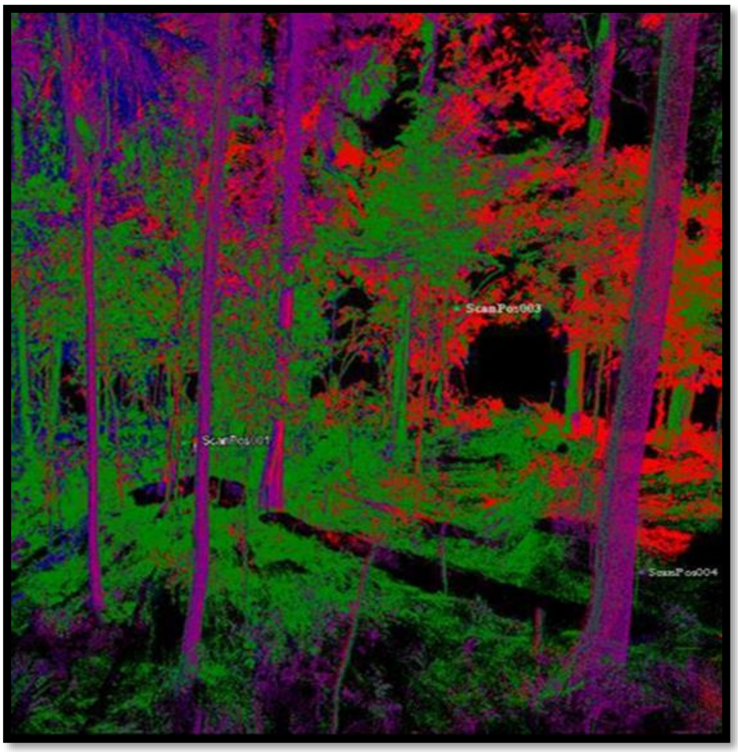
3.5. Data Processing

3.5.1. Biometric Data Processing

The collected data from the field were entered a Microsoft Excel sheet for further processing and analysis. Plot radius, GPS coordinates of the plot center, DBH, X and Y coordinates of each tree measured in each plot were entered the Excel sheet. X and Y coordinates of individual trees within the plot were collected using tablets, and it is used for matching the corresponding tree on the Airborne LIDAR CHM. In this study, a total of 1033 trees were measured and scanned in the field from all 32 sampled plots.

3.5.2. Pre-processing of TLS point cloud data

The first step in the pre-processing of TLS point cloud data is registration. Registration is the process of merging all the individual scans into a single point cloud data. After the point cloud data was exported from the Terrestrial laser scanner, RiSCAN PRO V 2.4.2 software was used for registration and pre-processing of the point cloud. According to Holopainen et al., (2014) artificial retro-reflectors are used to undertaking registration of multiple scans. The central scanning position was used as a reference position to register all the three outer scanning positions since it has the most overlap with the outer scanning positions. Therefore, the three outer scanning positions were registered towards the central scan positions with a minimum of five best value of common tie points selected automatically by the software. Also, to displaying and select the corresponding recto-reflectors between the center and any of the outer scanning position and registered automatically, the Tie Point List-Scanner Own Coordinates TPL (SOCS) in the RiSCAN PRO software was used. Moreover, to reduce the standard deviation and to form 3D of all trees in the plot, multiple station adjustment (MSA) of the multiple scans was used. Figure12 shows the registered 3D point cloud of a sample plot used for individual tree extraction and parameters measurement. For all 32 plots, the MSA accuracies were very high with a standard deviation of ≤0.01 m (Table 4).



Plot 13

Figure 12: Sample registered point cloud data displayed in four colors representing four scan positions.

Table 4: Plot level registration error of the multiple scan positions.

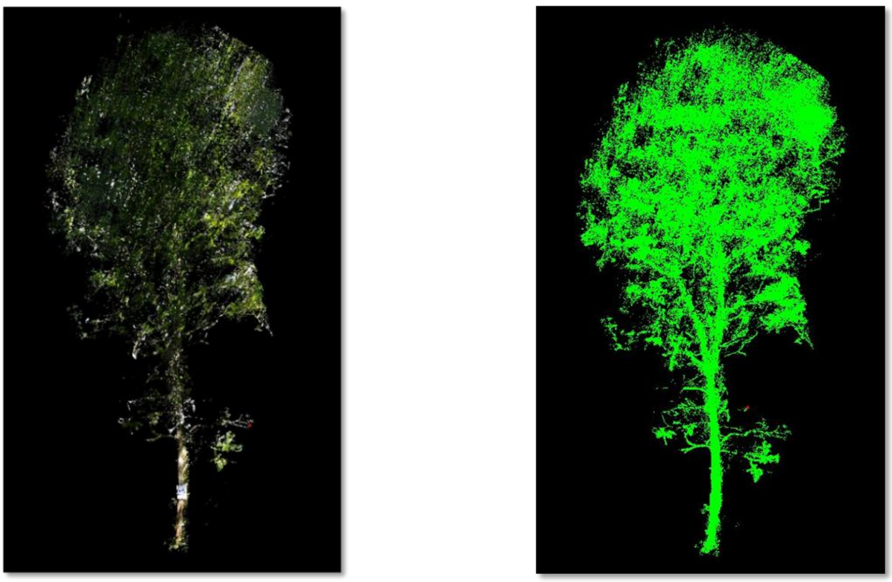
Plot No.	1	2	3	4	5	6	7	8
Standard deviation(m)	0.008	0.010	0.006	0.012	0.008	0.008	0.009	0.008
Plot No.	9	10	11	12	13	14	15	16
Standard deviation(m)	0.011	0.009	0.010	0.007	0.011	0.010	0.008	0.007
Plot No.	17	18	19	20	21	22	23	24
Standard deviation(m)	0.010	0.005	0.0.016	0.005	0.006	0.009	0.009	0.006
Plot No.	25	26	27	28	29	30	31	32
Standard deviation(m)	0.006	0.010	0.010	0.008	0.008	0.009	0.009	0.008

3.5.2.1. Extraction of Plot

After registration of each plot multiple scan positions, extraction of the plot was undertaken through filtering of the point cloud covering radius of 12.62 m from the center scan position. Filtering of the plot was required because during scanning in the field point clouds were collected involuntary outside of the area of interest. Therefore, filtering of the point cloud was done by manually delineating the outer boundary of the plot using the three outer scanning positions and excluding all point clouds that do not fall within the area of interest using selection tool in RiSCAN PRO software. The extracted point cloud covering the area of interest of all plots were saved in a new polydata from which extraction of individual trees and parameter measurements were undertaken.

3.5.2.2. Extraction of Individual Trees

During field measurement, all trees those DBH ≥10cm in all plots were tagged with laminated tree numbers which helped for the extraction of individual trees measured in the field from the point cloud data. To identify the tagged tree numbers, the polydata was displayed in 3D true color linear scale. Accordingly, using the selection tool in RiSCAN PRO software, extraction of the individual tree in all plots was done. This process has been done by selecting all point cloud data corresponding to a single tree. Figure 13 showed an example of an extracted tree in true and false color.



Plot 3: Tree number 23 (in True color) Plot 3: Tree number 23 (in False color)

Figure 13: Manually extracted sample tree from point cloud data in true and false color.

3.5.2.3. Measurement of Tree Height and DBH

From the 3D point clouds of the individual trees, the DBH was measured on the stem at 1.3 m height from the ground from the extracted 3D point clouds of individual trees by using distance measurement function tool in RiSCAN PRO software. Figure 14 shows how DBH measurement was done in RiSCAN PRO.

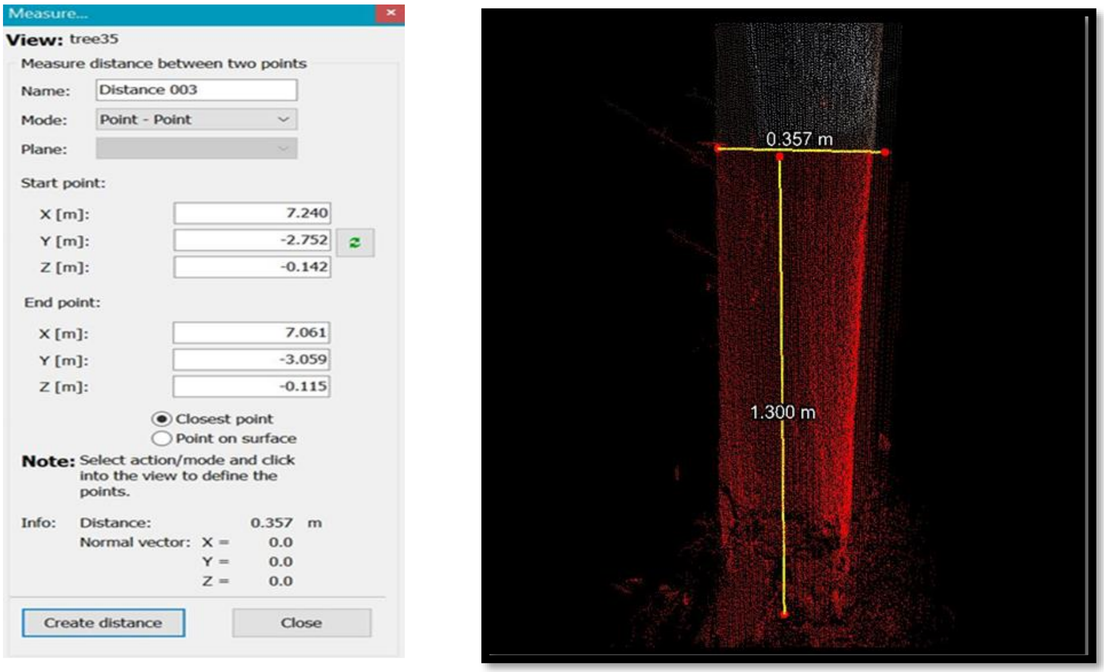


Figure 14: Tree DBH measurement (plot 13, tree number 35).

Similarly, the height of trees was also measured manually from the lowest point of the stem on the ground to the highest top of the tree using distance measurement function tool in RiSCAN PRO software. X, Y, Z values are recorded by the measurement and the difference in the highest and lowest value of Z was considered as the tree height. According to Prasad et al. (2016), the high accuracy of tree parameter is obtained using manual measurement method. Figure 15 shows an example of how tree height measurement was done in RiSCAN PRO.

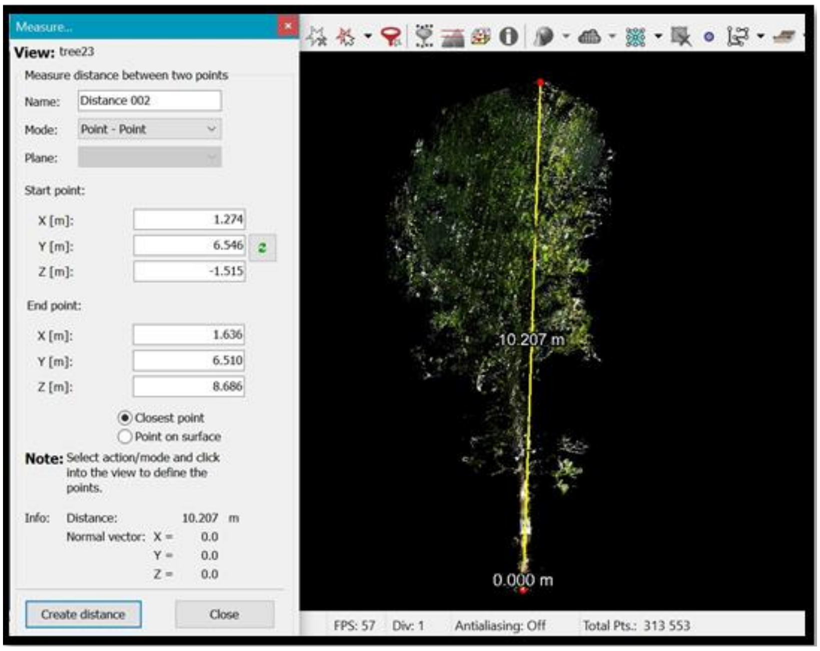


Figure 15: Tree height measurement (Plot 3, tree number 23).

3.5.3. Airborne LIDAR Point Cloud Data Processing

A cell size of 1m is used to construct pit or hole free canopy height model(CHM) from the Airborne LIDAR point cloud data in "las" format. The density of the LIDAR point cloud data for this study is 5-6points/m^2, which basically determines the cell size. Arc GIS is used to display and generate a digital surface model (DSM) and digital terrain model (DTM) from the first and last returns respectively. By subtracting digital terrain model (DTM) from the digital surface model (DSM) using raster calculator in Arc GIS, CHM was generated. The originally created CHM had pits and holes because of the first LIDAR return is far below the canopy due to the LIDAR beam penetrate the branches before creating first return (Heurish et al., 2003). These pits hinder the accurate extraction of tree parameters from CHM. Therefore, these pits were removed.

3.5.3.1. Segmentation

Segmentation is a technique used for segmenting and clustering of pixels in an image into meaningful homogeneous units or objects (Clinton et al., 2010). There are two approaches in segmentation that can be done. These are the bottom-up and top-down approach. In the bottom-up approach, pixels are merged to obtain larger meaningful object based on homogeneity criteria. Whereas in the top-down approach, large objects are clustered into smaller objects (Rahman & Saha, 2008).

Even though, there are different segmentation techniques, according to Witharana & Civco (2014) multi resolution segmentation technique is most commonly used. This technique works based on bottom-up and region-based approach. For a given resolution of the image object, this technique minimizes the average heterogeneity.

Giving appropriate value for the different criteria are the necessary condition to get the required homogeneous unit or object. Scale parameter, shape and compactness are mainly determining the homogeneity of an object. Therefore, the size of the image object is influenced by these scale parameters since it modifies the values of the image. It determines the maximum allowable heterogeneity of the segmented image object. Giving higher scale parameter leads to more merging and producing bigger objects, less homogeneity and vice versa (Rahman & Saha, 2008). Determination of appropriate scale parameters depends on the judgment of the user since it is a trial and error process until optimum scale parameter is achieved that satisfies the user.

Therefore, for this study, using eCognition software, multiresolution segmentation was adopted using the homogeneity criterion which is the scale parameter which determines the homogeneity of the object, shape which determines the spectral value of the segmented objects. Giving more value for shape, makes the segmented object having more spatial uniformity than spectral homogeneity. Moreover, the compactness value used to produce a compacted segmented object. The values of these homogeneity criteria (color+ shape =1, and compactness +smoothness=1). Accordingly, 12 for scale parameter, 0.8 and 0.5 for shape and compactness respectively were found to be optimal for this study. The multiresolution segmentation process is shown in Figure 16.

LIDAR CHM (Canopy Height Model) was used as input to delineate individual tree crown which was used for the extraction of upper canopy trees height. Segmentation, watershed transformation, and tree morphology were employed in a subset. Then after this complete rule set was implemented for the entire study area.

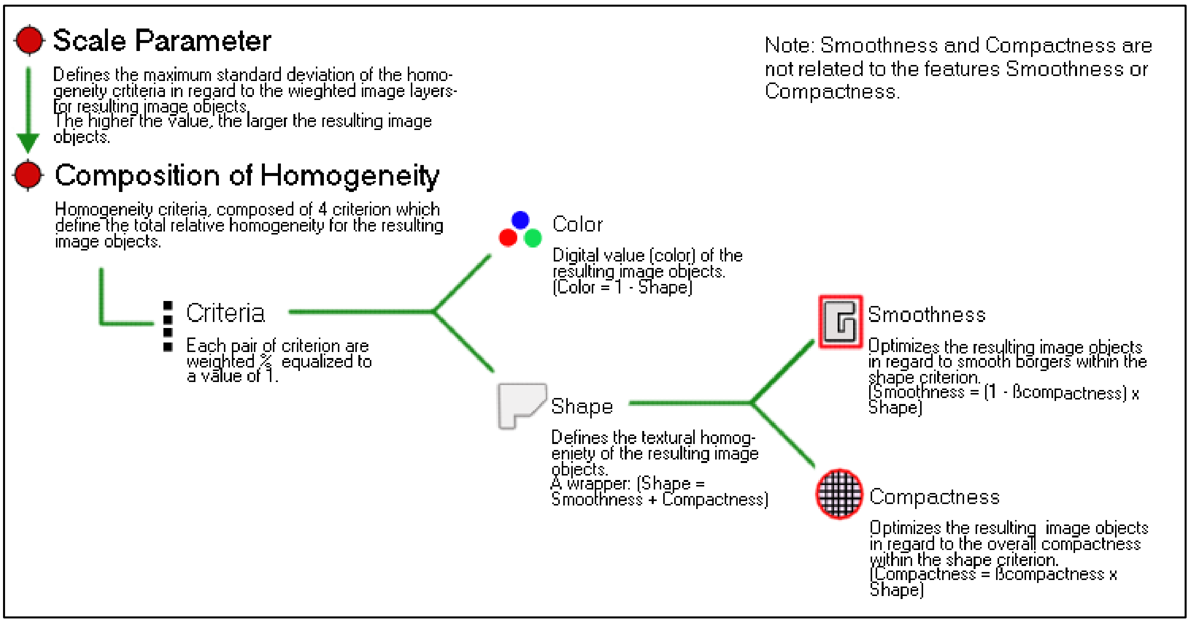


Figure 16: Process of multi resolution segmentation. Source: (Definiens Developer, 2012).

3.5.3.2. Segmentation Accuracy Assessment

As revealed by Clinton et al. (2010) assessment of the accuracy of the segmented polygon is based on comparing with the predefined reference training set with segmented output's geometric extent. As a result, the over and under segmentation determine the quality of produced segment.

Therefore, segmentation accuracy assessment was done by comparing automatically segmented tree crowns with the manually delineated tree crowns. The manual delineation of tree crowns was undertaken for randomly selected visually identified tree crowns. Accordingly, 15% proportion of field measured trees from each of the 32 sampled plots were manually delineated. Thus the total reference polygons are 157. Based on the following equations the over segmentation, under segmentation and "D" value (goodness of fit) was calculated. The "D" value ranges from 0 to 1 and values close to 0 indicates high matching whereas if it is close to 1 shows less match. Moreover, the two extremes, 0 indicates a perfect match between the reference polygon and the automatically segmented polygons while 1 is the minimum mismatch between the two.

Equation 1: Calculation of over segmentation

$$\textit{Over segmentation} = 1 - \frac{Area(xi \cap yi)}{Area(xi)} \text{ .... Equation 1}$$

Equation 2: Calculation of under segmentation

$$\textit{Under segmentation} = 1 - \frac{Area(xi \cap yi)}{Area(yi)} \text{ .... Equation 2}$$

Equation 3: Calculation of segmentation goodness of fit

$$D = \sqrt{\frac{\textit{Over segmentation}_{ij}^2 + \textit{Under segmentation}_{ij}^2}{2}} \text{ .... Equation 3}$$

Where;

xi: Manually delineated reference crowns

yi: Automatically segmented crowns

D: Segmentation goodness of fit

The error created in automatic segmentation is known from the result of segmentation goodness (D). A study conducted by Zhan et al., (2005) revealed that at least a 50% overlap between the segmented polygon and reference polygon is acceptable. Moreover, in their study, they emphasized that size, shape, and position determine completeness and correctness of the matched objects. Figure 17 shows matching of segmented and referenced polygons.

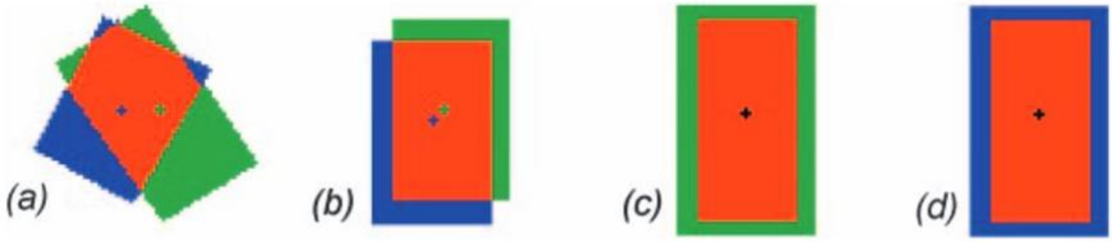


Figure 17: Matching of segmented and referenced polygons. Source: (Zhan et al. (2005).

(a) More than 50% match between the reference and segmented object, (b) same size and shape of the object but difference in location matched each other, (c) and (d)Reference and segmented objects matched each other at the same position but different in spatial extent.

3.5.3.3. Upper Canopy Tree Height Extraction and Matching

The segmented airborne LIDAR CHM was used as a base to differentiate lower and upper canopy trees in each plot in the study area. After the assessment of the segmentation accuracy for individual tree crowns, for each plot, the local maxima height was applied for each segment in the CHM by applying zonal statistics and extraction of multi value to point. By doing this, the local maxima height of trees in which complete crowns are observed by airborne LIDAR for each plot is obtained. From the height of those trees, the minimum height of the tree used as a threshold to separate upper canopy trees from lower canopy trees in both multiple and single upper canopy layer plots. Those trees below this minimum threshold are lower canopy trees, and the tree parameters were derived from TLS. The field recorded trees were matched with the TLS extracted trees using the laminated numbers tagged in each tree during scanning in the field. Moreover, the upper canopy trees were identified based on the height threshold from the segmented LIDAR CHM which was matched with their corresponding DBH using the GPS coordinates taken in the field.

3.5.4. Above Ground Biomass and Carbon Stock Estimation

The allometric equation is used to estimate AGB for large-scale analysis through non-destructive methods. The equation is developed based on the relationship of the biophysical parameters of trees mainly DBH and tree height are used as the main input parameters (Ketterings et al., 2001). The equation can be either species specific or generic. However for highly diversified species of trees like in Berkelah tropical forest, the use of local or species specific allometric equation is not appropriate(Gibbs et al., 2007). Therefore, for this study, the generic allometric equation developed by Chave et al. (2005) is employed (Equation 4).

Equation 4: Allometric equation used for AGB estimation

$AGB = 0.0673\ X(\rho D^2 H)^{0.976}$………………………………………………. Equation 4

Where,

AGB: Above ground biomass (Kg)

ρ: Specific wood density (g/cm^3) (Reyes et al., 1992) of wood density for tropical forest tree species which is 0.57g/cm^3

D:Diameter at breast height(cm)

H: Height(m)

Carbon is derived from above ground biomass, and it is assumed that approximately 50% of dry biomass is carbon (Basuki et al., 2009; Drake et al., 2003). Therefore, to calculate the carbon stock, AGB is multiplied by a conversion factor (CF) of 0.47 (Aalde et al., 2006)(Equation 5).

Equation 5**:** Above ground carbon stock estimation

$C = AGB\ X\ CF$ ………………………………………………………………….. Equation 5
Where,
C-carbon stock (Mg); AGB-Above-ground biomass (Mg); CF-conversion factor which is 0.47

3.5.5. Effect of Forest Stand Density on AGB Estimation and Number of Missed Trees

Assessment of the effect of forest stand density on both missed trees from TLS point cloud data due to occlusion and above ground biomass estimation was examined. To assess the effect of forest stand density on missed trees, a scatter plot was done between number of missed trees per plot against the total stand basal area in hectare. A scatter plot of above ground biomass in hectare against total stand basal area per hectare was used to assess the effect of forest stand density on the estimation of aboveground biomass. Moreover, linear regression analysis was carried out to quantify the magnitude of the effect of stand basal area on above ground biomass using stand basal area as an explanatory variable and above ground biomass as a predicted variable. In addition to the forest stand density, the effect of number of trees per plot on missed trees per plot and above ground biomass per plot was investigated. Accordingly, a scatter plot between number of missed trees per plot against number of trees measured in the field in each plot was used to assess the effect of the number of trees per plot on missed trees from TLS point cloud data due to occlusion. A linear regression analysis was also used with number of missed trees per plot as dependent variable and number of trees measured in the field as an explanatory variable to quantify the magnitude of the effect. Finally, to assess the effect of number of trees per plot on above ground biomass estimation, a scatter plot of above ground biomass per hectare against number of trees per plot was employed. According to Elledge & Barlow (2012) and You & Need (1999), the basal area/tree and the total stand basal area per plot in hectare are calculated using equation 6 and 7.

Equation 6: Calculation of individual tree stand basal area

$\text{Basal area/Tree}(m^2) = \frac{\pi * (\text{DBH})^2 * 0.0001}{4}$…………………………………….. Equation 6
Where π is constant which is 3.14, DBH is diameter at breast height(cm), 0.0001 is a constant used to convert the measured centimeter square into meter square

Equation 7: Calculation of total stand basal area per plot

$\text{Total stand basal area}(\frac{m^2}{\text{ha}}) = \frac{\text{Sum of basal area for each tree}}{0.05} = sum\ of basal\ area\ X 20$... Equation 7
Where 0.05 is plot size in hectare and 20 is a constant used to extrapolate the measurement of basal area from per plot (m^2/plot) to per hectare (m^2/ha)

3.5.6. Effect of TLS Tree Height Inaccuracy on the Estimation of AGB

After quantifying the errors in TLS tree height measurement, sensitivity analysis of AGB was done. The error in TLS tree height measurement was quantified by assessing its accuracy with airborne LIDAR tree height measurement which is considered as ground truth since it is more accurate than any handhold instrument to measure tree height (Bazezew, 2017; Sadadi, 2016).

To carry out the sensitivity analysis, 96 (15%) individual trees were selected by using systematic sampling from upper canopy trees of all sampled plots in the study area since these samples are sufficient to understand the effect of TLS height inaccuracy on the estimation of AGB. The RMSE of the selected trees from the TLS measurement was used to inflate and deflate the tree height values of the 96 trees (Hongoa, 2017; Sadadi, 2016). The sensitivity of AGB is assessed through TLS derived trees height varied by error margin as inputs for the allometric equation using graphical and statistical methods of sensitivity analysis(Frey & Patil, 2002). Moreover, two sample t-test was also implemented to test whether the mean difference of AGB estimated using the actual height and the height varied by the error margin was statistically significant. The mean biomass difference and percentage of mean biomass difference was calculated using the following equations.

Equation 8: Calculation used for mean biomass difference

Biomass difference = mean biomass (with actual height) – mean biomass (adjusted height) ……… Equation 8

3.5.7. Method of Data Analysis

In this study, various statistical analyses methods were employed using SPSS and Microsoft Excel. Regression analysis, correlation, descriptive statistics and t-tests were applied to answer the stated research questions. Mainly linear regression analysis was applied to investigate the accuracy of DBH derived from TLS as compared with field measured DBH and to validate the TLS height with ground truth (ALS height) to get the error margin(RMSE) for AGB sensitivity analysis. Moreover, linear regression analysis was employed to assess the effect of basal area on AGB and the effect of number of trees per plot for missed trees. To address the research question regarding the effect of occlusion on TLS scanning on tree detection and effect of forest stand density on AGB, mainly descriptive statistics were also employed. To check whether there is statistically significant difference between two observations t-test was used. Moreover, correlation analysis was also used to assess the relationship between variables. In this study, the DBH and height derived from the TLS point cloud data are validated by the field DBH and the height derived from airborne LIDAR respectively. The residual mean square error (RMSE)(Equation 9) was used to assess the deviation of the dependent variable from the measurements used as ground truth (Liang et al., 2012).

Equation 9: Calculation used for residual mean squared error

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(yi - \widehat{yi})^2}{n}}$$ ………………………………………………………….. Equation 9

Where;
RMSE-Root Mean Squared Error; yi-Measured value of dependent variable; ŷ-Predicted value of dependent variable; n- Number of observations

4. RESULTS

4.1. Field Biometric Data of the Study

During the field work, a total of 1033 trees were measured and scanned from all 32 sampled plots. Biometric data mainly diameter at breast height (DBH)measured in the field were entered in Microsoft Excel. The field measured trees were matched with the corresponding trees in Terrestrial laser scanner (TLS) and Airborne LIDAR using tree numbering, and GPS locations of each individual trees were taken during the field work.

4.1.1. Relationship Between TLS and Field Measured DBH and Accuracy Assessment

Out of 1033 trees measured in the field, 855 trees were extracted from TLS point cloud data, and DBH was measured for those trees. The DBH derived from the TLS point cloud data was validated by the field measured DBH. The accuracy assessment result of DBH derived from TLS using DBH measured in the field using diameter tape is shown in Table 5.

Table 5: Accuracy assessment result of DBH derived from TLS by DBH measured at the field.

Descriptive statistics	Values
Correlation	0.995
R square	0.990
Adjusted R square	0.990
RMSE[cm]	1.37
Observations	855

Moreover, to see the relationship between DBH measured in the field and derived from TLS point cloud data, a scatter plot is used. As it is shown from the scatter plot (Figure 18), there was almost one to one relationship between the two DBH measurements. The residual mean square error (RMSE) of DBH of the model is found to be 1.37cm which shows there was a slight underestimation of DBH measurement using TLS system. Summary of the detail statistical analysis showing the relationship between field and TLS DBH measurements is shown in Appendix 1.

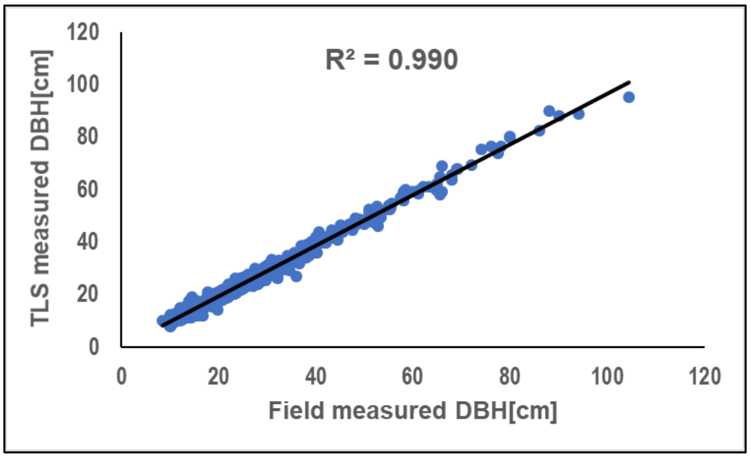


Figure 18: Scatter plot showing field and TLS DBH relationship.

The Pearson correlation coefficient (r) revealed that there is a very strong correlation between field and TLS DBH measurements. Furthermore, to check whether there is a statistically significant difference or not between field and TLS DBH measurements, a t-test was carried out. The test result (Table 6) also confirmed that there was no statistically significant difference between DBH measured in the field and the one derived from TLS point cloud data using Alpha equal to 0.05 significance level.

Table 6: t-Test for DBH measured from field and TLS.

	Field DBH(cm)	TLS DBH(cm)
Mean	22.8	21.9
Variance	194.8	182.7
Observations	855	855
Pooled Variance	188.7	
Hypothesized Mean Difference	0	
df	1708	
t Stat	1.34	
P(T<=t) one-tail	0.08	
t Critical one-tail	1.64	
P(T<=t) two-tail	0.17	
t Critical two-tail	1.96	

The overall descriptive statistics for the DBH measured in the field and derived from the TLS point cloud data is shown in Table 7.

Table 7: Over all descriptive statistics for field and TLS DBH measurements.

	Field measured DBH(cm)	TLS measured DBH(cm)
Mean	22.82	21.91
Standard Deviation	13.96	13.52
Minimum	10	7.8
Maximum	104.5	95
Observation	855	855

Furthermore, the descriptive statistics of DBH measured at the field and derived from TLS point cloud data at the plot level is provided in Appendix 5.

4.2. Individual Tree Extraction from TLS Point Cloud Data

The extraction of individual tree varies from one sample plot to another. The minimum extraction percentage of individual trees per plot was 73.3% while the maximum is 100%. The overall extraction and missing percentage of individual trees were 82.77% and 17.23% respectively. Details of the number of trees measured and scanned in the field, the percentage of extraction and missing trees in each sample plot are shown in Table 8.

Table 8: Number of trees measured in the field and extracted from TLS.

Plot No.	Field measured	TLS extracted	Extraction in %	Missed trees	Plot No.	Field measured	TLS Extracted	Extraction in %	Missed trees
1	30	25	83.3	5	17	38	32	84.2	6
2	45	36	80	9	18	45	33	73.3	12
3	33	26	78.8	7	19	32	26	81.3	6
4	36	29	80.6	7	20	42	34	81	8
5	33	26	78.8	7	21	29	25	86.2	4
6	36	29	80.6	7	22	43	35	81.4	8
7	31	28	90.3	3	23	22	20	90.9	2
8	36	29	80.6	7	24	22	21	95.5	1
9	35	29	82.9	6	25	28	25	89.3	3
10	39	31	79.5	8	26	28	24	85.7	4
11	37	29	78.4	8	27	30	25	83.3	5
12	25	22	88	3	28	16	15	93.8	1
13	44	35	79.5	9	29	34	28	82.4	6
14	15	15	100	0	30	23	21	91.3	2
15	34	27	79.4	7	31	33	27	81.8	6
16	34	27	79.4	7	32	25	21	84	4

Total Plots	Total field measured	Total TLS extracted	TLS extraction (%)	Missed trees	Missed trees (%)
32	1033	855	82.77	178	17.23

Correlation analysis was carried out to assess the relationship between a total number of trees measured in the field and the total number of trees extracted from TLS point cloud data at the plot level. Pearson correlation coefficient (r) is found to be 0.95. Therefore, there is a very high relation between the two values. A t-test was undertaken to check whether there is a statistically significant difference or not between a total number of trees measured in the field and the total number of trees extracted from TLS point cloud data at the plot level. The test result confirmed as there is no statistically significant difference between the number of trees measured in the field and extracted from the TLS point cloud data at 95% confidence interval or Alpha 0.05 significance level (Table 9).

Table 9: t-test between a total number of trees measured in the field and extracted from TLS.

	Trees measured at field	Trees extracted from TLS point cloud
Mean	32.28	26.72
Variance	59.88	35.24
Observations	32	32
Pooled Variance	47.56	
df	62	
t Stat	1.48	
P(T<=t) one-tail	0.07	
t Critical one-tail	1.66	
P(T<=t) two-tail	0.14	
t Critical two-tail	1.99	

4.2.1. Relationship Between Basal Area and Number of Trees per Plot

Basal area was calculated for all measured individual trees in each sample plot. To get the total stand basal area per plot, all trees stand basal area was summed. To extrapolate into per hectare, the total basal area per plot was multiply by 20 since the plot area is 5% of a hectare. Table 10 shows the number of trees measured in the field and number of trees extracted from TLS point cloud data at plot level with their corresponding total stand basal area per ha.

Table 10: Number of trees and stand basal area per plot.

Plot	Number of trees measured at field	Extracted from TLS	Total stand basal area of field measured(m^2/ha)	Total stand basal area(m^2/ha) after tree extraction
1	30	25	30.78	25.90
2	45	36	31.33	28.54
3	33	26	16.92	13.19
4	36	29	27.00	25.57
5	33	26	40.95	36.39
6	36	29	34.74	28.28
7	31	28	28.53	28.18
8	36	29	40.81	38.19
9	35	29	26.41	21.02
10	39	31	39.93	31.97
11	37	29	22.78	17.71
12	25	22	25.80	25.56
13	44	35	45.04	26.08
14	15	15	4.46	4.46
15	34	27	40.81	37.65
16	34	27	39.31	28.16
17	38	32	53.61	46.10
18	45	33	49.29	42.56
19	32	26	42.90	41.18
20	42	34	48.52	42.40
21	29	25	56.59	54.43
22	43	35	41.40	33.70
23	22	20	55.59	50.69
24	22	21	12.14	11.75
25	28	25	41.97	40.64
26	28	24	17.80	15.66
27	30	25	35.99	27.17
28	16	15	11.98	10.91
29	34	28	70.55	62.53
30	23	21	13.87	12.10
31	33	27	45.66	40.68
32	25	21	11.87	10.61

A scatter plot of stand basal area per plot against the corresponding trees per plot was used to assess the relationship between stand basal area and number of trees per plot in the study area. Accordingly, coefficient of determination R^2 of 0.27 is obtained, and this result indicates the existence of low relationship between stand basal area and number of trees per plot (Figure 19) The low relationship was expected, and it is because of the forest of the study is a natural forest, there is wide variation in DBH and trees height measurements among trees in the sample plots and it also varies from one sample plot to another.

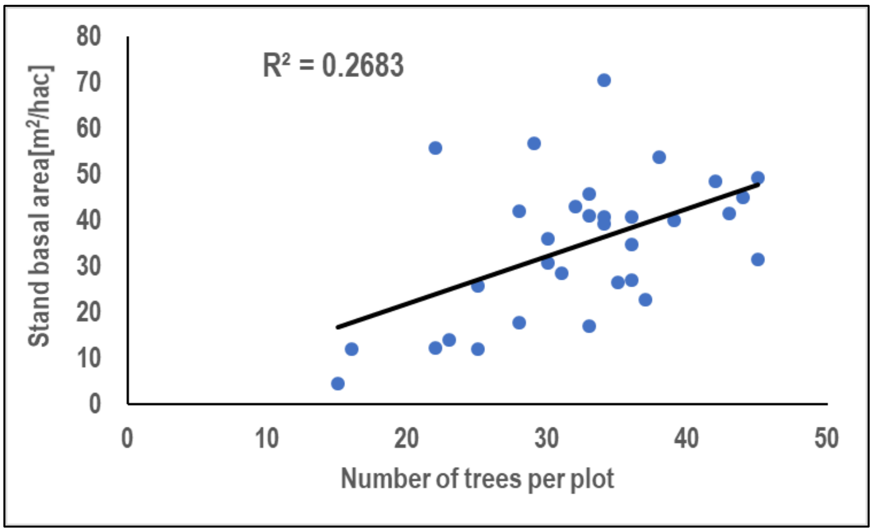


Figure 19: Scatter plot showing the relationship between number of trees and stand basal area.

4.3. Relationship Between Number of Trees per Plot and Tree Extraction from TLS Point Cloud Data

The purpose of this analysis was to check whether number of missed trees is directly related to the number of trees measured and scanned in the field. Consequently, the assumption is that as the number of missed trees increase the occlusion increase and vice versa. A scatter plot was used to assess the effect of number of trees per plot on missed trees from TLS point cloud data due to occlusion regardless of the size of missed trees. As it is shown in Figure 20, the coefficient of determination(R^2) of missed trees per plot against number of trees per plot is 0.892. This result revealed only the existence of a very strong relationship between number of missed trees per plot and number of trees per plot due to occlusion regardless of the size of missed trees.

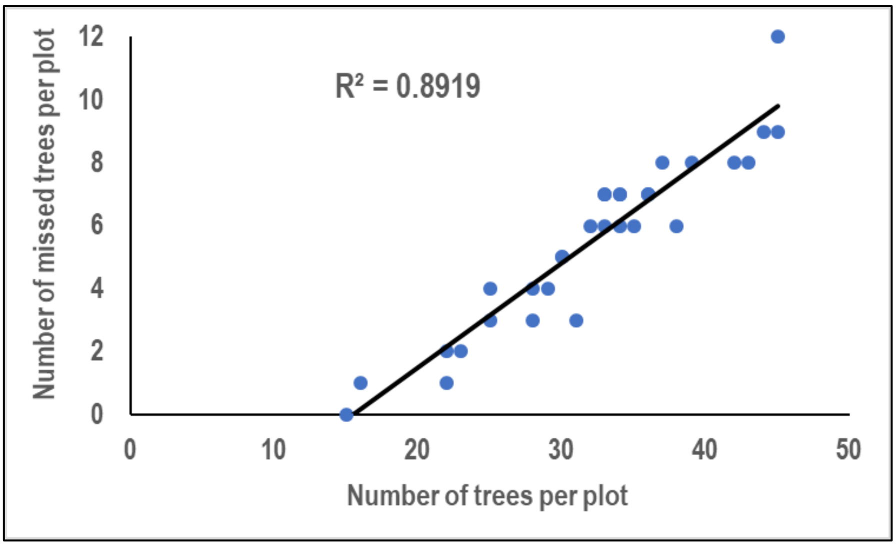


Figure 20: Scatter plot showing the relationship between missed trees versus number of trees.

Moreover, linear regression analysis has been carried out with the number of missed trees per plot as predicted variable and the total number of trees measured in the field per plot as an explanatory variable since these variables have a higher relationship. The linear regression analysis result is shown in Table 11. The details of the statistical analysis showing the relationship between number of trees and missed trees per plot are shown in Appendix 2.

Table 11: Linear regression analysis result of missed trees against total number of trees.

Explanatory variable	Coefficient	Standard error	t-statistics	P-value
Intercept	-5.165	0.701	-7.372	0.000
Number of trees per plot	0.332	0.021	15.731	0.000***

Note: *** Indicate statistically significant at $\alpha = 0.01$ significance level

4.3.1. Size and Location of Missed Trees Within Sample Plots

Of 178 missed trees out of 1033 trees measured and scanned in the field, 51.7% of trees were located at the center of sampled plots. While 48.3% of trees were located at the edge of sampled plots. Even though the total number of missed trees located at the center of sampled plots are higher than the total number of missed trees located at the edge of the sampled plots, the mean DBH of missed trees located at the center of sampled plots is lower compared to the mean DBH of missed trees located at the edge of sampled plots. The overall mean DBH of missed trees is 13.96cm of which 13.13cm is the mean DBH of missed trees located at the center of sampled plots and 14.83cm is the mean DBH of those missed trees located at the edge of sampled plots. From the table below, one can easily understand as there is no direct relationship between number of missed trees and total DBH of the corresponding missed trees per plot. Table 12 shows size and location of missed trees inside sample plots for all 32 sampled plots measured and scanned in the field.

Table 12: Size and location of missed trees inside sample plots.

Plot	Missed trees	Location in the plot		Total DBH(cm)	Total DBH of Missed trees(cm)	
		At the center	At the edge		At the center	At the edge
1	5	3	2	65.8	34	31.8
2	9	4	5	130	64.3	65.7
3	7	3	4	105.5	41.9	63.6
4	7	3	4	83.7	31.3	52.4
5	7	3	4	110.8	45.2	65.6
6	7	3	4	97.3	45.1	52.2
7	3	2	1	31.9	21.9	10
8	7	3	4	90	38	52
9	6	3	3	91.7	44.8	46.9
10	8	4	4	111.2	59	52.2
11	8	6	2	110	74	36
12	3	2	1	38.3	26.3	12
13	9	6	3	123.4	78.3	45.1
14	0	0	0	0	0	0
15	7	5	2	95.2	60.8	34.4
16	7	4	3	103.2	60.5	42.7
17	6	4	2	81.2	51.5	29.7
18	12	4	8	152.4	45	107.4
19	6	5	1	77.5	62.5	15
20	8	3	5	115.8	37.5	78.8
21	4	2	2	52.2	26.3	25.9
22	8	1	7	109.2	11.3	97.9
23	2	1	1	32.5	15.7	16.8
24	1	1	0	11.5	11.5	0
25	3	3	0	35.1	35.1	0
26	4	2	2	49.7	23.7	26
27	5	2	3	84.6	27.5	57.1
28	1	0	1	16.7	0	16.7
29	6	4	2	88.7	56.7	32
30	2	1	1	32.4	13.8	18.6
31	6	2	4	101.1	22.3	78.8
32	4	3	1	55.6	42.7	12.9
Total plots	Total missed trees at the center	Total missed trees at the edge		Mean DBH of missed trees	Mean DBH of missed trees at center	Mean DBH of missed trees at edge
32	92(51.7%)	86(48.3%)		13.96	13.13	14.83

4.4. Relationship Between Forest Stand Density and Tree Extraction from TLS Point Cloud Data

The relationship between stand basal area as a measure of forest stand density and number of missed trees per plot was examined. A scatter plot is developed between number of missed trees per plot against total stand basal area per plot. However, as it is depicted in Figure 21, there is no strong relationship between these variables compared to the relationship obtained between missed trees per plot against number of trees per plot. The coefficient of determination(R^2) obtained in this relationship is 15%, and it is also regardless of the size of missed trees.

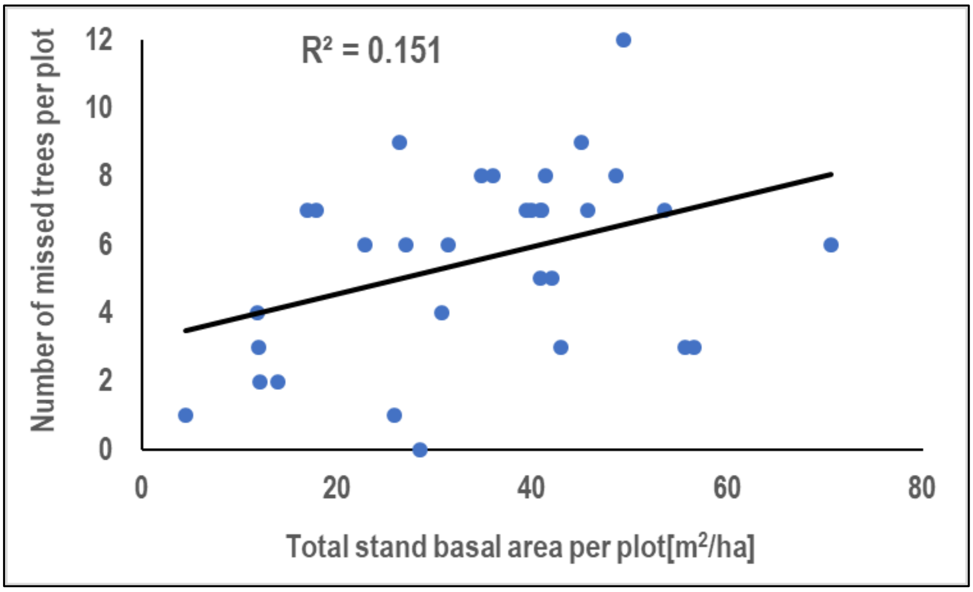


Figure 21: Scatter plot showing the relationship between missing trees versus stand basal area.

4.5. Airborne LIDAR Tree Height Measurement

From the given airborne LIDAR point cloud data, DTM and DSM were created after rasterizing the "las" format. By subtracting the DTM from DSM Airborne LIDAR canopy height model (CHM) was created with a spatial resolution of 1meter to derive height of upper canopy trees. In the process since all points below 5 and above 50 are not considered to be a tree, all points below 5 and above 50 were filtered. Figure 22 shows the CHM used for this study.

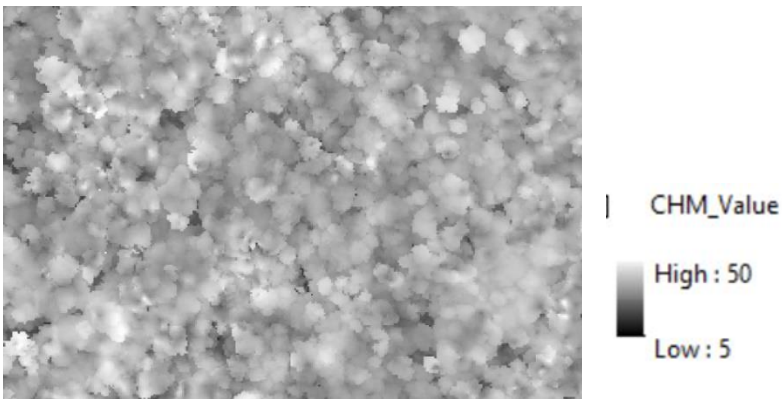


Figure 22: Airborne LIDAR CHM used for the study.

4.5.1. Tree Crown Delineation on Airborne LIDAR CHM

Automatic image segmentation was done on the pit free ALS-CHM to identify crowns of individual trees using multi-resolution segmentation algorithm. The segmentation is used to separate upper canopies from lower canopies. In eCognition software, for segmentation of individual tree crowns, an appropriate value for scale parameters was used. Accordingly, 12 for scale parameter, 0.8 and 0.5 for shape and compactness respectively were found to be reasonable ruleset for the segmentation of this study. Figure 23 shows a portion of the multi-resolution segmentation result.

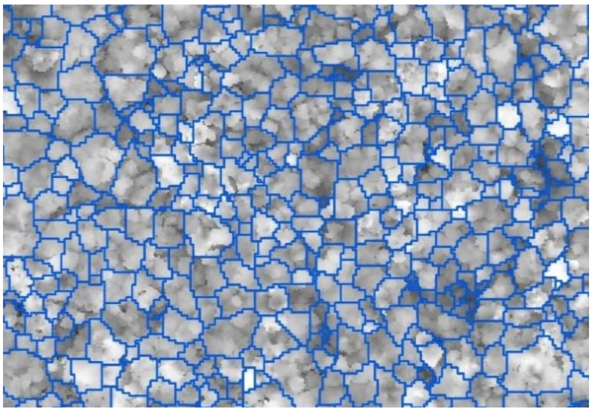


Figure 23: Individual tree crown segmentation from Airborne LIDAR CHM.

4.5.2. Segmentation Accuracy Assessment

Manually delineated polygons were used as a reference to assess the accuracy of automatic segmentation carried out using the eCognition software. Clearly visible crowns of 15% proportion of the field measured trees in each sampled plot were manually digitized on screen in ArcMap. Over and under segmentation was assessed by comparing the automatically segmented polygons with manually delineated reference polygons (Figure 24).

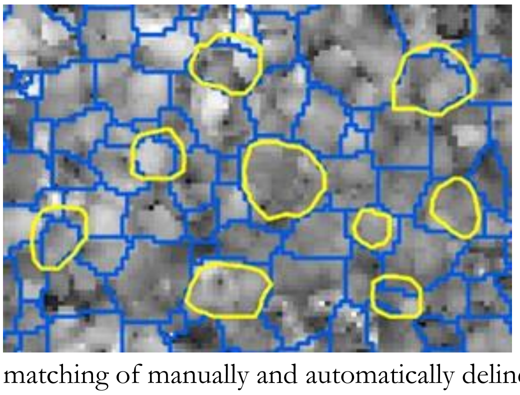


Figure 24: Sample matching of manually and automatically delineated tree crowns.

After calculating the value of over and under segmentation, the D value (goodness of fit) was calculated to assess the segmentation accuracy. Accordingly, the segmentation error was found to be 29%. Therefore, the accuracy of crown delineation was 71% while the result of 1:1 manual matching of polygons was 74% accuracy (Table 13).

Table 13: Segmentation accuracy result.

	Total reference polygons	Total 1:1 matched polygons	Over Segmentation	Under Segmentation	Goodness of fit (D)
	157	116	0.3	0.5	0.29
Accuracy (%)		74			71

4.5.3. Extraction of Individual Tree Height

The accuracy of Airborne LIDAR segmentation was reasonable to identify and delineate the crown of individual trees. As a result, for the identified trees in each sampled plot, zonal statistics and extraction of multi values to points were applied to obtain the local maximum value of the segmented CHM. During the field work, both multiple upper canopy layer and single upper canopy layer plots were sampled. For those plots having multiple upper canopy layers (emergent, medium and lower canopy trees), 14m was used as a threshold to separate upper canopy from lower canopy trees hence 14m was the minimum height of tree observed by ALS in those plots. However, in those plots having single upper canopy layer, 9m was a threshold to separate lower and upper canopy. Therefore, 14m and 9m were used as a threshold to separate upper canopy from lower canopy trees in multiple upper canopy and single upper canopy layers respectively. Trees with their height below this threshold in the corresponding plots were considered as lower canopy trees, and the height was derived from TLS.

Accordingly, based on the threshold, of 1033 trees measured and scanned in the field, 657(63.6%) were identified as upper canopy trees and matched with DBH derived from TLS. While 198 trees (19.17%) were classified as lower canopy trees. Table 14 shows the overall descriptive statistics for trees identified as upper and lower canopies measured by ALS and TLS respectively.

Table 14: Over all descriptive statistics for trees identified as upper and lower canopies.

Descriptive statistics	ALS upper canopy trees height (m)	TLS lower canopy trees height(m)
Mean	24.90	10.08
Standard Deviation	6.54	2.71
Minimum	9.03	5.1
Maximum	48.19	13.9
Observation	657	198

4.6. Estimation of Above Ground Biomass

In this study, the AGB was calculated with tree inventory parameters derived from TLS and ALS using allometric equation given in (Equation 4). Height derived from ALS and DBH derived from TLS was used to calculate upper canopy trees AGB while tree height and DBH derived from TLS was used to estimate AGB for lower canopy trees. Total AGB for each sampled plot and the entire study area was estimated by adding AGB estimated from lower and upper canopy trees. Figure 25 shows the distribution of AGB in Mg across sample plots in ascending order.

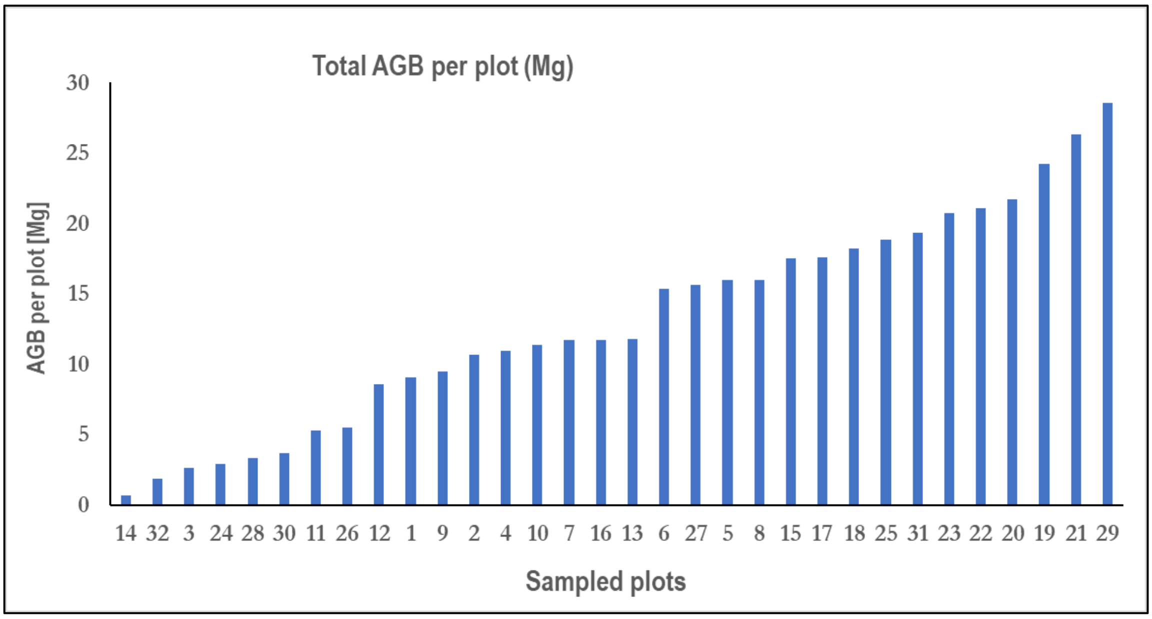


Figure 25: Distribution of AGB in Mg across sampled plots in ascending order.

Furthermore, the overall descriptive statistics of AGB obtained from lower and upper canopy trees is also done and summarized in Table 15.

Table 15: Overall descriptive statistics of estimated AGB.

Descriptive statistics	Upper canopy AGB(Mg)	Lower canopy AGB(Mg)	Total AGB(Mg)
Mean/plot	12.31	0.75	13.07
Mean/ha	246.2	15	261.4
Standard Deviation	7.39	0.56	7.54
Minimum	0.35	0.15	0.70
Maximum	27.98	2.38	28.58
Sum(Mg)	394.05	24.09	418.14
Sample plots	32	32	32

From the total of 418Mg AGB estimated from all sampled plots, 394Mg (94%) were obtained from upper canopy trees while 24Mg (6%) were estimated from lower canopy trees with parameters derived from TLS. The overall mean AGB of the sampled plots was13Mg (i.e., 261Mg per ha) while 12Mg and 0.75Mg per plot were for upper and lower canopy trees respectively (Table 15).

4.7. Estimation of Above Ground Carbon Stock

The estimated above ground biomass was multiplied by a conversion factor of 0.47 to estimate above ground carbon stock of the measured trees. A total amount of 185Mg and 11Mg of above ground carbon stock were obtained from upper canopy trees and lower canopy trees respectively. The overall mean AGC of the sampled plots was 6Mg (i.e., 122Mg per ha). Table 16 shows the overall descriptive statistics of the estimated above ground carbon stock from the sampled plots.

Table 16: Overall descriptive statistics of estimated Above ground carbon.

Descriptive statistics	Upper canopy trees AGC(Mg)	Lower canopy trees AGC(Mg)	Total AGC(Mg)
Mean/plot	5.79	0.35	6.14
Mean/ha	115.8	7	122.8
Standard Deviation	3.47	0.26	3.54
Minimum	0.17	0.07	0.33
Maximum	13.15	1.12	13.43
Sum(Mg)	185.20	11.32	196.52
Sampled plots	32	32	32

4.8. Relationship Between Forest Stand Density and AGB

The relationship between forest stand density and aboveground biomass was assessed using scatter plot and linear regression. Accordingly, a scatter plot of above ground biomass against stand basal area per plot was carried out. As it is shown in Figure 26, there is a very strong positive relationship between above ground biomass and stand basal area per plot hence the coefficient of determination (R^2) is 0.91.

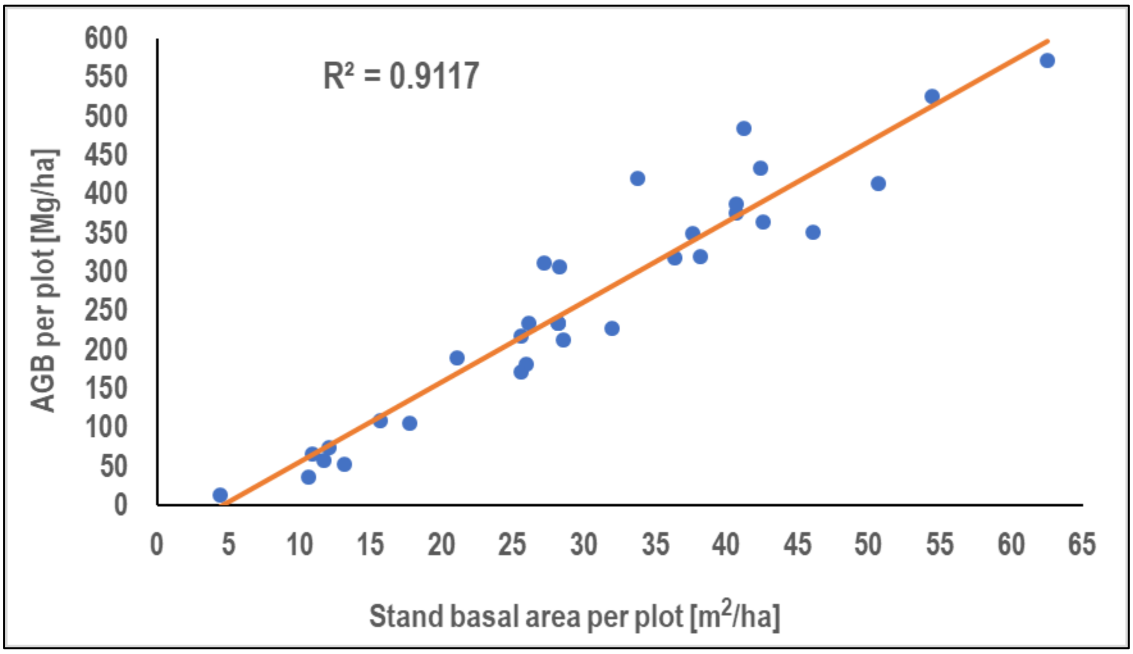


Figure 26: Scatter plot showing the relationship between AGB versus stand basal area per plot.

Furthermore, linear regression analysis was conducted with above ground biomass per plot (Mg/ha) as the dependent variable and total stand basal area per plot (m²/ha) as an explanatory variable since the relation of these variables is very strong. Summary of the detail statistical result showing the relationship between stand basal area and AGB per plot is shown in Appendix 3. The linear regression analysis result is shown in Table 17.

Table 17: Linear regression analysis result of stand basal area and AGB.

Explanatory Variable	Coefficient	Standard error	t-statistics	P-value
Intercept	-47.722	19.346	-2.467	0.020
Stand basal area (m^2/ha)	10.301	0.586	17.575	0.000***

Note: *** Indicate statistically significant at α =0.01 significance level

4.9. Relationship between Number of Trees per Plot and AGB

A scatter plot of above ground biomass against number of trees per plot is used to assess the relationship between number of trees per plot and above ground biomass per plot. As it is shown in Figure 27, the coefficient of determination R^2 is found to be 18% or 0.178. This result revealed the relationship between number of trees per plot and above ground biomass is very low. Of course, it was expected in the beginning since the forest of the study is a natural forest with a lot of variation in tree parameters among trees.

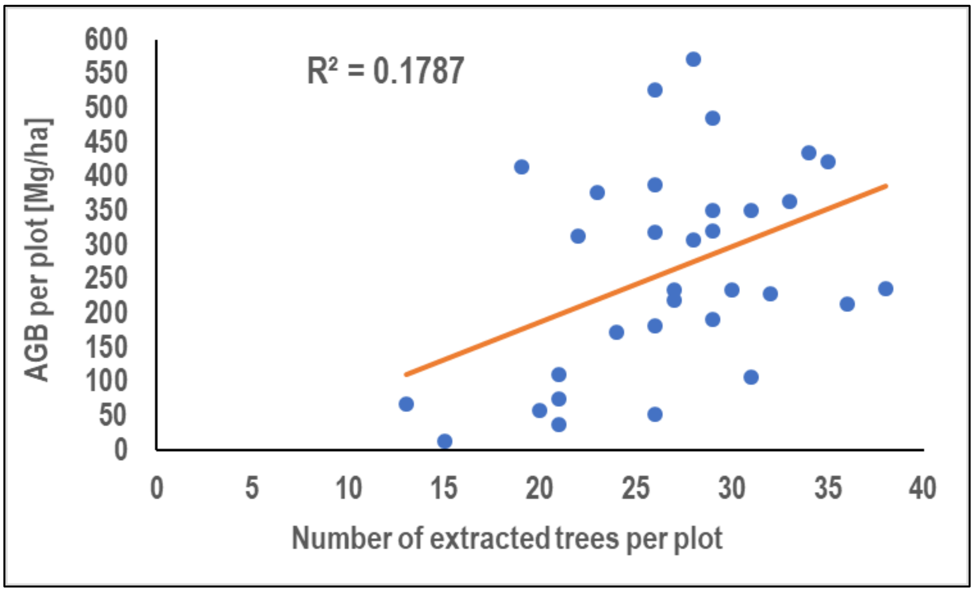


Figure 27: Scatter plot showing the relationship between AGB versus number of trees per plot.

4.10. Effect of TLS Tree Height Inaccuracy on the Estimation of AGB

The error in the TLS tree height measurement was associated with the structure of the canopy. Because of the availability of multiple upper canopy layers and canopy intermingle or overlap, it was difficult for the instrument to scan the entire tree structure. To assess the effect of TLS height inaccuracy on the estimation of AGB, the actual TLS trees height was validated by the height of the corresponding tree obtained from Airborne LIDAR because the airborne LIDAR was considered as a standard since it can see the top of the tree, as a result, the error is almost negligible. Accordingly, in linear regression, when the actual TLS trees height measurement was regressed against the corresponding trees height measurement obtained from airborne LIDAR, the residual mean squared error of 2.42m approximated to 2.5m, the coefficient of determination(R^2) of 0.72 and 0.85 Pearson correlation coefficient was achieved for the selected 96 individual trees. Summary of the detail statistical analysis results showing the relationship between Airborne and TLS tree height for sensitivity analysis is shown in Appendix 4. Therefore, to assess the sensitivity of AGB due to TLS height inaccuracy, the actual TLS tree height was adjusted two (2) times by the error margin of ±2.5m.

The effect of TLS derived trees height measurement differences on the estimation of AGB for the selected 96 individual trees is shown in Table 18 and bar chart Figure 28.

Table 18: Effect of TLS height measurement difference on AGB estimation.

Descriptive statistics	AGB deflated(Mg)	AGB actual(Mg)	AGB inflated(Mg)
Mean biomass	0.49	0.56	0.63
Standard deviation	0.81	0.90	0.99
Minimum biomass	0.02	0.03	0.03
Maximum biomass	5.03	5.48	5.94
Sum	47.37	53.79	60.18
Selected trees	96	96	96

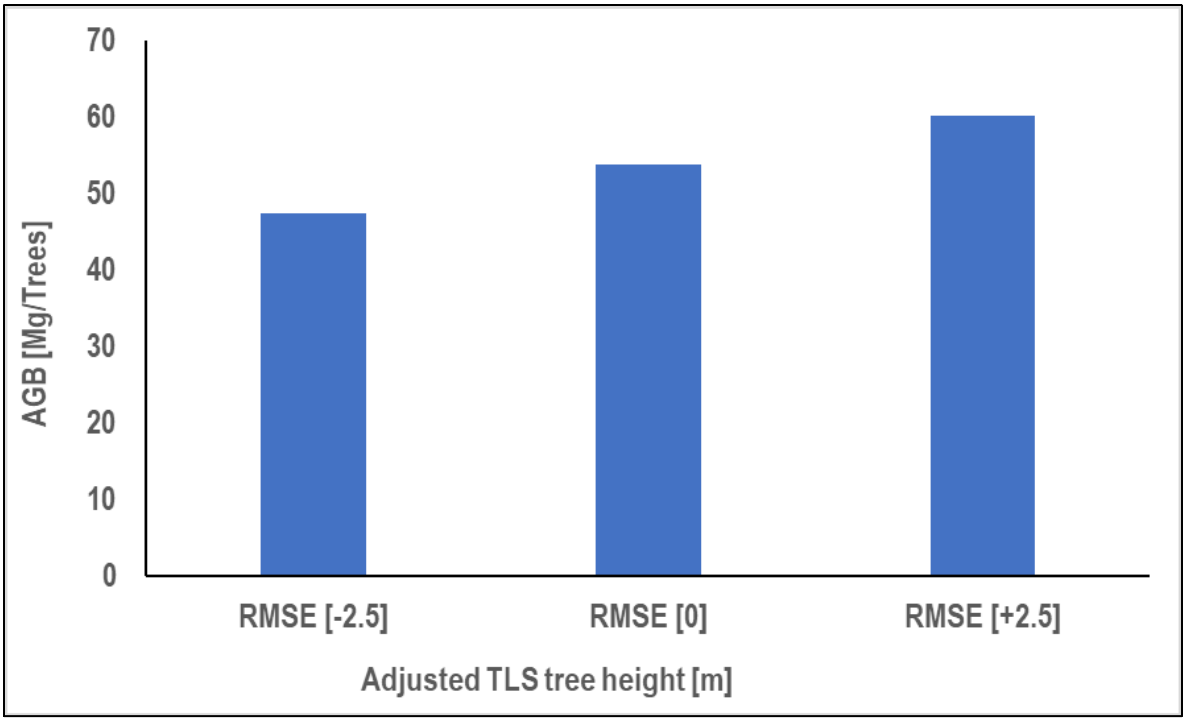


Figure 28: AGB sensitivity analysis to TLS tree height adjusted based on RMSE.

To test whether the mean difference of the estimated AGB from the adjusted TLS tree height measurement by the residual mean square error (RMSE) of ±2.5m was statistically significant or not at 95% confidence interval, a t-test was employed (Table 20). The mean difference of above ground biomass estimated from the deflated and inflated TLS tree height was calculated, and the result is depicted in Table 19.

Table 19: Results of estimated AGB mean difference.

Mean value of parameters	AGB(Mg)
Actual mean of AGB	0.56
Mean of AGB deflated	0.49
Mean of AGB inflated	0.62
Mean AGB difference(deflated)	0.07
Mean AGB difference(inflated)	0.06

Even though there is a slight difference in the total AGB and mean difference of AGB estimated using the actual height and adjusted TLS derived trees height based on RMSE, the result of the t-test statistics revealed that there is no statistically significant difference between the mean difference of the AGB estimated from the TLS derived trees height adjustment (deflated and inflated) by the RMSE of ±2.5m at Alpha equal to 0.05 significance level. The results of the t-test between mean biomass difference estimated from inflated and deflated TLS tree height is shown in Table 20.

Table 20: t-test between mean biomass difference estimated from inflated and deflated TLS height.

	Deflated biomass difference	Inflated biomass difference
Mean	0.07	0.06
Variance	0.0083	0.0083
Observations	96	96
Pooled Variance	0.0083	
df	190	
t Stat	0.015	
P(T<=t) one-tail	0.49	
t Critical one-tail	1.65	
P(T<=t) two-tail	0.98	
t Critical two-tail	1.97	

5. DISCUSSION

5.1. Distribution of Field and TLS DBH Measurements

During the field data collection, diameter at Breast Height (DBH) was measured for a total of 1033 trees from 32 sampled plots and these sample plots were scanned with TLS. Of the total amount of trees measured at the field, 855 trees were extracted manually from the TLS point cloud data. For different statistical applications and procedures like t-test, regression, correlation, analysis of variance and other parametric tests, checking normality of the data is required to determine the validity of the data (Ghasemi & Zahediasl, 2012). The histogram is one of the way used to visually display normality distribution of the data by showing skewness of the distribution of the data. If the long tail is skewed to the positive direction, the probability distribution of a data is skewed to the right. While if the long tail is skewed to the negative direction, the probability distribution of a data is skewed to the left (Doane & Seward, 2011)(Figure 29).

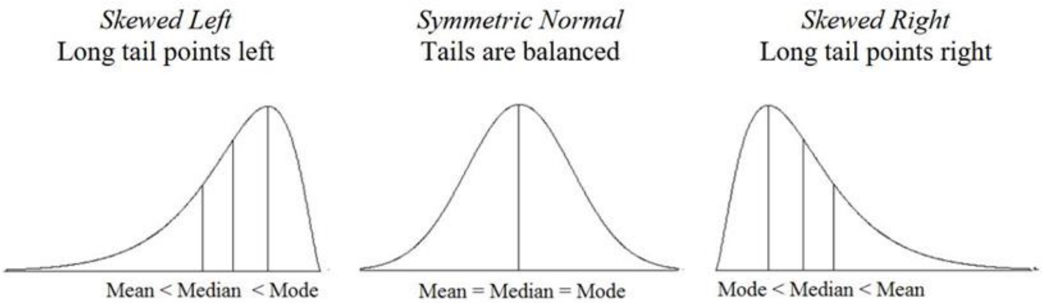


Figure 29: Histogram showing an illustration of skewness. Source: (Doane & Seward, 2011).

For this study, the normality distribution of DBH measured from the field and derived from TLS point cloud data was assessed hence DBH as an input takes the lion's share for the estimation of above ground biomass and consequently above ground carbon stock. There is a non-normal distribution with both DBH data measurements from the field and TLS. The distribution of both the DBH measured in the field and derived from the TLS point cloud data is skewed to the right as it is depicted from the histogram (Figure 30). The reason for the positive skewness of the DBH measurements is because of the measurements were taken only for those trees which their DBH is greater than or equal to 10 cm.

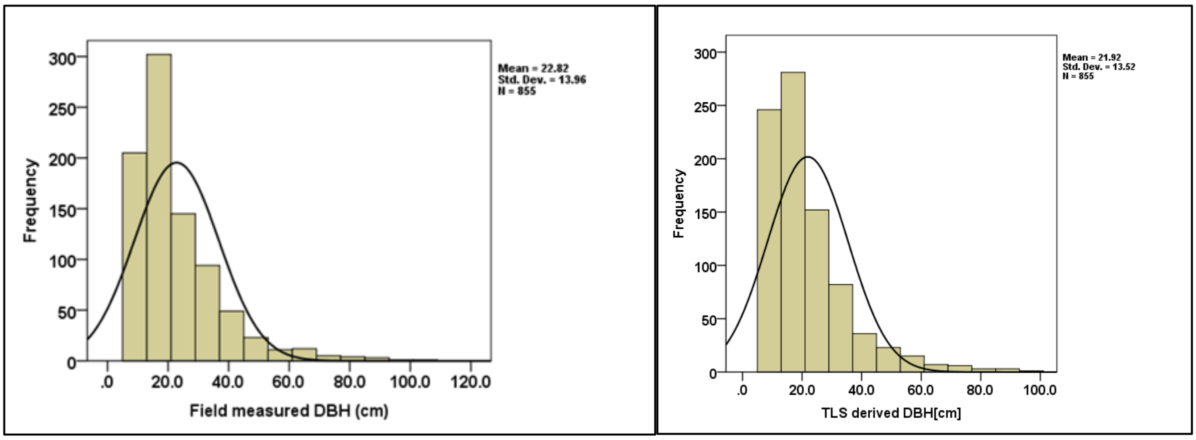


Figure 30: Histogram showing the distribution of DBH measurements from field and TLS.

5.2. DBH Measurements and Accuracy Assessment

Tree DBH is one of the most common input for the estimation of above ground biomass and carbon which can be derived from TLS point cloud data. A study conducted by Brown (2002) revealed that about 95% of the variation in above ground biomass estimation is explained by DBH. During the field data collection, DBH was measured at 1.3metre height from the ground using diameter tape which was not always practical in case of buttress trees (Figure 31). For those buttress trees, DBH was recorded by measuring tree stems above the buttress.

Figure 31: Buttress tree trunk.

The DBH measurement recorded in the field using diameter tape was used as a reference to validate the accuracy of DBH derived from TLS point cloud data. To check the variation of DBH measured in the field and derived from the TLS point cloud data, a multiple bar graph was done using the mean DBH measurement at plot level (Figure 32).

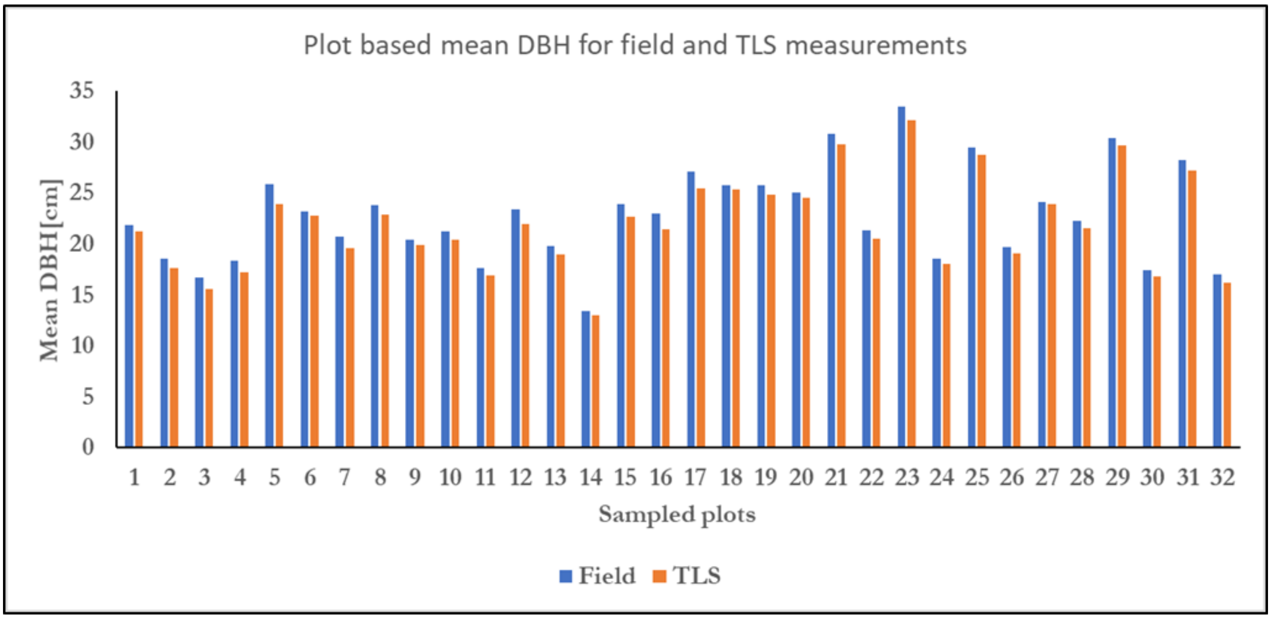


Figure 32: Plot based mean DBH distribution for field and TLS measurements.

As it is depicted in Figure 32, the variation between the mean DBH measured in the field and derived from TLS point cloud is very low. Furthermore, to confirm whether the mean difference between these DBH measurements is statistically significant or not, a t-test was carried out (Table 6). The test result revealed that as there is no statistically significant difference between the two DBH measurements. The Pearson correlation coefficient(r) also confirmed the existence of a very strong agreement (i.e., R^2=0.990 and r=0.995) between DBH measured in the field and derived from the TLS point cloud data (Table 5).

In this study, the achieved accuracy of TLS derived DBH is very high (Table 5). However, it is almost the same when compared with three other studies which have achieved the same coefficient of determination (R^2) between the DBH measured in the field and measured by TLS. The studies which have achieved comparable accuracy with the current study in the tropical rain forest are Bazezew (2017) achieved RMSE of 1.30 cm and coefficient of determination 0.9891, Ghebremichael (2016) also achieved an accuracy of RMSE 1.7 cm and coefficient of determination of 0.986. Furthermore, in a study conducted by Lawas (2016) the accuracy achieved was 1.03 cm of RMSE with a coefficient of determination 0.99. However, the achieved accuracy for the current study is a bit higher than a similar study conducted at tropical rainforest by Prasad et al. (2016) with RMSE of 2.7 cm and 0.95 coefficient of determination. The existence of occlusion due to undergrowth vegetation was mentioned as the main cause for the lower value of the achieved coefficient of determination. In this study, for the undergrowth vegetation extensive slashing and clearing has been done and this is the reason for the achievement of higher coefficient of determination compared to similar studies mentioned above.

Moreover, the accuracy achieved in this study is higher as compared with a study conducted by Srinivasan et al.(2015) in forest sites of Texas with a coefficient of determination ranged from 0.91 to 0.97 when TLS derived DBH was validated by field measured DBH. While Calders et al. (2015) in their study in native

Eucalypt Open Forest in Victoria, Australia they achieved a coefficient of determination of 0.97 and RMSE of 2.39 cm using five scanning positions, and Lindberg et al.(2012) which was conducted in Norway spruce dominated forest at Remningstorp estate in southern Sweden got RMSE of 38mm. The reason for mean DBH of the field measurement is a bit higher than the mean DBH derived from TLS in some plots is due to the size of some tree trunks. At the back of very large diameter tree trunk, it was challenging to confirm whether the position of the diameter tape is slanted or sags during field DBH measurement. As a result, the field DBH measurement of some trees which have large trunk is a bit higher than the TLS measurement.

5.3. Effect of Number of Trees per plot on TLS Tree Extraction and Accuracy Assessment

Out of 1033 trees measured in the field, 855 trees (82.77%) were extracted from the TLS point cloud data in all 32 sampled plots and 178 trees (17.23%) were missed (Table 9). Of the total missed trees, 52.7% of trees were located at the center of sampled plots. While 48.3% of those missed trees were located at the edge of sampled plots (Table 12). These trees were missed due to occlusion because of the existence of many trees in the plot, lower branches and due to adjacent trees blocking the tree numbers and reduce the density of the point cloud data because of blocking the pulses of TLS which makes it difficult to identify and extract individual tree. Moreover, a tree far away from the scanner is also another cause for missed trees because of the laminated tree number tagged on the tree could not be identified hence the point cloud density is low. For this reason, the tree detection percentage is low, when the tree is far from the scanner (Antonarakis, 2011; Liang et al., 2012).

In a study conducted by Antonarakis (2011) in managed and natural riparian forests along the Garonne River (SW France), 100% of the tree trunks were detected because of the existence of low undergrowth vegetation. Moreover, 97.5% of the trees were correctly detected in an Austrian forest in a study conducted by Maas et al.(2008). However, the overall accuracy achieved for individual tree extraction in this study is comparable with similar studies conducted in tropical rainforest such as Ghebremichael (2016) achieved 80.5% from 779 total number of trees measured in the field and Madhibha (2016) achieved 80.02% from 821 total number of trees measured in the field.

In this study, the extraction rate of individual trees varies from one sample plot to another depending on the number of trees in the corresponding plot and of course other factors like amount of undergrowth and standing position of trees in the plot. The collected data in the field per each sampled plot is used to assess the accuracy of individual tree extracted from the TLS point cloud data at the plot level. Plot 18 had the lowest tree extraction rate compared to other sampled plots because of the existence of occlusion due to a high number of trees measured and scanned in this plot (45 trees). The more trees in the plot, the more trees are missed from TLS point cloud data (Table 8 and Figure 33). Therefore, this result confirms as a number of trees are the main causes of occlusion for TLS scanning at plot level in the field.

The t-test result revealed that as there is no statistically significant difference between the total number of trees measured in the field and the total number of trees extracted from the TLS point cloud data at Alpha equal to 0.05 significance level. This indicates that despite some trees are missed from TLS point cloud data, the difference is not significant, and it couldn't lead to a difference in the estimation of AGB/carbon stock estimation (Table 9).

The number of missed trees per plot is plotted against the number of trees measured in the field per plot (Figure 20). The coefficient of determination was very high which is 89%, it is an indication as number of trees per plot has a high influence on the extraction of individual trees from TLS point cloud data due to being occlusion through trunk overlapping. The R^2 is interpreted as in ceteris paribus conditions, number of trees per plot contribute 89% for the missed trees from the TLS point cloud data regardless of the size of missed trees. However, the higher value of the coefficient of determination doesn't mean as number of trees per plot increase, more AGB is missed because of more trees are missed. In this study, the location of missed trees inside sampled plots and their corresponding size was assessed. The DBH of those missed trees is very low almost close to 10cm which doesn't contribute much to the AGB/carbon stock estimation. There is also another variable that might contribute to missed trees from TLS point cloud data other than number of trees in the plot. Some of these variables are the standing position of trees in the plot, shape of trees and personal experience of the operator but these variables are not captured in the model. Moreover, the analysis revealed that as there is no direct relationship between number of missed trees per plot and their corresponding total DBH. That means plots which have a relatively high number of missed trees have lower total DBH compared with the total DBH of a plot which has a low number of missed trees (Table 12).

The relationship between number of trees measured in the field per plot in ascending order and number of missed trees from TLS point cloud data per plot is depicted in a combined bar chart (Figure 33).

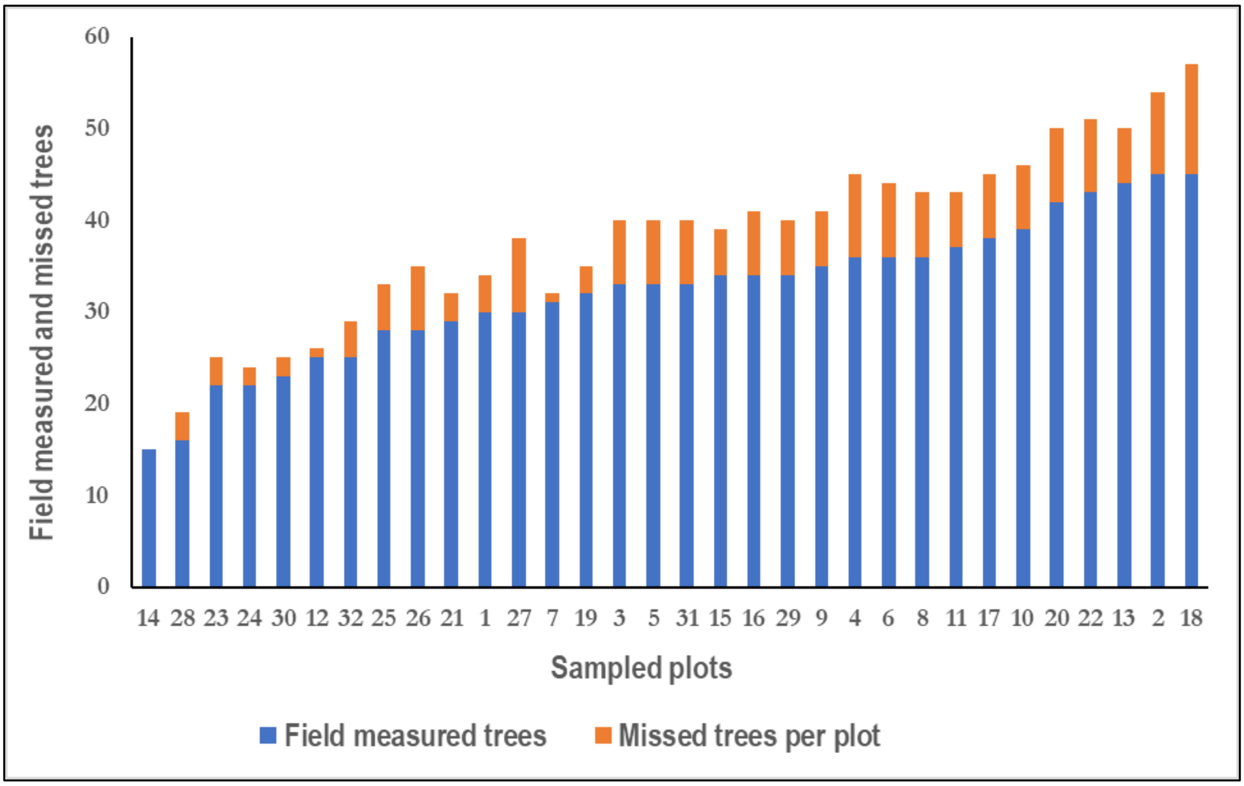


Figure 33: Combined chart for field measured and missed trees per plot.

As it is shown in Figure 33, the highest missed trees were in plot 18 hence the highest number of trees were measured and scanned in the field in this sample plot compared to other sampled plots. While in plot 14, the accuracy of individual tree extraction was 100% because of the lowest number of trees per plot were measured in this sample plot.

Furthermore, by using missed trees per plot as the dependent variable and a total number of trees per plot as an explanatory variable, linear regression analysis has been carried out. The linear regression analysis confirmed as number of trees per plot significantly affect the extraction of trees from TLS point cloud data at Alpha equal to 0.01 significance level. The magnitude of the influence of number of trees per plot for missed trees per plot is explained by its coefficient. Statistically, it is interpreted, as number of trees per plot increase by one unit, on average missed trees per plot increase by 0.33% keeping all things constant. That means if number of trees per plot increase by one tree, on average missed trees per plot increase by 0.33 tree (Table 11). However, since trees are indivisible, this interpretation doesn't make sense in this context even if this is the correct way of interpretation for significant variables of regression result, but it confirmed the relation visualized in Figure 20 and Figure 33. Note that, still this relationship doesn't consider the size of the missed trees. Therefore, this interpretation doesn't say anything about above ground biomass/carbon stock.

5.4. Effect of Forest Stand Density on TLS Tree Extraction

The coefficient of determination (R^2) for the scatter plot of number of missed trees per plot against stand basal area per plot was low which is 15% (Figure 21). The result indicates that the total stand basal area doesn't affect the extraction of individual trees from the TLS point cloud data. The relationship between stand basal area from trees measured in the field in m^2/ha per plot in ascending order and missed trees from TLS point cloud data per plot is shown in a combined bar chart (Figure 34).

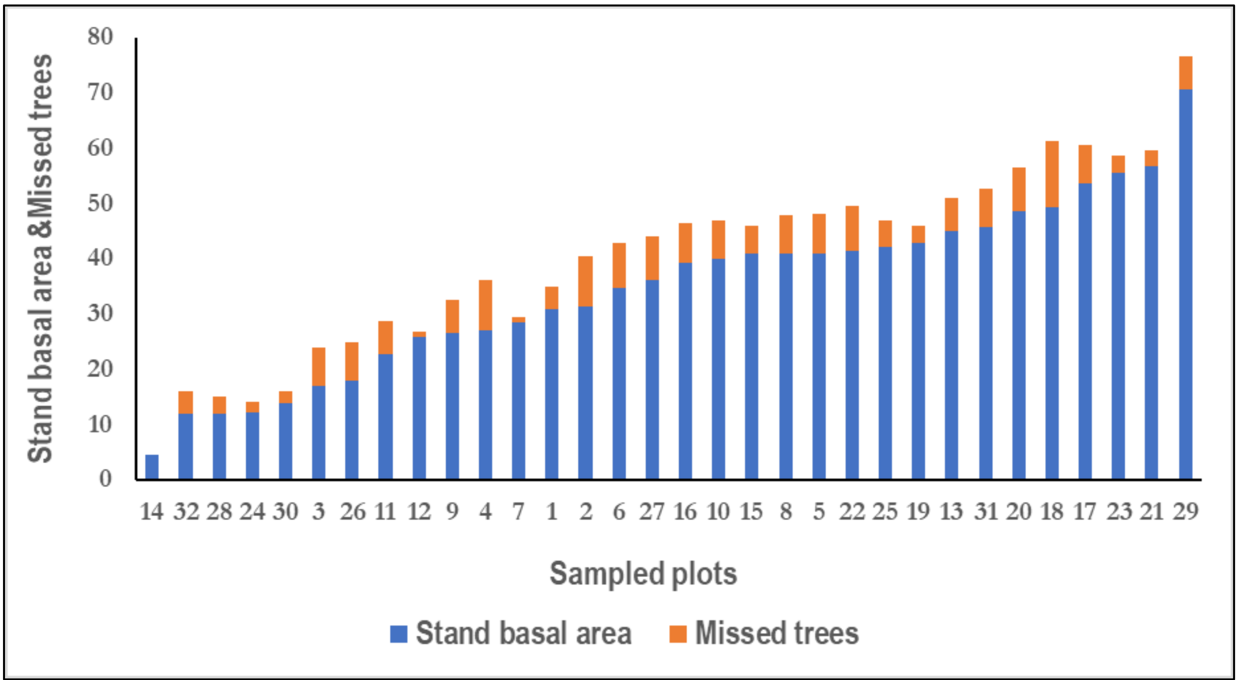


Figure 34: Combined chart for stand basal area and missed trees per plot.

As it is shown in Figure 34, there is no meaningful pattern that can show the direct relationship between stand basal area and missed trees at the plot level. The first reason for the low relationship between these two variables is the forest (Berkelah tropical rain forest) is a regenerative secondary forest that is why there were no more tree trunks which have large DBH which can hide the pulse of the TLS and create occlusion for the other trees in the sampled plots. The second reason is in the field, the choice of each of the four scanning positions in each plot take in to account the size of the tree trunk.

5.5. Effect of Forest Stand Density on the Estimation of AGB

There is a direct relationship between stand basal area and above ground biomass/carbon stock. In this study, there is a strong positive relationship between above ground biomass and stand basal area with Pearson correlation coefficient 0.95 and coefficient of determination 0.91 (Figure 26). The higher relationship between stand basal area and above ground biomass is because of both variables are directly related to the tree trunk diameter. For this reason, as the size of the tree trunk increases, the basal area increases hence it is the cross-sectional area of the stem measured at the breast height, and consequently the above ground biomass and carbon stock increases.

Linear regression analysis has been done using stand basal area per plot (m^2/ha) as an explanatory variable and above ground biomass per plot (Mg/ha) as the dependent variable. The regression result revealed there is a very strong positive relationship between stand basal area (m^2/ha) and above ground biomass (Mg/ha) at Alpha equal to 0.01 significance level. Statistically, this result is interpreted, as stand basal area increase by one unit, on average above ground biomass increases by 10.301 unit keeping all things constant. In this context, as stand basal area increase by $1m^2$/ha, on average above ground biomass increases by 10.301 Mg/ha keeping all things constant (Table 17).

In this study, the relationship obtained between stand basal area and above ground biomass (R^2=0.91) is comparable with other results of previous studies. Some of the studies are mentioned as follows: Torres & Lovett (2013) estimate above ground carbon stock using basal area in oak-pine forests of La Primavera Biosphere's Reserve, Mexico and they found coefficient of determination R^2 of 0.96 from linear regression between carbon and basal area using a total of 103 measured trees in the field. Phillips et al. (1998) explained the linear relationship between basal area and above ground biomass of trees of their DBH greater than or equal to 10 cm, with a coefficient of determination R^2 of 0.85 from 319 destructively harvested trees. Moreover, in a study conducted by Drake et al. (2003) in two areas of Central America along the Panama Canal and La Selva Biological Station in the Atlantic lowlands of north-eastern Costa Rica, the variation of above ground biomass using basal area as predictor is less than by 10% compared to the above ground biomass estimated using site-specific allometric equation. R^2 of 0.92 with a p-value less than 0.01 from 59 observations were obtained by a study conducted by Slik et al. (2010) using multiple regression analysis with stand basal area and stem density as explanatory variables and above ground biomass as a predicted variable. In all studies mentioned above, stand basal area is recommended as a proxy to estimate above ground biomass. Therefore, the result of the current study is strongly agreed with previous studies mentioned above. The combined bar chart was used to emphasize the relationship between above ground biomass (Mg/ha) and total stand basal area (m^2/ ha) in ascending order at the plot level (Figure 35).

As it is shown in Figure 35, plot 14 is the plot which has lowest above ground biomass because of its corresponding stand basal area is lowest compared to the stand basal area of all sampled plots in the field. This is because the DBH of trees measured in the field within this plot was very low since the trees were newly growing. The total DBH of trees measured in this plot was lowest compared to other sampled plots. Whereas, plot 29 is the plot which has highest above ground biomass since the corresponding stand basal area was the highest compared to other sampled plots. The highest stand basal area in plot 29 is because of this plot has the highest total DBH from all sampled plots measured in the field (Table 10 and Figure 36).

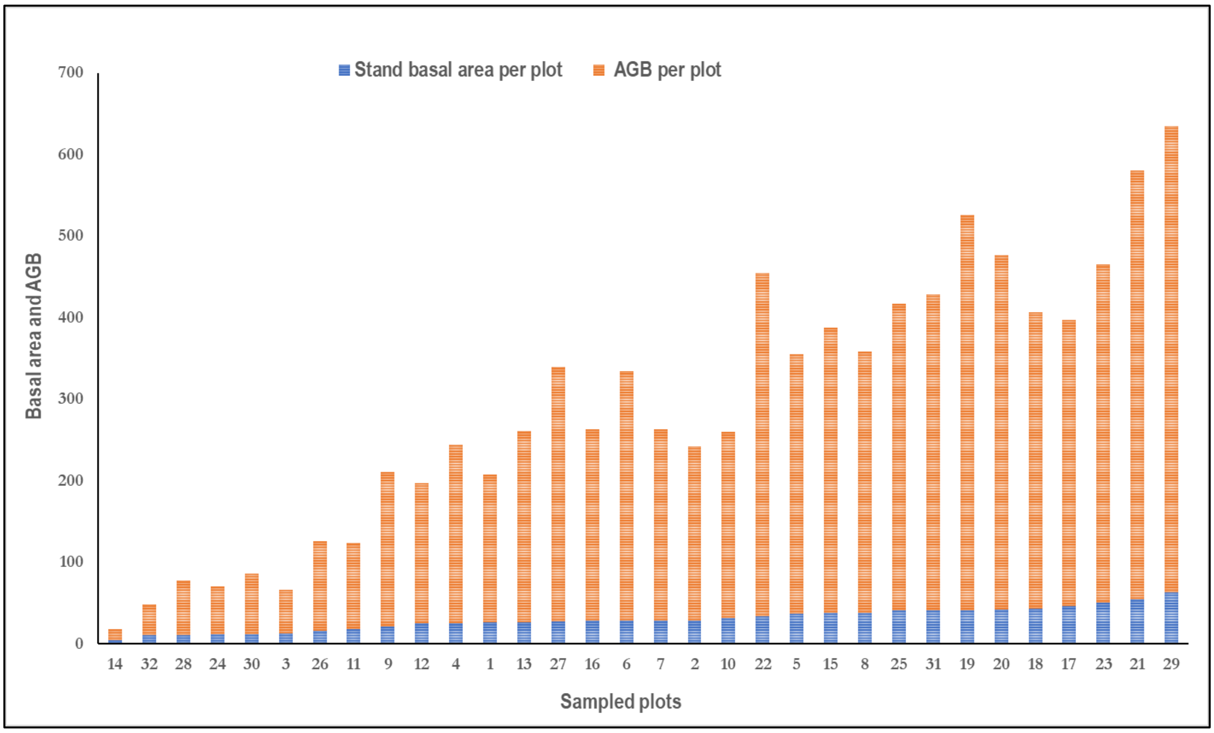


Figure 35: Combined chart for basal area and AGB per plot.

5.6. Effect of Number of Trees Per Plot on the Estimation of AGB

A scatter plot is done between above ground biomass(Mg/ha) per plot against number of trees per plot (Figure 27). The result of the coefficient of determination (R^2 = 0.178) shows as there is no strong direct relationship between above ground biomass and number of trees per plot. This is because of the forest of this study (Berkelah Tropical rainforest) is not even age forest since it is natural forest. That is why the forest is characterized by a wide variation in DBH and height measurements in all sampled plots. Of course, this low relationship between above ground biomass and number of trees per plot was expected hence the number of trees per plot cannot reasonably measure forest stand density in a natural forest because it doesn't consider the variation in the size of the trees. Figure 36 shows the number of trees in ascending order and their corresponding total DBH per plot.

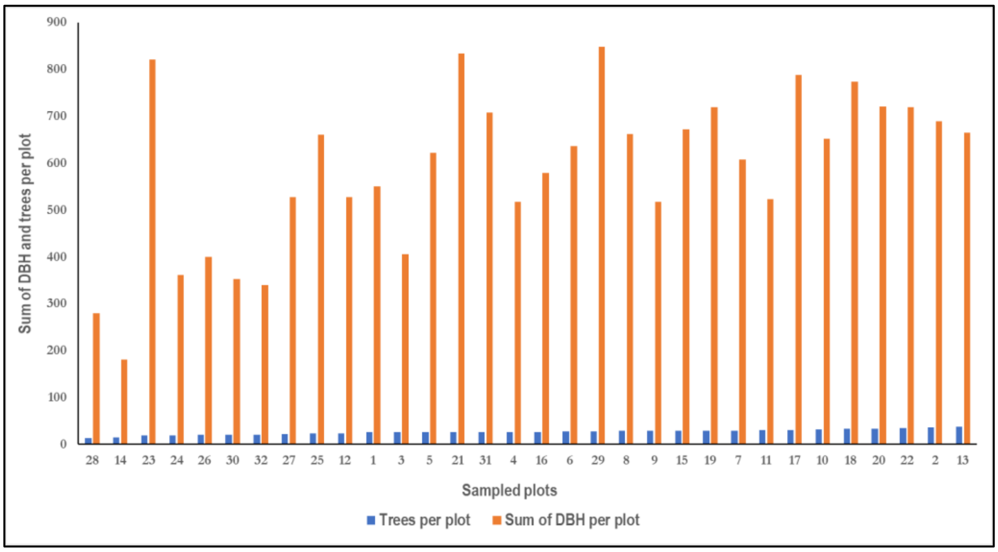


Figure 36: Bar chart for total DBH and number of trees per plot.

As it is depicted in Figure 36, for instance, plot 14 has the lowest total DBH compared to other sampled plots. However, the number of trees in plot 14 is higher than the number of trees in plot 28, but plot 28 has higher total DBH compared to plot 14. Moreover, plot 29 has a lower number of trees compared to plot 13 which has the highest number of trees from all sampled plots. However plot 29 has the highest total DBH from all sampled plots measured in the field.

Therefore, because there is a huge variation in tree parameter measurements among trees per plot, there is no direct relationship between number of trees per plot and above ground biomass. The combined chart between number of trees per plot in ascending order and above ground biomass per plot illustrates as there is no direct relationship between the number of trees and above ground biomass per plot in the study area.

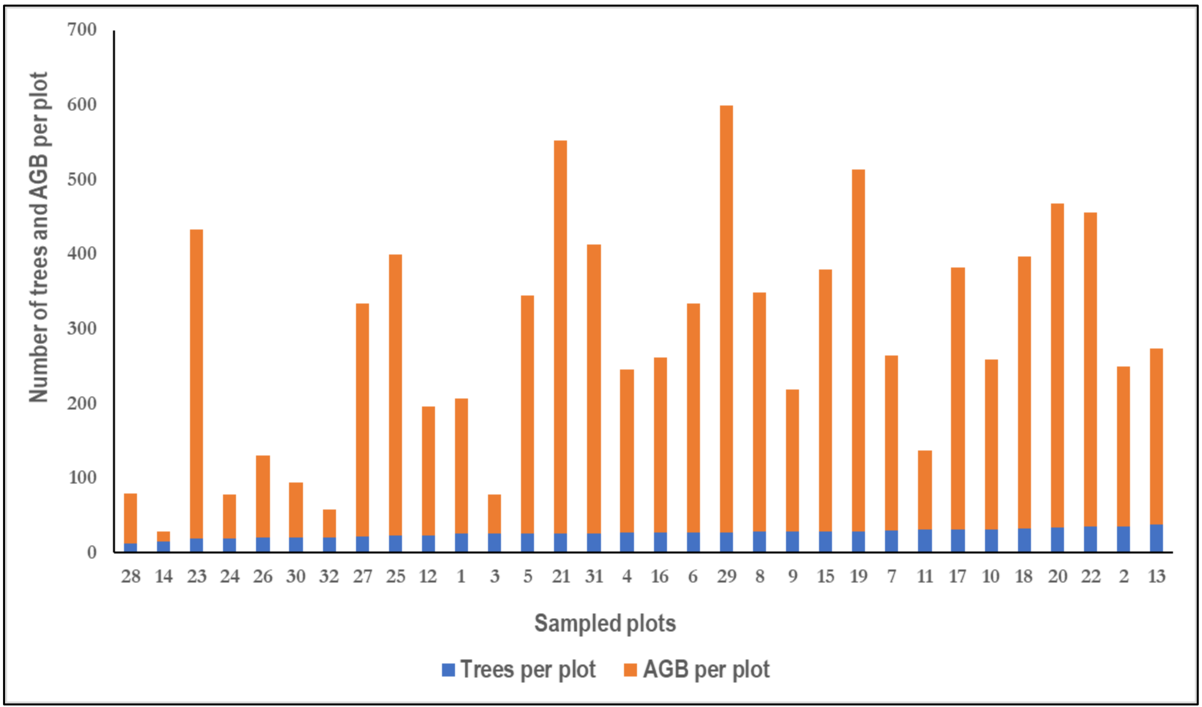


Figure 37: Combined chart for number of trees and AGB per plot.

As it is shown in figure 37, for instance, plot 13 has the highest number of trees compared to other sampled plots. However, the highest AGB recorded was in plot 29 in which it has a lower number of trees compared to plot 13. This is because of the tree parameter variation between the two plots. The total DBH of plot 13 is by far less than the total DBH of plot 29 (Figure 36).

5.7. Sensitivity Analysis of Biomass to TLS Tree Height Variation

In this study, the sensitivity analysis of AGB was carried out by using deflated and inflated TLS derived trees height measurements with constant DBH and wood density in the generic allometric equation. To this effect, a visual interpretation was made using bar chart developed for the above ground biomass obtained from the actual, deflated and inflated TLS tree height. The bar chart shows that as there is a slight difference in the total AGB estimated from the actual, deflated and inflated TLS derived trees height measurement for 96 selected trees and it is in line with the result of the descriptive statistics (Table 18 and Figure 28).

Furthermore, in addition to the graphical and descriptive statistical analysis, a t-test was carried out to test whether there is statistically significant difference between the mean differences of AGB obtained from the deflated and inflated TLS tree height measurements by the residual mean square error.
However, the test result was not significant as a result the biomass was not sensitive to TLS tree height measurement variation despite a slight variation in total and mean biomass (Table 20). The result of this study is contrasting with the results obtained from previous studies. When the height of the corresponding tree from the airborne LIDAR validated the TLS trees height of 25 selected trees, RMSE of $\pm 1.5m$ was obtained to adjust the actual TLS tree height of the 25 selected trees in a study conducted by Sadadi (2016) in tropical rainforest. Based on this procedure, it was reported that as the AGB obtained from the adjusted TLS tree height was sensitive and it was over or under estimated from the AGB obtained from the actual TLS tree height measurement. Hongoa (2017) did sensitivity analysis of above ground biomass with UAV and field tree height measurements and RMSE of $\pm 1.7m$ and $\pm 3m$ obtained for UAV and field tree height measurements respectively when the actual UAV and field trees height was validated by the corresponding trees height from Airborne LIDAR for 30 selected individual trees. Above ground biomass was found to be sensitive to the variation for both of height measurements. However, in both studies mentioned above, it was generalized from the graphical analysis, their finding was not confirmed by any test of statistical analysis. The other reason for the contrasting result might be the sample size and sampling technique used to select those trees for sensitivity analysis. In this study, the sample trees selected for sensitivity analysis of AGB is very high compared to the sample trees selected for sensitivity analysis in similar studies mentioned above. But the main cause that makes AGB was not sensitive to tree height is because of about 95% of the variation in above ground biomass estimation is explained by DBH measurement in which it was constant for the sensitivity analysis in the allometric equation (Brown, 2002).
In a study conducted by Calders et al. (2015) sensitivity analysis was carried out for a selected number of trees, however the focus of the study was to assess the robustness of the reconstruction method in the Quantitative Structure Models.

5.8. Limitation of the Study

Terrestrial LIDAR point cloud data acquisition and pre-processing like registration of the point cloud data, extraction of an individual tree, and manual measurement of trees parameters is a time-intensive activity.

There was an error in the GPS used to record the location of plot centers and measured trees in sampled plots. Due to this problem, there was a challenge to match some trees measured in the field with the segmented Airborne LIDAR CHM. To identify the direction of shifting and overcome the challenges of matching, the position of the tree in TLS scan, height and DBH measurements were used as an input.

Purposive sampling was adopted in the field to choose the unit of analysis since TLS is heavy instrument, it was a challenge to carry it to the terrain and areas of the forest which do not have road access

6. CONCLUSION AND RECOMMENDATION

6.1. Conclusion

The main objective of this study is to assess the effect of forest stand density on the estimation of above ground biomass/carbon stock using airborne and terrestrial LIDAR derived parameters in Berkelah Tropical Rain Forest, Malaysia. To achieve this objective, different statistical analysis methods were employed like regression, correlation analysis and descriptive statistics for the different parameters derived from field measurement, airborne and terrestrial LIDAR. Based on the findings what we have got in the analysis, the following conclusions are drawn for each stated specific research objectives and/or research questions.

1. *Is there a significant difference between DBH derived from TLS as compared with field measured DBH?*

The DBH derived manually from terrestrial laser scanner was validated by the DBH measured in the field. The two DBH measurements were highly correlated with a coefficient of determination(R^2) of 0.99, Pearson correlation coefficient of 0.995 and residual mean squared error (RMSE) of 1.37cm. According to the statistical significance test, there is no statistically significant difference between the DBH derived from TLS point cloud data and measured in the field. Therefore, the null hypothesis (Ho) stated "There is no significant difference between DBH derived from TLS and measured in the field" is not rejected because the calculated t-value (statistics) is less than the value of t-critical at Alpha equal to 0.05 significance level.

2. A) *Is there a significant difference between total number of trees extracted from TLS point cloud data as compared with total number of trees measured in the field?*

Number of trees measured in the field was used to validate number of trees extracted from the TLS point cloud data for each sample plot. The overall accuracy of trees extracted from the TLS point cloud data was 82.77%, and this result is comparable with the contemporary literature. There was also a high correlation between the number of trees extracted from TLS point cloud data and measured in the field with Pearson correlation coefficient of 0.95. The statistical test result revealed that there is no statistically significant difference between total number of trees extracted from TLS as compared with total number of trees measured in the field at Alpha equal to 0.05 significance level. Therefore, the null hypothesis (Ho) stated "There is no significant difference between total number of trees extracted from TLS as compared with total number of trees measured in the field" is not rejected because the calculated t-value is less than the value of t-critical.

B) *Is there a direct relationship between number of trees per plot and missed trees per plot from TLS point cloud data due to occlusion?*

A scatter plot was done between number of missed trees per plot against number of trees per plot measured and scanned in the field and the R^2 obtained was 0.89. Therefore, based on the findings, it is possible to conclude as there is a direct relationship between number of missed trees per plot and number of trees per plot measured and scanned in the field. The linear regression analysis result of number of missed trees per plot against number of trees per plot showed that number of trees per plot significantly influence extraction of trees from TLS point cloud data at Alpha equal to 0.01 significance level. However, the higher relationship between number of missed trees per plot and number of trees measured in the field per plot doesn't mean more AGB was missed in plots which have high tree density because of most trees are missed. The DBH of missed trees is very low (close to 10cm) due to this they cannot contribute much to AGB/carbon stock. Therefore, the null hypothesis (Ho) stated "There is no direct relationship between number of trees per plot and missed trees per plot from TLS point cloud data due to occlusion." is rejected.

C) *Is there a direct relationship between forest stand density per plot and missed trees per plot from TLS point cloud data due to occlusion?*
A scatter plot was done between number of missed trees per plot and stand basal area per plot and the R^2 obtained was very low which is 0.15. Therefore, there is no relationship between number of missed trees per plot and forest stand density. The null hypothesis (Ho) stated "There is no direct relationship between forest stand density per plot and missed trees per plot from TLS point cloud data due to occlusion" is not rejected.

3. A) *Is there a direct relationship between forest stand density and amount of AGB/carbon stock?*

The linear regression analysis result conducted between above ground biomass per plot against stand basal area per plot revealed that stand basal area per plot significantly affect above ground biomass at Alpha equal to 0.01 significance level. It was also confirmed with a scatter plot between above ground biomass per plot against stand basal area per plot hence R^2 of 0.91 was achieved. The statistical result revealed there is very strong and direct relationship between above ground biomass per plot and forest stand density per plot. Therefore, the null hypothesis (Ho) stated "There is no significant relationship between forest stand density and amount of AGB at Alpha equal to 0.01significance level" is rejected.

B) *Is there a direct relationship between number of trees per plot and amount of AGB/carbon stock estimation?*
The coefficient of determination R^2 obtained in a scatter plot between number of trees per plot versus above ground biomass per hectare was 0.18 which is very low. Therefore, there is no direct relationship between number of trees per plot and amount of biomass. As a result, the null hypothesis (Ho) stated "There is no direct relationship between number of trees per plot and amount of AGB/carbon stock estimation" is not rejected.

4. *What is the effect of TLS Tree height inaccuracy on the estimation of AGB for selected trees?*

Trees height obtained from the airborne LIDAR was used to validate the height of the corresponding trees obtained from TLS to quantify the error margin associated with tree height measurement from TLS. R^2 of 0.72, Pearson correlation coefficient of 0.85 and RMSE of 2.42m was achieved when the actual TLS tree height was validated by the corresponding tree height obtained by airborne LIDAR. The statistical test result made between the mean difference of above ground biomass obtained from the deflated and inflated TLS tree height revealed that above ground biomass is not significantly influenced by tree height measurement error from TLS for those 96 selected trees for sensitivity analysis at Alpha equal to 0.05 significance level. Therefore, the null hypothesis (Ho) stated "There is no significant effect of TLS height inaccuracy on biomass estimation at $\alpha = 0.05$ significance level" is not rejected because the t-statistics is less than the value of t-critical.

6.2. Recommendation

Based on the findings of this study, the following recommendation remarks can be drawn for each of the stated specific objectives for further consideration:

- During scanning in the field, increasing number of both cylindrical and circular reflectors is recommended to reduce registration error of the multiple scan positions and increase registration accuracy.

- Increasing scanning positions is recommended to increase the accuracy of tree detection and extraction from the TLS point cloud data in tropical rainforests like Berkelah tropical rain forest in plots which have a high number of trees.

- Since there is a strong relationship between stand basal area and above ground biomass and the measurement of the basal area from the ground is fast, stand basal area could be recommended as a proxy to estimate above ground biomass.

- In this study, the sensitivity analysis of AGB to TLS height variation was done using 96 sample trees. For future assessment of the sensitivity of above ground biomass to TLS tree height, increasing sample size is recommended.

- Careful extraction of individual tree trunks from polydata of TLS point cloud data is recommended to enhance the accuracy of tree parameter measurements.

- The actual location of some tree crowns was shifted because of the error in the GPS used to record location of plot center and trees in the field. Therefore, the use of highly accurate GPS like differential GPS is recommended for future studies will be conducted in tropical forests

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LIST OF APPENDICES

Appendix 1: Summary of the relationship between field and TLS DBH measurements

Summary Output: Validation of TLS derived DBH by field measured DBH

Regression Statistics	
Multiple R	0.990
R Square	0.990
Adjusted R Square	0.990
Standard Error	1.3715
Observations	855

ANOVA

	df	SS	MS	F	Significance F
Regression	1	154290.792	154290.792	82027.943	0.000
Residual	853	1604.454	1.881		
Total	854	155895.246			

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.060	0.090	0.668	0.504
Field DBH(cm)	0.963	0.003	286.405	0.000

RMSE: 1.37cm, R^2: 0.990, confidence interval: 95%, Decision: There is no significant difference

Appendix 2: Summary of the relationship between number of trees and missed trees per plot

Summary Output: Missed trees from TLS point cloud data

Regression Statistics	
Multiple R	0.944390211
R Square	0.89187287
Adjusted R Square	0.888268632
Standard Error	0.910233012
Observations	32

ANOVA

	df	SS	MS	F	Significance F
Regression	1	205.0192759	205.0192759	247.4511811	4.92038E-16
Residual	30	24.85572407	0.828524136		
Total	31	229.875			

	Coefficients	Standard Error	t Stat	P-value
Intercept	-5.165132055	0.700686273	-7.371533103	0.000
Number of trees per plot	0.33231774	0.021125586	15.73058108	0.000

R^2: 0.89, Confidence interval: 99%, Decision: It has significant effect

Appendix 3: Summary of the relationship between stand basal area and AGB per plot

Summary Output: Stand basal area

Regression Statistics	
Multiple R	0.954713389
R Square	0.911477656
Adjusted R Square	0.908526911
Standard Error	45.62212825
Observations	32

ANOVA

	df	SS	MS	F	Significance F
Regression	1	642932.6172	642932.6172	308.8974881	2.42311E-17
Residual	30	62441.35759	2081.378586		
Total	31	705373.9748			

	Coefficients	Standard Error	t Stat	P-value
Intercept	-47.72168734	19.34588665	-2.466761447	0.019566242
Basal area per plot(m^2/ha)	10.30098629	0.586099864	17.57547974	0.000

R^2: 0.91, Confidence interval: 99%, Decision: It has significant effect

Appendix 4: Summary of the relationship between Airborne and TLS tree height

Summary Output: Validation of TLS tree height by Airborne LIDAR

Regression Statistics	
Multiple R	0.847468373
R Square	0.718202644
Adjusted R Square	0.715204799
Standard Error	2.440674361
Observations	96

ANOVA

	df	SS	MS	F	Significance F
Regression	1	1427.110548	1427.110548	239.573037	1.35324E-27
Residual	94	559.9477855	5.956891335		
Total	95	1987.058333			

	Coefficients	Standard Error	t Stat	P-value
Intercept	2.243313561	1.051429226	2.13358494	0.035480422
ALS height(m)	0.74232418	0.047959499	15.47814708	0.000

RMSE: 2.42m, R^2: 0.72, Confidence interval:99%, Decision: There is significant difference

Appendix 5: Descriptive statistics of DBH measurement from field and TLS at the plot level.

		Field measured DBH(cm)				TLS measured DBH(cm)			
Plot	TLS extracted trees	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max
1	26	21.89	12.70	10	58	21.17	12.01	10	55.8
2	36	18.55	11.20	10	59.8	17.66	10.87	10	59
3	26	16.69	6.81	10	36.2	15.58	6.17	10	33
4	27	18.29	14.68	10	86	17.25	13.89	10.2	82.5
5	26	25.90	15.15	10.2	65	23.90	14.62	10.2	62
6	28	23.13	10.61	11	52	22.74	10.14	12	51.3
7	30	20.74	12.69	10	66	19.62	11.35	10	59.2
8	29	23.84	16.73	11	94	22.82	15.47	11	88.6
9	29	20.37	10.21	10.5	55.5	19.90	9.60	11.5	53.2
10	32	21.18	13.92	10	72	20.36	13.45	10	69.2
11	31	17.60	7.49	10	38	16.86	6.70	10	36.7
12	24	23.38	11.73	11.8	61	21.97	11.29	11	58.5
13	38	19.81	9.19	11	55.2	19.00	8.53	10.5	52.5
14	15	13.39	3.62	10.5	25	12.94	3.42	10	23.7
15	29	23.91	15.46	10	68	22.71	14.42	10	65.4
16	27	23.00	11.84	10	52.8	21.42	10.39	10	48.2
17	31	27.09	14.85	10	77.5	25.42	13.89	11.2	73.6
18	33	25.79	12.70	10.5	55	25.36	12.29	10.6	53.8
19	29	25.72	15.85	10.5	76	24.81	15.81	9.6	76.5
20	34	25.01	13.18	10	61	24.53	13.20	9.8	59.5
21	26	30.78	20.04	10	69.2	29.77	19.97	8	69
22	35	21.29	12.84	10.5	74	20.53	13.01	9.3	75.2
23	19	33.44	24.77	11.6	104.5	32.14	23.93	10.8	95
24	20	18.50	5.82	10.1	32	18.04	5.43	8.7	28.6
25	23	29.45	16.43	11.1	78	28.73	16.48	11.4	76.3
26	21	19.63	9.69	10.8	45.4	19.03	9.37	9.9	43.9
27	22	24.10	14.69	10.3	69	23.94	14.83	8.7	67.9
28	13	22.27	6.46	12.3	31.3	21.49	6.29	11.9	31.4
29	28	30.35	22.80	10.2	90	29.64	22.86	9.9	87.9
30	21	17.42	8.16	10	39	16.78	8.34	9.1	40
31	26	28.23	14.41	10	64.8	27.20	14.20	7.8	60
32	21	17.02	5.81	11	34.5	16.19	5.06	10.5	29.3

Appendix 6: Field data collection sheet

DATA SHEET FOR BERKELAH FOREST RESERVE, MALAYSIA								
Plot radius:					**Slope: (%)**		**Date:**	
Plot centre	**Latitude:**		**Longitude:**				**Plot No:**	
Canopy Density (%)								
Photography			Name of recorder					
Tree No:	Latitude	Longitude	Species	DBH (cm)	Stem height	Tree shapes	Crown diam. (m)	Canopy density (%)
1								
2								
3								
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Appendix 7: Some field work photographs