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(RESEARCH ARTICLE)



Single-species allometric equations for above-ground biomass of most abundant long-lived pioneer species in semi-deciduous rain forests of the central region of Cameroon.

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Abstract

The implementation of REDD+ and AFR100 mechanisms require the availability of reliable allometric models, which are mathematical functions for estimating forest biomass from independent variables such as diameter at breast height (dbh), crown diameter, wood density and tree height. Although many equations have been developed to estimate tree biomass in undegraded forests, very few models have been developed for secondary forest species. The aim of this study was to establish single-species allometric models for estimating biomass of pioneer species in semi-deciduous forests in the central region of Cameroon and to evaluate their accuracy. Data of above-ground biomass were obtained from destructive sampling of 103 pioneer trees belonging to three species: *Distemonanthus benthamianus, Musanga cecropioides* and *Trema orientalis*. Model comparison were based on Akaike Information Criterion (AIC), average deviation and the coefficient R²adj. The different tests with combinations of dendrometric variables shows that whatever the species considered, the diameter at breast height appears as a good single predictor of biomass (Adjuted R²adj > 0.97 in all three species). The use of the crown diameter in the model in *Musanga cecropioides* has considerably improved the quality of the fit. However, the consideration of these three variables in the model gave even better results (Adj.R² = 0.978-0.988). The comparison of these present models with the equations previously developed shows that the models in this article provide a better estimate of biomass. However, several important data from semi-deciduous forest remain essential for the adjustment of multi-specie models.

Keywords: Allometric equations; Pioneer species; Biomass; REDD+; AFR100; Secondary forest.

1. Introduction

Forest destruction and degradation represents a rate ranging from 10 to 12 % of global anthropogenic CO_2 emissions (Le Quéré *et al*, 2015). In Cameroon, these forests cover nearly 190,000 km² (FAO, 2011) and their loss is a major threat to the planet (OFAC, 2012), they play a major role in the absorption and accumulation of greenhouse gases on a world scale of approximately 2 billion tons of carbon dioxide equivalent per year (FAO, 2018). The result of these degradations are a strong expansion of secondary forests where pioneer species are very abundant. With the increasing area of these degraded forests, the extension of the geographic scope of the REDD+ mechanism (reducing emissions from

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deforestation and forest degradation) to secondary forests remains essential to mitigating the effects of climate change (storms and hurricanes, floods, drought, tropical cyclones, desertification, earthquakes). In parallel to this REDD+ mechanism, since 2015 during the 21st yearly session of the Conference of the Parties (COP), AFR100 is committed to accelerate the restoration of 100 million hectares of degraded and deforested landscapes in Africa by 2030 to improve food security, increase resilience and mitigate climate change and poverty. However, the implementation of these mechanisms depends crucially on reliable protocols for monitoring, reporting and verification (MRV) of carbon storage in the field.

Among the four components of PREREDD+ (Capacity Building Project in REDD+), the second attempt to build technical capacity to measure and monitor carbon stocks in the forests of the Congo Basin. To respond to the objective of subcomponent 2b, which aims at establishing allometric equations for the main forest types, only the allometric equations for estimating the above-ground biomass of pioneer species have been developed.

The objectives of this study were (1) to develop single-species allometric models for *Distemonanthus benthamianus, Musanga cecropioides* and *Trema orientalis* species in order to effectively contribute to the implementation of the REDD +, (2) to evaluate the accuracy of these models and (3) to select the best ones.

2. Material and methods

2.1. Study sites

This study was carried out in Mbankomo district located in the Mefou Akono Division of the Center Region of Cameroon. This district is located about 25 km from the political capital of Cameroon (Yaounde). Phytogeographically, this area belongs to the domain of semi-deciduous forests with savannas included (Letouzey *et al.*, 1985). However, with the intensity of anthropogenic activities in this area, producing a global appearance of semi-deciduous secondary forests, this study area is located between 3°46'59 " North latitude and 11°22'59" East longitude. The relief in this area is relatively low and varies from 400 to 800 m above sea level. Mbamkomo is topographically located on the upper basins of the Nyong and Sanaga rivers. From the pedological point of view soils are essentially ferralitic. The prevailing climate is typically sub-equatorial with two unequally distinct seasons of distribution during the year: a rainy season (April-October) and a dry season (November-March). However, it should be noted that these seasons are interspersed with seasons that are not clearly distinct and comparable to small dry seasons and small rainy seasons. The average annual temperature is 25 ° C; an average of one hundred and fifty-three days (PNDP, 2011).

2.2. Data Collection

In this study, data were collected exclusively on three species *Distemananthus benthamianus*, *Musanga cecropioides* and *Trema orientalis*. Data collection for the establishment of allometric equations of these pioneer species was carried out on a total of 103 trees (Table 1): 35 trees of *Distemananthus benthamianus* (diameter ranging from 5 to 82 cm), 38 trees of *Musanga cecropioides* (diameter ranging from 5.8 to 97.5 cm) and 30 trees of *Trema orientalis* (diameter ranging from 6-35 cm). Biomass data collection was obtained by destructive method, so each selected tree was fell, cut and weighed separately by compartments: stump, trunk, branches and leaves. The weighing of the compartments required a scale with a capacity of 300 kg. Disc-shaped samples were collected at different levels of the strain, trunk and branches. Samples of the leaves were also collected. These samples were weighed using a precision electronic scale and then sent to the Botany and Systematic Laboratory of the University of Yaounde I where they were oven-dried at 105° C for wood samples and 70°C for leaf samples until the constant weight was obtained (Ngoukwa, 2016). The resulting dry mass was used to estimate the total dry mass of each compartment of the tree. The total dry mass of each tree corresponds to the sum of the dry mass of the stump, trunk, branches and leaves.

Dry biomass of the sample = $\frac{\text{fresh mass x dry mass of sample weight}}{\text{fresh mass of sample}}$ (Brown and Pearson, 2005).

Total biomass = trunk biomass + stump biomass + leaves biomass + branch biomass

Table 1 Sample of trees whose biomass was destructively measured at Mbankomo, near Yaounde, Cameroon. n is the number of sampled trees, wood specific gravity calculated in this study and range of diameter at breast height (dbh range).

Species	Family	N	Wood density (g.cm3)	dbh range (cm)	
Distemonanthus benthamianus	Fabaceae	35	0.72 ± 0.007	5 – 82 cm	
Musanga cecropioides	Urticaceae	38	0.22 ± 0.017	5,8 – 97.5 cm	
Trema orientalis	Canabaceae	30	0.34 ± 0.022	6 – 35 cm	

In addition to the biomass data collected on each tree sampled, dendrometric parameters were also measured (dbh, total height and crown diameter); the dbh was measured at 1m 30 cm above the ground. For species such as *Musanga cecropioides*, due to the presence of stilt roots beyond 1.30 m, their diameter was measured at 30 cm above these stilt roots. The height was measured directly on the felled tree using a penta dekameter. Crown diameter of the trees was obtained by the calculation of the average of four diameters measured along the north-south, east-west, north-east/south-west and north-west/south-east orientations.

2.3. Wood density

The calculation of the wood density requires knowledge of the dry weight of the sample and its volume (Zane *et al.*, 2009). In the field, the fresh weight was obtained using an electronic suspension balance (before being dried in the oven until it reaches constant weight) and the volume of the fresh weight of the sample was obtained according to the Archimedes principle. According to this principle, a immersed solid is subjected to a force equal to the weight of the water, directed upwards. In a graduated cylinder containing water, we immersed the sample of fresh wood; the weight of the displaced water was read on the precision balance; the dry mass being known, its ratio to volume made it possible to formulate and calculate the density of the wood according to the formula:

WD_i =
$$\frac{M_i}{V_i}$$
 (Fearnside *et al.*, 1997)

Where Mi is the dry mass (g), Vi is the volume of the sample in the fresh state in cm³ and WDi is the wood density (g.cm⁻) of the wood sample i. For each tree, the density at the base, middle of the trunk and top parts were calculated. The average density of the tree corresponds to the average of the wood densities of the three levels.

2.4. Data analysis

For the adjustment of the models, the independent variables were the diameter of the tree, the total height and the crown diameter. The response variable was total dry mass. Graphical explorations of the pairs of variables allowed us to have an idea of the mathematical expression of the model used for the adjustment. Thus, among the three functions: arsinus, square root and logarithm, the logarithmic function was used in this study for linearization, thus avoiding heteroscedasticity problems (Xiao *et al.*, 2015). In addition, it is the most recommended function in the establishment of allometric equations for the estimation of tree biomass (Picard *et al.*, 2012; N. Fonton *et al.*, 2017).

The exercise consisted first of testing models that only take the diameter of the tree as an independent variable. Then, models that take 2 independent variables (dbh - height and dbh - crown diameter) and, thirdly; models that take these three variables (diameter, height and crown diameter). Combinations of variables such as $D^2 \times H$, $D^2 \times C$, $D^2 \times H \times C$ were also tested in this study. Since logarithmic transformations introduce biases into the models, these biases have been corrected for each model using the correcting factor (CF), which is expressed by the following relationship:

 $CF = \frac{RSE^2}{2}$ (Djomo *et al.*, 2016); RSE being the residual standard error.

Several additional tests that are indicators of the quality of fit of the equations tested were also included in this study. Those considered in this study given that they are most commonly used in the context of allometric equations are: Akaike Information Criterion (AIC), RSE, adjusted R² (Akaike *et al*, 1974; Alvarez *et al*., 2012; Chave *et al*., 2005; Djomo *et al*., 2017). Parameters such as mean error and RRMSE (Relative Root Means Square Error) were also calculated for each model. These errors are given by the following formulas respectively:

Average error or Deviation (%) = $100 \ge \frac{1}{n} \sum_{i=1}^{n} \left(\frac{M_{pi} - M_{i}}{M_{i}}\right)$,

$$\text{RRMSE} = \sqrt{\frac{1}{n}} \; (\frac{M_{pi} - M_i}{M_i})^2$$

Mpi represents the dry weight of the tree predicted by the regression equation, Mi the observed weight and n the total number of trees.

AIC = 2k - 2 ln L

k - Number of parameters in the regression model,

L- Probability of the adjusted regression model (Nelson et al., 1999; Basuki et al. 2009)

The functions commonly used in the literature are as follows the Power function ($Y = aX^b$), the Exponential function ($Y = a \exp(bX)$) which is a rewrite of the power model and the Polynomial function ($Y = a + bX + cX^2 + dX^3$).

Several models were tested in this study to select the best ones based on the comparison criteria, these models were the most common for allometric equation (Chave *et al.*, 2014; Djomo *et al.*, 2010, 2016; Ploton *et al.*, 2015).

(1) $\ln B = a + b \times \ln D + E$,

(2) $\ln B = a + b \times \ln(D \times C) + \varepsilon$,

(3) $\ln B = a + b \times \ln(D \times H) + \varepsilon$,

(4) $\ln B a + b x \ln(D^2 x H) + \varepsilon$,

(5) $\ln B = a + b \times \ln(D^2 \times C) + \varepsilon$,

(6) $LnB = a + b \times ln(D) + c \times ln(C) + E$,

(7) $\ln B = a + b \times \ln D + c \times \ln D^2 + \varepsilon$,

(8) $\ln B = a + b \times \ln(D) + c \times \ln(H) + \varepsilon$,

(9) $\ln B = a + b \times \ln(D^2 \times C) + c \times \ln(H) + \varepsilon$,

(10) $\ln B = \ln B \cot = a + b \times \ln(D^2 \times C) + \varepsilon$,

(11) $\ln B = a + b \times \ln(D) + c \times \ln(C) + d \times \ln(H) + \varepsilon$,

(12) $\ln B = a+b\times\ln(D) + c \times (\ln(D))^2 + d \times (\ln(D))^3 + \varepsilon$.

3. Results

3.1. Adjustment of allometric equations

The allometric equations were developed using data composed of 103 trees with diameter between 5 and 97.5cm. Graphical exploration is essential for the choice of the potential model for this regression, it shows the nature of the relationship between these 2 variables in the absence or otherwise of logarithmic transformations for the 3 pioneer species considered in this article.



Figure 3 Correlation between diameter and above-ground biomass (left) and between crown diameter and above-ground biomass (right) of (a) *Distemonanthus. benthamianus* species, (b) *Musanga cecropioides* and (c) *Trema orientalis.*

Single-species allometric models were developed from a data set of 35, 38 and 30 trees respectively for *Distemonanthus. benthamianus, Musanga cecropioides* and *Trema orientalis* using destructive method, with dbh ranging from 5 to 97.5 cm. Twelve models were tested for each species (36 models in total), based on the AIC comparison criterion and residual error, we selected five models per species (15 models in total) that were considered effective in describing the biomass data.

M1. $Ln(Btot) = a + b \times .ln(D) + \varepsilon$

M2. Ln(Btot) = $a + b \times \ln(D) + c \times \ln(H) + \varepsilon$

M3. Ln(Btot) = $a + b \times ln(D) + c \times ln(C) + \varepsilon$

M4. $Ln(Btot) = a + b \times ln(D) + c \times ln(C) + d \times ln(H) + \varepsilon$

M5. Ln(Btot) = $a+b\times ln(D) + c \times (ln(D))^2 + d \times (ln(D))^3 + \varepsilon$

Of all these models, dbh was the main variable, it appears to be a good predictor of above-ground biomass with (adjusted R ²= 0.973, AIC = 11.02, RRMSE = 0.295). The results of Table2 show that the introduction of total height in the model (dbh and Height) did not significantly improve the quality of fit (Adj.R²=0.972, AIC = 12.35, RRMSE = 0.288, Average deviation = 7.72%). On the other hand, the addition of the crown diameter improved the quality of the model (Adj.R² = 0.978, AIC = 4.78, RRMSE = 0.257, Average deviation = 6.39%); AIC thus increased from 11.02 to 4.78. When the three independent variables (diameter, total height, and crown diameter) were introduced together in the model, they improved the quality of the prediction (Adj.R² = 0.978, AIC = 4.66, Average deviation = 6.20%). We also tested the following model with a single input: $\ln(Btot) = 8,30 + -8.13 \times \ln(D) + 3.51 \times (\ln(D))^{2} + -0.380 \times (\ln(D))^{3}$; compared to the previous case, the fit quality is even better with this single input model (Aj.R² = 0.981, RSE = 0.222, AIC = -0.42, RRMSE = 0.217, Average deviation = 04.67%)

3.2. Models of Musanga cecropioides species

A sample of 38 individuals of *Musanga cecropioides*, with diameters ranging from 5.8 - 97.5 cm, allowed us to study the different relationships between total biomass and the different independent variables. Among the models tested, five were considered effective in estimating the aboveground biomass of *Musanga cecropioides*.

We first studied the relationship between biomass and dbh; this independent variable alone appears to be a good predictor of above-ground biomass with Adjusted R² of 0.976; RSE =0.323, AIC = 26.00, RRMSE = 0.415. Adding the diameter of the crown (ln(Btot) = $a + b \times ln (D^2 \times C) + \varepsilon$) to the variable dbh, improves the model; AIC increases from 26.00 to 11.91. However, with the model integrating dbh and height, (lnBtot= $a+b\times ln(D)+c\times ln(H)+\varepsilon$), the quality of fit is less interesting; AIC increases from 11.91 to 27.65 with a slight variation in the Adjusted R². However, when the 03 variables are simultaneously integrated into the model ln(Btot)= $a+b\times ln(D)+c\times ln(C)+d\times ln(H)+\varepsilon$, the quality of the fit is significantly improved (R² adjusted: 0.983, RSE: 0.272, AIC: 13.72). The single input model (ln(Btot) = $a+b\times ln(D) + c \times (ln(D))^2 + d\times (ln(D))^3 + \varepsilon$) positively improves the three-variable model (Adj.R2 0.981, RSE :0.292, AIC : 19.93). Among the 05 models selected as biomass potential predictors, the single input model : ln(Btot) = $5.83 + -6.52 \times ln(D) + 2.8 \times (ln(D))^2 + -0.28 \times (ln(D))^3$), based on its low AIC and the high value of the Adjusted R² (0.981) appears as the best of the 05 models; the relationship between biomass and dbh is better.

3.3. Models of Trema orientalis

Before adjusting, we first explored several relationships between the biomass variable and the other variables (Figure 3c). We used a data of 30 trees to adjust the selected models. The diameters varied from 6 to 35 cm, all diameter classes represented. Among the models tested, 05 were selected with adjusted R² coefficients greater than 0.97 and a low residual value. Models M11, M15 and M13 {ln(Btot)= $a +b \times ln(D) + \varepsilon$, lnBtot= $a +b \times ln(D) + c \times (ln(D))^2 + d \times (ln(D))^3 + \varepsilon$ and lnBtot= $a +b \times ln(D) + c \times ln(C) + \varepsilon$ } first integrating the dbh, therafter the dbh and crown diameter simultaneously establishes a strong link with adjusted R² greater than 97%. However, when the dbh is associated with the height and crown diameter (M14: lnBtot= $a + b \times ln(D) + c \times ln(C) + d \times ln(C) + d \times ln(H) + \varepsilon$), the fit is significantly better; the adjusted R² is significantly improved (R² adjusted > 98%), RRMSE = 0.096, the residues are even lower.

Table 2 Allometric equations for biomass estimation. Btot: Total biomass; D: diameter at chest height; H: height of tree; C: crown diameter; N: sample size; a, b, c and d are adjusted model parameters; RRMSE: Relative Root mean square error; RSE: residual standard error; Adj R²: determination coefficient; AIC: Akaike Information Criterion and CF: correcting factor.

Parameters Models	N	D range	a	b	с	d	RRMSE	RSE	Adj.R ²	AIC	CF
Distemonanthus benthamianus											
M1. $\ln Btot = a + b \times . \ln(D) + \varepsilon$	34	5-82cm	-1.217***	2.196***			0.295	0.268	0.973	11.02	0.036
M2. lnBtot= $a + b \times ln(D) + c \times ln(H) + \varepsilon$	34	5-82cm	-1.402***	2.063***	0.209 ^{ns}		0.288	0.269	0.972	12.35	0.036
M3. $\ln Btot = a + b \times \ln(D) + c \times \ln(C) + \varepsilon$	34	5-82cm	-1.052***	1.906***	0.348**		0.257	0.242	0.978	4.78	0.029
M4. lnBtot=a + b× ln(D) + c× ln(C) + d× ln(H) + ε	34	5-82cm	-1.332***	1.674***	0.374**	0.330 ns	0.246	0.238	0.978	4.66	0.028
M5. $\ln Btot=a+b\times\ln(D) + c \times (\ln(D))^2 + d \times (\ln(D))^3 + \varepsilon$	34	5-82cm	8.300**	-8.132**	3.513***	- 0.380***	0.217	0.222	0.981	-0.42	0.025
Musanga cecropioides		-									
M6. lnBtot= a +b×.ln(D) + ε	38	5.8-97.5 cm	-3.264***	2.423***			0.415	0.323	0.976	26.00	0.052
M7. lnBtot = $a + b \times ln(D^2 \times C) + \varepsilon$	38	5.8-97.5 cm	-1.950***	0.778***			0.305	0.269	0.984	11.91	0.043
M8. lnBtot= $a + b \times ln(D) + c \times ln(H) + \varepsilon$	38	5.8-97.5 cm	-3.138 ***	2.498 ***	-0.137ns		0.487	0.327	0.976	27.65	0.053
M9. lnBtot=a + b× ln(D ² ×C) + c× ln(H) + ε	38	5.8-97.5 cm	-1.843***	0.792***	-0.087ns		0.291	0.272	0.983	13.72	0.037
M10. lnBtot=a+b×ln(D) + c × (ln(D)) ² + d× $(ln(D))^3$ + ε	38	5.8-97.5 cm	5.835 ^{ns}	-6.521*	2.800**	-0.281*	0.340	0.292	0.981	19.93	0.043
Trema orientalis											
M11. lnBtot= $a + b \times .ln(D) + \varepsilon$	30	6-35 cm	-0.715***	1.784***			0.145	0.146	0.973	-26.60	0.011
M12. lnBtot= $a + b \times ln(D) + c \times ln(H) + \varepsilon$	30	6-35 cm	-0.677 ***	0.933 ***	1.007***		0.099	0.104	0.986	-45.76	0.005
M13. lnBtot= $a + b \times ln(D) + c \times ln(C) + \varepsilon$	30	6-35 cm	-1.197 ***	2.206 ***	-0.373*		0.134	0.136	0.976	-29.67	0.009
M14. lnBtot=a + b× ln(D) + c× ln(C) + d× ln(H) + ε	30	6-35 cm	-1.057***	1.313***	-0.292*	0,952***	0.096	0.095	0.988	-50.10	0.005
M15. lnBtot=a+b×ln(D) + c × (ln(D)) ² + d× $(ln(D))^3$ + ε	30	6-35 cm	2.911 ^{ns}	-2.204 ^{ns}	1.430 ^{ns}	-0,168 ^{ns}	0.137	0.149	0.972	-23.53	0.011

Note: The results are significant at a 95% confidence interval. ** p < 0.01; * p < 0.05; and ns(non-significant) p > 0.05. P-value of all models: 2.2e_16. *** p < 0.001.

4. Discussions

For each of the three species, we compared 05 single-species allometric models to test the predictive value of three descriptive parameters: diameter (dbh), height (H) and crown diameter for AGB biomass. Models incorporating a single independant variable for the three species were adjusted with R² greater than 0.97 following the application of a correcting factor; as in several existing models (Chave et al., 2014; Diomo and Chimi., 2017; Favolle et al. 2018), dbh alone appears to be a very good biomass predictor; the high value of R² (> 0.97) reflects a strong link between biomass and dbh; biologically, diameter growth of the tree explains that of biomass whose biosynthesis is stimulated by light acting on photosystems. However, the addition of height of the tree or the crown diameter as a second predictor provides a slight improvement in adjustment (adjusted R^2 : 0.97 - 0.98). This is explained by the fact that the canopy of secondary forests is well open, the trees capture light without competing; therefore, the height of the tree must be an essential characteristic of this species. The climatic stage of this ecosystem better promotes the calibration of crown height and diameter during inventories by minimizing error (Djomo et al., 2017). When the three variables are simultaneously considered (Table 2), adjusted R² coefficient varies slightly around 0.98 with a remarkable drop in AIC while the biases range from 04.67% to 07.96% in Distemonanthus benthamianus, 07.01% to 10.87% in Musanga *cecropioides* and from 0.25% to 01.95% in *Trema orientalis*. However, the model: Btot = $a+b \times \ln(D) + c \times (\ln(D))^2 + d \times \ln(D)$ $(\ln(D))^3 + \varepsilon$ also remains efficient in the case of the three species. The prediction with the model Ln(Btot) = $a+b\times\ln(D)$ + c × $(\ln(D))^2$ + d× $(\ln(D))^3$ + E compared to the model $\ln(Btot)$ = a +b× $\ln(D)$ + E makes a difference but it remains small.

Overall, the order of magnitude of the biases in our estimates remains below 10% compared to 26 to 32% in Ebuy et al., (2011). These results are similar to those of many authors such as Basuki et al., (2009) who worked in a Dipterocarpus forest on a sample of 122 individuals with diameters ranging from 6 to 200 cm. These models were adjusted with R² coefficient ranging from 0.963 to 0.989 and a deviation of 19.6% and 0.956% respectively in Ngomanda et al. Distemonanthus benthamianus, Musanga cecropioides, Trema orientalis for a first reason do not appear in the list of inventory data of Fayolle et al., (2013, 2018); Ngomanda et al., (2014); moreover these species are pioneers of secondary forests. Therefore, their models cannot reliably estimate the biomass of these three species which are that of semi-deciduous forests. In addition, Traoré et al., (2018) adjusted two models to estimate the biomass of Acacia mangium respective correlation coefficients R^2 : 0.97 and 0.98 [AGB = exp(-1.073 + 2.081 × ln (D)), AGB = exp(-3.455 + 2.081×ln (C)]. Bias values remained below 5%. In addition, Vahedi *et al.*, (2014) developed mixed models for the species F. orientalis and C. betulus of the hyrcanian forest, the R² adj coefficients were 0.95 and 0.96 and the deviations were between 10% and 20%. Specific and mixed (commercial) models were adjusted for some species (Dipterocarpus, Hopea, Palaquium sp, Shorea sp, Shorea sp) from forest to Dipterocarpus by Basuki et al., (2009); adjusted R² coefficients had varied between 0.97 and 0.99; deviations between 10% and 20%. The authors showed that mixed equations explain less the tree biomass compared to mono specific models. This point of view is shared because comparisons of our models to existing equations (mostly mixed) confirm Basuki et al's., (2009) point of view.

These results corroborate observations made by Pltoton (2016) and Goodman (2014), who mention the influence of crown diameter on fit quality. Due to the presence of clouds in the tropics, despite the high spatial resolution of the sensors, the accuracy of remote sensing estimates is reduced; crown diameter has been cited by several authors as the best predictor of biomass by the remote sensing method.

At present, according to the information collected in the PREREDD platform, five models have already been adjusted to estimate the volume of *Distemonanthus. benthamianus*, however no single-species allometric models have yet been developed for this species in the biomass calculation. In addition, some mixed models that have integrated some pioneer secondary forest species into the dataset gives an estimate of the equally relative biomass. The overestimation of the biomass of the *D. benthamianus* species with the Chave *et al.*, (2014) model is 43.08%, 102.08% with Fayolle *et al.* (2018). These exactions are normal, especially since allometric equations are site- or ecosystem-specific; this publication evaluates allometric equations of pioneer species in semi-deciduous forests (Letouzey, 1985). Like model 5 which overestimates biomass by only 04.67%, the other 04 models of *D. benthamianus* adjusted in this article are also recommended.

Author	Models	Average error (%)	RRMSE		
Distemonanthus benthamianus					
Chave <i>et al.</i> (2014)	AGBest = $0,0673 \text{ x} (\phi \text{ D}^2\text{H})^{0.976}$	42.74	0.64		
Fayolle <i>et al</i> . (2018)	AGB = 0,125 x $\phi^{1,079}$ x D ^{2,21} x H ^{0,506}	48.30	0.67		
Model 5	$AGB = exp(8,324-8,132x \ln(D)+3,51x (\ln(D))^2-0,38x(\ln(D))^3$	04.04	0.21		
Musanga cecropioides					
Model 7	$\ln B tot = -1,950 + 0,778 \times \ln(D^2 \times C)$	09.22	0.30		
Chave <i>et al.</i> (2014)	AGBest = $0,0673 \text{ x} (\phi \text{ D}^2\text{H})^{0.976}$	34,34	1.80		
Fayolle <i>et al</i> . (2018)	AGB = 0,125 x $\varphi^{1,079}$ x D ^{2,21} x H ^{0,506}	-98.7	0.98		
Model 14	$\ln Btot = -1,057+1,313 \times \ln(D) + 0,29 \times \ln(C) - 0,95 \times \ln(H)$	0.10	0.096		
Chave <i>et al.</i> (2014)	AGBest = $0,0673 \text{ x} (\phi \text{ D}^2\text{H})^{0.976}$	-7.45	0.43		
Fayolle <i>et al.,</i> (2018)	AGB = $0,125 \ge \phi^{1,079} \ge D^{2,21} \ge H^{0,506}$	3.84	1.24		
Huy et al., 2012	log biomass=(-2.88418)+0.735931 x log((DBH)^2 x (H))+ 0.18307	24.24	5.71		
	x log((DBH)^2 *(CA))		-		
Huy <i>et al.,</i> 2012	Log(Biomass) = (-2.87966)+2.13303 x log((DBH))+ 0.595399 x log((H))	44.58	7.34		
Huy et al., 2012	log biomass=(-3.60457)+0.964949*log((DBH)^2*(H))	-3.41	4.34		

Table 3 Comparison of our models with previously published equations.

With reference to the information collected in the PREREDD platform, *Musanga cecropioides* species so far does not have its own models in the sub-region for biomass estimation; Model 7 adjusted in this publication overestimates this biomass at a rate of 9.22% against 60.61% with Chave *et al.*, (2014), 13.76% with Ngomanda *et al.*, (2014); Fayolle *et al.*, (2018) overestimates it at -98.67%. Depending on the inventory data available (dbh, crown diameter, tree height and wood density), we recommend models M6, M7, M9 and M10 with residue proportions less than 10% and adjusted R² greater than 0.97. However, the model 7 (lnBtot = $a + b \times ln(D^2 \times C) + \varepsilon$) remains more efficient and recommended due to its wide canopy. This justifies the predictive nature of the crown diameter.

For *Distemonanthus benthamianus* species, Ngomanda *et al.*, (2014) model overestimates the biomass by 19.89%; it can be used if there is no other choice; but with our five models (M1, M2, M3, M4, M5) fitted and considered effective (Table 2), we recommend them. If the best of the five models has to be selected, it is N°5: (AGB= Exp(8.324-8.132 x ln(D)+3.51x $(ln(D))^2$ -0.38x $(ln(D))^3$) it is overestimated by 04.04% and therefore even more efficient and recommended. The residual error is very high with the authors: Chave *et al* (2014) and Fayolle *et al* (2018); this is normal especially since their equations are mostly mixed and are not those of semi-deciduous forests. The same observations are given in Figure 5, where Model 5 of D. benthamianus is almost confused with the black curve (observed biomass), which justifies the low bias (04.04%, Table 3) obtained in the prediction of *D. benthamianus* biomass by Model 5. However, Ngomanda(2014), Chave(2014) and Fayolle (2018) overestimate the biomass of *Distemonanthus benthamianus* in increasing order, hence the order of magnitude of their high bias.



Figure 5: Comparison of our models with previously published equations for Distemonanthus benthamianus species

For Musanga cecropioides, Model 7 (red curve in Figure 6) is almost confused to the black curve (observed biomass), hence the low value of the bias with Model 7 (09.22%, Table 3). Compared to the observed value, Ngomanda (2014) underestimates while Chave(2014) overestimates the biomass.



Figure 6: Comparison of our models with previously published equations for Musanga cecropioides species

The model 14 represented by the red curve in Figure 6 is almost confused with the black curve (observed biomass), hence the low value of the difference between observed value and the biomass value predicted by this model 14. Huy(2012) and Chave(2014) predict with a large overestimate while Ngomanda(2014) underestimate with a very large deviation; their models are not appropriate for predicting the biomass of *T. orientalis*. Model 14 is recommended.





Several equations have already been adjusted in Vietnam by Huy et al., (2012) for the estimation of T. orientalis biomass. It can be seen from Table (3) that the model: log biomass = $(-3.60457)+0.964949*\log((DBH)^2*(H))$ adjusted in Vietnam among many others is applicable with the residual error of -3.41%. The Chave et al., (2014) model (AGBest = $0.0673 \times (D2H)0.976$) can also be applied to our data by underestimating the biomass by -7.45%. The final choice is our fourteenth model (M14: lnBtot = $-1.057+1.313 \times \ln(D) + 0.29 \times \ln(C) - 0.95 \times \ln(H)$) which explains the biomass with a residual error of 0.098%, this model is efficient and recommended.

5. Conclusion

In this study, which is a key element for the implementation of the REDD+ mechanism, the calculation of the adjusted R^2 coefficients, average error and the analysis of the residues associated with the AIC for model comparison allowed us to define reliable models for the prediction, to avoid underestimated prediction, the application of the correction factor made it possible to considerably reduce the biases resulting from the logarithmic transformation, so that fifteen models were selected as predictive with correlation coefficients all greater than 97% and relatively low residual errors. However, the challenge would be to increase the size of data on these pioneer species in order to adjust models that could explain the biomass of several species in this ecosystem.

Although the fifteen models selected for biomass estimation of *D. benthamianus, Musanga cecropioides* and *Trema orientalis* species all remain efficient ($R^2 > 97\%$), we recommend single input models for these three species:

Musanga cecropioides: $\ln Btot = 8,30 + -8.13 \times \ln(D) + 3.51 \times (\ln(D))^2 + -0.380 \times (\ln(D))^3$

Musanga cecropioides: $\ln Btot = 5.83 + -6.52 \times \ln(D) + 2.8 \times (\ln(D))^2 - 0.281 \times (\ln(D))^3$

Trema orientalis: $\ln Btot = 2.911 - 2.204 \times \ln(D) + 1.430 \times (\ln(D))^2 - 0.168 \times (\ln(D))^3$, they're more efficient.

Compliance with ethical standards

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Conflict of interest

The authors declare no conflict of interest.

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