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Simple Allometry To Estimate The Aboveground Tree Biomass For Five Cool-Broadleaved Species Of Bhutan Himalaya

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Abstract – Million tons of carbon was found to be stored in the forest biomass with maximum storage capacity in the broadleaved trees. Developing tree biomass allometric equation being considered fundamental to determine the carbon sequestration potential of tree species. Thus, five broadleaved tree species of *Quercus lamellosa, Beilschmiedia sikkimensis, Castanopsis hystrix, Persea clarkiana* and *Symplocos sumintia* were destructively sampled using Randomized Branch Sampling technique (RBS) to develop allometry for aboveground biomass estimation in cool broadleaved forests in Bhutan. The total of 159 sample trees with minimum 32 trees from each species under different diameter class (5 cm < 90 cm), height class (4 m < 46 m) from four physiographic zones were sampled. The observed total aboveground dry biomass of the trees ranges from 4.12 < 5579.31 kg; 3.62 < 3464.51 kg; 5.99 < 3600.52; 8.89 < 3689.82 kg; kg and 7.08 < 2993.22 kg respectively for above five species. Linear regression was attributed to heteroskedasticity with un-equal distribution of the residual errors. While linearized regression with transformed variables exhibited the best fit line for biomass estimation. Significant prediction of aboveground tree biomass was observed with natural log base transformed linearized power function of DBH -tree height relationships ($t(29) = 11.91, 1.63, p \leq .001$) $R^2 = .98$) followed by the transformed model of DBH as independent variable ($t(30) = 34.31, p \leq .001$) $R^2 = .97$). Therefore, the study concluded that, linearized power function with antilog bias correction factor seemed better in predicting aboveground tree biomass of cool broadleaved species in Bhutan.

Keywords – Model, Allometry, Biomass, Diameter (DBH), Carbon, Logarithmic, Estimation.

I. INTRODUCTION

Estimating biomass and quantifying carbon was important aspects to study climate change. Forest, covering 31 percent of the global land area [1], had been considered one of largest carbon sinks with capacity to store four times the amount of carbon present in atmosphere ([2], [4]). Globally the vegetation biomass alone was estimated to store 283 Giga-tons of carbon, among other carbon pools [5]. The annual carbon emitted through land use change was estimated to 1.6 billion tons with highest percent contributed through forest degradation and deforestation ([6], [7]). Hence, estimation of aboveground tree biomass remained instrumental for quantifying forest carbon [8]. Different methods were specified to quantify forest biomass and carbon, such as, direct measurement, indirect methods, volumetric equation, remote sensing and allometry relationship [9]. Commonly applied technique to estimate tree biomass was found to be allometric equation. The term allometry was defined as the relationships between part of an organism and its whole [10]. The allometry method, considered as the robust methods to quantify aboveground tree carbon had been used to convert inventory data to biomass and carbon [11]. It was developed as a relationship of easily measurable variables such as diameter, tree height, basal area and wood density ([12], [13]).

Several allometry equations were available specific to species, sites, and predictor variables. "Ref. [14]" had used semi destructive technique to develop the allometric model for *Olea europaea* trees, using diameter and the tree height, in Mana Angetu forest in Africa. While [15] have used four variables such as diameter at breast height, function of diameter, trunk bole height and crown cover for biomass prediction of *Sequoia sempervirens* in California. Similarly, the site specific height-diameter general model was developed by [16], to estimate the tree biomass in Tanzania forest.

Himalayan forest were considered to have the highest net productivity and biomass production [17]. Accordingly, Bhutan has forest coverage of 71% [18] of the total land acreage. However very minimal research and documentation available in forest biometrics and carbon quantification in the country. Therefore, Bhutan has limited species-specific allometric equation to estimate the above ground tree biomass for forest carbon quantification. Such limited research documentation and specified methodology on estimating the above ground tree biomass had constrained the forest carbon quantification at the national level.

Currently, most of the research on aboveground tree carbon quantification were based on bole volume equation along with wood density which greatly undermines the tree component carbons such as foliar, dead wood, branch and roots. It was evident that proportions of component biomass such as branch and foliage biomass contribute significantly to total aboveground tree biomass, as was evident from findings of [19]. Allometric technique incorporates bole, foliage, branch and deadwood biomass to estimate the total above ground tree biomass ([21],[20],[22]).

Often general allometry had been commonly used in absence of species-specific equation for biomass estimation. Although, general allometry equation had been less resource intensive for biomass estimation, it implies to specific countries leading to a large source of uncertainties [11]. These uncertainties primarily have occurred due to limited sample size and sites [24] and wider scale application [16]. Therefore, development of a country specific equation was instrumental as indicated by [25], where general equation resulted into inaccurate biomass estimation. The species-specific allometry equation has the advantage to determine the carbon sequestration potential of trees at the species level.

Thus, this study tried to develop the reliable, simple and efficient biomass function using the covariates such as diameter at breast height, tree height, and basal area. The study was conducted with destructive methods using randomized branch sampling techniques. The expected outcome was to develop species specific allometric equation to estimate aboveground tree biomass for five selected broadleaved tree species of Bhutan. The species specific allometry equation were assumed to be specific to Bhutan, and can be widely used by the policy makers, forest managers, academicians to estimate the aboveground tree carbon more accurately. It can also help the government to timely monitor and report the carbon stock of the country to international bodies.

II. Methods and Materials

2.1. Study area

Field research was conducted in Bhutan located in South East Asia along the eastern Himalayan range. The altitude ranges from 150 m in the Sub-Himalaya in the south to more than 7000 m in the Great Himalaya in the north, while sampling was done within 1503 m to 2530 m along cool broadleaved forest. The samples were collected from the four different physiographic zones: (1) western region (W); (2) west central region (WC); (3) east central region (EC) and (4) eastern region(E) of the country as illustrated in the map (Figure 1). The collected representative samples from different physiographic zones were assumed to avoid the biasedness, and represent whole population along all the eco-regions of the country.

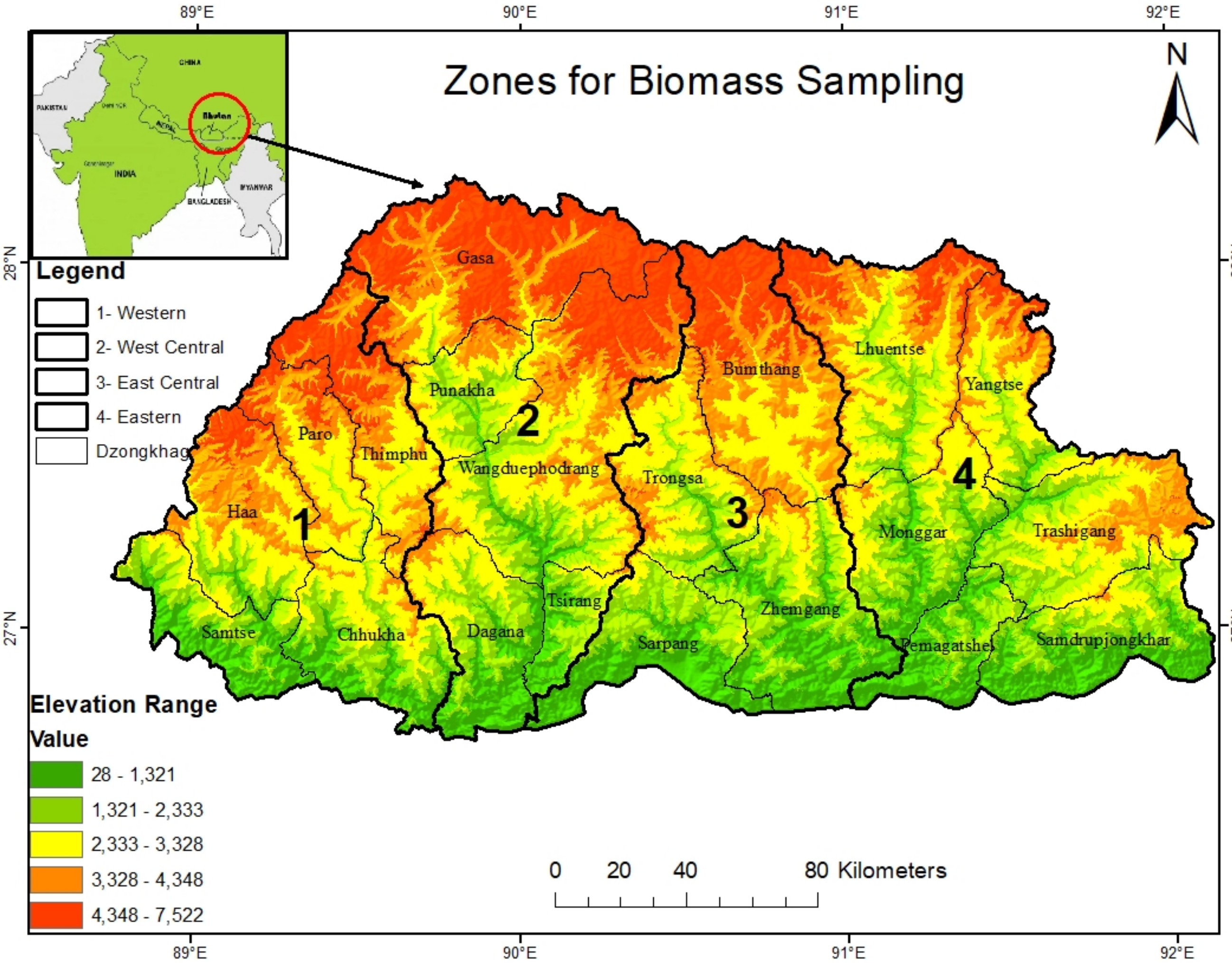

Figure 1: Map illustrating biomass sampling area

2.2. Field Sampling method

The study was direct sampling method of biomass estimation derived through felling, sampling and weighing the biomass as described by [33], and the method had been considered to be more robust. The total aboveground dry biomass under this method was a function of branch biomass, foliage biomass, bole biomass and deadwood biomass [26]. The Randomized Branch Sampling (RBS) technique, a destructive sampling method was applied as per the existing RBS field protocols ([28], [29], [27]). Randomized branch sampling was initially introduced by [33], to estimate the quantity of fruits on the tree using the probability sampling and later the method was found to be efficient in estimating other tree components like foliar, dry aboveground biomass [28]. They also found out that the inverse probability weighing techniques in RBS usually avoids biasness and estimation was more precise.

The RBS involved felling of the selected sample trees, measurements of the necessary parameters, and selecting the two pathways for collection of the branch and foliage biomass samples. The four-disc samples from the main boles, pathway samples from each internode of selected paths, deadwood samples, fruit or cone samples, foliage samples and epicormic branch samples were collected for oven drying. The samples were dried in the ovens and recorded systematically under range of temperatures according to sample types i.e., 70˚c, 80˚c, 100˚c for foliar, branch and bole disc respectively till it reached the constant weight. Finally, all the component dry biomass was computed and summed to the total aboveground dry biomass (TAGTBM) of tree for regression modeling.

2.3. Sample size and sample collection

The sample trees of *Quercus lamellosa, Beilschmiedia sikkimensis, Castanopsis hystrix, Persea clarkiana* and *Symplocos sumintia* were collected from the four physiographic zones representative of the population (Figure 1). The selection of the tree species was based on the dominance, common timber species and those species having existing volume equation of the country. The total of 159 trees with sample size of minimum 32 trees per species, and 8 numbers of trees per physiographic regions were sampled. The representative sampling within each zone were done in a random scattered way under different physiological conditions.

The selected samples represented range of diameter classes (Diameter class of 5-10; 10.1-20; 20.1-30; 30.1-40; 40.1-50; 50.1-60; 60.1-70 and 70.1-100) with diameter range of 5 cm – 90 cm. The samples collected within fixed diameter class under different ecological zones maintained the size consistency of sample trees.

The collected sample trees were sound and representative of the population. Selection of sample trees followed certain criteria to minimize the sampling biasness. Sample tree collected from each region were based on the four different crown classification (Table 1), dominant, co-dominant, intermediate and the suppressed trees, as described by [31]. The selection of samples from the population was done subjectively and followed the prescribed criteria (Table. 1) depending upon the ground feasibility. Similar procedure was followed by [32] where subjectively selected samples ensured educate representation to the population and diameter range.

Table 1:Field sample selection criteria

Sl No.	Canopy Types	No. of samples	Physiographic zones
1	Dominant	32	W, WC, E & EC
2	Co-Dominant	32	W, WC, E & EC
3	Intermediate	32	W, WC, E & EC
4	Suppressed	32	W, WC, E & EC

Highly precision equipment's were consistently used by the trained field crews to obtain the accurate measurements of the variables minimizing the measurement errors. The field measurement technique were in line with the field guide for forest biomass and carbon estimation [33].The following field instruments were used; (a) diameter tape for measuring scale diameter of bole and large branches;(b) digital caliper for measuring the diameter for small branches; (c) measuring tape for measuring the height; (d) Global Positioning System Garmin(GPS) for recording the coordinates and altitudes; (e) Suunto clinometer for measuring the slope percent; (f) Suunto compass for measuring the aspects; (g) Auto electric oven for drying the samples; (h) digital weighing balance to gram scale for weighing the samples; (i) RBS excel field template for data entry in the field and (j) power chainsaw and hand saw for extracting the samples. Basically, there were two variables viz dependent variables and independent variables in scale and nominal measurements. The dependent variables included observed total aboveground tree dry biomass (TAGTBM) in kilogram(kg) and independent variables were diameter at breast height measured at 1.37 m aboveground in centimeter (DBH cm), tree height in meter (H m), basal area in meter square (BA m^2) and abiotic factors like altitude, slope percent (%) and aspects.

2.4. Analysis

The constant dry weight of individual component samples was recorded for computing the dry biomass of whole component. The dry biomass of different component (i.e. branch, deadwood, cone, bole and epicormic branch) summed up to total aboveground tree biomass which was the observed biomass of the individual trees.

$$TAGTBM = \sum(BBM + \mathrm{FBM} + \mathrm{DWBM} + PWBM)$$

Where TAGTBM (kg)-total aboveground tree biomass; BBM (kg)-bole biomass; FBM (kg)-foliage biomass, DWBM (kg)-deadwood biomass and PWBM (kg)-pathway branch biomass, all measured in a unit kilogram(kg).

The computed data were further imported to R-Statistics, version 4.1.0 and analyzed using linear and non-linear allometric functions to explore the relationship with multiple co-variates.

TAGTBM = *f* (DBH, BA, H, abiotic factors)

TAGTBM (kg) (Predicted Total above ground dry biomass of the tree components); DBH (Diameter of tree at breast height, 1.37m above ground in centimeter(cm)); Ba (Basal area of the tree in meter square(m^2); Ht (Total tree height in meter(m).

Several regression models were analyzed using easily measurable tree dimensions and abiotic factors. The first model was regressed using all the co-variates both using tree dimensions and other abiotic factors. The variables were TAGTBM as target variable, and DBH, H, region, altitude, slope and aspect as the independent variables. The model was regressed to see if there were any single predictor variables with linear relationships having ability to predict the aboveground tree biomass. The hypothesis was formulated as H0=B1=B2=B3=B4=0; HA at least one Bj≠ 0 (j=1,2,3,4). The f-test through multiple linear regression was conducted to test the hypothesis. Then the variables for further modeling were selected based on the t-statistics and significance level.

The detail analysis result of *Beilschmiedia sikkimensis* had been presented in this paper and similar statistical process being applied to remaining four tree species. The final model outcome and other model parameters was presented for all the five-tree species.

2.5. Equation formulation

Simple linear regression (SLR) model as a base has been used to improve the fit line for estimating aboveground tree biomass (Eq. 1). The probable co-variates used were DBH (cm), H (m), and BA (m^2).

$$Y = b_0 + b_1X + e_i \tag{1}$$

$$\hat{Y} = \hat{b}_0 + \hat{b}_1X_i + \hat{e}_i \tag{1.1}$$

Where Y is the target variable TAGTBM (kg), b0 is the intercept and the b1 is the slope of the model, X is the dependent variables and ei is the error terms assumed to be normally distributed with zero mean and SD σ. The equation 1.1 indicates the simple linear prediction model with the hats on model parameters. This simple linear regression (Eq. 1) was further examined using the log transformed variables. Similarly, the multiple linear regression was also examined using multiple co-variates in the model (Eq 2).

$$\mathrm{Y} = b_0 + b_1X_1 + b_1X_2 + \cdots + b_pX_p + e_i \tag{2}$$

$$\hat{Y} = \hat{b}_0 + \hat{b}_1X_{1,i} + \hat{b}_2X_{2,i} + \ldots + \hat{b}_pX_{p,i} + \hat{e}_i \tag{2.2}$$

where, Y denotes target variable (TAGTBM kg) and X1, X2……...Xp represents the multiple co-variates for model fitting. The Eq 2.2 is the prediction model for multiple linear regression.

Several possible models were evaluated using the least square fit method taking the above two equations as a base for developing biomass equation. Occasionally, different order polynomial model has been used to counteract the nonlinearity relationships between independent and dependent variable (Eq 3). The polynomial model was considered having flexible fit line to fit the model smoothly along curvature of the plots.

$$Y = b_0 + b_1X_i + b_2X_i^2 + -------b_iX_i^h + \epsilon \tag{3}$$

The h denotes the degree of polynomial for ith variable, described as h=2 as quadratic, h=3 as cubic and h=4 as quartic, and the ϵ is the independent error term assumed to be normally distributed with mean as zero and equal variance σ^2.

The diameter based power model which has been commonly used for tree biomass and tree volume estimation (Eq 4) adopted from [34]. The model was a nonlinear logarithmically transformed model. The power model was further linearized using natural log in both dependent and independent variables (Eq 4.1). The convenience way to use the relationship was taking the natural log of intercept α_0 and taking the slope α_1 as a power to predictor x variable: Y $=\alpha_0X^{\alpha_1}$.

$$\hat{Y} = \beta_0X^{\beta_1} \tag{4}$$

$$\text{LnY} = Ln(\beta_0) + \beta_1\big(Ln(X_1)\big) = \alpha_0 + \alpha_1\,(Ln(X_1) = \alpha_0 X^{\alpha_1} \quad (4.1)$$

Another model constructed was the log-log multiple regression model using log of height and log of basal area or diameter as the predictor variable and log of biomass as the target variable (Eq 5).

$$\text{LnY} = Ln(\beta_0) + \beta_1\big(Ln(X_1) + \beta_2(Ln(X_2) + e)\big) = \alpha_0 + \alpha_2\,(Ln(X_1)\alpha_2\,(Ln(X_1) \quad (5)$$

Where LN(Y) is the predicted natural logarithmic biomass and LN (Xi), LN (Xi) are natural log transformed ith independent variables, β_0 is the intercept, while $\beta_1$and β_2 are the natural log base slope coefficients of the variables.

The final equation constructed was natural log transformed model with compound variable, regressing biomass with the function of transformed independent variable(x) (Eq 6), where f(x) is the compounded interactive variable of diameter square times height(D2H).

$$\text{LNY} = \beta_0 + \beta_1 LN(D2H) \quad (6)$$

Where D2H is the function f(x) of DBH square times tree height relationship, while β_0 and β_1 are coefficients for the model parameters. The logarithmic model (Eq 3.1 & 3.2) was considered to have systematic biasness in prediction during back transformation of the prediction ([35], [36]). However, slight underestimation of the biomass was minimized using the correction factor (Eq 7 & 7.1) proposed by [37] and [38]. That is CF = exp (MSE/2). This correction factors had been widely used to reduce logarithmic transformation biasness in forest science.

$$SEE = \frac{\sqrt{\Sigma(logY_i - log\hat{Y}_i)^2}}{N - npars} \quad (7)$$

$$\text{Correction Factor (CF)} = \exp\left(\frac{SEE^2}{2}\right) \quad (7.1)$$

The best fit line for individual tree species were evaluated using following model evaluation criteria to meet the required global model assumptions. (1) the statistical significance of parameters and models; (2) homogeneity of the variance and normality of residuals; (3) minimum standard residual errors; and (4) non-biasness. The given criteria were evaluated using (1) coefficient of determination(R^2); (2) F ratio; (3) Akaike information criterion (AIC). Similar model evaluation criteria were followed by different researchers ([42], [40], [41], [12]).

The final models were evaluated using the model fit criteria of R^2, RMSE, MSE, AIC and other global model assumptions of fit (Eq 8, 9, 10 & 11).

$$\text{Root mean square error: } RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{n}} \quad (8)$$

$$\text{Residual standard error: } RSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{(n-p-1)}} \quad (9)$$

$$\text{Coefficient of determination: } R^2 = 1 - \sqrt{\frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (10)$$

$$\text{Akaike's Information Criteria: } AIC = 2P + n\log\left(\frac{RSS}{n}\right) \quad (11)$$

The lower the RMSE, RSE and AIC values, better the consideration of the prediction of the model. The values for coefficient of determination R2 is maximum to 1, and closer R2 value to the 1 indicates better model fit, which considers maximum percentage of variation being explained by the model.

2.6. Cross validation and testing of the models

Validation and testing of the desired model was important to measure the model efficacy and its predictive power. Cross-validation (CV) and testing of regression model was usually done before its actual application. It basically estimates prediction error to evaluate the model accuracy [43].

Since this study was done with limited representative sample size, model validation approach adopted was repeated k-fold cross-validation with 5-folds, and the method had been widely adopted as a model selection criterion [44]. Which was also recommended by [45], to use 5-folds for the sample size less than 40. Further adoption of repeated 5-fold CV was supported by [46], considering it as less biased error estimator. In principle, repeated cross validation iteratively splits the data set into training set and the testing set for k_{th} fold times. The statistical prediction errors for 5 folds were averaged for final evaluation. The models were evaluated based on their prediction accuracy such as higher coefficient of determination(R2), lower residual mean square error (RMSE) and mean absolute error (MAE) as summarized under table 5 [47]. Similar model evaluation indicators were applied in developing the national scale allometric equation under UN-REDD program in Vietnam [48].

After the validation and testing process, all the samples in the data sets were reused for developing the estimators for final selected allometric models. The advantage of this approach was being able to use whole sample data for final modeling.

III. Results & Discussions

3.1 Data summary

The selected five broadleaved tree species were considered to be dominant in nature with their respective ecological existence playing vital roles ecologically as well economically. The distribution of the TAGTBM among five species exhibited slightly different trends. However, there was not much significant difference in the tree biomass within the species under different physiographic zones. The tree diameter ranged from 4.20 cm to 88.00 cm with the minimum height of 4.85 m to maximum of 41.77 m tall (Table 2). The total aboveground tree biomass (TAGTBM kg) of five cool broadleaved tree species of Bhutan exhibited its dry biomass in the following descending sequence (*Quercus lamellosa*> *Beilschmiedia sikkimensis*> *Persea clarkiana* >*Castanopsis hystrix* >*Symplocos sumintia)*. It was observed that, among the 5-tree species, TAGTBM (kg) was relatively low for the *Symplocos sumintia*, while *Quercus lamellosa* indicated higher TAGTBM (kg). Significant variation was observed in the biomass accumulation between different species. The observed total aboveground biomass (TAGTBM) of the trees ranged from 3.62 kg of *Beilschmiedia sikkimensis* to maximum of 5579.51 kg of *Quercus lamellosa* species (Table 3

Table 2:Data summary for five tree species

Species	*Sample size.*	*DBH (cm)*	*Height(m)*	*Altitude(m)*	*Slope (%)*	*TAGTBM (kg) Min-Max*
Quercus lamellosa	32	4.62-86.00	4.85-36.8	1663-2488	20-92	4.12-5579.31
Beilschmiedia sikkimensis	32	4.20-82.50	5.72-41.77	1503-2119	10-95	3.62-3464.51
Castanopsis hystrix	32	6.70-82.00	5.96-38.35	1656-2132	5-87	5.99-3600.52
Persea clarkiana	32	6.00-88.00	5.40-34.72	2054-2530	5-10	8.89-3689.82
Symplocos sumintia	31	6.50-78.00	5.90-26.70	1650-2308	8-80	7.08-2993.22

The quantile-quantile plot in figure 2 indicated that all possible variables were approximately normally distributed. However, the variable TAGTBM, DBH and H data exhibited slight skewness with possible outliers which necessitated transformation.

Table 3:Observed biomass summary of five tree species

Species	*Sample size.*	*CBM(kg) Min-Max*	*EBM(kg) Min-Max*	*DWBM(kg) Min-Max*	*TBM(kg) Min-Max*	*PWBM (kg) Min-Max*	*BBM(kg) Min-Max*	*TAGTBM(kg) Min-Max*
Quercus lamellosa	32	0-2.58	0-8.82	0-33.8	1.89-473.11	0-3268.35	2.24-2882.16	4.12-5579.31
Beilschmiedia sikkimensis	32	0.0-0.0	0.0-0.0	0-35.36	1.42-385.84	0-1172.62	2.02-2882.51	3.62-3464.51
Castanopsis hystrix	32	0.0-0.0	0.0-0.0	0-48.43	2.47-640.67	0-1732.22	4.38-3396.58	5.99-3600.52
Persea clarkiana	32	0.0-0.0	0.0-0.0	0-28.62	0.20-503.82	0-1091.94	3.18-2669.74	8.89-3689.82
Symplocos sumintia	31	0.0-0.0	0.0-0.0	0-63.58	2.25-448.06	0-966.04	4.498-1555.46	7.08-2993.22

It was observed that, DBH, BA and tree height indicated very strong relationships (Figure 3) with total aboveground tree biomass (r = 0.91, r = 0.93 and r = 0.81). The other physical factors such as region, altitude, aspect and slope % has not much effect on tree biomass production (r=.09, r=-.02, r=.03, r=-.03).

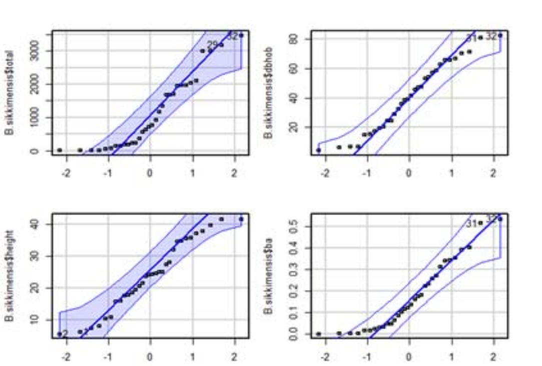

Figure 2: QQ plot for Normality distribution of the variables

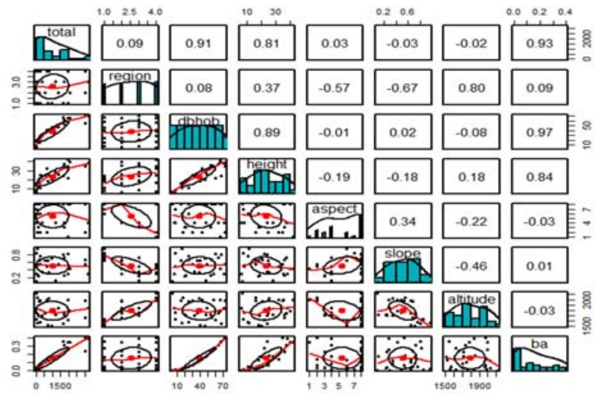

Figure 3: Bivariate correlational matrix plots

3.2 Results

The scatter plot in figure 4 - a, b. c and d of untransformed model indicated strong relationships. The test through analysis of variance also revealed strong evidence (F (32, 6) =23.19, p=<.001)) to prove at least one of the covariates were not equal to 0, therefore null hypothesis of $H_0=B_1=B_2=B_3=B_4=0$ was rejected. These indicated some of the potential co-variates had strong dimensional relationships to predict the tree biomass. The finding was strongly supported by the cross-validation results which identified BA, DBH and height as the important explanatory variables for biomass estimation indicating strong dimensional relationships.

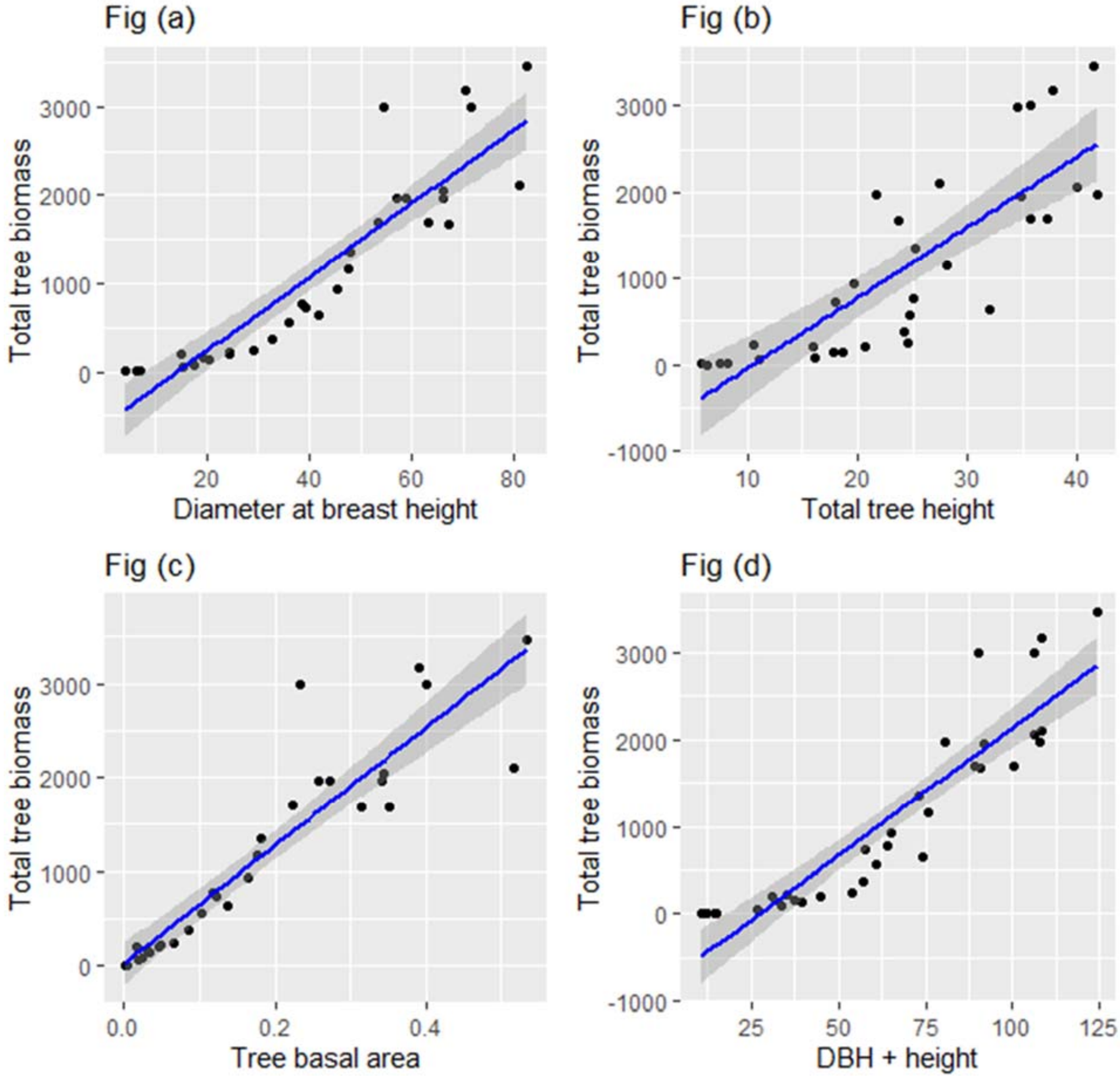

Figure 4: Distribution of TAGTBM (kg) in relation to tree dimensions for Beilschmiedia sikkimensis

It was visible that, figure 4- a, b and d predicted the biomass negatively with severe underestimation of biomass for the trees with <10 cm DBH. However, figure-c, the model with BA as independent variable indicated the perfect relationships with predictions in positive values for all the diameter classes ($t(30) = 13.2$, $p \leq .001$) $R^2 = 0.85$.

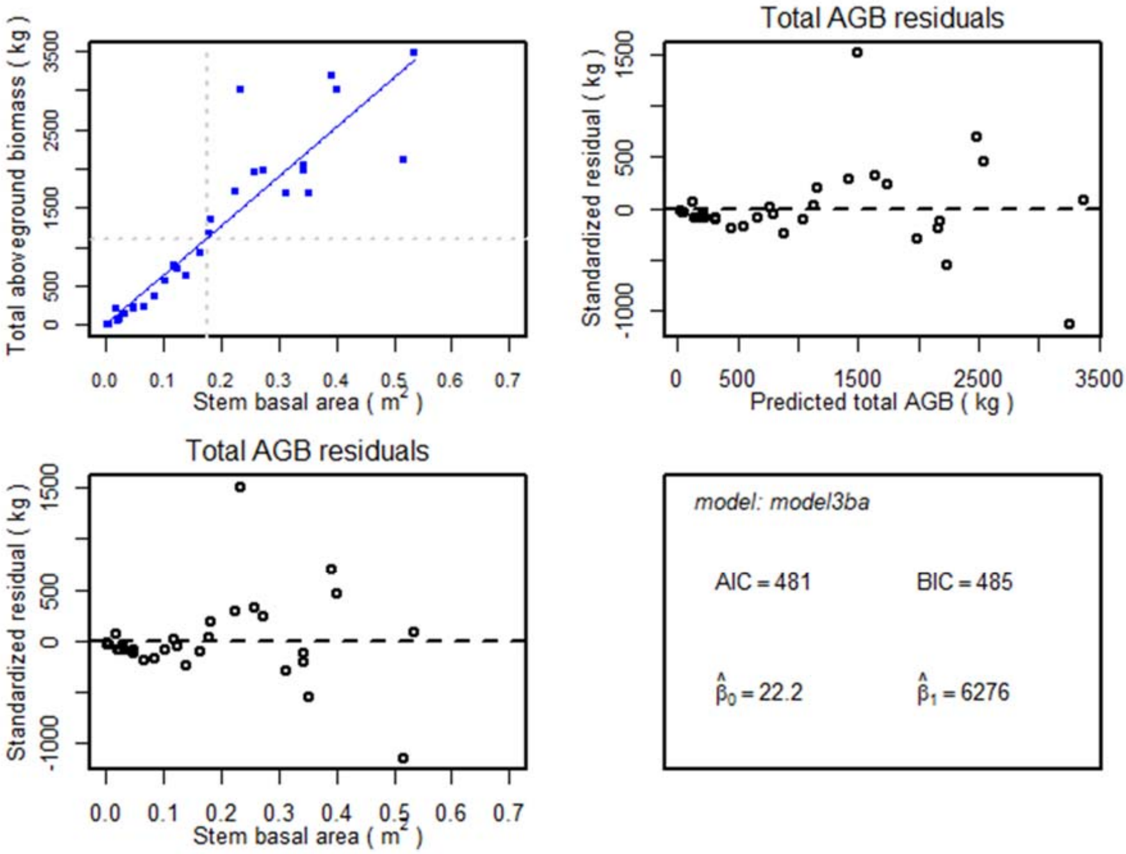

Figure 5: Model 1(TAGTBM~BA) scatter plots for Beilschmiedia sikkimensis

Table 4: Summary of model-1 basal area with aboveground tree biomass

Model total~ba

	Estimate	**Std.Error**	**t value**	**P**
Intercept	22.2	111.1	0.2	0.84
BA(m²)	6276	476.9	13.2	5.4e-14***

p=<.001, *Adj.* R^2 =0.85

The model with basal area explained 85% of the variation of the total aboveground biomass of the *Beilschmiedia sikkimensis* trees (Table 4). However, it was observed that untransformed basal area model slightly overestimated the biomass for the trees with lower diameter classes. The standardized plot in figure 5 exhibited slight skewness of the data indicating the presence of heteroskedasticity.

The cross validated and tested models for both the transformed and untransformed variables resulted to promising outputs (Table 5). The results indicated good performances for all evaluated models explaining 75% to 99% of the variation. In general, models with transformed variables had better prediction powers than the untransformed variable models (Table 5). The models with basal area and diameter as predictor variables indicated almost similar results (Table 5 model 7 and 8). However, it was observed that model with BA and H as the independent variable indicated slightly higher predictive power with less prediction errors in both the untransformed and transformed variables (R^2= .93; RMSE=334 & MAE = 264) and (R^2= .99; RMSE=.196 & MAE = .175) respectively.

Table 5: Averaged results of k-fold (5) cross validation for prediction powers of *Beilschmiedia sikkimensis*

Sl No	*Model Form (Untransformed variables)*	*R2*	*RMSE*	*MAE*
1	$\hat{Y}=\beta_0+\beta_1 DBH$	0.888	380.348	323.442
3	$\hat{Y}=\beta_0+\beta_1 BA$	0.910	288.961	200.928
2	$\hat{Y}=\beta_0+\beta_1 DBH+\beta_2 Height$	0.913	362.765	303.761
4	$\hat{Y}=\beta_0+\beta_1 BA+\beta_2 Height$	0.928	334.062	263.964
5	$\hat{Y}=\beta_0+\beta_1 (D2H)$	0.884	504.550	352.366
6	$\hat{Y}=\beta_0+\beta_1 (B2H)$	0.746	634.567	480.106
	Model Form (Transformed variables)			
7	$LN\hat{Y}=\beta_0+\beta_1 LN(DBH)$	0.980	0.270	0.218
8	$LN\hat{Y}=\beta_0+\beta_1 LN(BA)$	0.974	0.283	0.213
9	$LN\hat{Y}=\beta_0+\beta_1 LN(DBH)+\beta_2 LN(Height)$	0.965	0.387	0.315
10	$LN\hat{Y}=\beta_0+\beta_1 LN(BA)+\beta_2 LN(Height)$	0.992	0.196	0.175

According to results of cross validated and tested models (Table 5) the models with variable BA and DBH alone or the BA and DBH with height as the covariates were suggested for the aboveground tree biomass prediction. Inclusion of height in the model as second predictor was felt reasonable as biomass was depended upon height-diameter relationships.

Among untransformed variables, model with BA and second order polynomial did relatively better performance than the other models (Figure 4c and 5). However, the untransformed basal area model overestimated the biomass at the lower diameter class, while polynomial model slightly underestimated biomass throughout the diameter range. Through the validation process, it was confirmed untransformed variable models were not able to predict the tree biomass as expected. Several linear models with untransformed variables failed to minimize the residual errors. As such untransformed linear models could not satisfactorily explained the variances of tree biomass as expected. Therefore, it was concluded that untransformed regression model failed to meet linear assumption with equal variances and zero constant for biomass estimation. It was observed increasing variances with the increase in size of the independent variables. The natural log transformed models (log-log models) seemed better in predicting the aboveground tree biomass almost making the residuals homoscedasticity.

There was no significant difference in explaining the variances among natural log transformed models of basal area and diameter (Model 2, 3 & 4, Table 6 and 7). Similarly transformed models with BA-H relationships and DBH-H relationship also exhibited the similar results. Considering the time required for basal area computation in the field scenario, it was recommended to use log diameter and log height as the predictor variables. The model parameters for transformed DBH and H, second order polynomial and compound DBH-H model for *Beilschmiedia sikkimensis* are presented in the model summary. (Table 6 & 7).

Table 6: Model summary table1 with model coefficients for *Beilschmiedia sikkimensis* trees

Sl No	*Model form (Untransformed variable)*	β_0	β_1	β_2	*CF*	*t-value*	*P*
1	$\hat{Y}=\beta_0+\beta_1 DBH+\beta_2 DBH^2$	-220.35	15.17	0.321		2.1	*
	Model Form (Transformed variables)						
2	$LN\hat{Y}=\beta_0+\beta_1 LN(DBH)$	-2.197	2.37	-	1.050	34.313	***
3	$LN\hat{Y}=\beta_0+\beta_1 LN(DBH)+\beta_2 LN(Height)$	-2.537	2.11	0.415	1.096	11.907; 1.632	***
4	$LN\hat{Y}=\beta_0+\beta_1 LN(D2H)$	5.34	0.893		1.05	33.8	***

Table 7: Model summary table 2, with model evaluation criteria for *Beilschmiedia sikkimensis* trees

Sl No	*Model form (Untransformed variable)*	*r*	*R²*	*RMSE*	*MAE*	*AIC*	*RSE*	*F*	*P*
1	$\hat{Y}=\beta_0+\beta_1DBH+\beta_2DBH^2$	0.923	0.849	395.747	265.291	482	415.7	88.3	***
	Model form (Transformed variables)								
2	$LN\hat{Y}=\beta_0+\beta_1LN(DBH)$	0.987	0.974	0.301	0.212	20	0.311	1177.0	***
3	$LN\hat{Y}=\beta_0+\beta_1LN(DBH)+\beta_2LN(Height)$	0.982	0.976	0.288	0.221	19	0.303	622.7	***
4	$LN\hat{Y}=\beta_0+\beta_1LN(D2H)$	0.987	0.974	0.305	0.239	21	0.315	1144.0	***

The log base transformed linearized power function of DBH satisfactorily explained ($t(30) = 34.31$, $p \leq .001$) $R^2 = .97$) total aboveground biomass of *Beilschmiedia sikkimensis* trees. It was observed that model 2 in table 7 and 8 explained 97% of the variance of the total aboveground biomass using log DBH as the predictor $F(1, 31) = 1177$, $p \leq .001$. Thus, according to model 2 in table 6, 1 percent (%) increase in diameter at breast height of *Beilschmiedia sikkimensis* trees, increases its total aboveground biomass by 2.4 % on an average. It was observed that elasticity of the beta coefficient of independent variable in model 2 increases positively with increasing size of variables. The lognormal distribution of standardized residual over predicted-value and predictor variable seemed normally distributed (Figure 6). Thus, parameter DBH alone could well predict the tree biomass explaining maximum variation by the model.

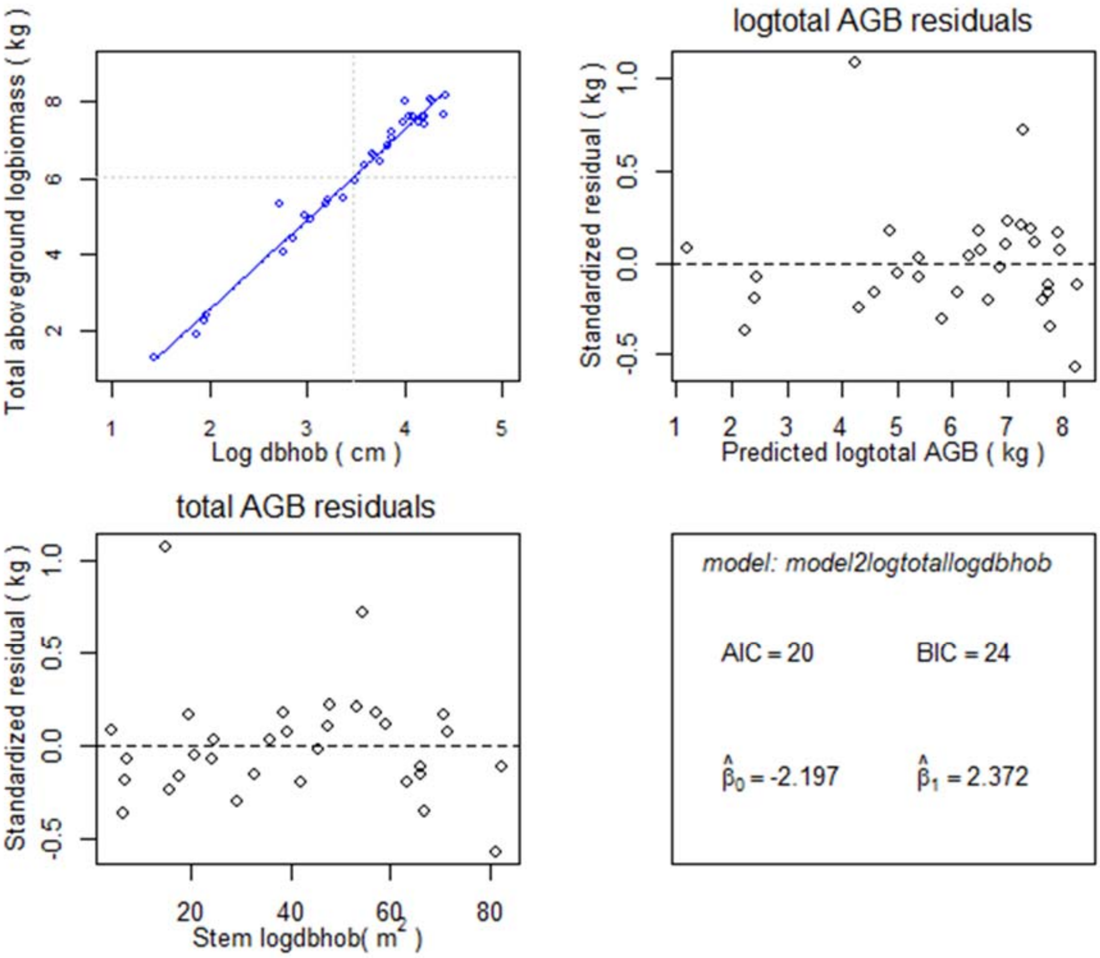

Figure 6: Scattered plots of model diameter and biomass with transformed variables of *Beilschmiedia sikkimensis*

The prediction can be calculated as followed. Supposed the diameter at breast height (DBH) of the tree is 47.5 cm. and the model parameters: B0=-2.19665; B1=2.37201 & CF = 1.05.

LnY $= Ln(\beta_0) + \beta_1\big(Ln(X_1)\big) = \alpha_0 + \alpha_1\,(Ln(X_1) = \alpha_0 X^{\alpha_1}$ * cf

TAGTBM (kg) = Exp $^{(-2.19665+LN\ (47.5)\ *2.37201)}$ *1.05= **1107.466 Kg**

Or use the power equation form ($y=aX^b*cf$) by taking the antilog of the intercept by exponential:

Exp (-2.19665) = .111175 and taking the slope parameter as power of X variables. DBH^2.37201.

TAGTBM = 0.111175**DBH**$^{\wedge 2.37201}$

TAGTBM (kg)= .111175*47.5^2.30271*1.05=**1107.466 Kg**

Accordingly, multiple linearized transformed model of log DBH and Log H as the predictor also exhibited significant prediction results with lower RMSE, MAE and AIC values (0.288, 0.221 & 19.18 respectively) as indicated in table 7 and 8. The residuals seemed normally distributed as viewed in standardized residual plot in figure 7. In the log transformed multiple model log DBH was a significant predictor ($t\ (29) = 11.91, 1.63, p \leq .001$), although, tree height has some issue in predicting the biomass ($t\ (29) = 1.63, p \leq .113$), $R^2 = .98$. However, overall the model explained 98% of the variances of the tree biomass $F\ (2, 30) = 622.7, p \leq .001$. The model 3 explains that, keeping the Bo constant, 1 % increase in DBH and height increases the aboveground tree biomass by 2 % and 0.42 % respectively as given in example below. The positive elasticity of beta coefficient of DBH and H increases with increasing independent variables. The prediction of biomass with transformed variables of DBH and H can be estimated as below. Supposed the diameter at breast height (DBH) of the tree was 47.5 cm, height of the tree was 28.13 m and the model parameters: B_0= -2.5367; B_1= 2.1052; B_2= 0.4148 & CF = 1.05.

LnY $= Ln(\beta_0) + \beta_1\big(Ln(X_1) + \beta_2(Ln(X_2) + e)\big) = \alpha_0 + \alpha_2\,(Ln(X_1)\alpha_2\,(Ln(X_2)$

TAGTBM = EXP (-2.5367+LN (47.5) * 2.1052+LN (28.13) * 0.4148) *1.05 = **1112.371 kg**

Or use multiple power function: $y=B_0*X_1{}^{B}{}_1*X_2{}^{B}{}_2*CF$ taking exponent of intercept Exp (2.1052) = 0.07913

Y= $\alpha_0 + \alpha_2\,(Ln(X_1)\alpha_2\,(Ln(X_2)$

TAGTBM = (0.07913*47.5^2.1052*28.13^0.4148) *1.04 = **1112.371 kg**

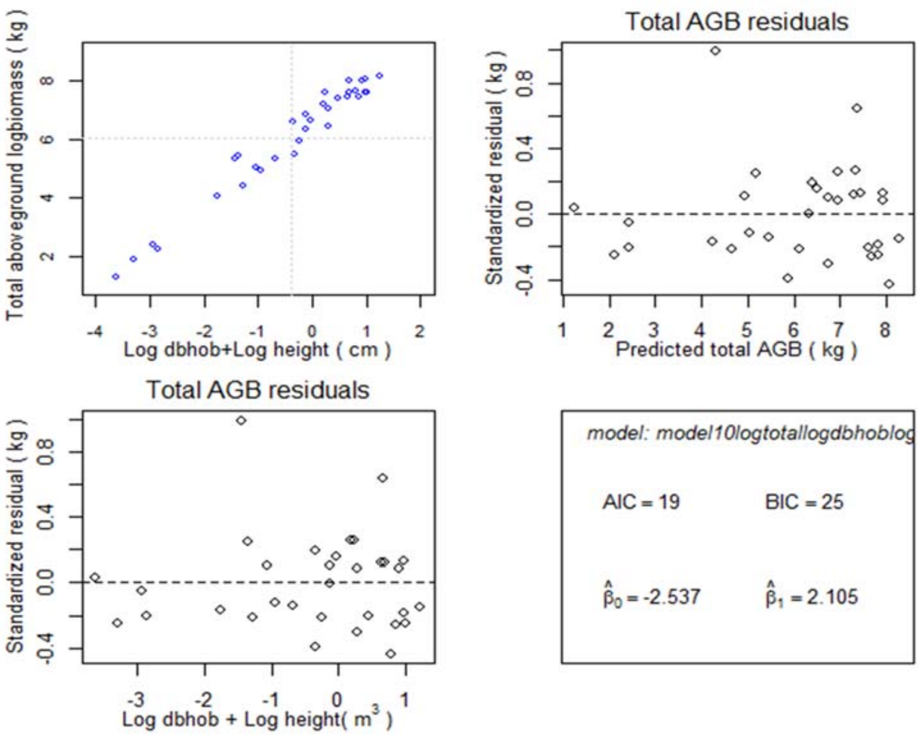

Figure 7: Scatter plots of model diameter, tree height and biomass for transformed variables of *Beilschmiedia sikkimensis*

The natural log transformed model with BA alone, BA-H relation, DBH alone, DBH-height relations seems to significantly predict the total aboveground biomass of five broad leaved tree species. However, model fitted with transformed BA and DBH exhibited similar result, because of which basal area model had been excluded from the final summary table 8 and 9.

Under the linear model, the second order polynomial model predicted the biomass fairly good. But the polynomial model slightly under estimated the biomass in general with extreme underestimation for the smaller DBH trees (Model 2, Figure 8). However, model fitted with the new compounded variable of diameter square and tree height (D2H) also significantly predicted the aboveground tree biomass (*t (30) = 33.82*, p ≤ *.001*). The natural log transformed variable of D2H as independent variable was able to explain 97% of the variances in aboveground tree biomass of *Beilschmiedia sikkimensis F* (2, 30) = 1144, *p* ≤ .001. Still, due to slight overestimation and inconsistency in prediction along DBH class, transformed D2H model may be used as a second option in absence of model 2 and 3 under table 6 and 7.

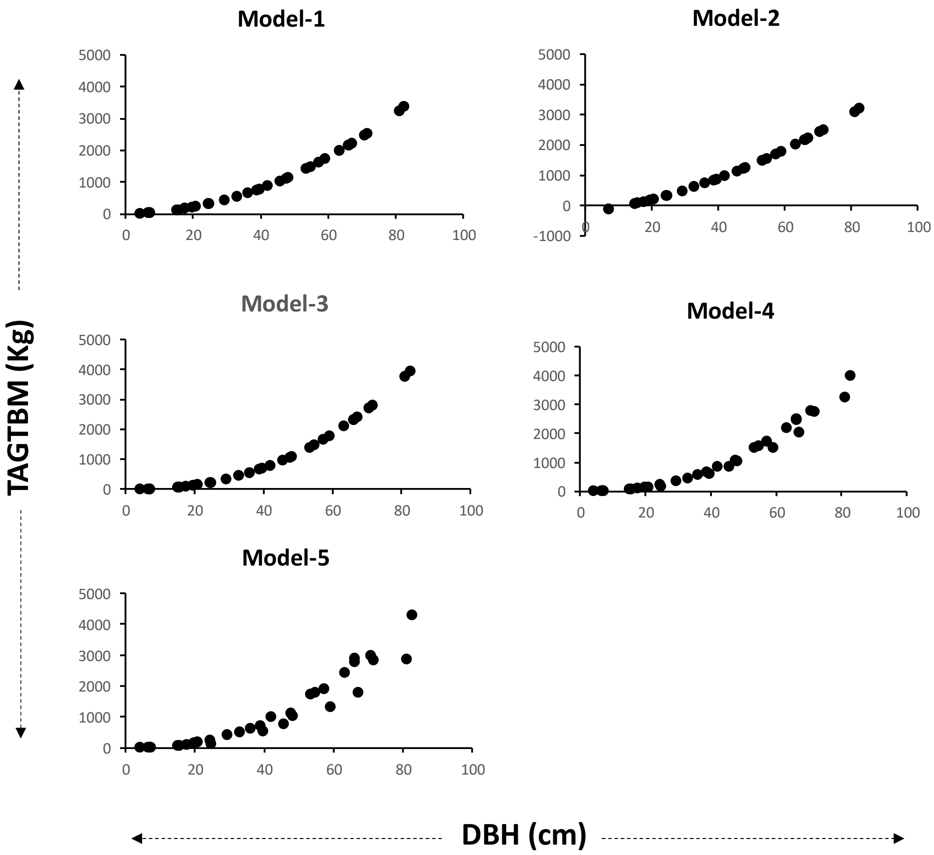

Figure 8: Five different best fit line for *Beilschmiedia sikkimensis* species

Similar model fit and evaluation were carried out for other four species of *Quercus lamellose, Persea clarkiana*, *Castanopsis hystrix* and *Symplocos sumintia*. All of the four broad leaved species exhibited the result at par with the *Beilschmiedia sikkimensis.* The model summary for fit test and model parameters are presented in the summary table 8 and 9. It was observed that, the five broadleaved species indicated significant relationships with the logarithmically transformed tree dimensions (DBH, H & BA). Tree diameter was found to be the most important independent variable for tree biomass prediction. This was followed by basal area, compound variable of DBH and height and tree height respectively, as they revealed strong relationships with tree biomass. The strong allometry relationship of tree dimensions with aboveground tree biomass indicated its strong predictive accuracy. Thus, species-specific and country-specific model with allometric relationships was highly recommended for the aboveground biomass estimation.

Table 8: Transformed and untransformed models with model parameters and its significance for five cool broadleaved tree species of Bhutan

Sl No	Model form	*β_0*	*β_1*	*β_2*	*CF*	*t-value*	*P*
A	***Beilschmiedia sikkimensis***						
	Untransformed variables						
1	$\hat{Y}= \beta_0+ \beta_1 BA$	22.20	6276			13.2	***
2	$\hat{Y}= \beta_0+ \beta_1 DBH+\beta_2 DBH^2$	-220.35	15.17	0.321		2.1	*
	Transformed variables						
3	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)$	-2.20	2.372		1.01	34.3	***
4	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)+ \beta_2 LN(Height)$	-2.54	2.105	0.415	1.00	11.9	***
5	$LN\hat{Y}= \beta_0+ \beta_1 LN(D2H)$	5.34	0.893		1.05	33.8	***
B	***Quercus lamellosa***						
	Untransformed variables						
1	$\hat{Y}= \beta_0+ \beta_1 DBH+\beta_2 DBH^2$	57.28	-9.33	0.711		4.8	***
	Transformed variables						
2	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)$	-2.38	2.443		1.03	45.5	***
3	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)+ \beta_2 LN(Height)$	-2.63	2.208	0.360	1.03	11.1	***
4	$LN\hat{Y}= \beta_0+ \beta_1 LN(D2H)$	5.46	0.918		1.03	44.0	***
C	***Persea clarkiana***						
	Untransformed variables						
1	$\hat{Y}= \beta_0+ \beta_1 DBH+\beta_2 DBH^2$	101.87	-12.074	0.616		7.0	***
	Transformed variables						
2	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)$	-2.33	2.366		1.02	47.5	***
3	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)+ \beta_2 LN(Height)$	-2.60	2.242	0.234	1.02	20.7	***
4	$LN\hat{Y}= \beta_0+ \beta_1 LN(D2H)$	5.21	0.926		1.03	39.6	***
D	***Castanopsis hystrix***						
	Untransformed variables						
1	$\hat{Y}= \beta_0+ \beta_1 DBH+\beta_2 DBH^2$	48.89	-8.494	0.632		5.8	***
	Transformed variables						
2	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)$	-2.57	2.459		1.02	45.5	***
3	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)+ \beta_2 LN(Height)$	-2.58	2.450	0.015	1.02	17.5	***
4	$LN\hat{Y}= \beta_0+ \beta_1 LN(D2H)$	5.37	0.935		1.04	35.3	***
E	***Symplocos sumintia***						

	Untransformed variables						
1	$\hat{Y}= \beta_0+ \beta_1 DBH+\beta_2 DBH^2$	219.34	-21.73	0.665		8.4	***
	Transformed variables						
2	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)$	-2.36	2.294		1.03	36.9	***
3	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)+ \beta_2 LN(Height)$	-2.67	2.002	0.464	1.02	12.4	***
4	$LN\hat{Y}= \beta_0+ \beta_1 LN(D2H)$	5.10	0.869		1.02	37.4	***

Table 9: Model evaluation criteria and test statistics for five cool broadleaved tree species of Bhutan

Sl No	*Model form*	*r*	*R²*	*RMSE*	*MAE*	*AIC*	*RSE*	*F*	*P*
A	***Beilschmiedia sikkimensis***								
	Untransformed variable								
1	$\hat{Y}= \beta_0+ \beta_1 BA$	0.923	0.847	404.919	243.203	481	418.00	173.0	***
2	$\hat{Y}= \beta_0+ \beta_1 DBH+\beta_2 DBH^2$	0.923	0.849	395.747	265.291	482	415.7	88.3	***
	Transformed variables								
3	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)$	0.987	0.974	0.301	0.212	20	0.311	1177.0	***
5	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)+ \beta_2 LN(Height)$	0.982	0.976	0.288	0.221	19	0.303	622.7	***
7	$LN\hat{Y}= \beta_0+ \beta_1 LN(D2H)$	0.987	0.974	0.305	0.239	21	0.315	1144.0	***
B	***Quercus lamellosa***								
	Untransformed variable								
1	$\hat{Y}= \beta_0+ \beta_1 DBH+\beta_2 DBH^2$	0.952	0.902	399.405	236.976	482	419.60	143.5	***
	Transformed variable								
2	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)$	0.993	0.985	0.229	0.183	2.490	0.237	2073	***
3	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)+ \beta_2 LN(Height)$	0.990	0.986	0.223	0.182	3	0.235	1055	***
4	$LN\hat{Y}= \beta_0+ \beta_1 LN(D2H)$	0.992	0.984	0.237	0.201	5	0.245	1934.0	***
C	***Persea clarkiana***								
	Untransformed variable								
1	$\hat{Y}= \beta_0+ \beta_1 DBH+\beta_2 DBH^2$	0.969	0.939	242.866	158.731	450	255.1	241.00	***
	Transformed variables								
2	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)$	0.993	0.986	0.199	0.164	-6	0.206	2256	***
3	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)+ \beta_2 LN(Height)$	0.983	0.987	0.194	0.156	-6	0.204	1154	***
4	$LN\hat{Y}= \beta_0+ \beta_1 LN(D2H)$	0.991	0.981	0.238	0.199	5	0.246	1571.0	***
D	***Castanopsis hystrix***								
	Untransformed variable								

1	$\hat{Y}= \beta_0+ \beta_1 DBH+\beta_2 DBH^2$	0.970	0.940	279.801	163.487	459	293.90	242.0	***
	Model Form (Transformed variables)								
2	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)$	0.993	0.985	0.215	0.156	-2	0.222	2068	***
3	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)+ \beta_2 LN(Height)$	0.980	0.985	0.215	0.156	0.34	0.226	999.5	***
4	$LN\hat{Y}= \beta_0+ \beta_1 LN(D2H)$	0.988	0.976	0.276	0.217	14	0.285	1243.0	***
E	***Symplocos sumintia***								
	Untransformed variable								
1	$\hat{Y}= \beta_0+ \beta_1 DBH+\beta_2 DBH^2$	0.943	0.919	163.398	109.746	412	171.90	170.4	***
	Transformed variables								
2	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)$	0.989	0.978	0.217	0.177	-1	0.224	1358	***
3	$LN\hat{Y}= \beta_0+ \beta_1 LN(DBH)+ \beta_2 LN(Height)$	0.986	0.980	0.203	0.158	-3	0.214	746.4	***
4	$LN\hat{Y}= \beta_0+ \beta_1 LN(D2H)$	0.990	0.979	0.214	0.159	-2	0.221	1397.0	***

3.3 Discussion

The significant difference in total aboveground tree biomass (TAGTBM kg) was observed for five cool broadleaved tree species of Bhutan. The variation in the dry biomass between species could be attributed to difference in wood density and branching characteristics of individual species, which was also noted by [48], where variation in biomass among trees greatly depended upon wood density and species. Tree biomass revealed strong dimensional relationships with three tree dimensions (BA, DBH & height) exhibiting the strong predictive powers. The observation was in accordance with several other research where tree dimensions were identified as the significant predictor variables for tree biomass estimation ([14], [37], [47], [49]).

The models were well fitted using the ordinary least square fit both with single predictor as well as multiple predictor variable. However, heteroskedasticity was apparent as the common phenomena restricting the linear fit in the model, and was correspondingly perceived by [50]. Several linear models with untransformed variables failed to minimize the residual errors. As such untransformed linear models could not satisfactorily explained the variances of tree biomass as expected. The finding was as described by [37] with unequal variances distributed throughout the samples. The increase in variances with increasing tree dimensions were evident in the observation. Similar trend was expressed by [34], where conditional variances of the tree biomass increases with tree size and was further supported by the findings of [39], in which tree component biomass increased with tree diameter class.

The variances in the model was drastically reduced, with increased predictive powers through variable transformation. Therefore, logarithmic transformation of the model was deemed necessary to best fit the biomass equation and reduce the inconsistent distribution of the variances. Several researchers in the past had suggested the use of logarithmic model for tree biomass and volume estimation ([37], [38], [51]). Further [34] strongly supported the use of logarithmic model as it has the ability to deal with the heterogenous conditional variance of Y given by X variables. Although, transformed model has been often used by many researchers especially in forest science, some researchers criticize the use of logarithmic transformed model as it creates systemic bias while back transformation of the estimation to arithmetic units. However, logarithmic transformation were still a choice and reasonable tool for fitting curvilinear relationships [52]. "Ref. [37]" supported the use of logarithmic transformation of the nonlinear datasets to validate the limits of uncertainty and compare the regression constants. Simultaneously recommended to use the relevant correction factor to minimize the systematic bias while back transforming to arithmetic units. Therefore, correction factor applied in this study was $\exp(SEE^2/2)$ proposed by [37] which was supported and used by many other researchers ([11], [34]).

In this study logarithmically transformed linearized power function with DBH alone ($Biomass = \exp(\beta_0)DBH^{\beta_1} * cf$) and DBH-height relationships ($Biomass = \exp(\beta_0)DBH^{\beta_1}H^{\beta_2} * cf$) as the independent variable performed promising for 5 cool broadleaved tree species of Bhutan.

The tree diameter at breast height (DBH) of 1.37 m aboveground was observed as the best independent variable compared to other tree dimensions with higher predictive accuracy. Similar result was evident from other research ([39], [53], [54]), where diameter was considered as most significant predictor variable to estimate aboveground tree biomass. Finding was correspondently supported by [55], where, DBH as lone predictor resulted to lowest net bias and outperformed other models having multiple predictors in the studies carried out for national scale biomass estimation in Columbia. However, [56], was of the view that using only DBH as predictor may increase uncertainty with increasing deviance while applying model at national and regional scale. Therefore inclusion of regional and local data for model validation and construction purpose deemed crucial to obtain the reliable biomass prediction while using single independent variable ([21], [57]).

In the multiple regression model, DBH-height relationships was assumed to be the best predictor model for tree biomass, which corresponds to the findings of [11], where he considered important to include height as predictive variables as it explains the variation caused due to climate and environmental factors. Similarly, [34] and [48] attributed strong DBH-height relationships with better biomass estimation to additional knowledge added by tree height. However, in most of the research activities and inventory database height data are unavailable and often attributed to difficulty in measurement, inaccuracy in measurement, lack of precision equipment and time constraint. Inconsistent availability of height data resorted the researchers in developing alternative models. Therefore, model with only diameter as easily measurable explanatory variable was also developed for biomass estimation.

The selected models were validated and tested using the repeated 5-fold cross validation technique, owing to limited sample size. The k-fold cross validated resulted to strong predictive powers for all the evaluated biomass models. The models were first cross validated and tested iteratively with 5-fold cross validation and then all the samples were reused for final model fit. The advantage of k-fold CV was it didn't violate the rule of having independent data sets for both model fitting and testing [58], and further helped to reduce bias due to small sample size [59]. Evaluation criteria used for model selection were lower RMSE, AIC values, and higher adjusted R^2 and F-tests.

It is strongly recommended to use the species specific and country specific allometric model to increase the prediction rate which reduces the variation caused due to multiple climatic and environmental variables. However, in absence of which, general allometry model for mixed species was used [16], resulting to prediction biasness due to variation in wood density, tree structure, and growing sites ([60], [61]). Moreover, general models were applied at regional and country level under different forest types, which does not take an account of specific site and species. Thus, many researchers emphasized site- and species-specific model as preferred model with higher accuracy in biomass estimation ([57], [62], [63]).

IV. Conclusion

In general, models were well fitted using the ordinary least square fit for both single and multiple predictor variable. It was strongly recommended to use the species-specific and country-specific allometric model to increase the prediction rate which drastically reduces the variation caused due to multiple climatic and environmental variables. The nature of relationships between biomass and tree dimensions suggested variable transformation to counteract the heteroskedasticity problems. The aboveground ground tree dry biomass estimation of five cool broadleaved species can be efficiently carried out using linearized allometric model in the power form. Despite, having small sample size, samples collected randomly under different diameter class from four physiographic zones were assumed to be representative of the population. The resource intensity and time constraint were some of the limitation confronted during the biomass research work. Increased sample size with detail experimentation on the influence of physical and climatic variables on biomass accumulation of specific tree species is recommended to build up better relationships.

Although, DBH model $_{\beta 1}DBH^{\beta 2}$ indicated very strong predictive power, the DBH-height relationship model $_{\beta 1}DBH^{\beta 2}\, H^{\beta 3}$ may be applied depending upon availability of height data. The diameter at breast height and total tree height was found to be the most important predictor variable explaining maximum variability of aboveground tree biomass. The selected models in this paper may be used within the given diameter range, to minimize the variation of biomass estimation through overestimation and underestimation. The extrapolation of the diameter range beyond the range of model development are usually not recommended to achieve reliable biomass estimation.

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