THE EFFECT OF TREE DENSITY ON THE ASSESSMENT OF ABOVE GROUND BIOMASS USING TERRESTRIAL LASER SCANNER AND QUANTITATIVE STRUCTURE MODELLING IN BERKELAH TROPICAL FOREST, MALAYSIA

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FEBRUARY, 2018

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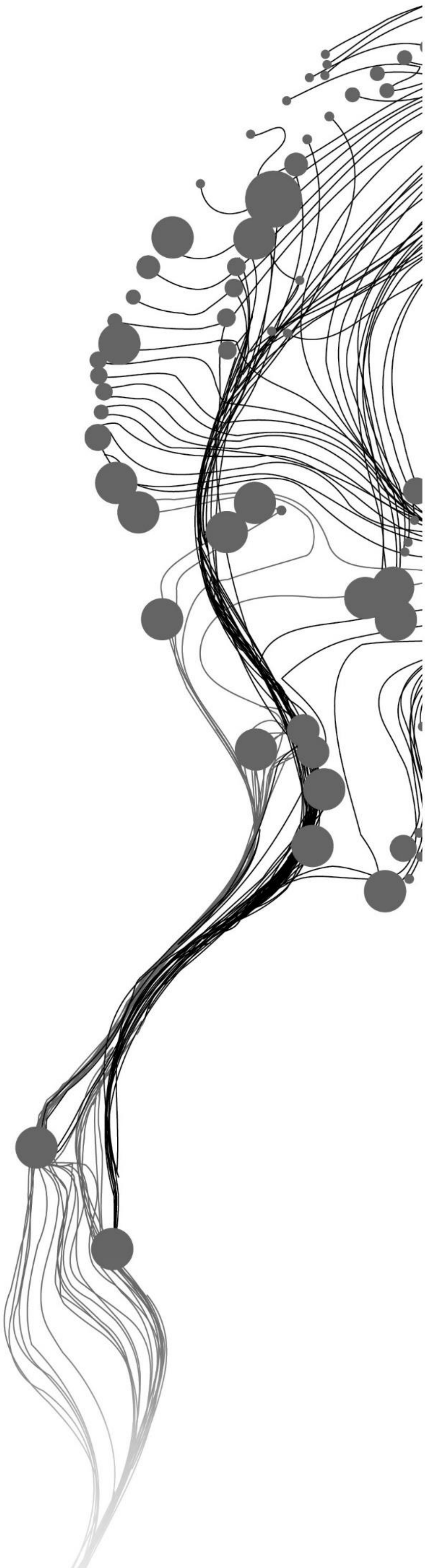

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EDWARD JUSTINE
Enschede, The Netherlands, February, 2018

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

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ABSTRACT

This research investigates the effect of tree density on estimating Above Ground Biomass (AGB) using Terrestrial Laser Scanner (TLS) and Quantitative Structure Modelling (QSM) in the tropical rainforest of Berkelah in Malaysia. A total of 32 plots with 1033 trees were measured and scanned in the field. Using a circular plot of 500 m^2, REIGLVZ 400 TLS was used in the field and all inventory parameters were collected within the circular plot. To increase information captured by TLS for the individual tree and minimize occlusion, multi scans were conducted. Pre-processing, registration of points cloud and extraction of the individual tree were done in RiSCAN PRO software. Out of 1033 trees, 855 trees were extracted from point cloud whereby Diameter at Breast Height (DBH) and height of each individual tree was measured. Based on stand basal area, tree density was classified into three categories which are low (1-20m^2/ha), medium (21-40m^2/ha) and high (41m^2/ha- and above). A total of one hundred and twelve (112) trees were selected for reconstruction of the individual tree in QSM in which 33, 37 and 42 trees are in low, medium and high tree densities respectively. AGB for each class was calculated by multiplying the volume of the tree from QSM and specific wood density. DBH and height from TLS were also used to calculate AGB using allometric equation. AGB from the field was also estimated using height from Airborne Laser Scanner (ALS) and DBH from the field. DBH measured from the field was compared with DBH derived from TLS. In different trees densities (low, medium and high) AGB derived from QSM was compared with AGB estimated from corresponding classes in both TLS and field.

The DBH measured from the field showed high agreement with DBH derived from TLS with the high coefficient determination of 0.989 and RMSE of 1.37cm. AGB estimated from the field in low, medium and high tree densities were compared with AGB estimated from QSM in low, medium and high shows high correlation of 0.911, 0.953 and 0.926 with RMSE of 31.91 Kg/tree, 31.26 Kg/tree and 60.97Kg/tree respectively. No significant difference was observed in both methods of estimating AGB from different tree densities. From three classes of tree densities, AGB was estimated from QSM and compared with AGB derived from TLS and shows high correlation coefficient of 0.896, 0.908 and 0.881 with RMSE of 41.05 Kg/tree, 57.54 Kg/tree and 71.7 Kg/tree in low, medium and high trees densities respectively. No significant difference was observed in both methods used for estimating AGB from different tree densities.

For reconstruction of the individual tree in QSM, trees with dense points from Terrestrial Laser Scanner were selected. The visible parts of the tree is reconstructed by cover with cylinders. From cylinders volume, biomass can be estimated. In this study, only trees with sufficiently points were selected hence the effect of trees densities was not observed due to the basic assumption of QSM.

Keywords: Above ground biomass, tree density/forest stand density, basal area, TLS and QSM.

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Edward Justine
Enschede, The Netherlands
February, 2018

Dedicated to my late father, Justine Lotha who has been my source of inspiration.

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EQUATION

LIST OF ACRONYMS

3D	Three Dimensions
AGB	Above Ground Biomass
ALS	Airborne Laser Scanner
CO_2	Carbon dioxide
DBH	Diameter at Breast Height
DSLR	Digital Single-Lens Reflex camera
GHG	Green Houses Gases
IPCC	Intergovernmental Panel on Climatic Change
LIDAR	Light Detection and Ranging
LULUCF	Land Use, Land-Use Change and Forestry
MRV	Measuring, Recording and Verification
QSM	Quantitative Structure Modelling
REDD	Reducing Emissions from Deforestation and Forest Degradation
RGB	Red, Green and Blue
RMSE	Root Mean Square Error
SAR	Synthetic Aperture Radar
SDI	Stand density Index
SFM	Sustainable Forest Management
TLS	Terrestrial Laser Scanner
UN	United Nation
UNFCCC	United Nations Framework Convention on Climate Change
VHRS	Very High Resolution Image

1. INTRODUCTION

1.1. Background information

Forests provide ecosystem services to human life, support plant species and harbour population of many endangered animals (Medjibe et al., 2011). Also, these forests are essential in the global carbon cycle; they store about 50% of the global terrestrial carbon (Bunker et al., 2005). It has been reported that countries like Malaysia, Indonesia and Philippines export about 80% of their forest products (timber) as a vital source of income (Berry et al., 2010). In the case of Cameroon, forestry sector contributed about 6% to the national Gross Domestic Product (GDP) in 2004 and created more than 150,000 formal and informal jobs (Gideon et al., 2014). Despite its importance when the forest is deforested carbon stored below and above are released into the atmosphere as carbon dioxide. The increase of $C0_2$ concentration in the atmosphere affects global climatic change (Soares et al., 2010).

United Nation Framework Conversion on Climate Change (UNFCCC) was established in 1992 with the aim of stabilising greenhouse gases concentration at the level that will prevent dangerous anthropogenic interference with the climate system (UN, 1992). Reducing Emissions from Deforestation and Forest Degradation (REDD+) is an example of climatic mitigation programme which aims at providing financial incentive to developing countries, sustainable forest management and enhancement of forest carbon stock (Loki et al., 2014). Biodiversity conservation, environmental quality, livelihoods of indigenous and local communities and ecological conservation are also considered in REDD+ programme (FFPRI, 2012).

Financial incentive in REDD+ programme relies on forest carbon stock change that is Measuring Recording and Verification (MRV) (FFPRI, 2012). Payments for carbon offsets under REDD+ depend on reliable and accurate estimates of carbon stock and change over time (Mauya et al., 2015). Carbon stock can be derived from above ground biomass (AGB) with the assumption that half (50%) of tree biomass is carbon (Basuki et al., 2009). Destructive/harvesting method is considered as an accurate way of estimating above ground biomass. It includes harvesting, drying until constant weight and weighting of tree parts (Gibbs et al., 2007). The method is expensive, time and resource consuming, and it is impractical in large scale (Rahman et al., 2017). Most preferred methods of estimating forest carbon stock involve field measurement and remote sensing techniques (FFPRI, 2012). Field measurements use tree parameters such as height and Diameter at Breast Height (DBH) in the allometric equation to estimate tree biomass (Brown et al., 1989; Chave et al., 2005). The method is time-consuming, labour intensive, difficult to implement especially in remote areas and cannot provide the spatial distribution of biomass in vast areas (Lu, 2006).

Remote sensing techniques supported by ground measurement can be used to estimate above-ground biomass and used as the means of MRV in REDD+ program (Defries et al., 2007). The main advantage of these techniques is that they can acquire information from areas which are difficult to access. The Airborne Laser Scanner (ALS) provides detailed information on forest structure and canopy to estimate Above Ground Biomass (AGB) (Popescu et al., 2011). In dense forest, ALS gives less information on the woody components of the trees which is useful for estimating volume, biomass and carbon (Lovell et al., 2003). Terrestrial Laser Scanner (TLS) can be used to complement

ALS since it scans the tree structure from the bottom up rather than top-down (Van der Zande et al., 2006).

TLS is a remote sensing technique that captures high-resolution three-dimension (3D) structure of the trees within a short time with less labour (Olagoke et al., 2016). TLS is collecting its data on plot based e.g. 500 square meters circular plot of radius 12.62 meters. Point clouds from TLS can be used to reconstruct accurate and precise 3D model of the tree structure (i.e. stem, branches, twigs) by the process known as Quantitative Structure Modelling (QSM). The model was first introduced by Raumonen et al. (2013). It present a tree as hierarchical collection of cylinders which provide volume and height of the whole trees and branches distribution (Krooks et al., 2014a). From the model biomass ca be calculated by multiplying the volume of the tree by specific wood density.

1.2. Problem statement and justification

Despite the fact that deforestation and human activities destroy the forest, the remain forests have high potential to assimilate and store a significant proportion of carbon (Berry et al., 2010). To benefit from the new global REDD+ initiative, carbon stock in forest needs a Monitoring, Recording and Verification system (Kenzo et al., 2009). In Sustainable Forest Management (SFM) there is a need to balance between environmental, economic, and cultural values for the benefit of present and future generations (IUCN, 2009). The estimation of above ground biomass in the forest is necessary to demonstrate the sustainability of the management regime (D'Oliveira et al., 2012). The most accurate method for the estimation of biomass is through cutting of trees and weighing of their parts (Basuki, et al., 2009). It is destructive sampling method but it has been applied in the most forests to establish allometric equation to estimate above ground biomass and validate other methods (Mohd Zaki., et al 2018). The technique takes a huge amount of resources and it is limited to large area. Remote sensing and light detection and ranging (ALS and TLS) techniques are promising methods that provide efficient means of producing highly detailed 3D data from the forest (Krooks et al., 2014a). TLS points cloud data can be modelled to provide detailed information of a tree such as branch distribution and above ground biomass by a process known as Quantitative Structure Modelling (Raumonen et al., 2015).

Amongst the methods of estimating biomass, QSM is a relatively new technique that is promising. It reconstructs a 3D model of the tree. Thus, tree volume can be obtained and used to estimate biomass. Point clouds from TLS can be used as input in QSM. Terrestrial Laser Scanner has been used in the assessment of forest stand parameters (e.g. height, DBH, canopy dimension and stem volume) due to its ability to acquire three-dimensional data of standing trees rapidly and accurately (Dassot et al., 2011). Increase in tree density and branching intensity may influence the level of information that can be captured by TLS. The quality of information derived from low, medium and high trees density is varying depending on point cloud captured in TLS. In high trees densities the quality of data captured by TLS is lower due to high number of trees stems and density canopy (Watt & Donoghue, 2005). It is also hard to get the whole structure of the tree using TLS in the high dense forest due to occlusion and intermingling of branches and surrounding trees (Dassot et al., 2011). This phenomenon reduces the number of points per tree, and therefore, only part of the tree is detected. Therefore, as Watt & Donoghue, (2005) reported earlier, it can be hypothesised that in the case of low and medium tree densities level of occlusion and intermingling of branches is low hence level of information that can be captured by TLS is high. According to Watt & Donoghue, (2005) different tree densities or forest stand density can have an influence on the quality of the data captured by TLS and thus can reduce the accuracy of assessing AGB/carbon stock using TLS-QSM.

The use of TLS-QSM in estimating above ground carbon in tropical and temperate forests is relatively new. Some studies have used TLS-QSM for AGB estimation, most of which are done in temperate forests. Tilon, (2017) investigated the effect of foliage in estimating AGB using TLS-QSM in the temperate forest at Amtsvenn, Germany. On her research, she concluded that there is no significant difference between ABG derived from QSM and allometric equation in both seasons (winter and summer). This means that QSM can be an accurate technique for MRV to ascertain the sustainability of management systems. Calders et al., (2015) researched Eucalyptus Open forest in Victoria, Australia and discovered that TLS-QSM overestimates AGB by 9.68% while the allometric equation underestimates by AGB 29.8%- 36.57%. They also found that using the allometric equation to estimate biomass leads to an error which increases exponentially with increase in DBH while TLS-QSM is not affected by DBH. This reflects the fact that density may influence the use of QSM for carbon estimation. Madhibha, (2016) reported the feasibility of TLS-QSM to determine AGB in the tropical forest of Malaysia. She found that no significant different in estimating AGB using TLS and QSM. However the use of TLS-QSM in estimating above ground carbon in a tropical and temperate forest is fairly new, there is hardly any literature available on the effect of tree density on carbon estimation using TLS-QSM in a tropical forest. This research is aiming at study the effect of tree density on the accuracy estimation of ground biomass/carbon stock using TLS and QSM in Berkelah tropical forest, Malaysia.

1.3. General Objective

The main objective of this study is to assess the effect of tree density on the accuracy of estimating above ground biomass/carbon stock using TLS-QSM in Berkelah tropical forest, Malaysia.

1.3.1. Specific Objectives

1. To assess the relationship between DBH derived from TLS and the one measured in the field from different trees densities or forest stand densities.
2. To compare the accuracy of assessing AGB/carbon stock derived from TLS-QSM with AGB/carbon stock derived from TLS in different trees densities or forest stand densities.
3. To compare the accuracy of assessing AGB/carbon stock derived from TLS-QSM with AGB/carbon stock derived from field measurement in different trees densities or forest stand densities.
4. To compare the accuracy of assessing AGB/carbon stock derived from TLS with AGB/carbon stock derived from field measurement in different trees densities or forest stand densities.
5. To assess the effect of trees densities or forest stand densities on the accuracy of estimating AGB/carbon stock derived from TLS-QSM.

1.4. Research Questions

1. What is the relationship between DBH derived from TLS and the one measured in the field from different trees densities or forest stand densities?
2. How accurate is AGB/carbon stock derived from TLS-QSM compared to AGB derived from TLS in different trees densities or forest stand densities?
3. How accurate is AGB/carbon stock derived from TLS-QSM compared to AGB/carbon stock derived from field measurements approach in different trees densities or forest stand densities?

4. How accurate is AGB/carbon stock derived from the field compared to AGB/carbon stock derived from TLS approach in different trees densities or forest stand densities?
5. What is the effect of different trees densities or forest stand densities on the accuracy of estimating AGB/carbon stock using TLS-QSM?

1.5. Hypothesis

1. **H_0**: There is no significant difference between DBH derived from TLS and the one measured in the field from different trees densities or forest stand densities.
   H_1: There is a significant difference between DBH derived from TLS and the one measured in the field from different trees densities or forest stand densities.
2. **H_0**: There is no statistically significant difference between the accuracy of assessing AGB/carbon stock derived from TLS-QSM and AGB/carbon stock derived from TLS in different trees densities or forest stand densities.
   H_1: There is a statistically significant difference between the accuracy of assessing AGB/carbon stock derived from TLS-QSM and AGB derived from TLS in different trees densities or forest stand densities.
3. **H_0**: There is no significant difference between the accuracy of assessing AGB/carbon stock derived from TLS-QSM and AGB derived from field measurement in different trees densities or forest stand densities.
   H_1: There is a significant difference between the accuracy of assessing AGB/carbon stock derived from TLS-QSM and AGB derived from field measurement in different trees densities or forest stand densities.
4. **H_0**: There is no significant difference between the accuracy of assessing AGB/carbon stock derived from field measurement and AGB derived from TLS in different trees densities or forest stand densities.
   H_1: There is a significant difference between the accuracy of assessing AGB/carbon stock derived from field measurement and AGB derived from TLS in different trees densities or forest stand densities.
5. **H_0**: There is no significant difference between the accuracy of assessing AGB derived from TLS-QSM in different trees densities or forest stand densities.
   H_1: There is a significant difference between the accuracy of assessing AGB derived from TLS-QSM in different trees densities or forest stand densities.

2. CONCEPTS & DEFINITIONS

2.1. Biomass estimation

Biomass is defined as the mass of life or dead organic matter per unit area (Gibbs et al., 2007). According to IPCC, (2003) on good practice guidance for Land Use, Land-Use Change and Forestry (LULUCF) biomass is divided into above ground biomass (AGB) (stem, stump, branches bark, leaves and seed) and below ground biomass (BGB) (roots). Indirect and direct are methods used to estimate above ground biomass. In the direct method, trees can be harvested, dried until constant weight and weighted for estimating biomass (Gibbs et al., 2007). The method is accurate, but it is time and resource consuming and labour intensive. The direct method is not feasible in a large area and cannot be used to monitor biomass when the result is largely extrapolated (Basuki et al., 2009). Indirect methods involve sampling and the use of tree parameters such as DBH and height to estimate tree biomass. Determining the amount of forest biomass is very important for monitoring and estimating the amount of carbon that is lost or emitted during deforestation(Mauya et al., 2015). It also gives an idea of the amount of carbon sequestered and stored in the forest ecosystem (Vashum & Jayakumar, 2012). Carbon stock is assumed to be 50% of above-ground biomass (Bunker et al., 2005).

2.2. Allometric Equation

Allometric equation relates one or more easily measurable tree variables or biophysical parameters such as height and DBH to assess biomass (Forrester et al., 2017; Ketterings et al., 2001). The equation can be used to estimate biomass at large geographic footprint. Due to variation in volume and wood density of various tree species, the allometric equation is considered to be both species and geographical site-specific (Cohen et al., 2013). In the tropical forest where there are many tree species (e.g. 1ha has more than 300 different plant species or more than 50 trees species), it is difficult to come up with one specific allometric equation to estimate above ground biomass (Oliveira and Mori, 1999). Due to the presence of many species per hectare in tropical forest various allometric equations were developed for the tropical forest (Basuki, et al., 2009; Brown, 2002; Chave et al., 2005). IPCC has adopted a general allometric equation based on ecology and forest type at different levels from local to regional (Chave et al., 2005). Equation 1 shows allometric equation developed by Chave et al. (2005) which is also used in this study.

$AGB=0.0673*(\rho D^2H)^{0.976}$ ……………………………………………………………………Equation 1

AGB= Above ground biomass (kg)

D=Diameter at Breast Height (cm)
H= Height (m)
ρ= Specific wood density (g/cm^3)

2.3. Quantitative Structure Modelling

QSM is a comprehensive model used for the reconstruction of visible parts of a tree from Terrestrial Laser Scanner points cloud data. The model takes into consideration the woody structure of the tree that describes the topological (branching structure), geometric and volumetric properties of the tree quantitatively (Krooks et al., 2014a). It involves the use of different algorithms to reconstruct individual tree. Filtering is a major step in the reconstruction of the individual tree using QSM whereby some ground and understories points are removed. Reconstruction of the tree without removing outliers/points cloud which are not part of the tree cause error during reconstruction (Raumonen, 2017). Filtered points cloud are covered with small sets (cover set) corresponding to connected surface patches on the tree surface (Krooks et al., 2014a). Cover sets are small units/building blocks used to segment the point cloud into different tree components (e.g., trunk, stem, branches, sub-branches and twigs) by following the surface structure of the tree from the base to the top (Raumonen et al., 2015). Cover sets are connected to each other by neighbour relationship.

In QSM, cover sets are segmented into different tree components until the whole structure of the tree is obtained. Cylinders are fitted to each segment by the least square method, to minimise the distance between cylinders a tree is assumed to be a cylindrical object (Kaasalainen et al., 2014). Cylinders are segmented into an individual tree by following botanical rule whereby stem is first segmented (one-by-one) then the 1st order branches (one-by-one) then the 2nd order branches until all the whole tree is constructed (Raumonen et al., 2015). If there is no parent-child relationship during segmentation, it creates the gap between the cylinders (Krooks et al., 2014a). To have a good structure of the tree, the cylinders between the gaps are either extended, or new cylinder is introduced to fill in the gap (Kaasalainen et al., 2014). From the cylinders, branch size distribution, volume and branching structure can be approximated for both whole or part of the tree (Kaasalainen et al., 2014). Biomass of a tree can be estimated by multiplying the volume of the cylinders by the specific wood density (Raumonen et al., 2013). Figure 1 shows the segmented point cloud and cylinders mode.

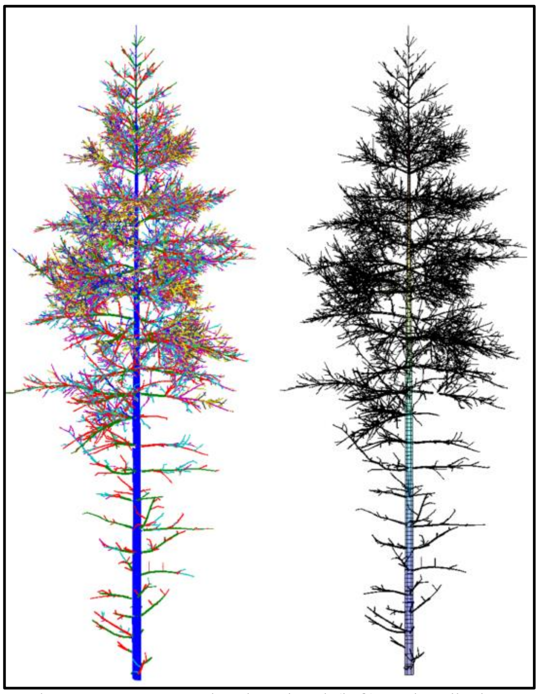

Figure 1: Segmented point cloud (left) and Cylinder model (right) of artificial Scots pine (Raumonen et al., 2013).

2.4. Terrestrial Laser Scanner (TLS)

TLS also known as ground-based LiDAR, is an active remote sensing technique which generates millions of points and represents an object into a 3-dimensional structure (Wilkes et al., 2017). It emits hundred thousand of pulses per second which travel from the transmitter to the target and back to the receiver (Dassot et al., 2011). From the points cloud tree parameters such as DBH and height can be derived. It is also possible to mount digital single-lens reflex cameras (DSLR) whereby the image from the camera can be used to assign the real value (RGB) to the point clouds (Wilkes et al., 2017). Figure 2 indicates the TLS equipment and its specification that was used in this study.

Technical specification (RIEGL VZ-400)	
Laser Wavelength (nm)	1550
Min. Range (m)	0.5
Max. Range (m)	600
Horizontal field of view	0-360deg
Vertical field of view	100 (30-130
Beam divergence	0.35mra
Angular step	user define
Pattern	panorama_40
Accuracy (mm)	5

Figure 2: RIEGL VZ-400 with a camera.

Phase-shift and pulsed time-of-flight are two main techniques used for the range measurement in current laser scanner system (Liang et al., 2016). In the phase shift, distance is measured by analysing the shift between the emitted and received laser wave. It is characterised by wide-field view, high accuracy, high acquisition rate, medium measurement range and recording only one discrete return per direction (Dassot et al., 2012). In time-of-flight distance are measured by analysing the time between emission and reception of a laser pulse. It is characterised by a narrow field of view, lower accuracy, lower acquisition rates and long measurement ranges (Dassot et al., 2011). In this study, RIEGL VZ-400 TLS measurement was performed by phase-shift techniques. TLS mounted on the tripod (Figure 3) and rotated 360^0 with the configurable setting to allow good description of points cloud and reduce scanning time.

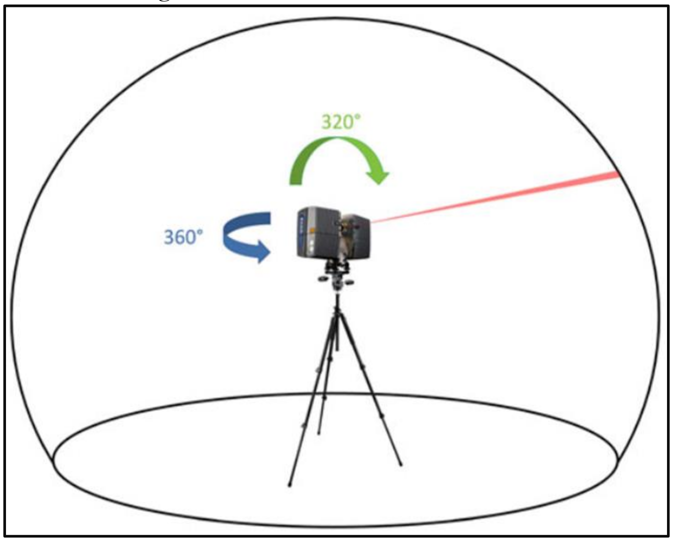

Figure 3: Operation principle of TLS (source: Dassot et al. 2011).

TLS measurements on sample plots can either be single or a multi-scans. In a single scan method, the laser scanner is positioned in the centre of sample plot and objects are scanned once. In the multi-scans approach, several scans are made inside and outside of the plot (Dassot et al., 2011) as shown in Figure 4. The single scan is a simple and quick approach. However, one part or one side of the object will be scanned while the others are missing (Bienert et al., 2006). Multiple scans are time consuming but describe the detailed 3D structure of an object hence it is the most accurate approach to map all trees in one sample plot (Dassot et al., 2011). In this study, multiple scans (4 scans) was used.

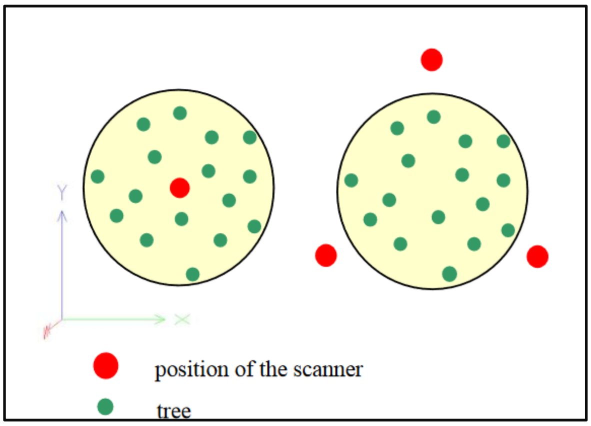

Figure 4: Single and multiple scan mode (source: Bienert et al., 2006).

2.5. Tree density or Forest Stand Density

For the purpose of this research tree density or forest stand density has to be clearly defined. In general, density is a measure of how compact the mass of materials is in a volume. However, a tree density or called forest stand density is a measure of tree cover on an area, that is amount of the tree material per unit area or space (Brack Cris, 1999). Tree density/forest stand density is the fuction of number of trees, tree size (stem, crown & root) and spatial distribution of tree on the ground (Brack Cris, 1999). According to Ginrich, (1967) it may also be defined as the degree of crowding of the stems within the area, using various growing space ratios based on crown length or diameter, tree height or diameter, and spacing. Stand Density Index (SDI) is usually well correlated with stand volume and growth, and several variable-density yield tables have been created using it. Basal area, however, is usually a satisfactory measure of SDI and because it is easier to calculate it is usually preferred over SDI (Avery & Burkhart, 2002). The number of trees in a defined area may be a satisfactory index of density if trees size is uniform, that is if the trees are in even-age stand (figure 5), e.g. having similar DBH and height. However, in a case of the natural forest such as tropical rain forest, variation in age, DBH and height will be very high. Therefore, the only measure that can be used in such a case in basal area per unit area (e.g. ha) as a measure of trees density or forest stand density (Elledge & Barlow, 2012; Fastie, 2010; Ginrich, 1967; Moss, 2005; Nix, 2017; Sagar, S.A, & Singh, 2003). Basal area is cross-sectional area of a single tree at breast height (Slik et al., 2010). It is measured at 1.3m height and expressed in m^2/plot or m^2/hectare.

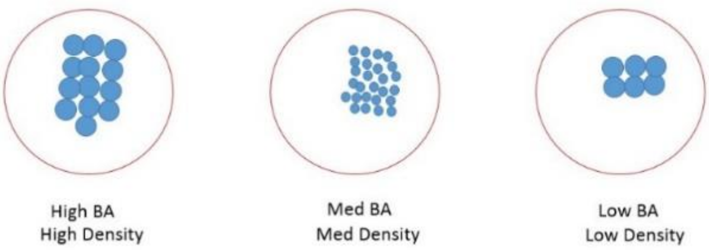

Figure 5: Relationship between basal area and trees density in even-even age forest.

3. MATERIALS AND METHODS

3.1. Study area

Berkelah Forest Reserve is located in Jengka central state of Pahang region. It lies between latitude 3°46'1"N and longitude 103°1'1"E, about 234 km to the north-east of Kuala Lumpur (Zakaria, 2013). The forest is located 218 km to the North-east of Forest Research Institute of Malaysia (FRIM) (Sulaiman, 1997). It is dominated by dipterocarp (lowland and upper hill dipterocarp) and mangrove. The forest is structured into logged and primary forest (Zakaria, 2013). Logging is allowed every 30 years and only eight trees per hectare of commercial timber species with the DBH of > or = 50 cm are allowed to be harvested (Zakaria, 2013). The forest is also dominated by a high percentage of species of the red Meranti group of *Shorea* (Sulaiman, 1997). Figure 6 shows the study area location map.

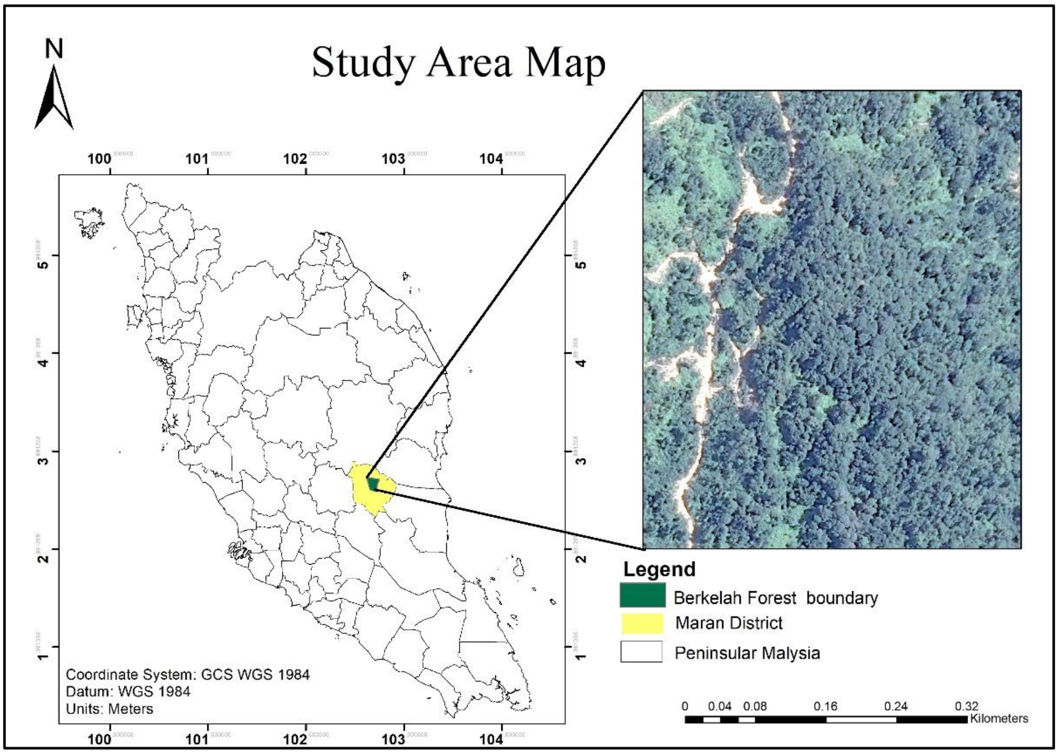

Figure 6: Study area map.

3.1.1. Climate and Topography

The maximum and minimum monthly temperatures are 30^0C and 20^0C respectively with an average temperature of 23^0C. The relative annual rainfall is 1132mm while the altitude ranges between 204 m and 236 m with a gentle slope (Sulaiman, 1997).

3.1.2. Biodiversity

Berkelah Forest Reserve is the habitat of many different bird species such as Bulbul, Yellow-bellied, Purple-naped, Sunbird and Woodpecker, small and large mammals, and arthropods. The forest is also dominated by dipterocarp tree under family Dipterocarpaceae (Zakaria, 2013).

3.1.3. Soil

Soil profiles in Berkelah Forest Reserve can be categorised as Durian Series in the ultisols order. The texture of the soil is sandy loam soil (Sulaiman, 1997).

3.2. Materials

To meet the objectives of this research, different materials (software and hardware) were taken into consideration. The following sections present the software and hardware which were used during the whole time of this study.

3.2.1. Field equipment and data used for study

Field equipments listed in Table 1 were used during the field work for different purposes. Different field equipment such as TLS, iPAQ, GPS were prepared and tested in advance before real fieldwork.

Table 1: Field equipment used in this research.

Field Equipment	**Uses/function**
Diameter Tape	Measure the DBH of the tree
TLS (RIEGL VZ 400)	Scanning forest and point cloud acquisition
Garmin GPS	Coordinate record
Worksheet	Field data recording
Marker (chalk)	Marking trees
Pencil and eraser	Write field data
Densitometer	Measuring canopy density

3.2.2. Software

Different software packages were used in this research according to their function, as shown in Table 2.

Table 2: List of software used in this study.

Software	**Function**
MATLAB	Tree reconstruction in QSM
RiSCAN PRO v 2.4.2	Point cloud processing DBH and height measurement
SPSS and Excel	Statistical analysis
MS office 2016	Proposal writing
Arc GIS	Generate study area map

3.3. Research Method

The method used in this research comprised of mainly four (4) major steps. The first step was field data collection whereby diameter tape was used to measure the DBH of all trees with DBH greater or equal to 10cm at 1.3m height from the ground. Using height from ALS and DBH from the field, biomass was estimated in different tree densities. In the second stage, TLS was used to scans (multiple scans) all plots and generate the points cloud. Points cloud from TLS were processed in RiSCAN PRO software whereby individual trees were extracted manually. The height and DBH of an individual tree from TLS were measured and used to estimate the AGB from different tree densities. Allometric equation from Chave et al. (2005) was used to estimate biomass from field and

TLS. The third stage included the use of points cloud from TLS in QSM to estimate biomass of individual tree together with specific wood density. The fourth part of the study was to compare above ground biomass derived from QSM, and that derived from TLS in different tree densities while the above ground biomass from the field was taken as reference/truth biomass. Figure 7 shows the detailed flow-chart of the method.

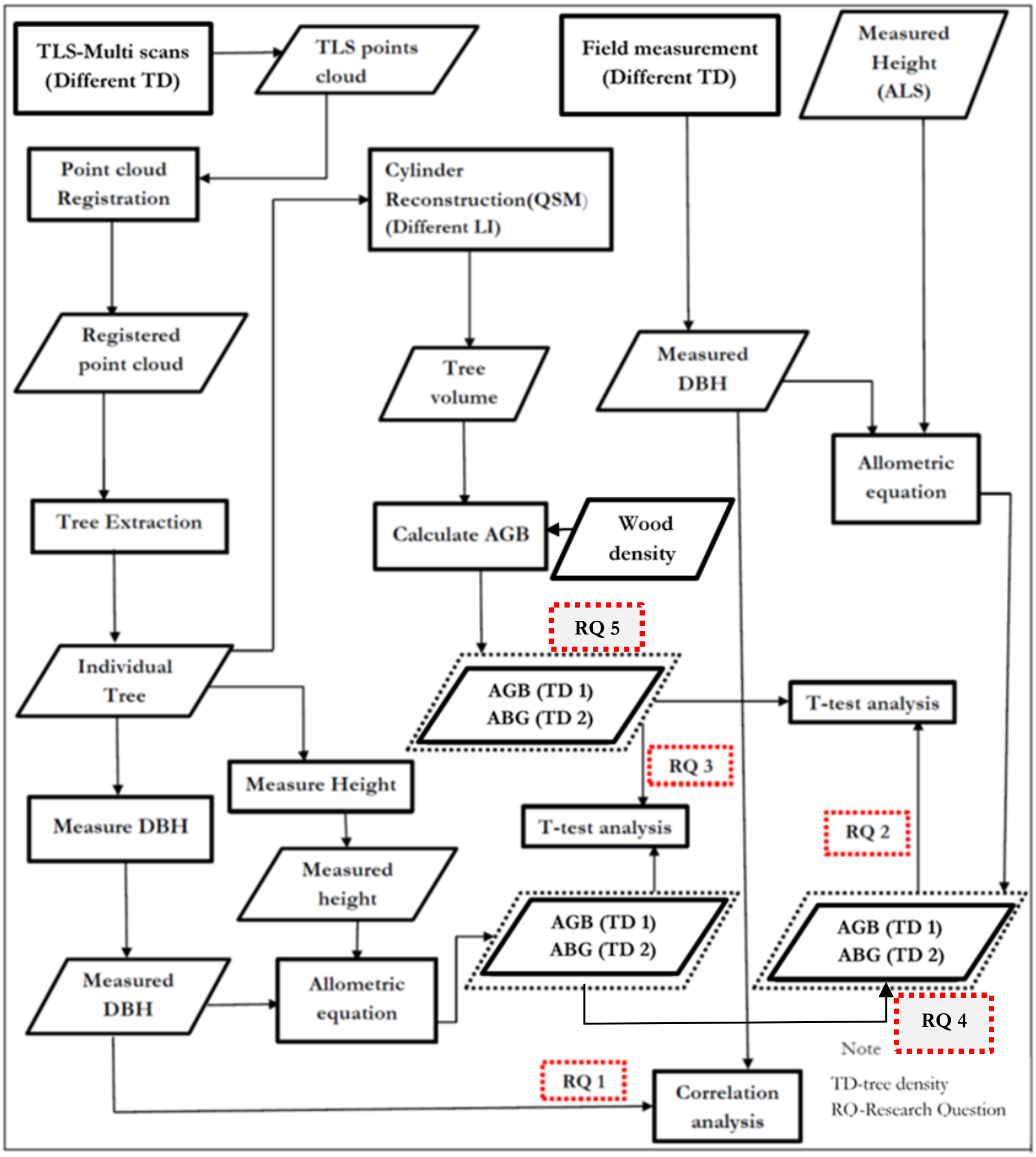

Figure 7: Flowchart showing the methods used in the study.

3.4. Pre-fieldwork

Several activities were carried out before going to the field. These are: preparing tale sheets (Appendix 1), collect and test different instruments to be used in the field such as TLS and understand how its work, prepare study area map and upload into iPAQ and generate same grid map and sampling units.

3.5. Plot size

Circular plots of a radius of 12.62 m were used as the sampling unit. In each plot DBH, forest canopy and tree coordinates were measured and recorded. According to Ruiz et al. (2014) plot area of 500-

600 m^2 is commonly used for estimation of biomass, volume and basal area. In this study, plot size was 500 m^2 and the trees which have a DBH of greater or equal to 10 cm were measured. The trees with DBH below 10 cm were not measured because contribution to biomass is insignificant (Brown, 2002). In this study, the circular plots were used because they have one dimension (radius) that defines plot boundary and minimises plot boundary effect due to its smaller circumference (Mauya et al., 2015). Furthermore, in the circular plot, the single coordinate is needed which is the centre of the plot to match data source geographically compared to rectangular or square plots (Mauya et al., 2015).

3.6. Sample design

Purposive sampling was used in this research. This is a non-probability sampling method where a sample is chosen from a population based on the interest of the researcher (Teddlie & Yu, 2007). By considering the terrain of Berkelah forest reserve, weight of TLS (27kg) and the time to navigate to the sampling plots is limited, purposive sampling was chosen. Sample plots which were easily accessible and have less undergrowth were selected to save time. Slashing undergrowth which might cause occlusion of the targeted trees during scanning was time consuming process.

3.7. TLS plot setup

After identifying the plot, several steps were taking place before starting scanning the plot using TLS. These steps are: plot centre identification, clearing undergrowth, tree labelling and putting retro-reflectors (cylindrical and circular) within a plot. Each step is explained in detailed in following sections.

3.7.1. Plot centre identification

After identifying the sample plot, the centre was defined based on an ocular judgment by selecting it randomly, measure the radius of 12.62 m circularly from the centre and identify other three outsider scans positions. Central positions for all 32 plots were located in such a way that there was minimum occlusion during scanning. Based on positions of outer scans (2, 3 and 4) and undergrowth plot centre was also identified. In sloppy plots levelling of TLS was the main challenge during the field work.

3.7.2. Tree tagging

During inventory process, trees which are within the radius of 12.62 m and have DBH greater than or equal to 10 cm were marked with chalk and labelled with unique A4 printed in bold black laminated paper with tree number (Figure 8). The numbers were pinned on the stems of trees and face directly to the central scan position. The main aim of tree tagging is to facilitate early identification of scanned trees in RiSCAN PRO software during data processing. It also facilitates the matching process of trees measured in the field and scanned by TLS at the same time during extraction of an individual tree.

Figure 8: Tagged trees in the sample plots.

3.7.3. Clearing of undergrowth

Berkelah forest reserve was logged thirty (30) years ago, this lead to a rapid increase of undergrowth which prevents selected trees and reflectors to be seen clearly during scanning. Undergrowth was cleared to get a clear view of trees and reflectors during scanning. It also minimises occlusion and gives a clear scan of the whole structure of the tree. Clearing of undergrowth is a time-consuming process, especially when there is a lot of shrubs hence more time is needed to scan one plot.

3.8. Terrestrial Laser Scanner data acquisition

To minimise occlusions and obtain the best information about the wood structure of the tree, multiple scans are better than single scan (Dassot et al., 2012). Using RIEGL VZ 400 multiple scans (4 scans) were implemented in this study, one from the centre and three outside the plot. Using multi-scans is more advantageous because the whole object e.g. tree can be detected and it is a more accurate approach to map the sample plot (Bienert et al., 2006). After scanning the centre position, the outer scans were set 2-3 m (Figure 9) outside the plot boundary. The outer scans positions were set at 120^0 apart from each other and retro-reflectors were placed according to setting position of TLS.

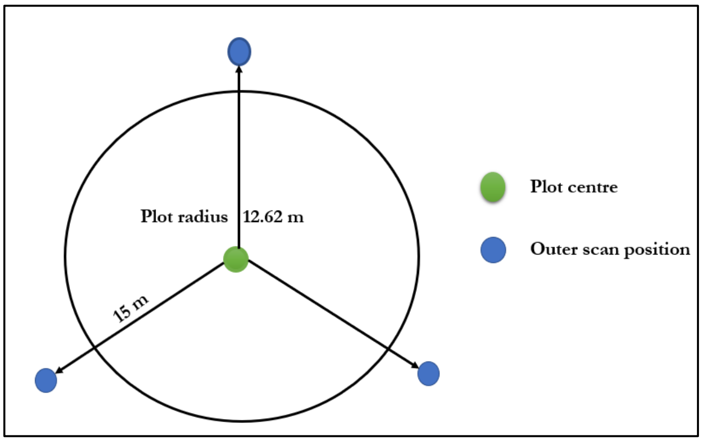

Figure 9: TLS plot scan position.

3.8.1. Setting of retro-reflector/tie point

In the case of multi-scans, it requires tie points registration to merge all scans positions in one single points cloud by geometric transformation in RiSCAN PRO software (Wilkes et al., 2017). In this study, a total of 18 retro-reflectors were used (12 cylindrical and 6 circulars) as a tie point for registration. Circular reflectors (50 mm diameter) were pinned on the stem of the tree (Figure 10 left) facing the direction of the scanner while cylindrical reflectors (height 15 cm * diameter 50 cm) were mounted on the top of the stick to be seen by the scanner in different positions (Figure 10 right). All reflectors were placed facing the scanner at the centre position in each plot so that it can be scanned. Apart from being seen from the centre it is also placed such that it can be visible from outer scans positions.

Figure 10: Circular (left) and cylindrical (right) retro-reflector used as a tie point.

3.8.2. Setting TLS and Scanning

After identifying plot centre TLS (RIEGL VZ 400) was placed on a tripod stand with the camera mounted on top. A digital camera was used to acquire high-resolution photo which was used to coloured individual points like corresponding pixels of the assigned image (Dassot et al., 2012). Tripod stand legs were set to a certain height on the ground and TLS was mounted with a camera firmly fixed by the screw at the base of TLS. To reduce row, pitch and yaw, TLS was levelled by adjusting the tripod legs until the bubble position is at the centre (Figure 11). After setup TLS position, TLS settings are used as in Table 3 to all 32 plots on this study.

Figure 11: Levelled Terrestrial Laser Scanner (source: RIEGL, 2014).

Table 3: RIEGL-VZ-400 scanner setting.

Minimum range	1.5m
Reflector diameter	0.10
Reflectance threshold	0.10
Image acquisition	ON
Reflector Search	ON
Register reflector auto	ON
Registration Mode	Reflector local
Scan Mode	Panorama 40

Before beginning scanning new project was created (Figure 12) for each plot, four scans positions were saved in one project. The camera was also set to capture images in 360^0 and to allow overlapping of images in the field.

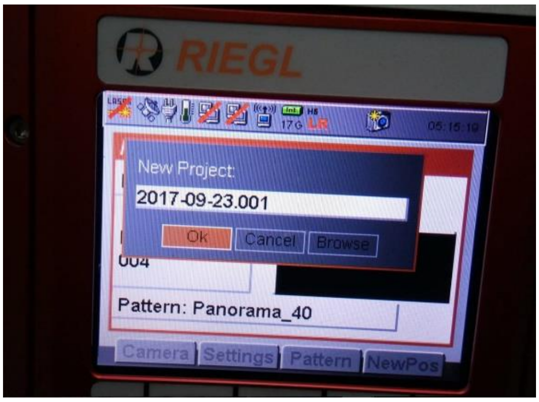

Figure 12: New project setting in the TLS.

3.9. Biometric Data After identification of the plot

Measuring of DBH, canopy density, record plot centre and tree coordinates are the main activities which were done in the field work from mid-September to 14th October 2017. Trees with DBH ≥ 10 cm and are within a boundary of sample plot were measured at the height of 1.3m from the base of the trees while trees with DBH ≤ 10cm were not recorded. This is because trees with DBH ≤ 10cm contributes less to biomass (Brown, 2002). Diameter tape, densitometer and GPS were used to measure DBH, canopy density, and record co-ordinate respectively. To maintain consistency of measuring DBH, DBH stick of 1.3m was prepared and used to define the measuring point of the DBH to all 32 plots. The DBH collected from the field was used to validate the accuracy of DBH estimated from the TLS. Both DBH from field and TLS were also used as input parameters in the allometric equation to estimate biomass. Forked trees below 1.3 m were counted as two separate trees while those trees which are forked above 1.3 m were counted as one tree. Measuring DBH of trees which have large buttresses were the main challenge during the field work. After fieldwork, DBH from the field was analysed by using Microsoft Excel and SPSS.

3.10. Point cloud data pre-processing

Point clouds are unstructured data that must be reconstructed by dedicated programmes to provide meaningful information (Dassot et al., 2011). Different software were available to process points cloud from TLS depends on the different purpose. In this research RiSCAN PRO v2.4.2 software was used to register and pre-process point cloud from RIEGL VZ 400. The following section explains pre-processing of the points cloud.

3.10.1. Scan position registration

Points cloud of each plot was downloaded from RIEGL VZ 400 and imported to RiSCAN PRO v2.4.2 for pre-processing. With “help” function in RiSCAN PRO menu, a new project was created, and all scanned files were imported using download and conversion wizard. All scans positions were automatically registered by the software. Using the tie point/reflectors, all outer scans positions were registered to the central scan position. The process of registration in RiSCAN PRO depends on the tie point/retro-reflector which is managed by Tie Point List (TPL) (RIEGL, 2014). Outer scans positions (2, 3, and 4) were registered one by one to the central position where RiSCAN PRO software automatically identified common tie point by finding corresponding points (FCP). All scans positions in RIEGL VZ 400 are in Scanner Own Coordinate System (SOCS), each scan position has its own local SOCS. Scanner Coordinate System deliver the raw data and describe coordinate of each position with respect to the centre (RIEGL, 2014). To register one project, multiple scans which have different local SOCS must be transformed into one Project Coordinate system (PRCS) which is defined by the user (RIEGL, 2014). To reduce the error during registration each scan must include at least 3 or 4 reflectors within its field of view, but the more reflectors, the better (Hilker et al., 2012). In this study, more than six reflectors per plot were detected during registration. Registration error differs from plot to plot as shown in Table 4. Registered sample plot was displayed in single scanned colour from four scanned positions as shown in Figure 13. Points cloud were selected and converted into poly-data using "poly-data selection tools" in RiSCAN PRO for individual tree extraction.

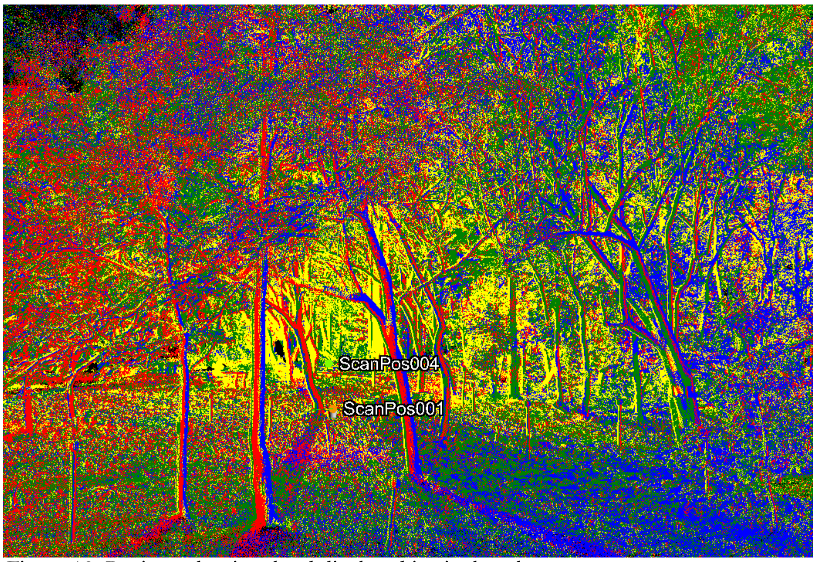

Figure 13: Registered point cloud displayed in single colour.

Table 4: Plot registration error.

Plot No.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Error	**0.0078**	**0.01**	**0.0059**	**0.0112**	**0.0081**	**0.0081**	**0.0092**	**0.0084**	**0.0107**	**0.0091**	**0.0101**	**0.0072**
Plot No.	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Error	**0.0105**	**0.0099**	**0.0084**	**0.0074**	**0.0096**	**0.0049**	**0.0158**	**0.0064**	**0.0067**	**0.0088**	**0.0086**	**0.0057**
Plot No.	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**				
Error	**0.0066**	**0.0143**	**0.0094**	**0.0083**	**0.0082**	**0.0093**	**0.0092**	**0.0075**				

3.10.2. Extraction of Individual tree

The registered points cloud of each sample plot was processed in RiSCAN PRO software and individual trees were manually extracted. Points cloud were displayed in true colour for easy identification of trees with the help of tree tags which were labelled during the field work. Using "selection tools" from the RiSCAN PRO software, individual tree points cloud was identified and separated from sample plot. All the points that associated with a single tree was delineated manually by looking at the structure of the tree. Mostly, points from the selected tree can include points from the nearest trees especially points from the canopy parts. Outlying points from the closest canopy, undergrowth and other trees were deleted until reasonable representation of the tree is obtained by making a visual inspection. Individual tree extraction is a time-consuming process, especially when the plot has many trees and undergrowth. Figure 14 shows extracted tree from the points cloud.

Figure 14: Extracted tree in true colour.

3.11. Extraction of tree parameter

DBH and height of the individual tree were measured in the RiSCAN PRO software. The following section explains how DBH and height were measured.

3.11.1. DBH measurement

Points cloud of the extracted tree was saved as poly-data using "copy selection tool" into new poly-data in RiSCAN PRO software. DBH of the tree was measured at 1.3m height from the ground using distance measuring tools in RiSCAN PRO software. For buttress trees, DBH was measured above the buttress while forked trees below 1.3 m considered as separate trees and DBH was measured independently. Figure 15 shows measurement of DBH from the point cloud.

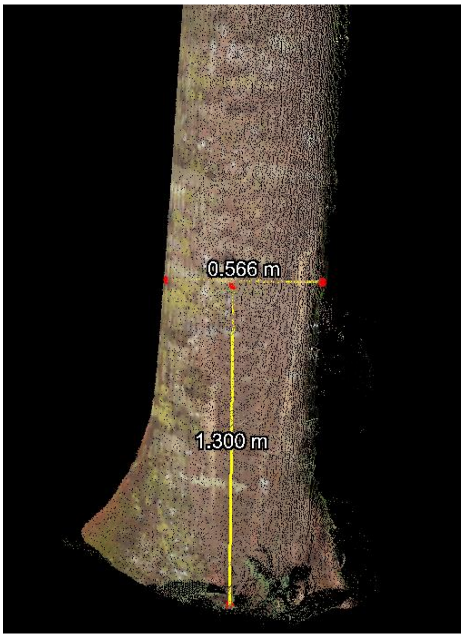

Figure 15: Measuring DBH at 1.3 m above the ground.

3.11.2. Height Measurement

Using the "measurement distance between two points" tool in RiSCAN PRO software, tree height was measured by identifying the difference between the highest points and base/lowest points (ground points) (Bienert et al., 2006). Figure 16 shows height measurement in RiSCAN PRO.

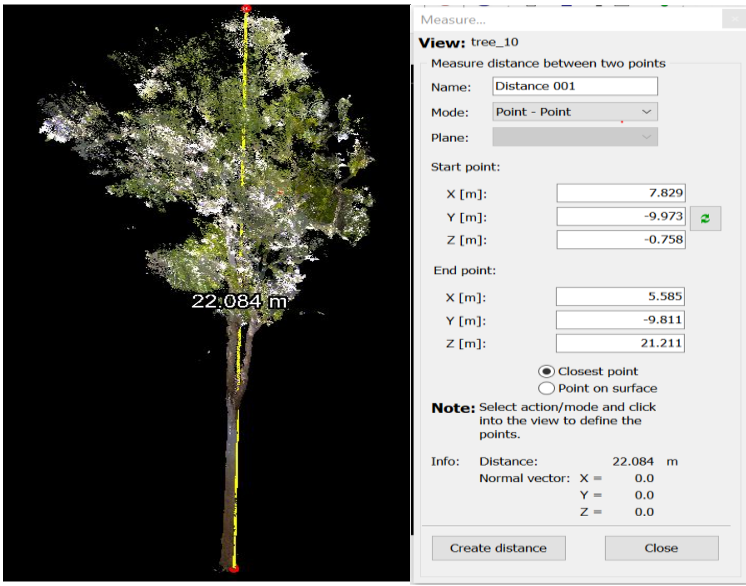

Figure 16: Tree height measurement in RiSCAN PRO.

3.12. Quantitative Structure Modelling

Points cloud of the individual tree was exported and converted into x, y, z format (ASCII text) file before running QSM in MATLAB (R2017a) software. The following steps were taken in MATLAB before getting to the structure of the tree.

3.12.1. Conversion of point cloud into ASCII

For TLS points cloud tree data to run through QSM in MATLAB, points cloud were exported and converted into x, y, z format. Using export function in RiSCAN PRO v2.4.2 software, total of 112 trees were selected and converted to ASCII text format so that can be readable in MATLAB for reconstruction of the individual tree.

3.12.2. Filtering of point cloud

In the reconstruction of the individual tree in QSM, points cloud are assumed to be part of the stem or branches, and it is used in the reconstruction process. However, not all points are used in QSM. Unwanted points which are not part of the woody structure of the tree can cause noise/error during reconstruction (Raumonen 2017). According to Akerblom, (2012) unwanted points can be caused by ground (undergrowth and a small part of the ground) and other trees (other trees can grow near to the targeted tree). To ensure good reconstruction of the individual tree in QSM, unwanted points should be filtered out before reconstruction (Figure 17 right). Filtering of points involves three main steps (Akerblom, 2012). The first step is during pre-processing of points cloud whereby points which are far away from the tree are discarded. The second step is initial filtering which does not involve the structure of the tree, but it removes a group of isolated points (noise) which have empty cover set. The third step is to remove noise that is not clear sampled of any surface but is generated by scanning process itself.

Filtering of noise in the points cloud is based on the cover set (Raumonen et al., 2013). Unwanted points are covered with small balls and reject balls which contain a small number points. (Raumonen et al., 2013). The size of the ball and the number of the points is depending on the density of points of an individual tree (Raumonen et al., 2013). The following diameters command were used in filtering based on local points cloud.

Pass=filtering(P0, r1, n1, d2, r2, n2 Scaling All points)

P0	Unfiltered point cloud
r1	Radius of the balls used in the first filtering, defines the volume
n1	Minimum number of points in the accepted balls of the first filtering, defines the point density together with r1
d2	Minimum distance between the centres of the balls in the second filtering
r2	Radius of the balls used in the second filtering
n2	Minimum number of balls in the components passing the second filtering
Optional input	default value false:
scaling	If true, the first filtering threshold "n1" is scaled along the height with average point density
All points	If true, does the first filtering process for every point

The radii and distances (r1, r2 and d2) are in the same units (meter). Filtering of cover sets is randomly generated which lead to different results for each run despite the same input parameters (Raumonen et al., 2013).

r1= smallest size of the branches to be modelled (Akerblom, 2012) (0.015m-0.02m used in this research)

d2=recommended value range from 1cm-3cm (0.01-0.03m) (Raumonen et al., 2013)

r2= r2> d2 it advised that r2 should be greater by half a centimetre or centimetre than d2 (Raumonen et al., 2013)

Scaling and Comp= 1if true or 0 if false

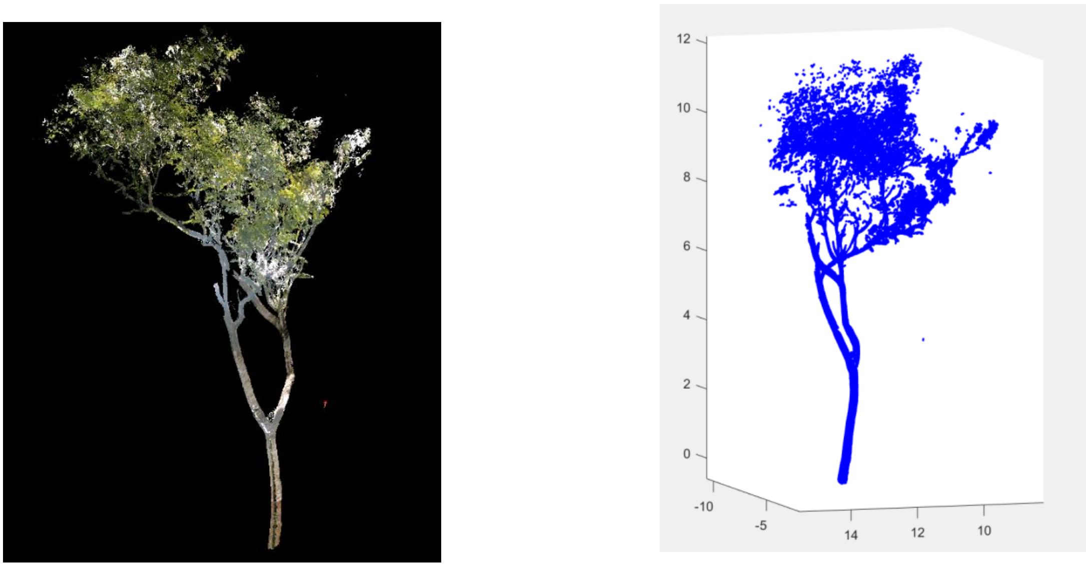

Figure 17: Extracted tree (525 174 points) left and filtered tree (401 664 point) right.

3.12.3. Optimization of input parameters in QSM

To get a reasonable structure of tree after filtering input parameters should be optimized. In QSM the tree is reconstructed using the following commands/code:

qsm_tree(P,PatchDiam1,BallRad1,nmin1,PatchDiam2Min,PatchDiam2Max,BallRad2,nmin2,lcyl,OnlyTree,Tria,string,FilRad); where

P	(Filtered) point cloud, (m_points x 3)-matrix, the rows give the coordinates of the points.
PatchDiam1	Cover set size of the first uniform-size cover.
BallRad1	Ball size used for the first cover generation.
nmin1	Minimum number of points in BallRad1-balls.
PatchDiam2Min	Minimum patch size of the cover sets in the second cover.
PatchDiam2Max	Maximum cover set size in the base of the stem in the second cover.
BallRad2	Maximum ball size used for the second cover generation.
nmin2	Minimum number of points in BallRad2-balls.
lcyl	Cylinder length/radius ratio. Can have multiple values in which case makes as many models with the same segmentation.
OnlyTree	Logical value, true if only points from the tree to be modelled, in which case defines the base of the trunk as the lowest part of the point cloud.
Tria	Logical value, if true, then make triangulation for the stem up to first branch.
string	Name string for saving output files.
FilRad	Optional input, relative radius for outlier point filtering. Can have multiple values in which case makes as many models with the same segmentation.

When PatchDiam2Min and lcyl change in the input parameters the structure of the whole QSM result also change. To get a reasonable structure of the tree, there is need to choose the accurate input parameters. PatchDiam2Min, PatchDiam2Max and lcyl are three input parameters which optimisation method depend on (Raumonen et al., 2013). The following list elaborates on how the input parameters work and how it was set to obtain the reasonable structure of the tree.

- PatchDiam1: It is large and uniform in size which ranges from 5 to 15 cm (Raumonen et al., 2015). It removes points that do not belong to the tree, makes initial segmentation for branch connection and controls average size of the cover set (Raumonen et al., 2013). The smaller the cover set, the more detailed can be captured, and smaller branches can be separated (Akerblom, 2012). However, smaller cover sets increase modelling time and use more computer memory (Raumonen et al., 2015). The value of PatchDiam1 used in this study ranges from 0.1m-0.13 m. PatchDiam1 is usually smaller than BallRad1 and BallRad2, and it's usually not very important because it has a little effect on the final result (Akerblom, 2012).
- BallRad1 and BallRad2: To ensure that cover set next to each other are neighbours, BallRad1 and BallRad2 should be greater than PatchDiam1 and PatchDiam2Max. Meanwhile, BallRad1 should be greater than BallRad2 (Raumonen et al., 2013). In this research value, 0.15m and 0.14 m were used for BallRad1 and BallRad2 respectively.
- PatchDiam2Max: This is small and variable size parameter which can be specified by the user. It controls the points at the base of the tree during reconstruction (Akerblom, 2012). In this study values, 0.08m to 0.12m were used depending on the tree to be modelled.
- PatchDiam2Min: It is also a small and variable parameter which can be controlled by the user. It controls the points from the tips of branches and stems for detail structure of the tree. The cover sets near the tips of the branches should be small to see more detailed part of the branches (Akerblom, 2012). For every branch, the value of PatchDiam2Min varies from the base to the tip and decrease quadratically at the base and faster at the tip of the branch (Raumonen et al., 2013). In this study, the value used for PatchDiam2Min ranges from 0.03m to 0.05m, and it depends on the tree to be modelled.

- Lcyl (length/radii): It controls the average relative length of the cylinder. When Lycl is shorter, branches can be reconstructed accurately but when the tree face different direction can lead to noise hence inaccurate fitting of cylinders to each other (Raumonen et al., 2013). The bigger the cylinder, the longer fitted cylinder on average. Lcyl have variable values depend on the structure of the tree. In this study, Lcyl ranges from 1.5-8 and it depends on the tree to be modelled.
- FilRad: Relative radius of outlier points cloud can be defined by the user before the least squares fitting method (Raumonen, 2017). For example, if FilRad=3.5, this means that points farther than 3.5 times estimated radius from the axis are filtered from the region (Akerblom, 2012). Depending on the noise of the points cloud and registration, FilRad can be large or small. When the data are not noisy, and registration is accurate FilRad range from 3-3.5 but when data have more noise and registration is not accurate, FilRad is low, it ranges from 1.5- 2.5 (Raumonen et al., 2013). In this study FilRad values ranges from 1.5-3.5 depending on the tree to be modelled.
- Nmin: Minimum points in a single cover set. When Nmin is small, cover set will also be small and more detailed can be captured hence smaller branches can be seen separately. Smaller value of Nmin can cause a branch to be segmented into multiple branches hence cause overestimation of branch volume and size (Raumonen et al., 2013). A large value of Nmin can combine smaller branches into one big branch, during segmentation cylinders can be too large thus cause over/underestimation of cylinders volume (Raumonen, 2017).

User interaction is required during reconstruction of the tree in QSM. Careful selection and optimisation of three input parameters (PatchDiam2Min, PatchDiam2Max and lcyl) have an influence on the structure of the tree to be obtained in QSM.

3.12.4. Main steps in reconstructing tree in QSM

The main steps of reconstruction of the individual tree from QSM are shown in Figure 18.

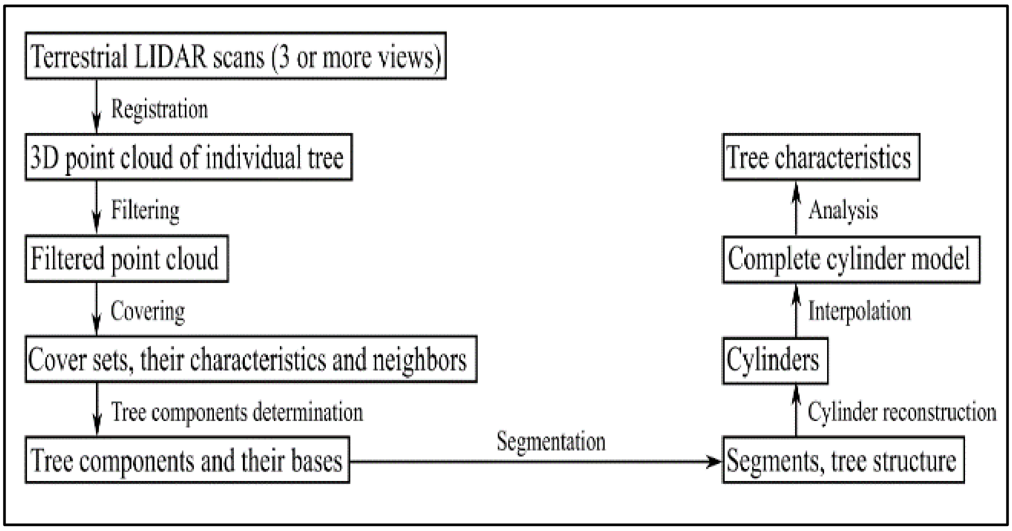

Figure 18: Main steps of reconstructing tree using QSM (Raumonen et al., 2013).

3.12.5. Cover sets, their characteristics and neighbours

Reconstruction of the tree from QSM use a cover set approach whereby points cloud are partitioned into small sets that correspond to small patches on the surface of the tree (Raumonen, 2017). Cover set is randomly generated depending on the input parameters (PatchDiam, BalllRad and nmin) and it differs from each run. The generation of cover set produces Voronoi partition of the points cloud so that the cell size (maximum diameter) is controlled and varied with PatchDiam and

PatchDiam2Max (Akerblom, 2012). Cover set is generated randomly by Voronoi partition process by selecting random seed point (example point Q) and define the ball radius (BallRad) (Raumonen, 2017). When PatchDiam is defined it prevents points from one cover set to be the centre of other cover sets (Raumonen et al., 2013). Another cover set is selected randomly by selecting a point (example point R) as a centre and define PatchDiam, BallRad and nmin. The centre of point (point R) will not be centres of other cover sets (e.g. point Q). Cover set generation continues until all points are included in some balls. Due to the intersection of the ball (BallRad), points may belong to multiple balls, but those points which are far away from the centre of the ball are assigned to the nearest ball (Akerblom, 2012).

When one BallRad of cover set intersects with another BallRad of cover sets, they form neighbour relation (Raumonen, 2017). To ensure there is neighbour relation between one cover set and another, BallRad should be little bigger than PatchDiam which controls average cover set (Raumonen et al., 2013). When the cover set is smaller in size, more detail of the tree can be captured but form more disconnected structure (Figure 19 left), and smaller branches can be seen separately (Raumonen et al., 2013). Small sets can segment a branch into multiple smaller branches if the branches are not fully covered with points cloud (Raumonen, 2017). On the other hand, when cover sets are big, smaller branches may not be separable (Figure 19 right). Thus, at the beginning of each branch, cover set may be less accurate during reconstruction, and the cylinder may be too large (Raumonen et al., 2013).

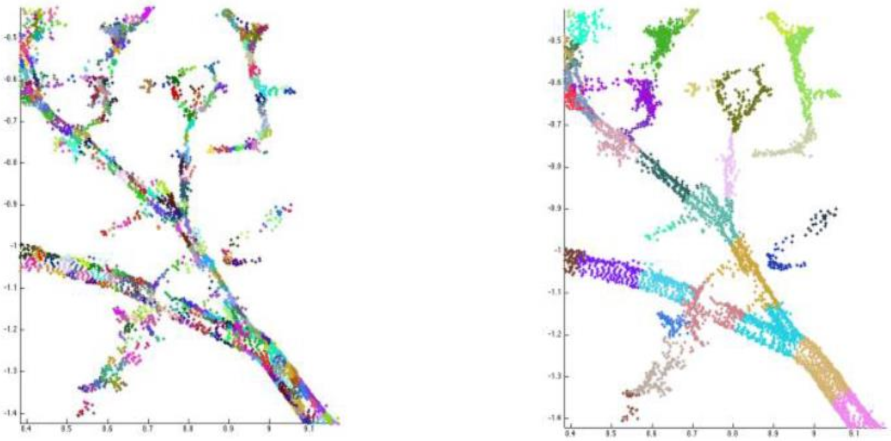

Figure 19: Minimum cover set 2 cm (left) and maximum cover set 10 cm (right) (Raumonen et al., 2013).

3.12.6. Tree components and their bases

Tree components are defined after generation of first cover sets and neighbour relation is determined. Before determining tree components, points from the ground, understories and non-tree point are removed followed by segmentation of the base of the stem by identifying neighbour relation (Raumonen et al., 2013).

Tree component is first identified by defining all cover sets that are parallel to approximation trunk direction and redefine the trunk by including neighbour cover sets (Raumonen et al., 2013). By defining the connected component of the trunk, outliers and ground points are removed and the trunk base is defined at the lowest part (Raumonen, 2017). After defining the base of the trunk, tree components is also defined from the base of the trunk. Tree components are identified by determining the connectivity with other components for segmentation process until the whole tree is reconstructed (Akerblom, 2012).

3.12.7. Segmentation

After defining tree components, the tree is segmented into stem and branches. Tree components are partitioned into segments that correspond to the whole part of the real branch or trunk (Raumonen, 2017). The process of segmentation starts at the base of the trunk and step by step proceeds along the stem. In each step in possible segmentation bifurcation is determined and define child and parent relations for each branch (Raumonen et al., 2013). In this way, stem is segmented, and branches are separated from it. After segmentation of the stem, the base of the branches is defined, and segmentation process continues while possible bifurcation is determined at branch level (Akerblom, 2012). The same process continues from the base of the branch found until all branches are defined. In this process, the stem is first determined, then the 1st order branches follow by 2nd order branches until the whole tree is segmented (Raumonen et al., 2013). Segmentation process stops when every cover set belongs to a segment. The process is relatively independent of the size of the tree, and it is based on the local topology of the tree (Raumonen et al., 2015).

3.12.8. Cylinder Reconstruction

A cylinder is fitted to the segment using the least square fitting method after segmentation (Akerblom, 2012). The average length of the cylinder is controlled by input parameter lcyl (length/radii). The bigger lcyl, the longer the fitted cylinder while the shorter lcyl, the shorter the cylinder which can be better to model the diameter of the branches (Raumonen et al., 2013). If the user defines the appropriate size of cylinders, the first cylinder is accepted and fitted to each region followed by the second cylinder until the whole tree is constructed by cylinders (Akerblom, 2012). Fitting cylinder radii of the branches differ from one branch to another particularly for thinner branches, to control this variation the radius of the child branch is always smaller than the radius of the parent branch (Akerblom, 2012).

3.12.9. Completing Cylinder model

Cylinder fitted to the segment should connect to each other continuously in the sense that there are no gaps between individual cylinders (Raumonen et al., 2013). The points cloud of the individual tree can have multiple connections to different tree components which can create gaps between the components (Akerblom, 2012). If there is a gap between cylinders, it can lead to errors in the tree statistics. To reduce the error, the model identifies the gaps between fitted cylinder by fitting the gaps using the previously fitted cylinder (Raumonen et al., 2013).

3.12.10. Tree characteristics

From the cylinders tree characteristics such as total volume, volume of the trunk, volume of the branches, height and DBH of the tree, the total number of the branches and branch order can be estimated depending on the quality of data. Above ground biomass is estimated by multiplying the volume of the tree with specific wood density. Appendix 2 shows the QSM output.

3.13. Relationship between tree density and basal area

Tree density was computed by counting number of trees per hectare or plot. It is also reflects the degree of crowding of trees within an area (Ginrich, 1967). Basal area is cross-sectional area of a single tree at breast height (Slik et al., 2010). It is measured at 1.3m height and expressed in m^2/plot or m^2/hectare. Basal area of the plot was calculated by using the formula $\pi D^2/4$ whereby $\pi = 3.14$ and D= diameter at breast height (m). In the even-aged forest, DBH and height are uniform to all trees. Therefore tree density or forest stand density can be measured by taking the number of tree per unit area since all trees have similar DBH and height (Figure 20).In even-aged forest tree density is directly related with and biomass However, in uneven-aged forest or natural forest, like Berkelah, trees are growing randomly, DBH and height are different, thus the number of trees cannot be used as a measure of density because all the trees have different DBH and Height. Biomass in uneven-age forest is not related to tree density due to the above reason. Therefore the only way to assess trees density or forest stand density is to use basal area per unit area e.g., ha (Elledge & Barlow, 2012; Fastie, 2010; Ginrich, 1967; Moss, 2005; Nix, 2017; Sagar et al., 2003). In forest management/silviculture tree density and basal area have been associated with growth rate and timber production (Slik et al., 2010). In this study, basal area was used as a measure of tree density.

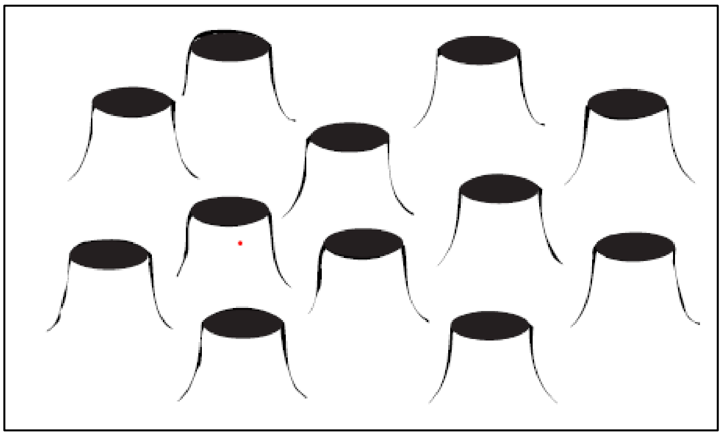

Figure 20: Stems with the same diameter in even-age forest (Source: Wiant, 2009).

4. RESULTS

4.1. Analysis of biometric field data

DBH, canopy density and tree coordinate are mainly forest biometric data which were recorded in the field. DBH is the main important parameter of the tree that provides information about the tree structure and biomass (Rahman et al., 2017). Trees which are within the plot boundary and have DBH greater or equal to 10 cm were measured at 1.3 m height from the ground. Forked trees below 1.3m were measured as two separate trees while trees which have buttress, DBH was measured above the buttress.

4.1.1. Diameter at breast height (DBH)

Mainly DBH of all trees in 32 plots were measured from the field and entered in excel sheet for analysis. Trees which were observed in the field and detected by TLS were used in this research. During the fieldwork, a total of 1033 trees which have DBH greater or equal to 10 cm were recorded. TLS was also used to scan all the plots and 855 trees were detected out of 1033 trees recorded in the field. The DBH measured from the field was used to validate DBH measured from TLS where they have a very high coefficient determination of 0.989 and RMSE of 1.37cm. Appendix 4 shows summary of the Field and TLS measured DBH.
It is clear that DBH measured in the field and DBH estimated from TLS is high correlated (Figure 26). To have good visualisation average DBH from the field and TLS was calculated and distribution of DBH was evaluated by further plotting multiple bar graph. Figure 21 shows mean DBH from Field and TLS at the plot level.

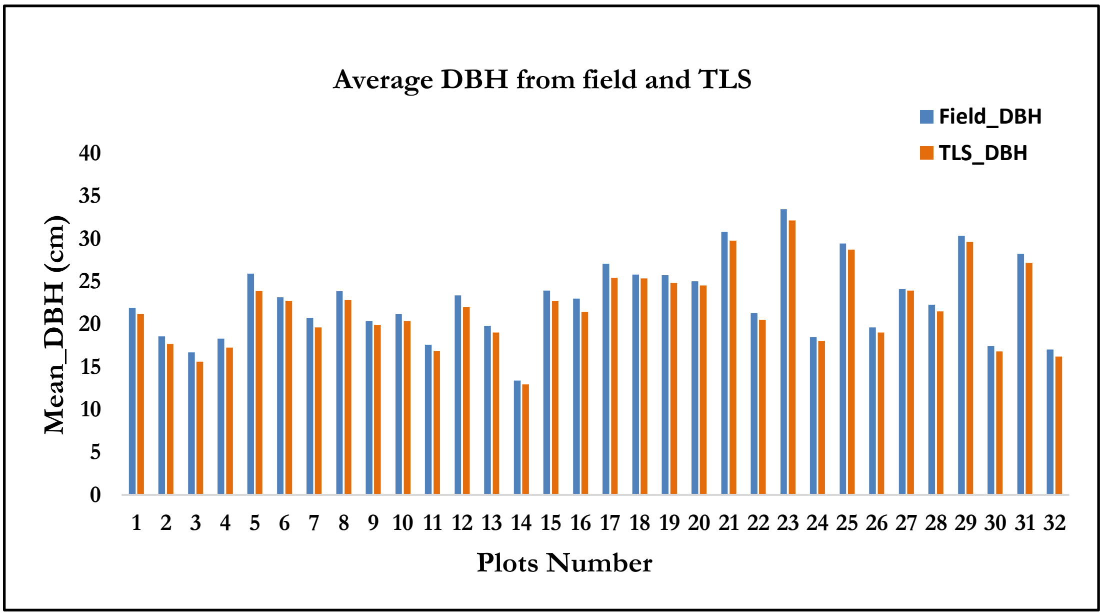

Figure 21: Distribution of mean DBH from the field and TLS.

4.2. Extraction of individual tree

Throughout the fieldwork a total of 1033 trees were measured in the field from 32 plots. Out of 1033 trees, 855 were manually extracted successfully using RiSCAN PRO software from the TLS points cloud data. From 1033 trees, 178 trees were recorded missing and this differs from plot to plot. Individual tree identification and extraction percentage from all the plots was 82.77%. Figure 22 shows number of trees measured in the field and extracted from TLS. Appendix 5 shows a total number of tree extracted, missed and their percentage per plot. Figure 23 shows example trees extracted from RiSCAN PRO software.

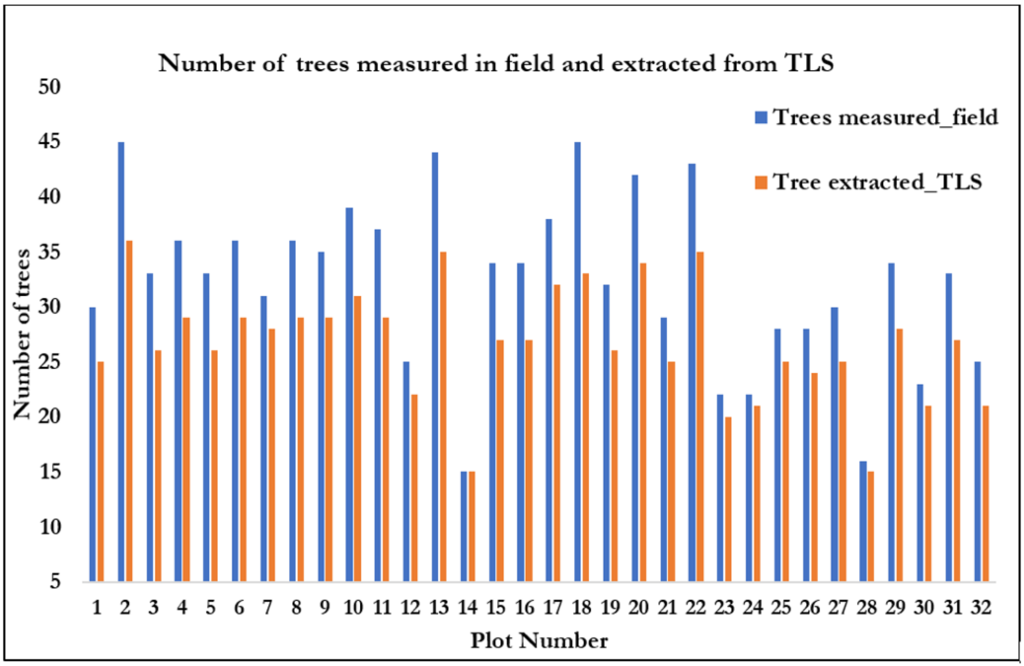

Figure 22: Number of trees measured in field and extracted from TLS.

Figure 23: Example of trees extracted in true colour.

4.3. Descriptive Statistic

DBH measured from the field, height and DBH from the TLS were analysed using SPSS. The following section describes descriptive in details.

4.4. DBH and height

Descriptive statistics were carried out in both DBH from the field and height and DBH from TLS. A mean DBH of 22.4cm (Figure 24 b) was recorded from the field while mean DBH and height from TLS were 21.7 cm (Figure. 24 a) and 12.9m (Figure 25) respectively.

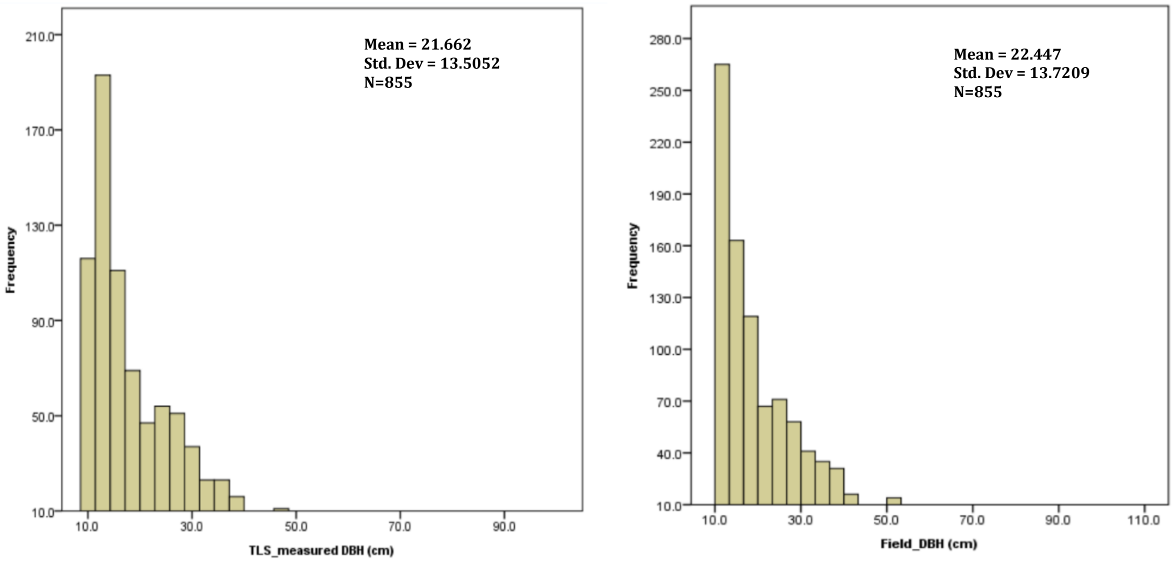

Figure 24: Distribution of DBH (a) TLS_DBH and (b) Field DBH.

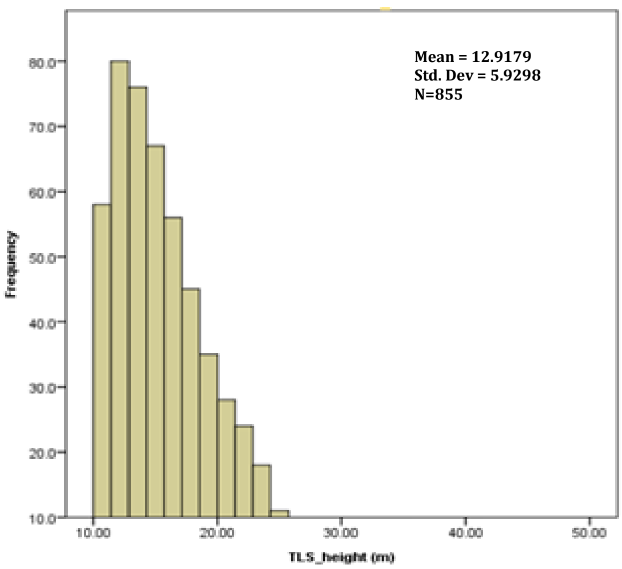

Figure 25: Height distribution from TLS.

4.5. Relationship between DBH measured from the field and DBH from TLS

During fieldwork DBH of individual trees within a plot were measured and recorded while TLS was used to scan the plot after measuring the DBH. A total of 855 trees were used to assess the relationship between DBH measured from the field against DBH derived from TLS. Field measurement DBH was used as an explanatory variable while TLS DBH was used as dependent variable. The comparison of field measured DBH against TLS derived DBH is shown in Figure 26. The linear regression shows an RMSE of 1.37cm (R^2) of 0.989.

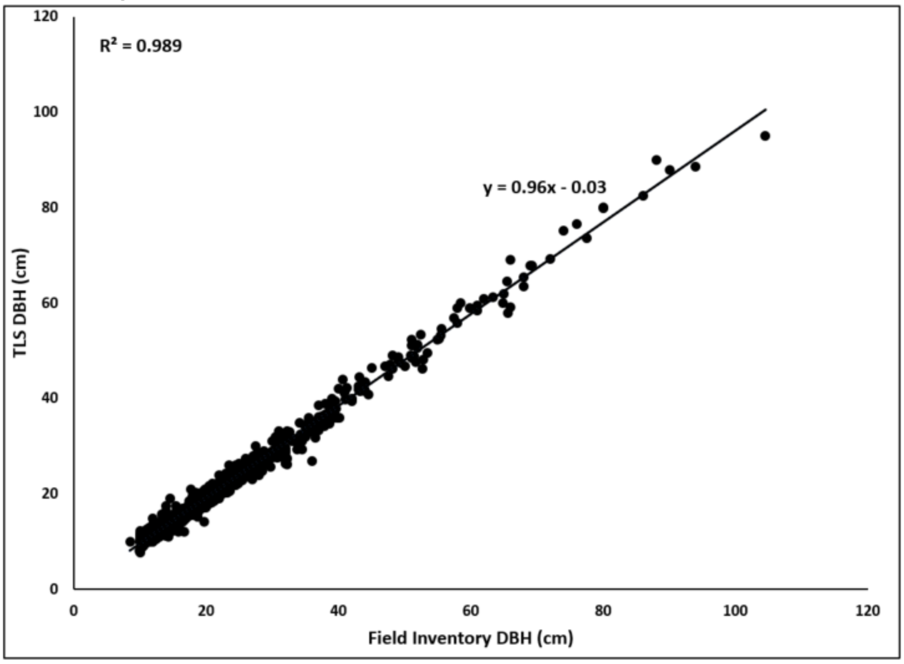

Figure 26: Comparison of Field measured DBH with TLS-derived DBH.

t-test assuming equal variance

To test if there is a significant difference between DBH measured from the field and DBH derived from TLS, a t-test of equal variance was used at 95% confidence interval (α=0.05) to test the null hypothesis. According to t-test as shown in Table 5 there is no significant difference between DBH measured from the field and DBH derived from the TLS. Hence, the null hypothesis was accepted since t statistic is less than t critical at 95% confidence interval.

Table 5: t-test of DBH from Field and TLS.

	Field _DBH (cm)	TLS _DBH (cm)
Mean	22.56	22.35
Variance	203.24	190.36
Observation	855	855
Pooled Variance	196.85	
df	1708	
T Statistic	1.24	
P(T<=t) one tail	0.11	
T critical one tail	1.65	
P(T<=t) tow tail	0.22	
T Critical two tail	1.96	

4.6. Quantitative Structure Modelling Above ground Biomass

Out of 855 trees in 32 plots which were measured in the field and detected by TLS, only 121 trees which have enough points were selected and used in quantitative structure modelling. In 121 trees, 112 trees (92.56%) show good result whereby trunk volume is greater than branch volume. Finally, 112 trees were used in estimation of above ground biomass. The remaining nine (9) trees (7.44%) which branch volume is greater than trunk volume were not used in the analysis. For the tree to be reconstructed in QSM it must have enough points and the whole tree structure must be scanned. Different input parameters were used to reconstruct a tree in QSM. Points cloud of the individual tree in RiSCAN PRO was converted to Ascii format and run 5-8 times in MATLAB software until the good structure of the tree was obtained. Each run gave different result despite the same input parameters. Example of QSM output is given in Appendix 2. QSM also gives other output as shown in Figure 27(right) and 28. Biomass per tree was obtained by multiplying total volume derived from QSM and specific wood density. In this study specific wood density of 0.57g/cm^3 adapted from Chave et al., (2005) was used to estimate above ground biomass.

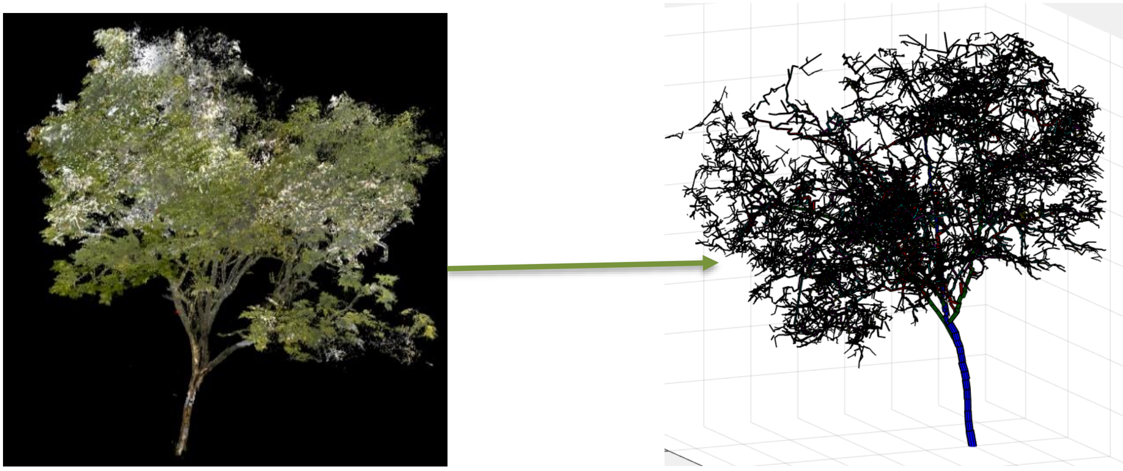

Figure 27: Modelled tree from TLS (left) and modelled tree from QSM (right).

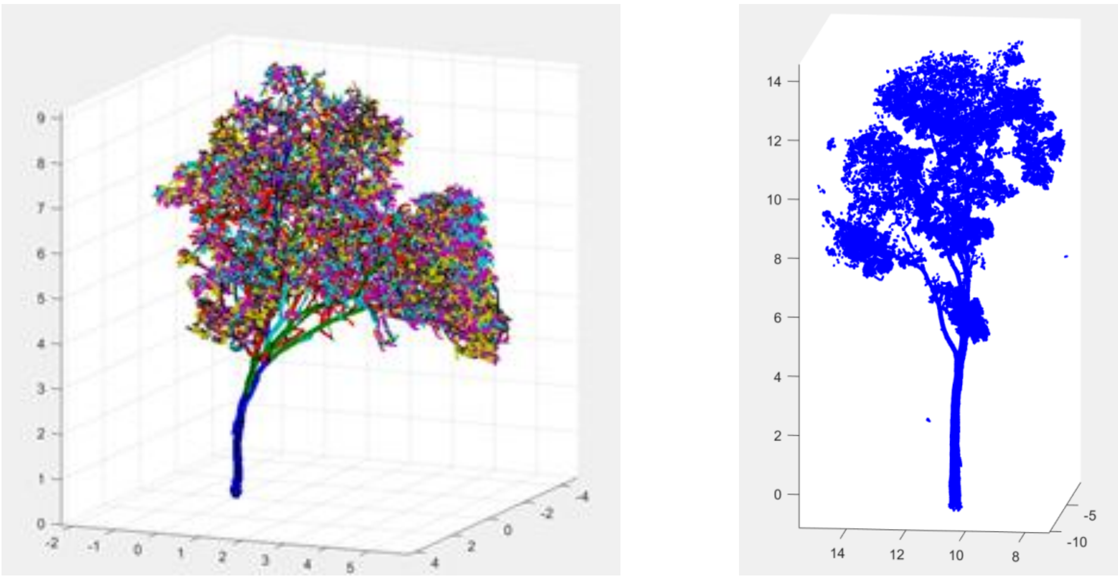

Figure 28: Segmented point cloud (left) and filtered point cloud (right) from different trees.

4.7. Above ground biomass and carbon estimation

4.7.1. Above ground biomass from the field

Based on tree DBH measured from the field and height from ALS, above ground biomass was calculated using allometric equation ($AGB = 0.0673*(\rho D^2H)^{0.976}$) from Chave et al. (2005). Above ground biomass was calculated for each tree in a plot and used as ground truth/reference to assess the accuracy of ground biomass estimated from TLS and QSM.

4.7.2. Above ground biomass estimated from TLS

The individual trees which were extracted manually, their DBH and height were measured and used in the allometric equation ($AGB = 0.0673*(\rho D^2H)^{0.976}$) from Chave et al. (2005) to estimate biomass. Out of 1033 trees measured from the fieldwork, 855 trees were detected in field and TLS points cloud. Appendix 5 shows numbers of trees lost per plot. To assess the accuracy of estimating above ground biomass from TLS, above ground biomass from field was compared against a above ground biomass derived from TLS (Figure 29) with 657 trees which were detected from both ALS and TLS.

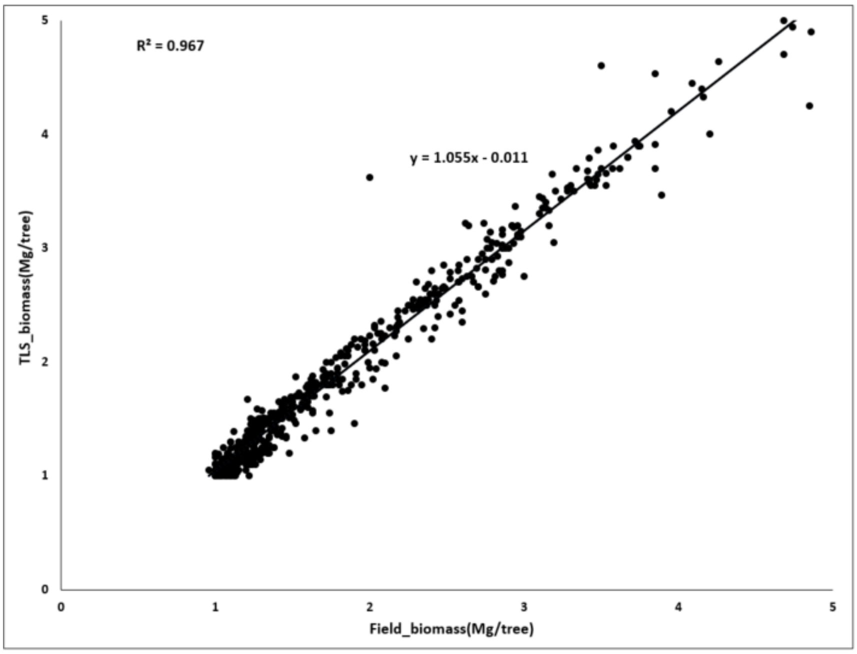

Figure 29: Comparison of AGB estimated from the field and AGB derived from TLS.

4.7.3. Above ground biomass estimated from QSM

Quantitative structure model is comprehensive tree model that depends on point cloud from TLS. Points cloud from TLS are covered, segmented into branches and stem and cylinders are fitted to each tree component until the whole tree is reconstructed. One of the outputs in QSM is the tree volume whereby above ground biomass is calculated by multiplying the volume and specific wood density (0.57g/cm3) from Chave et al. (2005). To assess the accuracy of estimating AGB from QSM, scatter plot was plotted (Figure 30) with a coefficient of determination (R^2) of 0.96 and RMSE is 45.079 Kg/tree using the data set of 112 trees.

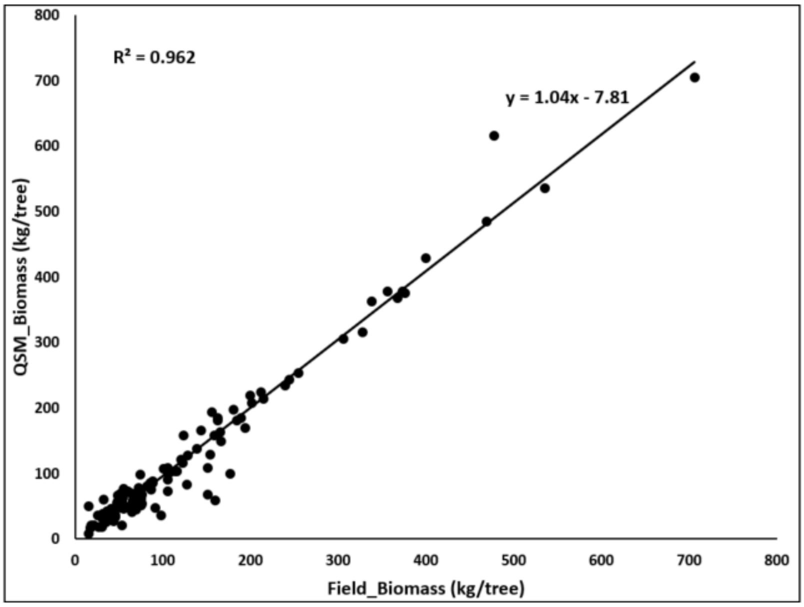

Figure 30: Relationship between ABG from field and AGB from QSM.

4.8. Relationship between AGB from TLS and QSM in different tree densities

Tree density was computed by counting number of trees per plot and compared with AGB estimated from the field. Figure 31 showed a relationship between number of trees as the measure of tree density and biomass. Tree density was found to have the poorest significant relationship with field biomass. Example if we compare tree density and basal area in figure 33, plot 3 and 29 have 33 and 34 trees respectively but there is big difference in their basal area. Due to this poor relationship basal area was used as the measure of trees density or forest stand density. Basal area of each tree was calculated and sum up per plot. Sum of the basal area of each tree in plot is called stand basal area(m^2/hectare). Stand basal area was compared with field biomass. Stand basal area shows a reasonable relationship (Figure 32) with field biomass. Based on stand basal area as a measure of trees density, basal area was classified into three main parts which are low (green), medium (orange) and high (blue) basal area as shown in Figure 33. Table 6 shows a descriptive statistic of the basal area for all 32 plots. Plots are classified according to the following:

- Low basal area range from 1-20m^2/ha,
- medium basal area range from 21-40m^2/ha
- and the high basal area is from 41m^2/ha and above

This is supported by Moss, (2005) and Schultz et al., (2005) who consider these classes. Individual tree reconstructed from QSM which fall into the above categories was classified according to low, medium and high stand basal area of trees density or forest stand density.

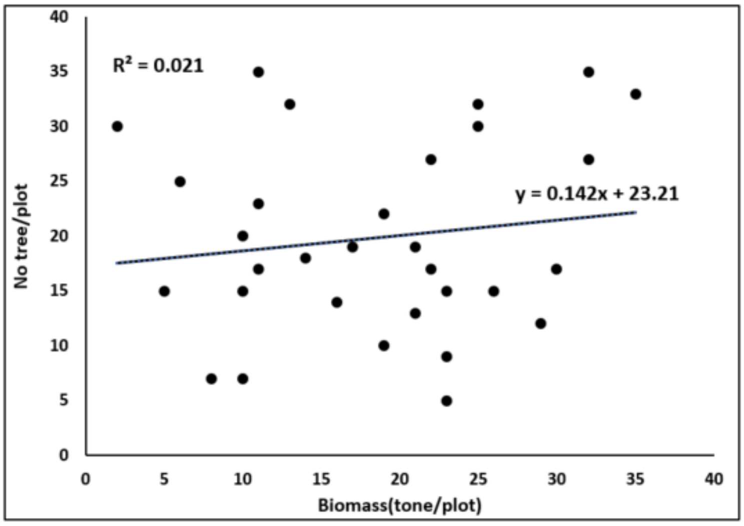

Figure 31: Scatter plot biomass and number of trees as a measure of tree density.

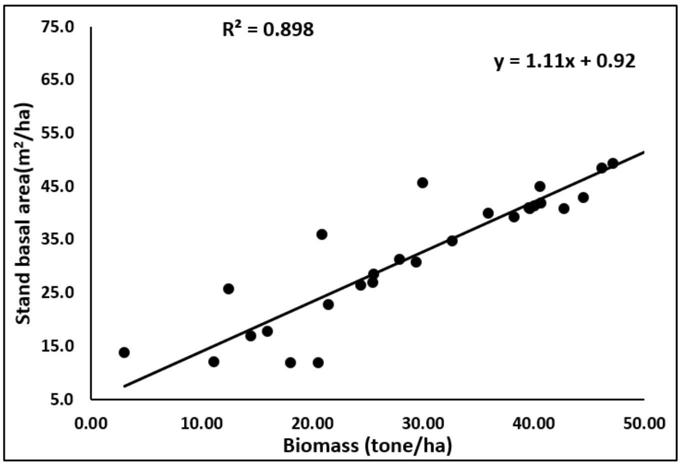

Figure 32: Scatter plot of biomass and stand basal area as the measure of tree density

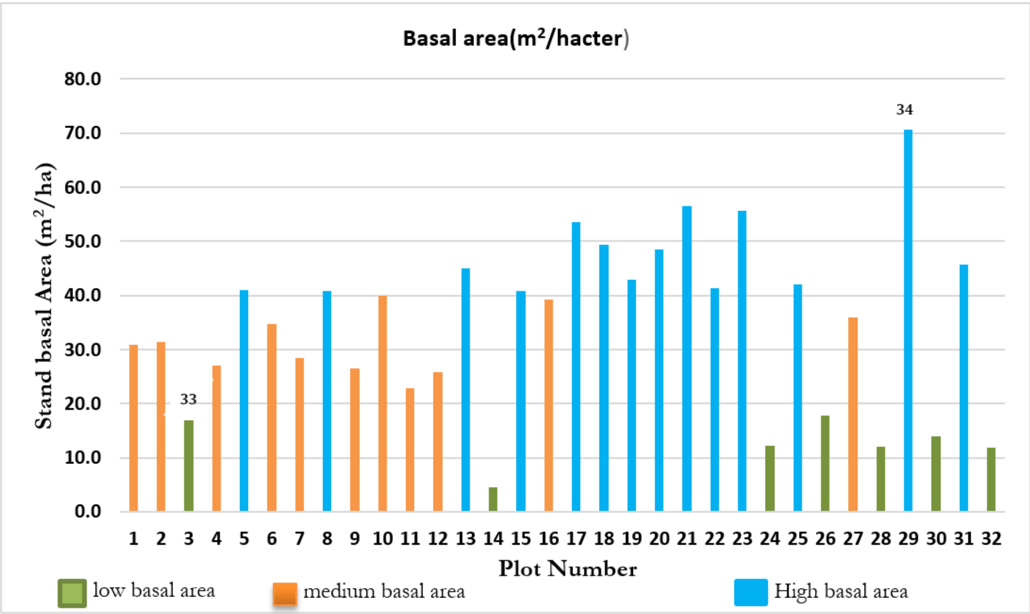

Figure 33: Classification of tree density based on stand basal area with number of tree in plot 3 & 29.

Table 6: Descriptive statistic of basal area.

Basal area (m^2/ha)	
Mean	34.53
Standard Error	2.73
Median	37.64
Standard Deviation	15.47
Sample Variance	239.60
Range	66.09
Minimum	4.45
Maximum	70.54
Sum	1105.27
Count	32

4.8.1. Relationship between AGB from TLS and QSM in different tree densities

Out of 855 trees, 112 trees (13.09%) were used in QSM for reconstruction of the individual tree. Total of, 33 trees (24.09), 37 trees (11.86%) and 43 trees (10.59%) were categorised low, medium and high tree densities respectively. In both categories corresponding height and DBH derived from TLS was used to estimate AGB using allometric equation from Chave et al. (2005). The volume of an individual tree from QSM was multiplied by specific wood density (0.57g/cm^3) to obtain the biomass. AGB derived from TLS was compared with AGB derived from QSM in both classes. Figure 34, 35 and 36 shows the relationship between AGB derived from TLS and that derived from QSM in low, medium and high tree densities respectively. The result showed coefficient of determination (R^2) are 0.896, 0.908 and 0.881 with a RMSE (Kg/tree) of 41.05, 57.54 and 71.7 in low, medium and high tree densities respectively.

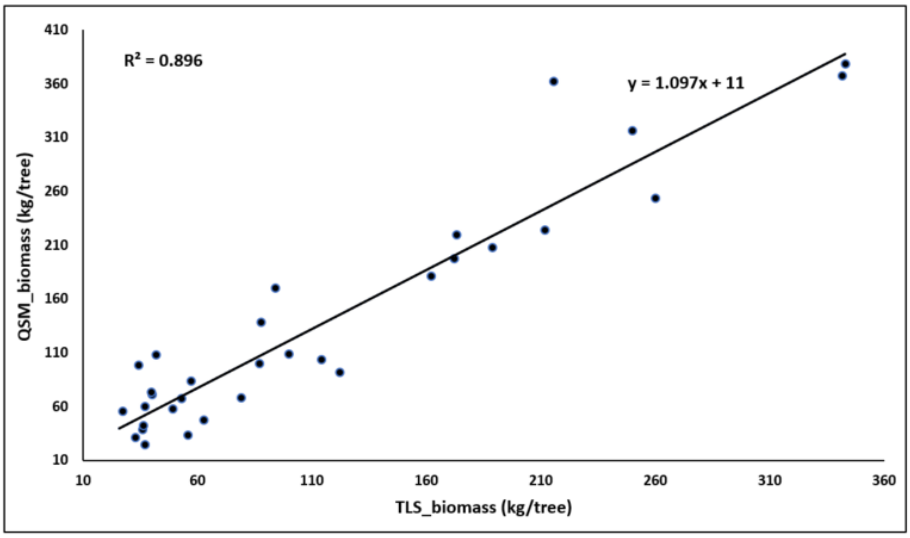

Figure 34: Scatter plot TLS_AGB and QSM_AGB in low tree density.

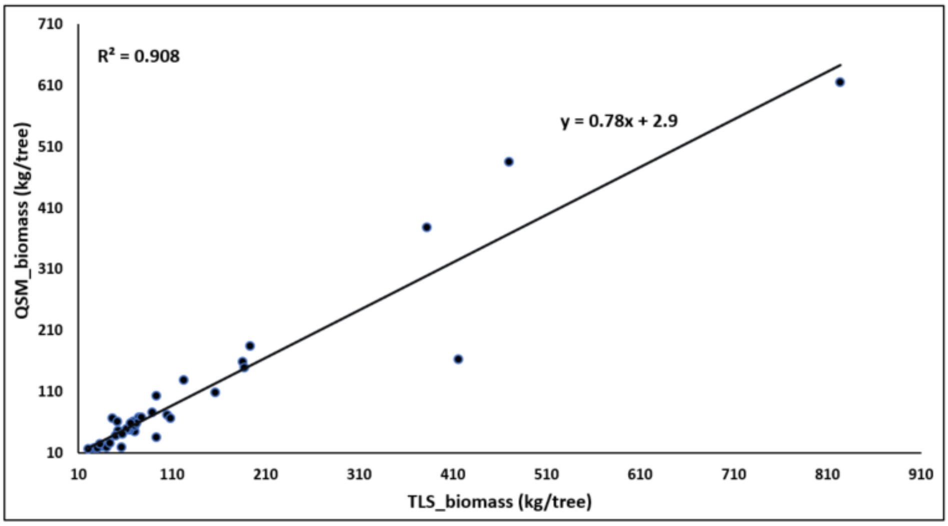

Figure 35: Scatter plot TLS_AGB and QSM_AGB in medium trees density.

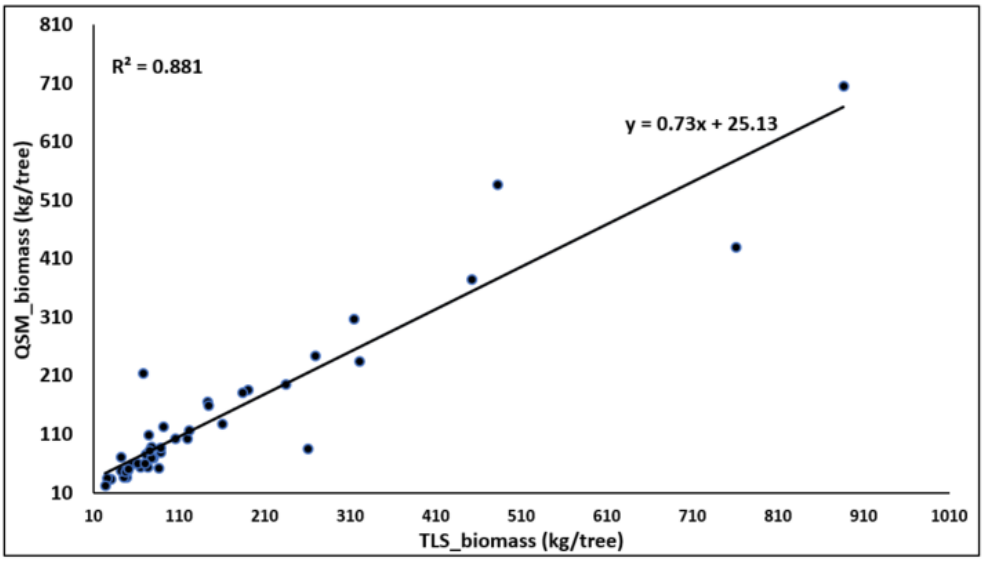

Figure 36: Scatter plot TLS_AGB and QSM_AGB in high trees density

Testing the relationship between TLS and QSM Biomass in different tree density

Furthermore, significance level between biomass derived from TLS and that estimated from QSM from different tree densities was tested. The t-test (assuming equal variance) was used to test if there is a significant difference between AGB derived from TLS and QSM. From Table 7, 8 and 9 there is no significant difference between AGB derived from TLS (α=0.05) compared to that AGB derived from QSM at low, medium and high tree densities respectively.

Table 7: t-test TLS and QSM above ground biomass at low trees density.

t-test: Two-Sample Assuming Equal Variances.

	TLS_biomass (kg/tree)	QSM_biomass (kg/tree
Mean	111.18	133.05
Variance	8350.78	11226.31
Observations	33	33
df	64	
t Stat	-0.89	
P(T<=t) one tail	0.19	
t critical one tail	1.67	
P(T<=t) tow tail	0.37	
T Critical two tail	1.99	

Table 8: t-test TLS and QSM above ground biomass at medium trees density.

t-test: Two-Sample Assuming Equal Variances.

	TLS_biomass (kg/tree)	QSM_biomass (kg/tree
Mean	125.59	133.05
Variance	24949.71	16634.33
Observations	37	37
df	72	
t Stat	0.72	
P(T<=t) one tail	0.23	
t critical one tail	1.67	
P(T<=t) tow tail	0.46	
T Critical two tail	1.99	

Table 9: t-test TLS and QSM above ground biomass at high trees density.

t-test: Two-Sample Assuming Equal Variances.

	TLS_biomass (kg/tree)	QSM_biomass (kg/tree
Mean	157.39	139.45
Variance	33854.41	20263.42
Observations	43	43
df	84	
t Stat	0.51	
P(T<=t) one tail	0.31	
t critical one tail	1.66	
P(T<=t) tow tail	0.61	
T Critical two tail	1.99	

4.9. Relationship between ABG from field and QSM in different trees densities

Height from ALS and DBH measured from the field were used as an input parameters in allometric equation developed by Chave et al. (2005) to estimate biomass from the field. Due to occlusion and intermingling of branches in the tropical forest, it is difficult to measure height directly from the field so tree height from ALS was used to estimate AGB from the field. Only trees which were detected from both TLS and ALS were used. Based on the classification (low, medium and high) of tree densities, biomass estimated from the field was assessed according to the tree density and compared with biomass from QSM.

A total of 7 plots with 129 trees which were measured from the field (DBH) and detected by both ALS and TLS was classified in low tree density. Out of 129 trees, 33 trees (25.58%) from the field were used to calculate biomass and reconstruction of an individual tree from QSM. In medium tree densities out of 213 trees, 37 trees (17.37%) were selected while in high tree density, 43 trees (7.33%) were selected out of 315 trees. The regression analysis was carried out to see the relationship between AGB estimated from field compared with AGB derived from QSM in different tree densities. Figure 37, 38 and 39 show scatter plot of the relationship between AGB derived from field and that derived from QSM in low, medium and high tree densities respectively. The result showed that the coefficient of determination (R^2) is 0.911, 0.953 and 0.926 in low medium and high respectively. Similarly, RMSE of 31.91Kg/tree, 31.26Kg/tree and 60.97Kg/tree were obtained in low, medium and high tree densities respectively.

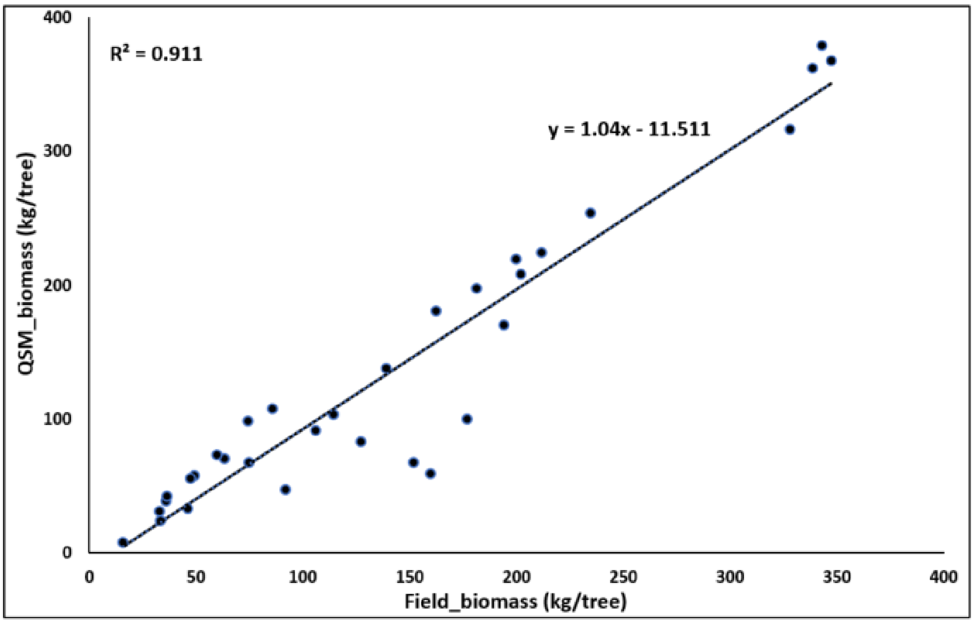

Figure 37: Scatter plot Field_AGB and QSM_AGB in low tree density.

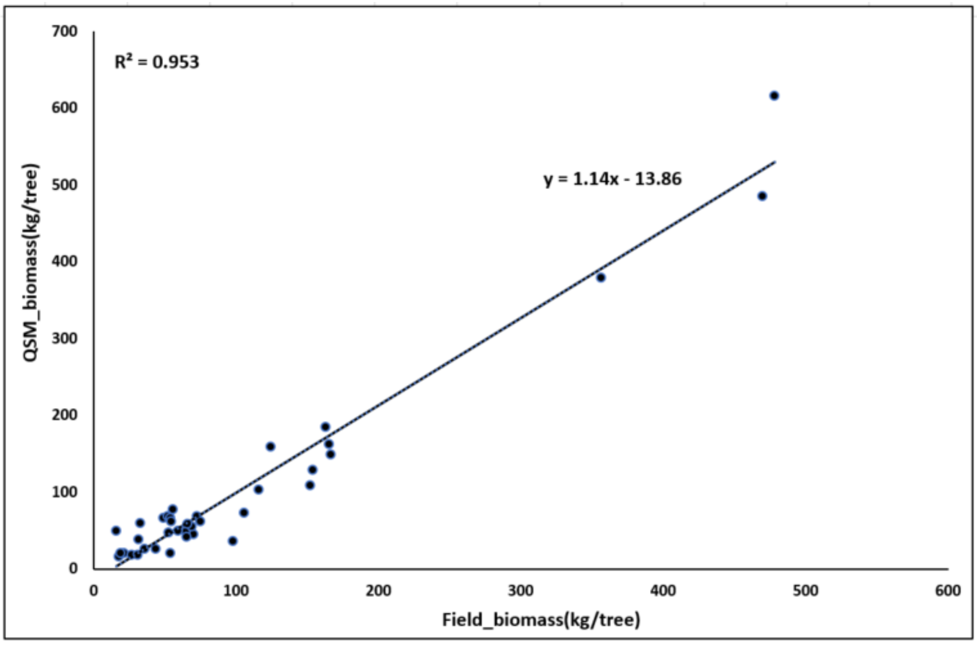

Figure 38: Scatter plot Field_AGB and QSM_AGB in medium tree density.

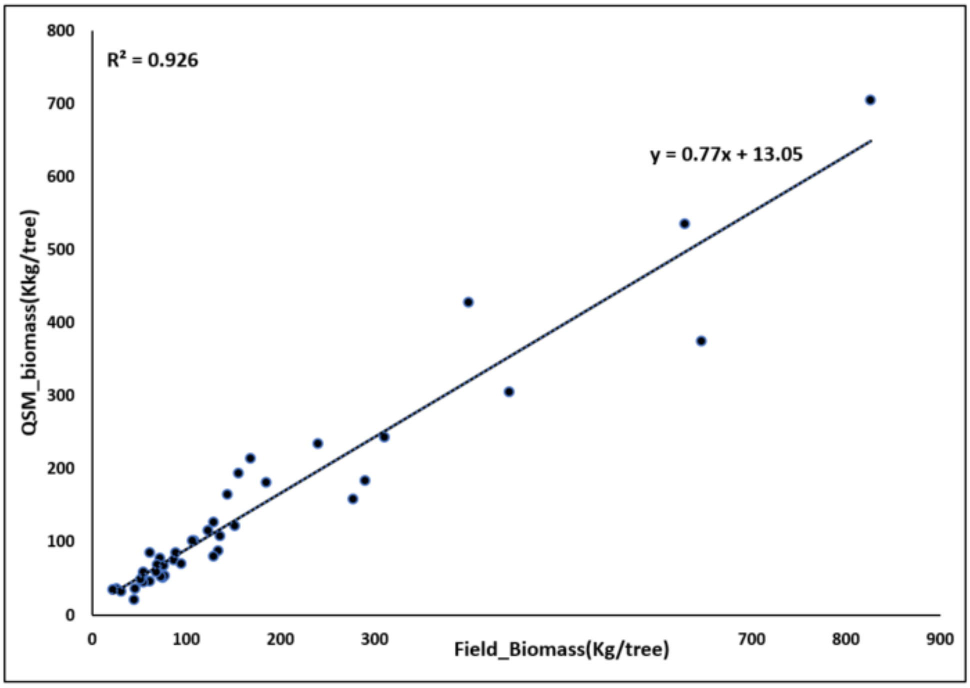

Figure 39: Scatter plot Field_AGB and QSM_AGB in high tree density.

The relationship between Above ground biomass from Field and QSM in different trees densities

A t-test (assuming equal variance) was used to test if there is a significant difference between AGB derived from field and that derived from QSM. From Table 10, 11 and 12 there is no significant difference between AGB derived from the field at 95% confidence interval (α=0.05) compared to that AGB derived from QSM in low, medium and high tree densities respectively.

Table 10: t-test field and above ground biomass at low tree density.

t-test: Two-Sample Assuming Equal Variances.

	Field_biomass (kg/tree)	QSM_biomass (kg/tree
Mean	139.45	133.81
Variance	9701.01	11569.09
Observations	33	33
df	64	
t Stat	0.22	
P(T<=t) one tail	0.41	
t critical one tail	1.67	
P(T<=t) tow tail	0.83	
T Critical two tail	2	

Table 11: t-test field and QSM above ground biomass at medium tree density.

t-test: Two-Sample Assuming Equal Variances.

	Field_biomass (kg/tree)	QSM_biomass (kg/tree
Mean	100.78	100.70
Variance	12273.57	16634.33
Observations	37	37
df	72	
t Stat	0.37	
P(T<=t) one tail	0.50	
t critical one tail	1.67	
P(T<=t) tow tail	1	
T Critical two tail	1.99	

Table 12: t-test field and QSM above ground biomass at high trees density.

t-test: Two-Sample Assuming Equal Variances

	Field_biomass (kg/tree)	QSM_biomass (kg/tree
Mean	164.25	139.45
Variance	31696.92	20263.42
Observations	43	43
df	84	
t Stat	0.71	
P(T<=t) one tail	0.21	
t critical one tail	1.66	
P(T<=t) tow tail	0.48	
T Critical two tail	1.99	

4.10. Relationship between AGB from Field and TLS biomass in different tree densities

Based on figure 32 plots, 162, 378 and 493 trees were classified in low, medium and high tree densities respectively. Out of 162 trees, 129 trees (79.6%) were measured in the field, detected in both TLS and ALS and categorised in low tree density. In medium tree density, only 213 trees were detected in both TLS and ALS while in high tree density, 315 trees were also detected by ALS and TLS out of 493 trees. Height from ALS and DBH from the field were used to calculate above ground biomass from the field while biomass from TLS was estimated from height and DBH derived from TLS. ABG estimated from TLS was compared with ABG derived from the field in different tree densities. Figure 40, 41 and 42 show the relationship between AGB estimated from the field and that derived from TLS in low, medium, and high tree densities respectively. The result showed the coefficient of determination (R^2) of 0.976, 0.932 and 0.907 in low, medium and high tree density with RMSE of 0.112Mg/tree, 0.177Mg/tree and 0.186Mg/tree respectively.

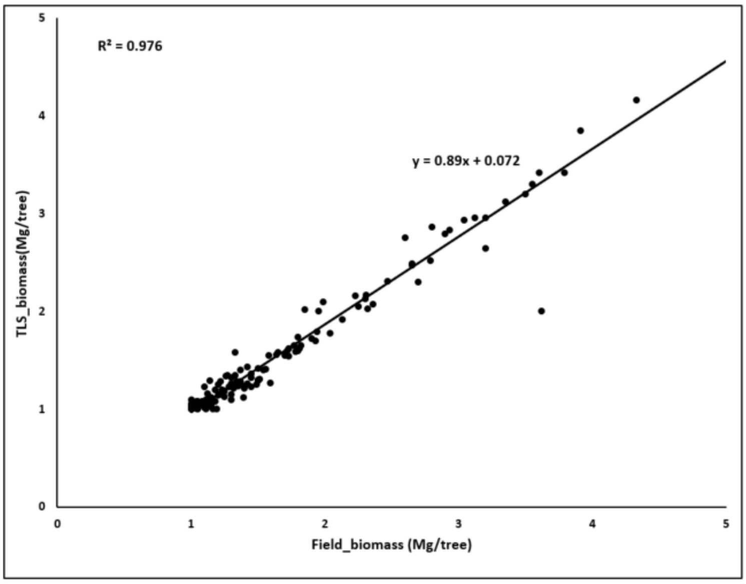

Figure 40: Relationship between AGB from Field and TLS biomass in low trees density.

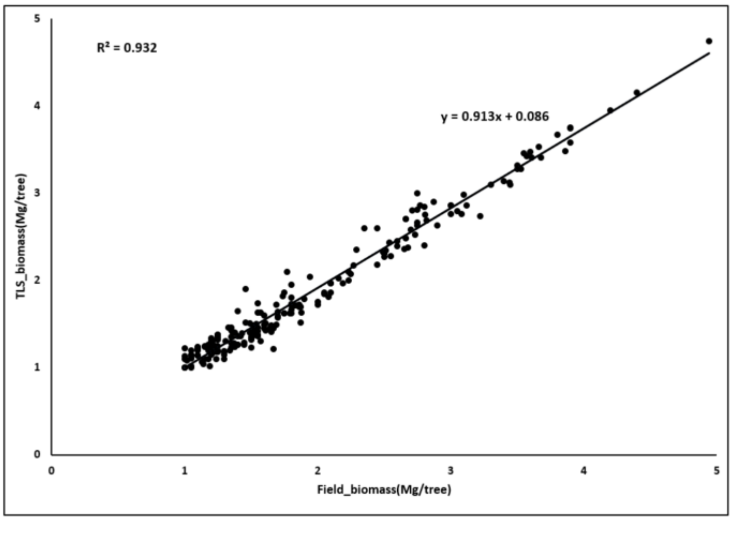

Figure 41: Relationship between AGB from Field and TLS biomass in medium trees density

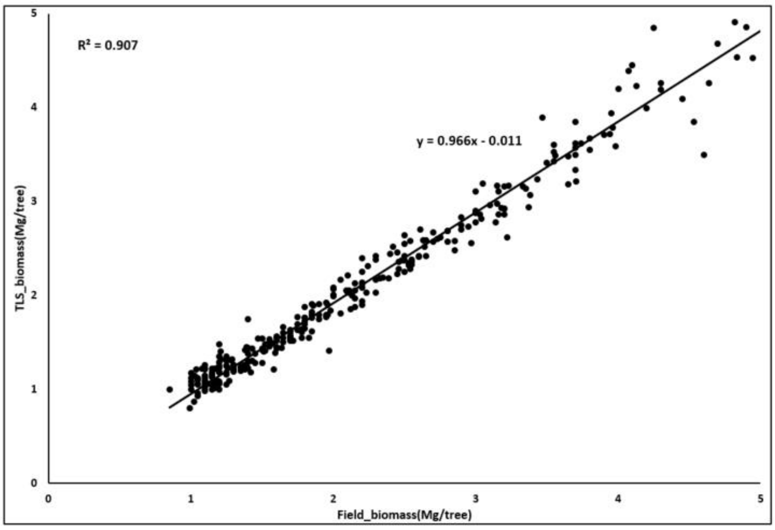

Figure 42: Relationship between AGB from Field and TLS biomass in high trees density

Testing relationship between AGB estimated from field and TLS in low trees density

To test if there is a significant difference between AGB derived from field and that derived from TLS in different tree densities, a t-test (assuming equal variance) was used. The results from Table 13, 14, 15 show that there is no significant difference between AGB derived from TLS and that estimated from the field at 95% confidence interval (α=0.05).

Table 13: t-test Field_biomass and TLS_biomass at low trees density.

t-Test: Two-Sample Assuming Equal Variances.

	Field_biomass (Mg/tree)	TLS_biomass (Mg/tree
Mean	1.946	1.939
Variance	1.438	1.468
Observations	129	129
df	256	
t Stat	0.127	
P(T<=t) one tail	0.489	
t critical one tail	1.666	
P(T<=t) tow tail	0.979	
T Critical two tail	1.993	

Table 14: t-test Field_AGB and TLS_AGB in medium trees density.

t-Test: Paired Two Assuming equal variance.

	Field_biomass (Mg/tree)	TLS_biomass (Mg/tree
Mean	1.865	1.946
Variance	1.344	1.483
Observations	213	213
df	424	
t Stat	0.299	
P(T<=t) one tail	0.037	
t critical one tail	1.687	
P(T<=t) tow tail	0.074	
T Critical two tail	2.026	

Table 15: t-test Field_AGB and TLS_AGB from in high trees density.

t-Test: Two-Sample Assuming Equal Variances.

	Field_biomass (Mg/tree)	TLS_biomass (Mg/tree
Mean	1.828	1.946
Variance	1.201	1.483
Observations	315	315
df	628	
t Stat	0.447	
P(T<=t) one tail	0.328	
t critical one tail	1.666	
P(T<=t) tow tail	0.656	
T Critical two tail	1.993	

4.11. Effect of trees density on estimating above ground biomass using QSM

The different between biomass derived from QSM at low, medium, and high tree densities were assessed in statistical analysis. One way Analysis of Variance (ANOVA) was done to assess the variance of the means between QSM biomass derived from three different trees densities. The result of ANOVA (Table 16) shows that there is no significant different between biomass derived from QSM in different tree densities.

Table 16: Single factor ANOVA for low, medium and high biomass derived from QSM.

Groups	count	Sum	Average	Variance
Low_QSM_Biomass	33	4390.69	133.05	11226.3
Medium_QSM_Biomass	37	3725.83	100.69	16634.33
High_QSM_Biomass	42	5996.31	139.45	20263.4

ANOVA.

Source of variation	*SS*	*df*	*MS*	*F*	*P-value*	*F-critical*
Between Groups	32966.7	4	8241.67	0.492	0.7416	2.45577
Within Groups	1809141.44	108	16751.31			
Total		112				

5. DISCUSSION

5.1. DBH Measurement and accuracy assessment

Tree diameter at breast height is a fundamental measurement of forest inventory and important predictor of height and above ground biomass of the individual tree (Yao et al., 2011). Trees with large DBH are taller and have large biomass. Trees which are not perfectly circular, a tape measure can lead to some error, especially trees with large DBH where it's difficult to wrap the diameter tape at the back of the tree (Olagoke et al., 2016). However, except on extremely irregular trees, this method seems to average out the trees shape to an acceptable estimate (Yao et al., 2011). Trees with large DBH (Figure 43 left) and large buttress (Figure 43 right) present challenges during data collection.

Figure 43: Tree with large DBH and buttress.

The manually extracted of DBH from the point cloud was validated using DBH measured from the field. Field measured DBH was compared with TLS derived DBH as shown in Figure 26. The DBH derived from TLS was highly correlated with DBH measured from the field with R^2 of 0.989 with RMSE of 1.37cm. The result indicated that 98.9% of DBH derived from TLS is explained by DBH measured in the field.

Rahman et al., (2017) got a similar result on their study on estimating above ground biomass of individual using TLS in a tropical forest. They got R^2 of 0.969 with RMSE of 0.062 cm with four scanned positions. On their study underestimation of DBH measurement was caused by two things. Firstly, cylinders were mostly fitted to the inner side of the point clouds. Secondly, occlusion of tree stems and uneven distributions of point clouds within the area of the tree trunk for DBH measurements that caused improper fitting of the cylinder which results in a small error in DBH estimation.

Watt & Donoghue, (2005) have used TLS to measure forest structure in a conifer forest (Kielder Forest District) and one of their objectives was to compare DBH measured from the field and that derived from TLS. They have used automatic method for extraction of individual tree and measure DBH at 1.3 m height above the ground. When they compared DBH measured from the field with the laser DBH, the relationship was linear and positive ($R^2 = 0.92$) and RMSE of 4 cm. They got R^2 which is slightly lower compared to this study because trees are partially obstructed by other stems in the sample plots.

Calders et al., (2015) use TLS to estimate above ground biomass in native Eucalypt open forest in Victoria, Australia. They use semi-automatic approach to extract individual tree from registered point clouds, they got linear regression of R^2 0.98 with RMSE of 0.02 m which is the same as in this study. Comparison between field measured DBH, and TLS derived DBH showed high accuracy because their circular fitting method works well. Points cloud at stem area of the trees were partially occluded. In circular fitting method when there is occlusion of point cloud (Figure 44) at 1.3m height above the ground can lead to underestimation of TLS derived DBH. Their regression coefficient is the same with this study result despite the method used to extract trees from the plot. In this study, intensive clearing and slashing of the undergrowth within the plot to both positions were done before scanning. This reduce occlusion at 1.3m and contributes high value of R^2.

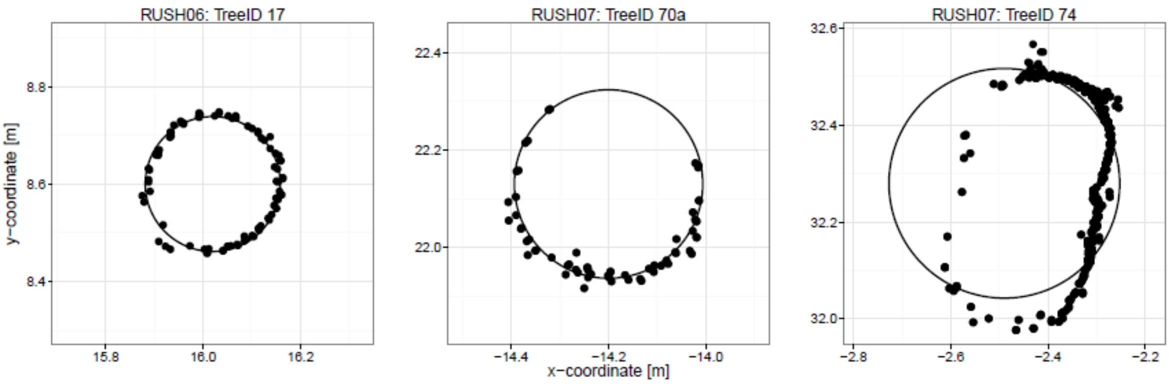

Figure 44: Example of TLS derived DBH through circular fitting method (source: Calders et al., 2015).

5.1.1. Distribution of field DBH and TLS DBH

Diameter at Breast Height (DBH) was measured and recorded for all trees in 32 plots during the field work. Both DBH measured from the field and DBH from the TLS were analysed after field work and showed that are not normally distributed (skewed). Skewness of the data can either be positive or negative. According to Knox et al., (1989) positive skew indicates that the tail on the right side is longer or fatter than the left side like in this study. In this study both DBH from the field and from TLS are positively skewed as shown in Figure 24 because only trees with DBH greater or equal to 10cm were measured. Trees which their DBH are below 10 cm were not measured because they insignificant contribute to biomass (Brown, 2002). This result was also obtained by Mulat, (2017) and Sadadi, (2016) when they look at the distribution of DBH measured from the field and that estimated from TLS.

5.2. Point cloud acquisition and registration

RIEGL VZ 400 terrestrial laser scanner was used to scan and generate points cloud for all 32 plots in this study. To have detailed points cloud that represents the sample plot, multiple scans (4-scans) were conducted, one in the centre (inside the plot) and three scans outside the plot. Points cloud in all four (4) positions were merged into a common data set by registration using tie point/retro-reflector that are placed in such a way that they were visible from all scans locations. In this study, the error of multiple registrations varies from 0.0049 m 0.0158 m with an average of 0.00869 m for all 32 sample plots. Madhibha, (2016) and Seidel et al., (2012) got average registration error of 0.0127m to 0.0224m and 0.002m to 0.0075m respectively. They got a slightly different error from the one obtained in this study because 6-8 retro reflectors were detected during registration hence reduce the registration error. According to Pazhouhan et al., (2017) and Wilkes et al., (2017) minimum of four (4) common targets/retro-reflectors are required between the scans to archive satisfactory registration. A higher number of common target/reflectors explain the higher accuracy of registration and less than four common target reflectors can lead to a large error during registration (Wilkes et al., 2017). In this study plots number 4, 9, 11 and 19 have slightly higher registration error compared to the rest of the plots. According to Fan et al., (2015) this could be due to misalignments between point clouds acquired from different scanner locations.

5.3. Extraction of individual tree

Total of 1033 trees were measured in the field and 855 (82.77%) were manually extracted using TLS points cloud data (e.g. Figure 14 & 16). 178 trees (17.23%) were recorded missing from TLS due to occlusion, (figure 44) presence of undergrowth and high stem density. Prasad et al., (2016), Mulat, (2017) and Madhibha, (2016) did their studies in tropical forest and got detection percentage of 90%, 91% and 80.02 respectively. The detection rate of Prasad et al., (2016) and Mulat, (2017) are slightly higher than 82.77% which was recorded in this study. This is due to occlusion to some of the plots. Three plots (2, 10, 13 and 18) show more occlusion compared to other plots. Othmani et al., (2011) also faced this challenge. Occlusion increases when trees are far away from the centre. Points cloud around the scanner show higher density than the point cloud data far away from the scanner (Krooks et al., 2014a). The trees which are far away from the scanner were partially scanned or not scanned because of the shadowing effects (Figure 45) of the laser light (Wang et al., 2017). This is one of the reasons that causes low detection of an individual tree during manual extraction. Pazhouhan et al., (2017) also observed this challenge.

TLS points cloud comprised undergrowth and non-related vegetation which was filter out until the points cloud for the individual tree of interest was obtained. Depending on the structure of the tree, manual extraction is a time-consuming process, and it is a very challenging process especially in the tropical forest such as Berkelah forest where there is a lot of intermingling of tree branches. Olagoke et al.,(2016) and Prasad et al., (2016) also reported this challenge when they took several hours to extract an individual tree from points cloud in Mangrove and tropical forest respectively. Occlusion caused by lower branches, surrounding trees and understories (Figure 46) are the major problems to overcome when using TLS in the forest environment (Dassot et al., 2011). It is also lower points density thus lower detection rate per plot which leads to the poor description (partially scanned) of the top parts of tree/crown (Van der Zande et al., 2006). This can introduce error especially in measuring the height and reconstructing of the individual tree in QSM when the whole crown is not fully scanned (Krooks et al., 2014a). Tree height can be measured by finding the difference between the highest point of the points cloud and lowest point (ground point cloud). If the whole crown is not scanned it lead to underestimation of tree height (Prasad et al., 2016). In the tropical forest, it is very challenging to separate all point clouds data belong to an individual tree due to overlapping of crown branches. This can also be a source of error in measuring tree height and reconstruction of the tree in QSM.

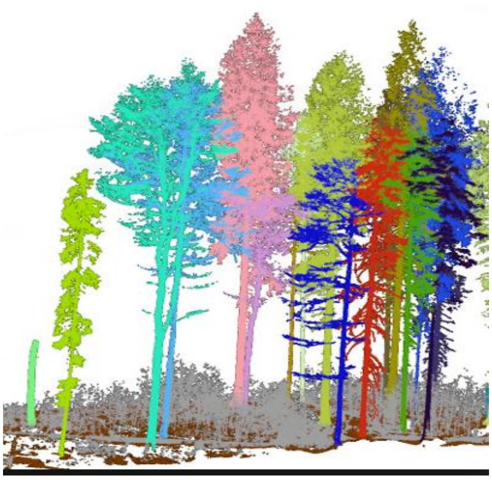

Figure 45: The trees in black colour is in the shadow effects of the laser light (source: www.3dforest.eu).

Figure 46: Dense undergrowth which causes occlusion.

5.4. Estimation of above ground biomass using allometric equation

The allometric equation used to calculate biomass in this study was adopted from Chave et al., (2014). $AGB=0.0673*(\rho D^2H)^{0.976}$ whereby D= is diameter at breast height, H= height from the tree and ρ= specific wood density (g/cm^{-3}). According to Nelson et al., (1999) it is possible to estimate above ground biomass using only DBH as an input variable in the equation with an average error of 10-15%. Tilon, (2017) had used only DBH to estimate above ground biomass when she investigated the effect of foliage on estimating above ground biomass using TLS_QSM. In the tropical forest where canopies are closed, trees are unevenly distributed and their branches are intermingling, it is difficult to get the exact or accurate height of the tree (Figure 47). This leads to an error in the estimation of above ground biomass.

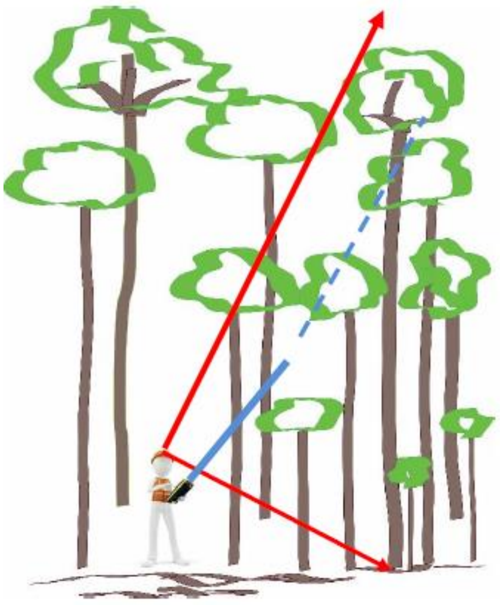

Figure 47: Error in field height measurement (source: Lawas 2016).

Using height from field underestimates above ground biomass by 20% (Chave et al., 2014). Similar result was also reported by Madhibha, (2016) when she used Leica DISTO D510 to measure a tree height in the tropical forest. She also reported that there is a bias in estimating height using Leica DISTO D510.

To avoid this potential error source, height from airborne LiDAR and DBH from the field were used to estimate above ground biomass. Several studies (Ghebremichael, 2015; Mohd Zaki et al., 2018; Sadadi, 2016) use ALS in the tropical forest to estimate height and use DBH measured from the field to calculate above ground biomass. Airborne LiDAR gives useful information of forest canopy which can be used in forest inventories (Mohd Zaki et al., 2018). It measures the vertical and horizontal structure of the forest from the top hence tree height can extracted accurately (Mauya et al., 2015). Several studies (Hansen et al., 2015; Mauya et al., 2015; Sibona et al., 2017) use height derived Airborne LiDAR to estimate above ground biomass and used as a reference to compare with AGB derived from TLS. Therefore, above ground biomass estimated from this research is considered reliable and used as a reference to compare ABG derived from QSM and TLS.

5.5. Classification of tree density based on basal area

In this study, number of trees as an indicator of trees density shows a weak relationship with above ground biomass compared to basal area. The same result was also obtained by (Slik et al., (2010) when they are investigating on environmental correlation of tree biomass, basal area, wood specific gravity and stem density gradients in Borneo's tropical forests. They found that AGB was only correlated with basal area, but not with stem density or number of trees and wood specific gravity. Based on the weak relationship between number of trees and biomass, basal area was used to classify tree density into three main classes (low, medium and high) for all 32 plots. According to Naidu & Kumar, (2016) different basal area in uneven-aged forest is due to difference in altitude, species composition, age of the trees, extent to disturbance, climate and soil properties. This lead to different classes from one forest to another. Means et al., (2000) classify basal area (m^2/ha) into four classes which are 6m^2/ha, 26-49m^2/ha, 47-70m^2/ha and 71-132m^2/ha when their done study on predicting forest stand characteristic with ALS. Their classification is a bit different from this study. Andreassen & Tomter, (2003) classify basal area in five different classes. Moss, (2005) and Schultz et al., (2005) use all most the same basal area classification as a measure of forest stand density used in this study (e.g. 1-20, 21-40, 40-70m^2/ha).

5.6. Effect of trees density on estimation of AGB using QSM

Watt & Donoghue, (2005) investigated the issue of how accurate ground based laser scanner can measure tree diameter in densely stocked plantation. They classified their site into high trees density (2800 stem/ha) as site one with Sitka spruce and lodgepole pine and site two as low trees density (600 stem/ha) with Sitka spruce only. Their classification differs from this study.

In low tree densities numbers of trees detected during scanning is high compared to numbers of trees detected at high trees density. In high trees density number of trees is high hence fewer trees were detected during scanning due to a high level of occlusion and intermingling of tree branches at canopy level. Watt & Donoghue, (2005) also obtained this kind of result whereby in high trees density, low level of information was captured by TLS for an individual tree. On low trees density level of information was substantially improved with individual trees resolved up to a distance of 30m from the scanner (Watt & Donoghue, 2005). Dassot et al., (2011) discussed this challenge too.

For an individual tree to be reconstructed in QSM, it must be sufficiently covered with enough points from the base to the top. To model real tree in QSM, points cloud is locally uniform and intensive enough for the reconstruction (Kaasalainen et al., 2014; Krooks et al., 2014b; Raumonen et al., 2013). The parts of the tree that are insufficiently visible such as branches and have no enough points are not reconstructed at all hence cause errors in estimate tree volume (Raumonen, 2017). To avoid this error only trees with sufficient points in different trees densities (low, medium and high) were selected and reconstructed in QSM. This is the condition of QSM otherwise it will not have an accurate result. Such result may lead to be bias on estimating above ground biomass using QSM because only good extracted trees were selected and effect of trees density may be masked. However, if we consider that there is no bias in the results of QSM, thus no significant difference between the R^2 of the AGB of field and QSM in low, medium and high tree densities. The same results in the case of R^2 of the AGB of QSM and TLS in three mentioned densities. Table 17 shows the summary of the R^2 of the AGB of field, QSM and TLS.

Table 17: Summary of the R^2 of AGB in the field and QSM and TLS in the upper part and the QSM and TLS in the lower part.

R square of AGB from QSM and TLS compared with Field (truth)		
Trees density	QSM AGB	TLS AGB
low	0.911	0.976
medium	0.953	0.932
High	0.926	0.907
R square of AGB from QSM compared with TLS		
Trees density		
low	0.896	
Medium	0.908	
High	0.881	

5.7. Estimation of above ground biomass using QSM

5.7.1. AGB derived from QSM compared to the AGB estimated from TLS in different tree densities

Height and DBH derived from TLS were used in the allometric equation to estimate above ground biomass. A total of 112 trees from different tree densities (low, medium and high) were used to estimate biomass from both QSM and TLS. Table 22 shows that there is a high level of agreement (average R^2 = 0.895) between ABG derived from TLS and AGB estimated from QSM. This result was expected because construction of tree in QSM depends on points cloud from TLS. No significant differences were found between above ground biomass from QSM and AGB from TLS in different tree densities. Low registration error of points cloud, accurately extracted tree with dense points and reasonable parameters chosen to reconstruct individual tree in QSM are among of the factors which contribute for higher coefficient of determination. Several studies (Calders et al., 2015; Tilon, 2017; Madhibha, 2016) were compared AGB estimated from TLS and compared with AGB derived from QSM and found that no significant difference between the methods. Their results are similar like in this study.

Calders et al., (2015) have used the destructive method to validate above ground biomass derived from QSM, TLS and field biomass using only DBH from the field, they determined errors in both methods.

Calders et al., (2015) and Krooks et al., (2014b) have discussed the possible sources of errors that causes overestimation of above ground biomass using QSM. These are:

- ❖ Occlusion of data caused by shadowing

Occlusion effect is a common situation in a forest environment, especially in the tropical forest like Berkelah forest where there are dense canopies and intermingling branches. During scanning, there is a possibility that other vegetation occludes individual tree, especially in dense plots where trees are close to each other and present of a lot of undergrowth. This can cause problems because only part of the tree can be detected hence minimise points per tree when a tree is scanned in different direction. For proper reconstruction of an individual tree in QSM, all parts of the tree should be scanned/detected. Several studies (Calders et al., 2015; Dassot et al., 2011; Hilker et al., 2012) reported that occlusion is the main challenge in the forest when using TLS. To minimise the effect of occlusion in this study pre-scan preparation such as clearing of undergrowth and multiple scans were conducted to detect all part of the tree. To avoid laser shadow effect, TLS was placed 2-3 m from the trees in all scans positions.

- ❖ Movement of trees during scanning

Weather condition may affect the amount of points cloud captured by TLS. Wilkes et al., (2017) reported that wet weather condition (mist, fog or rain) could not only affect the transmission of laser scanner but also the scattering properties of leaf surface. Wind can cause movement of tree and branches which can result in ghosting/increase the noise of points cloud and induce waves-shaped axes during scanning (Dassot et al., 2011). Figure 48 shows the effect of strong wind during scanning. Wind condition which causes an error due to the movement of the branches was also reported by Calders et al., (2015); Krooks et al., (2014a); Wilkes et al.,(2017). Seidel et al., (2012) recommend scanning in wind speed of less than 5m/s. In this study, scanning was not done in a raining or windy condition.

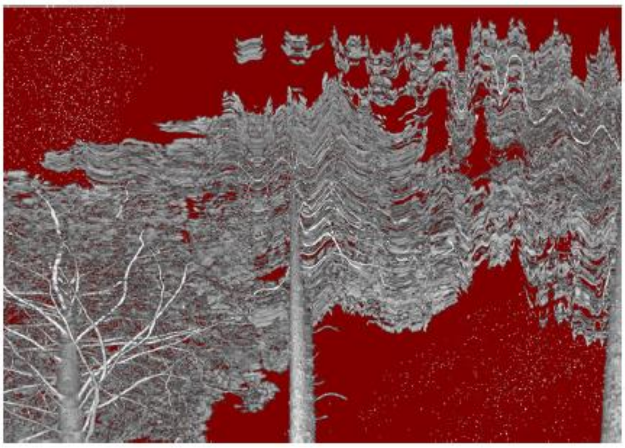

Figure 48: Intensity image show moving branches during scan (Krooks et al., 2014a).

- ❖ Non-wooden material:

The presence of non-wooden material such as needles, leaves and flowers can cause inaccuracy size measurement and make cylinder too large, especially the branches parts (Krooks et al., 2014a). Depending on parameters set by the user non-wooden materials should be removed during filtration process in QSM. If non-wooden materials are not filtered out they can be used in the reconstruction of an individual tree (Raumonen, 2017). This can result in too thick branches, formation of non-existing branches, and gaps between the cylinder in the canopy (Krooks et al., 2014a). This can lead to a large error in estimating the volume of the tree in QSM. Madhibha, (2016) reported this challenge whereby 71% of the trees she reconstructed had bigger proportional of AGB in the canopy level compared to stem which is abnormal. Her result was contradicting with the result obtained by Calders et al., (2015) where they got 80% of the above ground biomass is located at the stem while 60% is found at canopy level for all measured trees. In this study, the same error was obtained, but only 7% of all trees reconstructed from QSM show stem volume is less than canopy volume. The individual trees with canopy volume greater than stem volume were not used in the analysis. Figure 49 shows bad reconstruction of an individual tree from QSM in this study.

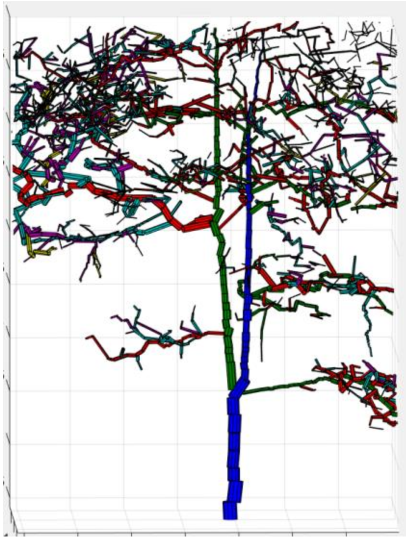

Figure 49: Bad or inaccurate reconstruction and cylinder gaps

❖ Registration error:

To have comprehensive coverage of the plot structure, registration is one of the pre-processing steps that was done in this study to merge all scan positions (4 scans) before extraction of individual tree manually in RiSCAN PRO software. When scans from different directions are registered into a common coordinate system can lead to small error (Raumonen et al., 2013). According to Burt et al., (2013) 1cm registration error can lead to 8.8% total volumetric overestimation across the data set. The error associated with registration process can increase or duplicate branch radius which is potential in biomass estimation in QSM where volume is proportional to the square of the radius (Burt et al., 2013). To minimise registration error in this study, 18 reflectors are distributed to sampled plot in such a way that all reflectors are seen from the central position (1 scan) and at least six reflectors are seen from outer scans (2, 3 and 4) during the scanning. Clearing of undergrowth to make sure that reflectors are seen in all positions during scanning was also done in the field before scanning to reduce registration error during data processing. In this study, registration error ranges from 0.0049 m to 0.0158 m.

❖ Error in modelling process

Construction of individual tree from QSM involve many input parameters that depend on each other. From the first step of filtering points whereby unnecessary points are remove. Depending on the input parameters set, under or over removal of points cause problem in tree reconstruction. Cover sets, cylinder length and radius, segmentation and cylinder fitting are among important input parameters in which their command code should be set accurately for reconstruction of a tree. Example in Figure 19 shows the effect of an increase or decrease cover sets. Kaasalainen et al., (2014) also reported on the effect of the large patch which leads to large segment, makes the volume of the trunk to be too large hence affect biomass estimation. In this study, optimum input parameters was selected to make sure that the tree is well reconstructed. Input parameters used in reconstruction of the individual tree in this study are in Appendix 3.

❖ Region with low point density

The tree and its details must be sufficiently covered with measured points so that it can be reconstructed accurately in QSM (Raumonen, 2017). Low points cloud in branches can cause a problem in reconstruction especially cylinder fitting hence can lead to under or overestimation of cylinder volume (Krooks et al., 2014a). According to Kaasalainen et al., (2014) branches with less points left unconstructed hence lead to error in the estimation of AGB from QSM. In this study trees with enough points were selected and used in the reconstruction of the individual tree in QSM.

- Non-circular branches and stem:

The basic assumption of QSM is trees are locally approximately cylindrical and it is covered with small sets, segmented and fitted with cylinders from stem to branches. In most cases, this assumption is not true, especially in the tropical rainforest like Berkelah where trees have different shapes from conical to cylindrical but in most cases cylindrical. For trees which have large buttress and conical shapes can lead to an error in the estimation of above ground biomass.

5.7.2. AGB derived from QSM compared to the AGB estimated from the field in different trees densities

Using specific wood density and volume from QSM, AGB was estimated in different tree densities. Total of 112 trees were selected for the reconstruction of the tree using QSM. Biomass from different tree densities was estimated by multiplying the volume of an individual tree with specific wood density (0.57g/cm3). Biomass from QSM was compared with biomass from the field in different tree densities. The result obtained in section 4.9 showed that in different tree densities there is no significant different between AGB derived from QSM compared to AGB estimated from the field.

Madhibha, (2016) did a study on the assessment of above ground biomass using TLS and QSM in tropical forest and one of her objectives was to compare AGB from QSM and AGB estimated from the field. Using height and DBH from the field, and specific wood density to estimate field biomass using allometric equation from Chave et al., (2014). She found that there is no significant difference between AGB derived from QSM with AGB estimated from the field. On her study she got coefficient of determination of 0.81 which is slightly different with the average of 0.93 in this study. She used Leica DISTO D510 to measure tree height may be the reason of slightly different in coefficient of determination. Using Leica DISTO D510 to measure tree height in tropical forest is very challenging to see the top of the tree due to occlusion and intermingling of branches (Madhibha, 2016). This can lead to error propagation in the estimation of ABG. To avoid this potential source of error, in this study height from ALS and DBH from the field were used.

Tilon, (2017) obtained similar result when she investigated the effect of foliage on the estimating above ground biomass using QSM and field in the temperate forest. She found that there is no significant difference between AGB estimated both in the field by QSM from leaf off and leaf on conditions despite the fact that she used only DBH to estimate AGB using allometric equation.

Calders et al., (2015) have used destructive method to validate above ground biomass derived from QSM and field biomass using only DBH. They found similar result with this study when they compare above ground biomass estimated from QSM and biomass derived from the field using only DBH in the allometric equation. Using the destructive method to validate biomass derived both QSM and AGB estimated from field they determined that there is an error in both methods. Allometric equation underestimated above ground biomass from 29.85% to 36.57% and the error increases exponentially with the increase in DBH while QSM does not depend on DBH. QSM overestimate above ground biomass by 9.68%.

5.7.3. AGB estimated from field compared to the AGB derived from TLS in different trees densities

In dense forest like Berkelah, ALS provide detail information of trees height compared to TLS. Height from ALS and DBH measured from the field were used to estimated AGB and compared it with biomass from TLS in different tree densities. The result presented in section 4.10 shows that in all tree densities, no significant deferent between above ground biomass estimated from the field compared with AGB derived from TLS. Similar result was obtained by Ghebremichael, (2015) and Bazezew, (2017) when they use height derived from ALS and DBH from the field to estimate AGB and compared it with AGB derived from TLS in tropical forest. Ghebremichael, (2015) and Bazezew, (2017) also got a high value of $R^2 = 0.968$ and 0.966 respectively which is similar to the average trees densities of $R^2 = 0.952$ in this study.

6. CONCLUSION AND RECOMMENDATIONS

6.1. Conclusion

This study aims to demonstrate the effect of tree density in estimating above ground biomass using Quantitative Structure Modelling in Berkelah tropical forest. Based on basal area, tree density was classified into three categories (low, medium and high). Total of 112 trees which show an even distribution of stem volume and canopy volume were selected and used in the reconstruction of the individual tree in QSM. Above ground biomass for each class was estimated without relying on information from allometric equation. Instead above ground biomass was estimated by multiplying volume of the individual tree from QSM with specific wood density. In low tree density a total of 33 trees were used to estimate biomass from QSM and compared with biomass derived from field and TLS. In medium and high trees densities AGB estimated from QSM were compared with biomass from field and TLS from both medium and high trees densities with 37 and 42 trees respectively. The results show high level of agreement in both methods in different tree densities. Tree density has an influence on the level of information captured by the ground based scanner. When the scanner is obstructed due to high canopy density and intermingling of branches, it is impossible to capture total height of the tree but it also reduces number of points cloud captured by the scanner per tree. This effect can be seen more in high trees density where there is high number of trees and dense canopy per plot/hectare. To ensure reasonable results for an individual tree to be reconstructed in QSM, tree parts must be sufficiently covered with points cloud. Thus, the resolution and number of scans around the tree need to be high enough to sufficiently catch the detail of the tree (Raumonen, 2017). To avoid error in reconstruction of trees in QSM, in this study, only well scanned trees were selected in both low, medium and high tree densities. Hence the effect of trees density was not visible due to the basic principle of QSM.

Terrestrial laser scanner was not only used in generating points cloud for reconstruction of the individual tree in QSM but also derived DBH and height. Height and DBH from TLS were also used to estimate biomass in different trees density and compared the results obtained from field biomass using allometric equation from Chave et al., (2014). Both biomass estimated using height and DBH from TLS reflect a high level of agreement with biomass calculated from the field. The DBH from TLS and DBH from the field also showed high correlation. This is because several activities were done within the plot before scanning. These activities are: intensive cleaning of the plots, multiple scans to ensure better distribution of points cloud and distribute reflectors equally to reduce registration error.

The analysis of this study shows that points cloud generated from TLS can efficiently be used in quantitative structure modelling to estimate AGB but due to the fundamental principle of QSM the effect of tree density cannot be assessed in QSM. The following are answers to research questions in this study:

What is the relationship between DBH derived from TLS and the one measured in the field from different trees densities?

The DBH individual tree was measured in the field and compared with DBH derived from TLS. Scatter plot was constructed between DBH derived from TLS and DBH measured from the field. Coefficient of determination of 0.989 was obtained from regression statistic. A t-test was used to test the level of significant; it shows that there is no significant difference between DBH measured from the field and DBH derived from QSM. Hence null hypothesis was accepted at (95%) confidence interval.

How accurate is AGB/carbon stock derived from TLS-QSM compared to AGB derived from TLS in different trees densities?

A total of 112 trees were used in reconstruction in QSM and estimate above ground biomass and compared with above ground biomass estimated from TLS using allometric equation. Both methods show high correlation and, a t-test was used to see if there is a significant difference of the estimate of ABG by both methods and it proves that there is no significant difference hence null hypothesis is accepted at 95% confidence interval.

How accurate is AGB/carbon stock derived from TLS-QSM compared to AGB/carbon stock derived from field measurements approach in different trees densities?

Using height from ALS and DBH from the field a total of 112 trees were used to estimate allometric equation from Chave et al., (2014) and compared with biomass derived from QSM in different trees density. Both methods show high correlation and a, t-test was used to see if there significant different between the estimate of ABG in both methods and it proves that there is no significant difference between the two methods on estimating AGB hence null hypothesis is accepted at 95% confidence interval.

How accurate is AGB/carbon stock derived from the field compared to AGB/carbon stock derived from TLS approach in different trees densities?

Height from ALS and DBH measured from the field was used in allometric equation to estimate above ground biomass from different trees density and was compared with AGB derived from TLS using DBH and height from TLS. The t-test was conducted to test whether there was a significant difference between above ground biomass derived from the field and AGB from TLS in different trees density. The result revealed that there is no significant different in above round biomass estimated by both methods in different trees density hence null hypothesis was accepted at 95% confidence interval.

What is the effect of different trees densities on the accuracy of estimating AGB/carbon stock using TLS-QSM?

Above ground biomass derived from QSM in low, medium and high tree densities was tested using ANOVA test to check if there is a significant difference between them. The result shows that there is no significant difference in biomass estimation in different trees densities at 95% confidence interval.

6.2. Recommendations

- Tree density have no effect on QSM because only tree with enough points are selected for reconstruction in QSM.

- Nmin have effect on crown volume, further investigation on the effect of increasing or decreasing nmin value on the crown of the tree in QSM reconstruction.

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LIST OF APPENDICES

Appendix 1: field measurement sheet.

DATA SHEET FOR BERKELAH FOREST RESERVE, MALAYSIA								
Author:			**Plot radius:**		**Slope: (%)**		**Date:**	
Plot centre		**Latitude:**		**Longitude:**			**Plot No:**	
Canopy Density (%)								
Photography			Name of recorder					
Tree No:	Latitude	Longitude	Species	DBH (cm)	Stem height	Tree shapes	Crown diam. (m)	Canopy density (%)
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2								
3								
4								
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Appendix 2: QSM output.

```
tree_9.txt
    All points: 525174, First filtering: 1419, Points left: 523755
    All points: 523755, Second filtering: 116091, Points left: 407664
    All points: 525174, All filtered points: 117510, Points left: 407664
---------------
pine, Tree = 1, Model = 1
PatchDiam1 = 0.1        0.15, BallRad1 = 0.12        0.17, nmin1 = 3
PatchDiam2Min = 0.02        0.03, PatchDiam2Max = 0.06        0.08, BallRad2 = 0.07        0.09, nmin2 = 1
lcyl = 3  5, FilRad = 3, Tria = 1, OnlyTree = 1
Progress:
  PatchDiam1 = 0.1
Cover sets        1.4 sec.   Total: 1.4 sec
Tree sets         1.4 sec.   Total: 2.8 sec
Initial segments 1.1 sec.   Total: 3.9 sec
Final segments   0.8 sec.   Total: 4.6 sec
  PatchDiam2Max = 0.06
  PatchDiam2Min = 0.02
Cover sets        3.4 sec.   Total: 8 sec
Tree sets         3.9 sec.   Total: 11.9 sec
Initial segments 1.7 sec.   Total: 13.6 sec
Final segments   1.2 sec.   Total: 14.8 sec
  lcyl = 3, FilRad = 3
Tree attributes:
  Total Volume = 342.3 L
  Trunk Volume = 206.9 L
  Branch Volume = 135.4 L
  Tree Height = 12.5 m
  Trunk Length = 11.13 m
  Branch Length = 267.8 m
  Number Branches = 444
  Max Branch Order = 10
  Total Area = 23.55 m^2
  DBH qsm = 0.2035 m
  DBH cyl = 0.2061 m
  DBH tri = 0.2035 m
  Tria Trunk Volume = 135.4 L
  Mix Trunk Volume = 135.4 L
  Mix Total Volume = 342.3 L
  Tria Trunk Length =8.34 m
  -----
Branch & data    7.2 sec.   Total: 27.2 sec
    Average cylinder-point distance:   10.6        30.3        34.3        42.7 mm
Distances         0.9 sec.   Total: 28 sec
```

Appendix 3: input parameter used in QSM.

Plot_No.	Tree_no	Patchdiam1	BallRad1	BallRad2	PD2MIN	PD2Max	lcy	FilRad	Nmi	Average distanc
20	26	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	11.2
21	20	0.13	0.15	0.14	0.05	0.1	2.5	1.5	2	16.2
22	12	0.13	0.15	0.14	0.05	0.12	1.5	3	1	19.3
	13	0.13	0.15	0.14	0.06	0.12	1.5	2.5	1	21.8
23	3	0.13	0.15	0.14	0.06	0.1	5	2.5	1	14.8
	8	0.13	0.15	0.14	0.04	0.9	4	3.5	2	46.1
	16	0.13	0.15	0.14	0.05	0.1	1	2.5	1	22.9
	18	0.13	0.15	0.14	0.05	0.9	3	3	1	31.8
24	2	0.13	0.15	0.14	0.04	0.1	4.5	3.5	3	17.5
	5	0.13	0.15	0.14	0.03	0.8	4	3	1	23
	10	0.13	0.15	0.14	0.03	0.6	3	2.5	1	19.9
	13	0.13	0.15	0.14	0.04	0.08	5	2	2	25.4
25	1	0.13	0.15	0.14	0.05	0.1	5	1.5	1	14.4
	12	0.13	0.15	0.14	0.03	0.07	3.5	3	2	19.6
	19	0.13	0.15	0.14	0.04	0.1	2.5	3.5	1	13.4
	23	0.13	0.15	0.14	0.05	0.12	5	2	1	15.2
	26	0.13	0.15	0.14	0.05	0.1	3	2.5	1	16.3
	28	0.13	0.15	0.14	0.05	0.12	4.5	3	3	21.5
26	15	0.13	0.15	0.14	0.03	0.08	4	2.5	1	19.3
	19	0.13	0.15	0.14	0.04	0.1	3	3.5	2	22.3
	23	0.13	0.15	0.14	0.05	0.12	1.5	4.5	1	17.9
27	16	0.13	0.15	0.14	0.04	0.09	2.5	1.5	2	28.4
28	1	0.13	0.15	0.14	0.05	0.1	1.5	3	1	32.5
	2	0.13	0.15	0.14	0.05	0.1	3.5	3	1	25.7
	5	0.13	0.15	0.14	0.05	0.1	1.5	3	1	8.7
	6	0.13	0.15	0.14	0.05	0.1	1.5	3	3	10.1
	7	0.1	0.14	0.13	0.04	0.1	3.5	2.5	1	31.8
	8	0.13	0.1	0.09	0.03	0.08	1.5	2	1	19.7
	9	0.1	0.14	0.13	0.05	0.12	5	1.5	1	23
	11	0.1	0.14	0.13	0.04	0.1	3	1.5	1	27.3
	12	0.13	0.15	0.14	0.05	0.1	3.5	3	1	21.9
	14	0.13	0.15	0.14	0.05	0.1	1.5	3	1	24.7
29	2	0.13	0.15	0.14	0.05	0.1	4.5	3.5	1	29.8
	5	0.13	0.15	0.14	0.05	0.1	4.5	3.5	1	15.1
	8	0.13	0.1	0.09	0.03	0.08	1.5	2.5	1	20.2
	12	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	17.8
	21	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	20.7
	23	0.13	0.15	0.14	0.05	0.1	1.5		3	16.6
	30	0.13	0.15	0.4	0.05	0.1	2.5	3.5	1	42.4
	58	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	29.7
30	2	0.13	0.15	0.14	0.05	0.1	2.5	3.5	1	33.4
	3	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	18.5
	6	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	21.2
	9	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	23.7
	13	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	25.6
	14	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	48.2
	22	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	17.5
	23	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	35.5
31	3	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	22.5
	7	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	18.5
32	1	0.13	0.15	0.14	0.05	0.1	2.5	2.5	2	42.7
	7	0.13	0.15	0.14	0.05	0.1	1.5	3.5	1	33.8
	21	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1.5	32.1
	23	0.13	0.15	0.14	0.05	0.1	2.5	2	1	17.3
	24	0.13	0.15	0.14	0.05	0.1	1.5	2.5	1	37

Appendix 4: Summary table of field and TLS measured DBH.

		Field measured DBH(cm)				TLS measured DBH(cm)			
Plot	No. trees	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max
1	26	21.89	12.70	10	58	21.17	12.01	10	55.8
2	39	18.55	11.20	10	59.8	17.66	10.87	10	59
3	26	16.69	6.81	10	36.2	15.58	6.17	10	33
4	30	18.29	14.68	10	86	17.25	13.89	10.2	82.5
5	26	25.90	15.15	10.2	65	23.90	14.62	10.2	62
6	28	23.13	10.61	11	52	22.74	10.14	12	51.3
7	31	20.74	12.69	10	66	19.62	11.35	10	59.2
8	29	23.84	16.73	11	94	22.82	15.47	11	88.6
9	26	20.37	10.21	10.5	55.5	19.90	9.60	11.5	53.2
10	32	21.18	13.92	10	72	20.36	13.45	10	69.2
11	31	17.60	7.49	10	38	16.86	6.70	10	36.7
12	24	23.38	11.73	11.8	61	21.97	11.29	11	58.5
13	35	19.81	9.19	11	55.2	19.00	8.53	10.5	52.5
14	14	13.39	3.62	10.5	25	12.94	3.42	10	23.7
15	29	23.91	15.46	10	68	22.71	14.42	10	65.4
16	27	23.00	11.84	10	52.8	21.42	10.39	10	48.2
17	31	27.09	14.85	10	77.5	25.42	13.89	11.2	73.6
18	33	25.79	12.70	10.5	55	25.36	12.29	10.6	53.8
19	29	25.72	15.85	10.5	76	24.81	15.81	9.6	76.5
20	34	25.01	13.18	10	61	24.53	13.20	9.8	59.5
21	26	30.78	20.04	10	69.2	29.77	19.97	8	69
22	35	21.29	12.84	10.5	74	20.53	13.01	9.3	75.2
23	19	33.44	24.77	11.6	104.5	32.14	23.93	10.8	95
24	20	18.50	5.82	10.1	32	18.04	5.43	8.7	28.6
25	23	29.45	16.43	11.1	78	28.73	16.48	11.4	76.3
26	21	19.63	9.69	10.8	45.4	19.03	9.37	9.9	43.9
27	22	24.10	14.69	10.3	69	23.94	14.83	8.7	67.9
28	13	22.27	6.46	12.3	31.3	21.49	6.29	11.9	31.4
29	28	30.35	22.80	10.2	90	29.64	22.86	9.9	87.9
30	21	17.42	8.16	10	39	16.78	8.34	9.1	40
31	26	28.23	14.41	10	64.8	27.20	14.20	7.8	60
32	21	17.02	5.81	11	34.5	16.19	5.06	10.5	29.3

Appendix 5: Number of trees measured in field and extracted from TLS.

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

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

Appendix 6: Field photo.