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Effect of forest stand density on the estimation of above ground biomass/carbon stock using airborne and terrestrial LIDAR derived tree parameters in tropical rain forest, Malaysia

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Abstract

Background: Forest stand density in tropical rainforests is crucial functional and structural variable of forest ecosystems in which above ground biomass can be derived. Currently, there is a growing demand for airborne and terrestrial LIDAR in measuring forest trees parameters for accurate assessment of forest biomass/carbon stock to meet the requirements of UN-REDD + program. Although several studies have been conducted on above ground biomass/carbon stock in tropical rainforest using forest inventory parameters derived from airborne and terrestrial LIDAR, no research was conducted on how the estimation of above ground biomass/carbon stock using airborne and terrestrial LIDAR derived parameters is affected by forest stand density in a tropical rainforest. Therefore, this study aims to analyze and investigate the strength of the relationship between forest stand density and its above ground biomass estimated using airborne and terrestrial LIDAR derived trees parameters. Purposive sampling approach was adopted for the selection of the unit of analysis. Results are based on data collected from 32 sample plots measured and scanned in the field. Airborne LIDAR was used to derive upper canopy trees height, while terrestrial LIDAR was used to derive the height of lower canopy trees and DBH of all lower and upper canopy trees. The DBH measured in the field was used to compute forest stand density and to validate the DBH manually extracted from TLS point cloud data. The DBH manually derived from TLS point cloud data was used to estimate AGB of the sampled plots for both upper and lower canopy trees.

Results: Descriptive statistics, linear regression and correlation analysis were used to answer the research questions of this study. Out of 1033 trees measured and scanned in the field, 855 trees (82.7%) were extracted from TLS point cloud data and 178 trees (17.3%) were missed due to occlusion. The Pearson correlation coefficient (r) between a total number of trees measured and scanned in the field and the total number of trees extracted from TLS point cloud data was 0.95. R^2 of 0.89 was found to explain the relationship between number of missed trees per plot against a number of trees measured in the field per plot. The strength of the effect of forest stand density on AGB is explained by R^2 which is 0.91.

Conclusions: Based on the findings, forest stand density have significant effect on above ground biomass at 1% significance level. Since there is a strong relationship between forest stand density and AGB and the measurement of forest stand density from the ground is fast, forest stand density could be recommended as a proxy to estimate above ground biomass.

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Keywords: AGB, Carbon stock, Forest stand density, LIDAR, Point cloud data, Tropical rainforest

Background of the study

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

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

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

In developing countries, both deforestation and forest degradation are the largest sources of greenhouse gas emissions which accounts about 11–13% of all global CO_2 emissions during the last decade (Kaisa et al. 2017). To overcome this problem, the United Nations Framework Convention on Climate Change (UNFCCC) designed a climate change mitigation action by reducing emissions from deforestation and forest degradation in its REDD + program (Eckert et al. 2011).

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

Currently, there is a growing demand for accurate and operational techniques for assessing forest biomass/

carbon stocks to meet the requirements of UN-REDD program (Prasad et al. 2016). However, so far accurate estimation of the forest above ground biomass remains a challenge. Above ground biomass can be estimated using either destructive (harvest) or nondestructive method. The destructive method (i.e., cutting down trees and weighing their parts) is very accurate to estimate biomass. However, it needs much time and labor, it is very expensive, sometimes it is illegal, it is not feasible for large-scale analysis, and often it is not environmentally friendly. To overcome, the limitations of the destructive approach, a nondestructive method is used using biophysical parameters of trees mainly tree height and DBH which are the most common inputs for large scale above ground biomass and carbon assessment through allometric models (Andersen et al. 2006; Ketterings et al. 2001). These parameters can be derived either directly or indirectly. But the direct measurement is very expensive because it needs much time, cost, labors and not applicable in large areas. For this reason, active remote sensing technologies like airborne and terrestrial LIDAR have been used as a solution to quantify above ground biomass quickly, efficiently and effectively in a nondestructive way. However, airborne and terrestrial LIDAR have their own inherent strength and weakness. Due to the top down perspective, airborne LIDAR focuses on the upper part of the canopy. Thus, it has limitations to characterize vegetation structure in the lower canopy. While terrestrial LIDAR returns typically focus on lower parts of the canopy, as a result it is difficult to assess the upper crown structure and tree heights (Van Leeuwen et al. 2011). Consequently, for this study, accurate heights of upper canopy trees was obtained using airborne LIDAR and accurate DBH for all upper and lower canopy trees and lower canopy trees height was derived from TLS.

Even though several studies (Drake et al. 2002; Gibbs et al. 2007; Prasad et al. 2016; Rahman et al. 2017) have been conducted on above ground biomass/carbon using forest inventory parameters derived from airborne and terrestrial LIDAR in tropical rainforest, according to the literature review, no research is conducted on how the estimation of above ground biomass/carbon stock using airborne and terrestrial LIDAR derived parameters is affected by forest stand density in tropical rainforest. Therefore, the aim of this study was (1) To assess the effect of number of trees per plot on occlusion using TLS scanning at plot level; (2) To investigate the strength of the relationship between forest stand density and its AGB estimated using airborne and terrestrial LIDAR derived trees parameters in Berkelah tropical rainforest, Malaysia.

Methodology

Description of study area

This study was conducted in Berkelah tropical rainforest, Malaysia. Berkelah Forest Reserve is located in the Pahang province of Malaysia (Fig. 1) roughly at latitude 3°46′1″N and longitude 103°1′1″E. The forest is found at 234 km to the North-East of Kuala Lumpur and 218 km to the North-East of Forest Research Institute Malaysia (Zakaria 2013).

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

Sampling design and determination of sample plot

In this study, purposive sampling approach was adopted to select the unit of analysis. Purposive sampling is a nonprobability sampling technique in which all elements in the population do not have an equal chance of being selected as a sample. Therefore, in this study to select the unit of analysis (plots), the terrain/slope of the area, time availability, weight of TLS, thickness of undergrowth, the

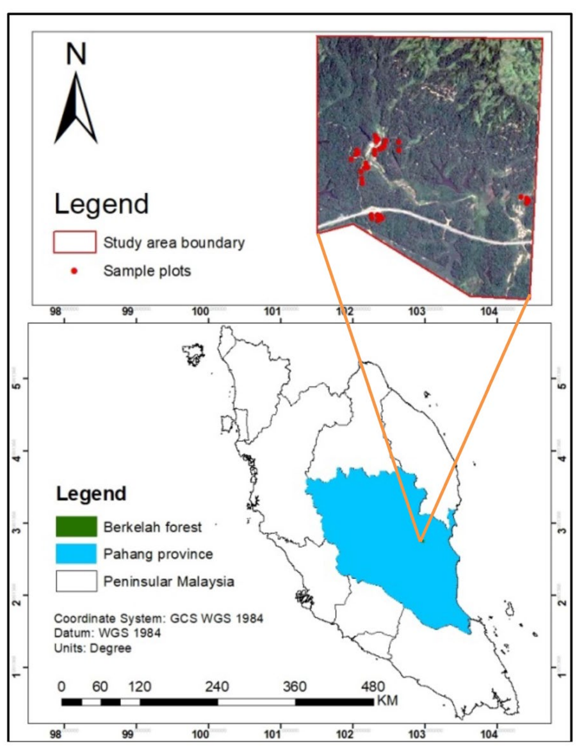

Fig. 1 Location map of Berkelah forest reserve, Pahang, Malaysia

density of the forest, proximity to the road were considered. A total of 32 circular plots with a radius of 12.62 m equivalent to 500 square metre were taken as the unit of analysis considering the variation in tree densities. According to Ruiz et al. (2014) plot size of the 500–600 square metre is recommended for biomass estimation because larger plot sizes increase the cost of fieldwork but do not significantly increase the accuracy of the result. For TLS multiple scan position, the circular plot is more preferred than rectangular or square shaped plot of the same size. Lackmann (2011) pointed out since the boundary of the plot is smaller in relation to the area, and thus the number of trees on edge is less, circular plots are less vulnerable to errors than square plots.

Plot preparation and TLS position set up

There are two types of TLS scanning approaches. These are single and multiple scan modes (Bienert et al. 2006).

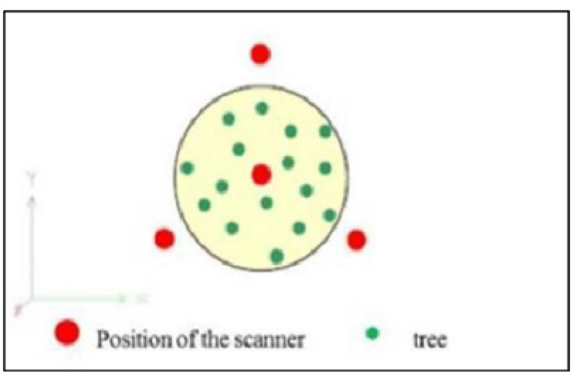

Fig. 2 TLS scan positions used for the study (Prasad et al. 2016)

For this study, a multiple scan mode with four scanning positions was undertaken (Fig. 2). The center of the plot was selected in the way it avoids or minimizes occlusion from the stem of the trees and undergrowth. According to Liang et al. (2012) trees or other undergrowth very close to the scanner can create a large area shadow behind. The outer three scanning positions of the plot were carried out at an angle of 120° determined using the TLS tripod stands at the center position backed up with visual judgment.

The model of the terrestrial laser scanner (TLS) used in this study was RIEGL VZ-400 and its specification is shown in Table 1 without and with the camera.

Setting of retro reflectors and tree numbering within the sample plot

After the plot preparation is completed, trees within the plot with their DBH equal or greater than 10 cm were tagged with laminated tree numbers which helped later for the extraction of tree parameters from the point cloud data. In order to register and georeferencing of the multiple scan positions with the home(reference) position, tie points were used during scanning of each plot in the field (Bienert et al. 2006). For this study, a total of 18 reflectors (tie points), 12 cylindrical and 6 circular were used in each plot. Cylindrical retro-reflectors were placed on top of a stick near to the three outer scanning positions on the way to be observable to the scanner at different scanning positions. Circular retro-reflectors which were pinned on selected tree stems facing towards the center scanning position (Fig. 3).

Biometric data processing

Plot radius, GPS coordinates of the plot center, DBH, X and Y coordinates of each tree measured in each plot

Table 1 Specification of RIEGL VZ-400 terrestrial laser scanner

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

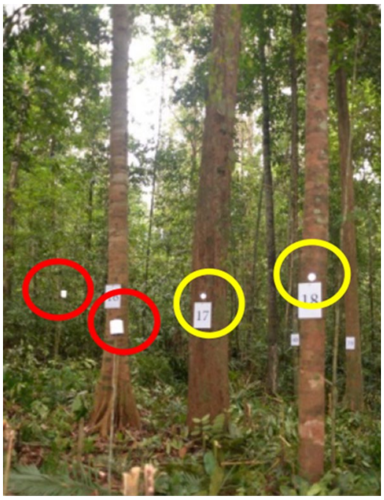

Fig. 3 Setting of circular (yellow color) and cylindrical (red color) reflectors in sample plots

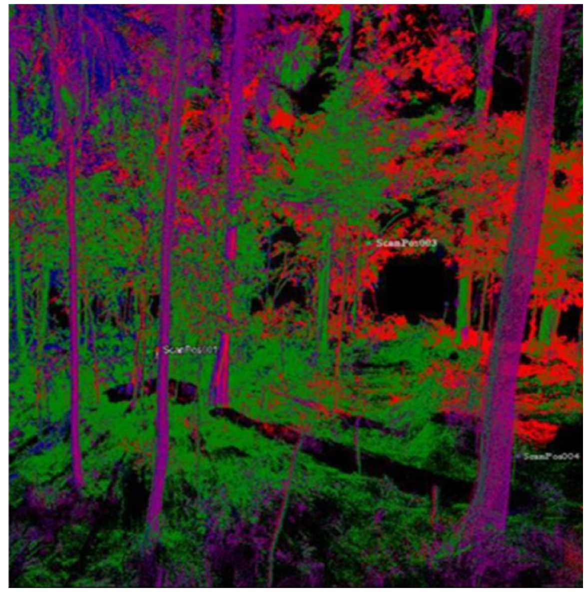

Fig. 4 Sample registered point cloud data displayed in four colors representing four scan positions

were entered the Excel sheet. X and Y coordinates of individual trees within the plot were collected using tablets, and it is used for matching the corresponding tree on the airborne LIDAR CHM. In this study, a total of 1033 trees were measured and scanned in the field from all 32 sampled plots.

Pre-processing of TLS point cloud data

The first step in the pre-processing of TLS point cloud data is registration. Registration is the process of merging all the individual scans into a single point cloud data (Fig. 4). After the point cloud data was exported from the terrestrial laser scanner, RiSCAN PRO V 2.4.2 software was used for registration and pre-processing of the point cloud. According to Holopainen et al. (2014) artificial retro-reflectors are used to undertaking registration of multiple scans. The central scanning position was used as a reference position to register all the three outer scanning positions since it has the most overlap with the outer scanning positions. Therefore, the three outer scanning positions were registered towards the central scan positions with a minimum of five best values of common tie points selected automatically by the software.

Extraction of individual tree and parameter measurement

After registration of each plot multiple scan positions, extraction of the plot was undertaken through filtering of the point cloud covering radius of 12.62 m from the center scan position extract individual trees manually. During field measurement, all trees those DBH $\geq$ 10 cm in all plots were tagged with laminated tree numbers which helped for the extraction of individual trees measured in the field from the point cloud data. To identify the tagged tree numbers, the polydata was displayed in 3D true color linear scale. Accordingly, using the selection tool in RiSCAN PRO software, extraction of the individual tree in all plots was done. This process has been done by selecting all point cloud data corresponding to a single tree.

From the 3D point clouds of the individual trees, the DBH was measured on the stem at 1.3 m height from the ground from the extracted 3D point clouds of individual trees by using distance measurement function tool in RiSCAN PRO software. Similarly, the height of trees was also measured manually from the lowest point of the stem on the ground to the highest top of the tree using distance measurement function tool in RiSCAN PRO software. X, Y, Z values are recorded by the measurement and the difference in the highest and lowest value of Z was considered as the tree height.

Airborne LIDAR point cloud data processing

Lite Mapper 5600 system was used with flying height 700 m to 1000 m, scan angle 60°, density of the LIDAR point cloud data was 5–6 points/m^2, which basically determines the cell size and the scan pattern was regular. A cell size of 1 m is used to construct pit or hole free canopy height model (CHM) from the airborne LIDAR point cloud data in "las" format. Arc GIS is used to display and generate a digital surface model (DSM) and digital terrain model (DTM) from the first and last returns respectively. By subtracting digital terrain model (DTM) from the digital surface model (DSM) using raster calculator in Arc GIS, CHM was generated. The originally created CHM had pits and holes because of the first LIDAR return is far below the canopy due to the LIDAR beam, penetrate the branches before creating first return (Heurish et al. 2003). These pits hinder the accurate extraction of tree parameters from CHM. Therefore, these pits were removed.

Segmentation and accuracy assessment

Segmentation is a technique used for segmenting and clustering of pixels in an image into meaningful homogeneous units or objects (Clinton et al. 2010). There are two approaches in segmentation that can be done. These are the bottom–up and top–down approach. In the bottom–up approach, pixels are merged to obtain larger meaningful object based on homogeneity criteria. Whereas in the top–down approach, large objects are clustered into smaller objects (Rahman Rejeur and Saha 2008). Even though, there are different segmentation techniques, according to Witharana and Civco (2014) multi resolution segmentation technique is most commonly used. This technique works based on bottom–up and region-based approach. For a given resolution of the image object, this technique minimizes the average heterogeneity.

Therefore, for this study, using eCognition software, multiresolution segmentation was adopted using the homogeneity criterion which is the scale parameter which determines the homogeneity of the object, shape which determines the spectral value of the segmented objects. Giving more value for shape, makes the segmented object having more spatial uniformity than spectral homogeneity. Moreover, the compactness value used to produce a compacted segmented object. The values of these homogeneity criteria (color + shape = 1, and compactness + smoothness = 1) (Definiens Developer 2012). Accordingly, 12 for scale parameter, 0.8 and 0.5 for shape and compactness respectively were found to be optimal for this study. LIDAR CHM (Canopy Height Model) was used as input to delineate individual tree crown which was used for the extraction of upper canopy trees height. Segmentation, watershed transformation, and tree morphology were employed in a subset. Then after this complete rule set was implemented for the entire study area.

As revealed by Clinton et al. (2010) assessment of the accuracy of the segmented polygon is based on comparing with the predefined reference training set with segmented output's geometric extent. As a result, the over and under segmentation determine the quality of produced segment. Therefore, segmentation accuracy assessment was done by comparing automatically segmented tree crowns with the manually delineated tree crowns. The manual delineation of tree crowns was undertaken for randomly selected visually identified tree crowns. Accordingly, 15% proportions of field measured trees from each of the 32 sampled plots were manually delineated. Thus the total reference polygons are 157. Based on the following equations the over segmentation, under segmentation and "D" value (goodness of fit) was calculated. The "D" value ranges from 0 to 1 and values close to 0 indicates high matching whereas if it is close to 1 shows less match. Moreover, the two extremes, 0 indicates a perfect match between the reference polygon and the automatically segmented polygons while 1 is the minimum mismatch between the two.

Equation 1: Calculation of over segmentation

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

Equation 2: Calculation of under segmentation

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

Equation 3: Calculation of segmentation goodness of fit

$$D = \sqrt{\frac{Over\ segmentation_{ij}^2 + Under\ segmentation_{ij}^2}{2}} \tag{3}$$

where *xi*: manually delineated reference crowns; *yi*: automatically segmented crowns; D: segmentation goodness of fit.

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

Biometric data collection and above ground biomass estimation

After delineation of plots, DBH were measured for all tree with their DBH ≥ 10 cm within the plot. As pointed out by Brown (2002) trees with DBH less than 10 cm have an insignificant contribution to biomass/carbon stock. DBH was measured using diameter tape at 1.3 m height from the ground. To be consistent with DBH measurement, 1.3 m measured stick was used. In case of the buttress and fork trees, DBH was recorded above the buttress while fork trees were considered as two trees if the fork is below 1.3 m and as one tree if the fork is above

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

$$AGB = 0.0673 \times \left(\rho D^2 H\right)^{0.976} \tag{4}$$

where AGB: above ground biomass (Kg); ρ: specific wood density (g/cm^3) (Reyes et al. 1992) of wood density for tropical forest tree species which is 0.57 g/cm^3; D: diameter at breast height (cm); H: height (m).

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

$$C = AGB \times CF \tag{5}$$

where C-carbon stock (Mg); AGB-above-ground biomass (Mg); CF-conversion factor which is 0.47.

Effect of forest stand density on AGB estimation

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

$$\text{Basal area/Tree (m}^2) = \frac{\pi * (\text{DBH})^2 * 0.0001}{4} \tag{6}$$

where π is constant which is 3.14, DBH is diameter at breast height (cm), 0.0001 is a constant used to convert the measured centimeter square into meter square

$$\begin{aligned}\text{Total stand basal area}\left(\frac{\text{m}^2}{\text{ha}}\right) &= \frac{\text{Sum of basal area for each tree}}{0.05}\\ &= sum\ of\ basal\ area \times 20\end{aligned} \tag{7}$$

where 0.05 is plot size in hectare and 20 is a constant used to extrapolate the measurement of basal area from per plot (m^2/plot) to per hectare (m^2/ha).

Results

Individual tree extraction from TLS point cloud data

The extraction of individual tree varies from one sample plot to another. The minimum extraction percentage of individual trees per plot was 73.3% while the maximum is 100% (Table 2). The overall extraction and missing percentage of individual trees were 82.77% and 17.23% respectively.

Correlation analysis was carried out to assess the relationship between a total number of trees measured in the field and the total number of trees extracted from TLS point cloud data at the plot level. Pearson correlation coefficient (r) is found to be 0.95. Therefore, there is a very high relation between the two values.

Relationship between number of trees per plot and tree extraction from TLS point cloud data

The purpose of this analysis was to check whether number of missed trees is directly related to the number of trees measured and scanned in the field. Consequently, the assumption is that as the number of missed trees increase the occlusion increase and vice versa. A scatter plot was used to assess the effect of number of trees per plot on missed trees from TLS point cloud data due to occlusion regardless of the size of missed trees. As it is shown in Fig. 5, the coefficient of determination (R^2) of missed trees per plot against number of trees per plot is 0.892. This result revealed only the existence of a very strong relationship between number of missed trees per plot and number of trees per plot due to occlusion regardless of the size of missed trees.

Moreover, linear regression analysis has been carried out with the number of missed trees per plot as predicted variable and the total number of trees measured in the

Table 2 Number of trees measured in the field and extracted from TLS

Plot no.	Field measured	TLS extracted	Extraction in %	Missed trees	Plot no.	Field measured	TLS extracted	Extraction in %	Missed trees
1	30	25	83.3	5	17	38	32	84.2	6
2	45	36	80	9	18	45	33	73.3	12
3	33	26	78.8	7	19	32	26	81.3	6
4	36	29	80.6	7	20	42	34	81	8
5	33	26	78.8	7	21	29	25	86.2	4
6	36	29	80.6	7	22	43	35	81.4	8
7	31	28	90.3	3	23	22	20	90.9	2
8	36	29	80.6	7	24	22	21	95.5	1
9	35	29	82.9	6	25	28	25	89.3	3
10	39	31	79.5	8	26	28	24	85.7	4
11	37	29	78.4	8	27	30	25	83.3	5
12	25	22	88	3	28	16	15	93.8	1
13	44	35	79.5	9	29	34	28	82.4	6
14	15	15	100	0	30	23	21	91.3	2
15	34	27	79.4	7	31	33	27	81.8	6
16	34	27	79.4	7	32	25	21	84	4
Total plots	Total field measured	Total TLS extracted		TLS extraction (%)		Missed trees		Missed trees (%)	
32	1033	855		82.77		178		17.23	

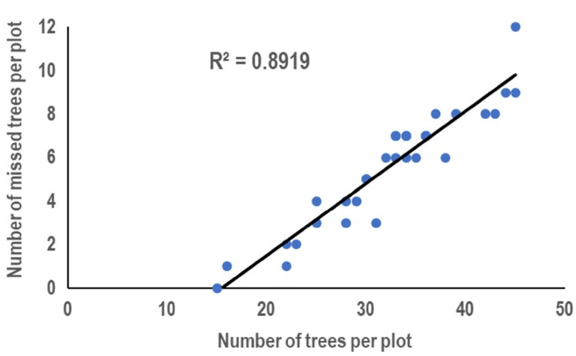

Fig. 5 Scatter plot showing the relationship between missed trees versus number of trees

Table 3 Linear regression analysis result of missed trees against total number of trees

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

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

field per plot as an explanatory variable since these variables have a higher relationship (Table 3).

Size and location of missed trees within sample plots

Of 178 missed trees out of 1033 trees measured and scanned in the field, 51.7% of trees were located at the center of sampled plots. While 48.3% of trees were located at the edge of sampled plots. Even though the total number of missed trees located at the center of sampled plots are higher than the total number of missed trees located at the edge of the sampled plots, the mean DBH of missed trees located at the center of sampled plots is lower compared to the mean DBH of missed trees located at the edge of sampled plots. The overall mean DBH of missed trees is 13.96 cm of which 13.13 cm is the mean DBH of missed trees located at the center of sampled plots and 14.83 cm is the mean DBH of those missed trees located at the edge of sampled plots. Therefore, from the result of this study, one can easily understand as there is no direct relationship between number of missed trees and total DBH of the corresponding missed trees per plot.

Operational integration of airborne and terrestrial LIDAR data

During the field work, both multiple upper canopy layer and single upper canopy layer plots were sampled. Zonal statistics and extraction of multi values to points were applied to obtain the local maximum value of the segmented CHM. Accordingly, for those plots having multiple upper canopy layers (emergent, medium and lower canopy trees), 14 m was used as a threshold to separate upper canopy from lower canopy trees hence 14 m was the minimum height of tree observed by ALS in those plots. However, in those plots having single upper canopy layer, 9 m was a threshold to separate lower and upper canopy. Therefore, 14 m and 9 m were used as a threshold to separate upper canopy from lower canopy trees in multiple upper canopy and single upper canopy layers respectively. Trees with their height below this threshold in the corresponding plots were considered as lower canopy trees, and the height was derived from TLS. Accordingly, based on the threshold, of 1033 trees measured and scanned in the field, 657 (63.6%) were identified as upper canopy trees and matched with DBH derived from TLS. While 198 trees (19.17%) were classified as lower canopy trees. Table 4 shows the overall descriptive statistics for trees identified as upper and lower canopies measured by ALS and TLS respectively.

Table 4 Over all descriptive statistics for trees identified as upper and lower canopies

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

Estimation of above ground biomass

In this study, the AGB was calculated with tree inventory parameters derived from TLS and ALS using allometric equation given in Eq. (4). Height derived from ALS and DBH derived from TLS was used to calculate upper canopy trees AGB while tree height and DBH derived from TLS was used to estimate AGB for lower canopy trees. Total AGB for each sampled plot and the entire study area was estimated by adding AGB estimated from lower and upper canopy trees. Figure 6 shows distribution of AGB in Mg across sampled plots in ascending order (Fig. 6).

Furthermore, the overall descriptive statistics of AGB obtained from lower and upper canopy trees is also done and summarized in Table 5.

From the total of 418 Mg AGB estimated from all sampled plots, 394 Mg (94%) were obtained from upper canopy trees while 24 Mg (6%) were estimated from lower canopy trees with parameters derived from TLS. The overall mean AGB of the sampled plots was 13 Mg (i.e., 261 Mg/ha) while 12 Mg and 0.75 Mg per plot were for upper and lower canopy trees respectively (Table 5).

Estimation of above ground carbon stock

The estimated above ground biomass was multiplied by a conversion factor of 0.47 to estimate above ground carbon stock of the measured trees. A total amount of

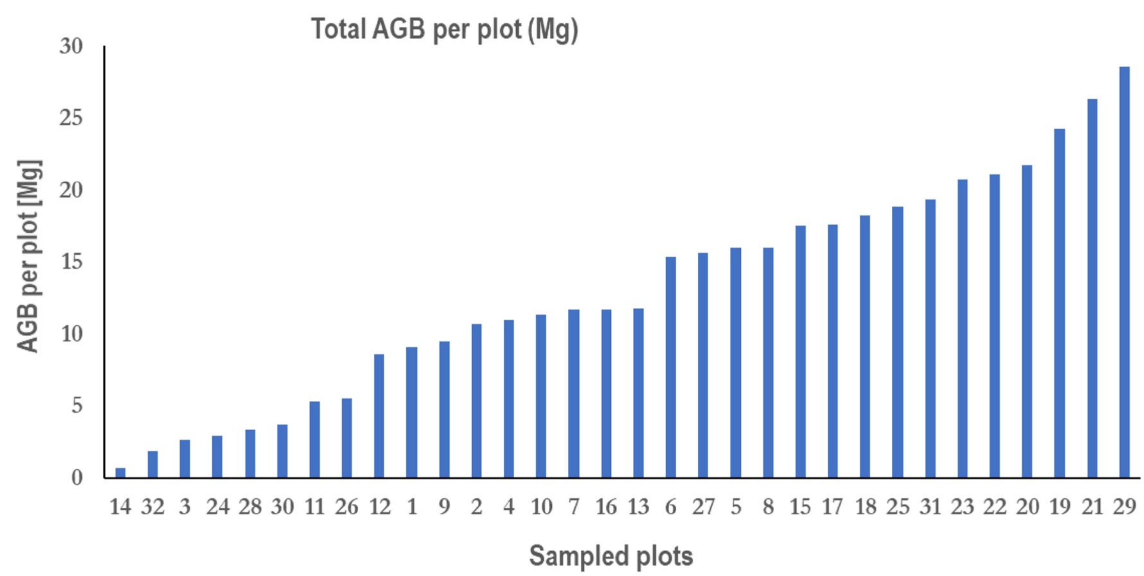

Fig. 6 Distribution of AGB in Mg across sampled plots in ascending order

Table 5 Overall descriptive statistics of estimated AGB

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

Table 6 Overall descriptive statistics of estimated above ground carbon

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

185 Mg and 11 Mg of above ground carbon stock were obtained from upper canopy trees and lower canopy trees respectively. The overall mean AGC of the sampled plots was 6 Mg (i.e., 122 Mg/ha). Table 6 shows the overall descriptive statistics of the estimated above ground carbon stock from the sampled plots.

Relationship between forest stand density and AGB

The relationship between forest stand density and aboveground biomass was assessed using scatter plot and linear regression. Accordingly, a scatter plot of above ground biomass against stand basal area per plot was carried out. As it is shown in Fig. 7, there is a very strong positive relationship between above ground biomass and stand basal area per plot hence the coefficient of determination (R^2) is 0.91.

Furthermore, linear regression analysis was conducted with above ground biomass per plot (Mg/ha) as the dependent variable and total stand basal area per plot (m^2/ha) as an explanatory variable since the relation of these variables is very strong. The linear regression analysis result is shown in Table 7.

Discussion

Effect of number of trees per plot on TLS tree extraction and accuracy assessment

Out of 1033 trees measured in the field, 855 trees (82.77%) were extracted from the TLS point cloud data in all 32 sampled plots and 178 trees (17.23%) were missed (Table 2). Of the total missed trees, 52.7% of trees were located at the center of sampled plots. While 48.3% of those missed trees were located at the edge of sampled plots. These trees were missed due to occlusion because of the existence of many trees in the plot, lower branches

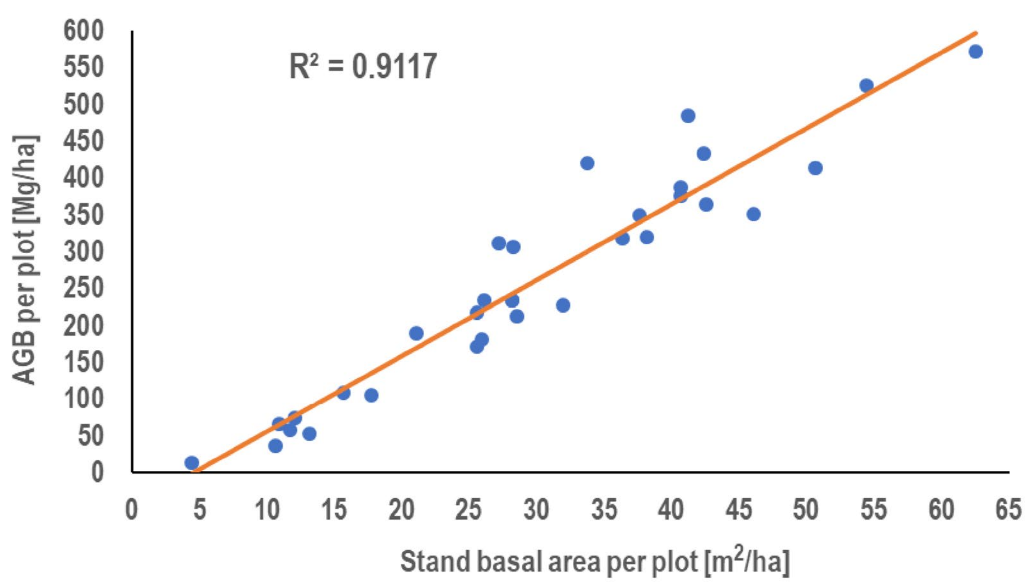

Fig. 7 Scatter plot showing the relationship between AGB versus stand basal area per plot

Table 7 Linear regression analysis result of stand basal area and AGB

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

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

and due to adjacent trees blocking the tree numbers and reduce the density of the point cloud data because of blocking the pulses of TLS which makes it difficult to identify and extract individual tree. Moreover, a tree far away from the scanner is also another cause for missed trees because of the laminated tree number tagged on the tree could not be identified hence the point cloud density is low. For this reason, the tree detection percentage is low, when the tree is far from the scanner (Antonarakis 2011; Liang et al. 2012).

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

In this study, the extraction rate of individual trees varies from one sample plot to another depending on the number of trees in the corresponding plot and of course other factors like amount of undergrowth and standing position of trees in the plot. The collected data in the field per each sampled plot is used to assess the accuracy of individual tree extracted from the TLS point cloud data at the plot level. Plot 18 had the lowest tree extraction rate compared to other sampled plots because of the existence of occlusion due to a high number of trees measured and scanned in this plot (45 trees). The more trees in the plot, the more trees are missed from TLS point cloud data (Table 2 and Fig. 8). Therefore, this result confirms as a number of trees are the main causes of occlusion for TLS scanning at plot level in the field.

The number of missed trees per plot is plotted against the number of trees measured in the field per plot (Fig. 5). The coefficient of determination was very high which is 89%, it is an indication as number of trees per plot has a high influence on the extraction of individual trees from TLS point cloud data due to being occlusion through trunk overlapping. The R^2 is interpreted as in ceteris paribus conditions, number of trees per plot contribute 89% for the missed trees from the TLS point cloud data regardless of the size of missed trees. However, the higher value of the coefficient of determination doesn't mean as number of trees per plot increase, more AGB is missed because of more trees are missed. In this study, the location of missed trees inside sampled plots and their corresponding size was assessed. The DBH of those missed trees is very low almost close to 10 cm which doesn't contribute much to the AGB/carbon stock estimation. There is also another variable that might contribute to missed trees from TLS point cloud data other than number of trees in the plot. Some of these variables are the standing position of trees in the plot, shape of trees and personal experience of the operator but these variables are not captured in the model. Moreover, the analysis revealed that as there is no direct relationship between number of missed trees per plot and their corresponding total DBH. That means plots which have a relatively high number of missed trees have lower total DBH compared with the total DBH of a plot which has a low number of missed trees. The relationship between number of trees measured in the field per plot in ascending order and number of missed trees from TLS point cloud data per plot is depicted in a combined bar chart (Fig. 8).

As it is shown in Fig. 8, the highest missed trees were in plot 18 hence the highest number of trees were measured and scanned in the field in this sample plot compared to other sampled plots. While in plot 14, the accuracy of individual tree extraction was 100% because of the lowest number of trees per plot were measured in this sample plot.

Furthermore, by using missed trees per plot as the dependent variable and a total number of trees per plot as an explanatory variable, linear regression analysis has been carried out. The linear regression analysis confirmed as number of trees per plot significantly affect the extraction of trees from TLS point cloud data at Alpha equal to 0.01 significance level. The magnitude of the influence of number of trees per plot for missed trees per plot is explained by its coefficient. Statistically, it is interpreted, as number of trees per plot increase by one unit, on average missed trees per plot increase by 0.33% keeping all things constant. That means if number of trees per plot increase by one tree, on average missed trees per plot increase by 0.33 tree (Table 3). However, since trees are indivisible, this interpretation doesn't make sense in this context even if this is the correct way of interpretation for significant variables of regression result, but it confirmed the relation visualized in Figs. 5 and 8. Note that, still this relationship doesn't consider the size of the missed trees.

Fig. 8 Combined chart for field measured and missed trees per plot

Therefore, this interpretation doesn't say anything about above ground biomass.

Effect of forest stand density on the estimation of AGB

There is a direct relationship between stand basal area and above ground biomass/carbon stock. In this study, there is a strong positive relationship between above ground biomass and stand basal area with Pearson correlation coefficient 0.95 and coefficient of determination 0.91 (Fig. 7). The higher relationship between stand basal area and above ground biomass is because of both variables are directly related to the tree trunk diameter. For this reason, as the size of the tree trunk increases, the basal area increases hence it is the cross-sectional area of the stem measured at the breast height, and consequently the above ground biomass and carbon stock increases.

Linear regression analysis has been done using stand basal area per plot (m^2/ha) as an explanatory variable and above ground biomass per plot (Mg/ha) as the dependent variable. The regression result revealed there is a very strong positive relationship between stand basal area (m^2/ha) and above ground biomass (Mg/ha) at Alpha equal to 0.01 significance level. Statistically, this result is interpreted, as stand basal area increase by one unit, on average above ground biomass increases by 10.301 unit keeping all things constant. In this context, as stand basal area increase by 1 m^2/ha, on average above ground biomass increases by 10.301 Mg/ha keeping all things constant (Table 7).

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

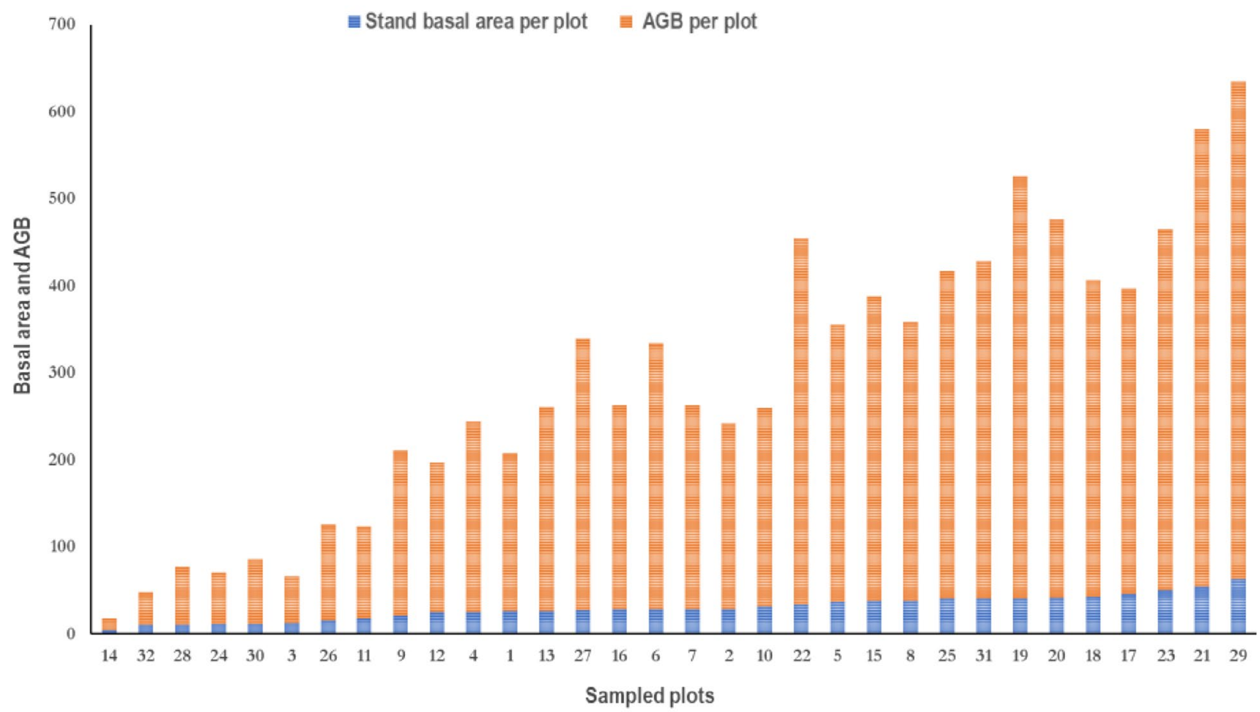

Fig. 9 Combined chart for basal area and AGB per plot

mentioned above, stand basal area is recommended as a proxy to estimate above ground biomass. Therefore, the result of the current study is strongly agreed with previous studies mentioned above. The combined bar chart was used to emphasize the relationship between above ground biomass (Mg/ha) and total stand basal area (m^2/ha) in ascending order at the plot level (Fig. 9).

As it is shown in Fig. 9, plot 14 is the plot which has lowest above ground biomass because of its corresponding stand basal area is lowest compared to the stand basal area of all sampled plots in the field. This is because the DBH of trees measured in the field within this plot was very low since the trees were newly growing. The total DBH of trees measured in this plot was lowest compared to other sampled plots. Whereas, plot 29 is the plot which has highest above ground biomass since the corresponding stand basal area was the highest compared to other sampled plots. The highest stand basal area in plot 29 is because of this plot has the highest total DBH from all sampled plots measured in the field.

Conclusion

This study shows as there is no statistically significant difference between total number of trees extracted from TLS as compared with total number of trees measured in the field at 5% significance level. Moreover, based on the findings, it is possible to conclude as there is a direct relationship between number of missed trees per plot and number of trees per plot measured and scanned in the field. There is very strong and direct relationship between above ground biomass and forest stand density. Since there is a strong relationship between forest stand density and above ground biomass and the measurement of forest stand density from the ground is fast, forest stand density could be recommended as a proxy to estimate above ground biomass.

Abbreviations

AGB: above ground biomass; ALS: airborne laser scanner; CHM: canopy height model; DBH: diameter at breast height; DSM: digital surface model; DTM: digital terrain model; LIDAR: light detection and ranging; REDD+: reducing emission from deforestation and forest degradation; RMSE: residual mean squared error; TLS: terrestrial laser scanner; UNFCCC: United Nations Framework Conventions on Climate Change.

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Authors' contributions
All authors had their own contribution from the inception of title selection to the final report of the study. Study design, data collection, and data analysis, critically review and provide comments on the content and structure of the paper. All authors read and approved the final manuscript.

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