# IMPACTS OF TREE HEIGHT-DBH ALLOMETRY ON LIDAR-BASED TREE ABOVEGROUND BIOMASS MODELING

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**ABSTRACT:**

Lidar has been widely used in tree aboveground biomass (AGB) estimation at plot or stand levels. Lidar-based AGB models are usually constructed with the ground AGB reference as the response variable and lidar canopy indices as predictor variables. Tree diameter at breast height (dbh) is the major variable of most allometric models for estimating reference AGB. However, lidar measurements are mainly related to tree vertical structure. Therefore, tree height-dbh allometric model residuals are expected to have a large impact on lidar-based AGB model performance. This study attempts to investigate sensitivity of lidar-based AGB model to the decreasing strength of height-dbh relationship using a Monte Carlo simulation approach. Striking decrease in $R^2$ and increase in relative RMSE were found in lidar-based AGB model, as the variance of height-dbh model residuals grew. I, therefore, concluded that individual tree height-dbh model residuals fundamentally introduce errors to lidar-AGB models.

## 1. INTRODUCTION

Forests play an important role in global climate change and can absorb $CO_2$ in the atmosphere via photosynthesis and store the sequestered carbon as biomass (Myneni et al., 2001; Pacala et al., 2001; Pan et al., 2011). Thus, accurate estimates of forest biomass are crucial for understanding global carbon cycle and predicting the future climate (Chen et al., 2015). Tree aboveground biomass (AGB) refers to the total amount of living aboveground organic matters present in trees, including leaves, twigs, branches, main bole and bark (Brown 1997). Field AGB measurements usually are not achievable at forests with dense canopies, and cannot cover extensive spatial area. Light detection and ranging (lidar) is a remote sensing technology that has been widely used to estimate forest biomass at plot and stand levels (Lefsky et al. 1999; Hyde, Nelson et al. 2007; Chen et al. 2012). Canopy vertical structural indices can be extracted from lidar measurements. Lidar-based canopy indices are used to construct regression models with ground reference AGB estimates, which are usually calculated from allometric models.

Tree diameter at breast height (dbh) is considered as the most reliable parameter for AGB estimates. Thus, AGB allometric models were widely developed based on dbh (Bartelink, 1996; Basuki et al., 2009; Jenkins et al., 2003; Nelson et al., 1999; Ter-Mikaelian and Korzukhin, 1997; Zianis and Seura, 2005). The fundamental assumption of using lidar canopy height indices to associate with ground AGB reference is that stands (plot) with the same height produce the same amount of biomass products. However, at individual tree level, there is considerable variation in tree height at given tree dbh. This variation is reflected as residuals existing fitted height-dbh allometric models. Tree height-dbh model residuals probably reduce the correlation between lidar canopy height indices and ground AGB reference, consequently introducing errors to lidar-based AGB models.

Exactly how and to what extent the tree level height-DBH allometric model residuals impact the plot level lidar-based AGB models remains poorly understood. Little study has addressed the lidar-based AGB model errors induced by height-dbh allometry. This study aims to exploring how lidar-based AGB model performance change with the decreasing strength of tree height-dbh allometric relationship. A Monte Carlo simulation approach was used to develop plots with varying strength of individual tree height-dbh relationship. For each height-dbh model scenario, 1000 realizations were created. Pseudo point clouds were collected from the simulated canopy surface. Mean canopy height (MCH) was extracted by averaging plot point cloud. Finally, a simply linear regression model was developed with reference AGB and MCH. Average $R^2$ and RMSE were reported for each simulation scenario. The changing patterns of $R^2$ and RMSE reveal sensitivity of plot level lidar-based AGB model to the varying individual tree height-dbh relationship. Some further implement suggestions and potential approaches of improving the model performance were proposed.

## 2. STUDY AREA and METHODS

### 2.1 Study area and field data

The study area is located in United States Forest Service Sagehen Creek Experimental Forest in California. A systematic sampling grid with 125 m space density was established. Plot size is 0.05 ha. For each plot, trees with dbh greater than 5 cm were measured. Tree species were recorded. Tree crown ratio was estimated.

### 2.2 Reference AGB calculation

USDA Jenkins allometric equation model (Jenkins et al., 2003) is available to generate AGB estimates in northern California. The general equation form is expressed as following:

$AGB = e^{\beta_0+\beta_1*\ln(dbh)}$ (1)

where AGB is the tree total aboveground biomass, e (2.71828) is the base of the natural logarithm, $\beta_0$ and $\beta_1$ are parameters that are dependent on specific tree species groups, DBH is diameter at breast height, and ln is natural logarithm .

Plot level biomass was converted to total biomass density, which is the sum of individual tree biomass present in the plot divided by the area of the plot.

## 2.3 Monte Carlo Simulation

### 2.3.1 Height-dbh model

Field tree height and dbh measurements were used to develop simple height-dbh model at log-transformed scale. Their relationship is presented in Figure 1. As it shows in Figure 1, considerable residuals exist in the height-dbh relationship. This model was the base to further establish tree height-dbh relationship with different strength scenarios.

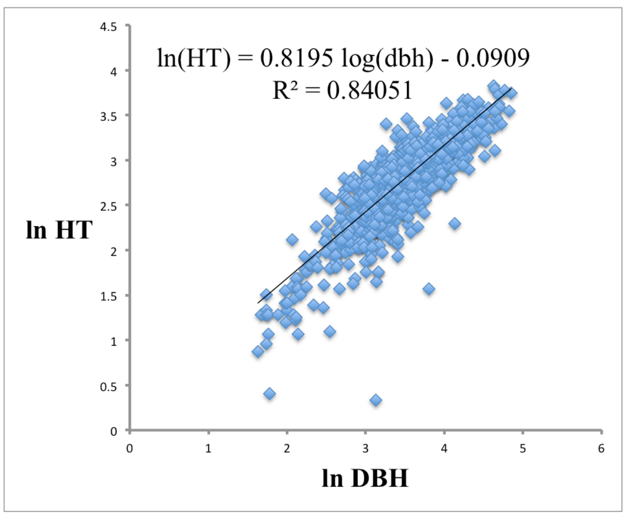


Figure 1.Constructed height – dbh allometric model at log-tranformed scale with field data

### 2.3.2 Simulation

*Step 1. deciding the location and crown diameter of each trees*

Plot tree density and dbh were obtained from field sample data. Tree relative locations were randomly assigned within each plot. Distance between any pairs of trees was determined with a rule that $Distance_{ij} \geq 1.5*(dbh_i + dbh_j)$ , where $Distance_{ij}$ is distance between the geometric centre of *ith* and *jth* trees, $dbh_i$ and $dbh_j$ are the dbh of *ith* and *jth* trees repectively. Crown diameter was determined by existing models developed by Gill et al. (2000).

*Step 2. generating simulated tree height from dbh using tree height-dbh allometric model under different scenarios*

For different scenarios, the strength of the log-transformed height-dbh allometric model was controlled by assigning variance of residuals ($\sigma^2$). The $\sigma^2$ was increase from 0 to 0.5. Totally, ten scenarios were performed. For each stime, the $\sigma^2$ was increased 0.05 compared with previous scenario.

For each tree, the height was generated with equation in 2.3.1, by adding a random residual. For all the simulated trees, the residual of log-transformed height-dbh model has the normal distribution N(0,$\sigma^2$).

*Step 3. Generate pseudo lidar point clouds*

Pseudo lidar point clouds were obtained from the simulated canopy surface with a density two to four returns per square meter. lidar MCH was extracted from the pseudo point clouds. All the returns were classified as ground returns and foliage returns.

*Step 4: Constructing LiDAR-AGB models*

Reference AGB estimates were calculated with Jenkins equations. And a simply linear regression was used to construct lidar-based AGB models with reference AGB and lidar MCH at log-transformed scale. The model is expressed as following:

$\ln(AGB) = \alpha_0 + \alpha_1 * \ln(MCH) + e_0$ (2)

where AGB is plot reference AGB density, $\alpha_0$ and $\alpha_1$ are the estimated parameters, and $e_0$ is the residual of the predictions. Model performance was evaluated with $R^2$ and RMSE.

*Step 5: Generating 1000 realizations for each tree height-dbh model scenario*

1000 realizations were generated for each scenario by repeating *step 1* to *4* to eliminate effect of random locations of trees and canopy overlapping. The average $R^2$ and relative RMSE (ratio between RMSE and mean reference AGB density) of regression models from 1000 realizations were recorded.

# 3. RESULT

The increasing variance of log-transformed height-dbh model residuals led to decreasing strength of height-dbh relationship. The $R^2$ of log-transformed lidar-based AGB model apparently declines, as consequence of decreasing strength of log-transformed height-dbh model (Figure 2). Theoretically, as height and dbh have perfect relationship (variance of residuals is zero), the $R^2$ of lidar-based AGB model is near 0.80, with a relative RMSE of 0.36. When the variance of log-transformed height-dbh model residuals increases to 0.5, average $R^2$ of lidar-based AGB model decreases to 0.61. The simulation result demonstrates the scattering of individual tree level height-dbh allometric relationship introduces errors to lidar-based AGB estimation.

# 4. DISCUSSIONS and CONCLUSION

Previous studies have extensively studied on the resources that cause variation in lidar's performance of AGB estimation. These resources include: various types of sensors (Zolkos et al., 2013), regression approaches (Chen et al., 2010; Chen et al, 2015; Dalponte et al., 2008; Garcıa-Gutiérreza et al.; Gleason and Im, 2012), and whether or not optical remote sensing data is fused with lidar data (Anderson et al., 2008; Koetz et al., 2007; Lefsky et al., 2005; Swatantran et al., 2011; Laurin et al., 2014). However, these sources introducing errors to lidar-based AGB models are more considered as external factors rather than the intrinsic limitations of further improving the performance of lidar in biomass estimation. The novelty of this study is to investigate the errors introduced by height-dbh model residuals using Monte Carlo approach. The general decreasing $R^2$ of lidar-based AGB model under scenarios of increasing variance of height-dbh model residuals manifested that the individual tree level height-dbh allometry is a fundamental factor impacting on the performance of lidar-based AGB models.

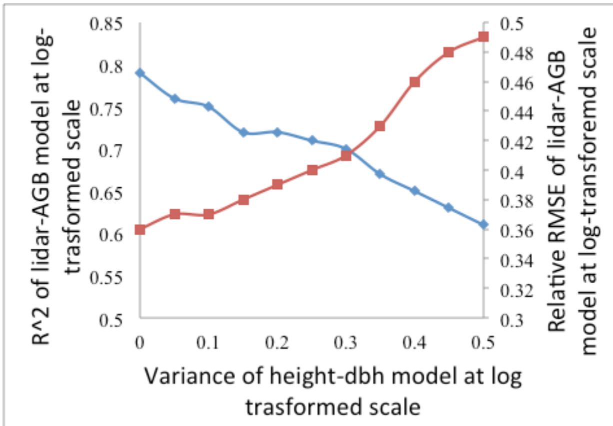


Figure 2. Simulation result: change in $R^2$ (blue diamond line) and relative RMSE (red square line) of log-transformed lidar-AGB model, under the scenarios of increasing variance of log-transformed height-dbh model residuals.

The result implies that if a generalized lidar-based AGB model is developed for a spatially spread area, the accuracy of the model is probably poor, due to the large discrepancy in the strength of height-dbh allometric relationship. Tree height-dbh allometry could vary at forests of different development stages, species compositions, and locations. While sampling trees and constructing lidar-based AGB models, foresters should take the tree height-dbh allometry into consideration.

Another suggestion is to add tree height as an extension variable in estimating reference AGB. Including tree height in reference AGB estimation could enhance lidar's association with ground reference AGB, because it directly provides the stand height variation at given basal area. Reference AGB estimates with extra height information are more related to lidar canopy vertical measurements. Some allometric models use both tree height and dbh as parameters for AGB estimation (Heath et al. 2009; Zhou and Hemstrom, 2010). Zhao et al. (2012) already found performance of lidar-based AGB models could be different, when different allometric equations were applied for estimating reference AGB. Their finding suggested including tree height in field AGB estimation largely influences the model's accuracy.

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