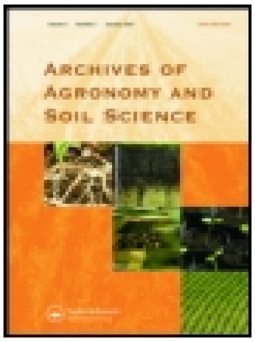

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Biomass and carbon projection models in *Hardwickia binata* Roxb. *vis a vis* estimation of its carbon sequestration potential under arid environment

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Abstract

Hardwickia binata, is an important fodder and timber tree of arid regions. Assessment of its biomass and carbon content is essential, for taking management decisions, and in ecosystem modelling. Seven models namely logistic, Gompertz, Chapman, Hill, Allometric, Linear and Monomolecular were tested for this purpose by using diameter at breast height (DBH). Allometric model ($Y = a \times DBH^b$) was found best performing with AIC value of 12.65. This model was then used to develop biomass equations for different tree components using DBH as independent variable. Developed equations showed high R^2 values (0.894 to 0.989). These equations were then used to assess the biomass and carbon stock of *H. binata* plantations of different age groups. Total biomass of plantations ranged between 63.61 Mg ha^{-1} (14 years) and 139.55 Mg ha^{-1} (36 years) with the corresponding carbon stock of 28.39 Mg ha^{-1} and 63.35 Mg ha^{-1} which translates into carbon sequestration rate of 1.60 and 2.02 Mg ha^{-1} a^{-1},

respectively. The developed equations provide a realistic assessment of biomass productivity and carbon stock with low error margin and would thus be very useful in taking suitable management decisions and in ecosystem modelling to explain impact of carbon management to policymakers.

Keywords: allometric model, biomass, carbon, *Hardwickia binata*, predictive models

Introduction

Carbon management from different land use systems at present is a major worldwide concern threatening the existence of life on earth. Atmospheric concentrations of CO_2 has increased from 310 ppm in 1950, to above 400 ppm in 2014 (IPCC 2014). Trees are a significant source of carbon sink on earth. Tree biomass estimation aids in measuring the concentration and stock of green house gases in relation to change in land use pattern (Cairns et al. 2003). The accurate estimation of individual tree biomass is important for carbon accounting, trading and management. To facilitate carbon stock accounting and verification, predictive models are required (Brown 1997; Chave et al. 2005; Bombelli et al. 2009; Gupta et al. 2011; Verma et al. 2014; Naik et al. 2018). Equations to estimate biomass are used globally and have long history. Most of these equations are generated for tropical, subtropical and temperate species worldwide (Navar 2009; Zapata-Cuartas et al. 2012; Henry et al. 2013). These developed equations were mainly allometric and described by the metabolic theory of West, Brown and Enquist for the origin of allometric scaling laws (West et al. 1997, 1999). Worldwide web platform like Glob Allome Tree is a free access database of various volume, carbon and biomass equations, though its first version only includes information from countries like Europe, Africa and Northern America. However, there is always a scope of upgrading of existing equations and inclusion of new equations based on different tree components and their carbon stock (Henry et al. 2013). The limited information on prediction models exists for various tree species of commercial use and those existing have very constricted sampling range in terms of area and aspect. Predictive model for biomass and carbon estimation specifically for arid zone trees are scarce (Kumar et al. 1999, Tewari et al. 2014; Tewari et al. 2016; Jaiswal et al. 2018).

Hardwickia binata Roxb. belongs to the family Leguminosae, sub-family Caesalpinioideae is a multipurpose, deciduous, nearly evergreen tree of great economic value (Chand and Singh 2001). It belongs to dry tropic and sub-tropic regions of central and south-east Asia with climate characterized by a long period of drought, scant to moderate rainfall, with extreme heat in summer season. It is considered to be a good nitrogen fixing tree gives extremely hard and durable timber as well as fuel-wood (Roy 1996) and highly palatable fodder rich in crude protein (Singh 1982; Patidar and Mathur 2017). It is amenable to pruning practices and coppices and pollards well. Further, in addition to tangible benefits the species provide range of intangible environmental benefits like soil and water conservation and mitigation of changing climate via sequestering carbon in woody biomass. But the projection models to estimate biomass and carbon in various tree components of *H. binata* is poorly reported worldwide. Furthermore, few studies are available on the carbon contents of tree components that may be used for the estimation of the carbon storage capacity. Therefore, present study was conducted to develop the best fit model for estimation of biomass and carbon in tree components of *H. binata.* Additionally, the carbon sequestration potential of this tree in different plantations under arid environment was estimated.

Material and Methods

Study site

The study was conducted at research farm of ICAR-Central Arid Zone Research Institute, Jodhpur. (26º14′ N 72º59′ E and altitude of 216 m). This location represents Koppen Climate

Classification subtype "Bsh" (Mid-Latitude Steppe and Desert Climate). It experiences very high temperature during the summers touching a maximum of 48ºC, short (December to mid-February) cool and dry winters (4.1–14 ºC), high evaporation (3.5–13.5 mm day^{-1}) and low humidity. About 95% of the average annual rainfall of 360 mm is received during 6–8 rain events. The soil of experimental site is classified as coarse loamy Typichaplocambids. At 0-15 cm soil depth pH of soils varied from 8.0-8.3 and have 0.14 % organic carbon, 14.20 kg ha^{-1} available P, 250.6 kg ha^{-1} available K.

Experimental Material

The study was conducted in a 25 years old plantation of *H. binata* maintained under integrated farming system. The trees were planted in paired rows (3m × 4m) forming an alley of 24 m between two pairs. Rainfed pearlmillet- legume rotation was followed in the alleys since establishment with standard management practices. No irrigation was applied to the plants after 2 years of establishment. Since, it was a part of an integrated farming system the trees were yearly lopped to 40 % from fifth year of establishment to 10th year and later on, it was increased to 60%. Therefore, the data pertaining to leaves used for developing predictive model was based on the single year growth.

Biomass and carbon estimation of trees

Twenty trees were selected; diameters at breast height (DBH) was measured for these trees and were classified into six diameter classes viz. 11-14, 14-17, 17-20, 20-23, 23-26, 26-29 cm. Sample size of 20-30 plants for developing the relationship between DBH and biomass of tree including entire range of DBH was supported by studies of Gupta et al. (2011) in *Populus deltoides*, Verma et al. (2014) and Rathore et al. (2018) in *Grewia optiva* and Guava, respectively. The trees were harvested and parts of each tree *viz.* bole, branches, leaves (above ground components) and roots (below ground components) were partitioned. Roots were excavated upto 1.5 m^3 volume of soil. The fresh weight of all the components was measured immediately after harvesting. To determine the dry weight 500 g sample of each component was placed in brown paper bags and oven dried at 60°C till it attained constant weight. The dried up sample of different tree parts were grounded to fine powder and carbon content of each sample was estimated using Eurovector C analyser. The carbon content of each component was multiplied by dry weight to get the carbon stock.

Model fitting, validation and application

Different linear and nonlinear predictive models were fitted to develop the correlation between the total biomass (kg tree^{-1}) and DBH (cm) of *H. binata* trees. To visualize the shape of the biomass and DBH relationship, scatter plot was drawn. The drawn plot indicated that linear, logistic, gompertz, chapman, hill, allometric, and monomolecular fit well in the recorded data of total biomass using DBH as explanatory variable. The recorded data of 20 trees was divided into two different sets; one of 15 trees (75%) used for model fitting and other of 5 trees (25%) used for validation. While fitting model along with the parameter estimates, R-square and Akaike information criteria (*AIC*) value were also calculated. AIC compares the quality of statistical models for measured data (Naik et al. 2018). Fitted models with highest R-square and lowest AIC values are considered to be the best fit model. Further, for statistical validation, residuals of the fitted models were tested to fulfil the null hypothesis that errors are independently distributed. Anderson–Darling test used for testing the normality of residuals, whereas, independence of errors was tested visually by plotting the errors. Validation of the fitted model using 25% data set was done using the procedure given by Gupta et al. (2011) and allometric model outperformed the basic principles of validation among the seven selected models. Hence, in the present study, allometric model ($Y = a \times DBH^b$) was used for predicting the biomass for *H. binata* components, where Y is biomass weight (kg tree^{-1}), DBH is diameter at breast height (cm), *a* and *b* are parameters of allometric model.

Allometric equations obtained were then applied for the biomass and carbon estimation in 14, 25 and 36 year old *H. binata* plantations with density of 1111, 494 and 400 trees ha^{-1}, respectively. To calculate the biomass stored in different components of tree measured, DBH value was fitted in respective component wise developed equations. The carbon stock of each constituent of tree (bole, branches, leaves and roots) was computed as the product of biomass and average carbon content. The total carbon stock of plantation was obtained by multiplying the carbon stock of trees with the plantation density. As carbon stock of roots, branches and bole locks up for longer period it is measured as stored carbon. Whereas, the carbon in leaves is stored for very short duration (used as fodder in our case) therefore it is measured as emitted carbon. Mitigated carbon was figured out by subtracting emitted carbon from stored carbon. Carbon sequestration rate of plantation was calculated by dividing stored carbon by age of plantation.

Statistical analysis

Descriptive statistics, fitting various growth models (parameter estimation, AIC and R-square values etc), residual diagnostics plots, validation of models using paired t-test and linear regression between observed and predicted data set were analysed using SAS 9.3 software. Non-linear models were fitted using Levenberg-Marquardt algorithm in SAS NLIN procedure. The best model was chosen which outperformed others on both the criteria of model fitting and validation.

Results and Discussion

Summary statistics of recorded variables from the harvested trees revealed that DBH of trees ranged from 11.78 to 28.66 cm and total biomass 41.0 to 411.1 kg $tree^{-1}$ with the average of 181.7 kg $tree^{-1}$. The total above ground biomass varied between 34.3 kg $tree^{-1}$ and 343.0 kg $tree^{-1}$, whereas, the below ground biomass ranged from 6.7 kg $tree^{-1}$ to 68.1 kg $tree^{-1}$ (Table

1). The mean contribution of above ground and below ground components to total biomass was 81% and 19 %, respectively above. The similar fraction of above ground (88%) and below ground (12%) biomass in litchi was reported by Naik et al. (2018). The percent contribution of bole, branches and leaves to total biomass was 74.5%, 16.5% and 9%, respectively. The results with high concentration of biomass in bole are supported by the findings of Gupta et al. (2011) and Urban et al. (2015).

Relationship between DBH (independent variable) and biomass (dependant variable) was tested in different models viz., logistic, gompertz, chapman, hill, allometric, linear and monomolecular. The biomass of trees was well predicted using data of DBH alone (R^2 values >0.87) and accordingly tree height was not included for biomass modelling. Also the continuous lopping of the tree for fodder under farming system mode of management does not give the reliable measure of the tree height. Moreover, measuring DBH of tall trees is more convenient compared to tree height (Montagu et al. 2005; Segura and Kanninen 2005; Gupta et al. 2011; Verma et al. 2014; Singh and Singh 2015; Kebede and Soromessa 2018; Naik et al. 2018).

The parameter estimates of models viz, logistic, gompertz, chapman, hill, allometric, linear and monomolecular fitted on estimated dataset with other related statistics is given in Table 2. The values of adjusted R^2 were above 0.876 for all the models (observed vs predicted) showing their equal competence. The maximum R^2 values were recorded for Hill model (R^2= 0.960) followed by allometric model (R^2=0.942). However, it is reported that values of R^2 alone cannot predict the best fitting model (Payandeh 1981; Gupta et al. 2006). To choose the best fitting function its behaviour and validation within and outside the observed range of the independent variable must be considered as well (Kaushal et al. 2016; Naik et al. 2018). Allometric model ($Y = a \times DBH^b$) with lowest *AIC* value of 12.65 fulfils the model fitting norms to the maximum followed by Hill model (*AIC*=19.98). However, all the models explained more than 85% variance in measured biomass. Linear models estimated negative values of predicted biomass when the values of explanatory variables are very low. These results are in line with the findings of Verma et al. (2014) and Naik et al. (2018).

To statistically verify the model the linear regression between observed and predicted (obs = a + b ×pred) should lead to ‘a’ value approaching to zero and ‘b’ value approaching to one, to gave lowest and closer to zero value for ‘a’ and almost unit value for ‘b’ compared to other model (Table 3). The model validation carried out using remaining 25% data set fulfilled these criteria (Table 3). Secondly, the paired t -test between observed and predicted values must give a non-significant ‘t’ value, with highest p value for allometric model compared to the other model. Since, allometric model fitted best in validation criteria, its residuals have also been tested for independence and normality for statistical validation. The test statistic for Anderson–Darling test was 0.648 ($p = 0.075$) signifying the acceptance of null hypothesis. Residuals of the algometric model have been plotted in Figure 1 (a-b) where form normally with mean zero and constant variance of the residuals can be visualized. Prediction error called as residual was calculated as the difference among observed and predicted values. Plotting of residuals along with predicted and independent variable DBH for allometric model ensured that there is no constant over or under estimation of residuals for tree biomass (Figure 1(c) and 1(d)). Accordingly, the allometric model, out of the seven models, was selected for predicting component wise tree biomass with DBH as explanatory variable as it met all the required criteria in both fitting and validation stage.

The biomass of various tree parts like bole, roots, leaves and branches was also tested in allometric model with DBH of the tree as independent variable (Table 4). The adjusted values of R^2 ranged from 0.894 to 0.989. The maximum value of adjusted R^2 value (0.989) was recorded for leaf biomass and minimum (0.894) for root biomass. The allometric curve was fitted for biomass of different tree component with the DBH of tree which showed the smooth parabolic lines for predicted biomass and all the observed values of biomass are touching the line (Figure 2) signifying the very strong correlation between the variables with high R-square values. Standard error estimates were found to be negligible. The paired t-test was used for validating allometric model statistically and t values were not found to be significant ($p>0.05$) denoting that observed and predicted values were not differing significantly. Allometric models found best performing fulfilling the criteria of validation in different species across Indian sub continent (Gupta et al. 2013; Verma et al. 2014; Kaushal et al. 2016; Rathore et al. 2018).

The total biomass allocated to different tree components followed the order as: bole>roots>branches>leaves. The above and below ground biomass contributed 78-82% and 18-22%, respectively to the total biomass. These values are in the range specified for trees (82% aboveground and 18% belowground) grown in agroforestry systems (Chaturvedi et al. 2016). Bole had the maximum proportion (74%) of above ground biomass followed by branches (15-17%) and 8-11% stored in leaves. The per cent contribution of the bole (28-82%) and branch biomass to aboveground biomass increases with increase in age and diameter (Chaturvedi et al. 2016). The relative distribution of total biomass in different components of tree depends on its age, branching habit, length of clean bole, rooting pattern and management practices (Bernardo et al. 1998; Osada et al. 2005; Newaj et al. 2016).

These developed models were then used to estimate the component wise biomass in different aged plantations of *H. binata* (Table 5). The total biomass of plantations ranged between 63.6 Mg ha^{-1} (14 years) and 139.5 Mg ha^{-1} (36 years). The mean annual increment ranged between 3.5 Mg ha^{-1} a^{-1}in 25 years to 4.5 Mg ha^{-1} a^{-1} in 14 year old plantation. The determined biomass values were equivalent to the biomass of 34 years old *H. binata* trees in study conducted in semi-arid hot region of Rajasthan with 450 mm annual rainfall (Gupta et al. 2019). Singh and Singh (2015) reported 1.8-54.3 Mg ha^{-1} biomass in an 18 year old plantation in arid region and Dash (2017) reported 60 Mg ha^{-1} biomass in 30 years plantation in silvipastoral system which are comparatively lesser than our estimates. This might be due to difference in tree density and climatic conditions. However, these values are less than the accumulated biomass at the age of 20 years (101 Mg ha^{-1}) in semi-arid Central India (Newaj et al. 2016) with higher rainfall and more favourable growing conditions than arid environments. The leaf biomass is however comparable (7.1 Mg ha^{-1}) which is a big incentive for incorporating this tree in agroforestry system of mostly livestock based farming systems of arid zone.

Specific allometric models are important not only for quantifying biomass but they are also reported to give accurate estimates of carbon storage in terrestrial ecosystem (Creighton and Kauffman 2008; Roxburgh et al. 2015). Carbon concentration of tree components ranged between 49.26% found in bole to 47.68% in leaves. C content in roots and branches were 47.95 and 47.83 % respectively (Figure 3). Verma et al. (2014) also reported that bole contains the highest concentration of carbon followed by roots, branches and minimum concentration of carbon was recorded in leaves. Carbon content varied widely across tropical species ranging from 41–51% (Thomas and Martin 2012; Navarro et al. 2013).

The stored biomass carbon stock ranged from 28.4 Mg ha^{-1} with sequestration rate of 1.6 Mg ha^{-1} a^{-1} in 14 years and 63.3 Mg ha^{-1} with sequestration rate of 2.0 Mg ha^{-1} a^{-1} in 36 years old plantation of *H. binata* (Table 6). It was comparable with carbon storage of 46.1 Mg C ha^{-1} with sequestration rate of 2.3 Mg C ha^{-1} yr^{-1} in 20 years old plantation of *H. binata* as reported by Newaj et al. (2016). Dhyani et al. (2016) reported the carbon sequestration potential in the range of 0.4 to 13.9 Mg C ha^{-1} a^{-1} in different block plantation in arid and semi arid regions of India. The net annual carbon sequestration rates in our study were lower than that of observed by Kaul et al. (2010) for fast growing species with short felling cycle like Poplar and Eucalyptus (6-8 Mg C ha^{-1} a^{-1}), comparable with moderate growing tree species like Teak (2 Mg C ha^{-1} a^{-1}) and higher than the slow growing species like Sal (1 Mg C ha^{-1} a^{-1}). Carbon mitigation in plantations with different age varied between 25.8 Mg ha^{-1} and 58.7 Mg ha^{-1} with maximum proportion of bole. The contribution of all the components increased with age. Carbon emitted by leaves ranged between 2.6 and 4.6 Mg ha^{-1} (Table 6). The sequestration of carbon in tree wood is influenced by number of factors like growth habit of tree, age, tree density, agroclimatic conditions and carbon content of species (Kanime et al. 2013, Navarro et al. 2013; Dhyani et al. 2016; Gupta et al. 2019). As wood density represents the amount of mass and carbon per unit volume, it is directly linked to total carbon stocks (Nam et al. 2018). Trees in arid regions have higher wood density (Gupta et al. 2017) which compensates slower growth (by volume) and slower carbon accumulation in this region. However, this difference in wood density warrants validation of these equations in other ecological settings for more accurate estimations. Although the model is developed from a comparatively smaller sample size; this limitation may be spared due to laborious data collection and high R^2 values of fitted models.

Conclusion

The present study was carried out to develop the models that can predict the biomass of *H. binata* species. Of the various models used for predicting biomass and carbon the allometric model was most steady with best fit in goodness of statistics. The paired t-test between observed and predicted values was used to check the consistencies of the models used. Though, these models are applicable in the measured diameter range as it does not include other source of variation. These developed models in future will help the farmers and tree growers to estimate the biomass and carbon stock of standing trees by only measuring the tree diameter. Additionally, these models will help farmers in decision making regarding the number of animals to be reared on available tree stand and *vice versa*, available fuelwood for market, amount of timber in stock (bole) etc. To the policy makers, it would be easy to estimate the carbon sequestered in farm forestry as well as agroforestry plantations and could be utilized for framing policies, carbon-credit trading etc.

Conflict of Interest: The authors declare that they have no conflict of interest.

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Table 1. Descriptive statistics for DBH (cm), Height (m) and biomass (kg tree^{-1}) for the harvested trees in *H. binata*

Parameters	Mean	Standard deviation	Kurtosis	Skewness	Minimum	Maximum	n
DBH (cm)	19.76	5.47	-1.44	0.16	11.78	28.66	20
Height (m)	8.30	1.99	-1.19	0.25	5.30	11.60	20
Biomass (component wise)							
Bole	109.1	77.84	-1.37	0.50	23.1	252.6	20
Branches	24.2	18.19	-1.00	0.66	3.7	60.9	20
Leaf	13.6	8.13	-1.25	0.40	3.5	29.5	20
Roots	34.8	23.53	-1.97	0.04	6.7	68.1	20
Above ground biomass (AGB)	146.9	103.66	-1.32	0.51	34.3	343.0	20
Below ground biomass (BGB)	34.8	23.53	-1.97	0.04	6.7	68.1	20
Total biomass	181.7	126.23	-1.46	0.41	41.0	411.2	20

Table 2. Parameter estimates of various functions fitted on 75% dataset for total biomass in *H. binata*

Model	Parameter estimates	R-square	AIC
Logistic	$Y = \dfrac{165.3625}{1 + \left(\dfrac{DBH}{34.0851}\right)^{-3.7337}}$	0.916	69.21
Gompertz	$Y = 221.4701 \times e^{-e^{-\left(\frac{DBH-33.2065}{14.9901}\right)}}$	0.916	45.32
Chapman	$Y = 454.2007(1 - e^{-0.0356 \times DBH})^{4.6311}$	0.915	70.98
Hill	$Y = \dfrac{7.6379 \times DBH^{-300.6490}}{1267.2389^{-300.6490} + BDH^{-300.6490}}$	0.960	19.98
Allometric	$Y = 0.0024 \times DBH^{3.0141}$	0.924	12.65
Linear	$Y = -38.6351 + 3.1431 \times DBH$	0.876	68.21
Monomolecular	$Y = 1 - (1 - 6.4527)e^{-(-0.0123 \times DBH)}$	0.901	75.91

Table 3. Validation of various models of total biomass DBH on 25% data set

Tree parameters	t value	Pr>|t|	R^2 of regression of observed vs. predicted	Linear regression between predicted and observed observations (pred=a+b×obs)	
Logistic	0.9756	0.3740	0.903	-0.569	1.165
Gompertz	1.0684	0.3341	0.940	-0.678	1.124
Chapman	0.6453	0.5471	0.813	0.879	1.569
Hill	0.7906	0.4649	0.947	-0.369	1.199
Allometric	0.6092	0.5689	0.967	0.289	1.056
Linear	0.4511	0.6707	0.853	-0.489	-1.135
Monomolicular	0.3765	0.7219	0.948	0.458	1.156

Table 4. Allometric relationship of *H. binata* data fitted for biomass content for different tree components [Y- component biomass (kg tree^{-1}) and X- DBH (cm)].

Biomass component	Parameters	Estimates	Standard Error	t-value	P-value	Adj R-Square
Branch biomass (kg)	a	0.0054	0.0054	1.0016	0.3298	0.8947
	b	2.7631	0.3095	8.9277	<0.0001	
Bole biomass (kg)	a	0.0283	0.0158	1.7921	0.0899	0.9628
	b	2.7164	0.1731	15.6939	<0.0001	
Leaf biomass (kg)	a	0.0158	0.0057	2.7959	0.0119	0.9731
	b	2.2328	0.1118	19.9733	<0.0001	
Root biomass (kg)	a	0.0363	0.0299	1.2136	0.2406	0.8868
	b	2.2738	0.2573	8.8356	<0.0001	
Above ground biomass (kg)	a	0.0428	0.0241	1.7755	0.0927	0.9606
	b	2.6792	0.1748	15.3278	<0.0001	
Total biomass (kg)	a	0.0700	0.0385	1.8196	0.0855	0.9595
	b	2.5907	0.1708	15.1701	<0.0001	

Table 5. Biomass estimates (component wise) ($Mg\ ha^{-1}$) and MAI ($Mg\ ha^{-1}\ yr^{-1}$) in different aged *H. binata* plantations

Age (a)	Average DBH (cm)	Bole biomass	Branch biomass	Root biomass	Leaf biomass	Total biomass	MAI
14	12.20±0.71	36.8±4.41 (57.78)	7.3±0.97 (11.47)	14.1±1.41 (22.28)	5.4±0.55 (8.47)	63.6±7.33	4.54
25	19.87±1.21	53.1±9.83 (59.92)	11.7±2.40 (13.18)	17.9±2.60 (19.38)	6.7±1.03 (7.52)	88.6±15.86	3.54
36	24.77±1.22	85.2±7.27 (61.07)	19.9±1.81 (14.25)	24.7±1.87 (17.73)	9.7±0.74 (6.95)	139.6±11.69	3.88

Values in parenthesis indicates % allocation in different tree components ± values indicate std. error

Table 6. Carbon estimates (Mg ha^{-1}) of various tree components in different aged *H. binata* plantations

Age (a)	Stored			Emitted	Mitigated	Sequestration rate (Mg ha^{-1} a^{-1})	CO_2 stored (Mg ha^{-1})
	Bole	Branches	Roots	Leaves			
14	18.1±2.17	3.5±0.46	6.8±0.68	2.6±0.26	25.8±3.05	2.0±0.24	94.8
25	26.2±4.84	5.5± 1.14	8.2±1.24	3.2±0.49	36.7±6.74	1.6±0.29	134.7
36	42.0±3.58	9.5±0.87	11.9±0.90	4.6±0.35	58.7±4.99	1.8±0.15	215.5

±values indicate std. error

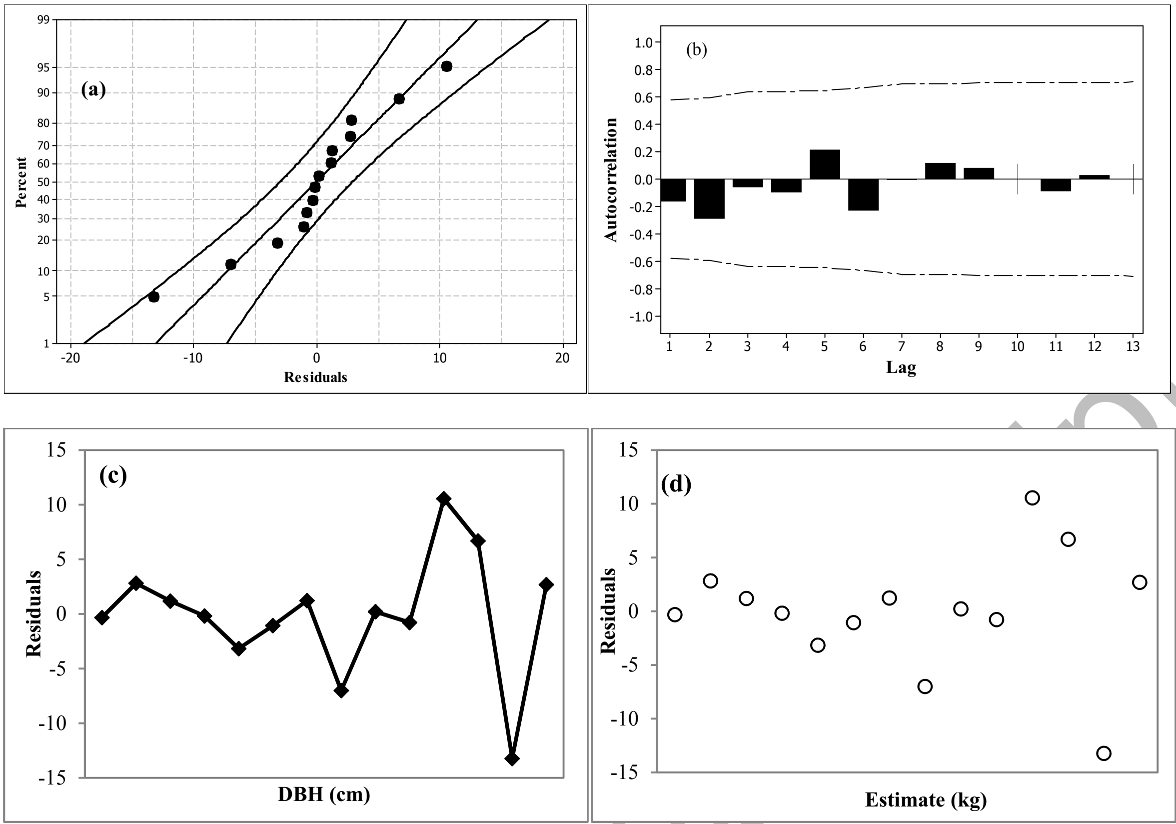

Figure 1. Plots of residuals against the value of predicted and explanatory variable for total dry biomass after fitting allometric model

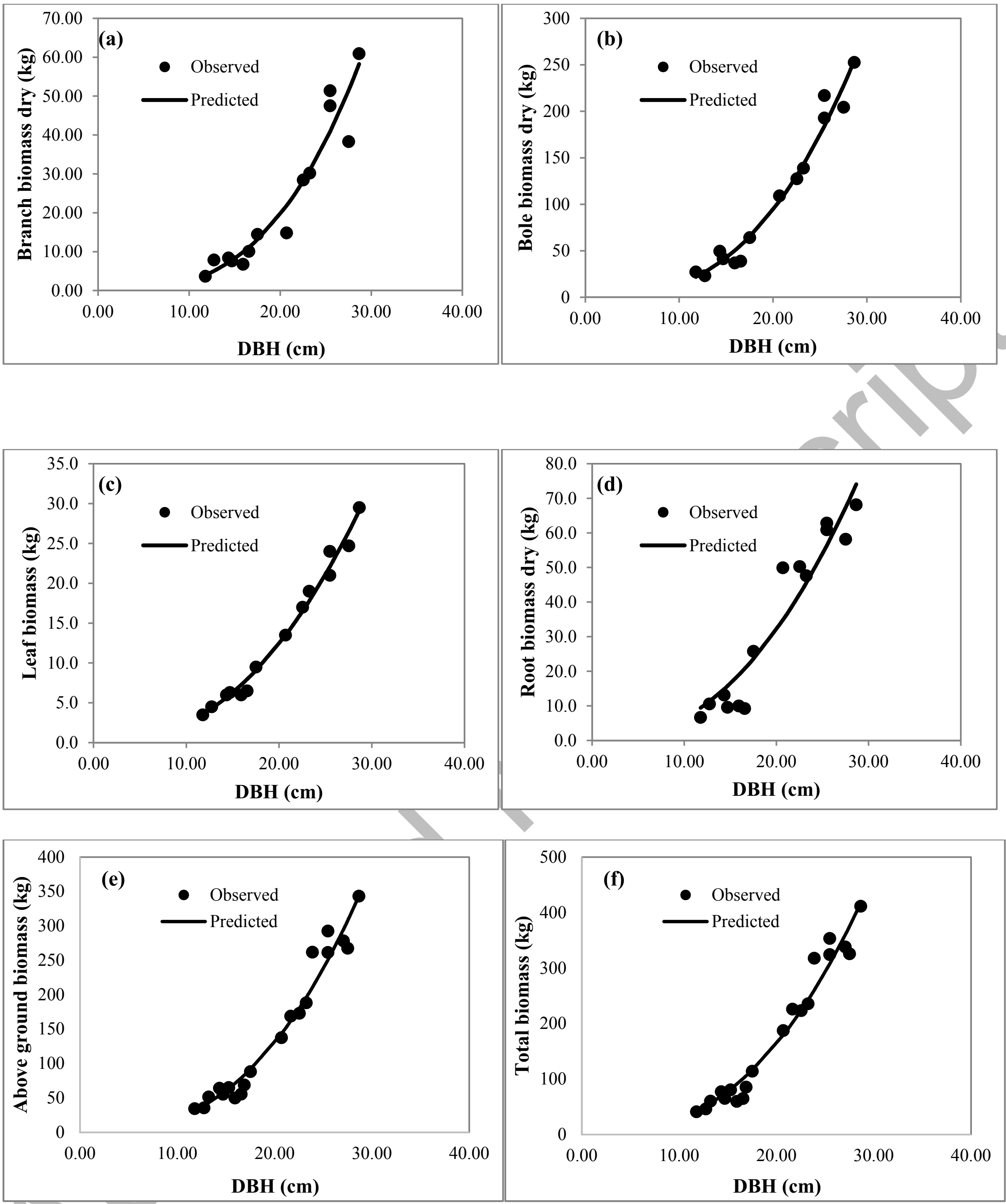

Figure 2. Observed vs predicted figure (a-f) for different biomass components using DBH (cm) as explanatory variable

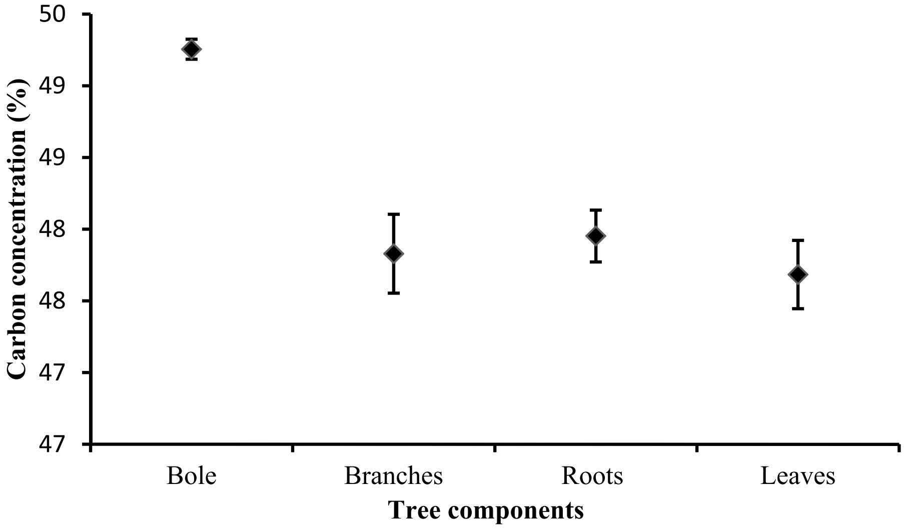

Figure 3. Carbon concentration in different components of *H. binata*