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Estimating Logged-Over Lowland Rainforest Aboveground Biomass in Sabah, Malaysia Using Airborne LiDAR Data

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ABSTRACT

Unprecedented deforestation and forest degradation in recent decades have severely depleted the carbon storage in Borneo. Estimating aboveground biomass (AGB) with high accuracy is crucial to quantifying carbon stocks for Reducing Emissions from Deforestation and Forest Degradation-plus implementation (REDD+). Airborne Light Detection and Ranging (LiDAR) is a promising remote sensing technology that provides fine-scale forest structure variability data. This paper highlights the use of airborne LiDAR data for estimating the AGB of a logged-over tropical forest in Sabah, Malaysia. The LiDAR data was acquired using an Optech Orion C200 sensor onboard a fixed wing aircraft. The canopy height of each LiDAR point was calculated from the height difference between the first returns and the Digital Terrain Model (DTM) constructed from the ground points. Among the obtained LiDAR height metrics, the mean canopy height produced the strongest relationship with the observed AGB. This single-variable model had a root mean squared error (RMSE) of 80.02 t ha^{-1} or 22.31% of the mean AGB, which performed exceptionally when compared with recent tropical rainforest studies. Overall, airborne LiDAR did provide fine-scale canopy height measurements for accurately and reliably estimating the AGB in a logged-over forest in Sabah, thus supporting the state's effort in realizing the REDD+ mechanism.

Key words: Aboveground biomass, Selective logging, LiDAR, Sabah

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1. INTRODUCTION

Over past decades the lowland rainforest of Borneo has disappeared at an alarming rate due to anthropogenic activities, with recent rates of deforestation at 1.7% per year between 2002 and 2005 (Langner et al. 2007). The land area of Sabah is 73631 km^2, representing slightly less than 10% of the total area of Borneo. Within Sabah, forest cover has declined rapidly from nearly 75% in 1975 (Ross 2001), to 60.1% in 1986 (FAO 1987). The rates of forest loss have varied over this time, with forest loss estimates of 1.37% per year for the period 1975 - 1985. The deforestation rate between 1990 and 2008 had recently increased to 1.6% per year (Osman et al. 2012). This sharp decline in primary or intact lowland forests in Sabah was due mainly to forest-agricultural land conversion and logging (McMorrow and Talip 2001; Osman et al. 2012) that accelerated carbon depletion. This leads to increasing carbon emissions into the atmosphere and thus contributes to global warming.

Reducing Emissions from Deforestation and forest Degradation (REDD) has been under negotiation by the United Nations Framework Convention on Climate Change (UNFCCC) to mitigate global warming since 2005. This scheme was later known as REDD+ after putting an emphasis on the roles of conservation, sustainable forest management and forest carbon stock activities enhancement as a mitigation strategy against the increasing carbon emissions due to land use and land cover change (UNFCCC 2009). Accurate carbon stock estimation and monitoring is

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important to REDD+ success. In order to implement REDD+ effectively it is recommended that remote sensing technology be applied with ground inventory (UNFCCC 2009). Ground inventory can be expensive and time consuming to produce consistent global data (Chave et al. 2005), hence it is necessary to apply remote sensing technology to assess forest condition information in large inaccessible areas (Saatchi et al. 2007).

Remote sensing technology, especially optical satellite imaging, has been widely used in aboveground biomass (AGB) estimation based on multispectral (Phua and Saito 2003; Langner et al. 2012) and texture information (Lu 2005). Conventionally, the spectral responses of the vegetation cover are related with estimated AGB through a statistical model (Brown 1997). Unfortunately, cloud cover, the shadow effect and low spectral band saturation level and derived indices (Gibbs et al. 2007) limits the application of medium resolution satellite remote sensing for AGB estimation. Additional information such as crown variables extracted from high-resolution satellite remote sensing improves the AGB estimation results (Palace et al. 2008; Phua et al. 2014). However, optical satellite remote sensing provides information only on the upper canopy trees and may substantially underestimate the AGB of a disturbed forest (Lu 2005, 2006). Anthropogenic disturbances, especially logging, create complex three-dimensional structures, including canopy height and sub-canopy topography, which are less likely to be detected by optical satellite remote sensing (Ioki et al. 2014).

Light Detection and Ranging (LiDAR) has the potential to overcome these problems. LiDAR is an active remote sensing that emits laser pulses to the target area and records the travel time of the reflected pulse. The emitted lasers fall on the canopy surface and also penetrate the forest canopy to assess the dense and complex forest structure. The reflected laser pulses generate three dimensional point clouds (x, y, z) to give a direct measurement of the horizontal and vertical forest structures (Wulder et al. 2012).

Numerous studies have highlighted the importance of airborne LiDAR in estimating AGB in temperate and boreal forests but only a few studies focused on tropical forests. Clark et al. (2011) demonstrates the effectiveness of small footprint LiDAR for AGB estimation in Costa Rica by deriving LiDAR height metrics to estimate the forest AGB. Asner et al. (2012c) examined the effectiveness of the extracted mean canopy height to estimate AGB in Panama, Peru, Madagascar, and Hawaii ($R^2 = 0.8$, RMSE = 27.6 Mg C ha^{-1}). In Borneo, Kronseder et al. (2012) and Jubanski et al. (2013) examined the use of LiDAR derived height metrics to estimate the AGB in logged peat swamp forest and unlogged lowland dipterocarp forest in Central Kalimantan. Ioki et al. (2014) tested the use of laser penetration rate from LiDAR data for AGB estimation of primary and degraded tropical montane forests of in Sabah, Borneo ($R^2 = 0.78$, RMSE = 27.6 t ha^{-1}).

Most of the lowland dipterocarps in Borneo were repeatedly logged and disturbed by anthropogenic activities. These logged-over forests have a highly heterogeneous forest structure. A disturbed forest recovers by undergoing growth in horizontal (e.g., diameter at breast height, DBH) and vertical structure (e.g., stand height) accompanied with the overall increase in AGB. Horizontal and vertical structures are inter-related with AGB, thus creating an opportunity for LiDAR to examine the forest in different structural conditions (Lefsky et al. 1999, 2002; Drake et al. 2002). High point density and multiple discrete heights from small footprint airborne LiDAR can retrieve such forest structures and predict AGB in fine spatial scale (Houghton 2005). Studies on the use of LiDAR to estimate logged-over lowland dipterocarp forests are relatively few. The objective of this study is to examine the use of airborne LiDAR data to estimate AGB in a logged-over lowland dipterocarp forest in Sabah, Malaysia.

2. MATERIAL AND METHODS

2.1 Study Area

The study area is located within the Sapat Kalisun catchment within the Ulu Segama Forest Reserve (5°N; 117°30'E) under the management of Yayasan Sabah (Fig. 1). It is located just outside Danum Valley Field Center (DVFC), which is about 70 km west of Lahad Datu town. The forest in this region is dipterocarp forest, with *Parashorea malaanonam* as the typical dominant tree species. The dipterocarp forest of Sapat Kalisun is dominated by species from Dipterocarpaceae and Euphorbiaceae while the understory is dominated by Rubiaceae and Melastomataceae families (Newbery et al. 1992).

The Sapat Kalisun catchment is generally undulating to hilly but not mountainous. This study site was selectively logged in 1988 and 1989, with an annual production volume of between 96 - 100 m^3 ha^{-1} (Tangki and Chappell 2008). The logging operation was conducted using a combination of tractor and high lead logging. After logging, the coupes were closed down and the study site was allowed to regenerate naturally.

2.2 Acquisition and Processing of Airborne LiDAR Data

Airborne LiDAR data were acquired in October 2013 using an Optech C200 sensor, mounted on a Nomad C22 aircraft. The LiDAR data collection mission was operated at an altitude of 600 m, speed of 41.2 m s^{-1}, scan angle of ±14° and pulse frequency of 175 kHz (Table 1). The sensor system also consists of a differential global navigation satellite system (DGNSS) receiver coupled to an inertial measurement unit, both components ensuring that a sub-decimeter differential position can be calculated for the aircraft in post-processing. A calibration site within a residential area (less than 20 km) was also scanned for LiDAR data processing.

We used the Applanix IN-Fusion™ single baseline processing approach to generate the optimal smoothed best estimate of trajectory (SBET) from the global navigation satellite system (GNSS) and inertial data in POSPac Mobile Mapping Suite (MMS). This approach requires the rover to be at most 70 km from the nearest reference station to initially resolve the correct ambiguities (Hutton et al. 2008). We established the reference station with Javad Triumph-1 on a surveying benchmark at Taliwas Forest Reserve during the LiDAR data acquisition. The GNSS base station data was post-processed with Javad's proprietary software (Justin). The generated SBET was used to calibrate the raw LiDAR range data in Optech's LiDAR Mapping Suit (LMS) software to calculate the boresight misalignments (x, y, z) for the calibration site. The boresight misalignments were estimated in LMS with iterative pitch shift, roll shift, mirror scale, and heading shift error calculations. The laser point clouds in las 1.2 format were extracted for further processing in Microstation V8i. Points that were obviously much higher than the surrounding points were removed as noise. The average point density of the point cloud was 25 points m^{-2}.

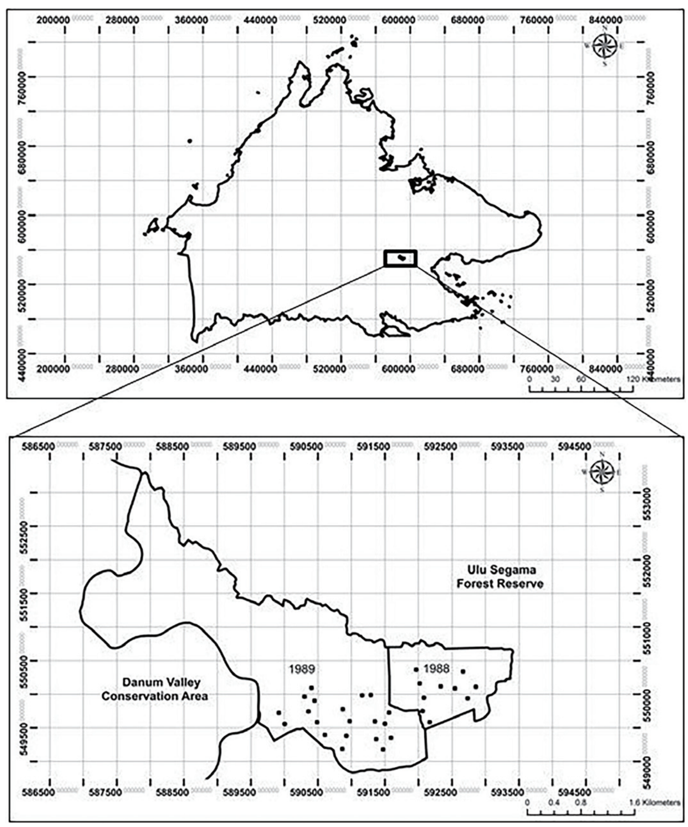

Fig. 1. Location of the study area. The study site comprised of logging coupes of 1988 and 1989 (plots in black color squres) in the Ulu Segama Forest Reserve, which is next to Danum Valley Conservation Area. Box in dashed line is LiDAR scanning area.

Table 1. Summary of LiDAR data acquisition using Optech C200 system.

System	Optech C200
Date of acquisition	11 October 2013
Platform	airplane (Nomad N22)
Flying altitude	about 600 m above ground
Average speed	41.2 m s^{-1}
Scan angle	±14°
Scanning frequency	70 Hz

We then used a filtering algorithm (Axelsson 2000) in TerraScan software to process and classify point clouds into ground and vegetation points. The ground points were distinguished by iteratively building a triangulated surface model with the following parameters: maximum building size = 60 m, terrain angle = 88°, iteration angle = 6°, and iteration distance = 1.4 m. The ground points were used to correct the pitch shift, roll shift, mirror scale, heading shift, and then z shift in TerraMatch. The overall elevation bias for the flight lines was 0.1044 m.

The terrain points were used to generate a Digital Terrain Model (DTM) (pixel size 1 m) with the triangulation method in ArcGIS. Figure 2 shows examples of the vegetation point cloud profiles (first returns) from plots. The canopy height was calculated by taking the height difference between the first returns and the DTM. Canopy height point clouds were clipped using plot boundary polygons. We then calculated LiDAR variables, including maximum (h_{max}) and mean (h_{mean}) canopy height as well as the 10th, 30th, 50th, 70th, and 90th percentiles (h_{10}, h_{30}, h_{50}, h_{70}, h_{90}) of canopy height, from the point clouds for all the plots.

2.3 Forest Inventory

The field data were collected in April, June, and October 2014. Thirty square plots (30 × 30 m) were randomly established within the study site to estimate AGB. All trees in the plot with DBH greater than 10 cm were measured. The structural variables included DBH, tree height (H) and crown diameter. Tree species were identified in the field by an experienced and field-botanist. Specimens were collected for species that could not be identified in the field for further determination at the DVFC herbarium.

The plot locations were determined using the Javad Triumph-1 receivers. We first established a base station at the DVFC weather station by referring to the nearest surveying benchmark at Taliwas Forest Reserve using the differential positioning method (static survey). A GNSS receiver was established at the base station while a rover was placed at the center of each plot to determine the plot's location at centimeter accuracy. The two DGNSS receivers received signals from the Global Orbiting Navigation Satellite System (GLONASS) and Global Positioning System (GPS) concurrently to allow GNSS data post-processing to correct the positioning error based on the difference between the signal ranges of these two points.

AGB for each tree was calculated from the DBH and height (H) data using an existing allometric equation (Yamakura et al. 1986). This allometric equation was developed in an undisturbed lowland dipterocarp forest at East Kalimantan, Indonesia. In the allometric equation AGB as dry weight (kg) of a single tree is calculated by summing up various tree components i.e., w_S (stem dry weight), w_B (branch dry weight), and w_L (leaf dry weight), calculated

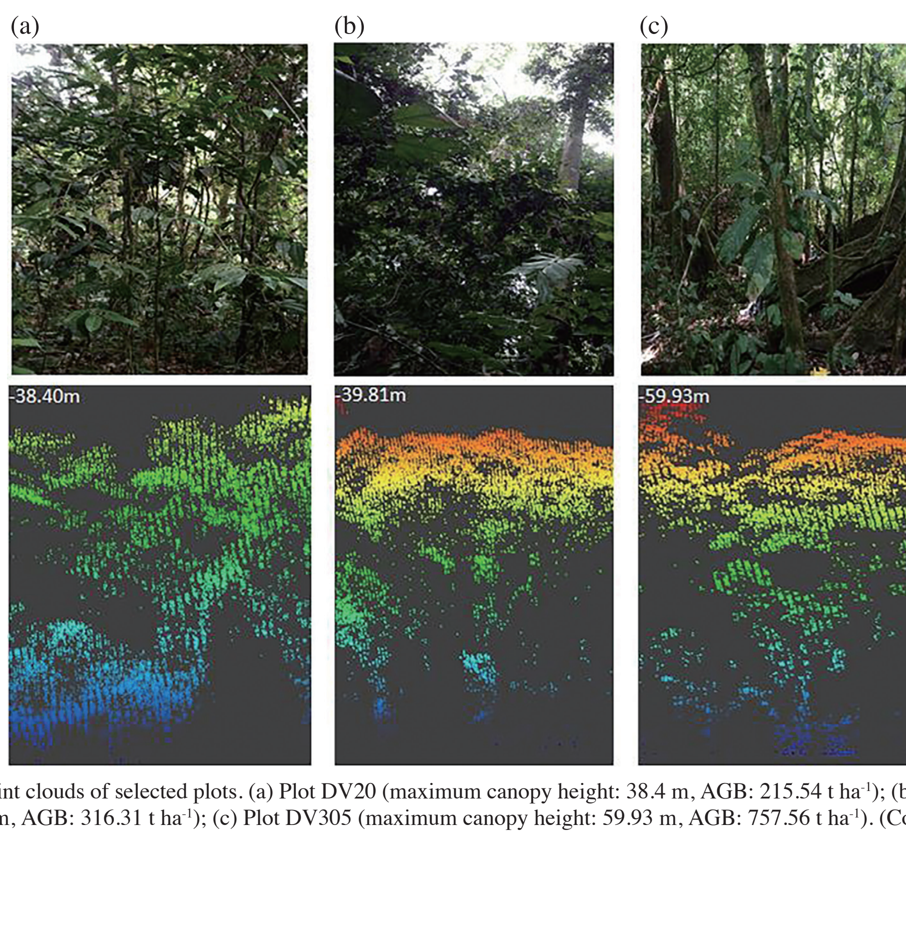

Fig. 2. The LiDAR point clouds of selected plots. (a) Plot DV20 (maximum canopy height: 38.4 m, AGB: 215.54 t ha^{-1}); (b) Plot DV05 (maximum canopy height: 39.81 m, AGB: 316.31 t ha^{-1}); (c) Plot DV305 (maximum canopy height: 59.93 m, AGB: 757.56 t ha^{-1}). (Color online only)

using the following equations;

$w_S = 2.906 \times 10^{-2} (DBH^2H)^{0.9813}$

$w_B = 0.1192\ w_S^{1.059}$

$w_L = 9.146 \times 10^{-2} (w_S + w_B)^{0.7266}$

$AGB = w_S + w_B + w_L$

The AGB (kg) for all trees within the plot were summed and used to calculate the plot level AGB in t ha^{-1}.

2.4 Statistical Analyses

One of the most common LiDAR approaches for AGB estimation was used in this study (Magnussen and Boudewyn 1998; Patenaude et al. 2004; Kronseder et al. 2012; Ioki et al. 2014). LiDAR variables calculated from the point clouds within the plots were regressed with field measurements. The LiDAR variables, including mean canopy height (h_{mean}), maximum canopy profile height (h_{max}), percentiles of canopy height corresponding to 10th, 30th, 50th, 70th, and 90th (h_{10}, h_{30}, h_{50}, h_{70}, h_{90}), were used as predictors in plot level AGB statistical analysis.

We first performed correlation analysis to explore the statistical association between the LiDAR variables and AGB. This was followed by simple regression analysis to examine the performance of the each variable in AGB estimation. Multiple linear regression analysis was then performed to examine any further model improvement by incorporating multiple LiDAR variables. The simple regression analyses were carried out with power models because the power models were successfully used to estimate AGB in tropical forests (Asner et al. 2012a, b; Jubanski et al. 2013). In the multiple regression analysis all LiDAR variables were transformed using the natural logarithm and stepwise regression using the Akaike Information Criterion (AIC) conducted to determine the final model. The independent variables with the lowest AIC value will be included in the final model. Coefficient of determination (R^2), the root mean squared error (RMSE) and RMSE as a percentage of the average AGB (RMSE %) were used for model evaluation. Leave-one-out cross-validation (LOOCV) was carried out for testing the overfitting of the final model using R software (http://cran.r-project.org/). One plot was selected as a validation sample while the remaining N-1 plots were used to train the model. The predictive value was assessed by comparing the cross-validated RMSE (RMSEcv) with the full model RMSE. A close agreement between the RMSEcv and RMSE indicates that the model is not overfitting the data and the predictive value is good.

3. RESULTS

3.1 Forest Structure and AGB of the Logged-Over Forest

Field measurements of the main structural variables i.e., DBH and H were examined to understand the logged-over forest characteristics. The mean DBH was 22.45 cm with a maximum of 135 cm. Tree height ranged between 4.1 - 65 m, with a mean of 18.5 m (Table 2). Tree height was strongly correlated to DBH with an R^2 of 0.74 (Fig. 3). There were only six trees greater than 50 m tall in the study areas. The estimated AGB ranged from 170.64 - 757.66 t ha^{-1}, with a mean (±SD) of 358.58 t ha^{-1} (±132.79), with trees between 20 - 50 m tall contributed the bulk of the AGB of the logged-over forest (Fig. 4).

Table 2. Summary of field measurements on the forest structure.

	Mean	SD	Min	Max
DBH (cm)	22.45	16.65	10	135
Height (m)	18.49	8.61	4.1	65
AGB (t ha^{-1})	358.58	132.79	170.64	757.66

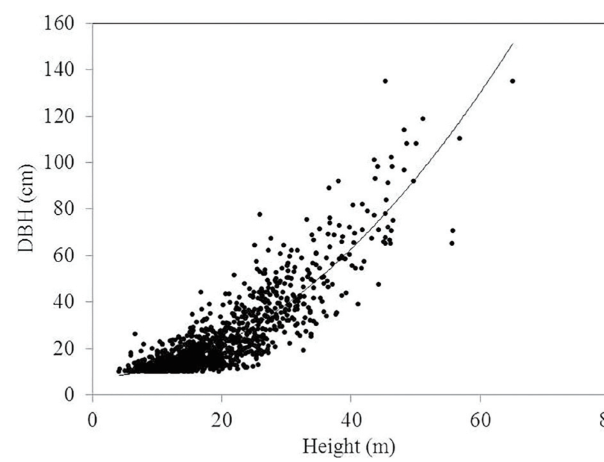

Fig. 3. Relationship between H (m) and DBH (cm) in the logged-over forest. Very few large trees were present due to past selective logging.

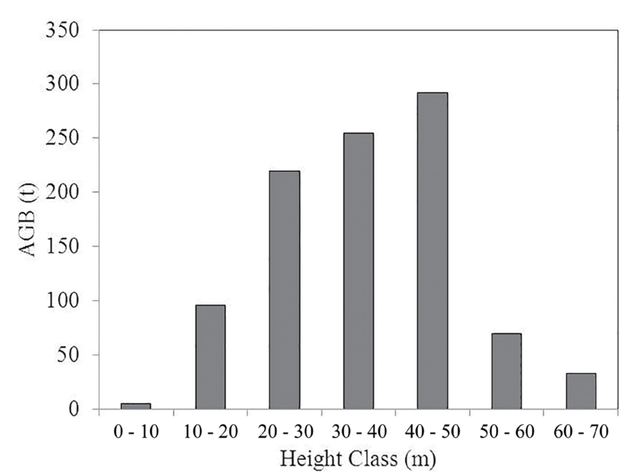

Fig. 4. AGB (t) distribution in height classes (m) based on field data.

3.2 AGB Estimation Model

Table 3 shows the correlations between AGB (t ha^{-1}) with different LiDAR variables estimated for the 30 plots. With a coefficient *R* (Pearson correlation) of 0.80, h_{mean} having the strongest correlation with AGB in the logged-over forest. This was followed by the 50^{th} percentile or median of canopy height with a coefficient *R* of 0.75. Only h_{max} had no significant correlation with AGB. The correlations decreased with lower and also higher percentile variables.

Simple regression with power models to estimate AGB were tested with all the LiDAR variables. The results indicate that h_{mean} was the best predictor of AGB compared to all other LiDAR variables (Table 3). The power model fitted to the plot data had a R^2 of 0.67 (*sig*. 0.01) (Fig. 5). In the stepwise multiple regression analysis, only h_{mean} was retained in the final model. The h_{mean} had the lowest AIC value in comparison to other multiple variable models (Table 4). The multiple regression analysis did confirm that the simple regression model with h_{mean} as the predictor is the best model to estimate the AGB for this forest. The full model RMSE was 80.02 t ha^{-1} or 22.31% of the average AGB. The RMSEcv calculated using LOOCV was 87.40 t ha^{-1} or 24.37%. The difference between the RMSE and the RMSEcv was 7.38 t ha^{-1} or about 2% relative to the mean AGB. A scatterplot of the observed AGB versus the LiDAR estimated AGB is shown in Fig. 6. The regression line was well-fitted between the observed AGB and LiDAR estimated AGB through the origin with a slope of 0.94.

4. DISCUSSION

Most of the lowland rainforest in Sabah had been logged at least once starting from the 1960s. The study site

Table 3. Correlation and simple regression analyses between AGB and LiDAR variables.

Variables	*R*	R^2 (power model)	RMSE (t ha^{-1})	RMSE (%)
h_{10}	0.50*	0.27*	115.95	32.34
h_{30}	0.62**	0.37**	106.27	29.64
h_{50}	0.75**	0.58	88.40	24.65
h_{70}	0.66**	0.48**	101.16	28.21
h_{90}	0.59**	0.39**	107.85	30.08
h_{max}	0.39	0.13	123.94	34.56
h_{mean}	0.80**	0.67**	80.02	22.31

*Note: *: significant at the 0.05 level; **: significant at the 0.01 level.*

Table 4. Multiple linear regression analyses results using Akaike Information Criterion (AIC).

Variables included in the model	AIC
h_{50}, h_{90}, h_{30}, h_{70}, h_{10}, h_{mean}	272.62
h_{90}, h_{30}, h_{70}, h_{10}, h_{mean}	271.35
h_{30}, h_{70}, h_{10}, h_{mean}	269.67
h_{70}, h_{10}, h_{mean}	268.07
h_{10}, h_{mean}	267.77
h_{mean}	266.29

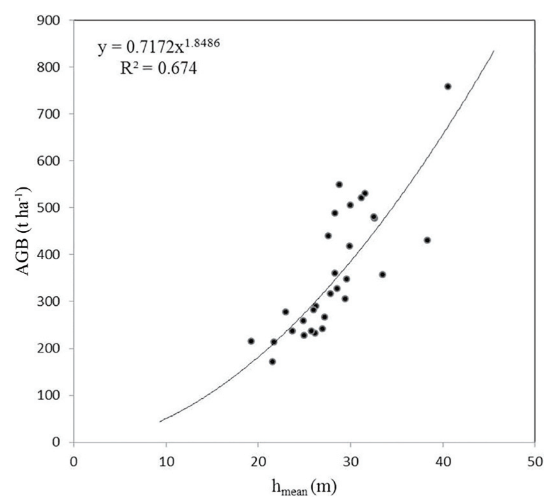

Fig. 5. Relationship between h_{mean} derived from the LiDAR data and AGB fitted with a power regression model.

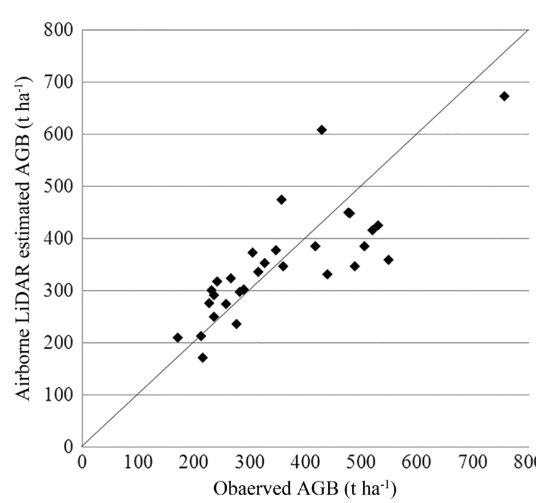

Fig. 6. Observed AGB (t ha^{-1}) versus LiDAR estimated AGB (t ha^{-1}).

was logged selectively 25 years ago and still shows clear impacts of the logging operation on both stand structure and AGB (Fig. 3). The DBH and height data for the plots had a right skew, with the mean H and DBH to the lower side of the data distribution (Table 2). The site had very few trees greater than 50 m, with most of the AGB contributed by the 20 - 50 m height class. Since the AGB was calculated with both H and DBH in the Yamakura's allometric equation, the mean AGB also skewed to the right side of the data distribution. While our estimated mean AGB of 358.58 t ha^{-1} (Table 2), is low compared to AGB estimate of 506.37 t ha^{-1} for a primary mixed dipterocarp forest (Tangki and Chappell 2008), it is, however, comparable to estimate obtained for logged-over mixed dipterocarp forests. Langner et al. (2012) reported a mean AGB of 335.8 t ha^{-1} for the logged-over forests of the Deramakot Forest Reserve.

We found a substantial variation in AGB within the sample of 30 plots (Figs. 3 and 4), suggesting that the past disturbances were not uniform and caused the regenerating forest to become highly heterogeneous (Brown and Lugo 1992). The AGB of the heterogeneous logged-over forest in the study site could be estimated from the mean canopy height (Fig. 5). Selective logging created canopy gaps (Johns 1988) allowing laser-pulse penetration through the forest canopy. Heterogeneous forest structure means differences in vertical layering (Asner et al. 2009). Loss of emergent and upper canopy trees enables the lower canopy trees to receive more laser pulses thus allowing for a better assessment of the lower vertical layer forest structure. By taking the mean of all laser pulse first returns, the mean canopy height considered trees in all sizes in the vertical layers, and thus accurately characterized the three dimensional tree distribution of the logged-over forest.

Mean height metric from LiDAR data has widely been used to develop the AGB or carbon estimation models: lowland rainforest in Central Kalimantan (Jubanski et al. 2013), rainforest in Panama, Peru, Madagascar, and Hawaii (Asner et al. 2012c), and tropical montane forest in Sabah, Borneo (Ioki et al. 2014). Although the model's coefficient of determination was not very high ($R^2 = 0.67$), the single-variable model had an RMSE of 22.31% of the mean AGB, which is lower than the RMSE of the single-variable model using mean canopy height (28% of the mean AGB) and multiple-variable model (26% of the mean AGB) (Ioki et al. 2014). Overall the estimated AGB corresponded well with the observed AGB (Fig. 6). Only a few plots had considerable over and under-estimation issues. Further examination of the plots with AGB over-estimation suggest that this was due to the presence of a few big trees in a relatively low density stand. As most of the LiDAR pulses were reflected by the few big trees, the h_{mean} values became relatively high, thus tending to over-estimate the AGB. On the other hand, AGB under-estimation occurred in a few plots with h_{mean} of more than 25 m but less than 30 m. These areas were heavily logged 25 years ago and provided a lot of gaps for regeneration. These areas are now constituted by mostly medium-size trees that are summed to a substantial amount of AGB. Nevertheless, these plots were within the RMSE with the exception of one plot. This plot had 70% more trees than an average plots with similar mean H and DBH, leading to a higher observed AGB than was derived from the LiDAR data.

5. CONCLUSION

This study examined the use of airborne LiDAR to estimate AGB in a logged-over forest in Sabah. Among the LiDAR variables, mean canopy height was best correlated with AGB in the logged-over forest. The AGB estimation model using mean canopy height had the lowest RMSE, suggesting it yields the most accurate AGB estimates and can be used as a reliable approach to estimate carbon stocks for REDD+. While the deployment of an airborne LiDAR sensor is relatively expensive, it greatly reduces the number of field plots required to accurately estimate the AGB of a highly heterogeneous logged-over forest. We suggest that LiDAR based estimates will be more time and cost effective, and provide a more realistic Measurement, Reporting, and Verification (MRV) system for REDD+. As most of the permanent forest estates in Sabah consist of logged-over forests, further studies are recommended to see if the mean canopy height is the universal predictor for AGB for other logged-over lowland rainforest sites in Sabah and to also investigate whether these findings can be applied to estimate carbon stocks in the remaining primary lowland rainforests.

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