Evaluation of allometries for estimating above-ground biomass using airborne LiDAR data in tropical montane forest of Northern Borneo

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Abstract. Tropical forests play a crucial component of the terrestrial carbon pool and estimate of above-ground biomass (AGB) with high accuracy is important in quantifying tropical forest carbon stocks. There are several allometries available for estimating tropical forest tree AGB using field measurements, the choice of allometric equation is a decisive factor that can influence the AGB estimation accuracy. This study examined the use of allometric equations to accurately estimate AGB using airborne LiDAR data. The LiDAR data of Ulu Padas area was acquired using Optech Orion C200. 56 field plots were established to collect data on diameter at breast height, tree height and tree species. Field AGB was calculated from allometric equations of Yamakura et al. (1986), Basuki et al. (2009), Chave et al. (2005) and Chave et al. (2014). All LiDAR-derived height metrics and variables were correlated with field AGB (R: 0.30-0.88). Based on stepwise multiple regression analysis, Chave et al. (2014) allometry had highest model R², explaining 81% of the variance of the field AGB. In short, allometry that includes wood density should be used in LiDAR applications on tropical forest AGB estimation.

Keywords: Small-footprint LiDAR, REDD+, biomass allometry, tropical montane forest, Sabah

1. Introduction

Forests are a key component of the global carbon pool because they are a dynamic ecosystem and carbon pools that cover a vast area [1-3]. Since 1990s, tropical forests have declined with an annual deforestation rate of nearly 0.6% and over 100 million hectares of tropical forests in the world were cleared, resulting in large amounts of carbon emissions [4]. Above-ground biomass (AGB) is the most important carbon component in these forests and almost 50% of the AGB are made up of carbon [5-6]. About 1,700 million hectares of the world tropical forests are found in Southeast Asia (SEA), representing a massive carbon pool in the world [7-8]. Accurate estimate of AGB is important to determine the amount and the dynamic of carbon stocks in these tropical forests.

Remote sensing-based methods have been the main-stream in AGB estimation due to their comprehensive observation and cost-effective performance [9-12]. Besides, high-resolution remotely sensed data are needed to accurate estimate AGB [13-15]. Light Detection and Ranging (LiDAR) is active remote sensing that allows high density photons penetrate a dense and structurally complex forest canopy, providing a direct estimate of ground elevation and forest vertical profile. Forest height metrics
(e.g. canopy height percentile, maximum canopy height and canopy cover) from high-resolution LiDAR data are capable in estimating AGB with a high accuracy [15-18]. However, the outcome calibration heavily depends on the accuracy of field AGB estimation. Reliable field AGB is one of the crucial factors in deriving an accurate AGB estimate.

Destructive harvest method is the most direct and accurate way to determine field AGB. This method involves a massive tree harvest event in the targeted study area to derive the total oven dry mass of each partition on the tree samples [19-20]. However, this is not only time and resource consuming, it is also limited to small sample size. Therefore, AGB allometry equation developed from this method provides an alternative way for assessing biomass and carbon stocks of forest because it establishes the relationship between tree physical parameters and AGB [21-25]. To date, there are several AGB allometries established for the tropical forest regions. In some cases, specific biomass equation is applied to dominant forest type or ecological region to achieve high accuracy of field AGB estimation. Yamakura et al. [21] developed biomass equation for dipterocarpaceae dominated tropical lowland forest in East Kalimantan and used DBH as the predictor to estimate biomass of various partitions on the tree. Basuki et al. [25] harvested four different types of tree genera (Dipterocarpus, Hopea, Palaquium, and Shorea) to develop a mixed species allometric equation for lowland mixed Dipterocarp forest. Chave et al. [23] established allometric equations for various forest types, dry, moist, wet for lowland, montane and mangrove forests across the pantropical region. Chave et al. [22] improved the allometric equations of Chave et al. [23] using a larger dataset of 4004 individually harvested trees collected from tropical forests in Latin America, Asia and Oceania.

To better understand the role of AGB allometry selection in determining high-resolution AGB estimation using small foot-print discrete LiDAR data, we estimated field AGB using five established AGB allometries for tropical forests and then examined the accuracy of AGB estimated using the LiDAR-derived metrics. The findings in this study could be relevant to other tropical regions.

2. Methodology

2.1. Study area
The study was conducted in the district of Sipitang, Sabah, Malaysia. The study area is located next to the border between Sabah, Sarawak, and Kalimantan, Indonesia. It lies in the transition zone of lowland and montane tropical forests with elevation ranges from 1000 to 1600 m above sea level. The study area consists of state lands and forest reserves licensed to Sabah Forest Industries Sdn. Bhd. (SFI). Field measurements were carried out at two sites where LiDAR data were collected.

2.1.1 Field measurement. Field data were collected within the two sites (Figure 1) from July 2017 to August 2018. Total 56 square plots were distributed throughout both study sites with three plot sizes depending on the forest condition (50 m x 50 m: 1 plot, 30 m x 30 m: 53 plots and of 20 m x 20 m: 2 plots). All trees with DBH ≥ 10 cm (DBH ≥ 5 cm for 20 m x 20 m plots) measured for diameter at breast height (DBH) and tree height and were identified to genus or species level. Wood specific gravity for each sampled tree species were obtained from tree functional attributes and ecological databases of World Agroforestry.

2.2. Field above-ground biomass estimation
DBH (cm), tree height H (m), wood specific gravity ρ (g cm⁻³) were the main variables used to estimate field AGB using three allometric equations for tropical forests. The allometries are as follows,
Figure 1. Study area.

i. *Yamakura allometric equation.* Field AGB were calculated from the summed dry weight per each tree by stem, branch and leaf (*Yamakura*). DBH and H were first used to calculate the dry weight for tree stem ($W_S$), dry weight for tree branch ($W_B$) was calculated using $W_S$ as the predictor variable and dry weight for tree leaf ($W_L$) was calculated using $W_S$ and $W_B$ as the variables.

\[
W_S = 2.903 \times 10^{-2} \times (DBH^2 \times H)^{0.9813}
\]

\[
W_B = 0.1192 \times W_S^{1.059}
\]

\[
W_L = 9.146 \times 10^{-2} \times (W_S + W_B)^{0.7266}
\]

Field AGB = $W_S + W_B + W_L$ .................................................. (Yamakura)

ii. *Basuki allometric equations.* Two allometric equations for mix-species were used to calculate field AGB.

\[
\ln(\text{Field AGB}) = -1.201 + 2.196 \times \ln(DBH) \...........................................(\text{Basuki A})
\]

\[
\ln(\text{Field AGB}) = -0.744 + 2.188 \times \ln(DBH) + 0.832 \times \ln(\rho) \............................(\text{Basuki B})
\]

iii. *Chave allometric equations.* Field AGB was calculated according to moist forest stand allometric equations from Chave *et al.* [23] as:

\[
\text{Field AGB} = \rho \times \exp(-1.499 + 2.148 \ln(DBH) + 0.207(\ln(DBH))^2 - 0.0281(\ln(DBH))^3). (\text{Chave A})
\]
iv. An improved allometric equation from Chave et al. [23]. The best fit AGB allometric model across the pantropical. Field AGB was calculated using DBH, H and ρ as the predictor variables.

Field AGB = 0.0673 × (ρ × (DBH^2) × H)^0.976 .................................................................(Chave B)

2.3. LiDAR data
LiDAR data were collected at two study sites on September 25th to 26th, 2017 with an Optech Orion C200, a discrete return laser measurement system, mounted on a Nomad C22 fixed-wing aircraft. The LiDAR data were collected at a speed of ±51 m/s at an altitude of approximately 600 m above ground level, ±20° scan angle and laser repetition frequency 100 kHz. The average LiDAR point density in Site 1 and Site 2 were 16.32 points/m² and 7.19 points/m², respectively.

The LiDAR data were pre-processed and then classified into two classes: ground and non-ground using MicroStation V8i software. From the ground points, a digital terrain model (DTM) was generated in 1 m spatial resolution using triangulate interpolated with natural neighbour. Maximum altitudes of return echoes amongst non-ground point were used to derive a digital surface model (DSM) at 1 m × 1 m pixel size. A canopy height model (CHM) was then derived by subtracting the DSM value to the DTM value. Mean and maximum value of CHM were calculated for each sample plot. LiDAR height metrics were calculated using non-ground normalized LiDAR data within each sample plot, such as maximum height (hmax), mean height (hmean), standard deviation, skewness and the 10th, 95th, 99th percentiles of the height distribution, as p10,…, p95, p99. Laser penetration rate of LiDAR data was calculated the proportion of last return at less than a certain given height (1 m, 2 m, 5 m, 7 m, 10 m, 12 m, 15 m, …, 37m) to the total number of laser pulse, giving LP1, LP2, LP5, LP7, LP10, LP12, LP15, …, LP37. Higher laser penetration rate will be found in open forest area (indicates low biomass), while low in dense canopy and intact forest (indicates high biomass) [26-28].

2.4. Statistical analysis and model development
All 5 sets of field AGB and 43 derived LiDAR variables were transformed to the natural logarithm. Data were analysed using linear regression method. Correlations between field AGB and each LiDAR variables were inspected using Pearson’s correlation. Stepwise multiple linear regression analysis was used to regress AGB with the LiDAR variables as follows,

\[ Y = a_0 + a_1X_1 + a_2X_2 + \ldots + a_nX_n \]

Where \( Y \) is AGB or Ln (AGB) in Mg/ha, \( X_1 \ldots X_n \) is the explanatory variables (original or transformed), \( a_0 \) is the intercept, \( a_1 \ldots a_n \) is the regression coefficient for the variables.

All statistical analyses were performed in R software. The best performance of AGB estimation model was selected based on adjusted coefficient of determination (\( R^2_{adj} \)), Akaike information criterion (AIC) and root-mean-square error (RMSE) and relative RMSE. RMSE was also calculated from leave-one-out cross-validation (RMSELOOCV) for model evaluations. A correction factor was applied to correct the systematic bias introduced by the logarithmic transformation [29] during back transformation of estimated AGB.

3. Results and Discussion
In this study, we investigated the performances of established allometric equations with LiDAR derived height metrics to develop an accurate AGB estimation model in tropical forest. Figure 2 shows LiDAR derived height metrics were well correlated with field AGB. The best biomass estimation models resulted from multiple linear regression analysis for the allometric equation are shown in Table 1. Except Basuki A, these estimation AGB models were able to explain about 69.7% to 80.8% of the field AGB variance using a combination of LiDAR height percentiles and laser penetration rates.
Estimation model with field AGB derived from Basuki A had the lowest $R^2$ value ($R^2 = 0.56$). Thus, best not to use for AGB estimation because it only includes DBH in the allometry. Although DBH is the most common field AGB predictor but considering the tree architecture form, AGB is greatly affected by tree height as well as wood specific gravity [30-31]. Our result also showed that inclusion of wood specific gravity into an allometry that uses DBH as predictor of field AGB (Basuki B and Chave A) yielded a satisfactory AGB estimation model using LiDAR height metrics (adjusted $R^2$: 0.697 to 0.757). Allometric equations that include tree height and DBH (Yamakura) seemed to be satisfactory (adjusted $R^2$: 0.702) but with the addition of wood specific gravity (Chave B), the estimation model resulted had the highest adjusted $R^2$. It can be considered the best model because it also had a low AIC value and RMSE % (Table 1 and Figure 3e).

![Figure 2. Pearson’s correlation (r) between the field AGB calculated from difference allometric equations and the LiDAR derived height metrics.](image)

**Table 1.** The AGB estimation models for allometric equations.

| Allometric equations | Models | $R^2_{adj}$ | RMSE (Mg/ha) | RMSE (%) | AIC   |
|----------------------|--------|-------------|--------------|----------|-------|
| Yamakura            | Ln(AGB) = -0.582LP17 + 0.052p55 + 4.48 | 0.702 | 63.36 | 23.22 | -1.68 |
| Basuki A            | AGB = 11.416p50 - 14.006 | *0.555* | 50.64 | 21.24 | 604.49 |
| Basuki B            | Ln(AGB) = -1.049LP20 + 0.036p50 + 1.764LP2 + 4.873 | 0.697 | 44.37 | 17.46 | -18.37 |
| Chave A             | Ln(AGB) = -1.785LP20 + 2.972LP2 + 0.043p55 + 5.155 | 0.757 | 74.61 | 20.21 | 4.11  |
| Chave B             | Ln(AGB) = -1.467LP20 + 0.049p60 + 2.333LP2 + 4.813 | 0.808 | 61.17 | 18.76 | -14.12 |

*R^2* value

In terms of the independent variables or predictors, LiDAR height metrics, height percentile and laser penetration rate, were the main variables selected in all five AGB estimation models. Previous studies have estimated AGB from LiDAR derived height metrics in subtropical forest and in lowland dipterocarp forest [32-33]. The inclusions of laser penetration rates can further improve the accuracy in AGB estimation model [26, 28]. The usefulness of laser penetration rate in modelling AGB may due to its direct link to the forest canopy structure and stand growth condition that provide an almost static penetration rate regardless the LiDAR point density [27].
4. Conclusions

Selection of allometry to derive field above-ground biomass (AGB) is important to AGB estimation using LiDAR data. We assessed five allometric equations that estimate field AGBs for determining the most suitable allometry to estimate AGB using LiDAR data. This study showed that the field AGB derived amongst the five allometric equations, the best estimation model was based on the field AGB calculated from Chave B allometry (Chave et al. [22]) that includes wood specific gravity, tree height and DBH. While it is acceptable to use an allometry that includes DBH with height or wood specific
gravity, it is advisable to avoid using an allometry that only uses DBH to estimate AGB using LiDAR data.

Acknowledgements
This project was funded by Ministry of Education Malaysia (Project: FRG0521) and Ministry of Energy, Science, Technology, Environment & Climate Change (Project: 04-01-10-SF0223). We would like to thank Universiti Malaysia Sabah for support and Sabah Forestry Department for research permission.

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