Effect of scanning positions of TLS on derivation of tropical forest inventory parameters and aboveground biomass estimation in Ayer Hitam, Malaysia.

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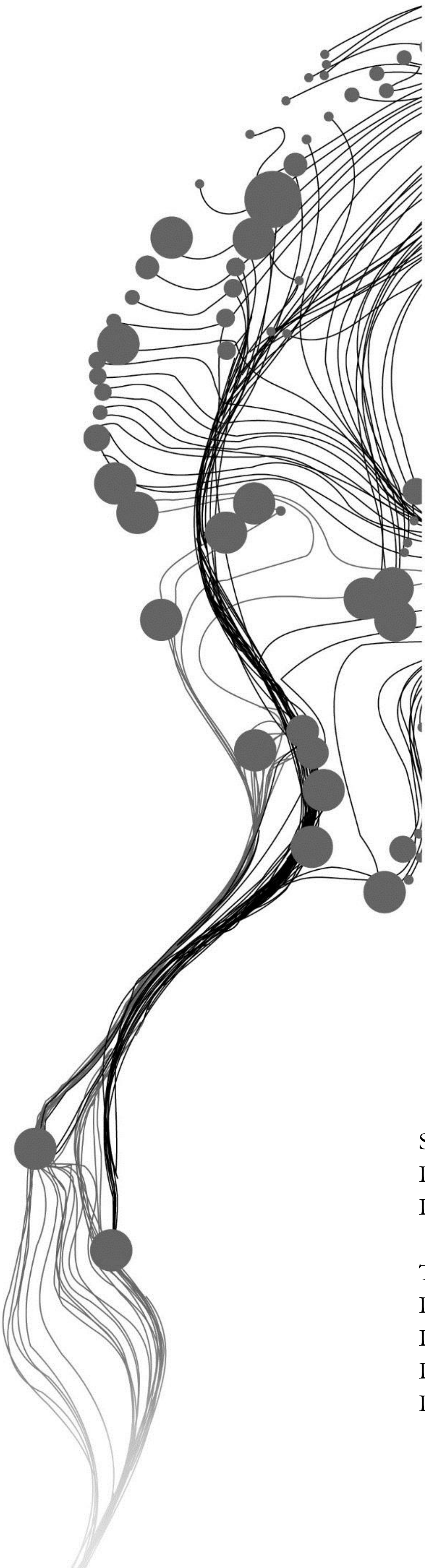

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Enschede, The Netherlands, February, 2017

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

Climate change alters the composition of the global atmosphere which are mainly caused by the increasing in greenhouse gasses particularly the increase in carbon dioxide in the atmosphere. Tropical forest plays a vital role in the global carbon balance through its unique carbon sequestration potential. However, recently tropical forests are degraded as a result of intensive deforestation and forest degradation. This situation geared towards the development of REDD+ (Reducing Emissions from Deforestation and Forest Degradation) with MRV as a central element which aims at quantifying and accurate measurement of the carbon stock and carbon change in the tropical forest.

Terrestrial laser scanner (TLS) has been the viable options for accurate biomass and carbon stock estimation. However, the accuracy of the derivation of forest inventory parameters (i.e. Diameter at Breast Height or and height) for aboveground biomass and carbon stock estimation depends on the type of scanning approach to be used. Thus the main objective of this study was to assess the effect of scanning positions of TLS on derivation of tropical forest inventory parameters and aboveground biomass estimation in the tropical rain forest of Ayer Hitam, Malaysia.

Therefore, for this study, four and five scanning position were used to derive forest inventory parameters and aboveground biomass or carbon stock estimation. A total of ten sample plot were established to collect validation data from field. Concurrently with the field data collection, the sample plot was scanned with TLS using four and five scanning positions. The point cloud data was then processed using manual and automatic extraction method in RiSCAN PRO and Computree software. Thus, the individual trees were extracted manually and automatically from the point cloud. Respectively, the overall manual extraction percentage of trees were 97.99% and 99.55% for the four and five scanning positions. Similarly, the automatic extraction of individual trees was analysed with respect to the collected field data and the result showed that 91% and 93.75% of the trees were extracted from the four and five scanning positions respectively. Moreover, the accuracy of the automatic and manually measured TLS DBH was validated using the field measured DBH as independent variable.

The root means square error (RMSE) for the manually derived DBH from the four and five scanning position was 1.66cm (8.06%) and 1.37cm (6.60) respectively. Similarly, the RMSE for the automatically derived DBH from the four and five scanning positions was 3.12cm (14.57%) and 2.36cm (11.47%) respectively. The RMSE of 3.17m (17.40%) and 3.68m (19.97%) for the automatically measured height from the five and four scanning positions. The result also showed R^2 value of 0.98 and RMSE of 0.077Mg for aground biomass calculated from five scanning positions. There was no significance difference of AGB 84.65Mg and 39.78 Mg of carbon from manually measured parameters and AGB of 77.24 Mg and 36.31 Mg of carbon measured from automatically measured parameters with four scanning positions. Similarly, the result of the aboveground biomass and carbon were calculated manually and automatically from the five scanning positions did not show a significance difference with a value of 101.2 Mg AGB and 47.48 Mg of carbon and 83.75 Mg of ABG and 39.36 Mg of carbon respectively. The result has shown that increasing the number of scanning position from four to five did not have any effect both in the derivation of parameters and aboveground biomass or carbon stock estimation. However, it has an effect on the extraction of individual trees from the point cloud data since increasing the number of scanning positions has the potential to capture all the trees within the sample area.

Keywords: Tropical forest**,** Aboveground biomass, Carbon stock, TLS, Climate change, REDD+ Scanning positions

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LIST OF ACRONYMS

AGB	Above Ground Biomass
CF	Carbon Fraction
DBH	Diameter at Breast Height
DTM	Digital terrain model
GPS	Global Positioning System
IPCC	Intergovernmental Panel on Climate Change
LiDAR	Light Detection and Ranging
MRV	Measuring Reporting and Verification
REDD	Reducing Emission from Deforestation and forest Degradation
RMSE	Root Mean Square Error
TLS	Terrestrial Laser Scanning
UNFCCC	United Nations Framework Convention on Climate Change

1. INTRODUCTION

1.1. Background

Climate change is attributed directly or indirectly to human activity that alters the compositions of the global atmosphere in addition to natural climate variability observed over a period of time (UNFCCC, 1992). It is mainly caused by the increase in greenhouse gasses particularly the increase of carbon dioxide in the atmosphere. Carbon dioxide is one of the greenhouse gasses that naturally exist in the atmosphere, which is produced by human activities (US EPA, 2016).

Forests have a great role in global carbon balance through their carbon sequestration potential which regulates global temperature rise. Biomass is one of the important parameters which indicates the carbon sequestration potential of the forest for assessing forest carbon balance (Barbosa et al., 2014). Thus, the amount of forest biomass provides information for the estimation of the carbon pool in the forest vegetation and enable us to understand the global carbon cycle (Brown, 1997). Estimating the contribution of the forest resource for carbon sink needs a reliable assessment of the amount of above ground biomass of forest ecosystem. However, estimating the contribution of the forest resource for the global carbon cycle is still with substantial uncertainty which requires accurate and reliable measurement methods (Clark et al., 2011).

Tropical forests are continuing to disappear at alarming rate as a result of deforestation and forest degradation. Deforestation and degradation are major factors contributing to the severe adverse impact on climate change (FAO, UNDP, & UNEP, 2008). Thus, Reduce Emission from Deforestation and forest Degradation (REDD) program has been proposed to tackle deforestation and to mitigate climate change by reducing greenhouse gas emissions (Angelsen et al., 2012). Although, deforestation is the main contributor of global greenhouse gasses emission, up to date information and accurate measurement of the carbon stock and carbon change in the forests is needed (Hewson et al., 2014). Because of this, United Nations Framework Convention on Climate Change (UNFCCC) has proposed Measurement, Reporting and Verification (MRV) of climate change mitigation action as one of the fundamental element of the REDD program. Accordingly, the REDD program highly emphasized on MRV of carbon stocks to obtain reliable and highly accurate data of forest carbon stock (REDD, 2012).

Accurate and reliable measurement of the forest biomass is, therefore, an important element for REDD program. In order to carry out accurate above ground biomass assessment and carbon stock estimation remote sensing technology has played a great role (Lu et al., 2014). Even though remote sensing techniques are useful, the use of optical remote sensing for above ground biomass estimation is still poor in tropical forests due to the complex structure of the forest stand (Lu et al., 2012). On the other hand, the current development of LiDAR technology and its application in the forest sector gained more attention as a rapid and efficient tool in the application of forest inventory parameter assessment and biomass estimation. Thus, airborne LiDAR and Terrestrial Laser Scanner (TLS) remote sensing technologies are proposed as the most promising technique for biomass estimation and forest inventory parameter assessment as compared to optical remote sensing techniques (Barbosa et al., 2014; Srinivasan et al., 2015; He et al., 2013). The application of airborne LiDAR for above ground biomass estimation leads to large uncertainty for a large area. On the other hand, the use of TLS combined with automatic data processing techniques may provide an option to bridge the gap between conventional inventory techniques and airborne laser scanning data processing schemes (Maas et al., 2008).

Terrestrial laser scanning also called terrestrial LiDAR is a tool which can assess forest structure in a three dimensional distribution of plant constituents. It has the potential to measure forest structure with high accuracy and reduce uncertainties in above ground biomass estimation since it estimates the complete tree volume (Calders et al., 2014). Moreover, there has been a growing interest in the use of TLS for forest inventory parameter measurement at plot level in the past few years. One of the advantages of TLS is its capacity in providing structural parameters which have not been addressed by traditional forest inventory (Newnham et al., 2015). However, so far most of the studies focused on assessing the potential of a terrestrial laser scanner for the derivation of inventory parameters with less attention on the factors that influence the scanned data and hence the retrieval of the inventory parameters (Pueschel et al., 2013).

Therefore, this study intended to derive forest inventory parameters from the terrestrial laser scanner and to assess the effect of scanning position on the retrieval of inventory parameters as well as on biomass estimation in the tropical rain forest of Ayer Hitam rainforest, Malaysia. In fact, there are a number of factors that affect TLS scanned data but this study intends to assess only the effect of scanning position on the retrieval of inventory parameters and in general on above ground biomass/carbon stock estimation in the tropical forest.

1.2 Problem statement

Reducing Emission from Deforestation and forest Degradation has been initiated as an approach to combat global climate change under the United Nations Framework Convention on Climate Change (UNFCCC). MRV is one of the important element in REDD mechanism that ensures transparency and accurate measurements (REDD, 2012).

Thus, MRV in the REDD mechanism requires accurate and precise information mainly for measuring and monitoring above-ground forest biomass and its change in the tropical forest. Estimation of aboveground biomass can be done by using allometric equations which use the indirect relationship of the tree inventory parameters such as height and diameter at breast height (DBH) (Bi et al., 2004; Chave et al., 2014). However, accurate and effective measurement and monitoring of forest biomass and its changes for developing countries which implement REDD program is still remaining as the main challenge (Kankare et al., 2013). This indicates that still there is a need for more robust, accurate and reliable forest inventory parameter measurements for above ground biomass estimation in the tropical forests.

Traditionally forest measurement has been conducted using manual ground survey technique by measuring tree parameters such as tree height and Diameter at Breast Height (DBH). However, this method is exposed to some measurement errors and difficulties to obtain accurate forest inventory parameters (Watt et al., 2003). Accurate measurement of forest inventory parameters and biomass/carbon stock estimation can be conducted only by using destructive inventory methods, but it is time-consuming and heavy labour work particularly for mature trees such as tropical forests. Also, estimation of above ground biomass can be conducted through non-destructive measurement method by measuring tree height and diameter at breast height and apply allometric equation (Chave et al., 2005).

The application of TLS measurement has been one of the viable and promising technique in deriving forest stand inventory parameters at the plot level in the recent years (Watt et al., 2003; Simonse, et al, 2003;

Kankare et al., 2013). It can estimate tree height accurately as compared to traditional field method, but still, it needs further investigation in high dense forest area (Disney et al., 2014, cited in Calders et al., 2015). Moreover, TLS with automatic data processing technique becomes the potential approach which can be combined with traditional forest inventory and remote sensing method (Maas et al., 2008). In general, several studies have been done on the applicability of TLS on the forest inventory and biomass/carbon stock estimation particularly in the temperate forest, semi-natural forest and plantation forests (García et al., 2010; Watt & Donoghue, 2005). The bases for the measurement of individual trees height and DBH as well as aboveground biomass and carbon stock is the derivation of induvial trees from the point cloud data.

Thus, some of the studies conducted on forest inventory have been focused on the measurement and derivation of individual trees from TLS point cloud data (Maas et al., 2008; Simonse et al., 2003; Brolly & Kiraly, 2009). The data acquisition of TLS based forest inventory could be conducted through three different approaches: namely single scan, multiple scan and multiple-single scan (Liang et al., 2016; Habib et al., 2010). One of the challenges in the forest inventory related with TLS point cloud data is that of occlusion of the individual trees by other objects. However, the problem can be reduced by using multiple scanning positions. But multiple scanning positions take time and processing costs as well as data storage (Ducey & Astrup, 2013).

Thus multiple scanning positions requires more personnel and time associated with distribution of the target objects for registration and identification of the scanning positions, particularly in tropical forest where there is a complex forest structurer. For this study a multiple scanning position with four and five scanning positions was selected. This study, therefore, intends to derive forest inventory parameters and assess the influence of the number of scanning position on the derivation of inventory parameters as well as on aboveground biomass/carbon estimation.

In general, the main objective of this study was to derive forest inventory parameters from terrestrial laser scanning and to assess of the effect of scanning positions on inventory parameter derivation and aboveground biomass estimation in the tropical rainforest of Ayer Hitam forest reserve, Malaysia. It is hoped that this study offered a significant contribution for REDD MRV mechanism and may be also a viable option for developing forest inventory methods in the tropical rainforest.

1.2 Objective

1.2.1 General objective

The general objective of this study was to derive forest inventory parameters from TLS and assess the effect of scanning positions on tree parameter detection and above ground biomass/ carbon stock estimation in the tropical rain forest of Ayer Hitam forest reserve, Malaysia.

1.2.2 Specific objectives

1. To detect individual trees manually and automatically from TLS point cloud data using four and five scanning positions point cloud data.
2. To measure and compare the accuracy of manually and automatically derived forest inventory parameter (DBH and height) from four and five scanning positions as compared to field DBH and ALS height measurement.
3. To estimate the above ground biomass/carbon stock using TLS derived forest inventory parameters from four and five scan positions and field measured data.
4. To compare the accuracy of aboveground biomass/carbon stock estimation using TLS with four and five scanning positions as compared to biomass calculated from field DBH and ALS height.

1.2.3 Research questions

1. How accurately individual trees are detected manually and automatically from the point cloud data using four and five scanning positions?
2. How accurately can tree parameters (DBH and height) be detected manually and automatically from the four & five scanning positions compared to ground measured DBH and ALS height?
3. How much biomass/carbon stock is estimated using TLS derived tree parameters using four and five scanning positions?
4. How accurately aboveground biomass/carbon can be estimated using TLS with four and five scanning positions as compared to biomass from field DBH and ALS height.

1.2.4 Hypotheses

1. H_0**:** There is no significant difference in the measurement and accuracy of tree parameter (DBH, height) detection using manual and automatic extraction from the four and five scan position as compared to field measured DBH and ALS height.
   H_1**:** There is a significant difference in the measurement and accuracy of tree parameter (DBH, height) detection using manual and automatic extraction from the four and five scan position as compared to field measured DBH and height.

2. H_0: There is no significance difference in aboveground biomass/carbon stock estimation using TLS with four and five scanning positions.
   H_1: There is significance difference in aboveground biomass/carbon stock estimation using TLS with four and five scanning positions.
3. H_0: There is no significance difference in the accuracy of aboveground biomass/carbon stock estimation using TLS with four and five scanning positions.
   H_1: There is significance difference in the accuracy of aboveground biomass/carbon stock estimation using TLS with four and five scanning positions.

2. LITERATURE REVIEW

2.1. Biomass and carbon

Above ground forest biomass is the amount of aboveground living organic matter of trees, which is expressed as oven-dry tons per unit area (Brown, 1997). Dry biomass consists of approximately 50% of Carbon (Malhi et al., 2004). According to IPCC (2006) the terrestrial ecosystem involving biomass consists of five different carbon pools, namely above ground biomass, below-ground biomass, deadwood, litter and soil organic matter. Tropical forests are one of the terrestrial ecosystems which plays an essential role for global carbon cycle since they store 46% and 11% of the world's living terrestrial and soil carbon pools respectively (Brown & Lugo, 1982). The major portion of carbon pool in the tropical forest ecosystem exists in the form of above ground biomass and it is the most vulnerable to the direct impact of deforestation and degradation (Gibbs et al., 2007). Estimation of aboveground forest biomass is, therefore, the main step for quantification of carbon stock from tropical forests (Gibbs et al., 2007) and it gives an information about the sequestration potential of the forest and monitoring of the forest resources (Vashum & Jayakumar, 2012).

2.1.2 Principle of Terrestrial Laser Scanner

LiDAR is an active remote sensing technology which emits lasers pulses and measures the distance between the target and the sensor by using the speed of light and the laser pulse travel time. TLS is also known as ground-based LiDAR, which uses laser pulse and scanner system to automatically measure the surrounding objects within a short period of time (Lefsky, Cohen, Parker, & Harding, 2002). The principle of TLS is based on the emission reception of the laser beam and thus, the emitted laser beam is deflected by the mirror and it scans the object automatically (Figure 2.1). The reflected laser beam together with the angular step values of the mirror allows for measurement of the distance and the creation of three dimensional point. Then, it produces a point cloud composed of millions of points which makes the 3D representation of the object viewed by the scanner (Dassot et al., 2011).

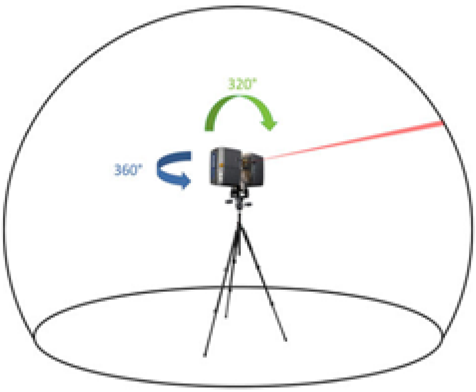


Figure 2.1: Operating principle of a terrestrial LiDAR scanner (FARO Photon 120)

Source: Dassot et a., (2011)

TLS can be used either in a single scan or multiple scan approach (Figure 2.2) to measure forest inventory parameters at sample plot level. In the case of single scan approach, the laser scanner is placed at the center of the plot and scan all the trees which are visible for the scanner whereas for multiple scans, the scanner is placed around the sample plot and scan all the trees inside and outside of the plot and provides various views of the trees. During scanning, the scanner is mounted on the tripod which situated on the ground to scan all the objects in the surrounding and artificial retroreflectors are placed inside the sample plot and later those retroreflectors are used to accurately co-register the different scans (Liang & Hyyppä, 2013). To merge the different scans into one point cloud, at least three of the reference targets used, which are common for all scans (Dassot et al., 2011).

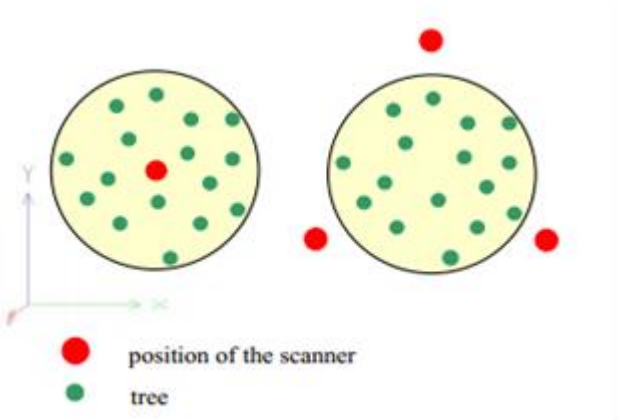


Figure 2.2: Single scan mode (left) and multiple scan mode (right) approaches

Source: Bienert et al., 2006

2.1.3 Allometric equations

Allometric equations are equations which developed based on the relationship of the biophysical parameters of trees such DBH and tree height. It is widely and commonly used method for biomass estimation of the forest since weighting of trees and their components for biomass estimation is destructive, expensive and time consuming activity (Temesgen et al., 2015). In the past, many researches have been done to develop allometric equations for biomass estimations of multispecies tropical forest (Brown 1997; Chave et al., 2005). Some of the developed allometric equations were for specific species and mixed species (Nelson et al., 1999), specific site (Ebuy et al., 2011), for regional (Montagu et al., 2005) and large global scale biomass estimation.

Ketterings et al., (2001) proposed allometric equation to estimate above ground tree biomass, which is appropriate for tree species having a DBH of 8-48 cm of trees in the mixed secondary forest of Indonesia. On the one hand, Segura & Kanninen (2005), developed allometric equation for the estimation of tree volume and above ground biomass in a humid tropical forest of Northern Costa Rica. However, the developed allometric equation is recommended only for trees which have DBH between 60 -105 cm. Thus, the trees included in this study are only larger trees.

Kenzo et al., (2009), also developed allometric relationship for above and below ground biomass estimation in the tropical secondary forest trees in Sarawak, Malaysia. The developed allometric relationship was between tree size parameters such as DBH, diameter at the ground surface, height, leaf, stem, small root (diameter < 5 mm) and total root biomass. In this study, they compared the equations with other above and below ground biomass equations of various tropical rain forests and found that the equations is largely different. Tree height and DBH are the most common forest inventory parameters used as a dependent variable for biomass estimations. But height measurement in the tropical forest has been difficult to measure and thus, most allometric equations for tropical forest are based on only DBH (Alder, 1998). Similarly, Montagu et al., (2005) stated in their study, allometric equation which incorporates tree height as a parameter decreases the performance of the equation as compared to allometric equation based on only DBH of the tree. On the other hand, Chave et al., (2005) stated that allometric equation which incorporate DBH and tree height provides accurate aboveground biomass estimation. Recently, there are a lot of allometric equations which take into account different biophysical parameters of the trees for forest biomass estimation. Thus the choice of allometric equations for biomass and carbon stock estimations is relevant since the allometric models differ for a different site, species and even the parameters used. Chave et al., (2014) stated that the development of locally derived diametre-height relationship allomeric models are recommended to minimize measurement bias. However, Vieilledent et al., (2012) revealed that, if allometric models are not available for a particular forest site, a simple height- diameter model is vital for accurate biomass and carbons stock estimation from plot inventories.

2.2 Methods for above ground biomass estimation

Estimation of the amount of biomass stored in the forest ecosystem is important for sustainable management and assessment of the productivity of the forest resource. It helps us to know the amount of carbon that can be emitted in the form of carbon dioxide from the forest due to deforestation or forest fire. It also enables us to know the amount of carbon dioxide that can be sequestered in the forest (Vashum & Jayakumar, 2012). Above ground biomass can be estimated through traditional field measurement which includes destructive and non-destructive measurement methods and remote sensing method. Traditional field measurement methods are relatively accurate, but they are still costy and time-consuming and thus limited to only small areas. On the other hand, remote sensing is accurate and more reliable alternative and approach for biomass estimation (Gibbs et al., 2007). Lu, (2006) and Gibbs et al., (2007) reviewed and summarized the different methods that can be used for above ground biomass estimation and carbon stock.

Currently, remote sensing methods play a great role than traditional field measurement methods for above ground biomass estimation at different scales. Although in general remote sensing methods are more accurate and reliable, optical remote sensing method tends to saturate and less applicable for biomass estimation in areas with complex tropical forests (Lu, 2006; Saatchi et al., 2011). LiDAR technology has been used for biomass estimation in the past few years (Popescu et al., 2004). Aboveground biomass estimation is related to many directly or indirectly measured forest inventory parameters such as height, diameter at breast height, stem density and branch distribution. However, tree height is the only structural parameters that airborne LiDAR can directly measure (Ni-Meister et al., 2010). On the one hand, terrestrial laser scanning becomes the most proficient and reliable method for direct measurement of the tree characteristic such as height, DBH, and positions (Liang et al., 2012).

2.3 Terrestrial Laser Scanner for forest inventory

Terrestrial laser scanning is an active remote sensing measurement technology which has its own source of light. It uses the wavelengths range between 0.5 and 1.5 μm and it can collect millions of three dimensional point clouds data within a few minutes (Pfeifer et al., 2007). It is one of the remote sensing techniques being used for forest inventory in the recent years. It is also becoming a complement for airborne LiDAR remote sensing technology since airborne LiDAR is less suitable for characterization of the woody component of vegetation (Lovell et al., 2003). Moreover, airborne LiDAR is not capable of observing and providing information about the lower canopy and crown structure (Vega et al., 2014). It is limited to the vertical structure of the vegetation which has less information about the shape and volume of the tree (Lovell et al., 2003). In the past ten years, the application of TLS in forestry becomes an important tool and it provides fast, efficient and automatic tools to extract basic forest inventory parameters such as DBH, height, number of trees and position of trees and also stem and crown shape structure (Bienert et al., 2006). Similarly, in the past years various researches has been done using terrestrial laser scanner as a technique for measuring forest inventory parameters and biomass estimation at plot level (Simonse et al., 2003; Watt et al., 2003; Palace et al., 2016; Bienert et al., 2006, and Mengesha & Hawkins, 2015). The aim of these studies was to analyze the possible application of TLS and its potentiality for forest inventory parameters measurement such as DBH and height at the plot level.

Different methods were developed for the determination of inventory parameters from TLS point cloud data in the past years. For instance, Huang et al., (2011), conducted a research to develop automated methods for DBH and height measurement with a commercial LiDAR. In this study, different algorithms for multi scan data acquisition, multi scan alignment, and terrain removal have been developed. In the mentioned study, the root means square error (RMSE) of DBH estimation was found 3.74cm using a multiple scan approach. On the other hand, Maas et al., (2008) calculated RMSE of DBH estimation 1.8cm using a single scan approach. However, both studies have been conducted in the different study area and forest type.

Some of the studies conducted using TLS for the measurement of tree attributes which are not measurable by using the conventional field measurement methods. For instance, Maas et al., (2008), conducted a research for the measurement of individual tree stem profiles and likewise Palace et al., (2016), used TLS for the measurement of the structure in the tropical forest which contains numerous quantifiable biometric components.

Calders et al., (2015), applied semi-automatic approach to extract individual trees from TLS point cloud data and found that TLS derived DBH showed high accuracy with field measured DBH. In this method different extraction steps were applied to extract individual trees from the point cloud, namely identification of individual stems through segmentation, cylinder fitting to these stems, sequential identification of point clouds and visual inspection against the whole point cloud. In additions, above ground biomass was estimated using allometric equation and TLS. Based on the result, the allometric equation which uses the indirect relationship of tree parameters increases the error for the above ground biomass estimation exponentially as increase in DBH of the tree. On the other hand, according to Calders et al., (2015), the error for above ground biomass estimation using TLS does not depend on the DBH of the tree.

Tansey et al., (2009), used multiple scan approach to estimate tree and stand variables in the coniferous tree stand. In this study two least-squares shape-fitting algorithms and a circular Hough transformation method were used for DBH measurement and found the RMSE in the range 0.019–0.037 m for DBH estimation using three measures. However, direct measurement of the top of the tree in the plot with a tree density of 1031 per hectare was not possible. Moreover, the study compared Hough transformation, square fitting and least square cylinder fitting algorithms for DBH estimation and found that least squares circle fitting algorithm was the most precise method.

Othmani et al., (2011) described and summarized the different state of the art methods used in the forestry inventory application for automatic extraction of DBH and height as well as volume. In this study, a new approach was developed which can be able to solve the problems related to 3D point cloud data segmentation like shadow and occlusion effect and 90% of the trees were detected correctly.

Feliciano et al., (2014), used TLS for mangrove above ground biomass estimation and revealed that TLS has the advantage for estimating the various source of uncertainties and acquiring tall mangrove trees which are difficult to measure by the traditional field methods. Moreover, the biomass estimated using TLS was comparable with mangrove allometric equation result and also they suggested that TLS method could be an alternative for the destructive sampling method which is used for allometric equation development.

3. MATERIALS AND METHODS

3.1. Study area

The study was conducted in the Ayer Hitam Tropical Rainforest reserve, Puchong Selangor, Malaysia, which is geographically situated in the southern edge of Kuala Lumpur city within 3º01´29.1''N and 101º38´44.4''E. The area represents the complex tropical rain forest with multiple layer of different species that makes the area appropriate for this particular study. Furthermore, the selected study area was under the university of Putra Malaysia and this was an opportunity for logistic requirements and local supports to conduct this study. The area is located at about 20 km southwest of Kuala Lumpur. It covers 1248ha of forest and surrounded by residential and development areas (Nurul-Shida et al., 2014). Since 1996 the forest has been leased for the University Putra Malaysia for 80 years for education, research and extension purpose (Ibrahim, 1999).

3.1.1. Vegetation and topography

The forest consists of diversified tropical tree species which is recognized as one of the oldest lowland forest. It is also one of the logged-over lowland Dipterocarp forest and secondary disturbed forest found in the Klang Valley. The elevation is range from 15-157m above sea level and the landscape of the area is undulated with low lying hillside, narrow river valley, and average terrain slope is 20% with many flat areas (Jusoff and Hasmadi, 1999). The forest area is classified into six compartments (1, 2,12, 13, 14 and 15) and each compartment has been logged in different years (Zakaria & Rahim, 1999). According to Ibrahim (1999), the forest consists approximately 430 seed plant, 33 fern,127 timber, 29 fruit tree, and 98 medicinal plant species.

3.1.2. Climate

The area has a tropical climate characteristic with a mean monthly temperature of 28.36^{o}c. The maximum and minimum temperature vary between 32 and 22.6^{o}c respectively. The annual precipitation of the area various between 2316.5mm and 4223.4mm with the highest rainfall in May and lowest rainfall in August (Jusoff and Hasmadi, 1999).

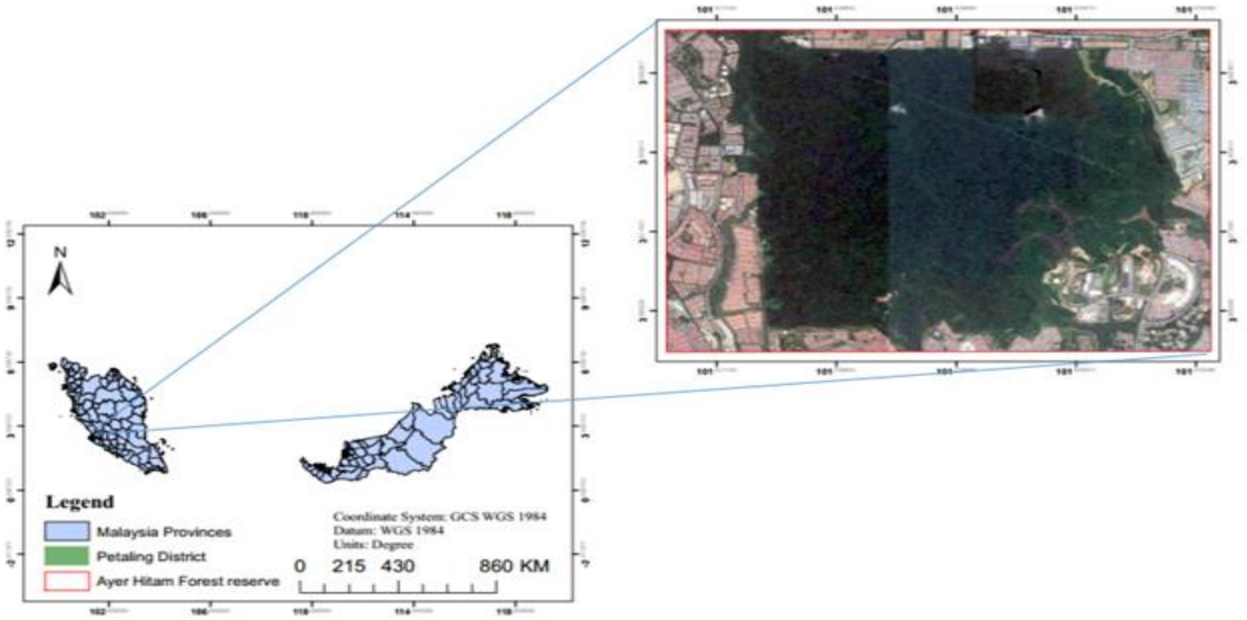


Figure 3.1: Location of the study area

3.2. Materials

3.2.1. Field instruments

Different field data collection materials were used to collect forest inventory parameters such as DBH and height and scanning of the trees with four and five scanning positions was done in each sample plot. The different instruments which were used in the field include measuring tape, diameter tape, RIEGL VZ-400, rangefinder, Compass, Clinometer, GPS, and data recording sheet. The details of the different instruments and their uses in the field are summarized in (Table 3.1 and 3.2).

Table 3.1: List of instruments and its use

Instruments	Use
TLS (RIEGL VZ-400)	Data collection (Scanning of trees)
Tablet	Navigation
Garmin GPS	Navigation and positioning
Leica DISTO D510	Height measurement
Measuring tape	Plot delineation
Diameter tape/caliper	DBH measurement

Table 3.2: RIEGL VZ- 400 Terrestrial Scanner Specifications

Technical specifications	
Maximum Range	600
Minimum Range	1.5
Laser Beam Divergence (mrad)	0.35
Laser wavelength	Near infrared
Accuracy (mm)	5
Precision (5mm)	3

Figure 3.2: Terrestrial Laser Scanner (RIEGL VZ-400) technical specification

Source: RIEGL, 2016

3.2.2. Software

Different software packages were employed for the processing and analyses of the collected terrestrial LiDAR and field data. Some of the software used for this study and their specific application are listed in (Table 3.3).

Table 3.3: List of software used in this research and its application

Software	Use
RiSCAN PRO	TLS data registration and processing
R-Studio and SPSS 23	Statistical analysis
Computree	Automatic height and DBH measurement, DTM generatic
CloudCompare	3D point cloud processing, manual measurement
MS Office (Excel sheet)	Filed data entry (DBH, height, species)
ArcGIS 10.3.1	GIS related tasks e.g. mapping

3.3. Methods

In order to conduct this study, a combination of different methods and techniques were employed. Thus, the method applied for this study was composed of three main parts, namely field measurements of tree biometrics, scanning of the sample plots with TLS in 4 and 5 scan positions and data processing. The detailed procedure of the method is presented in the flowchart (Figure 3.3).

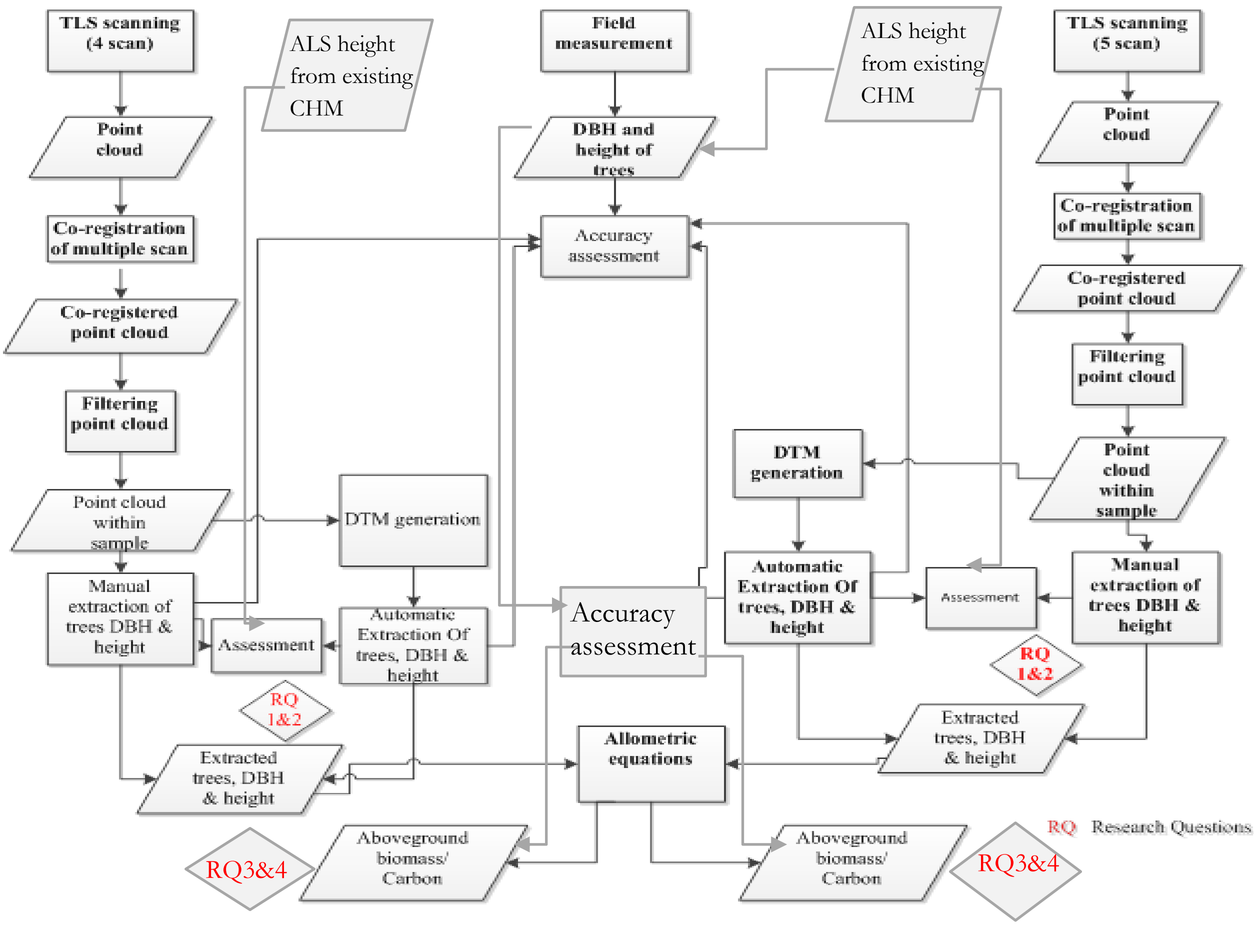


Figure 3.3: Flow chart of the study

3.3.1. Field work preparation

To conduct this study a number of activities has been carried out before the actual field work. The activities carried out were preparation of field data record sheet, testing and familiarized with the different instrument to be used for field data collection. For instance, TLS and height measurement instruments such as Leica DISTO D510, were tested before the actual field work. Moreover, a data sheet was designed for the data to be collected in the field.

3.3.2. Sampling design

In this study a purposive sampling design method were employed. Since most of the areas are inaccessible and rugged. The sample plots were selected based on the terrain orientation, topographic features and stand density (Otukei & Emanuel, 2015). A purposive sampling approach was adopted in order to cover the variation in complexity due to the dense undergrowth and slope steepness. The selection of sample points was hampered by the terrain conditions (slope steepness) and the dense undergrowth of the forest, in combination with the fact that the weight of the TLS (approx. 30 kg) made it difficult to move inside the forest. Hence the final selection of the plot was determined by the terrain and distance from the road as well as in areas where there was low undergrowth vegetation as there was a need to slash of the undergrowth vegetation to reduce the effect of occlusion on the individual trees by the undergrowth species and some shrubs. In total 10 plots were established by considering the above mentioned reasons so that it enabled to move easily inside the forest with the TLS.

3.3.3. Plot size

Circular plot with a radius of 12.6m were established to collect biophysical parameters such as DBH and height of trees. The area of each plot was 500m2 (0.05 ha). Ruiz et al., (2014) conducted a study to analyze the influence of plot size and LiDAR data point density on forest structure attribute estimation and found that the rate of improvement of the model to estimate forest attribute decreases as the plot size in increases in the range of 500-600m2. Circular plots are less vulnerable to errors in the plot area than square plots since the boundary of the plot is smaller in relation to the area and thus the number of trees on the edge is less. Figure 3.4 shows sample of a circular plot with a radius of 12.62m that was used during field data collection. When required, the radius of the plot was corrected for slope steepness.

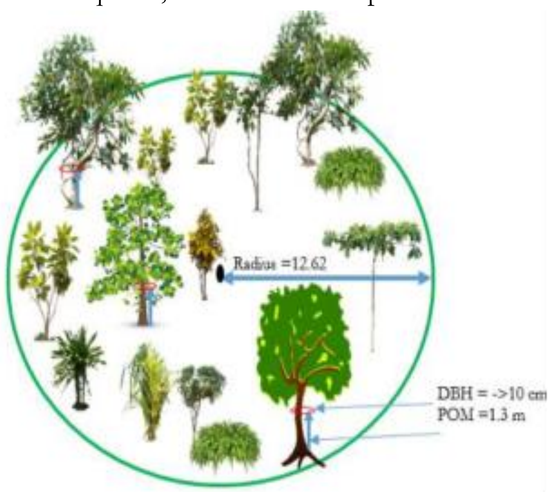


Figure 3.4: Circular sample plot (Source Sumareke, 2016)

3.4. Fied data collection

3.4.1. Biometric data

The field data collection was conducted between Septembers and October 2016 for a total of 21 days. The main objective of the field data collection was to get data for the validation and comparison of the data extracted from TLS. A preliminary field visit was conducted ahead of the actual field day to explore the topographic feature, forest condition, and accessibility into the forest. Within each plot, tree height, DBH, x and y coordinate of each individual tree and the coordinate of the center of the plot were collected during the fieldwork (see Appendix 1). Within each plot, tree height, DBH, x and y coordinate of each individual tree and the coordinate of the center of the plot were collected during the fieldwork and presented in the (see Appendix 1).

Trees with a diameter equal or greater than 10 cm were measured in the field. The height and DBH of each individual tree within the sample plot were measured using Leica DISTO D510 and measuring tape respectively. DBH of the tree were measured at 1.3m above the ground using a measuring tape. In addition, trees inside the sample plot were tagged with tree numbers in order recognize the individual trees in the TLS scan, allowing comparison of field measured DBH and the DBH extracted from the TLS point cloud. Next to this, the scientific names of trees were recorded with the help of the local botanist.

3.5. TLS data acquisition

Concurrently with the ground data collection, TLS was deployed in the same plot with four and five scanning positions to scan the sample plot. The vertical and horizontal field of view of the scanner was 100^0 and 360^0 respectively (RIEGL, 2016). All of the sample plots in the study area had dense undergrowth vegetation, which had to be removed in order to make all the tagged trees and reflectors visible for the scanner from the different positions. Each sample plot was then scanned twice with RIEGL VZ-400 terrestrial laser scanner with four and five scanning position. One in the center, three or four scanning positions outside the sample plot (see Figure 3.5).

The outer scanning positions were placed 1 – 2 meter away from the boundary of the sample plot to capture a full coverage of all the trees within the sample plot. Before the actual scanning of the plot, several procedures were taken into consideration to get good quality point cloud data. For instance, setup of the scan position and distribution of the retroreflectors within the sample plot were among them. The tripod was placed on each scanning position for the four and five scanning position method and the GPS reading of each scanning position was taken by the scanner. The outer scanning position was distributed with an angle of approximately 90 and 120^0 for the five and four scanning position method (Figure 3.5). Trees within the sample plot with DBH ≥ cm were marked and tagged with numbers. After this preparation the plot was scanned with four and five scan positions.

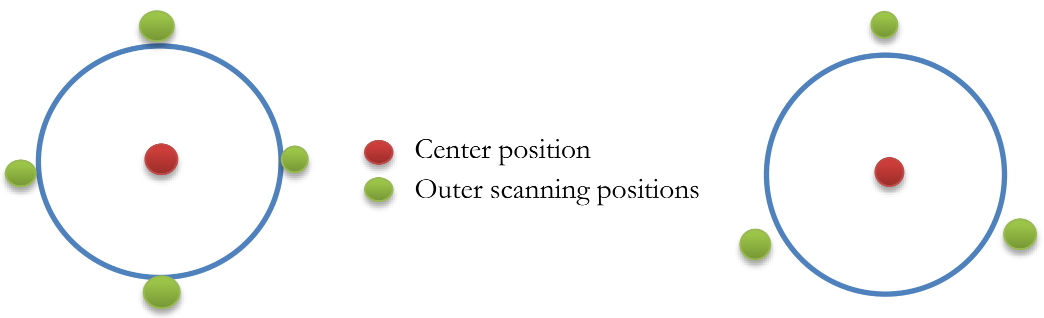


Figure 3.5: Five (left) and four (right) scanning positions setup

3.5.1. Distribution of retro-reflectors within the sample plot

The retro-reflectors are highly reflective objects which were used as a reference point for the registration of the multiple scanning positions into one single point cloud data. Fifteen cylindrical and four circular reflectors were evenly distributed inside the plot in a position where they could be viewed from different scanning positions (see Figure 3.6). The cylindrical retro-reflectors were placed on top of sticks to be viewed by the scanner from the different scanning position whereas the circular retro-reflectors were placed on some of the selected tagged tree stems which faced towards the central scanning position. The cylindrical retro-reflectors were used for the registration of the outer scanning position to the central scanning position to produce one point cloud data.

Figure 3.6: Distribution of retro-reflectors inside the sample plot

3.5.2. Setting TLS

The TLS instrument was fixed on the tripod before scanning each plot. After fixing the instrument on top of the tripod, a new project was created and saved as a new project in the scanner. In the main menu of the scanner, all the settings were fixed once before scanning. The scanner was adjusted to panaroma-60 resolution as well as the camera was mounted on top of the scanner for the acquisition of images that were used to color the point cloud data. The scanner was adjusted to perform fine search and automatic registration of the retro-reflectors when it finishes scanning of the plot. Then the plot was scanned by the TLS from the different scanning positions and produced a digital representation of the 3D surfaces of the sample plot.

3.6. Data processing

3.6.1. Biometric data processing

The collected data were arranged and entered into a Microsoft Excel sheet for further analysis. In the data sheet the following items were entered: the GPS coordinate of the center of the sample plot, the tree parameter's DBH, height and species, plot radius, x and y coordinate of each individual tree, and slope information. A total of 377 trees were measured in the ten sample plots.

3.6.2. Pre-processing of TLS data

The first stage in the pre-processing of TLS data was the registration of the outer scanning position to the central scanning position. The registration of multiple scans usually carried out using artificial retro-reflectors that are distributed in the plot (Holopainen, et al., 2014). After the TLS data was imported into the software, the RiSCAN PRO version 2.1 "Download and convert" tool from the help menu was used to automatically register the scan positions with the help of the reflectors. The imported TLS data was saved as a new project in the software. All the scan position were automatically registered when the TLS data imported into the software. Then all the scan positions, except the central scanning position, were unregistered. The central scanning position was then taken as a common reference for overlapping of the objects that found in the other outer scanning positions. The outer scan positions were then registered to the central scanning positions. The tie points were used for the registration of the outer scan positions to the central scanning positions. The common tie points between the two scanning position were selected automatically by the software and registered automatically. The Tie Point List-Scanner Own Coordinates TPL (SOCS) in the RiSCAN PRO software was used to display and select the corresponding tie points between the two scanning positions and registered automatically.

Thus a minimum of four tie points which had best values and common for two scan positions was identified automatically by the scanner to link the border scanner to the central scanning position. Then all the scan position were registered into one single point cloud data as it is shown in (Figure 3.7). Multiple station adjustment of the multiple scans was used to reduce error in registration of multiple scans. The registration error for the multiple scans varies from one plot to the other. The overall standard deviation errors were 0.025m and 0.023m for the four and five scan positions respectively. The standard deviation in multiple scan registration of each sample plot is given in (Table 3.4).

Table 3.4: multiple scan position registration accuracy and standard deviation.

Plot No. (a)	1	2	3	4	5	6	7	8	9	10
Std. Dev. (m)	0.0185	0.0229	0.0242	0.0221	0.0283	0.0253	0.0386	0.0233	0.0231	0.0198
Plot No. (b)	1	2	3	4	5	6	7	8	9	10
Std. Dev. (m)	0.0204	0.0183	0.0281	0.0224	0.0214	0.0243	0.023	0.0221	0.0263	0.0234

a) four scanning positon and b) five scanning positions

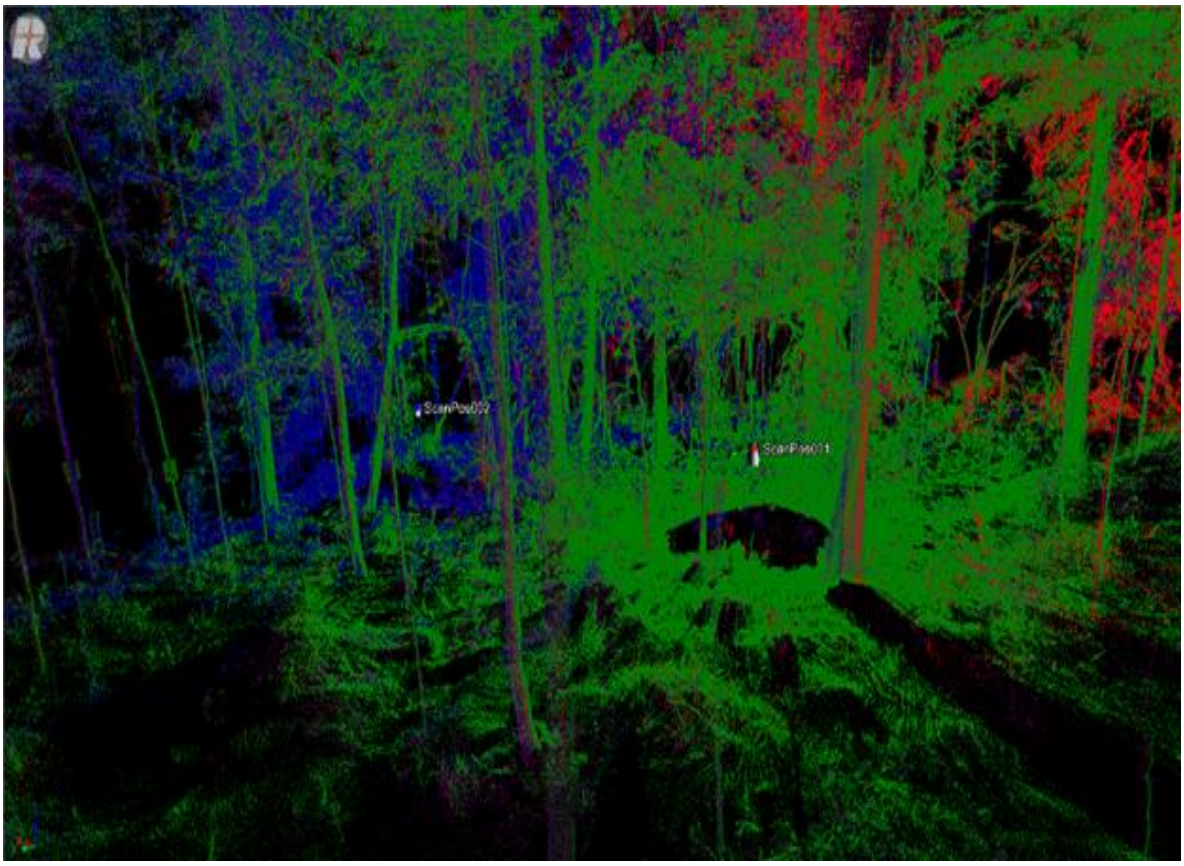


Figure 3.7: Registered point cloud data from different scanning positions which is displayed in green blue purple and red color.

3.6.3. Sample plot extraction

The registered multiple point cloud were used as a source to extract the area of interest for further analysis and extraction of individual trees. The actual area scanned by TLS was larger than the plot size. So, in order to obtain the point cloud of only the plot the "selection" tool in RiSCAN PRO software was used to delineate the boundary of the sample plot and filter out all the point cloud data outside the area of interest (Figure 3.8a).

The extracted point cloud data was saved as a polydata file in the RiSCAN PRO software and used for the manual and automatic extraction of DBH and height of individual trees. In addition, the original point cloud was exported as LAS file and imported into Computree software to extract the sample plot with a radius of 12.62m for automatic extraction of DBH and Height.

The extracted sample plot was used for both manual and automatic extraction of individual trees in RiSCAN PRO and Computree software respectively. The registered point cloud data and the extracted sample point cloud is shown in (Figure 3.8).

a b

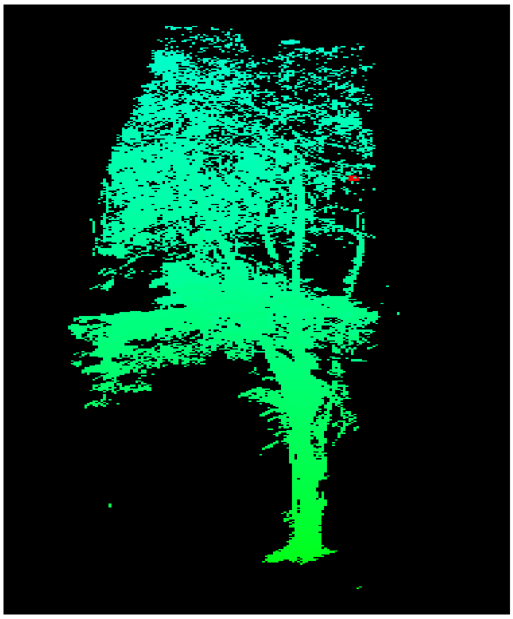
Figure 3.8: Registered multiple scan data in true color (a) and automatically extracted sample plot (b) displayed with intensity color.

3.7. Manual extraction and measurement of individual trees

3.7.1. Manual extraction of individual trees

Within the extracted point cloud of the area of interest, the selection tool in RiSCAN PRO software was also used to manually extract the point cloud data belonging to each individual tree and the resulting point cloud was saved as a new poly-data file. In order to identify the individual trees, the point cloud data of the plot (area of interest) was converted into color image to allow visualization of individual trees. On the photographs which were taken by the TLS during scanning the tags with the tree number were visible. By superimposing these true color images on top of the point cloud of the plot the individual trees could be assigned the corresponding tree number. An example of manually extracted individual tree is shown in (Figure 3.9).

Plot 5: Tree No.5 (in true color)



Plot 5: Tree No.5 (in false color)

Figure 3.9: Manually extracted individual trees

3.7.2. Manual measurement of individual tree DBH

The point cloud associated with each individual tree was extracted from the sample point cloud data and saved as polydata in RiSCAN PRO software. The "distance measuring" tool in the RiSCAN PRO software was used to measure the DBH of each individual tree. The diameter of the tree was measured at 1.3m above the ground at the base of the trunk (Figure 3.10a). The measurement of DBH was taken from point to point along the horizontal distance of each individual tree stem at height of 1.3m above the ground (Figure 3.10b).

a b

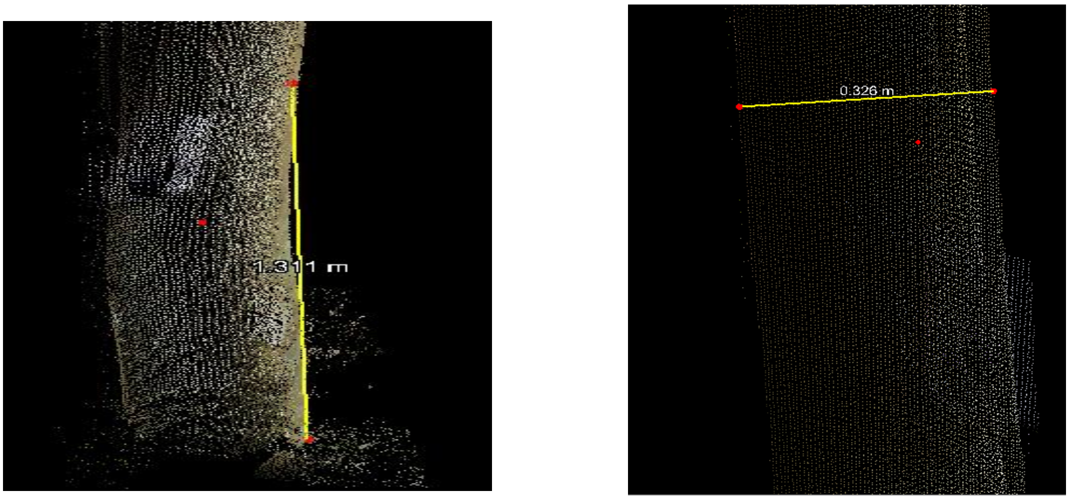


Figure 3.10. Manual DBH measurement at a height of 1.3m above the base of the tree.

3.7.3. Manual measurement of tree height

Tree height is the vertical distance between the base of the tree and tip of the branch of the tree. The "distance measuring" tool in RiSCAN PRO software was used to measure the height of each individual tree. It measures the distance between the base and the most tip part of the tree (Figure 3.11).

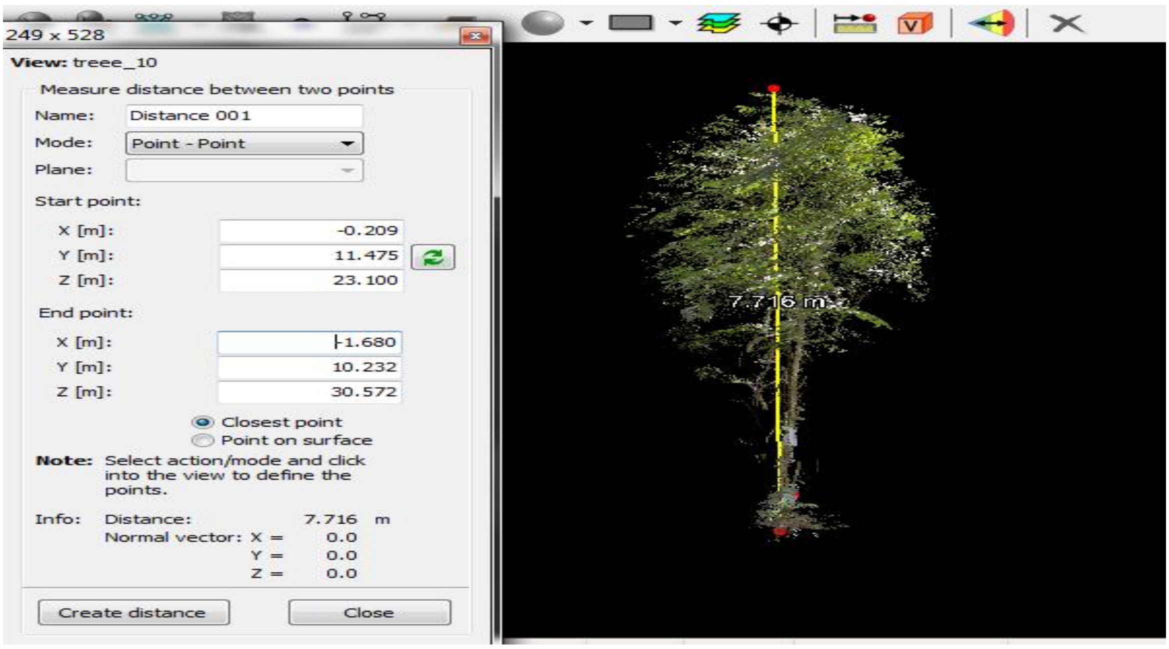


Figure 3.11: Manual tree height measurement in RiSCAN PRO software.

3.8. Automatic extraction of individual trees

3.8.1. Automatic measurement of DBH

The original point clouds were saved as polydata in RiSCAN PRO and exported as LAS file and imported into Computree to automatically generate DBH, and height from individual trees. First the sample plot was extracted with a radius of 12.62 in Computree software. The next step was the separation of point clouds, which belongs to the soil from the points belongs to the vegetation and generation of Digital Terrain Model (DTM) was followed. The separated vegetation point clouds data were further processed for horizontal clustering and slicing and merging. During clustering, all the points which belong to a particular tree stem were grouped as a cluster of points, followed by horizontal slicing and vertical merging of clusters into logs. This step then was followed by fitting and filtering of cylinders by logs to remove those trees which have diameters less than 10cm. The diameter of each individual tree was then computed by fitting a cylinder at a height of 1m and 1.6m above the local DTM and then the DBH was done by extrapolating the value to the height of 1.3m above DTM.

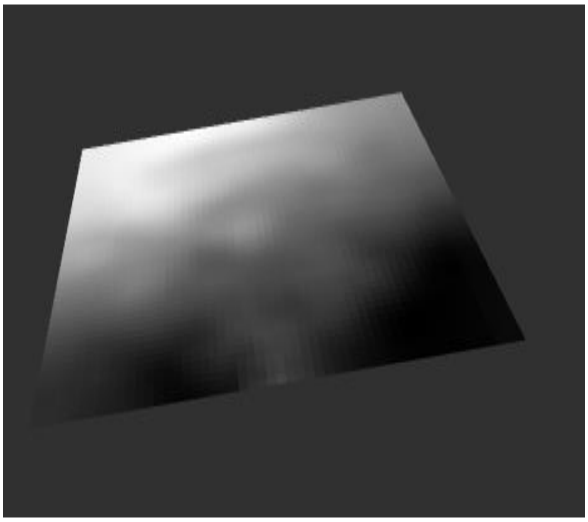
The procedures for the automatic measurement of DBH are described in the following section.

3.8.2. Soil extraction and DTM generation

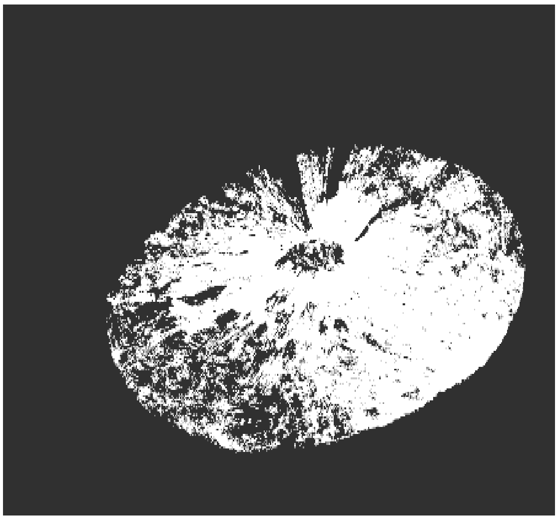
This step separates the point cloud data which belongs to the soil and vegetation in each sample plot. At this step digital height model, digital terrain model, digital surface model, soil points and vegetation points were generated from the sample point. Thus this steps reduces the point cloud data by only finding and separating the point clouds which belongs to the vegetation and soil separately. A horizontal grid was created at a specified resolution (50cm by 50cm in this case) and for each cell the lowest Z value was stored in the "Zmin grid" (Othmani et.al. 2011).

The minimum density of points for each cell (Zmin and Zmin+32) was established and each cell with a value of 200pts/m2 were separated as null soil points. The local DTM was then computed from the Zmin grid and interpolated with Delaunay triangulation technique. Some of the outputs of soil extraction and DTM generation step are shown below in (Figure 3.12).

A. DTM



B soil points



C Digital Height Model

D, Extracted sample plot (12.62m)

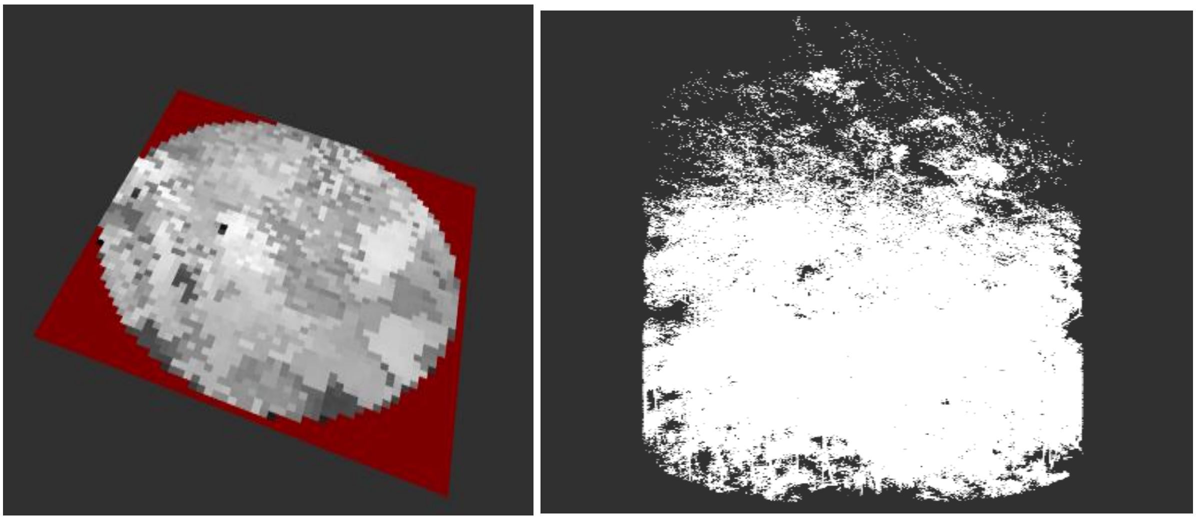


Figure 3.12: soil extraction and DTM generation outputs

3.8.3. Horizontal Clustering of vegetation points

The main purpose of this step was to cluster a group of points which belongs to a particular tree stem. To do this, the vegetation points was sliced in a horizontal Z layers with a thickness of 1cm and grouped based on their proximity. A cluster of points which are less than three points were filtered out and a circle is fitted by a least square routine.

3.9. Statistical analysis

Descriptive statistics were used to summarize all the data collected from the field and extracted from TLS using four and five scanning positions. Regression analysis was conducted to compare the relationship between the DBH measured from the field and TLS, ALS height and TLS height as well as aboveground biomass and carbon using the four and five scanning positions.

The root mean square error (RMSE) was calculated to analyse the deviation of DBH measurement using TLS as compared to the field measured DBH (Equation 3.1). Also the RMSE was calculated for manually derived tree height as compared to ALS height as well as the aboveground biomass and carbon as compared to biomass calculated from field DBH and ALS height. Moreover, a t-test was done to test and examine if there was a significance difference between field measured DBH and TLS measured DBH as well as aboveground biomass and carbon stock estimation using four and five scanning positions.

Equation 3.1. RMSE calculation

$$\mathbf{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n}}$$

Where

RMSE	Root mean square error
Yi	Measured value (dependent variable)
Ŷ	Estimated value
n	The number of observation
ȳ	Measured value mean
RMSE %	$\frac{100*\text{RMSE}}{\bar{y}}$

3.10. Aboveground biomass and carbon stock estimation

To estimate aboveground biomass/carbon stock allometric models was used. Recently, there are a lot of allometric equations available for above ground biomass estimation of tropical forests. Some of the available models are specific for a particular site, species and regions. Meanwhile, there are also other general models which could be used across tropical vegetation types. Since there is no site specific equation available for this particular study site, the generic allometric model developed by Chave et al., (2014) was applied (Equation 3.2). According to Chave et al., (2014) this model has been performed well across the different forest type and bioclimatic conditions.

Equation 3.2. Aboveground Biomass calcaulation (AGB)

$$AGB_{est} = 0.0673\times (\boldsymbol{p}D^2H)^{0.976}$$

Where D represents DBH in cm, H represents height in m, *p* is in g cm^{-}
By using the above allometric equation the total aboveground biomass were calculated. Then the amount of aboveground biomass was convert into above ground carbon. According to (Houghton, 2005), the amount of carbon is 50% of the total biomass of the tree. For this study, IPCC, (2006) guideline were used to convert the total above ground biomass to aboveground carbon stock (Equation 3.3).

Equation 3.3. Aboveground carbon calculation (C)

$$C= AGB*CF$$

Where C represents carbon stock (Mg), ABG: aboveground biomass (Mg); CF conversion factor=0.47

4. RESULTS

4.1. Field collected data

All the required forest parameters such as DBH and height were collected during field data collection and filtered out those trees which were used for the analysis. The DBH measured in the field ranges from 10cm to 72 cm and the standard deviation varied between 8.20 cm and 15.92cm among the sample plots. The tree height measured in the field also ranged from 4 m and 36.03 m and the standard derivation varies between 4.33 m and 8.86m.

4.2. Individual tree detection from the TLS

4.2.1. Manual detection of individual tree

The TLS data was collected with four and five scanning positions from 10 sample plots. All the scanned data were registered in the RiSCAN PRO software and the point cloud data within the sample plot were extracted. The point clouds of each individual tree were then extracted from the sample point cloud in the RiSCAN PRO software. Tree numbers which tagged in the field on each individual tree were used to identify the related individual tree in the point cloud data. The manual detection of each individual tree from the point cloud data was varied from plot to plot in both four and five scanning positions.

Thus the individual tree extraction percentage per plot also varied from 89.47 to 100% in the four scanning position. Whereas in the five scanning position the variation was 95.45 to 100 percent. Trees which were obscured by the other trees were not detected from the point cloud data. A total of 8 trees were missed in the four scanning position and only two trees were missed in the five scanning position. The overall extraction percentage in the four scanning positons was 97.99 percent. Whereas the overall extraction percentage in the five scan position was 99.55%. As it is shown in Table 4.1 except for plot 10, all the trees were extracted in the five scan position. The details of the detected tree and the percentage of extraction in each sample plot is shown in (Table 4.1).

Table 4.1. Manually extracted individual trees from four (a) and five (b) scan positions

Plot(a)	1	2	3	4	5	6	7	8	9	10
Total tree	35	39	42	44	40	35	38	34	43	44
Extracted tree	35	38	41	44	40	35	34	34	42	43
Extraction %	100	97.44	97.62	100	100	100	89.47	100	97.67	97.72
Plot (b)	1	2	3	4	5	6	7	8	9	10
Total tree	35	39	42	44	40	35	38	34	43	44
Extracted tree	35	38	41	44	40	35	34	34	43	42
Extraction %	100	100	100	100	100	100	100	100	100	95.45

4.2.2. Automatic detection of individual trees

The automatic extraction of individual trees was processed using Computree software and the result was compared with the field data in terms of the number of trees detected. The detection rate of individual trees from each sample plot was varied between 86.57 and 97.67 percent in the four scan position and 85.71 and 100 percent in the five scan position. The details of the automatic extraction of trees and the percentage of extraction in each sample plot are shown in (Table 4.2). The overall extraction percentage in the four scanning positon was 91% whereas the overall extraction percentage in the five scan positon was 93.75%.

Table 4.2. Automatically extracted individual tree from four (a) and five (b) scan position.

Plot (a)	1	2	3	4	5	6	7	8	9	10
Total tree	35	39	42	44	40	35	38	34	43	44
Extracted tree	31	38	38	40	38	31	33	30	42	38
Extraction %	88.57	97.43	90.47	90.9	95	88.57	86.84	88.23	97.67	86.36

Plot(b)	1	2	3	4	5	6	7	8	9	10
Total tree	35	39	42	44	40	35	38	34	43	44
Extracted tree	32	39	42	43	37	30	33	33	41	40
Extraction %	91.42	100	100	97.72	92.50	85.71	86.84	97.05	95.34	90.9

The number of trees which were missed during the extraction of individual trees from the point data using manual and automatic extraction method with five and four scanning position is presented in (Figure 4.1).

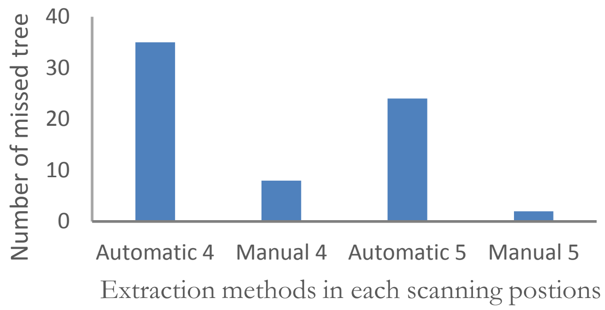


Figure 4.1: Undetected individual trees with manual and automatic extraction method from the four and five scanning positions

4.3. Individual tree parametre measurement from TLS

4.3.1. DBH measurement

The DBH of each individual tree was extracted from the sample point cloud data using manual and automatic extraction method. The manual extraction of DBH was carried out in the RISCAN PRO software using the "distance measurement" tool whereas the automatic extraction of DBH was conducted in Computree software. The manual and automatic measurement of DBH was done for both the four and five scanning positions independently. The descriptive statistic for the measurement of each individual tree DBH which is extracted manually and automatically from the four scanning positions is summarized in Table 4.4

As it is shown in Table 4.4 that the descriptive statistics results (mean, max, min, and std.) of DBH measured from field was almost similar with DBH extracted manually from TLS using four scanning positions. Thus, based on the descriptive statistics value there is no much variation in the measurement of DBH from field and TLS. There is a relationship between manually derived and field measured DBH. In the case of automatic measurement of DBH, there was some difference as compared to the field measured DBH. Based on the descriptive statistics result, there is variation in the maximum DBH per plot as well as the overall average maximum DBH. This is because some of the higher trees were under estimated by the software.

The correlation analysis between the field, manual and automatic measured DBH was conducted for the five and four scanning positions and summarize in (Table 4.3).

Table 4.3 Correlation (r) between the mean DBH measured from field, manual and automatic method

	Four scan positions		Five scan positions	
	Manual	Automatic	Manual	Automatic
Field	0.99	0.89	0.99	0.90

Table 4.4: Summary of statistics for the DBH extracted manually and automatically from the four scanning position

Plot	DBH measurements											
	Field				Manual				Automatic			
	Min	Max	Mean	Std.	Min	Max	Mean	Std.	Min	Max	Mean	Std.
1	10.00	42.20	19.17	8.36	9.20	38.60	18.34	8.16	7.50	32.64	15.76	5.71
2	11.00	66.00	21.26	13.42	8.60	60.90	20.95	13.42	9.11	48.15	20.78	10.31
3	10.00	50.00	19.83	11.36	8.50	51.60	18.99	11.79	8.10	42.36	18.53	8.82
4	10.00	53.10	21.25	13.12	7.40	54.40	20.89	13.21	7.91	49.27	19.27	11.83
5	10.10	55.60	22.36	12.76	9.60	53.10	21.84	12.38	8.35	48.09	21.83	11.64
6	10.50	48.00	23.00	12.59	10.20	49.50	22.12	12.74	6.89	40.24	21.33	11.32
7	10.00	64.70	28.53	15.64	7.70	63.00	27.48	15.65	9.67	51.34	23.97	11.43
8	10.50	42.70	20.59	8.20	9.20	40.30	19.74	8.20	8.31	37.02	19.27	7.63
9	10.00	72.00	19.05	12.56	8.50	68.80	17.66	12.29	6.98	58.29	17.07	10.58
10	10.00	42.00	19.69	9.19	9.10	39.00	18.60	8.82	7.50	31.85	17.32	7.65
Average	**10.21**	**53.63**	**21.47**	**11.72**	**8.80**	**51.92**	**20.66**	**11.67**	**8.03**	**43.93**	**19.51**	**9.69**

Moreover, for the sake of visualizations of differences in mean DBH measured from field, manually and automatically from TLS is presented in (Figure 4.2).

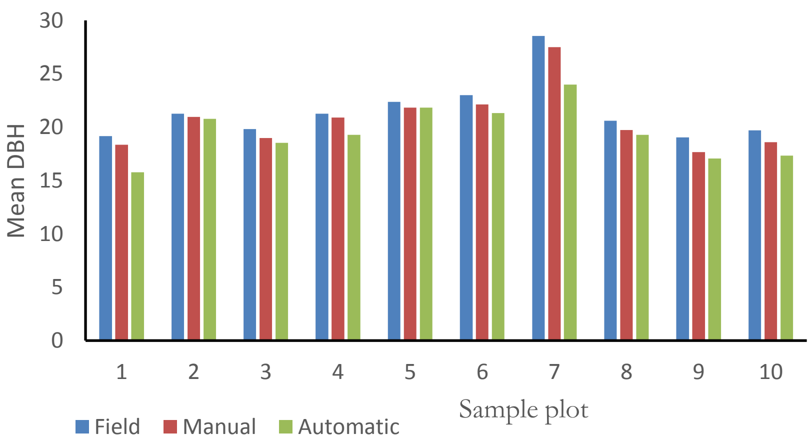


Figure 4.2: Distribution of the mean DBH of trees measured from field, manually and automatically from the four scanning positions.

The descriptive statistic for the measurement of individual tree DBH which is extracted manually and automatically from the five scanning positions is summarized in (Table 4.5).

It is clearly shown in (Table 4.5) that the statistical results (mean, max, min, and std.) of DBH measured from field was almost similar with DBH extracted manually from TLS using five scanning positions. Thus, based on the descriptive statistics value there is no much variation in the measurement of DBH from field and TLS. The result also almost similar with DBH extracted manually from the four scanning positions.

Thus this implies that there is no much variation in manual measurement of DBH from the point cloud data with four and the five scan position.

Table 4.5: Summary of statistics for the DBH extracted manually and automatically from the five scanning position

Plot	DBH measurements											
	Field				Manual				Automatic			
	Min	Max	Mean	Std.	Min	Max	Mean	Std.	Min	Max	Mean	Std.
1	10.00	42.20	19.17	8.36	10.10	41.10	18.77	8.38	7.50	34.37	18.02	6.99
2	11.00	66.00	21.09	13.19	10.00	64.90	20.80	13.35	8.69	54.48	18.22	9.73
3	10.00	50.00	19.96	11.20	9.10	49.60	19.63	11.21	7.98	42.06	17.54	8.19
4	10.00	53.10	21.25	13.12	9.80	53.00	20.76	12.98	7.89	42.69	17.58	9.86
5	10.10	55.60	22.36	12.76	10.30	53.70	21.83	12.36	7.29	48.42	21.08	11.62
6	10.50	48.00	23.00	12.59	10.60	46.90	21.76	12.24	9.21	47.61	20.93	12.01
7	10.00	64.70	26.06	14.96	10.40	63.50	25.74	14.62	7.77	77.35	27.51	16.71
8	10.50	42.70	20.59	8.20	10.10	40.20	19.95	8.00	8.85	39.42	19.26	8.41
9	10.00	72.00	19.05	12.56	9.70	72.30	18.36	12.67	7.21	53.02	18.47	10.00
10	10.00	42.00	19.52	9.06	9.00	40.60	18.82	8.95	8.24	34.44	18.77	7.99
Average	**10.21**	**53.63**	**21.20**	**11.60**	**9.91**	**52.58**	**20.64**	**11.48**	**8.06**	**47.39**	**19.74**	**10.15**

The result of the automatically measured DBH shows that there is some variation in DBH measurement as compared to field measured DBH. Some of the big trees DBH were also underestimated by the software. The distribution of mean DBH measured from field, manually and automatically from TLS using five scanning positions is presented in (Figure 4.3).

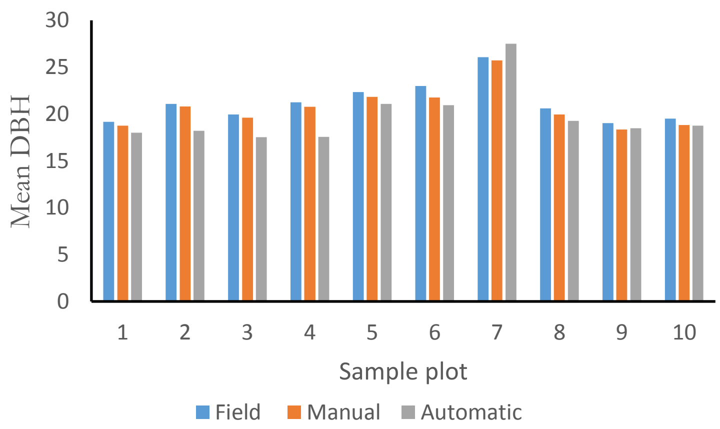


Figure 4.3: Distribution of mean DBH measured from field, manually and automatically from TLS using five scanning positions

4.3.2. Height measurement

The tree measurement was done by two different methods: namely manual measurement in the RiSCAN PRO software using the "distance measurement" tool and the automatic tree height measurement using Computree software. The height of the individual trees was then measured manually from both the four and five scanning position. However, those trees which were obscured by the other trees were not detected and measured.

A total of 273 individual tree heights were measured manually from the four scanning position. The plot level descriptive statistics of the measurement of height including the automatic height measurement from the four scanning positions are presented in (Table 4.6). Based on the descriptive statistics (mean, max, min and std.) of the manual tree height measurement there is variation between the manual and automatic measurement in each plot. Because in the automatic measurement, some of the trees were overestimated by the software. Some of the small trees which are found under the canopy of the higher trees were overestimated in the automatic height measurement. Thus the main reason for the overestimation of some trees particular the smaller trees was intermingle of the smaller trees with the nearby trees. Thus the software has segmented those trees which found under the canopy of the higher trees by including the canopy of the higher trees and this increases the height of the smaller tree.

Table 4.6: Summary of statistics for the height extracted manually and automatically form the four scanning position.

Plot	Height measurement											
	Field				Manual				Automatic			
	Min	Max	Mean	Std.	Min	Max	Mean	Std.	Min	Max	Mean	Std.
1	6.48	24.00	13.21	4.33	9.32	17.26	13.21	2.55	11.25	17.72	13.91	1.81
2	4.00	33.00	14.09	7.13	7.45	29.01	14.10	4.97	9.21	26.73	16.88	5.10
3	7.00	34.00	16.53	7.85	9.13	29.06	15.53	4.82	7.25	28.71	15.08	5.16
4	7.50	36.03	18.21	8.86	6.98	28.84	17.08	5.60	5.85	31.34	16.86	6.54
5	10.10	31.60	16.37	4.91	10.4	27.43	16.55	4.64	7.48	30.02	18.21	5.50
6	6.97	25.60	14.66	5.44	8.06	24.2	15.33	4.84	5.31	26.62	16.73	6.36
7	6.40	33.20	17.28	6.70	8.48	29.94	19.08	6.43	7.69	31.21	17.67	5.84
8	6.20	29.40	14.20	4.64	8.53	22.1	14.52	3.37	7.17	18.18	13.95	2.80
9	7.29	28.70	14.29	5.78	7.8	27.01	14.58	5.22	8.45	24.25	15.55	4.50
10	6.00	29.20	15.58	6.12	9.55	28.48	15.28	4.77	5.84	30.66	17.25	6.18
Average	6.79	30.47	15.44	6.18	**8.57**	**26.33**	**15.53**	**4.72**	7.55	26.54	16.21	4.98

Table 4.7 Correlation between the mean heights measured using field, manual and automatic method

	Four scan positions		Five scan positions	
	Manual	Automatic	Manual	Automatic
Field	0.87	0.57	0.87	0.58

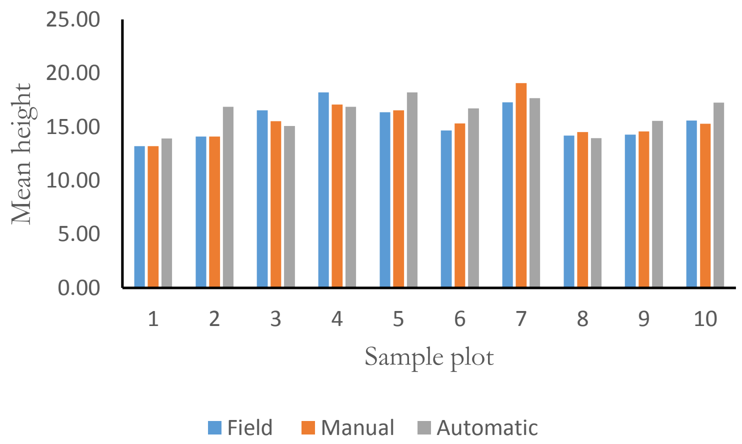


Figure 4.4 Distribution of mean height measured from field, manually and automatically from TLS using four scanning positions.

At the same time, a total of 283 individual tree heights were measured manually from the five scanning position. The plot level descriptive statistics of the measurement of height including the automatic height measurement from the five scanning positions is summarized and presented in Table 4.8. The result shows that there is a variation in the measurement of tree height between the manual and automatic measurement method in each plot (Table 4.8). Based on the mean value of the manual tree height measurement, the five scanning position had a little variation as compared to the four scanning position. However the variation is not too much.

In the case of automatic height measurement some of the trees were overestimated by the software (Appendix 2). The trees which found under the canopy of the higher trees were overestimated in the automatic height. On the other hand some of the trees were also underestimated by the automatic measurement method. Thus the main reason for the overestimation of individual trees particular the smaller trees was the overlapping canopy structure of the forest. Thus the software has segmented those trees which found under the canopy of the higher trees with the canopy of the higher trees and this increase the height of the tree.

Table 4.8: Summary statistics of height extracted manually and automatically form the five scanning position

Plot	Height measurement											
	Field				Manual				Automatic			
	Min	Max	Mean	Std.	Min	Max	Mean	Std.	Min	Max	Mean	Std.
1	6.48	24.00	13.21	4.33	7.9	17.9	13.5	2.8	9.95	22.97	13.28	2.37
2	4.00	33.00	14.09	7.13	8.4	32.5	15.0	5.4	8.45	33.56	16.03	4.50
3	7.00	34.00	16.53	7.85	8.4	29.2	15.8	4.7	7.23	29.64	15.99	5.17
4	7.50	36.03	18.21	8.86	9.6	29.9	17.6	5.3	8.70	32.90	16.13	4.64
5	10.10	31.60	16.37	4.91	11.1	29.6	17.4	4.4	7.91	27.63	18.15	4.79
6	6.97	25.60	14.66	5.44	10.6	27.0	16.5	4.8	11.91	29.36	16.12	2.84
7	6.40	33.20	17.28	6.70	4.9	31.7	18.4	6.7	8.05	30.15	19.63	6.15
8	6.20	29.40	14.20	4.64	8.6	23.4	15.1	3.4	7.81	27.32	16.89	3.40
9	7.29	28.70	14.29	5.78	9.5	27.0	15.2	4.9	7.35	28.46	16.02	6.39
10	6.00	29.20	15.58	6.12	10.0	28.8	16.0	4.4	9.14	25.10	16.68	4.96
Average	**6.79**	**30.47**	**15.44**	**6.18**	**8.90**	**27.68**	**16.06**	**4.68**	**8.65**	**28.71**	**16.49**	**4.52**

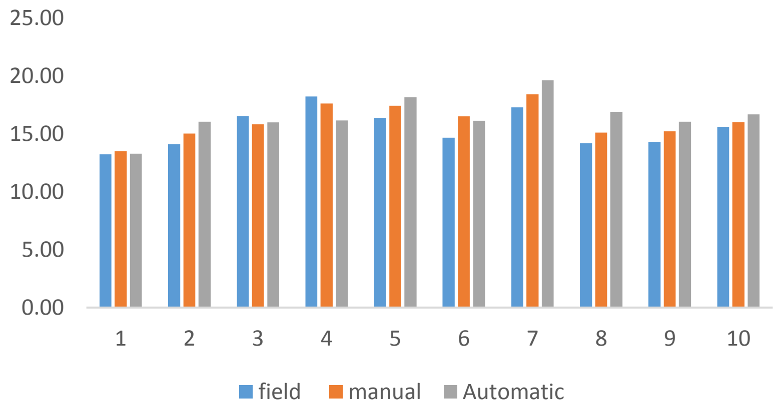


Figure 4.5 Distribution of mean height measured from field manually and automatically from TLS using five scanning positions.

4.4. Accuracy of manually derived tree height from TLS

Regression analysis was conducted to see the relationship of manually derived tree height and ALS height of the selected trees. The trees extracted from TLS were matched with trees from Airborne LIDAR and then a total of 166 trees were selected for the analysis for the four and five scanning positions. The trees selected for validation of manually derived height were those trees which matched with ALS height derived from CHM of Airborne LIDAR. The linear regression showed an RMSE of 1.77m (9.75%) and R^2 value of 0.85 for the manually measured tree height from the four scanning positions Table 4.10.

Also the relationship of manfully derived tree height from the five scanning positions was evaluated with respect to the ALS height and showed a linear relationship with R^2 value of 0.86 and RMSE of 1.74m (9.30%) Table 4.10. As the RMSE shows that there is no much variation in the manual measurement of tree height as compared to ALS height in the four and five scanning positions.

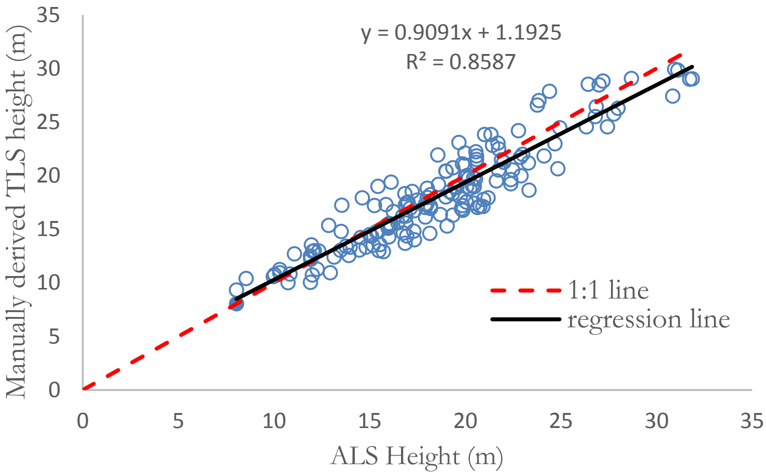


Figure 4.6: Relationship between ALS heights and manually derived TLS height from the four scanning positions

Furthermore, the significance of the relationship between the manually derived TLS height and ALS height derived from CHM of LIDAR was evaluated and the result showed that there is no significance difference in the manual tree height measurement as compared to ALS height both in the four and five scanning positons (Table 4.9 and Table 4.11). Thus the null hypothesis was accepted. Table 4.9 and Table 4.11 shows the summary result of the t-statistics between ALS height and manually derived TLS height with four and five scanning positions.

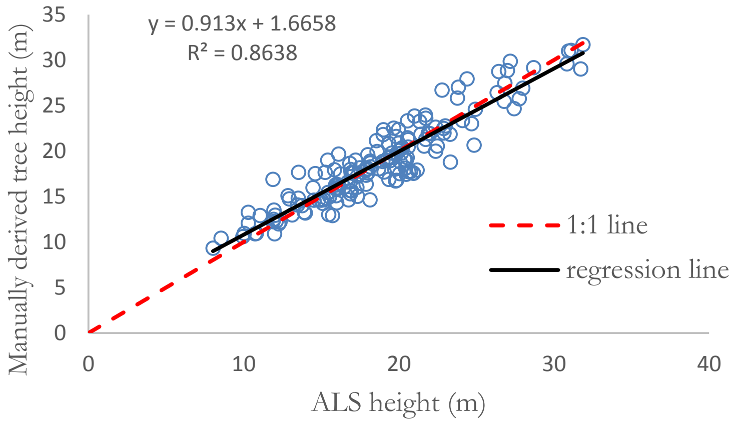


Figure 4.7 Comparison between ALS height and manually derived TLS height from the five scanning positions

Table 4.9. T-test for ALS height and manually measured height from the four scanning position

	ALS_H_m	TLS_4_scan_H_m
Mean	18.705	18.20
Variance	23.275	22.40
Observations	161.000	161.00
df	320.000	
t Stat	0.953	
P(T<=t) two-tail	0.341	
t Critical two-tail	1.967	

Table 4.10 Summary of regression statistics for ALS height and manually derived from TLS with four and five scanning position.

Summary of fit for height comparison		
	Four scan positions	Five scan positions
Correlation coefficient	0.9091	0.913
R Square	0.859	0.864
Adjusted R Square	0.858	0.863
Standard Error	1.819	1.786
Observations	161	161
RMSE (m)	1.77	1.74

Table 4.11. T-test for ALS height and manually measured height from the five scanning position

	ALS_H_m	TLS_5scan-H_m
Mean	18.705	18.744
Variance	23.275	22.462
Observations	161.000	161.000
df	320.000	
t Stat	-0.072	
P(T<=t) two-tail	0.942	
t Critical two-tail	1.967	

4.5. Accuracy of automatically extracted TLS height

To carry out the accuracy assessment of automatically derived tree height from TLS, ALS height which is considered the truth was taken as a reference point. Thus trees extracted automatically from the four and five scanning positions were matched with the corresponding ALS-CHM derived tree height. As a result, a total of 131 trees were selected which were common both in the four and five scanning positions. Then the regression analysis was carried out to see the relationship between the two measurement results in both scanning positions. The result showed a positive linear relationship with R^2 value of 0.48 and 0.46 for the automatically measured tree height with five and four scanning positions respectively. Similarly, the result reflects RMSE value of 3.17m (17.40%) and 3.68m (19.97%) for height measured from five and four scanning positions respectively. The significance of the relationship was also assessed and the result revealed that there is no significance difference for the height measurement as compared to ALS height for automatically extract trees from the four and five scanning positions (Table 4.12 and Table 4.13).

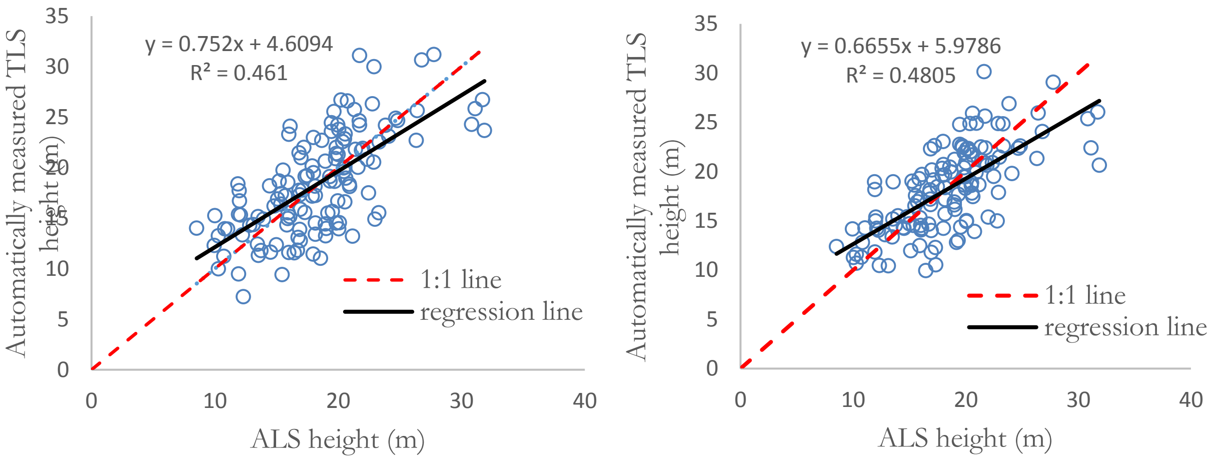


Figure 4.8: Comparison between ALS height and automatically derived TLS height from the four (left) and five (right) scanning positions

Table 4.12 T-test for ALS height and automatically measured height from the four scanning position

	ALS_H_m	Automatic height
Mean	18.378	18.430
Variance	20.643	25.325
Observations	131.000	131.000
df	260.000	
t Stat	-0.088	
P(T<=t) two-tail	0.930	
t Critical two-tail	1.969	

Table 4.13 T-test for ALS height and automatically measured height from the five scanning position

	ALS_H_m	Automatic height
Mean	18.378	18.210
Variance	20.643	19.028
Observations	131.000	131.000
df	260.000	
t Stat	0.306	
P(T<=t) two-tail	0.760	
t Critical two-tail	1.969	

4.6. Comparison between DBH measured from field and manually derived from TLS.

During the field data collection, DBH of each individual tree were measured and recorded within each sample plot. Concurrently the sample plots were also scanned with TLS using four and five scanning position setup. The DBH of each individual tree were then extracted from the point cloud data. The field measured DBH and manually extracted DBH from the four and five scanning positions point cloud data were plotted to see their relationship Figure 4.9.

The field measured DBH was used as independent variable whereas the manually extracted DBH used as a dependent variable to assess their relationship. Thus the relationship between field and manually extracted DBH from TLS showed a linear and positive correlation with R^2 of 0.98 for both four and five scanning position. The RMSE between field measured DBH and manually extracted DBH from the four and five scanning positions point cloud data was 1.66 (8.06%) and 1.37 (6.60%) respectively.

As the RMSE indicates that, there is no much deviation in DBH measurement both in the four and five scanning positions. Thus based on this result increasing the number of scanning position from four to five does not have any effect on the relationship of field and manually extracted DBH from the point cloud data.

In addition, the significance of the relationship between field-measured DBH and manually derived DBH from the four and five scanning position was assessed. To do this, a t-test was employed for 273 and 283 observations obtained from four and five scan position TLS data respectively. The analysis result using four scanning position TLS data showed a value of $P (T<=t) = 0.437$ which is greater than the critical value of 0.05. Similarly the t-test result for the five scanning position TLS data showed a value of $P (T<=t) = 0.622$ which is higher than the critical value of at 95% confidence level.

As the t- test result between the two parameters indicates that there is no significance difference between field measured DBH and manually derived DHB from TLS both in the four and five scanning positions. Thus increasing the number of scanning position from four to five scan does not have a significance differences for DBH measurement. Therefore, the null hypothesis was accepted since the t-calculated is less than the t-statistics at 95% confidence level. Moreover, the scatter plot which shows the relationship between field measured DBH and manually derived DBH from TLS using four and five scanning position point cloud data is shown in (Figure 4.9). The summary of fit for DBH comparison is also shown in (Table 4.14 and Table 4.15).

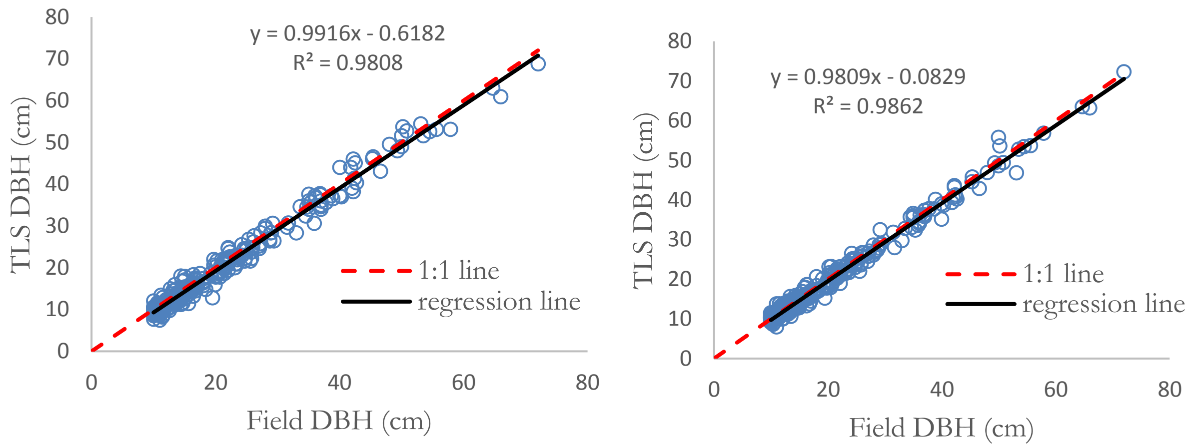


Figure 4.9. Comparison of field and manually measured DBH from the four (left) and five scanning position (right)

Table 4.14. Summary of regression statistics for field DBH and manually derived from TLS from four scanning position.

Summary of fit for DBH comparison	
Correlation coefficient	0.9916
R Square	0.9808
Adjusted R Square	0.981
Standard Error	1.666
Observations	273
RMSE (cm)	1.660

Table 4.15. Summary of regression statistics for field DBH and manually derived from TLS from five scanning position

Summary of fit for DBH comparison	
Correlation coefficient	0.992
R Square	0.9862
Adjusted R Square	0.981
Standard Error	1.668
Observations	283
RMSE (cm)	1.37

4.7. Comparison of DBH measured from field and automatically derived from TLS.

The automatic extraction of DBH was conducted using Computree software. During field data collection a total of 377 trees were collected within 10 sample plots. On the hand, a total of 247 and 256 tree were extracted automatically from TLS point cloud data using four and five scanning position respectively. The field measured DBH and automatically extracted DBH from the four and five scanning position TLS data were plotted to compare their relationship.

The field measured DBH used as independent variable whereas the automatically extracted DBH was used as dependent variable to assess their relationship. Thus the relationship between field and automatically extracted DBH from TLS showed a linear and positive relationship with R^2 of 0.93 and 0.95 for the four and five scanning position respectively.

The deviation of the automatically measured DBH from the field DBH was calculated by using RMSE. Thus the RMSE was 3.12cm (14.57%) for automatically derived DBH from the four scanning position whereas the RMSE for automatically derived DBH from five scanning position was 2.36cm (11.47%). The scatter plot which shows the relationship between the field measured DBH and automatically extracted DBH from TLS using four and five scanning position is shown in (Figure 4.10).

Moreover, the significance relationship between the field DBH and the automatically extracted DBH was analysed using t- test statistics for the five and four scan position TLS data independently. The analysis result using four scanning position TLS data showed a value of P (T<=t) = 0.288 which is higher than the critical value of 0.05. Similarly the t-test result for the five scanning position TLS data showed a value of P (T<=t) = 0.085 which is higher than the critical value at 95% confidence level.

a) b)

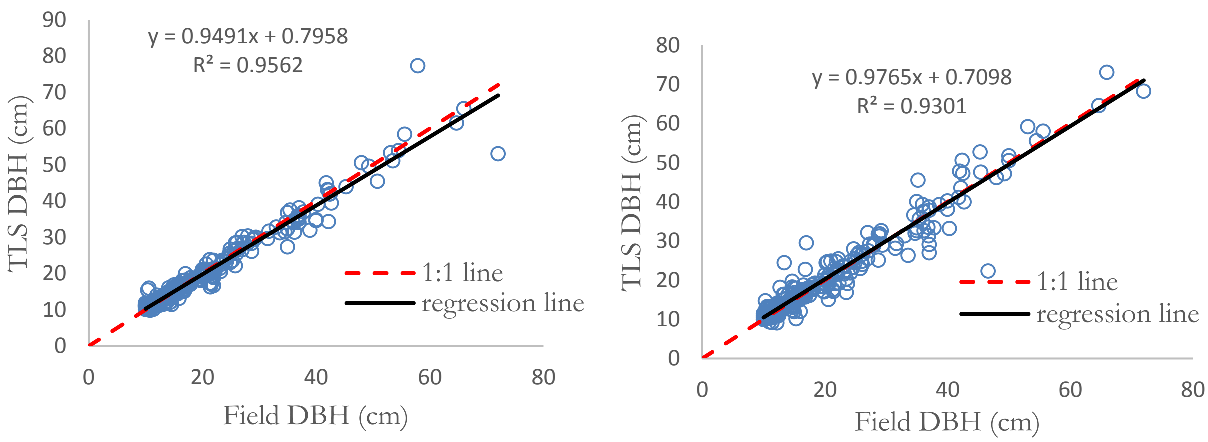


Figure 4.10: Relationship of field and automatically derived DBH from five (a) and four scanning position (b)

Thus, based on the t-test result there is no significance difference between the field measured and automatically derived DBH from the four and five scanning position at 95% significance level. Therefore, the null hypothesis was accepted. The summary of t-test analysis result for the five and four scanning positions is shown in Table 4.16 and Table 4.17 respectively.

Table 4.16: t-test for field DBH and automatically extracted DBH from the five scanning position.

	Field DBH (cm)	Automatic DBH (cm)
Mean	20.83	20.57
Variance	135.35	127.52
Observations	256.00	256.00
Pearson Correlation	0.98	
df	255.00	
t Stat	1.73	
P(T<=t) two-tail	0.08	
t Critical two-tail	1.97	

Table 4.17: t-test for field DBH and automatically extracted DBH from the four scanning position.

	Field DBH (cm)	Automatic DBH (cm)
Mean	21.17	21.38
Variance	136.08	139.51
Observations	247.00	247.00
Pearson Correlation	0.96	
df	246.00	
t Stat	-1.07	
P(T<=t) two-tail	0.29	
t Critical two-tail	1.97	

4.8. Above ground biomass and carbon estimation

4.8.1. Aboveground biomass

The aboveground biomass was calculated based on the trees extracted from the four and five scanning position. The allometric equation which uses height, DBH and wood density of each individual tree as input parameters were used to calculate the aboveground biomass of each individual tree in sample the plot. The variables needed for above ground biomass estimation was then measured using manual and automatic extraction methods from TLS point cloud with four and five scanning positions separately. Therefore, in this study individual tree biomass which was derived manually and automatically from the four and five scanning positions were calculated with Chave et al., (2014) allometric equation.

Table 4.18: Estimated aboveground biomass for the total tree from the four and five scanning positions

	Four scan		Five scan	
Statistics	Manual	Automatic	Manual	Automatic
Mean (Mg)	0.31	0.313	0.36	0.33
Standard Deviation	0.51	0.237	0.59	0.50
Minimum	0.01	0.019	0.03	0.03
Maximum	3.34	1.613	4.13	3.63
Total Biomass (Mg)	84.65	77.244	101.02	83.75
Number of sample (trees)	273	247	283	256

Out of the manually derived trees, a total of 161 trees were selected from the four and five scanning positions. The selected trees were matched with the corresponding ALS-CHM height for aboveground biomass accuracy assessment. The aboveground biomass calculated from field measured DBH and ALS measured height of the sample trees were used as reference data to assess the accuracy of the biomass calculated from the four and five scanning positions with manual and automatic method.

Therefore, to assess the relationship of the aboveground biomass calculated from TLS with four scanning position and aboveground biomass calculated from field DBH and ALS height were plotted on a scatter plot (Figure 4.11). The result showed R^2 value of 0.96 and RMSE of 0.109Mg (22.79%) for the biomass calculated from manually derived tree parameters from the four scanning positions.

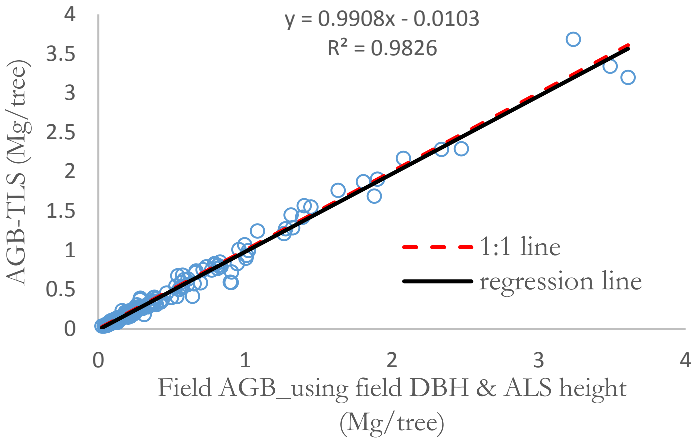


Figure 4.11 Scatter plot of AGB calculated from field DBH and ALS height with TLS derived AGB from five scanning positions

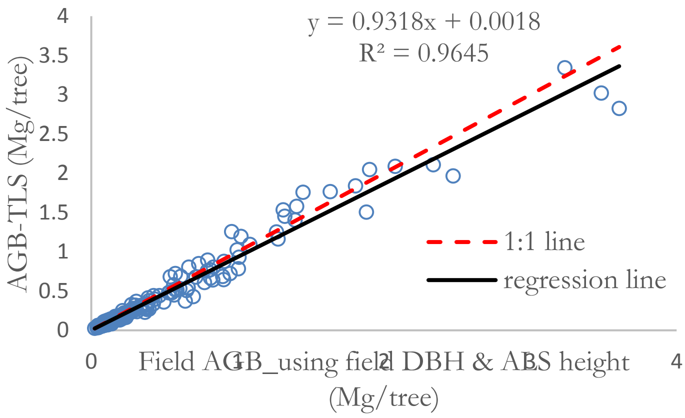


Figure 4.12: Relationship of AGB calculated from manually derived parameters from four scanning positions and AGB using ALS height and field DBH

The significance difference between the aground biomass calculated from manually derived parameters with four scanning positions and the biomass calculated from field DBH and ALS height was evaluated with t-test. The result revealed that there is no significance difference in the aboveground biomass calculated from manually derived parameters from TLS with four scanning positions and field biomass calculated using ALS height and field DBH. Similarly, the biomass calculated from manually derived parameters with five scanning positions was also plotted against with the reference aboveground biomass. The result reflects R^2 value of 0.98 and RMSE value of 0.077Mg (15.55%) (Table 4.19).

Table 4.19: Summary of the relationship between AGB from field DBH and ALS height and manually measured AGB from the four and five scanning position

Summary of fit for AGB		
	Four scan positions	Five scan positions
Correlation coefficient	0.93	0.99
R Square	0.9659	0.985
Adjusted R Square	0.9657	0.985
Standard Error	0.1155	0.078
Observations	160	160
RMSE (Mg)	0.109	0.077

Furthermore, the aboveground biomass calculated from the four scanning positions with manual and automatic extraction method was tested if there was a significance difference between the calculated biomass. To do this t-test was employed for the manually and automatically extracted trees biomass. The result showed a value of P (T<=t) =0.82 which is higher than the critical value of 0.05. The amount of biomass from the four scanning positions with manual and automatic extraction method did not show a significance difference based on the statistical test. Similarly, the aboveground biomass calculated with manual and automatic measurement method from the five scanning positions showed a p value of 0.49 which is greater than a t-critical value of 0.05. Therefore, there is no significance difference between AGB of the manual and automatic for the five scan positions based on the statistical test.

4.8.2. Above ground carbon estimation

According to IPCC (2007), carbon is composed of 47% of the aboveground biomass. The amount of carbon for each individual tree was, therefore, calculated from the above ground biomass of each individual tree Equation 3.3. The total aboveground carbon of trees extracted manually and automatically from the four scanning positions was 39.78 and 36.31Mg respectively whereas the total aboveground carbon of trees extracted manually and automatically from the five scanning position was 47.48Mg and 39.36 Mg respectively. Similarly the t-test was conducted to check whether there was a significance difference between the manually and automatically derived trees carbon stock using the four and five scanning positions. The result indicates that there is no significance difference on the above ground using manual and automatic extraction method from four and five scanning positions.

Table 4.20: Above ground carbon estimation

Statistics	Four scan		Five scan	
	Manual	Automatic	Manual	Automatic
Mean (Mg)	0.15	0.147	0.17	0.15
Standard Deviation	0.24	0.237	0.28	0.23
Minimum	0.01	0.009	0.01	0.01
Maximum	1.57	1.613	1.94	1.70
Total carbon (Mg)	39.78	36.305	47.48	39.36
Number of sample (trees)	273	247	283	256

The aboveground carbon also calculated from the four and five scanning position. A total of 161 trees were selected out of the manually measured trees which are common for the four and five scanning positions for accuracy assessment. The accuracy of the aboveground carbon calculated from the four and five scanning position was then evaluated against the aboveground carbon calculated from the field DBH and ALS tree height. Linear regression was used to compare the aboveground carbon calculated from the four and five scanning positions using manual and automatic method. The aboveground carbon calculated from field DBH and ALS height was used as a reference measurement to assess the accuracy of aboveground carbon calculated from TLS with four and five scanning positions.

The RMSE was calculated for the manually measured aboveground carbon from the four scanning positions with respect to the reference aboveground carbon. Thus the result showed an RMSE of 0.05Mg and R^2 value of 0.96 (Table 4.21). Similarly, the regression result from the five scanning positions show R^2 value of 0.98 and RMSE value of 0.08Mg and a slope of 0.99.

Table 4.21. Summary of regression statistics for AGC calculated from manually measured AGC from the four and five scanning position

Summary of fit for AGC		
	Four scan positions	Five scan positions
Correlation coefficient	0.93	0.99
R Square	0.966	0.985
Adjusted R Square	0.966	0.985
Standard Error	0.054	0.036
Observations	160	160
RMSE (Mg)	0.05	0.08

The significance difference was also assessed for the aboveground carbon calculated manually from the four and five scanning positions. To do this t-test was employed for the aboveground carbon calculated from the field and TLS with four and five scanning positions. The analysis result showed a value of P (T<=t) = 0.443 and 0.174 for the four and five scanning positions. In both case the t-calculated is less than the t-critical value meaning that there is no significance difference between the field measurement using ALS tree height and manual measurement from TLS using four and five scanning positions.

Table 4.22. T-test for AGC calculated from field DBH and ALS height and manually measured AGC from the four scanning position.

	Field_Carbon (Mg)	Carbon _4scan_(Mg)
Mean	0.239	0.225
Variance	0.086	0.078
Observations	160	160
df	318	
t Stat	0.443	
P(T<=t) two-tail	0.658	
t Critical two-tail	1.967	

Table 4.23 T-test for AGC calculated from field DBH and ALS height and manually measured AGC from the five scanning position..

	Field_Carbon (Mg)	Carbon _5scan_(Mg)
Mean	0.239	0.233
Variance	0.086	0.086
Observations	160	160
df	318	
t Stat	0.174	
P(T<=t) two-tail	0.862	
t Critical two-tail	1.967	

5. DISCUSION

Nowadays the demand for accurate biomass and carbon estimation is growing. Therefore, there is a need for accurate biomass and carbon estimation method and technique for better and accurate biomass estimation in the tropical forest. TLS could be a viable option for the accurate measurement of forest inventory parameters for accurate biomass and carbon stock estimation. The main objective of this study was, therefore, to derive forest inventory parameters and to assess the effect of the scanning position on forest inventory parameter derivation and overall aboveground biomass and carbon estimation. Therefore, for this particular study four and five scanning position was selected.

5.1. Distribution of field and manually derived DBH from TLS

During the field data collection, a total of 377 trees were measured from 10 sample plots and each sample plot was scanned with TLS using four and five scanning positions. Similarly, a total of 273 and 283 trees were detected manually from the four and five scanning positions TLS data respectively. A normal frequency distribution was done to check the distribution of DBH measured from the field and manually extracted from the point cloud data. The probability distribution of a data can be negatively skewed which inclines to the left in the negative direction and positively skewed with a long tail in the positive direction of the distribution (Doane & Seward, 2011). Therefore, in this study, the DHB distribution showed a non-normal distribution with a high skewness value for both field measured and manually derived DBH from TLS as shown in (Figure 5.1). The skewness value indicates that the data is inclined to the left side of the mean. The main reason for the non-normal distribution of DBH was that the measurement of DBH in the field was considered only trees which had DBH greater than 10 cm.

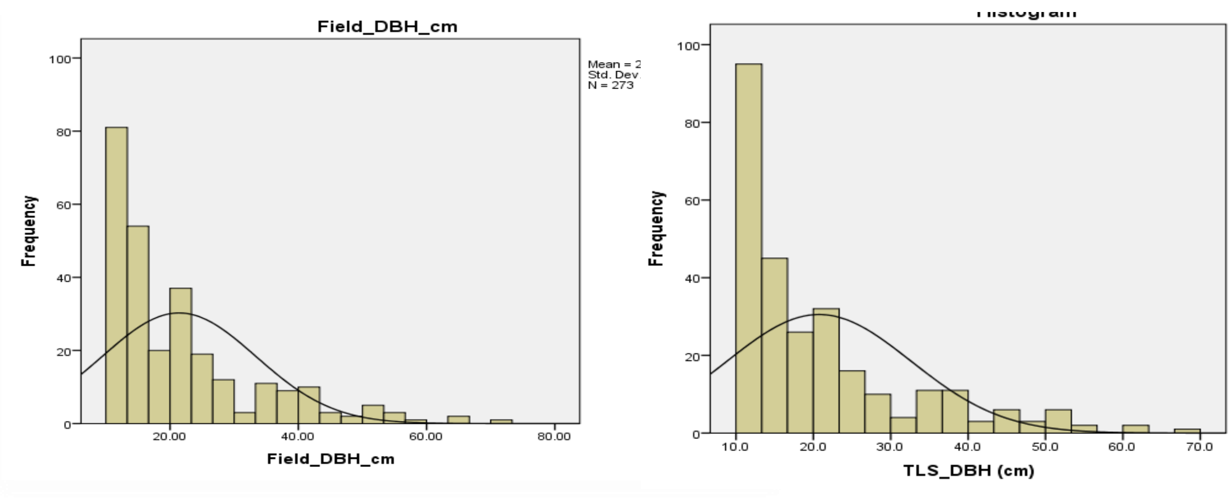


Figure 5.1: Histogram showing the distribution of DBH measured from field (left) and manually derived from TLS (right).

5.2. Individual tree detection and accurecy assessment

5.2.1. Manual detection of individual trees

The individual trees were derived manually and automatically from the point cloud data. The accuracy of individual tree detection from the point cloud data was then assessed per each sample plot with respect to the collected data in the field for both the four and five scan position.

In the case of four scanning position, all the trees were detected except the trees found in sample plot 2, 3, 7, 9 and 10 (Table 4.1). In those sample plots, a total of 8 trees were missed. Those trees were obscured by other trees and sometimes found far from the centre of the plot and thus could not be detected from the point cloud data. Thus the overall detection rate of individual trees was 97.99% from the 10 sample plots. This result was higher than the studies conducted by Prasada, (2015) which obtained 89% using manual extraction methods from four scanning positions TLS data.

Prasada (2015) mentioned that the main reason for the lower detection rate was occlusion due to dense undergrowth vegetation. However, in this study, an extensive cleaning and slashing of the undergrowth vegetation were done to reduce the effect of occlusion on the extraction of the point cloud data.

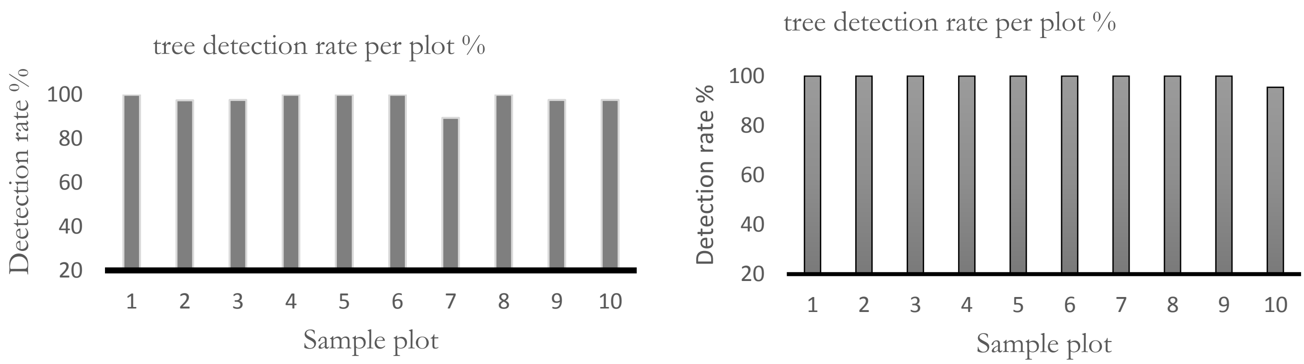


Figure 5.2: Manual detection rate of trees per plot both in the four (left) and five scanning positions (right).

Similarly, the accuracy of individual tree detection from the five scan point cloud data was evaluated in each sample plot with respect to the actual data collected in the field. As a result, all the trees were extracted manually from all the sample plots except sample plot 10 in which 2 trees were missed (Table 4.1). Thus the average overall manual detection rate was 99.55 % from all the sample plots. The manual extraction of individual trees using five scanning position was higher than the detection rate from the four scanning position. In the five scanning position the possibility to visualize all the trees were higher as compared to the four scanning positions since the scan was done from the four sides of the plot where a higher overlapping of the different scanning position occurred.

5.2.2. Automatic detection of individual trees

The automatic extraction of individual trees from the point cloud data were done in the Computree software. The accuracy of individual tree detection from the four and five scanning position was evaluated based on the data collected in the field. The detection rate in both scanning position was varied from plot to plot. Table 4.2 summarizes the automatic extraction of individual trees per plot using four and five scanning positions. The result indicates that the average automatic extraction of individual trees using four and five scanning positions was 91% and 93.75% respectively. The automatic extraction from the five scan position was good as compare to the four scanning position even if the difference is not big.

Othmani et al., (2011), reported an average detection rate of 90.6% with single scan mode using automatic extraction method on a study conducted a mixed forest which is composed of beech and oak plantation. On the other hand Prasad, (2015) conducted study on the tropical rain forest of Malaysia and revealed an average detection rate of 90 % with four scanning position using automatic extraction method from point cloud data. The result of this study is almost similar with the above mentioned studies.

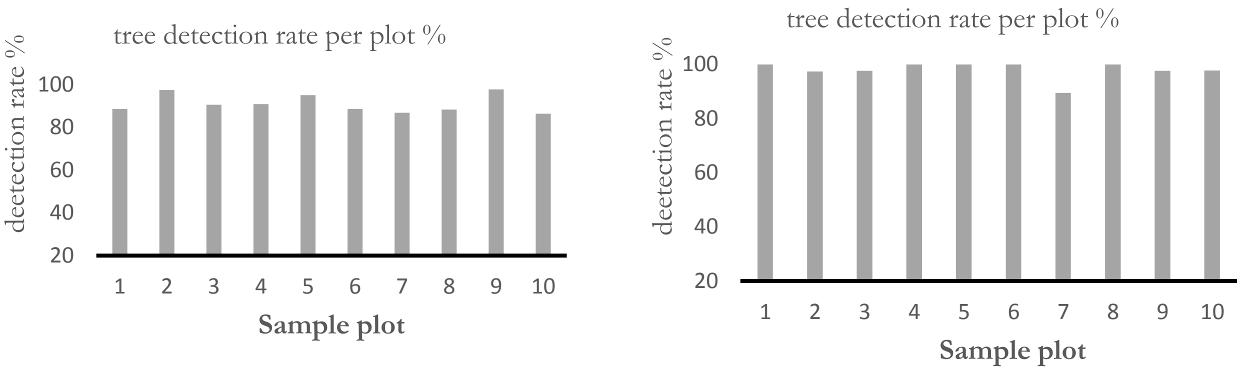


Figure 5.3: Automatic detection rate of trees per plot both in the four (a) and five scanning positions

5.3. DBH measurement and accuracy assesment

Tree DHB is one of the important forest inventory parameter for above ground biomass and carbon estimation which could be extracted from the TLS point cloud data. It explains 95% of the variability in above ground biomass estimation (Brown, 2002). However, the measurement of DBH in the field is exposed for different sources of errors since the DBH is measured at 1.3m from the tree base which is not always practical. This is due to the fact that the measurement is subjected to the variability in marking 1.3m above the base of the tree due to the height of the person who conduct the measurement. The other source of error might be the base of the tree trunk is not always levelled and this might cause the measurement of DBH to be at a height of more or less than 1.3m above the base of the tree. Even though the measurement of DBH can face these technical and practical source of errors, the measurement is better and taken as reference to check the accuracy of DBH extracted manually and automatically from TLS. The distribution of field measured and manually derived DBH from TLS using four and five scanning position was evaluated to check the variation in the measurements of DBH per plot. The distribution of DBH was then plotted in a bar graph that shows the mean DBH measurement per plot Figure 5.4.

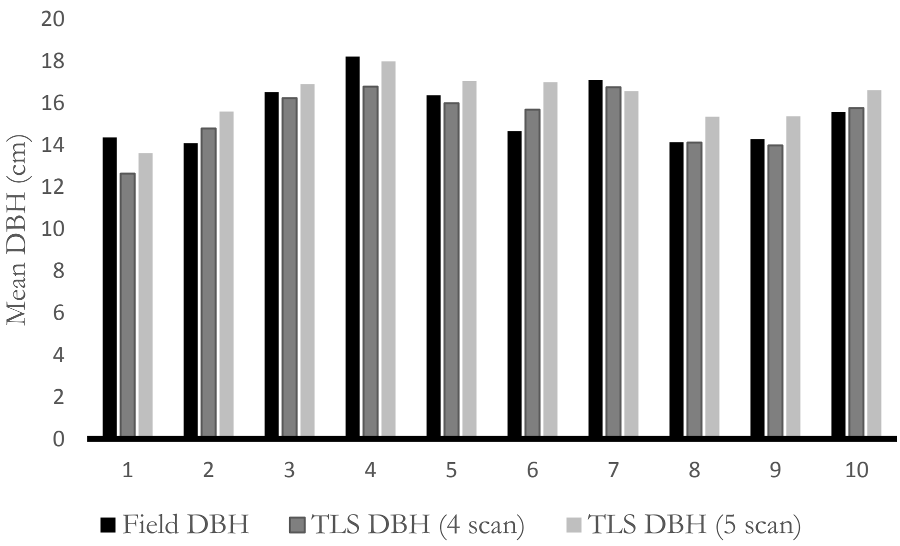


Figure 5.4: Distribution of average field and manually measured DBH from four and five scanning positons per plot

As it is shown in Figure 5.4 the mean DBH variation between the field measured and manually derived DBH TLS using four and five scanning positions was very low. The correlation between the two variables was further validated by plotting the TLS measured DBH against the field measured DBH on scatterplot.

The manually extracted DBH from the point cloud data was then evaluated for the accuracy of its measurement using the ground measured DBH as a reference point. Thus TLS measured DBH was plotted against the field measured DBH to check the relation between the two variables (Figure 5.5). The manually derived DBH for both four and five scan positions showed a highly accurate result with R^2 value of 0.98 with RMSE of 1.66 (8.06%) for the four scanning positions (Table 4.14). The result indicates that 98% of the TLS measured DBH variability is explained by field measured DBH using the four scanning positions.

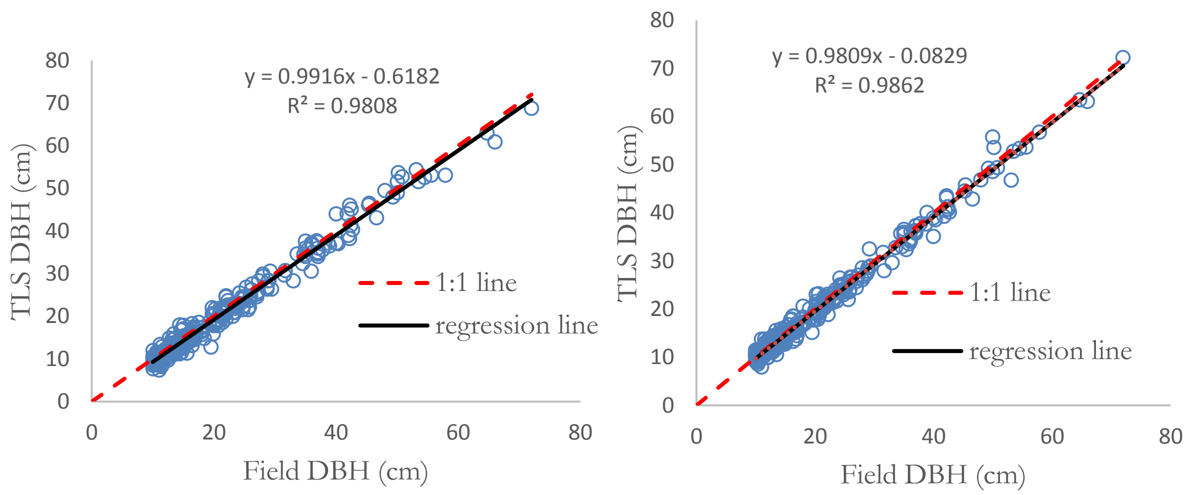


Figure 5.5: Comparison of field and TLS measured DBH derived from four (left) and five (right) scanning positions

Therefore, there is a very high agreement between the field measured DBH and manually derived DBH from the TLS data. This study has achieved better DBH estimation accuracy than other studies. For instance, Prasad, (2015) reported an average R^2 value of 0.95 with RMSE of 2.7cm for the relationship of field DBH and manually derived TLS DBH with four scanning positions. In the above mentioned study, occlusion due to undergrowth vegetation was reported as the main reason for the lower value of R^2. However, for this study extensive cleaning and slashing of the undergrowth vegetation was done and this could be the reason that the R^2 value is better than the above mentioned study.

Kankare et al., (2013) also reported similar result with the above mentioned study for DBH estimation. They achieved R^2 of 0.95 and RMSE of 1.48cm using the manual measurement from TLS point cloud data so the result is nearly similar with the current study. In the case of five scanning positions, a similar R^2 value of 0.98 with RMSE 1.37cm was found. The result indicates that there is no difference in the relationship of field and manually measured DBH from the four and five scanning position. However, there is some variation in the RMSE value between DBH derived from four and five scanning position which indicates that the measurement within each individual tree DBH are slightly different.

The automatic measurement was done using Computree software which is an open source software that uses point cloud data. Similarly, the relation between field-measured and automatically derived DBH was found an R^2 value of 0.93 with RMSE of 3.12cm for the four scanning position. Some other studies also reported a result which supports the current study. Maas et al., (2008) reported an accuracy (RMSE) of 1.8cm in automatic DBH determination of Spruce and Beech plantation plots. Similarly Simonse et al., (2003) also reported an error of 1.7cm for the comparison between field measured and automatically derived DBH from the TLS point cloud.

In the case of five scanning position R^2 value of 0.95 with RMSE of 2.36cm was achieved with automatic measurement of DBH. Liu et al., (2017) reported RMSE value of 6.38% for mean DBH estimated using matched point clouds of multiple scans with five scanning positions. In the mentioned study it is stated that matched multiple scans with five scanning position enhanced the correctness of the stem mapping because of the full coverage of the point cloud. The result indicates that there is no big difference in the measurement of DBH using four and five scanning positions.

The null hypothesis was that there is no difference in DBH measurement using manual and automatic extraction method from the four and five scan position. Therefore, based on the result, the null hypothesis was accepted. One of the challenges in the automatic derivation of DBH from the point cloud data was that the software could not detect big tree in both the four and five scanning positions. The measurement of DBH was also affected by the form of the tree stem and its nature, this is because some of the trees stem shape was not circular and straight and thus the cylinder couldn't fit with it. Moreover, some of the leaning trees were not detected by the software because the shape of the tree was not straight so that the cylinder could not fit with it.

5.4. Tree height measurement

In this study multiple scanning position with four and five scanning position was employed. A total of 10 sample plots were scanned with four and five scanning positions alternatively. The point cloud was then processed involving registration of multiple scan, detection and extraction of individual trees. The registered point clouds were then display in the RiSCAN PRO software with true color to easily identify and extract the trees. The height measurement of each individual tree from the point cloud data was done after processing and extraction of individual trees. The measurement of tree height from point cloud was done by two methods: namely manual and automatic measurement.

The manual tree height measurement was done after processing and extracting of each individual trees from the point cloud data. This method involves some difficulties in identifying and differentiating the point cloud which belongs to a particular tree crown, especially in areas where the crowns are intermingled (Figure 5.6). The trees were tagged with tree numbers during the field data collection and thus tree numbers were used for the identification and extraction of individual trees from the point cloud data.

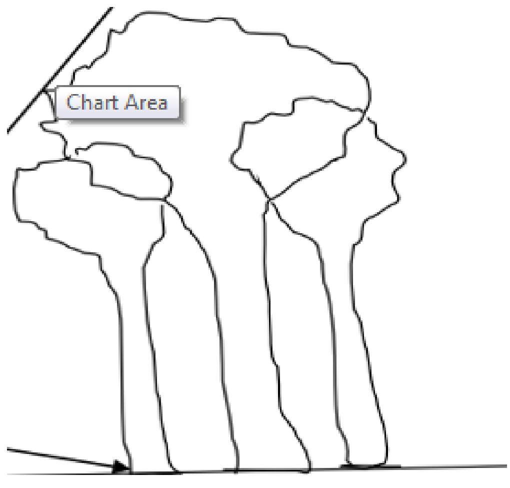


Figure 5.6: Structure of tree canopy which incorporate error in tree height measurement

Source (Prasad, 2015)

A total of 273 and 283 trees were derived manually from the four and five scanning positions point cloud data respectively. Similarly, the tree height were measured automatically using Computree software from the four and five scanning positions and summarized in (Table 4.6 and Table 4.8).

The accuracy of manually and automatically measured tree height from the four and five scanning positions was validated by using ALS height which is considered as accurate tree height measurement. Thus the number of trees extracted manually and automatically from the four and five scanning positions TLS were matched with tree height derived from Airborne LiDAR.

Therefore, out of the manually derived individual trees, a total of 161 trees were selected for the accuracy assessment of tree height. The selected trees were common both in the five and four scanning positions and also matched with ALS height derived from Airborne LIDAR.

The manually measured tree height from TLS with four and five scanning positions was compared against with the ALS measured tree height in (Figure 4.6 and Figure 4.7). The manually measured tree height from both four and five scanning positons showed a good linear fit with the reference tree height which is ALS height. The R^2 value and RMSE with respect to the ALS height was 0.85 and 1.77m for the manually measured tree height from the four scanning positions whereas the R^2 and RMSE was 0.86 and 1.74m (9.30%) meaning that 90.70% accuracy when the manually measured tree height from the five scanning positions validated using ALS height as a reference height.

Some other studies reported a similar result which is in line with the result of this study. For instance, Ghebremichael, (2015) reported an accuracy of (RMSE) 2.15m and R^2 value of 0.87 in comparison of ALS height and manually measured TLS using four scanning positons carried out in the tropical rain forest of Malaysia. Similarly, in the same study area Sadadi, (2016) revealed RMSE of 1.33m and R^2 value of 0.91 for the comparison of ALS height and manually measured height from TLS using four scanning position. Thus the result of the current study is comparable with the abovementioned studies. Hilker et al., (2010) compared the height obtained from ALS and TLS and reveled R^2 value of 0.86 for the study that was conducted in the coniferous forest of Canada.

Similarly, the tree height extracted automatically from the four and five scanning positions was also validated using ALS height. The result showed R^2 value of 0.48 with RMSE of 3.17m for the automatically measured tree height from the five scanning positions. Also, R^2 value of 0.46 and RMSE of 3.68m was achieved for the automatically measured tree height from the four scanning positions.

The main challenge in the automatic tree height measurement were the intermingled nature of the tree crown. Some of the trees were overestimated due to the overlapping nature of the crown particularly the small trees. Thus during segmentation of the point cloud the small trees which are under the canopy of the big trees were included into the canopy of the big trees. Therefore the height of the small trees become overestimated.

5.5. Aboveground biomass

The above ground biomass of each individual tree was derived from those parameters which extracted from TLS with five and four scanning positions. The variables needed for the allometric equation were derived from the TLS point cloud data. In this study, the biomass was calculated for individual trees derived manually and automatically from TLS with four and five scanning positions.

The aboveground biomass then calculated with allometric equation developed by Chave et al., (2005) which needs height, DBH and wood density as input parameters. In this study, the wood density value of

0.570g/m^3 which is specific for the tropical tree species of Asia (REDD, 2012) was used rather than the individual wood density since the aim of the study was to assess the effect of scanning position on forest inventory parameters. The aboveground biomass was calculated for 273 and 283 trees which were manually derived from the four and five scanning positions respectively. Simultaneously, the aboveground biomass also calculated for 247 and 256 trees which were automatically derived from the TLS data with four and five scanning positions respectively. Respectively, the total amount of above ground biomass from the four scanning position TLS data was 84.65Mg and 77.24Mg using manual and automatic extraction method. In addition, the total amount of above ground biomass calculated from TLS with five scanning positions was 101.02 Mg and 83.75 Mg using manual and automatic extraction method respectively. Table 4.18 summarized the mean, maximum, minimum and total above ground biomass for both manually and automatically extracted trees with four and five scanning positions.

From the manually measured individual trees, a total of 161 trees were selected for aboveground biomass accuracy assessment using field DBH and ALS height. The trees selected for the accuracy assessment were those tree which matched with the trees derived from Airborne LiDAR height.

Therefore, in this study R^2 value of 0.96 and 0.98 and RMSE of 0.109Mg and 0.077Mg was achieved for the biomass calculated from manually derived DBH and height of individual trees from the four and five scanning position respectively. A comparable result with R^2 value of 0.93 and RMSE of was reported by (Prasad, 2015) in a study that was conducted in the tropical forest of Malaysia. Similarly, (Kankare et al., 2013) reported R^2 value of 0.90 and 0.91 with RMSE of 22.12kg and 26 kg in a study conducted in the scots pine and Norway spruce forest.

Furthermore, the significance difference on aboveground biomass extracted manually and automatically from the four and five scanning positions was evaluated. To do this, t- test was conducted between the aboveground biomass calculated from the four scanning positions with manual and automatic extraction methods as well as the biomass calculated from the manually and automatically derived parameters from the five scanning positions. In the case of four scanning position a p-value of 0.82 was obtained which is higher as compared to the critical value of 0.05. Similarly, a P value of = 0.49 was obtained for the biomass calculated from the five scanning positions using manual and automatic extraction method. As the result showed that there was no significance difference between the biomass calculated with manual and automatic extraction method in both scanning positions.

5.6. Aboveground carbon estimation

The aboveground carbon was calculated from the aboveground biomass of each individual trees derived from four and five scanning positions with manual and automatic extraction method. According to (IPCC 2007), 47% of the aboveground biomass is carbon. Thus for this study 0.47 was taken as a conversion factor which is used to estimate the total aboveground carbon. Thus the aboveground biomass calculated using four and five scanning positions was converted into aboveground carbon. Table 4.20 summarizes the mean, maximum, minimum and total aboveground carbon of trees with manually and automatically derived parameters from the four and five scanning position.

In this study the mean aboveground carbon stock for the total sample tree was 0.15 Mg for manually extracted trees and 0.147 Mg for the automatically extracted trees with four scanning positions. Similarly, the mean aboveground carbon stock was 0.17Mg and 0.15 Mg for the manually and automatically extracted individual trees from the five scanning positions.

Furthermore, a t-test was applied to check if there was a significance difference for the aboveground carbon stock calculated from the four and five scanning position with manual and automatic extraction method. The t-test result value for the four scanning position with manual extraction. The t-test value was P (T<=t) =0.80 for carbon stock derived manually and automatically from the four scanning position where as for the carbon stock calculated from the five scan position with manual and automatic measurement method showed a value of 0.49. Generally, the t- test result sowed a higher p value as compered the critical value in both cases. Thus the result indicates that there is no significance difference in the aboveground carbon stock calculated manually and automatically from the four and five scanning positions.

In this study the main focus was on the individual trees parameters to understand the influence of the number scanning position on the variation on the parameters measurement derived from TLS and the aboveground biomass and carbon stock as a whole.

5.7. Effect of scanning position on tree detection and inventory parameter derivation

Terrestrial laser scanner is a tool that can provide a full information about the characteristics of the forest structure and vegetation particularly if the scanning is takes place with multiple scanning positions (Dassot et al., 2011). For efficient and effective derivation of forest inventory parameters from the point cloud data, the number of scanning positions needs to be considered. Because it affects the detection rate of the most important inventory parameters of forest such as DBH and height. A number of approaches has been proposed for the derivation of important inventory parameters using single scan mode which is less time consuming as compared to multiple scanning positions (Aschoff & Spiecker, 2004).

On the other hand multiple scanning position can provides 3D full coverages of trees by reducing the occlusion effect of one tree over the others (Pueschel et al., 2013). In this a study, a multiple scanning approach with four and five scanning positions were selected to see how the scanning positions affect the derivation of inventory parameters and aboveground biomass

In the case of manual individual trees detection from five scanning position showed very accurate result of 99.55 % for the overall tree detection from the ten sample plot. The result is higher as compared to the four scanning positions since the overlapping of different scanning position is high to get the full coverage of the trees. However, as for the measurement of the parameters i.e. DBH and height did not show a significance difference between the five and four scanning positions. Some other studies have been conducted on the effect of scanning position on individual tree detection and inventory parameter derivation. For instance Maas et al., (2008) has done a study to validate the quality of TLS and automatic data processing schemes using single scan and multiple scanning with three scanning position setup. In this study, a high accuracy of DBH was achieved in plots scanned with three scanning positions as compared to a single scanned plot and showed that the number of scanning positon has an effect on the accuracy of inventory parameter measurement.

However, in this study increasing the number of scanning position from four to five did not show a significance difference in the measurement of height and DBH as well as on aboveground biomass and carbon stock. On the other side, even though it did not show a significance difference on the measurement of DBH and height, it has an effect on the detection of trees and quality of point cloud.

5.8. Source of errors

Terrestrial laser scanner is a tool that can be used to derive forest inventory parameters from the point cloud. DBH is one of the important forest inventory parameter that can be measured from field and derive from the TLS point cloud data. However, the accuracy of DBH measurement both in the field and TLS point cloud data is affected by different factors. Manual measurement of DBH in the field can face different sources of errors since the DBH is measured at a height of 1.3m above the ground is not always practical to mark at the specified height. Similarly, errors could be from the different measurement tools used in the field.

On the other hand, the DBH measurement from the TLS point cloud data cloud be affected by different factor which incorporate errors in the measurement of the parameter and consequently affect the overall aboveground and carbon stock estimations. Occlusion and the intermingled nature of the crown was one of the source of errors that affected extraction and measurement of height and DBH from point cloud data (Ducey & Astrup, 2013).

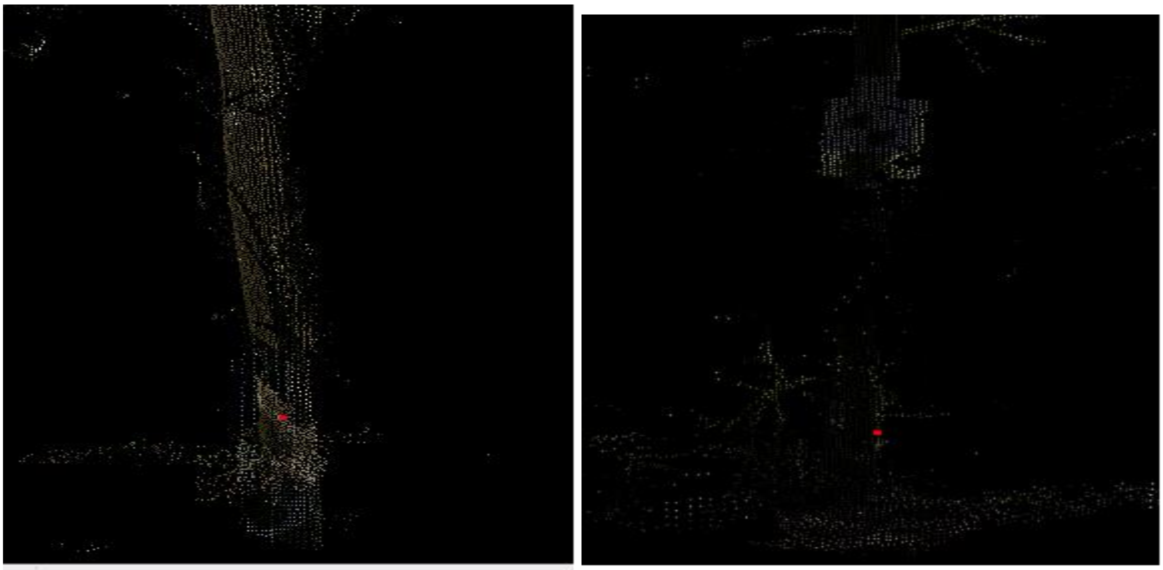


Figure 5.7: The same trees detected from the point cloud using five (left) and five (right) scanning positions

The measurement of DBH and height using manual and automatic measurement from the point cloud depends on the quality of the point cloud data. Figure 5.7 shows the same trees detected from the point cloud data using four and five scanning positions. As it is shown in (Figure 5.7) the trees detected from the four scanning positions had low point cloud due to occlusion which made it difficult to measure the DBH at a height of 1.3m above the base of the tree. Thus, this leads to error in the measurement of DBH.
Similarly, the same tree was detected from the five scanning position which had enough point cloud as compared to the four scanning positions. Thus the amount of the point cloud could lead to error in the measurement of forest inventory parameters since the measurement of DBH and height was done from one point to the other point on the point cloud on the stem of tree. The other source cloud be errors associated with the registration of the different scanning positions where all the scanning positions registered to form the 3D of the point cloud. The registration cloud be a source of error if the point cloud taken from different position couldn't overlap each other or miss matched. Individual tree detection also contains errors since the extraction is exposed to the judgment of the expertise who conduct the measurement and detection of trees.
The measurement of tree height was also associated with some sort of errors in a situation where there was overlapping of tree canopy. Maas et al., (2008) reported occlusion as one of the major challenge and source of error for tree height measurement from TLS point cloud which leads to over and underestimation of tree height. Therefore the error for the aboveground ground biomass estimation arise from all the above mentioned parameters and also from the allometric equations applied.

6. CONCLUSION AND RECOMMENDATIONS

6.1. Conclusion

Terrestrial laser scanning has the potential for the derivation of the most important forest inventory parameters for accurate forest biomass and carbon stock estimation. The data acquisition approach for the derivation of inventory parameter, however, vary which affect the quality and extraction of the parameters. The TLS data acquisition methods cloud be in a single scan or multiple scans with two or more scanning positions (Liang et al., 2016). Thus in this study, multiple scanning positions with four and five scanning positions were chosen for the derivation of inventory parameters and above ground biomass estimation. This study has emphasized on the extraction of individual tree parameters and study the effect of scanning positions on the derivation of tree parameters and the overall aboveground biomass and carbon stock estimations in the tropical forest of Ayer Hitam, Malaysia.

Assessing and quantification of the amount of aboveground biomass and carbon using TLS requires the extraction of individual trees from the point cloud data and measurement of parameter either manually or automatically. The accuracy depends on the number of trees extracted from the TLS and its measurement accuracy. Thus the accuracy of individual tree detection from TLS with four and five scanning positions was assessed with respect to the field collected data. The overall detection rate of individual trees from the ten sample plots was 97.99 and 99.55 percent for the four and five scanning positions respectively. Thus the detection rate of individual trees from TLS point cloud data with five scanning positions was very good because the overlapping of different scanning positions to capture the full coverage of the tree is very high as compared to the four scanning positions.

Similarly, the accuracy of automatically and manually extracted DBH and height from the four and five scanning positions was evaluated with respect to the field measured DBH and ALS height. The aboveground biomass and carbon stock calculated from the four and five scanning position with manual and automatic extraction method was also evaluated independently.
In general, the derivation of forest inventory parameters and its accuracy with different scanning position was analyzed and evaluated to answer the following research questions:

1. How accurately are individual trees detected manually and automatically from the point cloud data using four and five scanning positions?

The automatic and manual detection rate of individual trees were evaluated per plot with respect to field collected data. The manual detection rate was varied from plot to plot within the four scanning positions. In the four scanning positions a total of 8 trees were missed from ten sample plots. However, in the five scanning positions only two trees were missed. Thus the overall accuracy of manual detection of a tree in the five scanning positions was very accurate as compared to the four scanning positions. On the other hand, the automatic detection of individual trees was evaluated and found an overall detection rate of 91 and 93.75 percent from the total sample plot.

2. How tree parameters (DBH& height) can be detected manually and automatically from the four and five scanning positions.

The individual tree height and DBH were measured manually and automatically from the four and five scanning positions TLS data independently. A t-test analysis was done for the manually and automatically derived individual tree DBH from the four and five scanning positions separately. The t-test confirmed that there was no difference in the measurement of DBH and height using the manual and automatic method in both cases. The significance difference of height measurement from TLS data was validated by using ALS as reference point and the result indicates that there was no significance difference in height measurement for both manual and automatic extraction method from the five and four scanning positions.

Based on the statistical result, the null hypothesis which was stated that there is no difference in tree parameter (DBH, height) detection using manual and automatic extraction from the four and five scan position was accepted since the t-calculated is less than the t-critical value at 95 % confidence level.

3. How accurately can tree parameters (DBH and height) be detected manually and automatically from the four & five scanning positions compared to field measured DBH and ALS height

The study confirmed that there is no significance difference in the measurement of DBH from the four and five scanning position using manual and automatic measurement method. Field measured DBH was considered as accurate for the validation of the manually and automatically measured DBH from the four and five scanning positions. As a result, an RMSE of 1.66 (8.06%) and 1.37 (6.60%) was found between field measured DBH and manually extracted DBH from the four and five scanning positions respectively. This indicates that 91.94 % and 93.4 % of DBH was measured accurately from TLS with four and five scanning positions respectively. Similarly, the automatically extracted DBH was validated by using field measured DBH and the result showed an RMSE of 3.12 (14.57%) for the automatically derived DBH from the four scanning position and an RMSE of 2.36 (11.47%) for automatically derived DBH from the five scanning positions.

The automatically and manually measured height from the four and five scanning positions was validated using ALS height. Thus the result showed RMSE of 3.68m (19.97%) and 3.17m (17.40%) for the automatically measured tree height from the four and five scanning positions. Also, RMSE of 1.74m (9.30%) and 1.77m (9.75%) for the manually measured tree height from the five and four scanning positons respectively.

The null hypothesis was formulated by stating that there is no significance difference in the accuracy of tree parameter (DBH, height) detection using manual and automatic extraction from the four and five scan position as compared to field measured DBH and ALS height. Therefore, based on the result the null hypothesis was accepted meaning there was no difference in the accuracy of DBH and height measurement using manual and automatic measurement in both cases.

4. How much biomass/ carbon stock is estimated using TLS derived tree parameters using four and five scanning positions?

The aboveground biomass and carbon stock were calculated for the individual trees extracted from the four and five scanning position with manual and automatic extraction method. The t-test was conducted to check whether there was a significance difference in the aboveground biomass and carbon stock estimation using manual and automatic measurement method from the four and five scanning positions independently. The result revealed that there was no significance difference in the aboveground biomass and carbon stock estimation using manual and automatic measurement method in both scanning positions. The total calculated aboveground biomass using the manual and automatic measurement from the four scanning position was 84.65 Mg and 77.24 Mg respectively. Similarly, the aboveground biomass calculated from the five scanning position with manual and automatic measurement method was 101.2Mg and 83.75Mg respectively.

Concurrently, the aboveground carbon stock was calculated from the manually and automatically extracted parameters with four and five scanning positions and t-test was done to check if there was a significance difference. The result indicates that there is no significance difference between the manfully and automatically measured carbon stocks whereby the manually and automatically measured carbon was 39.78Mg and 36.31Mg respectively from the four scanning positions.

Similarly, the total carbon stock measured with manual and automatically from the five scanning positions was assessed and evaluated their significance difference. The result confirmed that there is no significance difference for the total carbon stock measured with manual and automatically from the five scanning positions. The null hypothesis for this research equation was stated that there is no significance difference in the amount of biomass/ carbon stock estimated using TLS with four and five scanning positions. Therefore, based on the result the null hypothesis was accepted which means there is no significance difference in the aboveground biomass or carbon calculated from the four and five scanning positions with manual and automatic measurement.

5. How accurately aboveground biomass/carbon can be estimated using TLS with four and five scanning positions as compared to biomass calculated from field DBH and ALS height.

The aboveground biomass calculated from the manually and automatically measured parameters from the four and five scanning positions was validated with aboveground biomass calculated from field DBH and ALS height. The study found out R^2 value of 0.96 and RMSE of 0.109Mg (22.79%) from the four scanning positions whereas R^2 value of 0.98 with RMSE of 0.077Mg (15.55%) was achieve for the manually measured AGB from the five scanning positions. Similarly, R^2 value of 0.96 with RMSE of 0.05Mg and R2 of 0.98 with 0.08Mg was achieved for the manually measured AGC calculated from the four and five scanning position. In general, there was no significance difference in biomass and carbon stock estimation with manual extraction method from the four and five scanning potions.

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APPENDICES

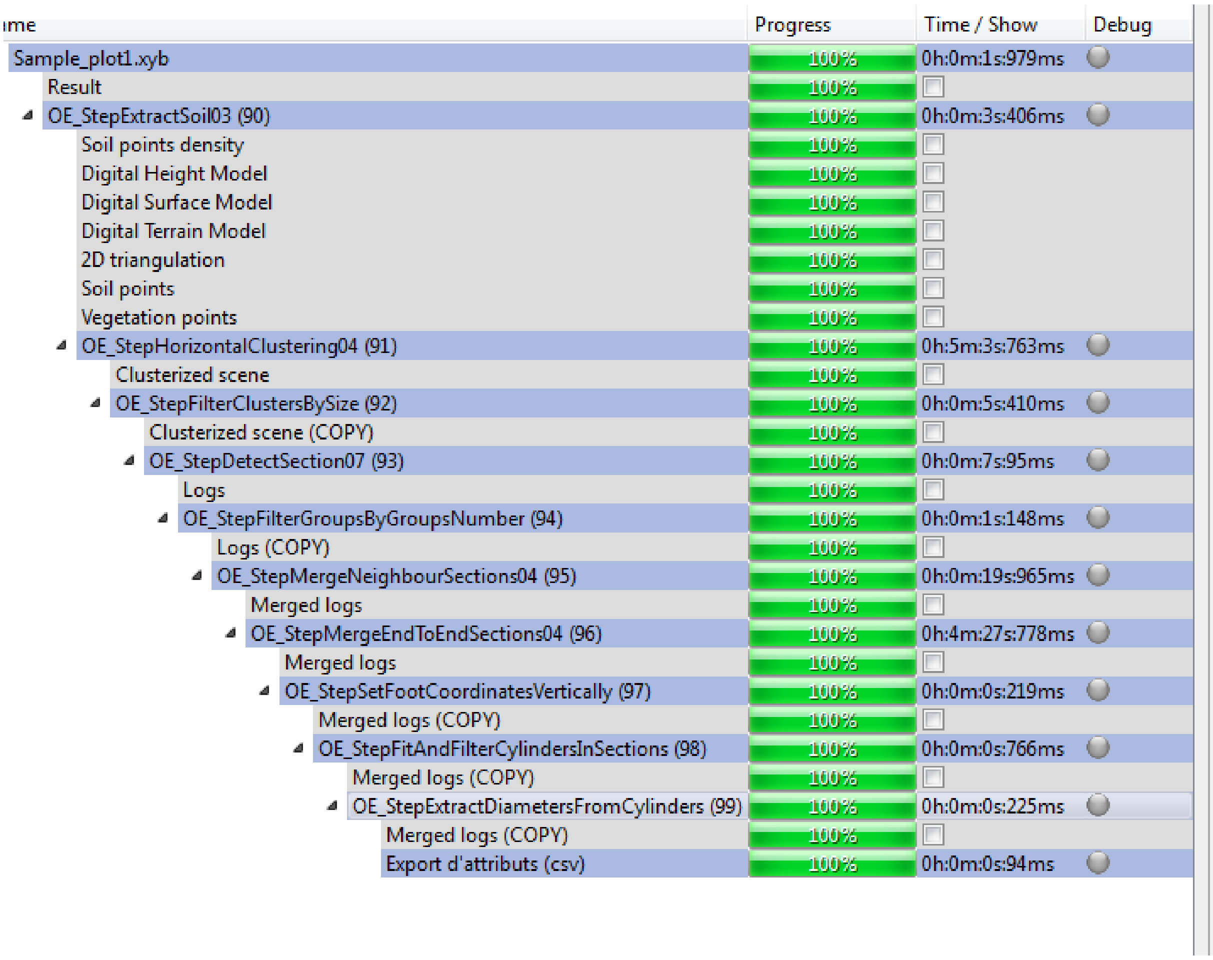
Appendix 1: Data collections sheet format

Author: Mariam		Sample: 1	Slope (%):	Plot radius: 12.6		Data: 30-09-2016	Ayer Hitam, 2016	
GPS Plot		Latitude: 3.00115	Longitude: 101.64479				Crown diam. (m)	Crown cover (%)
ID	Tree No.	Latitude	Longitude	Species	DBH (cm)	Field height (m)		

Appendix 2: Automatically extracted height and DBH

Plot no	Tree no	Automatic DBH (cm)	Automatic height	ALS height (m)
1	13	10.25	14.03	12.25
1	25	12.24	14.66	16.71
1	18	12.51	14.24	16.09
1	48	12.59	15.52	13.97
1	19	12.87	11.30	10.73
1	47	13.14	9.96	16.46
1	17	13.21	12.37	8.53
1	16	13.51	12.47	15.92
1	2	16.18	14.25	14.52
1	1	16.35	12.81	10.82
1	44	16.83	15.37	12.02
1	27	17.33	10.43	13.13
1	15	18.08	11.29	10.02
1	73	18.35	14.16	9.95
1	3	18.87	18.17	11.92
1	10	20.03	18.97	13.54
1	26	20.21	16.66	16.89
1	5	23.84	10.68	10.29
1	72	29.50	14.98	11.99
1	4	31.41	14.00	16.94
2	19	11.93	14.53	16.00
2	29	14.72	14.53	13.76

Appendix 3: Steps for automatic extraction of DBH



Appendix 4: Normal distribution of manually measured TLS DBH