Integrating Airborne LiDAR and Terrestrial Laser Scanner derived forest parameters for accurate estimation of above-ground biomass/carbon in Ayer Hitam tropical forest reserve, Malaysia

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Abstract

Parameters of individual trees can be measured from Airborne LiDAR scanner (ALS) point cloud data provided that the laser point is dense enough and trees in multiple canopy layers are visible from the top. However, retrieving tree parameters in a complex biophysical environment of tropical forests using single LiDAR technology could still be inadequate. This paper presents new approaches of acquiring tree parameters for estimating above-ground biomass (AGB) through integrating ALS and Terrestrial laser scanner (TLS). Two ways of data acquiring were implemented: ALS data was used to detect and extract upper canopy tree parameters while TLS complemented for tree stems and lower canopy trees height measurements. Initially, multi-resolution segmentation of ALS canopy height model (CHM) was executed to delineate individual tree crowns of upper canopy trees. The result showed segmentation accuracy of 73% and 1:1 correspondence of 78% with the reference tree crowns. About 62% of trees were delineated from ALS-CHM while the remaining lower canopy trees were identified from TLS data. ALS detected trees were then co-registered and linked with the corresponding tree stems detected by TLS for diameter at breast height (DBH) use; 93.5% of the field recorded trees were recognized from TLS data for DBH measurements. DBH derived from TLS was validated using manually measured-field DBH, and coefficient of determination (R^2) of 0.989 and root mean square error (RMSE) of 1.30 cm (6.52%) were achieved. Two-way tree height validations were implemented; upper and lower canopies tree heights. The R^2 and RMSE between field and ALS-measured upper canopy trees height were found to be 0.61 and 3.24 m (20.18%), respectively. R^2 of 0.69 and RMSE of 1.45 m (14.77%) were achieved between field and TLS-based lower canopy trees height. The AGB or carbon regression model that the relationship between AGB derived from remote sensing (ALS + TLS) and traditional field method at the plot level resulted in R^2 of 0.97 and RMSE of 0.62 Mg (7.64%) where field method underestimates with the bias of –0.289 (–3.53%) Mg.

Keywords: ALS, Canopy, CHM, Multi-resolution segmentation, Point cloud data, TLS

1. Introduction

Efficient and accurate ways of quantifying and monitoring carbon stock at regional, continental and global scale is highlighted to be very important for atmospheric carbon emission balance (Boudreau et al., 2008). Countries agreed under the Kyoto protocol of United Nations Framework Convention on Climate Change (UNFCCC) are, therefore, required to reporting annually on their emissions and offsets of CO_2 from the atmosphere. A number of forest carbon stock estimation approaches are currently being implemented. Lu (2006) review showed that traditional field-method, geographic information system, and earth observation data are the common approaches of above-ground biomass (AGB) or carbon estimation methods.

Traditional field method of AGB assessment is time-consuming and labor intensive which requires tedious effort over large areas and so are not well suited for monitoring and estimating carbon stock changes. Lack of field inventory data in remote areas and inconsistent inventory methods over large regions or overseas are constraints of acquiring reliable biomass estimations. Formerly estimated biomass carbon has, therefore, used for several years without carbon stock change updates (Sileshi, 2014). Earth observation data offer an alternative means to ground inventory field methods which could give spatial information and carbon stock monitoring even in inaccessible areas.

Uncertainties in above-ground biomass (AGB) estimation occurs mainly in tree parameter measurement errors. Tree height from traditional field-based instruments like hypsometers and handheld lasers height measure devices are associated with uncertainties due to structural nature of forests. Especially, height measurement accuracy in tropical forests is ambiguous, as these forests have a dense and multi-layered structure which makes it difficult to see tree-tops. Larjavaara & Muller-Landau (2013) highlighted that using handheld laser instruments for tree height measurements in closed complex forests where tree tops are not visible, provides inaccurate tree height readings.

The growing need for spatially explicit mapping and monitoring change in forest biomass and the use of earth observation satellites has grown continuously in order to acquire forest inventory data over large areas at regular intervals (Dong et al., 2003). Remote sensing approach could improve spatial forest inventory and reduce efforts in field assessment even in remote areas, and are cost-effective (Patenaude et al., 2005).

Optical remote sensing satellite data have been widely used in biomass assessments of different forest based on their sensitivity of optical reflectance to variation in forest canopy structure (Song & Dickinson, 2008). Even though low and medium spatial resolution images provide a potential of AGB estimation, a spectral mix of pixels, atmospheric effect, and spectral response saturation are found to be problems in complex forest ecosystems (Lu, 2005; Hyde et al., 2006). For instance, studies of Steininger (2000) and Foody (2003) have shown that estimating AGB of tropical forests using Landsat Thematic Mapper (TM) and Synthetic Aperture Radar (SAR) is difficult due to spectral response saturation and overlap of many species from optical sensors and backscatter from SAR. Thus, relying only on low and medium resolution imagery approaches in dense tropical forests lead to high uncertainties of AGB.

To overwhelmed this problem modern earth observation technologies of Light Detection and Ranging (LiDAR) provides promising result in forest biomass estimation as this technique has no saturation problem with biomass increment (Huang et al., 2009). These active remote sensing techniques could offer direct tree height, DBH and other tree parameter readings and modelling which have a direct relationship with biomass (Apostol et al., 2016). LiDAR technologies which include Airborne LiDAR or Laser Scanner (ALS) and Terrestrial Laser Scanner (TLS) are growing fast as these methods can provide a vertical and horizontal structure of the forest through target scanning with laser pulses (Jung et al., 2011). Now a day's these methods are found to be the most favorable remote sensing technologies to delineate individual tree crowns. Several studies showed that ALS and TLS provides height, diameter at breast height (DBH), crown area and the position of trees with very high accuracy (Hyyppa et al., 2012; Ramirez et al., 2013; Ferraz et al., 2016).

Airborne LiDAR Scanner (ALS) offers accurate geospatial data of Digital Terrain Model (DTM) and Digital Surface Model (DSM) (Popescu et., 2002) which are used for extracting absolute height of the trees. Using canopy height model (CHM) derived from DTM and DSM, individual tree crowns can be identified and the canopy height of the local maxima is determined from tree crown segments. The method is recognized as it is more precise and efficient way than the field and optical remote sensing methods (Lim et al., 2003). Andersen et al. (2006) confirmed that ALS provide tree height with accuracy ranges from 0.02 ± 0.73 m. Yamamoto et al. (2011) and Kronseder et al., (2012) studies have also confirmed ALS technology offers tree height with a very high accuracy.

Terrestrial Laser Scanner (TLS) is rapidly growing laser technology which provides highly accurate three-dimensional data and automatic tree positions. The instrument offers efficient and accurate extraction of basic tree inventory parameters of DBH and height (Bienert et al., 2006). Watt & Donoghue (2005), Maas et al. (2008) and Kaasalainen et al. (2014) findings showed that TLS data can replace tedious traditional forest inventory methods through offering highly accurate tree parameters.

Although ALS and TLS are confirmed to provide accurate forest inventory parameters, independent application of these technologies in complex multiple canopy structure of tropical forests seems unrealistic in biomass estimation. ALS can only provide highly accurate heights of higher canopy trees of tropical forests with the limitation of the laser to penetrate and provide information in undergrowth lower canopy trees. Study of Clark et al. (2004) showed that ALS can provide accurate crown projection area (CPA) and height under a wide range of canopy conditions. On the other hand, TLS data could only offer the highly accurate height of lower canopy trees of tropical forests up to the angle of view of the sensor where blocking of the laser with tree crowns is minimal. Henning et al. (2006) proved that TLS provides DBH measurements with an error not exceeding 1 cm, and height accuracy of <2 cm from a height of trees up to 13 m. Independent use of TLS in a tropical forest could give uncertainties in tree height measurements of the higher trees since the complex structure of canopies and very tall trees make it difficult for the instrument to view all tree tops.

In the circumstance of tropical rainforests having more than one canopy layer, integrative use of ALS and TLS data can potentially detect trees under different canopy condition and provide more accurate tree parameters with minimal need for traditional field-based manual measurements. ALS and TLS have been combined to determined canopy structures at plot level (Hilker et al., 2010). In the present study, ALS and TLS are integrated at tree level. One of the few studies where ALS and TLS data are combined at tree level is Lindberg et al. (2012) who found approximately one-third of trees detected by TLS could be linked to ALS detected trees.

Integrative use of ALS and TLS data requires co-registration of the two data sets. The height of the trees under different canopy condition was then measured from the corresponding ALS and TLS data. Trees identified from ALS data were linked with the registered TLS point cloud data for DBH use. Since GPS positions of trees measured under canopy layers are less accurate, the trees recorded in the field were matched with the corresponding ALS and TLS data using stem attributes and TLS positions. DBH measurement can be done either manual detection and measurements (Hopkinson et al., 2004) or cylindrical fitting using least square regression (Bienert et al., 2006).

The objective of this study is to develop an approach for more accurate estimation of AGB and carbon through integrating ALS and TLS derived forest parameters in comparison to traditional field-based methods in Ayer Hitam tropical rainforest of Malaysia. In this paper, region growing segmentation of ALS-CHM was adopted to delineate individual tree crown projection area (CPA) of upper canopy trees. The local maxima of each CHM segments were executed and considered as the absolute height of the individual tree. Tree stems DBH and lower canopy trees height were measured from TLS data, and statistically compared with traditional field-based methods.

2. Materials and methods

2.1. Study area

Ayer Hitam tropical rainforest reserve is located in the Selangor State of Malaysia. The forest is situated in southern Kuala Lumpur capital city at (3º0'0" to 3º2'0" latitude and 101º38'0" to 101º40'0" longitude **(Fig. 1)**. Altitude of the forest ranges from 15 to 233 m a.s.l. Currently, the forest covers around 1248 ha. The forest is the only natural lowland forest left in Putrajaya district and is leased by University of Putra Malaysia (UPM) since 1990 used for education and research purpose in the field of forestry (UPM, 2016). It encompasses about 430 seed plant species with 203 genera and 72 families (Hunum, 1999). The forest is characterized by its emergent, canopy and thick lower canopies, and the dominant tree species are Dipterocarpaceae (Nurul-Shida et al., 2014). Ayer Hitam tropical forest reserve is characterized by an average annual temperature range from 23 to 32°C for 1980 to 2008 trend study. The area has high rainfall distribution throughout the year with an annual average precipitation of 1, 765 mm with higher precipitation occurs from October to February (Toriman et al., 2013). It is also characterized by relatively high average monthly humidity ranging from 94 to 97%.

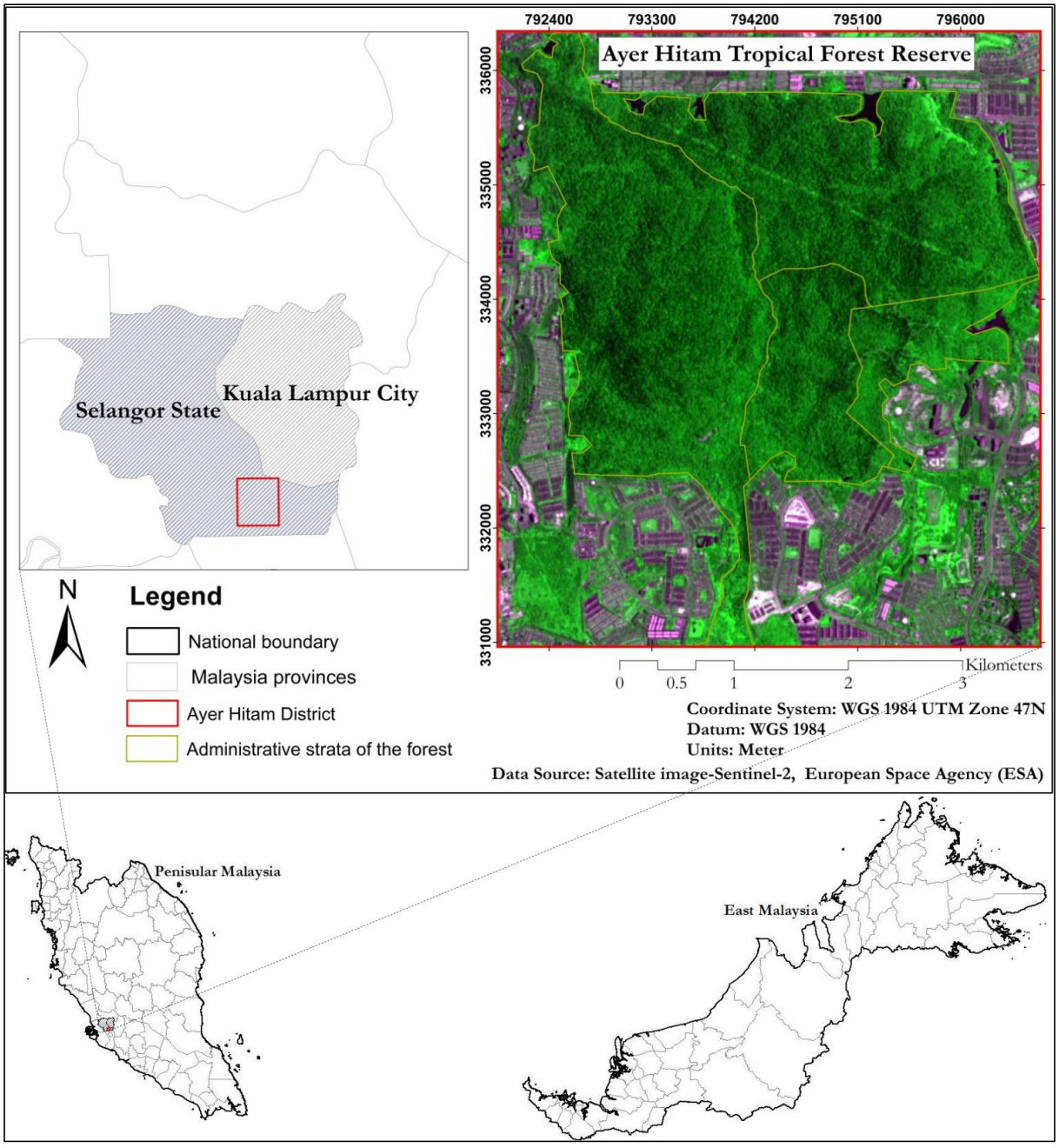


Fig. 1. Study area location map

2.2. Filed data

Field data were collected during September and October 2016. Considering terrain orientations and impenetrability of the forest in the field work area, a purposive sampling approach was used, aiming at covering the variation in forest structure types. The actual samples were selected based on slope steepness and distance to the road where it was possible to carry TLS equipment. A total of 27 circular plots with a size of 500 m^2 (12.62 m radius) were used. In slopping areas, a slope correction factor was also applied to maintain an area of 500 m^2 when vertically projected. Navigation for plot selection was done using Orthophoto image which was acquired concurrently with Airborne LiDAR data.

Tree species were recorded in each plot. Diameter at breast height (DBH) was measured with diameter tape at 1.3 m from the ground for each tree with DBH ≥ 10 cm, and tree height was also recorded with Leica DISTO D510. Next to that crown diameter of the dominant upper canopy trees, and canopy density were measured using a measuring tape and a Densiometer, respectively. Location of each individual tree was also recorded using handheld Garmin GPSMAP 60CSx.

2.3. Terrestrial Laser Scanner (TLS) data

TLS data was acquired during September and October 2016 simultaneously with field data collection. RIEGL VZ-400 was used, and the scanner records multiple returns up to four per emitted pulse. The instrument can give measurement ranging from 1.5 to 600 m with a wavelength of 1, 550 nm. The instrument provides data with precision 3 mm and accuracy of 5 mm. The scanner has 30 mm of footprint size at 100 m, and beam divergence of 0.35 mrad. The scanner has line scan angle range of 100^0 with pulse rate ranging from 44 to 122 kHz.

To improve canopy height observation and enhance 3D representation of the trees, multiple scan method with 4 scanning positions was applied in each field plot. A complete of 360^0 scenes of the horizontal plane were collected at each scanning position. Three positions were located at outer side of the circle with 120^0 far apart, and one is located centrally. All trees inside the plot with DBH ≥ 10 cm were labeled with A4 laminated numbers. The tree labels were placed on the stem of the tree facing the direction of the central position. The labels were used to identify the trees on the scanned point cloud data and later used to find the corresponding tree identified by the ALS data for DBH linking. Twelve (12) cylindrical and 4 circular retro-reflectors were placed in the plot for registration and geo-referencing. Cylindrical retro-reflectors were placed at near the outer scan positions. Circular retro-reflectors were placed in a way that were observable by the central scan position and at least one of them was visible from each of outer scan position. Thus, it was ensured that minimum of 5 retro-reflectors (4 cylindrical and 1circular retro-reflectors) were visible as a tie point in registration and geo-referencing process.

Every position in the plot was scanned with Panorama 60 resolutions which offer acceptable return points for 3D construction of the individual tree. Each scanning position accompanied 13 overlapping images with a digital camera mounted on the top of the TLS used to color the point cloud data.

2.4. Airborne LiDAR Scanner (ALS) data

The ALS data were collected on July 23, 2013, by the University Putra Malaysia (UPM). It was acquired using LiteMapper 5600 waveform-digitizing LiDAR system for terrain and vegetation mapping. The point cloud density was 5 to 6 points/m^2. The pulse rate is varied from 70 kHz to 240 kHz with a wavelength of 1064 nm, and the average flying height is ranging from 700 to 1000 m. The specification of the LiDAR is summarized in **Table 1**. The last return points were used to model the ground surface while the first returns were used for vegetation modelling.

Table 1
LiteMapper 5600 Airborne system specification

Sensor feature	Description
Pulse rate	Range between 70 kHz and 240 kHz
Scan angle	60°
Scan pattern	Regular
Beam divergence	0.5 mrad
Line/sec	Max. 160
A/c ground speed	90 kts
Target reflectivity	20 - 60% (vegetation 30%, cliff 60%)
Flying height	700 - 1000 m
Laser points/m^2	5 to 6 points with 808 m to 1155 m swath width
Spot diameter (laser)	0.35 - 0.50 m
Max (above ground level)	1040

2.5. Methods

The method developed in this study is an approach for accurate forest biomass or carbon estimation based on single tree analysis from ALS and TLS point cloud data where height and DBH were used as measured input parameters. The method used for this research is briefly outlined in **(Fig. 2)**. Image processing was done in ERDAS Imagine and ENVI, LiDAR data in LAStool, CHM segmentation in eCognition, and LiDAR CPA local maxima and mapping were done using ArcGIS. TLS data processing and measurement were done in RiSCAN PRO software. Statistical analysis and validation of forest parameter measurements were done using SPSS and R Studio.

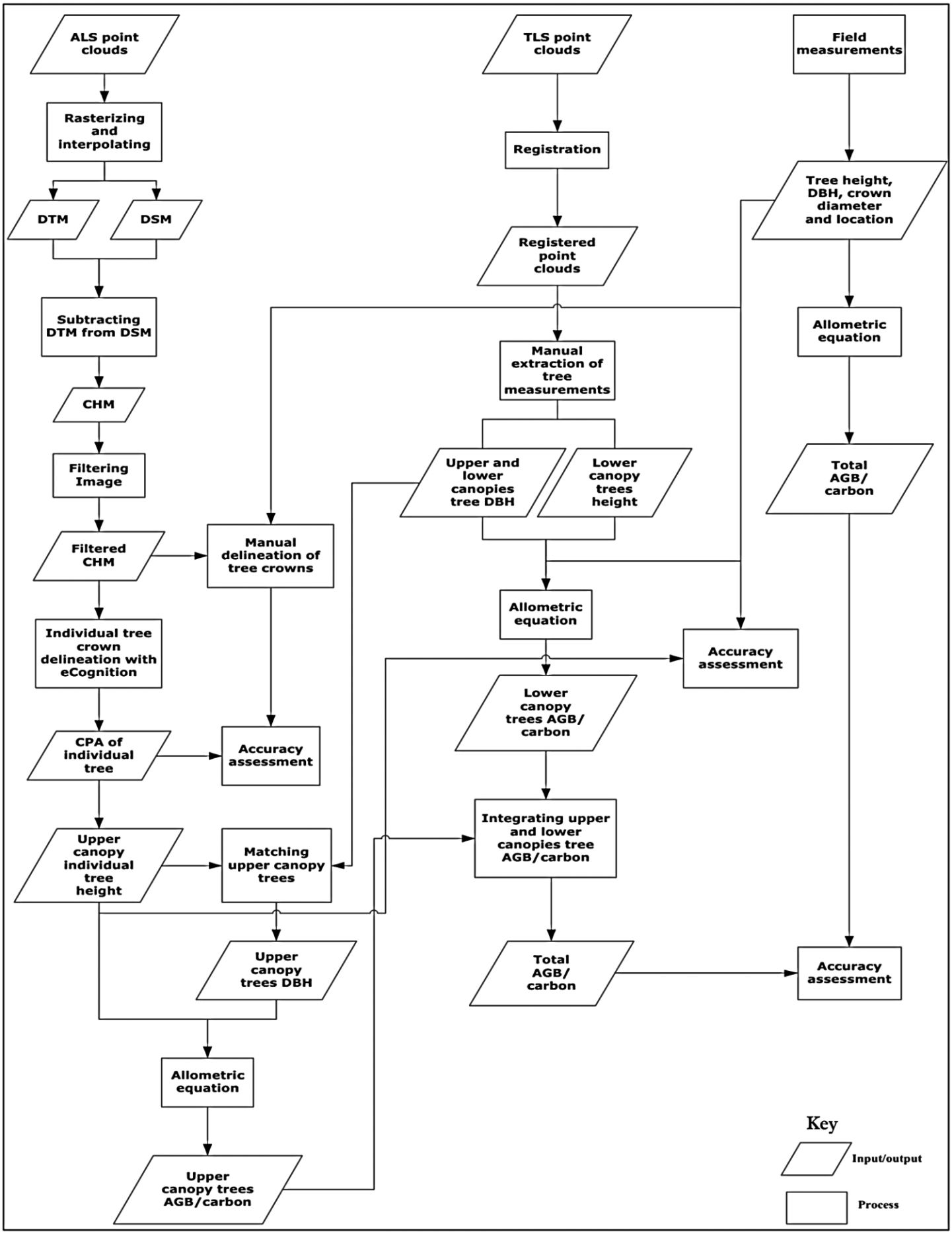


Fig. 2. Methodology flowchart of the study

TLS data processing

The point cloud data from the four scanning positions were registered into common reference system using RISCAN PRO allowing the construction of a 3D point cloud. Registration is the transformation of local systems into common reference system (Bienert et al., 2006). Marker-based registration method using the retro-reflectors was used to match the outer scan positions to the central scan. This method matches common tie points (retro-reflectors) with the corresponding retro-reflectors on the central scan automatically. To form a 3D view of the plots with low standard deviation, multi-station adjustment (MSA) was then applied. The scanned plots were registered with small registration errors. The average MSA registration errors were ranged from 0.018 to 0.028 m **(Table 2)**. **Fig. 3** shows the final constructed 3D point cloud of cluster trees used for tree extraction and parameter measurements.

Table 2
Registration error resulted from multi-station adjustment (MSA) of scanning positions in 3D construction of point cloud data

Plot No.	1	2	3	4	5	6	7	8	9
Standard deviation (m)	0.0185	0.0229	0.0242	0.0221	0.0283	0.0253	0.0186	0.0233	0.0231
Plot No.	10	11	12	13	14	15	16	17	18
Standard deviation (m)	0.0198	0.019	0.021	0.025	0.022	0.021	0.023	0.026	0.0201
Plot No.	19	20	21	22	23	24	25	26	27
Standard deviation (m)	0.0248	0.0217	0.0244	0.018	0.024	0.026	0.021	0.024	0.022



Fig. 3. Example of registered 3D cluster of trees within the plot, based on four scanning positions

The registered point cloud of each plot was then filtered to the extent of the circular plot, viz. 500 m^2. Filtering method was done in RISCAN PRO software by manually selecting the outer boundary using the spot of the outer scan positions and excluding everything which does not fall within the outer boundary. The filtered point cloud was then saved to new Polydata object which was used as an area of interest for individual tree extraction and parameters measurements. The Polydata was displayed in 3D true color linear scale to be able to identify the tags with tree numbers.

Individual tree DBH was measured on the stem at 1.3 m height from the ground using distance measurement function in RISCAN PRO. Similarly, the height of individual tree was measured. The measurement records X, Y, Z values, and the difference of lowest and highest Z value was considered as the height of the tree. A manual measurement method using this software offers higher accuracy since the most top and bottom of the tree is identified manually by removing occlusions.

In the scanned TLS data, the upper canopies of the forest were representing with a lower concentration of point clouds where the number of returns reaching to the upper parts was affected by occlusions of dense tree crowns. In this study, the effect of occlusion was minimal in lower canopy parts which offered a higher concentration of returns. Only trees in lower parts of forest canopies could easily be identified from the TLS data. Thus, height measurement was done for trees with a higher concentration of point clouds with completely visible from tree-tops.

ALS data processing

The LiDAR data has x, y, z-coordinates of each point and is geo-referenced to WGS 1984 UTM Zone 47N. Each coordinate was acquired through an Inertial Measurement Unit (IMU) of GPS receiver installed in a Helicopter. The laser points were classified as ground and non-ground based on progressive triangular network (TIN) method (Lindberg et al., 2012). The first return laser points were interpolated to a regular grid which represented

the digital surface model (DSM) while the ground returns were interpolated that corresponds to digital terrain model (DTM). The extracted DSM and DTM were rasterized into 1 m pixel size. The height accuracy of DTM was anticipated to be about 25 cm in flat parts of the study site (Reutebuch et al., 2003; Hodgson et al., 2004) even though it might vary in different topographical parts of the forest area. The canopy height model (CHM) (1 m cell size) corresponds to the absolute height of the trees was obtained by subtracting DTM from DSM. The cell size was determined by the point density (5 to 6 points/m^2) of the original data. The original CHM has contained pits or holes occurred from sub-layers which are mainly branches below the top of the trees. The pits were removed through CHM free algorithm (Khosravipour et al., 2014). Based on field-based tree height measurements, the ALS point clouds with the height below 0 m and above 50 m were dropped in LAStool software. The pit free CHM is displayed in 2D and 3D view **(Fig. 4)**.

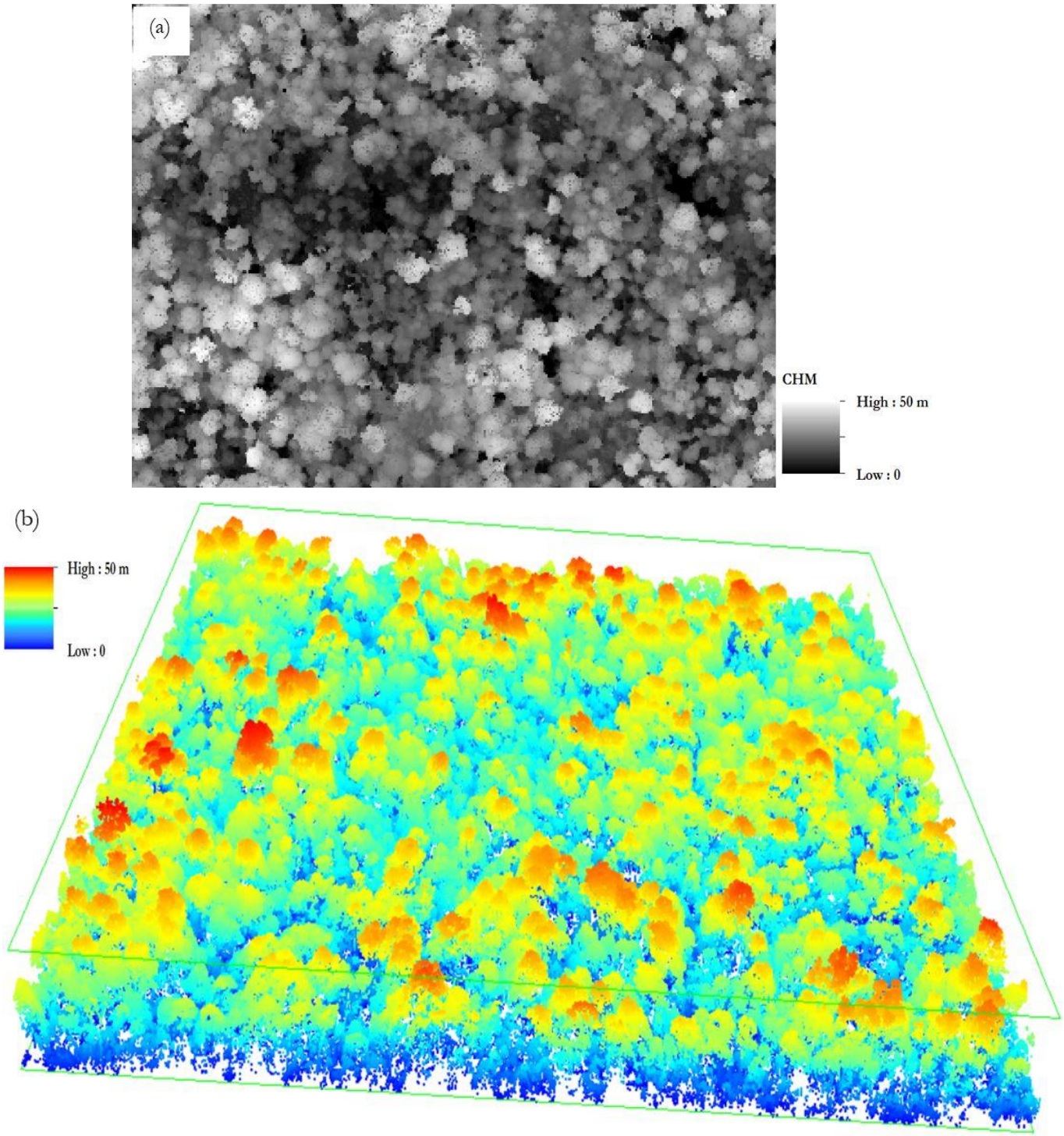


Fig. 4. Airborne LiDAR point cloud CHM; sample obtained by subtracting DTM from DSM. (a)-2D view, (b)-3D view

Delineation of individual tree crowns was based on ALS-CHM segmentation. The segmentation method was done using multi-resolution image segmentation approach. This method follows bottom-up algorithm where pixels are merged into a real world large objects until no more adjacent pixels comply the algorithm setting. The homogeneity criteria are based mainly on scale parameter, shape and compactness (Carleer et al., 2005). The method

is, therefore, identifies geographical features using scale and homogeneity parameters of the CHM values. The segmentation was executed in three phases: segmentation, classification and accuracy assessment.

For each segments representing crown projection area (CPA), the local maxima value of CHM within the segment was used as the height of the trees. Each crown segments were matched with the corresponding tree stems recorded in the field and detected from the TLS.

CHM segmentation accuracy assessment

Accuracy assessment was conducted to recognize the number of trees identified by Airborne LiDAR for tree matching; assuming each image segment was a single tree as stated by (Yao et al., 2014). Manual delineation of recognized tree crowns was done on Airborne LiDAR-CHM based on visually identified trees and the crown diameter of reference trees recorded in the field. Accuracy assessment of crown segmentation was done based on an approach developed by Möller et al. (2007). The method is based on relative area comparison between automatic segments and manually delineated reference tree crowns. The segmentation quality is defined in terms of over and under-segmentation (Eqs. (1); (2)) and segmentation goodness (D) (Eqs. (3)). D-value refers to closeness measure of segmentation output in relation to reference segments and is between 0 and 1. The result indicates an error occurred in automatic segmentation. As the D-value increases, the deviation of automatically segmented crowns from the corresponding reference crowns increases, which implies increment of mismatching between tree crowns.

$$\text{Over segmentation} = 1 - \frac{\text{Area}(xi \cap yi)}{\text{Area}\,(xi)} \quad (1)$$

$$\text{Under segmentation} = 1 - \frac{\text{Area}(xi \cap yi)}{\text{Area}\,(yi)} \quad (2)$$

$$D = \sqrt{(\text{Over Segmentation}_{ij}^2 + \text{Lower segmentation}_{ij}^2)/2} \quad (3)$$

Where xi: Manually delineated reference crowns; yi: Segments from automatic segmentation; D: Segmentation goodness

Zhan et al. (2005) also indicated segmented polygons considered to be 1:1 matched if it is overlapped with the reference polygon by at least 50%, and matching considers position, shape and size, completeness and correctness of an object.

Canopy separation and parameter measurements

Accurate measurement of forest parameters of all trees was challenging in the tropical forest due to natural complexity character of the forest. Jung et al. (2011) indicated that in forests with multiple canopy layers, tree parameter extraction using ALS is effective in detecting emergent canopy trees. TLS-based height measurements in a tropical forest are also challenging due to multiple canopies, tall trees and dense interlocking crowns make it difficult for the instrument to view the top of crowns of upper canopy trees (Strahler et al., 2008).

In this study, the height of the trees was measured from corresponding ALS and TLS point cloud data based on their higher detectable capability of the forest layers. Therefore, the forest was separated into two canopies; viz. upper and lower canopies. To separate upper and lower canopy, ALS-CHM segmented image was used. Then, the local maxima height value of each segment in the CHM was extracted for each plot to determine the minimum height of the complete tree crown that can be detected by airborne LiDAR. This minimum height was set as the lower boundary of the upper canopies. The trees with below the threshold were considered as lower canopies and tree heights were extracted using TLS data. ALS-CHM has, therefore, used to extract upper canopies tree height while the TLS was used to measure DBH of upper and lower canopies tree, and the height of lower canopy trees.

Allometric equation and above-ground biomass estimation

Since the study area is a forest with mixed high diversity species, AGB was estimated based on the generic allometric equation for tropical forest developed by Chave et al. (2014) (Eqs. (4)). Reyes et al. (1992) of the wood density of tropical forest tree species was adopted for the chosen allometric equation. Field and TLS DBH, height derived from the field, TLS and ALS, and wood density of each tree species was used as input parameters. The carbon content of the trees was obtained based on IPCC (2006) conversion factor of 0.47 (Eqs. (5)).

$$AGB = 0.0673 * (\rho D^2 H)^{0.976} \quad (4)$$

Where ABG-Above-ground biomass (kg); D-Diameter at breast height (DBH) (cm); H-height (m); and ρ-wood density (g/cm^3)

$$C = AGB \times CF \quad (5)$$

Where C-carbon stock (Mg); ABG-Above-ground biomass (Mg); CF-conversion factor which is 0.47 of AGB.

Statistical analysis

The performances of ALS and TLS tree detection in the tropical forest were measured based the capability of the instruments in providing highly accurate tree heights under different canopy conditions. It was assumed that ALS offered higher canopies tree height accurately while TLS was efficient and accurate for lower canopies tree heights (Eqs. (6); (7)).

$$\text{ALS tree detection (Upper canopies) (\%)} = \frac{\text{No.of trees detected by ALS}}{\text{No.of field observed trees}} \times 100 \quad (6)$$

$$\text{TLS tree detection (Lower canopies) (\%)} = \frac{\text{No.of trees detected by TLS}}{\text{No.of field observed trees}} \times 100 \quad (7)$$

A scatter diagram between two related variables was performed to assess their relationships. The coefficient of determination (R^2) and correlation coefficient(r) were calculated to show the percentage deviation between field and remotely sensed (ALS and TLS) variables of tree height, DBH and AGB. The RMSE and bias were also executed to explain the deviation between the measured and model-predicted values these variables (Eqs. (8)–(11)).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{n}} \quad (8)$$

$$\text{RMSE (\%)} = \frac{\text{RMSE}}{\left(\frac{\sum_{i=1}^{n}(y_i)}{n}\right)} \times 100 \quad (9)$$

$$\text{Bias} = \frac{\sum_{i=1}^{n}(y_i - \hat{y})}{n} \quad (10)$$

$$\text{Bias (\%)} = \frac{\text{Bias}}{\left(\frac{\sum_{i=1}^{n}(y_i)}{n}\right)} \times 100 \quad (11)$$

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

To observe the significance difference among measurement means, student t-Test was performed among different variables derived from remote sensing and traditional field-based methods. The TLS-based DBH was validated against manually measured values. On the other hand, field-based heights were validated using the corresponding ALS and TLS measured tree heights; where the ALS and TLS measured tree heights considered as the ground-truth reference. Finally, AGB calculated from remotely sensed and field-based method was compared.

3. Results

3.1. DBH Measurement and Accuracy Assessment

Of 786 total trees recorded in the field, 735 (93.5%) trees were identified by the TLS and used for DBH measurements. The extracted DBH from a 3D point cloud data of TLS was validated for its accuracy using field-measured DBH. It was observed that for all matched trees, TLS-based DBH measurement had no significant impact on the model inferences where linear regression fit model was very close to the one-to-one line **(Fig. 5)**. R^2 showed that TLS-based height was best predicted at 0.99 with RMSE of 1.3 cm (6.52%). The TLS method had a minor underestimation of DBH measurements with the measurement bias of –0.52 (–2.63%) **(Table 3)**. Based on t-Test assuming equal variance, there was no statistically significance difference between DBH measured from the field and TLS data **(Table 4)**.

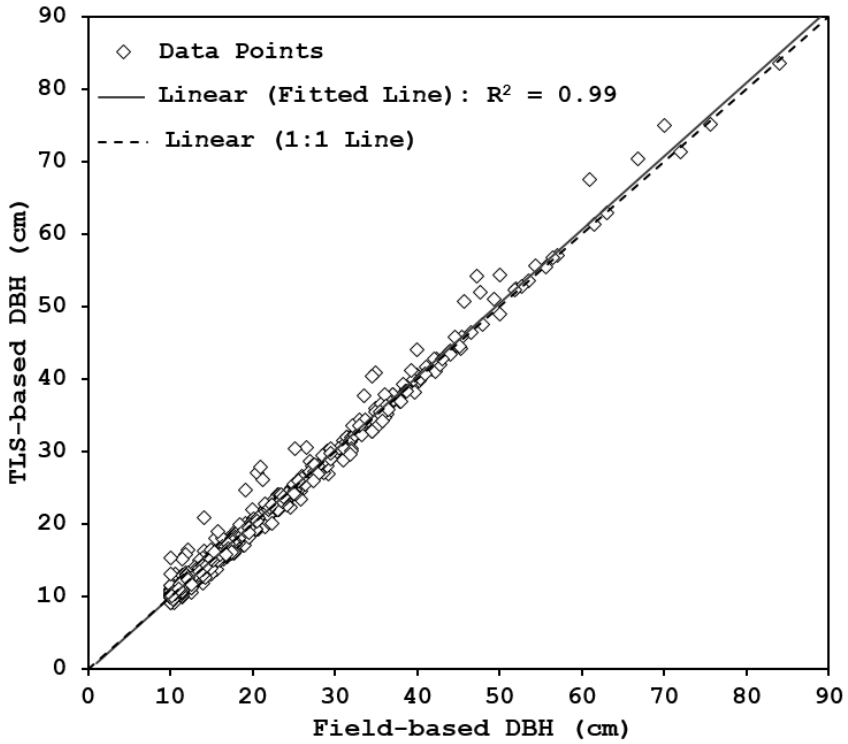


Fig. 5. Scatterplot of TLS vs. field-measured DBH

Table 3
Summary of fit between field and TLS-based DBH

Tree parameter	No. of observations	Adjusted R^2	Correlation coefficient	Standard error	Intercept	Slope	RMSE		Bias	
							(cm)	(%)	(cm)	(%)
DBH	735	0.989	0.994	1.156	–0.3601	1.0153	1.299	6.52	–0.52	–2.63

Table 4
Summary of statistical test of DBH derived from field and TLS

	Mean DBH (cm)		Variance DBH (cm)							
Test	Field-based	TLS-based	Field-based	TLS-based	df	t Stat	P(T<=t) one-tail	t Critical one-tail	P(T<=t) two-tail	t Critical two-tail
t-Test	19.98	19.93	117.457	122.412	1468	0.0954	0.4620	1.6459	0.924	1.9616
Conclusion: The result showed that there was no statistically significant difference between DBH measured from the field and TLS ((|t Stat| < t Critical).										

3.2. Validation of crown projection area (CPA)

Scale parameter 10, shape 0.7 and compactness of 0.5 were found to be a reasonable accurate rule set for segmentation in eCognition ALS-CHM. The validation was obtained using 1:1 spatial area correspondence and segmentation goodness (D) of accuracy measures for manually delineated reference tree crowns. Over- and under-segmentation and D values were 0.24, 0.30 and 0.27, respectively. The segmentation error was 27%, which means the overall segmentation accuracy of 73%. A one-to-one correspondence matching of segmented crowns with the referenced crowns was executed. Of 132 reference polygons, about 103 of automatically generated polygons were correctly matched which accounts a 78% segmentation accuracy **(Table 5)**.

Table 5
Segmentation accuracy result

	Reference polygons	1:1 matched polygons	Over-segmentation	Under-segmentation	Goodness of fit (D)
	132	103	0.24	0.30	0.27
Accuracy (%)		78			73

3.3. Canopy separation and combination of ALS and TLS

The segmentation result showed that the ALS-CHM had reasonable accuracy when it comes to identifying and mapping of CPA of an individual tree. Two approaches were used to set canopy separation threshold. One for plots with multiple and one for single upper canopy layers. Multiple canopy layers were plots with many top emergents, medium and under canopy trees. For these plots, the minimum height of trees where the complete crown was visible on the ALS-CHM was 12 m. Thus, 12 m was used as a threshold for the upper canopies. The remaining trees with a height of ≤ 12 m were considered as lower canopy trees. On the other hand, single layer plots were higher top canopy trees have more or less the same height, a threshold of 8 m was applied to separate upper and lower canopies due to the fact that trees with a height of > 8 m were detectable on the ALS-CHM. **Fig. 6** shows an illustration for assessment of sample plots for separating upper and lower canopies from segmented CPA of Airborne LIDAR-CHM. The height of the corresponding trees of the delineated CPA was measured with ALS while the remaining trees where the top of the crowns were not visible by ALS-CHM were considered for TLS method height measurements. A higher proportion of trees detected from ALS could be co-registered and linked with corresponding TLS identified stems for DBH use by cross-correlating with field recorded coordinates, stem characteristics and position of trees from TLS scanning positions.

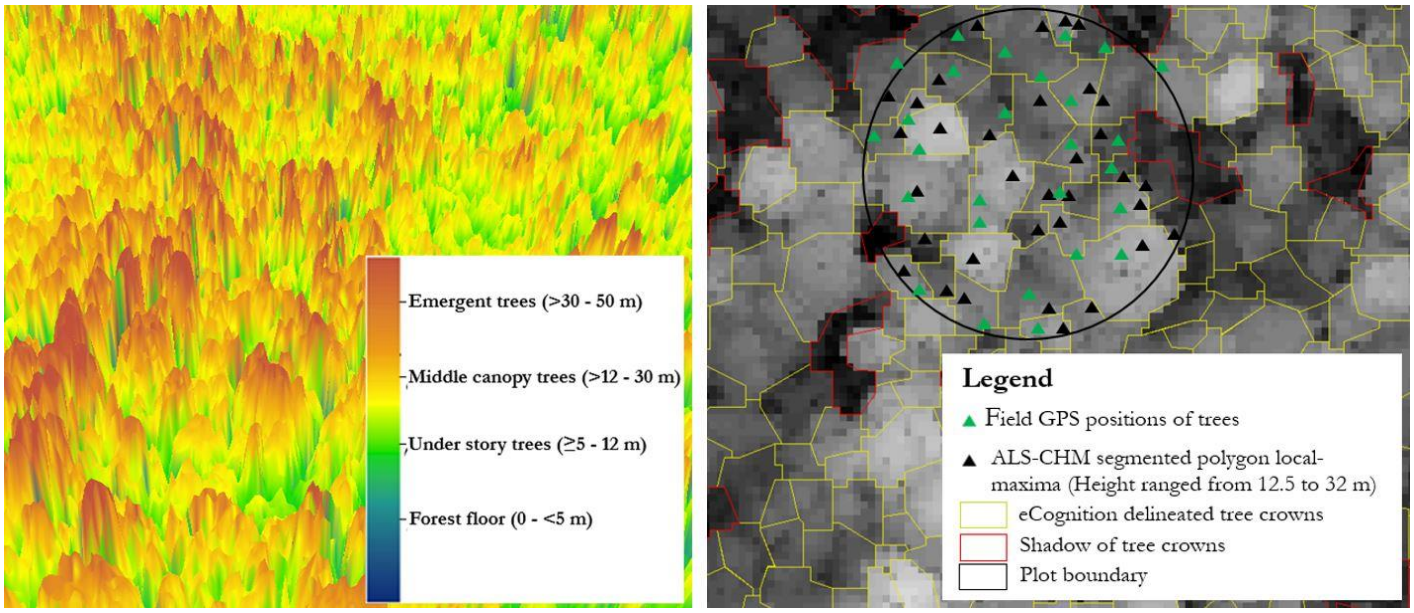


Fig. 6. 3D view of canopy classification from Airborne LIDAR data (the left CHM image); where forest floor and understory trees CPA are not clearly delineated in ALS-CHM. The method of setting a threshold for canopy separation in LiDAR-CHM (the right image); the green color shows the local maxima of segmented CPA while the yellow color is the field GPS location of the trees. The local maxima of CHM were considered for the height of trees. In this plot, ALS-CHM was able to see crown tops with a height of the trees ≥ 12.5 m (12.5 to 32 m).

3.4. Tree height accuracy assessment

Based on the tree-top detectable capacity of ALS and TLS, two-way height measurements and validations were applied, viz. upper canopies and lower canopies tree height accuracy assessments. Of the total trees identified in the field, 486 (61.83%) trees were categorized as upper canopies whereas the remaining 300 (38.17%) trees were considered as lower canopies based on the height detection threshold. Of all upper canopy trees, 451 trees could be matched with the corresponding trees in the field. A total of 290 lower canopy trees were matched with field identified trees, and height was measured from TLS data.

The mean height of all trees detected from ALS and TLS were 18.03 and 9.42 m, respectively. Field-based height had a significant influence on measurement accuracy where both upper and lower canopies linear regression fitting model were far from one-to-one regression line (**Fig. 7**).

Pearson's correlation coefficient was calculated for upper and lower canopies tree height variables. The relationship of field and TLS-based lower canopy trees height was found to be with RMSE of 1.45 m and bias of 0.42 m; indicating field-based method over-estimates the height. On the contrary, field method measurement underestimated the upper canopy tree heights when it compared to the ground-truth reference ALS heights with the bias of –1.20 m **(Table 6)**. The statistical test showed that there was a statistically significant difference between ALS, TLS and field-based tree height measurements of the tropical forest **(Table 7)**.

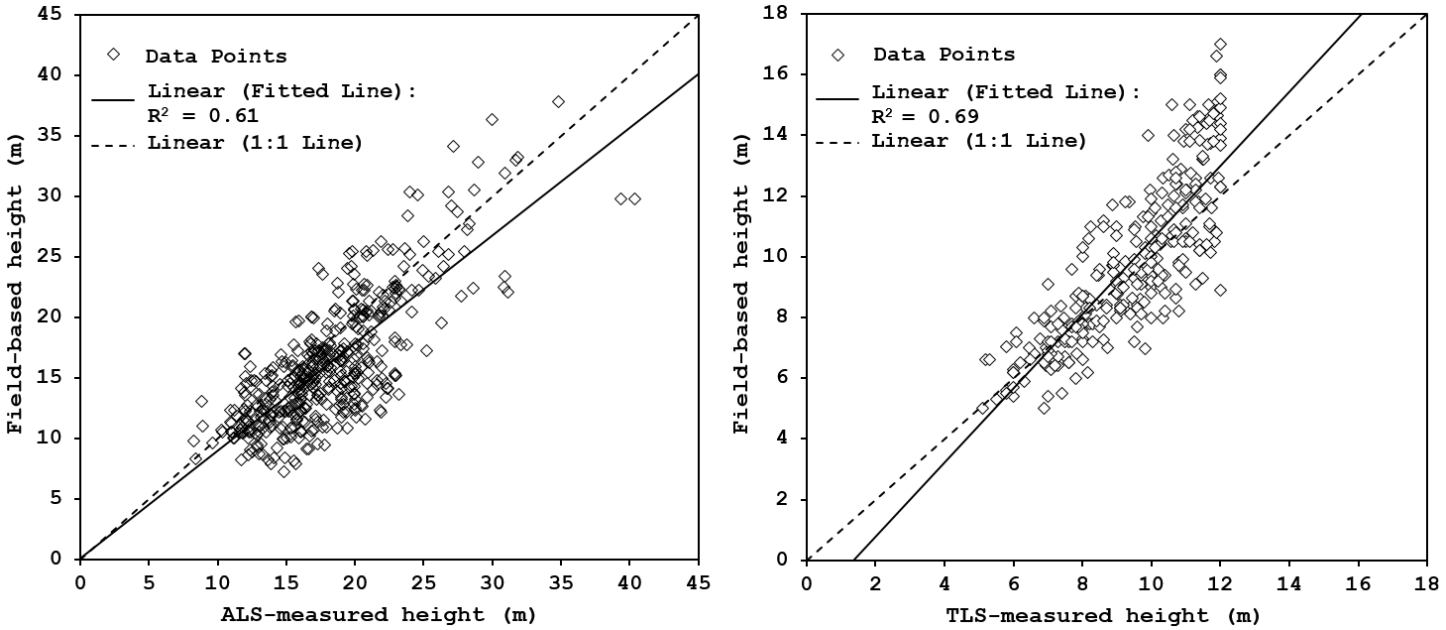


Fig. 7. Scatterplot of field vs. ALS-based upper canopy trees height (the left graph), and field vs. TLS-measured lower canopy tree heights (the right graph). The model evaluated the linear function of ALS and TLS measured height with the traditional field-based height.

Table 6
Summary of fit between upper canopy (ALS) and lower canopy (TLS) measured height and the corresponding field-based height

Tree parameter	No. of observations	Adjusted R^2	Correlation coefficient	Standard error	Intercept	Slope	RMSE (m)	RMSE (%)	Bias (m)	Bias (%)
Upper canopy trees height	451	0.607	0.779	3.252	–0.0392	0.8935	3.244	20.18	–1.20	–7.45
Lower canopy trees height	290	0.688	0.83	1.458	–1.6617	1.2212	1.453	14.77	0.42	4.29

Table 7
Summary of statistical test of upper and lower canopies tree height measured from remote sensing (RS) of ALS and TLS, and field method

Test	Tree parameter	Mean height (m) RS-based	Mean height (m) Field-based	Variance height (m) RS-based	Variance height (m) Field-based	df	t Stat	P(T<=t) one-tail	t Critical one-tail	P(T<=t) two-tail	t Critical two-tail
t-Test	Upper canopy trees height	18.03	16.08	20.85	27.02	900	5.9901	1.51E-09	1.6465	3.03E-09	1.9626
	Lower canopy trees height	9.42	9.84	3.16	6.83	578	–2.2715	0.0117	1.6475	0.0235	1.9641
Conclusion: The statistical result showed that there was a statistically significant difference between field-based and remote sensing (ALS and TLS) measured height at 95% confidence interval (|t Stat| > t Critical).											

3.5. Traditional field and remote sensing (RS)-based AGB comparison

The AGB calculated from the field and modern remote sensing (ALS and TLS) derived tree parameters were compared per plot. Total remote sensed-based AGB was calculated by adding lower and upper canopies tree AGB derived from TLS and ALS, respectively. **Table 8** shows the descriptive statistics of AGB within sample plots with different estimating approaches. Of a total of 247.15 Mg AGB calculated from remote sensing derived parameters, 228.02 Mg (92%) were accounted as upper canopy ALS based AGB, while 19.13 Mg (8%) of AGB was reserved in lower canopy TLS detected trees. Mean AGB of 8.44 and 0.71 Mg.plot^{-1} was estimated in upper and lower canopies tree, respectively. This implies an average of 0.71 Mg.plot^{-1} AGB was captured through the complimentary application of TLS which could not be identified by ALS. Based on traditional field-based parameters, a total of 220.76 Mg AGB was estimated with mean upper and lower canopies of 7.41 Mg.plot^{-1} and 0.77 Mg.plot^{-1}, respectively.

Table 8
Proportion of upper and lower canopies tree AGB estimated by remote sensing (RS) and traditional field-based method

Statistics	RS-based AGB (Mg) Upper canopy trees (ALS)	RS-based AGB (Mg) Lower canopy trees (TLS)	Field-based AGB (Mg) Upper canopy trees	Field-based AGB (Mg) Lower canopy trees	Combination of upper and lower canopies AGB (Mg) RS method	Combination of upper and lower canopies AGB (Mg) Field method
Mean/Plot	8.445011	0.708560	7.408448	0.76778	9.1536	8.1762
Std. Dev.	3.271395	0.376738	2.989925	0.41520	3.3146	3.0655
Min.	3.431590	0.091633	3.283845	0.02466	3.9807	3.9390
Max.	17.89105	1.621062	15.56155	1.92615	18.2316	16.0022
Sum	228.0153	19.13112	200.0281	20.7302	247.146	220.758

With remote sensing, 183.07 Mg.ha^{-1} of AGB or 86.04 183.07 Mg.ha^{-1} of above-ground biomass carbon (AGBC) was calculated. On the other hand, 163.52 Mg.ha^{-1} of AGB or 86.04 Mg.ha^{-1} AGBC was estimated with the traditional field-based method. Traditional field method has, therefore, underestimated the AGB by 19, 547 Kg.ha^{-1} (19.547 Mg.ha^{-1}) which accounted 10.70%. Thus, based on traditional field-based parameters, we could only estimate 89.3% of the tropical forest AGB. **Fig. 8** shows the overall share of AGB for different canopies with various estimation methods.

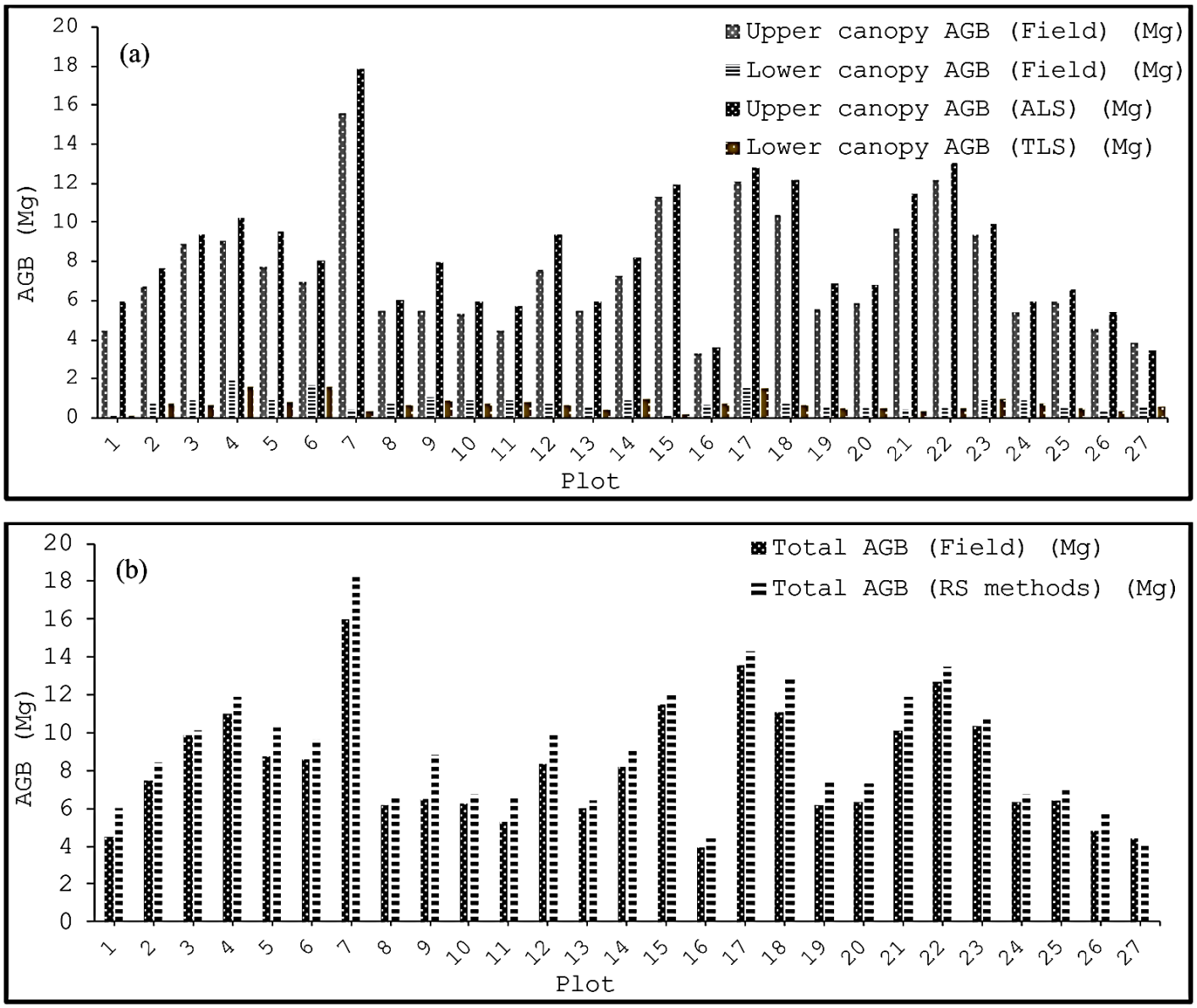


Fig. 8. Estimated AGB per plot; AGB proportion of the forest canopies estimated with different methods (a), comparison of traditional field vs. remote sensing methods total AGB (b).

Statistical analysis and validation of the model were conducted to analyse the linear relationship between variables of the field and RS-based AGB. A Linear regression model using RS-based AGB as independent variable explained 97% field derived associated variance for 27 sample plots of the dependent observation. We found that there is a strong correlation (0.98) between RS and field-based AGB or carbon with RMSE and Bias of 0.624 (7.64%) Mg and –0.289 (–3.53%) Mg, respectively. However, the linear regression fitting model confirms that traditional field-based method had a minor underestimation of AGB of the study site (**Fig. 9**). With our method, the unexplained variance is mainly associated with the errors due to traditional field-based height measurements. The measurement errors of field-based height in upper canopy trees (RMSE of 20.18% and bias of –7.45%) and lower canopy trees (RMSE of 14.77% and bias of 4.29%) accounts the principal variation in the estimated AGB. On the other hand, the observed TLS-based DBH effect on AGB calculation was insignificant. The statistical test showed that there was no significant difference between AGB calculated with traditional field methods and remote sensing based methods at a plot level (95% level of confidence).

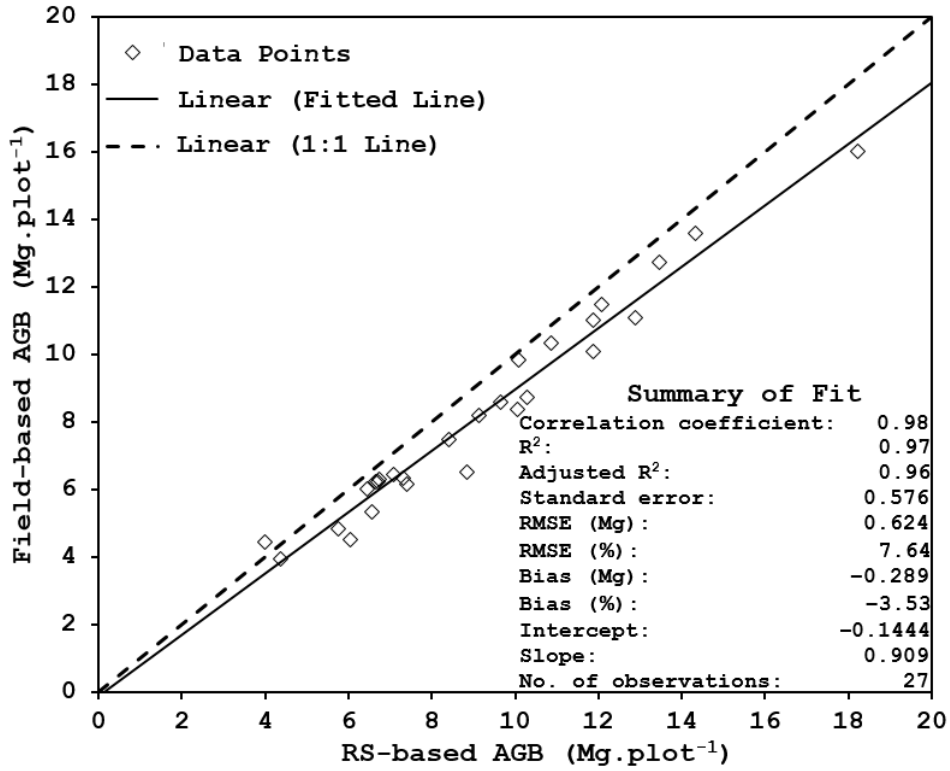


Fig. 9. Scatterplot of field vs. remote sensing-based AGB. Field-based AGB per plot was based on manually measured DBH and Leica DISTO D510 derived height while remotely sensed method of AGB was based on parameters of ALS-CHM and TLS measured tree height and TLS DBH.

4. Discussion

This study has presented a new method to complementary use of ALS and TLS data for AGB inventory at individual tree level. The method uses these LiDAR instruments based on their canopy detection capability. Tree crowns are segmented from ALS-CHM, and clearly unidentified trees from CHM were extracted from TLS data. Manual field measurements needed in each sample plot is to calibrate the TLS measured DBH, and height measurement deviations. This demonstrates to reduce the need for traditional field-based measurements for AGB estimation in tropical forests under complex forest structures.

The complementary application of TLS has enabled to identify 735 (93.5%) of tree stems for DBH use and some of the trees where crown tops clearly visible (38.17%) are measured for height from constructed 3D point cloud data of TLS. Studies have shown that the TLS can detect more than 90% of the tree trunks depending on the method of extraction. Maas et al. (2008) detect 97.5 % of trees in an Austrian forest. In areas with less undergrowth, for instance, the riparian forest in France, 100% of the tree trunks could be detected from TLS data (Antonarakis, 2011). The result of this study showed that considerably lower number of trees were detected compared to those studies. This is because the complex forest structure of the study area contributes to some trees having lower point cloud density which makes difficult to extract individual tree.

Validation of TLS-based DBH has been executed for all identified and matched tree stems with field measurements. The accuracy of DBH measurement from TLS in our study was high. The accuracy obtained was better than studies in forest sites of Texas; R^2 ranged from 0.91 to 0.97 (Srinivasan et al., 2015), and in Eucalyptus forest of Victoria, Australia with R^2 of 0.97 (Calders et al., 2015). However, the RMSE of the study is higher as compared to Norway spruce dominated forest which is 0.38 cm (Lindberg et al., 2012). All cited studies used TLS data collected from multiple scanning positions. Plots with complex dense forest structure contribute to some tree trunks having lower point cloud density. Besides, a limited number of intermingling growing trees has also contributed to some uncertainty in DBH measurements. For tree stems closer to the scanning position, the scanner measures the lowest part of the tree stems. On the contrary, for trees away from the trees, the tree stems might occluded by stems and undergrowth vegetation. However, in this study, the accuracy of TLS measured DBH has not been highly dependent on the distance of the scanning positions. This is because 4 scanning positions accompanied with the clearing of undergrowth possible occlusion vegetation could be enough for constructing 3D of the individual tree stem. It was confirmed that the TLS-DBH accuracy achieved in this study has no significant impact on AGB calculation.

Tree crown delineation was done from multi-resolution segmentation of ALS-CHM for canopy separation and individual tree height measurements. Multi-resolution segmentation is preferable for segmenting heterogeneous forest structure (Möller et al., 2007). The segmentation accuracy of this study was 73% for the 78% of the 1:1 matching polygons. The ALS point cloud of 5 to 6 points/m^2 used for this study potentially contribute to the effectiveness of tree delineation of dense forest crown overlapping tropical forest to be relatively lower. Hatami (2012) indicated the decrease in point cloud density from 164 to 4 points/m^2 results in an accuracy of tree detection decline from 79.0% to 66.1%. The effect of investigator dependant selected rule sets could also be contributed to the variation in the accuracy of the segmentation achieved.

It was observed that in this study site, detecting all trees crown tops with single remote sensing technology has been challenging. Airborne LiDAR has been effective to see middle and emergent canopies tree as the laser pulses cannot penetrate to the lower canopy parts. Jung et al. (2011) studies also confirm the overlapping effect of the top canopies crown in the forest prevented for lower canopy trees to be seen by the ALS. Canopy separation has, therefore, done by considering the missed trees from segmented Airborne LiDAR canopy projection area (CPA). Of 786 trees recorded in the field, 486 (61.83%) trees were identified with ALS-CHM. Based on height threshold detectability of ALS-CHM, about 300 (38.17%) trees have been considered as lower canopy trees. In Karlsruhe municipal forest of Germany showing that one-third of 831 trees has been accurately detected with TLS

for height parameter measurement and linked with ALS identified trees (Fritz et al., 2011). In Norway spruce tree dominated forest of Romania, only 40-61% of field-measured trees in different plots have been matched with Airborne LiDAR (Apostol et al., 2016).

The complementary use of ALS and TLS requires co-registration and matching of the tree stems detected from both data sources. Thus, TLS-based DBH measurement was used for both ALS and TLS identified tree stems. This is because the laser points of Airborne LiDAR CHM is hardly to delineate tree crowns accurately in complex tropical forest structure, causing uncertainty in DBH prediction. Another advantage of TLS was for height measurements of trees which are not detected from ALS-CHM. The standard deviation of the desirable accuracy of multi-station adjustment (MSA) for registration of multiple scan positions provides a highly accurate 3D structure of an individual tree. The MSA accuracy could be affected by a number of perfectly viewed tie points or retro-reflectors in each scanning position which can be influenced by occlusions and slope in the field. Manual tree height measurement tool used in RiSCAN PRO provides highly accurate tree heights compared to automatic height measurements.

The tree height could be measured from ALS and TLS. A large number of tree-tops were detected from ALS-CHM while about one-third of trees were detected from TLS. The vertical field of view of the TLS has been obscured with interlocking dense crowns at the top, makes only a few tree-tops were visible in the point cloud data. To link the positions of trees with manually measured tree heights from ALS and TLS data, the trees has been labeled with numbers made from laminated paper that could be clearly visible in the TLS central scanning position and identified for analysis. Field-based manual height measurement has been done with Leica DISTO D510 Laser technology with 360° tilt sensor give both angles and distances measurements.

Tree height validation in this study showed that field method measurement underestimates the tree height when compared to the ALS-CHM. A deviation up to 11 m has been recorded per individual tree. Study of Airborne LiDAR and field data in four tropical regions forest of Hawaii Island, Amazonian Peru, and Central Panama showed that the relationship between ALS and field height is R^2 of 0.77, 0.82 and 0.84, respectively (Asner et al., 2012). Karna et al. (2015) found R^2 of 0.76 in Kayar Khola watershed forest of Nepal. The study in isolated agroforestry trees in tropical studies of Atlantic lowlands, East Costa Rica with no occlusion, field height measurement, and Airborne LiDAR has shown a high relationship between the two measurements with R^2 of 0.95 and RMSE of 2.5 m (Andersen et al., 2006). Most of the studies in temperate open natural and plantation forests reported that Airborne LiDAR and conventional field-based tree heights have a high correlation. For instance, the studies of (Næsset & Økland, 2002) in Norway spruce dominated boreal forest, and Heurich (2008) in the Bavarian forest of Germany achieves high correlation between field and Airborne LiDAR-based height with R^2 of 0.91 and 0.98, respectively. Our study achieved lower correlation between field and ALS-based height measurements compared to those findings. However, the results obtained in this study are comparable with similar studies in the tropical rainforest of Malaysia who achieve R^2 of 0.61 and RMSE of 4.20 (21.45%) m (Sadadi, 2016).

In this study, Airborne LiDAR-CHM was used as a reference to validate field- based height measurements since the field measured height is not accurate due to the complex structure the forest. Andersen et al. (2006) study show Airborne LiDAR data with 6 points/m^2 reveals a high correlation with actual tree height as compared to conventional field measurement where the accuracy of tree height mean error is ± Std. Dev. of 0.73 ± 0.43 m. The study also indicate the error in tree-top detection due to the influence of Digital Terrain Model (DTM) could contribute only 10 to 20 cm in a flat area of Fort Lewis forest of Washington which might actually increase in dense and varied topographic area. Ginzler & Hobi (2015) have been also used Airborne LiDAR-CHM through matching stereo-image as ground-truth reference height to validate field-measured tree height in Swiss national forest inventory.

The correlation between TLS and field-based lower canopies tree height in this study was found to be low where TLS measurement taken as ground-truth reference. Height differences up to 5 m have been recorded in an individual tree observation where conventional field-based measurement tend to overestimate by the bias of 0.42 m. Despite the fact that occlusion has an effect in both TLS and handheld laser instruments, TLS has a potential to provide a full 3D structure of the lower canopy trees. But, field-based handheld laser instruments measurement is still highly affected by many branch leaves which block the laser to mark the tree-tops. It was experienced in the field, tree height measurements with handheld laser instruments showed substantial variation in height depending on distances from the tree and observers. Lindberg et al. (2012) proved that TLS provides highly accurate height measurements up to a vertical field of view in less occluded areas. Calders et al. (2015) study also showed that TLS height measurement is more accurate (with R^2 of 0.98 and RMSE of 0.55 m) than conventional field-based approach (with R^2 of 0.94 and RMSE of 1.28 m) when both measurements validated against destructively measured reference tree heights.

The study area is secondary tropical rainforest with complex vertical and horizontal structure which makes it difficult to get a clear view of the tree-tops. For tree height measurements with handheld instruments, it is pivotal to have considerable distance from the tree to view clearly the top of the tree. In reality, for a secondary tropical forest however it is challenging to get enough free space to comply with this requirement due to occlusions of branches and forest density. Using field method has, therefore, an ambiguous in providing accurate height measurements in forests with large trees and closed-stands. Larjavaara & Muller-Landau (2013) also pointed out field method tree parameter extraction in tall trees, wide crowns, dense canopies and interlocking branches of tropical forest studies produce errors in tree height measurements.

Correlation analysis revealed that the linear relationship between RS (ALS + TLS) and traditional field-based AGB or carbon was strong (0.98) and statistically significant at 95% interval of confidence. The overall strength of the estimated AGB relationships indicated here is higher compared to many other studies. For instance, the coefficient of determination between RS and field-based AGB ranged between 0.70 and 0.92 in studies of Næsset & Gobakken (2008), Meyer et al. (2013), Ioki et al. (2014), Olsoy et al. (2014) and Vaglio et al. (2014) where only single LiDAR application was used. The approach of integrating TLS with ALS used in this study contributed to recognizing of a substantial number of trees overlooked from ALS. The number of unobserved trees from both ALS and TLS in all sample plots was 45 with DBH ranged from 10 to 15 cm which could be added an insignificant amount of AGB. Besides, application of TLS data offered highly accurate DBH measurements for all ALS and TLS identified tree stems due to the fact that the CPA delineated from ALS-CHM (73% of accuracy) in the complex tropical forests could not be used to predict DBH. DBH can be predicted from Airborne LiDAR with the acceptable result in open plantation and natural forests where individual tree crown has clearly differentiated. For instance, Popescu (2007) and Yao et al. (2014) predicted DBH from Airborne LiDAR CHM with R^2 of 0.80 in temperate forest studies, which is an acceptable model for AGB calculation. But, in forests with complex canopy structure like our study site, tree crowns would not be accurately delineated.

The slight difference in the traditional field and RS method of AGB has, therefore, originated mainly from tree height measurement errors. Hunter et al. (2013) have been reported that height error ranging from 3–20% of the total height results about 5–6% of uncertainty in estimated biomass. The RMSE of 3.24 m (20.18%) and 1.45 m (14.77%) achieved for upper and lower canopies tree height, respectively could contribute to the variation of AGB or carbon (RMSE of 0.62 or 7.64% Mg) achieved in this study.

5. Conclusion

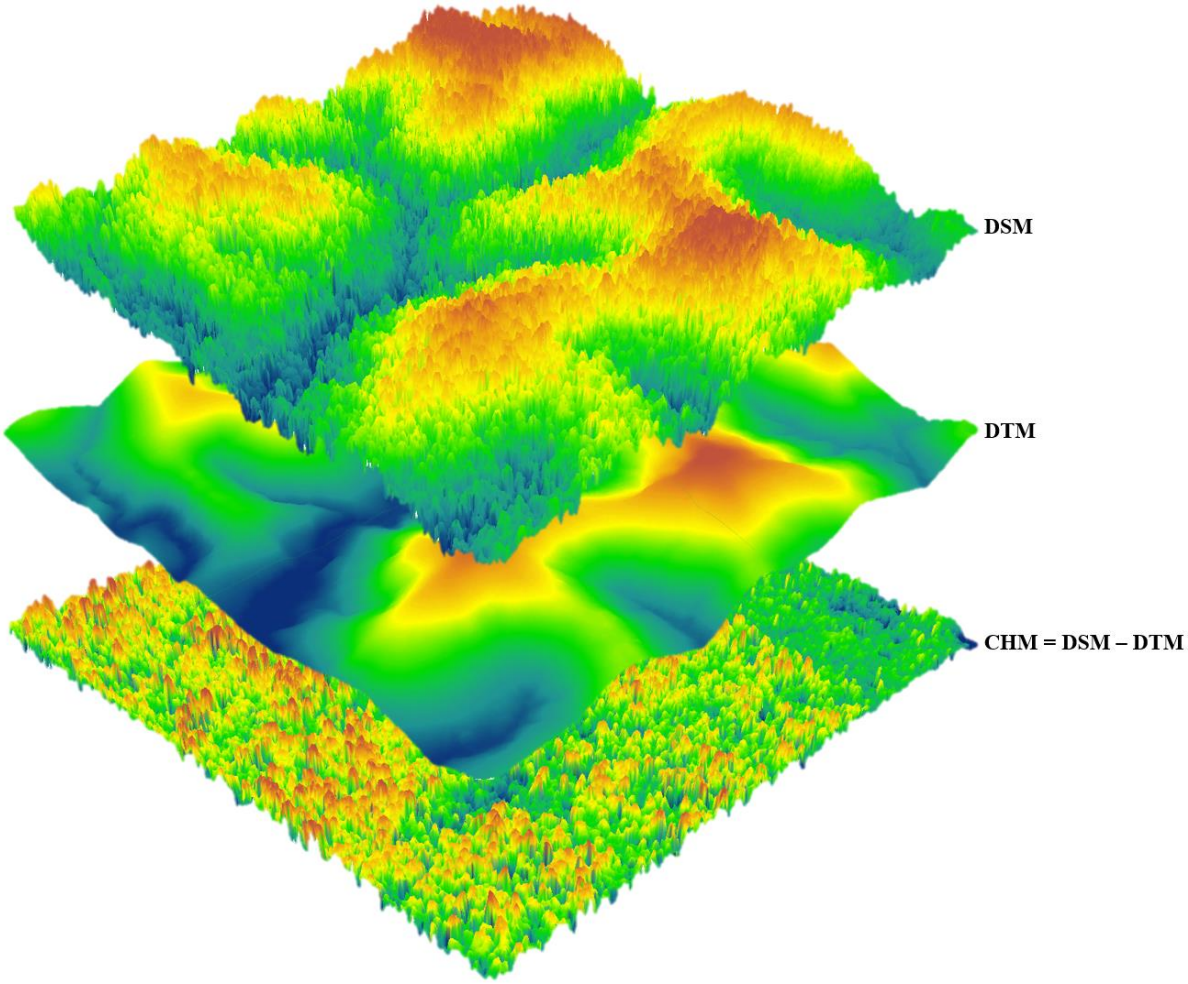
The number of trees detected from the combination of ALS and TLS data was almost comparable when using traditional field-based inventory method. This means that the integrative use of ALS and TLS data presented in this paper has a potential to detect trees in a complex stand structure under different canopy conditions and offers highly accurate tree parameters. It's confirmed that tropical forest AGB or carbon can be estimated from the integrative use of ALS and TLS data with a promising accuracy. We recognized that ALS-CHM data could only be operative for top dominant tree crown delineation in tropical rainforests. This paper offers an approach and methodology for countries to measure carbon accurately with modern laser RS technologies.

Acknowledgments

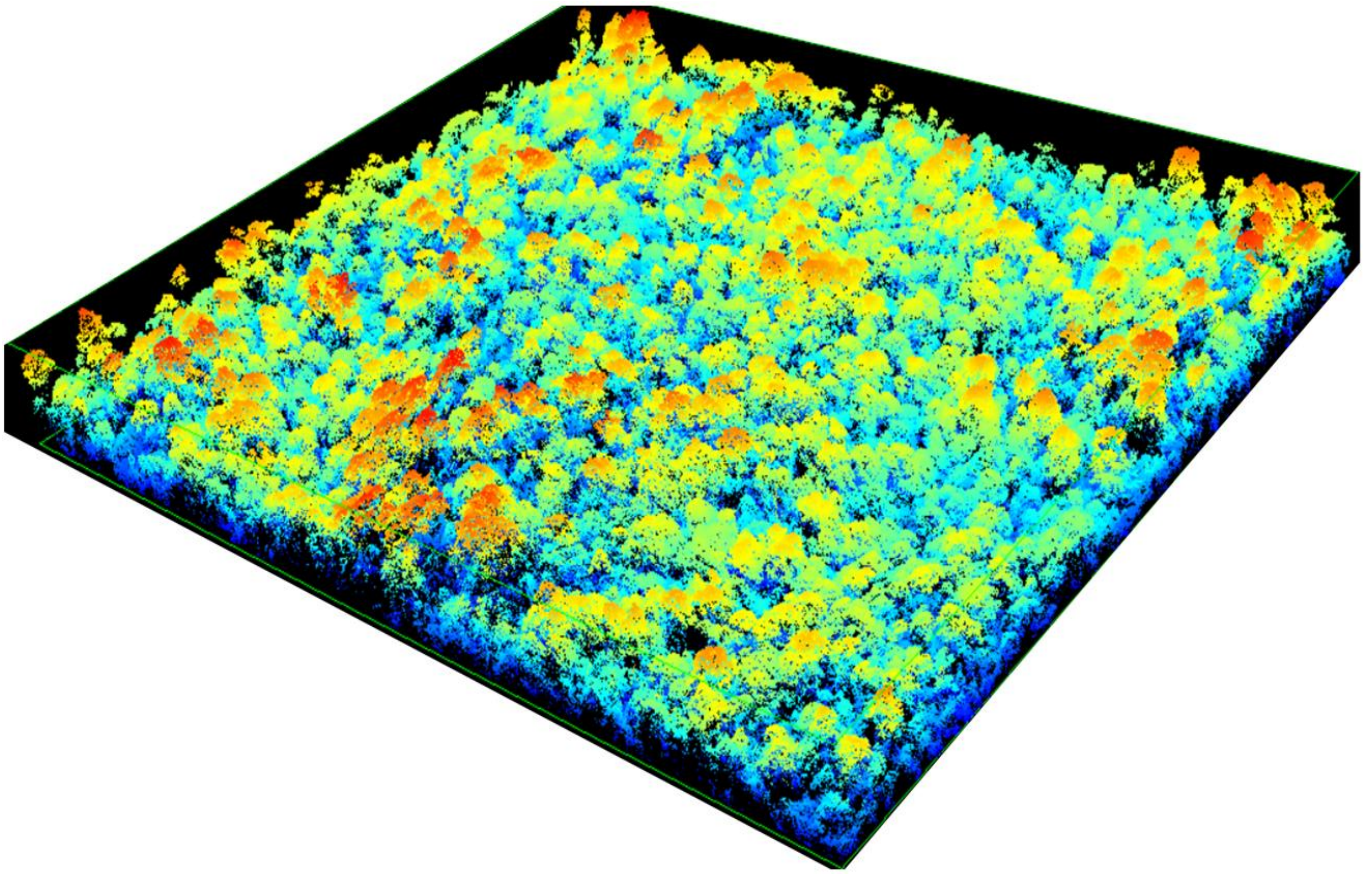
The research was carried out by collaborative of ITC, University of Twente, Netherlands and University of Putra Malaysia (UPM). We would like to acknowledge Siti Zurina, Fasil Bin, Jelani Bin, Fazrul Azree, Mohd Fakhrullah and Razael for helping us during field data collection. This work was financed by NUFFIC, Netherlands Fellowship Programmes (NFP).

Appendices

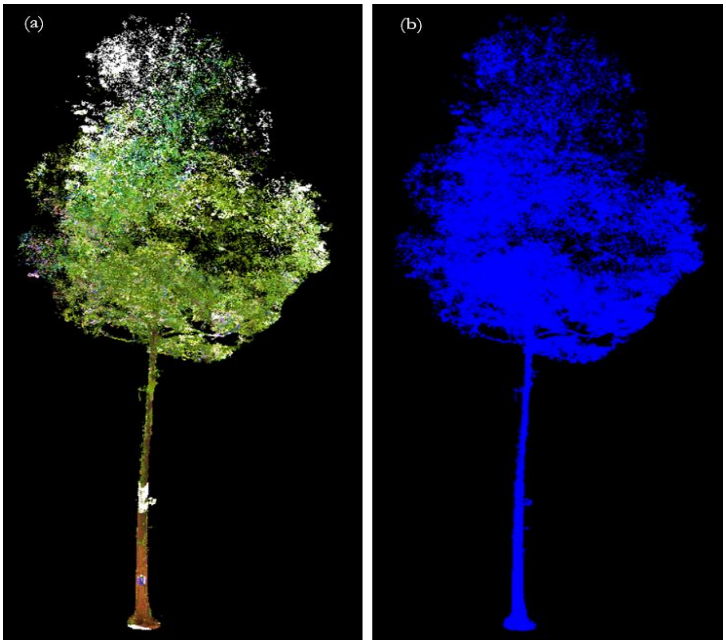
Appendix 1. Airborne LiDAR Scanning (ALS) data processing methods



Appendix 2. Trees derived form Airborne LiDAR Scanning (ALS) point cloud data



Appendix 3. Individual tree extracted from Terrestrial Laser Scanning (TLS) point cloud data (a-True color; b-False color)



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