Allometricaboveground biomass models forNorthern Delhi Ridge Forest

ABSTRACT

Bioenergy obtained through forest biomass is a promising renewable energy option that provides a more environmentally sustainable alternative to fossil resources by reducing the net flux of greenhouse gases to the atmosphere. India, a developing nation is also in the process of building forest biomass models tostudy the potential of forests in short and long- term carbon mitigation. Earlier,traditional and destructive sampling were the popular methods for the aforesaid purpose. Recently, non- destructive methods are being adopted applying different allometric equations mostly developed outside India. Thus, there was a need to develop non- destructive allometric aboveground (AGB) models complementing Indian climate. Also, there was scarcity of domestic/localAGB models for arid, semi- arid,northern tropical thorn forest of India. The objectives of this study were to develop site-specific and mixed- species allometric models to predict AGB, at the Northern Delhi Ridge Forest (NDRF) using nonlinear mathematical functions. The model has a wide scope and can be applied to adjoining areas as well having similar climatic conditions.Three allometric combinations were tried to fit the aboveground biomass data obtained from the ridge forest. A three-parametric Richard's model (with predictor variable $x=D^2H$) was best fitted to AGB (R^2_{adj}= 0.9463) values for larger trees. Meanwhile, for juvenile plants, a three- parametric Richard function was best fitted (R^2_{adj}= 0.9733) when (x= DH) was used as a predictor variable. Cross- validation of model parameters exhibited statistical stability.

Keywords: *forest biomass, renewable energy, greenhouse gases, allometric,aboveground biomass, non-destructive, nonlinear, Northern DelhiRidge Forest*

1.0 INTRODUCTION

Forest biomass (FBM) is a key indicator of productivity[1,2], resource availability[3], andcarbon storage, sequestration and emission capacity[4,5] in a forest ecosystem. As a developing country, India has also taken initiatives to increase forest biomass and carbon storage by restricting deforestation and enhancing afforestation activities, which positively supports and implements the mechanism of Reducing emissions from deforestation and forest degradation ($REDD^+$) in developing countries. Accurate assessment of forest biomass plays a vital role in afforestation and reforestation management planning, forest resource monitoring, in the assessment of the ecological value of forests, climate change impacts and policy formulation for forest harvesting, conservation and management. In recent times, large- scale mapping of biomass is routinely performed using remote sensing [6], with *in situ* ground methods required for calibration and validation of such datasets. However, methods of estimating biomass in fields remains a challenge for foresters. The assessment of forest biomass includes the estimation of both AGB and belowground biomass (BGB).The latter is not only difficult to quantify, but it is relatively small to the AGB. Therefore, the estimation of AGB has always been the main focus in biomass research. AGB calculations rely on real morphological and biophysical tree parameters, such as diameter at breast height (DBH) and tree height, which are used too often to calculate AGB by implementing nonlinear allometric biomass models, which can be very effective when applied to tree species and productivity ranges with reliable calibration data. Although, these models have been shown to be successful in predicting standing biomass, their availability and accuracy in estimating biomass from other environmental conditions can be highly variable [7].

Traditional methods for AGB measurement, involves cutting down trees and then drying them for weighing, are destructive, time-consuming, expensive and laborious, and are rarely adopted [8,9]. Moreover, destructive methods can be used only for a small area, as their accuracy could be compromised when used to estimate the AGB of a forest spanning over a larger region [10,11,12].Application of allometric models is one of the most viable options of the indirect method for estimation of forest biomass. The allometry of plant species establishes the quantitative relationships between easily measurable characteristics and other related attributes that are difficult to measure. Generally, diameter (D) alone and different combinations of D and tree height (namely DH and D^2H) are used to build aboveground biomass models using allometry.Biomass can be modelled applying linear and nonlinear mathematical functions. Since, the nonlinear simulation is a combination of power and exponential functions, model fitting is not easy as compared to linear and fraction forms of equations.

Earlier, priority was given to large- sized timber trees for development of allometric biomass models [13,14, 15]. Recently, some studies have also come up discussing allometric biomass models for juvenile plants as well [16,17,18,19]. Gathering aboveground biomass data for juvenile plants is essential as they significantly add to future forest, wildlife habitat and soil conservation [20]. In addition, the density of young plants is much higher than that of large- sized and matured trees. In spite of this, juveniles are generally excluded while carrying out inventories related to biomass and carbon stocks quantification mainly due to lack of allometric biomass models for young plants. As juveniles are indicators of net primary productivity, so estimating biomass of young plants is required for evaluating the stand potential for carbon storage and sequestration models. Young plants play a critical role in maintaining the balance of an overall forest ecosystem, and therefore cannot be undermined while assessing the amount of forest biomass and carbon.

India has huge amount of land under forests representing tropical, semi- arid conditions. Numerous direct/ indirect, species – specific, and mixed- species equations have been used in the past for biomass estimation but domestic biomass models that facilitated the prediction of AGBstocks non- destructively in this part of India is still lacking. Moreover, there is also a scarcity of information regarding estimation of AGB of juvenile plants as well which forms an important component of a forest ecosystem.The article thus deals with constructing aboveground biomass models for NDRF by applying non- destructive methods. The H-D data of trees were collected fromthe above-mentioned site and was grouped into two categories on the basis of DBH range. Low DBH values ranged from 1.59 – 9.17 cm and higher DBH ranged from 11.4- 77.08 cm. Richards, Power and Exponential functions were used for model fitting of AGB data. The proposed models can be applied to areas with similar climatic conditions as well. The results are being explained and interpreted in the present manuscript.

2.0 MATERIAL AND METHODS

2.1 Site description and climatic conditions

The northern Delhi Ridge also known as Old Delhi Ridge or Kamla Nehru Ridge is 87 ha forested area near University of Delhi. Due to elevated crust, it is geographically termed as a ridge. It lies between latitude 28°41’36.03’’N to 28°40’3.71’’ N and longitude 77°12’39.42’’E to 77°13’1.87’’E. The northern ridge is one of the four ridge forests found in Delhi which are a part of Aravalli Hill Ranges [21]. The climate of the area is semi- arid due to poor rainfall (66.6 cm annually) however, it receives significant rainfall in the monsoon. The vegetation here is thorny and scrub type, which is similar to arid and semi- arid conditions. The area falls under Northern Tropical Thorn Forest category of forest type classification of Indian forests[22].

2.2 Sampling Procedure

The aboveground biomass data came from 10 (0.1 ha) temporary circular plots (plot radius 17.85 m), covering a total area of 1 ha. Random sampling method was adopted to obtain unbiased data of the forest area.Non- destructive methods were adopted to gather the observed/experimental values of aboveground biomass data from Northern- Ridge Forest due to the fact that the area has been declared as a reserve forest vide. Notification dated 22/05/1994 under section 4 of the Indian Forest Act, 1927, hence cutting trees is always discouraged in this area. All the trees were measured for their diameter (1.3 m from ground) and total height within the plots. In all, 795 trees were measured in 1 ha land. Later, 795 trees were divided into sets of two diameter classes: first diameter class represented juvenile plants (DBH 1.59- 9.17 cm) and the other diameter class represented large and mature trees (DBH 11.4- 77.8 0cm). In all, 411 trees from class 1 and 384 trees from class two were used for data modelling. Species wise data was gathered which is presented in Table 1(a) and (b).

Allometric models for biomass estimation usually includes information on DBH, total tree height and wood density. Omitting wood density values results in poor overall prediction of aboveground biomass as it is an important predictive variable in regression models.Moreover, the use of total tree height as a predictor variable also overall improves the quality of forest growth/aboveground biomass models [23]. Hence, the allometric equations enable aboveground biomass to be easily estimated, provided the diameter, total tree height and wood density of trees are available. Mean values of DBH and total height of tree species were used in the present investigation to obtain standing bio-volume [24] applying the equation SBV= $(\pi/4^* D^2) H^* f$, where SBV is in m^3/species; π is constant (3.14); both D and H are in meters and *f* is the form factor. Here, a form factor of 0.4 was applied. The bio- volume was multiplied by respective wood densities (Kgm^{-3}) to get the aboveground biomass (AGB) in Kg. Wood- densities were obtained from the database of wood densities of tropical tree species [25] and from the web www.worldagroforestry.org[26]. The standard average density of 600 Kgm^{-3} was applied whenever density value was not available for tree species. AGB in kg was converted to Tons/species before fitting predicted values. The observed aboveground biomass values of species were placed in ascending order before model fitting.

Table 1 (a) D and H of juveniles sampled from the study site (DBH range 1.59- 9.17 cm) * ±SE

S. No.	Species Name	Mean DBH (m)	Mean H (m)	Density (no. of individuals/ha)	WD (Kg/m^3)
1	Salvadora oleoides L.	0.0159±0.17	0.85±0.11	23	590
2	Ficusbenghalensis L.	0.0184±0.23	0.78±0.19	11	390
3	Phyllanthus emblica L.	0.0207±0.13	1.89±0.13	15	800
4	Pongamia pinnata L.	0.0265±0.26	2.67±0.23	19	600
5	Bauhinia purpurea L.	0.0291±0.32	3.15±0.22	24	670
6	Mimusopuselengi L.	0.0319±0.39	2.33±0.24	33	720
7	Holoptelia integrifoliaRoxb.	0.0337±0.19	2.81±0.09	22	640
8	Azadirachta indica L.	0.0349±0.11	3.33±0.15	13	690
9	Cordia dichotoma L.	0.0353±0.47	3.49±0.16	15	530
10	Ehretia laevisRoxb.	0.0366±0.32	2.69±0.29	13	560
11	Ficusverines L.	0.0387±0.53	3.92±0.22	19	390
12	Morus alba L.	0.0393±0.27	3.94±0.16	11	600
13	Eucalyptus species	0.0399±0.51	5.67±0.27	9	590
14	Ficus religiosa L.	0.0466±0.23	3.08±0.57	15	390
15	Terminaliabellirica (Gaertn) Roxb.	0.0481±0.29	4.83±0.14	23	720
16	Cassia fistula L.	0.0549±0.75	3.27±0.39	24	710
17	Ficus racemosa L.	0.0605±0.21	3.250.11	14	390
18	Albiziaprocera (Roxb.) Benth	0.0658±0.33	5.23±0.37	39	520
19	Tectona grandis L.	0.0755±0.15	5.06±0.21	18	500
20	Bauhiniavariegata L.	0.0764±0.82	5.53±0.53	21	670
21	Albizia lebbeck (L.) Benth	0.0917±0.77	6.39±0.49	30	550

2.3 Modelling approach

The functional form of the model used was: y= *f*(x), which means that "y" is a function of "x" or "y" depends upon "x". Here, "y" is the dependent or response variable (aboveground biomass in this case) and "x" is independent or predictor variable. Different combinations of "x" as D, DH and D^2H were used for model fitting. Three nonlinear functions namely Richard's, Power and Exponential were applied for model fitting (Table 2). Here, α, β, and δ are parameters to be estimated, x is the predictor variable (used in different combinations), AGB is the aboveground biomass (in tons), *e* is the exponential, and ε is the random residual term error with mean 0 (Table 2).

2.4 Model fitting and evaluation

Nonlinear curve fitting was performed with Excel Solver which is an add-in function in Microsoft Excel, 2021. Adjusted- R^2 [27] and Residual Standard Error [27] were used for model evaluation. Model with maximum adjusted- $R^2$and minimum RSE values were considered to perform the best.

2.5 Cross - validation or statistical significance of model parameters

Statistical significance (cross- validation) of model parameters was determined through Jack-knife technique [28]. Model parameters were statistically tested to estimate uncertainties in their behaviour (Table 5) Jack-Knife technique is basically a resampling method which involved a leave-one- out strategy of the estimation of parameters in a dataset of "N" observations. To elaborate, if there are a total of "N" numbers in a dataset, the predictor is trained on N-1 training examples and tested on remaining one data point i.e., leave-one-out cross validation technique was implemented. Then, process was repeated "N" times and eventually predicted values of each sample was calculated.

Table 1 (b) D and H of large tree sampled from the study site (DBH range 11.4- 77.08 cm) *±SE

S. No.	Species Name	Mean D (m)	Mean H (m)	Density (no. of individuals/ha)	WD (Kg/m^3)
1	Bauhinia variegate L.	0.26±3.02	5.44±0.51	10	670
2	Holoptelia integrifoliaRoxb.	0.25±4.35	18.59±0.35	16	640
3	Acacia nilotica (L.) Willd. Ex Delile	0.25±2.53	11.21±0.57	21	900
4	Tectona grandis L.	0.29±3.59	28.2±0.57	18	550
5	Ficus benghalensis L.	0.64±3.73	5.8±1.05	8	390
6	Pongamia pinnata L.	0.39±5.44	6.8±3.72	17	600
7	Callistemon viminalis G. Don	0.18±1.89	6.58±0.33	15	600
8	Butea monosperma (Lam.) Taub.	0.32±2.37	13.3±1.34	11	480
9	Prosopis juliflora (Sw.) DC.	0.22±3.89	8.32±0.59	33	600
10	Delonix regia (Hook.) Raf.	0.19±4.16	14.1±1.17	14	600
11	Albizia procera (Roxb.) Benth.	0.17±6.15	7.12±2.13	19	520
12	Ficus racemose L.	0.77±5.81	9.47±1.94	21	390
13	Syzygiumcumini L.	0.37±0.42	6.58±1.23	13	600
14	Ziziphus jujuba Mill.	0.27±2.84	11.91±0.47	17	330
15	Dalbergia sissooRoxb. Ex DC.	0.57±1.97	7.83±0.37	12	600
16	Ficus religiosa L.	0.72±3.53	9.71±0.63	15	390
17	Phyllanthus emblica L.	0.13±3.85	6.5±0.71	8	880
18	Cassia fistula L.	0.18±5.36	11.37±0.63	9	640
19	Azadirachta indica L.	0.44±2.99	8.57±0.55	12	690
20	Casuarinaequisetifolia L.	0.21±3.14	23.59±0.43	17	830
21	Bauhinia purpureal.	0.16±2.17	10.41±0.56	9	670
22	Albizia lebbeck (L.) Benth.	0.24±4.02	6.71±0.65	21	550
23	Grevelia robusta A. Cunn	0.18±3.35	27.98±0.51	14	600
24	Ficus elasticaRoxb. Ex Hornem.	0.11±5.21	6.59±0.48	14	390
25	Morus alba L.	0.14±1.98	4.78±0.33	5	600
26	Milletiapeguensis Lock and Heald	0.13±2.79	4.31±0.43	7	600
27	Cordia dichotoma L.	0.14±2.65	6.13±0.43	8	530

Table 2: Nonlinear functions to build aboveground (stem) biomass models

S. No.	Model	Function	Parameter	Source
1	Richards	$AGB = \alpha\ (1-e^{-\beta X})^{\delta} + \varepsilon$	3	Richards, 1959 [29]
2	Power	$AGB = \alpha X^{\beta} + \varepsilon$	2	Huxley, 1932 [30]
3	Exponential	$AGB = \alpha e^{\beta X} + \varepsilon$	2	Bhandari, 2020 [31]

2.6 Residual analysis:

D' Agostino- Pearson test was performed to check for residual normality (Table 5). In addition, histograms with normal curve overlay were also created to test residual symmetry for all models. Only best - fit models from two datasets are depicted in figure 2 (a and b). Moreover, comparative analysis of residuals on basis of standard deviation, kurtosis and skewness was also conducted to come out with best results. All the analysis was implemented in Microsoft Excel, 2021 using Real Statistics Resource Pack.

As residual outliers can be very significant and canenlighten us about the study area and data collection process, hence it is essential to understand how outliers exists and whether they might reoccur again as the normal part of the process. In our case, we detected possible outliers from the residual datasets but it was neither deleted nor it was adjusted to increase the statistical significance of the model in question. Skewness is usually described as a measure of symmetry of a dataset. The normal distribution has a skewness of 0. As a general rule, if the skewness is between -0.7 and +0.7, then the data is fairly symmetrical. If the skewness is between -1 and -0.5 or between 0.5 and 1, the data is moderately skewed, and if the skewness is less than -1 or greater than 1, then the data is highly skewed.Kurtosis originally was thought to measure the peakedness (of flatness) of a distribution. However, it is now widely accepted that the kurtosis is a measure of the combined weight of the tails relative to the rest of the distribution [32]. It measures the tail- heaviness of the distribution. The value is often compared to the kurtosis of normal distribution, which is equal to 3. If kurtosis is close to 3, then a normal distribution is often assumed. These are called mesokurtic distributions. If the kurtosis is greater than 3, then the dataset has heavier tails than a normal distribution and is called leptokurtic distribution. If kurtosis is less than 3, then the dataset has lighter tails than a normal distribution and is called platykurtic distribution.

3.0 RESULT AND DISCUSSIONS

Allometric biomass models presented in Table 3 clearly explained the reason behind in using two variable models having tree diameter at 1.3 m height (D) and tree height (H). Out of 18 models constructed (M1- M9 for juvenile plants and M10- M18 for large trees) M2 and M12 came out to be the best- fit models with highest R^2 adjusted and lowest RSE values. All allometric models were constructed using 3 nonlinear functions and three sets of predictor variable (x) i.e., D, DH and D^2H. For juvenile plants, the best fit model was M2 having highest R^2_{adj} and lowest RSE (R^2_{adj} 0.9723, RSE 0.00036) which was followed by M3 (R^2_{adj} 0.9708; RSE 0.00037), M4 (R^2_{adj} 0.9307; RSE 0.00055) and M1 (R^2_{adj} 0.9305; RSE 0.00057). Here, a combination of DH and D^2H was found to be strongly correlated with aboveground biomass. For large trees, a combination of D^2H produced robust fitting results for Richard's and Power function (R^2_{adj}>0.94). The best-fit model among large trees was M12 showing fitting statistics (R^2_{adj} 0.9527; RSE 0.03724), followed by M15 (R^2_{adj} 0.9464; RSE 0.04049), M13 (R^2_{adj} 0.7767; RSE 0.08265) and M10 (R^2_{adj} 0.7670; RSE 0.08265). Exponential function did not produce powerful correlation for any of the three combinations (R^2_{adj} 0.68 - 0.75) hence was not given any ranking.

In order to develop allometric models for estimating stem biomass of NDRF, we used the widely acceptable biophysical field level variables i.e., diameter at breast height (DBH) and total tree height (H) and observed comparably weak relationships using single– variable(either D or H) and it became stronger with two-variable models. However, for juvenile plants D, as a predictor variable demonstrated good results for both M1 (R^2_{adj} 0.9305) and M4 (R^2_{adj} 0.9307) models. For large trees both D and H independently produced weak correlations to predict aboveground biomass, although correlation of D (R^2_{adj} 0.7419- 0.7767) was far better than that of H (R^2_{adj} 0.01- 0.10). The relationship of these variables (D, H) to the stem biomass was depicted and it indicated that the two variable models using both D and H was intuitive to predict stem biomass of NDRF.

Table 3: Allometric aboveground biomass models for two datasets * M1, M2...model designation

Model expression and evaluation				
	DBH < 10 cm (1.59- 9.17 cm)			
Model	**x**	**Equation**	**R^2_{adj}**	**RSE**
Richards	D [M1]	$AGB = 0.218(1-e^{-5.454x})^{3.372}$	0.9305	0.00057
	DH [M2]	$AGB = 0.057(1-e^{-1.013x})^{1.886}$	0.9723	0.00036
	D^2H [M3]	$AGB = 0.089(1-e^{-2.786x})^{1.034}$	0.9708	0.00037
Power	D [M4]	$AGB = 7.167x^{2.697}$	0.9307	0.00055
	DH [M5]	$AGB = 0.029x^{1.579}$	0.9733	0.00036
	D^2H [M6]	$AGB = 0.177x^{1.020}$	0.9720	0.00037
Exponential	D [M7]	$AGB = 0.022e^{42.287x}$	0.9302	0.00058
	DH [M8]	$AGB = 0.016e^{4.526x}$	0.9088	0.00067
	D^2H [M9]	$AGB = 0.026e^{41.604x}$	0.8387	0.00089
	DBH > 10 cm (11.4- 77.08 cm)			
Richards	D [M10]	$AGB = 183.964(1-e^{-0.043x})^{1.441}$	0.7670	0.08265
	DH [M11]	$AGB = 0.902(1-e^{-0.193x})^{1.990}$	0.7614	0.08363
	D^2H [M12]	$AGB = 0.890(1-e^{-0.263x})^{1.144}$	0.9527	0.03724
Power	D [M13]	$AGB = 0.892x^{1.329}$	0.7767	0.08265
	DH [M14]	$AGB = 0.051x^{1.225}$	0.7638	0.08500
	D^2H [M15]	$AGB = 0.234x^{0.786}$	0.9464	0.04049
Exponential	D [M16]	$AGB = 0.063e^{3.115x}$	0.7419	0.08886
	DH [M17]	$AGB = 0.073e^{0.268x}$	0.6753	0.09966
	D^2H [M18]	$AGB = 0.116e^{0.335x}$	0.7509	0.08730

In addition, we also conducted test for residual normality (d' Agostino- Pearson test) for all models along with outlier detection and also checked for residual symmetry (Table 5). We subsequently graphed histograms with normal curve overlay to test for residual normality for best- fit models from two different datasets (Figure 2 a and b). The d'- Agostino- Pearson test of residual normality of three best- fit models from two different datasets: [M2(D- stat= 5.484, p= 0.064)]; [M3(D- stat= 4.685, p= 0.096)]; [M4(D- stat= 4.233, p= 0.120)]; [M12(D- stat= 5.411, p= 0.067)]; [M15(D- stat= 4.553, p= 0.1030]; and [M13 (D- stat= 5.930, p= 0.052)] showed a p value greater than 0.05 suggesting that residuals do not violate the assumption of normal random error. A minimum of "0" and a maximum of "1" outlier was detected from residual analysis. The models with a single outlier were neither removed nor adjusted as it was a part of data collection process. Residual symmetry/asymmetry of all models suggested that most of the residuals were fairly symmetrical and non were highly skewed. Moreover, residuals for models M5- M9 were moderately skewed (Table 5). The values for kurtosis indicated that distribution was mesokurtic for M5, leptokurtic for M7, M8 and M9 and platykurtic for rest of models (Table 5).

Table 4: Cross- validation (statistical significance) of model parameters

		DBH 1.59- 9.17 cm		
	Predictor variable	**Model Parameters**		
Model	**x**	**α**	**β**	**δ**
Richards	D	0.218±0.008	5.454±0.099	3.372±0.029
	DH	0.057±0.014	1.013±0.022	1.886±0.017
	D^2H	0.089±0.017	2.786±0.325	1.034±0.011
Power	D	7.167±0.023	2.697±0.072	-
	DH	0.029±0.007	1.579±0.199	-
	D^2H	0.177±0.006	1.020±0.161	-
Exponential	D	0.022±0.014	42.287±0.789	-
	DH	0.016±0.011	4.526±0.127	-
	D^2H	0.026±0.021	41.604±0.178	-
		DBH 11.4- 77.08 cm		
Richards	D	183.964±2.555	0.043±0.019	1.441±0.111
	DH	0.902±0.004	0.193±0.002	1.990±0.010
	D^2H	0.890±0.012	0.263±0.002	1.144±0.099
Power	D	0.892±0.002	1.329±0.004	-
	DH	0.051±0.005	1.225±0.001	-
	D^2H	0.234±0.018	0.786±0.023	-
Exponential	D	0.063±0.0004	3.115±0.0088	-
	DH	0.073±0.0001	0.268±0.0002	-
	D^2H	0.116±0.0002	0.335±0.0003	-

Diameter at breast height (DBH) is a widely used representative indicator of biomass estimation, and trees with different DBH- sizes usually have different amount of biomass. For constructing aboveground biomass model for mixed-species in NDRF, we used this well- known tree DBH parameter along with maximum tree height (H), that can be measured conveniently in a real- life situation, and as a non- destructive method, it can be practiced in any restricted area where harvesting is prohibited. Thus, allometric models have wide applicability, particularly in forest areas where harvesting is not allowed. In this investigation, we analyzed three nonlinear regression equations with these easily measurable field variables (D and H) to build stem biomass models. Generally, adjusted R^2 value has been used for selecting best- fit models, but it can also give misleading results [33,34]. To overcome this possibility of misleading and to avoid taking any biased decision, we selected our best- fit models considering not only adjusted R^2 but also residual standard error (RSE) values. Highest adjusted R^2 and lowest RSE value offers best- fit model in selecting allometric models [35,36]. Best- fit allometric equation [M2] for estimating stem biomass of juvenile plants was AGB = 0.057 $(1-e^{-1.013x})^{1.886}$. It was a 3- parametric Richard's model, having diameter at 1.3 m height (D) and total tree height as predictor variables, i.e., x=DH. Here, α is the upper asymptote, β is the growth rate or scale parameter and δ is the shape parameter and inflection point. It is a classical sigmoid growth function which is often used to model individual tree growth and populations. The function is quite flexible, versatile, reliable and often used in forest growth modelling. All three parameters had biological meaning too. Similarly, for large trees, best- fit model [M12] had the equation AGB = 0.890 $(1-e^{-0.263x})^{1.144}$, here x represented a combination of D^2 multiplied by H. Again, it is a 3- parametric Richard's model. Our results are similar to other findings of tree volume and biomass allometric models where both D and H improves model fitting [37,38]. Moreover, in order to model stem biomass of young plants, a 2- parametric power function [M4] can also be used using

"D" as a single predictor variable (R^2_{adj}= 0.9307, RSE= 0.00055). All 18 allometric models along with model performance values (R^2_{adj} and RSE) has been mentioned in table 3.

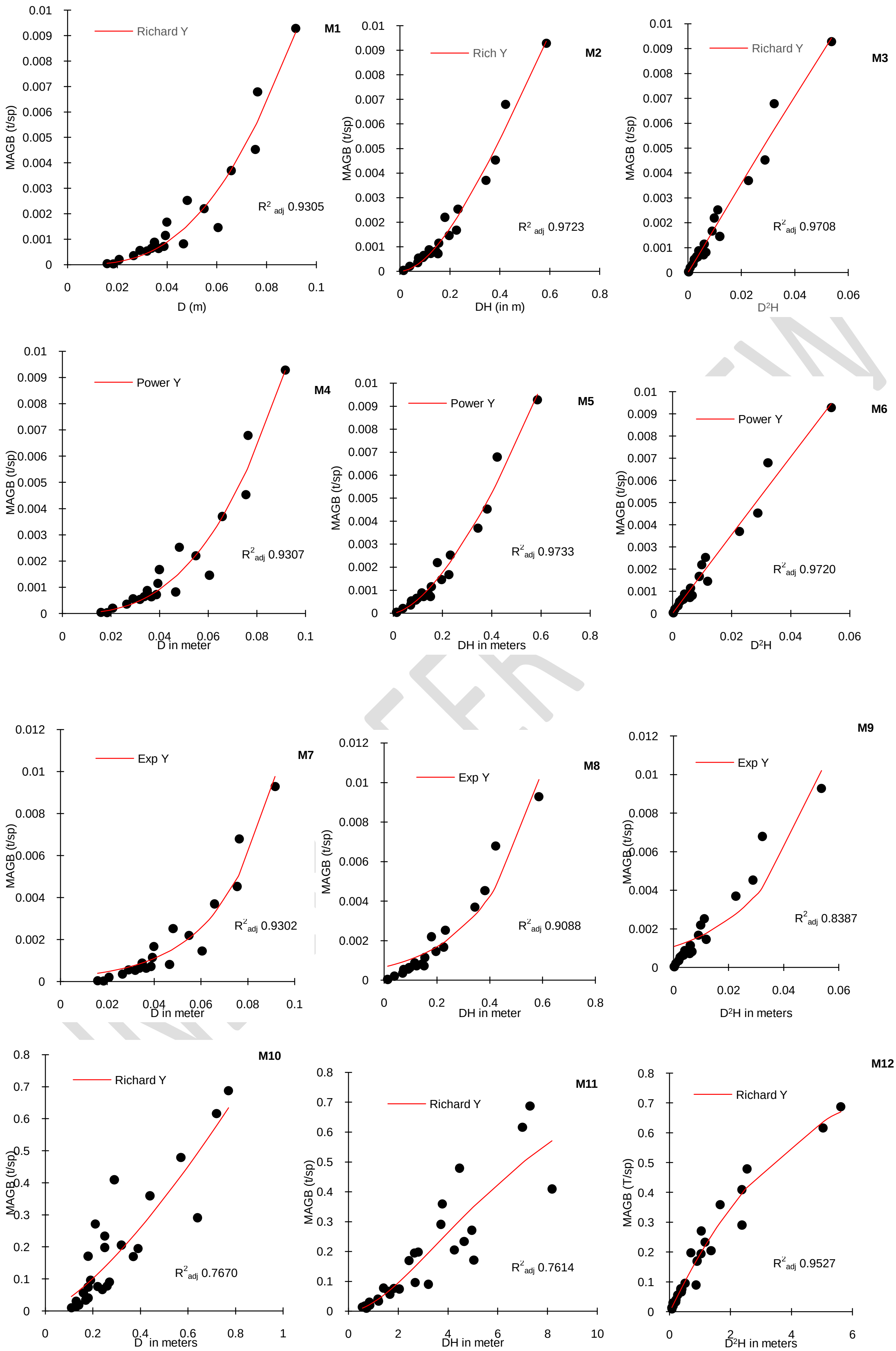
Table 5: Descriptive statistics and residual analysis:

		DBH < 10 cm (1.59- 9.17 cm)					
Model	**x**	**d' Agostino-Pearson test**	**p- value**	**Outlier**	**SD**	**Kurtosis**	**Skewness**
Richards	D	Yes	> 0.05	1	0.00058	2.275	0.681
	DH	Yes	> 0.05	1	0.00037	1.366	-0.738
	D^2H	Yes	> 0.05	1	0.00038	1.989	-0.627
Power	D	Yes	> 0.05	1	0.00057	2.239	0.414
	DH	No	< 0.05	1	0.00037	2.906	-1.396
	D^2H	No	< 0.05	1	0.00038	2.451	-0.851
Exponential	D	No	< 0.05	1	0.0006	3.046	-1.360
	DH	No	< 0.05	1	0.00068	4.730	-2.005
	D^2H	No	< 0.05	1	0.00091	3.513	-1.779
		DBH > 10 cm (11.4- 77.08)					
Richards	D	Yes	> 0.05	1	0.08577	1.916	-0.671
	DH	Yes	> 0.05	0	0.08527	0.464	-0.067
	D^2H	Yes	> 0.05	1	0.03795	2.133	0.564
Power	D	Yes	> 0.05	1	0.08571	1.957	-0.708
	DH	Yes	> 0.05	0	0.08673	0.804	-0.330
	D^2H	Yes	> 0.05	0	0.04112	0.947	-0.800
Exponential	D	No	< 0.05	1	0.09132	1.304	-1.057
	DH	Yes	> 0.05	0	0.10171	1.056	-0.659
	D^2H	Yes	> 0.05	0	0.08914	0.182	-1.005

Accurate and precise estimation of forest biomass is vital for successful implementation of climate change mitigation actions [39]. Allometric biomass models are regression models that typically use tree diameter and/or tree height to predict biomass. Despite emerging new technologies such as remote sensing, empirical allometric models remain central when predicting forest biomass. [40,41]. Diameter at breast height (D, at 1.3 m above ground) is a basic forest inventory variable [42] but for improved models using both D and H to produce tree volume or biomass is a common practice in forestry [43]. However, inclusion of H in the model would be of no use if D and H were perfectly correlated. Although, D and H are always correlated to some degree, their relationship varies greatly i.e., relationship is nonlinear [44] being influenced by genotype, competition and environmental conditions [45,46]. As a result, including H in allometric models has been shown to improve biomass prediction accuracy [47, 48]. Because D and H are correlated, the unique effect of each predictor (i.e., the main effect) is based on its unique information (disregarding shared information).

Collinearity between predictor variables (D and H in this case) increases standard errors and instability in parameter estimates [49]. Although, collinearity between D and H does not necessarily have adverse effects on biomass prediction [50], it is often avoided by using a combined predictor of the form of DH (diameter of tree trunk multiplied by total tree height) or D^2H (i.e., D^2 multiplied by H) based on argument that the aboveground biomass is proportional to the volume of a cylinder (tree trunk) of diameter D, and height, H. This combined predictor incorporates information from both D and H and, therefore produces more accurate biomass prediction than when using either D or H alone.

In this investigation, we developed these empirical models for estimating stem biomass in NDRF applying a non- destructive method that will allow us to use it for the estimation of biomass or carbon stocks in different forests and plantations having similar arid, semi- arid conditions. Although, non- destructive method provides relatively less accuracy than destructive method in estimation of tree biomass, yet it has an advantage ofpreserving the conservation value and biodiversity of a forest. The destructive method not only demands vast time and labor, but also it is unfeasible in developing countries like India where harvesting has been prohibited in order to conserve the existing limited forest resources [51,52].Therefore, our allometricmodels following non- destructive method can be an alternative way to build site- specific and mixed- species biomass models which can be an effective tool for continuous monitoring of biomass or carbon stocks of forest in this particular region of India.



M1
Richard Y
R2 adj 0.9305
MAGB (t/sp)
D (m)
M2
Rich Y
R2 adj 0.9723
MAGB (t/sp)
DH (in m)
M3
Richard Y
R2 adj 0.9708
MAGB (t/sp)
D2H
M4
Power Y
R2 adj 0.9307
MAGB (t/sp)
D in meter
M5
Power Y
R2 adj 0.9733
MAGB (t/sp)
DH in meters
M6
Power Y
R2 adj 0.9720
MAGB (t/sp)
D2H
M7
Exp Y
R2 adj 0.9302
MAGB (t/sp)
D in meter
M8
Exp Y
R2 adj 0.9088
MAGB (t/sp)
DH in meter
M9
Exp Y
R2 adj 0.8387
MAGB (t/sp)
D2H in meters
M10
Richard Y
R2 adj 0.7670
MAGB (t/sp)
D in meters
M11
Richard Y
R2 adj 0.7614
MAGB (t/sp)
DH in meter
M12
Richard Y
R2 adj 0.9527
MAGB (T/sp)
D2H in meters

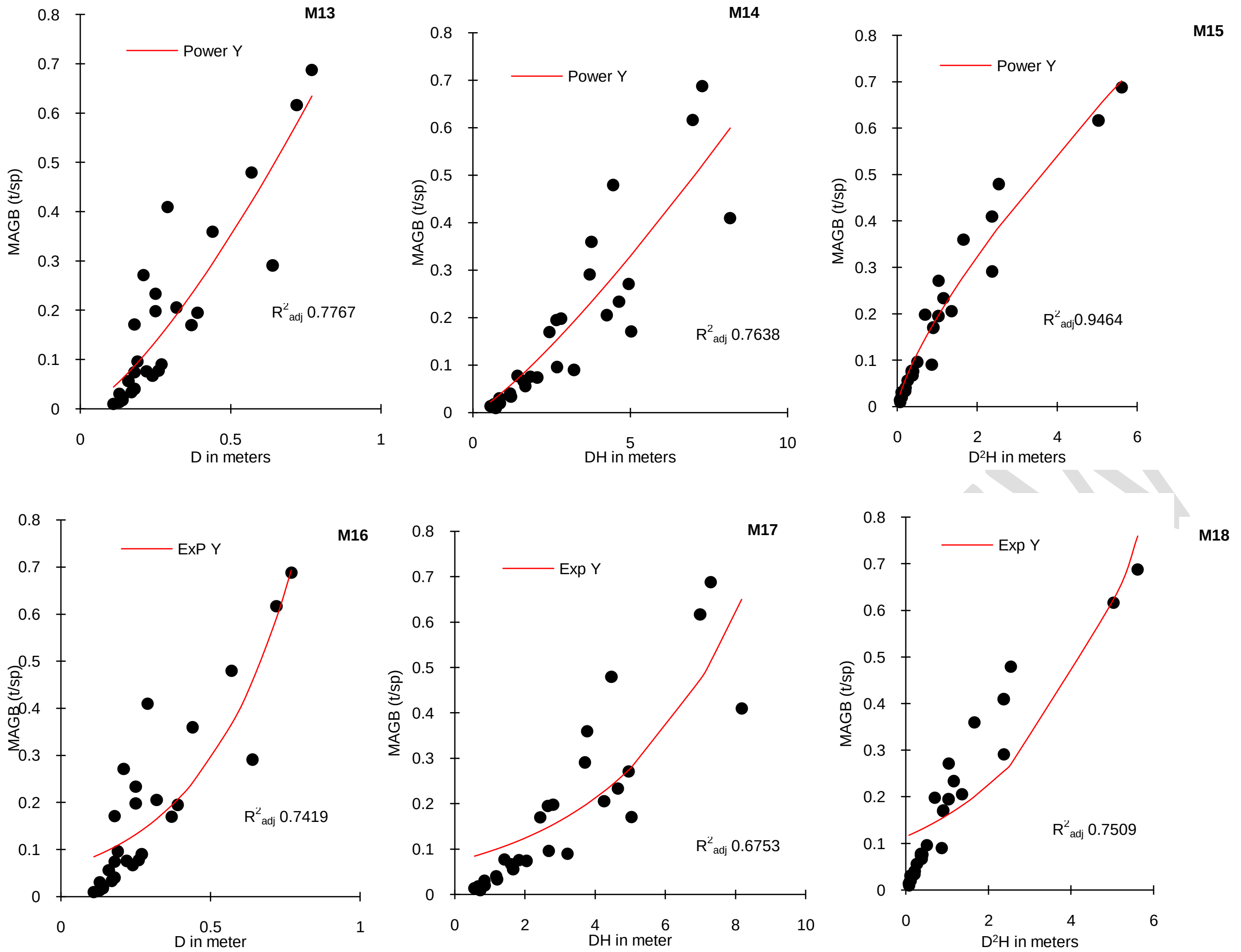


Figure 1: Allometric relationship between mean aboveground biomass and combinations of D and H for two datasets (* M1 – M9 for juvenile plants and M10–M18 for large trees) *circles are observed mean values of aboveground biomass (Tons/species)

Table 6. Correlation between aboveground biomass andpredictor variables of four best – fit models from each dataset; "r" is the Pearson correlation coefficient

S. No	Model	Predictor variables	r
1	M2	AGB Vs DH	0.9806
2	M3	AGB Vs D^2H	0.9999
3	M4	AGB Vs D	0.9516
4	M1	AGB Vs D	0.9552
5	M12	AGB Vs D^2H	0.9805
6	M15	AGB Vs D^2H	0.9926
7	M13	AGB Vs D	0.9969
8	M10	AGB Vs D	0.9969

4.0 CONCLUSION

In this study, we constructed 18 allometric models applying 3 nonlinear functions and three sets of predictor variable (x = D, DH, and D^2H), for two different datasets. It was observed that both D and H in combination are significant in predicting aboveground biomass of mixed species growing naturally at NDRF. The best- fit models were ranked on basis of R^2_{adj} and RSE values. For juvenile plants (DBH range: 1.59 – 9.17 cm), M2 was the best -fit model with x = DH, and for large trees (DBH range 11.4 – 77.08 cm), M12 performed the best, with a combination (x = D^2H). The allometric models can be applied to predict aboveground biomass for

NDRF and other adjoining areas having thorny type of vegetation which is suited to arid and semi- arid conditions.

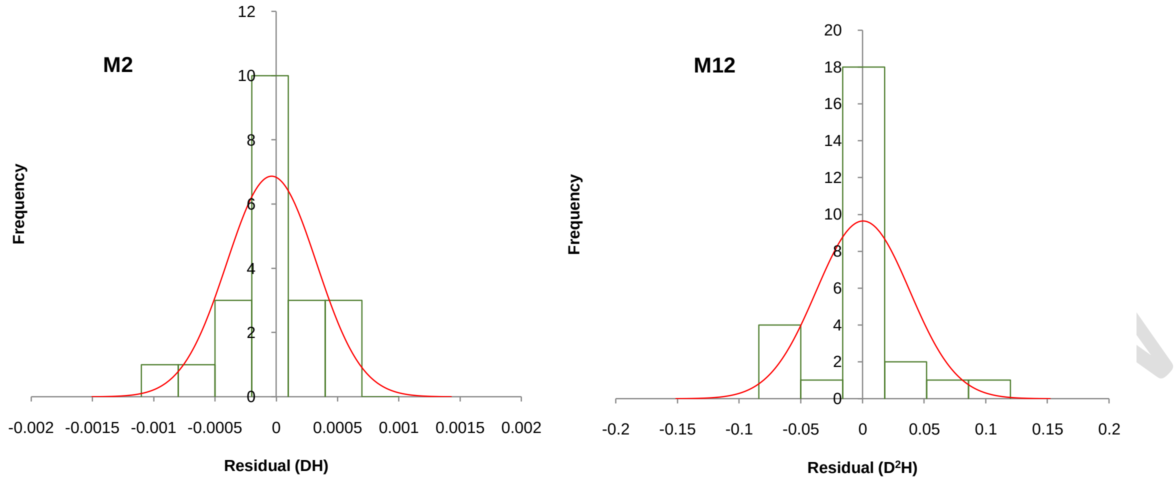


Figure 2: Frequency distribution of residuals for best- fit models for juvenile plants [M2] and large trees [M12]

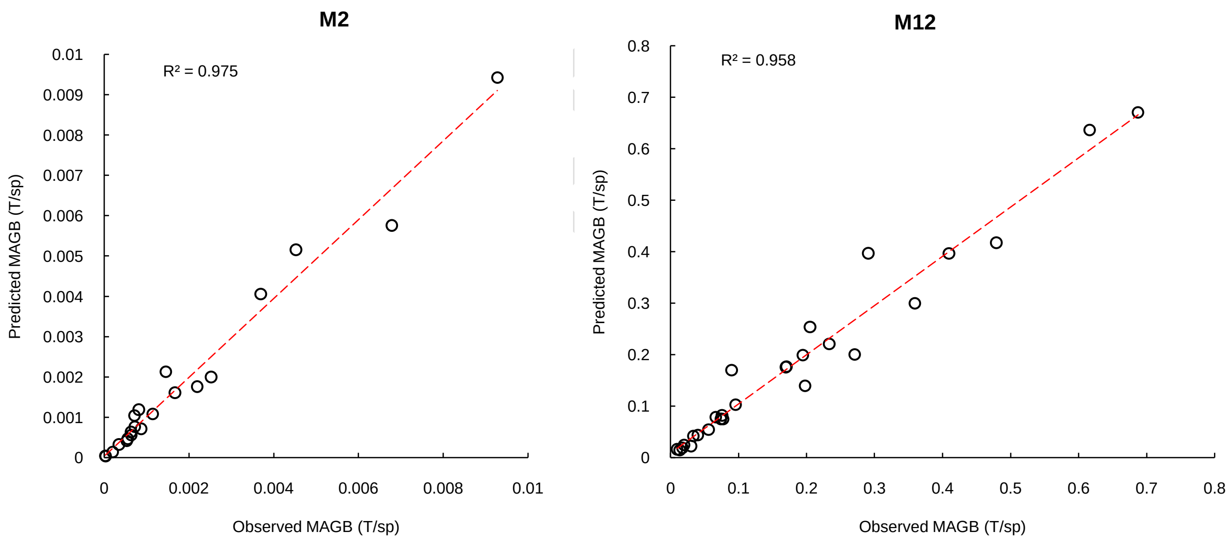


Figure 3. Graph of regression line of the predicted biomass against observed biomass. Best- fit models for juvenile plants [M2] and large trees [M12]datasets were used to produce these graphs

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