

## Site-specific allometric equations for biomass prediction of *Moringa oleifera* Lam. in the northern zone of Cameroon

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### ABSTRACT

**Aims:** *Moringa oleifera* is a species with multivariate uses. Despite its socio-economic importance in the northern part of Cameroon, it remains undervalued. Understanding its contribution to the fight against climate change requires precise quantification of its biomass. However, there is a lack of site-specific allometric equations for estimating this biomass. The development of site-specific allometric equations of *M.oleifera* is therefore imperative to facilitate this effort.

**Study design:** To achieve this objective, a sample of fourteen trees of *M.oleifera* was taken in from the two areas and divided into diameter classes between 5 and 13 cm.

**Place and Duration of Study:** Sample: Agroecological zones of High guinean savannahs and Sudano-sahelian zone of Cameroon between April and July 2021.

**Methodology:** The diameter at breast height of these trees and their height were measured. After tree cutting, biomass of compartments of leaves, branches, trunks and roots were determined after drying and weighing. Various allometric equations between biomasses and two parameters of the tree (the diameter and the height) were tested. The adjusted coefficient of determination ( $R^2_{adj}$ ), the residual standard error (RSE) and the Akaike Information Criteria were used for choosing the best models.

**Results:** The different analyses showed that diameter at breast height (DBH) is the variable that offers the best correlation for global above-ground (AGB) and below-ground (BGB) biomass in contrast to the other compartments. Thus, the best models for predicting total above-ground biomass of *M. oleifera* are  $-3.653-0.250\ln D+5.119\ln H$  (Sudano-Sahelian),  $-3.916 + 2.982\ln D$  (High guinean Savannahs),  $-2.340 + 2.117\ln D$  (Global) and finally for roots  $-6.426 + 2.182\ln D$ .

**Conclusion:** These mathematical models could help in estimating the biomass of *Moringa oleifera* in agroforestry systems under the ecological conditions of Cameroon.

*Keywords: allometric equations, biomass, M. oleifera, agroforestry systems, northern Cameroon*

## 1. INTRODUCTION

A major challenge in agroforestry is the choice of high-performance plant species. This issue is attracting more attention lately due to changing climatic conditions. *Moringa oleifera* represents a promising species to meet such challenges [1]. Indeed, *M. oleifera* has its origins in the regions of Agra and Oudh in northeastern India and those of Chenab in the south of the Himalayan mountain range [2,3]. This plant is now cultivated and acclimatized in many tropical and subtropical regions around the world [4,5]. *M. oleifera* is a species of socio-economic interest [6] which adapts well to local conditions [7]. The use of all its parts makes this plant an asset in contributing to the fight and prevention of malnutrition [8,9,10,11]. Several factors contribute to this widespread interest: its cultivation in a variable range of climatic and geographical conditions, its high production yields, nutritional relevance for humans and animals [12]. This shrub, belonging to the Moringaceae family, is widely exploited for its preventive and curative properties for several diseases [13]. The exploitation of the products from this plant makes it possible to improve the diet as well as the health of the population and to generate income for the producers [14]. However, knowledge on the biomass produced by this species is very limited in the ecological conditions of the northern zone of Cameroon. However, biomass provides important information on the ecological and economic performance of agrosystems [15,16]. Moreover, biomass provides information on the potential of atmospheric carbon sequestration by a species. This issue is particularly relevant to the global concern of climate change mitigation due to greenhouse gas emissions [17]. Indeed, climate change has received increasing attention, particularly with regard to the sustainable management of forest ecosystems [18]. These ecosystems, including sustainably managed agroforestry systems, can contribute to climate change mitigation [19,20,21,22]. It is with this regard that economic incentives such as REDD+ (Reduction of emissions from deforestation and forest degradation + conservation and sustainable management of forests) have been designed to offset carbon inputs by reducing emissions from deforestation and forest degradation [23]. The success of REDD+ thus relies on robust, reliable and efficient procedures for assessing carbon stocks [24]. Data on species of socio-economic importance such as *M.oleifera* must therefore be documented [25] to build a database to predict biomass and, in turn, carbon stocks. Specific biomass estimation models must be formulated. In the tropical forests of Africa, biomass estimates are hampered by the lack of accurate allometric equations [26,27]. Therefore, many biomass estimates in Africa have relied on pantropical models [28, 29]. However, the applicability of these general equations in tropical African ecosystems is questionable [30,26,27]. Species- and site-

specific allometric equations are therefore needed for reliable monitoring and verification of carbon stocks [18]. The objective of this study was to develop allometric equations that accurately predict the biomass of *M. oleifera* in agrosystems, thus addressing Goal 13 of the Sustainable Development Goals (to take urgent action to address climate change and its impacts) as well as the opportunities offered by the Clean Development Mechanism (CDM) and REDD+.

## 2. MATERIAL AND METHODS

### 2.1. Study sites

This study was carried out in the northern zone more precisely in the high Guinean savannahs and the Sudano-Sahelian zone of Cameroon. These areas are located between 6° and 8° North latitude, 10° and 16° East longitude for the High guinean savannahs (HGS) and between 7° and 10° North latitude and between 12° and 16° East longitude for the Sudano-Sahelian zone (SS) (Fig.1) [31]. The climate of the HGS has two distinct seasons (the rainy season followed by the dry season). The dry season extends from November to March [32]. The rainy season from April to October. During this period, the rhythm of the rains is sustained with more than 200 mm of monthly rain for five months and 1600 to 1800 mm/year. The SS zone is characterized by annual rainfall reaching 1290 mm/year. It is characterized by 6 to 7 months of rain (April to October) and 5 to 6 months of drought (November to March) [33]. Sudano-Sahelian type are ferruginous with a predominantly sandy texture, clayey horizon at depth [34,35]. Concerning the vegetation, the HGS are covered at more than 90% by a shrubby savannah or open tree whose dominant species are *Daniellia oliveri* and *Lophira lanceolata* [36]. As for the SS zone, it abounds in shrubby to wooded or tree savannahs and even open forests in the Bénoué basin. The main plant formations are: gregarious formations with *Isobertinia doka* and *Isobertinia tomentosa*, formations with *Boswellia odorata*, *Sclerocarya birrea*, *Prosopis africana* [37]. Livestock raising predominates peasant activities in the HGS [35,38]. The SS zone is marked by a dominant production system based on cotton and food crops [39].



were selected on the basis of their availability and the absence of human exploitation (traces of pruning or limping) or disease.

### **2.2.2. Data collection for the establishment of allometric models**

The felling down of trees was preceded by the measurement of their DBH. Each tree was then separated into trunk, branches and leaves as well as small twigs, following the method described by Picard et al. [41]. The different trunk compartments, branches and leaves were weighed using a 50 kg capacity scale after which the total wet weight of each compartment of the tree was determined in the field. Trunks, roots and large branches were cut into discs. A disc sample from the trunk, a branch and a leaf sample were taken and weighted. At the level of the root, disc samples were taken at random after clearing the roots of mud. Samples obtained were immediately stored in plastic bags and transported to the National school of agro-industrial sciences of the University of Ngaoundere precisely in the Physicochemical laboratory where their dry masses were determined. In the laboratory, samples of leaves, trunks, branches and roots were oven-dried at a constant temperature of 75°C to constant weight after 72 hours. The water content (WC) in the different compartments (leaves, branches, trunk, root) was determined after drying the samples according to the formula:

$$WC (\%) = ((WM-DM)/DM)*100 \quad (1)$$

Where: WC is the water content of the samples in percentage, WM and DM are respectively the wet mass (Kg) and the dry mass (Kg) of the sample.

From the water content of the samples, the total dry mass (TDM) of each compartment was calculated according to the French standard NF M 03-002 using the following formula:

$$TDM = 100 * TWM / (100 + WC) \quad (2)$$

Where: TDM is the total dry mass, TWM is the total wet mass (Kg). The total dry masses are called biomass and expressed in Kilograms (Kg) [42]. The total dry mass of each tree was estimated by adding the dry mass of the different compartments of the trees.

### **2.3. Data analysis**

Allometric equation were established using the physical parameters of the tree, namely diameter at breast height (DBH), height (H), and tree biomass (B) [43]. Prior to this step, since allometric relationships are influenced by growth stages [44], the relationship between tree height (H) and diameter (D) (H–D) was initially analyzed by plotting H (m) versus D (cm) to identify the diameter classes where the predictions were better. The models frequently found in the literature to predict biomass are of two types: the power

model and the polynomial model [45]. In this study, the power model was used because it has long been noted that a growing plant maintains the proportion of weight between different parts [46,47] and because the polynomial model frequently exhibits abnormal behavior outside their range of validity. The mathematical model commonly used to predict the phytomass was adopted:

$$B = aD^b \quad (3)$$

Where  $a$ ,  $b$  and  $c$  are the scaling or adjustment coefficients,  $D$  the DBH and  $B$  the aboveground biomass of a tree [44,48,49,50]. In this study, three allometric models [40] were evaluated to predict the aboveground biomass of *M.oleifera*:

$$B = aDb \quad (4)$$

$$B = a (D^2H)^b \quad (5)$$

$$B = aD^bH^c \quad (6)$$

In order to eliminate the influence of the heteroscedasticity of the data, the transformation in logarithmic form is regularly used to change the nonlinear model into a linear model [51]. Therefore, (4), (5) and (6) have been converted to (7), (8) and (9) respectively as follows:

$$\ln(B) = a + b \cdot \ln(D) \quad (7)$$

$$\ln(B) = a + b \cdot \ln(D^2H) \quad (8)$$

$$\ln(B) = a + b \cdot \ln(D) + c \cdot \ln(H) \quad (9)$$

For each of these models, the following indicators that permits good quality when a model is adjustment, were used to select the best model:

- The adjusted  $R^2$ : This coefficient, between 0 and 1, gives an idea of the proportion of the explained variability of the aerial biomass by the model.

The closer it is to 1, the better the model is [52]

$$R^2 = \frac{1-SCR}{SCT} \quad (10)$$

Where SCT: Sum of Total Squares and SCR: Sum of Residual Squares.

- The residual standard error (RSE): square root of the residual variance around the regression function. The lower a model has a CSR, the better it is:

- $$RSE = \sqrt{\frac{\sum (AGB_{obs} - AGB_{pred})^2}{n-2}} \quad (11)$$

Where RSE: Residual standard error; AGB obs: Measured above ground biomass; AGB pred: Predicted above-ground biomass, n=data points in population.

- Akaike's Information Criterion (AIC): The quality measurement of adjustment of a regression model proposed by [53]. The best model minimizes the value of the AIC obtained by the following formula:

$$AIC = -2 \ln(L) + 2p \quad (12)$$

with p the number of model parameters and L the maximized likelihood.

The logarithmic transformation of the data generally leads to a bias in the estimation of the phytomass [28,54]. A correction is necessary and consists in multiplying the estimated phytomass by a correction factor (CF) which is calculated as follows:

$$CF = \exp \{RSE^2/2\} \quad (13)$$

where CF is a number that is always greater than 1. For as long as these criteria are low (particularly RSE and AIC), and the higher the adjusted  $R^2$ , the better the model will be [28].

All these statistical analyses were performed with Microsoft office Excel 2016, and the allometric equations were developed in R Studio software who benefits from a strong community of users who can freely contribute to the development of the software by adding additional functionalities.

In R, producing an analysis generates a large number of results of all sorts with a display reduced to a minimum and the user can ask to see additional or more detailed results. However, as R is more like a programming language than a software itself, the learning curve can be a bit "steep", especially for those who have never programmed before. [55].

### 3. RESULTS

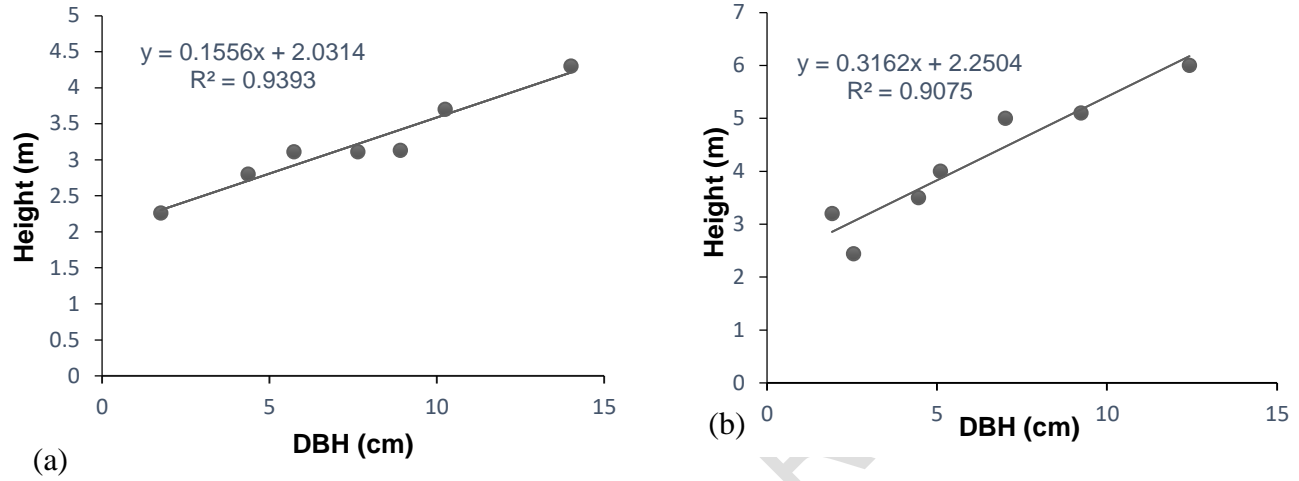
#### 3.1. Relationship between diameter and height

The correlation established between the diameter and the height of the individuals in the two zones is significant (Fig. 2) with a coefficient of determination of 0.93 and 0.90 respectively for the High guinean savannahs (HGS) and the Sudano-Sahelian zone (SS). In the field of forestry, height-diameter relationships make it possible to best estimate the

height of a tree knowing its diameter. Thus the allometric relationship of all the individuals measured fits better with the following equations:

(a) HGS:  $H = 0.316D + 2.250$ ,  $R^2 = 0.90$ ,  $n = 7$  and  $P < 0.001$ ;

(b) SS:  $H = 0.155D + 2.031$ ,  $R^2 = 0.93$ ,  $n = 7$  and  $P < 0.001$ .



**Figure 2: Relationship between diameter and height of *M.oleifera***

The diameter-height relationship is a good indicator of the ecological conditions for the growth of a species [56]. Studies conducted by Fayolle et al. [57] and Imani et al. [58] have suggested that the appropriateness of a model function for predicting tree height in forest sites may vary due to differences in height–diameter relationship of trees in different forest sites. The equations obtained present the determination coefficients in the order: 93.93% and 90.75%. They make it possible to predict the height of a tree from the diameter. This distribution model shows that it is in the middle diameter classes 5-9 cm that it is appropriate to predict the total height of the individuals studied. The biases observed are lower for the lower diameter class (class I) than those of the upper diameter class (class III) on the distribution of the point cloud.

### 3.2. Development of allometric equations specific to *Moringa oleifera*

The various data from the allometric equations obtained by testing the three mathematical models for each zone; High guinean savannah (HGS) and the Sudano-Sahelian (SS) zones, as well as a model grouping the data from the two zones (Global), are presented in Tables 1, 2, 3, 4, 5 and 6 according to the different compartments. The variables a, b and c are the model adjustment coefficients, N the number of samples,  $R^2_{aj}$  the adjusted coefficient of determination, CF the correction factor, RSE the residual standard error and AIC the Akaike information criterion.



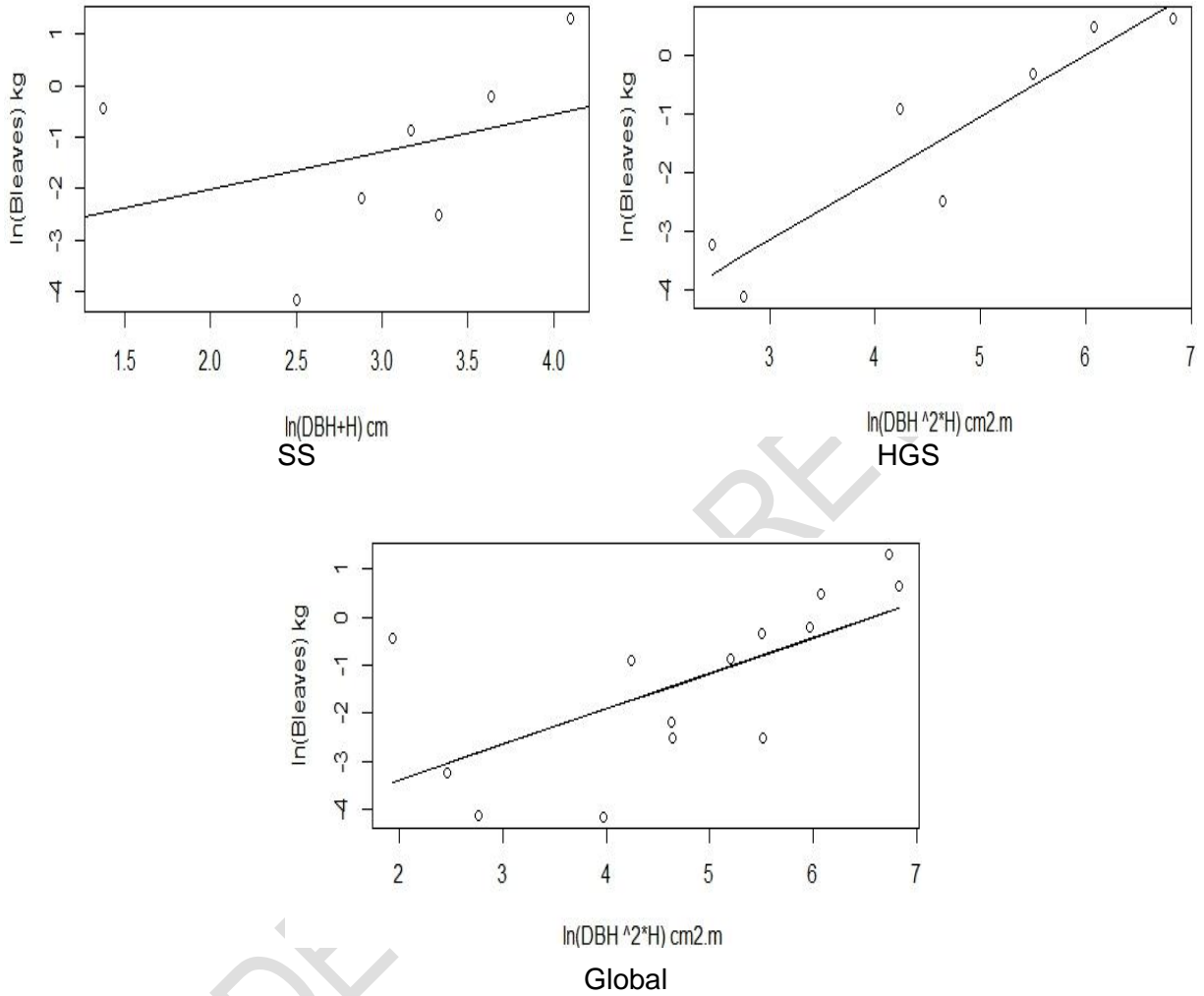
### 3.2.1. Leaves

The constants regression of all the equations retained except those of the SS zone are statistically significant ( $P < .05$ ). They range from  $P = .31$  to  $P = .49$  (SS),  $P = .004$  to  $P = .01$  (HGS) and  $P = .01$  to  $P = .03$  (Global). The presented prediction models explain the variation in the biomass of about -6.5 to 15.5%, 79.8 to 82.5% and 32.2 to 36.5% for the SS zone leaves, HGSs and the northern zone (Global) respectively. Linear models with DBH as the sole predictor predicted leaf biomass of *M. oleifera* as the least. The incorporation of height as a second variable in addition to DBH was necessary for a better estimation of leaf biomass (Table 1). The addition of height in these models improved the quality of the fit in the form  $\ln(B)=a+b\ln(D)+c\ln(H)$  (SS) and  $\ln(B)=a+b\ln(D^2H)$  (HGS and Global). This improvement is observed with the leaf models of the two zones as well as that grouping the two zones (AIC = 30.955; RSE = 1.65; Adj.R<sup>2</sup> = 0.155 (SS); AIC = 20.102; RSE = 0.784; Adj.R<sup>2</sup> = 0.825 (HGS) and AIC = 53.116; RSE = 1.406; Adj.R<sup>2</sup> = 0.365 (Global)). We can therefore adjust a simple linear regression for predicting  $\ln(B)$  relative to  $\ln(D+H)$  and  $\ln(D^2H)$  (Fig. 3).

**Table 1:** Allometric models of leaves

Zones	Allometrics models	a	b	c	R <sup>2</sup> adjusted	RSE	N	CF	AIC	P
SS	$\ln(B)=a+b\ln(D)$	-2.799 (2.17)	0.815 (1.11)		0.083	1.868	7	5.724	32.259	0.49
	$\ln(B)=a+b\ln(D^2H)$	-3.151 (2.44)	0.384 (0.48)		-0.065	1.852	7	5.556	32.141	0.46
	$\ln(B)=a+b\ln(D)+c\ln(H)$	-13.061 (6.88)	-3.801 (3.13)	16.417 (10.56)	0.155	1.65	7	3.901	30.955	0.31
HGS	$\ln(B)=a+b\ln(D)$	-5.564 (0.88)	2.544 (0.51)		0.798	0.841	7	1.424	21.087	0.004
	$\ln(B)=a+b\ln(D^2H)$	-6.343 (0.95)	1.059 (0.19)		0.825	0.784	7	1.359	20.102	0.002
	$\ln(B)=a+b\ln(D)+c\ln(H)$	-7.610 (2.1)	1.289 (1.27)	2.243 (2.74)	0.804	0.828	7	1.408	21.319	0.01
Global	$\ln(B)=a+b\ln(D)$	-4.194 (1.26)	1.631 (0.60)		0.323	1.452	14	2.869	54.020	0.01
	$\ln(B)=a+b\ln(D^2H)$	-4.853 (1.25)	0.736 (0.25)		0.365	1.406	14	2.686	53.116	0.01
	$\ln(B)=a+b\ln(D)+c\ln(H)$	-6.069 (1.83)	0.841 (0.85)	2.562 (2.00)	0.356	1.416	14	2.725	54.084	0.03

Biomass (B), diameter at breast height (D), height (H), Coefficient of regression model (a, b and c), specimen number (N), coefficient of determination adjusted ( $R^2_{adj}$ ), correction factor (CF), residual standard error (RSE) and Akaike information criteria (AIC).



**Fig. 3:** Regression models between biomass and physical parameters of trees (D and H) for the leaves

### 3.2.2. Branches

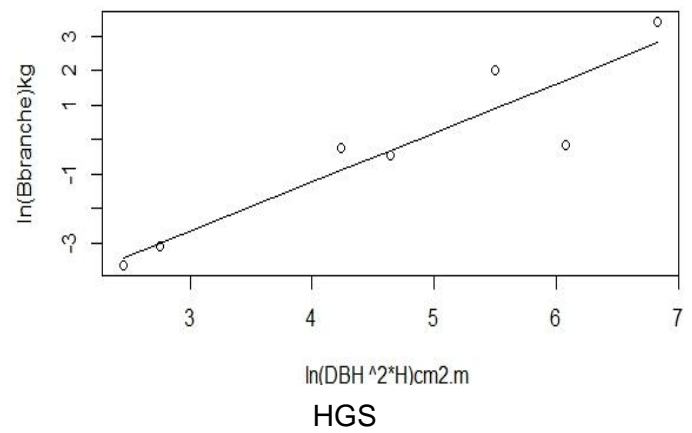
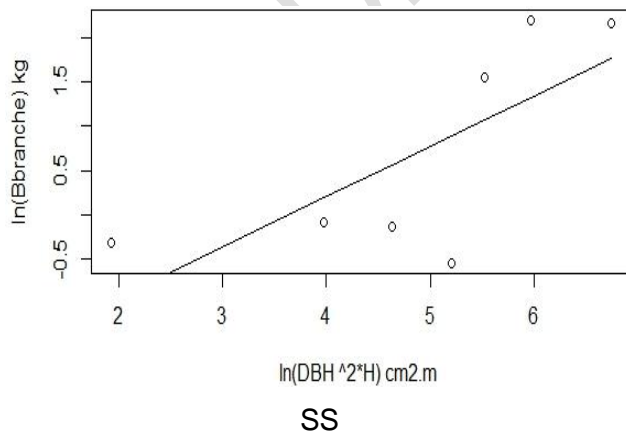
The constants regression of all the equations retained are statistically significant ( $P < .05$ ) except those of SS zone. They range from  $P = .06$  to  $P = .16$  (SS),  $P = .003$  to  $P = .02$  (HGS),  $P < .001$  (Global). The presented prediction models explain about 39-43.9%, 77.6-80.8% and 59.1-62.5% of the variation in branch biomass as regard the SS, HSG and Northern (Global) zones respectively. Linear models with DBH as the sole predictor were used to predict the biomass of the branches of the Global (AIC = 48.941; RSE = 1.211;

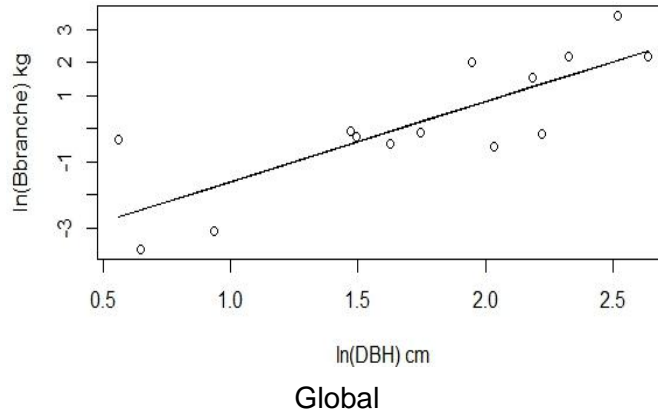
Adj.R<sup>2</sup> = 0.623). For the SS zone and the HGSs, the incorporation of the height as a second variable in addition to the DBH in the form  $\ln(B)=a+b\ln(D^2H)$  was necessary for a better estimation of the biomass of their branches (Table 2) and (Fig. 4).

**Table 2:** Allometric branches models

Zones	Allometrics models	a	b	c	R <sup>2</sup> adjusted	RSE	N	CF	AIC	P
<b>SS</b>	$\ln(B)=a+b\ln(D)$	-1.685 (1.08)	1.282 (0.55)		0.420	0.93	7	1.541	22.498	0.06
	$\ln(B)=a+b\ln(D^2H)$	-2.075 (1.20)	0.570 (0.23)		0.439	0.915	7	1.519	22.270	0.06
	$\ln(B)=a+b\ln(D)+c\ln(H)$	-4.996 (3.98)	-0.206 (1.81)	5.296 (6.11)	0.390	0.954	7	1.576	23.294	0.16
<b>HGS</b>	$\ln(B)=a+b\ln(D)$	-5.906 (1.16)	3.438 (0.66)		0.808	1.104	7	1.839	24.890	0.003
	$\ln(B)=a+b\ln(D^2H)$	-6.909 (1.30)	1.420 (0.27)		0.819	1.071	7	1.774	24.469	0.003
	$\ln(B)=a+b\ln(D)+c\ln(H)$	-7.356 (3.02)	2.550 (1.83)	2.084 (3.95)	0.776	1.193	7	2.037	26.420	0.02
Global	$\ln(B)=a+b\ln(D)$	-3.996 (0.93)	2.406 (0.50)		0.623	1.211	14	2.081	48.941	0.000
	$\ln(B)=a+b\ln(D^2H)$	-4.715 (1.08)	1.033 (0.21)		0.622	1.213	14	2.086	48.985	0.000
	$\ln(B)=a+b\ln(D)+c\ln(H)$	-4.337 (1.63)	2.263 (0.76)	0.465 (1.78)	0.591	1.261	14	2/214	50.855	0.002

Biomass (B), diameter at breast height (D), height (H), Coefficient of regression model (a, b and c), specimen number (N), coefficient of determination adjusted (R<sup>2</sup>adj), correction factor (CF), residual standard error (RSE) and Akaike information criteria (AIC).





**Fig. 4:** Regression models between biomass and physical parameters of trees (D and H) for the branches

### 3.2.3. Trunks

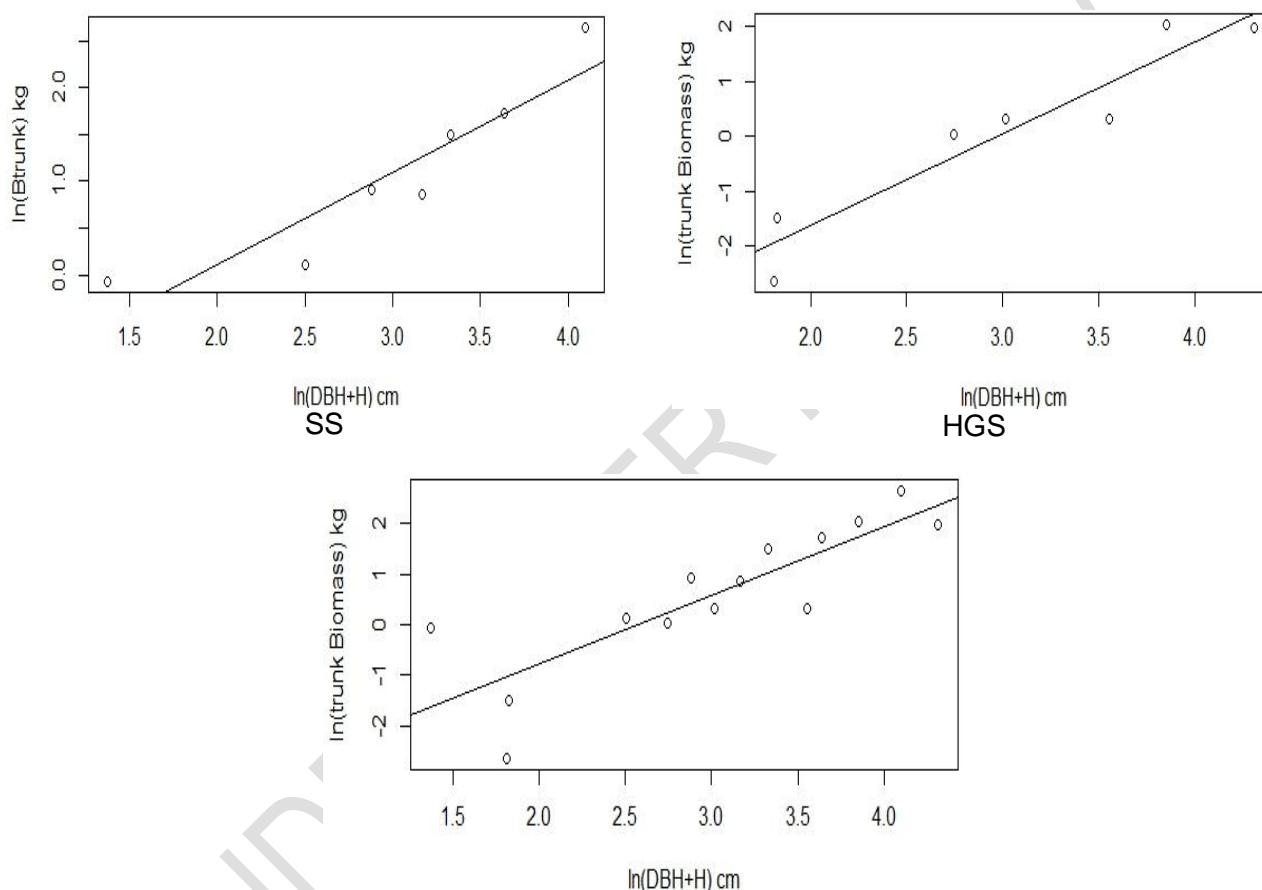
For the trunk biomass estimation models, the constants regression of all the equations retained were statistically significant ( $P < .05$ ). They ranged from  $P = .004$  to  $P = .01$  (SS),  $P < .001$  to  $P = .001$  (HGS),  $P < .001$  (Global). The presented prediction models explain about 77.6-84%, 90.9-95.2% and 74.2-78.9% of the variation in the biomass for SS zone tree trunks, HGSs and northern zone (Global) respectively. For all these areas, the incorporation of the height as a second variable in addition to the DBH giving the form  $\ln(B)=a+b\ln(D)+c\ln(H)$ , was necessary for a better estimation of the biomass of their trunks (Table 3) and (Fig. 5).

**Table 3:** Allometric trunk models

Zones	Allometrics models	a	b	c	R <sup>2</sup> adjusted	RSE	N	CF	AIC	P
SS	$\ln(B)=a+b\ln(D)$	-1.211 (0.52)	1.244 (0.26)		0.776	0.447	7	1.105	12.246	0.005
	$\ln(B)=a+b\ln(D^2H)$	-1.582 (0.55)	0.55 (0.11)		0.799	0.423	7	1.093	11.471	0.004
	$\ln(B)=a+b\ln(D)+c\ln(H)$	-3.832 (1.57)	0.065 (0.71)	4.192 (2.42)	0.840	0.378	7	1.074	10.333	0.011
HGS	$\ln(B)=a+b\ln(D)$	-3.942 (0.44)	2.471 (0.25)		0.94	0.417	7	1.090	11.289	0.000
	$\ln(B)=a+b\ln(D^2H)$	-4.574 (0.62)	1.002 (0.12)		0.909	0.511	7	1.139	14.135	0.000
	$\ln(B)=a+b\ln(D)+c\ln(H)$	-2.641 (0.94)	3.270 (0.57)	-1.871 (1.23)	0.952	0.372	7	1.071	10.102	0.001
Global	$\ln(B)=a+b\ln(D)$	-2.769 (0.50)	1.929 (0.27)		0.788	0.656	14	1.240	31.782	0.000

$\ln(B)=a+b\ln(D^2H)$	-3.244 (0.64)	0.807 (0.13)		0.742	0.723	14	1.298	34.526	0.000
$\ln(B)=a+b\ln(D)+c\ln(H)$	-2.068 (0.84)	2.224 (0.39)	-0.958 (0.92)	0.789	0.654	14	1.238	31.486	0.000

Biomass (B), diameter at breast height (D), height (H), Coefficient of regression model (a, b and c), specimen number (N), coefficient of determination adjusted ( $R^2_{adj}$ ), correction factor (CF), residual standard error (RSE) and Akaike information criteria (AIC).



#### Global

**Fig. 5:** Regression models between biomass and physical parameters of trees (D and H) for the trunks

#### **3.2.4. Above-ground biomass**

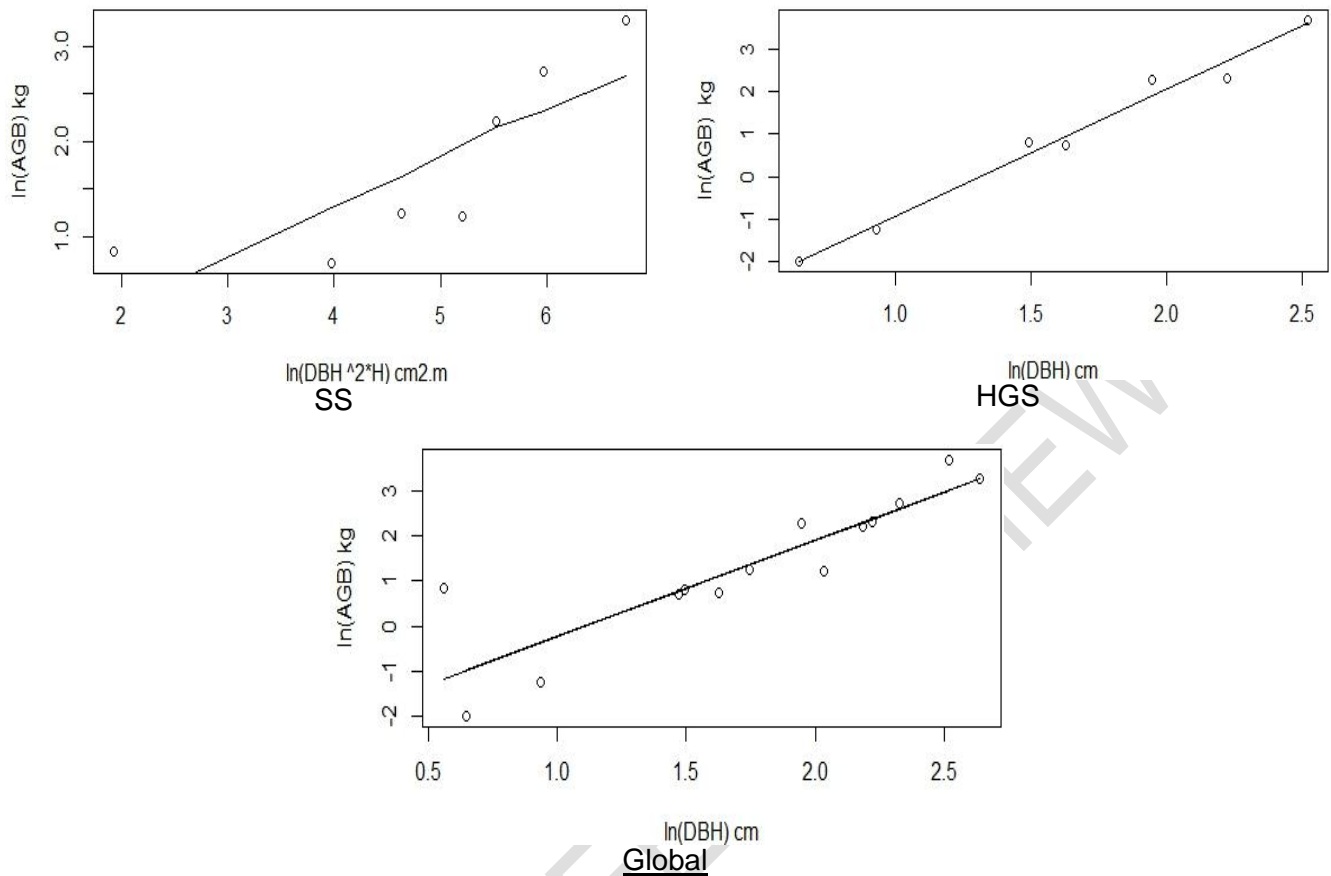
The constants regression of the equations retained are statistically significant ( $P < .05$ ). They range from  $P = .02$  to  $P = .04$  (SS),  $P < .001$  (HGS and Global). The presented prediction models explain about 60.3-66.5%, 97.5-97.9% and 74-76% of the variation in the total biomass of the SS zone, the HGSs and the northern zone (Global) respectively. DBH

as a single variable was found to be the best predictor of total biomass in HGSs and for the overall equation (Table 4) and (Fig. 6). In this model, the values of RSE and AIC are the lowest (0.291 and 6.271; 0.77 and 36.512) as well as the strongest adjusted  $R^2$  (0.979 and 0.760) compared to the two other models. As for the SS zone, the linear regression of this model expresses higher values of RSE and AIC (0.627 and 16.979) as well as a lower adjusted  $R^2$  (0.603). This model is therefore the least suitable for predicting the total biomass of *M.oleifera* in the SS zone.

**Table 4:** Allometric models of above-ground biomass

Zones	Allometrics models	a	b	c	$R^2_{\text{adjusted}}$	RSE	N	CF	AIC	P
<b>SS</b>	$\ln(B)=a+b\ln(D)$	-0.453 (0.73)	1.189 (0.37)		0.603	0.627	7	1.217	16.979	0.02
	$\ln(B)=a+b\ln(D^2H)$	-0.816 (0.80)	0.529 (0.15)		0.628	0.607	7	1.202	16.522	0.02
	$\ln(B)=a+b\ln(D)+c\ln(H)$	-3.653 (2.40)	-0.250 (1.09)	5.119 (3.69)	0.665	0.576	7	1.180	16.230	0.04
<b>HGS</b>	$\ln(B)=a+b\ln(D)$	-3.916 (0.30)	2.982 (0.17)		0.979	0.291	7	1.043	6.271	0.000
	$\ln(B)=a+b\ln(D^2H)$	-4.750 (0.37)	1.224 (0.07)		0.977	0.304	7	1.047	6.876	0.000
	$\ln(B)=a+b\ln(D)+c\ln(H)$	-4.223 (0.80)	2.794 (0.44)	0.441 (1.05)	0.975	0.319	7	1.052	7.973	0.000
<b>Global</b>	$\ln(B)=a+b\ln(D)$	-2.340 (0.60)	2.117 (0.32)		0.760	0.777	14	1.352	36.512	0.000
	$\ln(B)=a+b\ln(D^2H)$	-2.963 (0.70)	0.907 (0.14)		0.756	0.785	14	1.360	36.796	0.000
	$\ln(B)=a+b\ln(D)+c\ln(H)$	-2.554 (1.04)	2.027 (0.48)	2.027 (1.14)	0.740	0.809	14	1.387	38.429	0.000

Biomass (B), diameter at breast height (D), height (H), Coefficient of regression model (a, b and c), specimen number (N), coefficient of determination adjusted ( $R^2_{\text{adj}}$ ), correction factor (CF), residual standard error (RSE) and Akaike information criteria (AIC).



**Fig. 6:** Regression models between biomass and physical parameters of trees (D and H) for the Above-ground biomass.

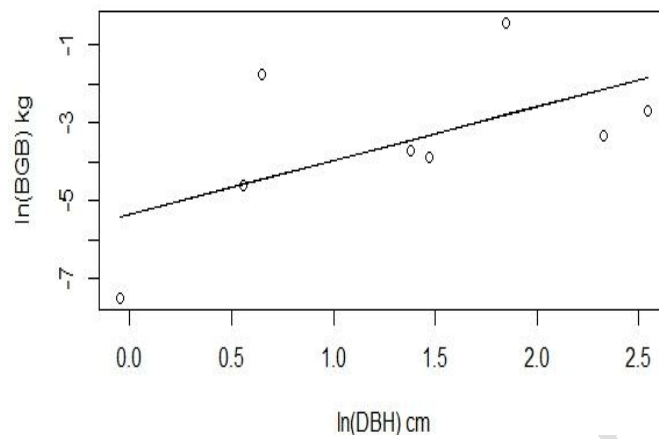
### 3.2.5. Belowground biomass

For the belowground biomass estimation models, the regression constants of all the equations retained were statistically significant ( $P < .05$ ) and ranging from  $P < .001$  to  $P = .003$ . The prediction models presented explain approximately 85.7 to 88% of the variation in belowground biomass. Belowground biomass using DBH as the sole variable performed better than that integrating height (adjusted  $R^2=0.880$ ;  $\text{RSE}= 0.719$ ;  $\text{AIC}=21.140$ ) (Table 5) and (Fig. 7).

**Table 5:** Allometric models of below-ground biomass

Allometric models	a	b	c	$R^2_{\text{adjusted}}$	RSE	N	CF	AIC	P
$\ln(B)=a+b\ln(D)$	-6.426 (0.47)	2.182 (0.30)		0.880	0.719	6	1.294	21.140	0.000

$\ln(B)=a+b\ln(D^2H)$	-7.227 (0.58)	0.952 (0.13)		0.877	0.728	6	1.303	21.327	0.000
$\ln(B)=a+b\ln(D)+c\ln(H)$	-6.709 (1.42)	2.090 (0.54)	0.329 (1.54)	0.857	0.784	6	1.359	23.068	0.003



**Fig. 7:** Regression models between biomass and physical parameters of trees (D and H) for the below-ground biomass



Taking into account the criteria for assessing the precision and accuracy of the models developed, the best models of allometric equations according to compartments and zones, retained are summarized in table 6.

Table 6: Summary of the best allometric models

Compartments	Zones	Allometric models	a	b	c	R <sup>2</sup> adjusted	RSE	N	CF	AIC	P
<b>Leaves</b>	<b>SS</b>	$\ln(B)=a+b\ln(D)+c\ln(H)$	-13.061 (6.88)	-3.801 (3.13)	16.417 (10.56)	0.155	1.65	7	3.901	30.955	0.31
	<b>HGS</b>	$\ln(B)=a+b\ln(D^2H)$	-6.343 (0.95)	1.059 (0.19)		0.825	0.784	7	1.359	20.102	0.002
	<b>Global</b>	$\ln(B)=a+b\ln(D^2H)$	-4.853 (1.25)	0.736 (0.25)		0.365	1.406	14	2.686	53.116	0.013
<b>Branches</b>	<b>SS</b>	$\ln(B)=a+b\ln(D^2H)$	-2.075 (1.20)	0.570 (0.23)		0.439	0.915	7	1.519	22.270	0.06
	<b>HGS</b>	$\ln(B)=a+b\ln(D^2H)$	-6.909 (1.30)	1.420 (0.27)		0.819	1.071	7	1.774	24.469	0.003
	<b>Global</b>	$\ln(B)=a+b\ln(D)$	-3.996 (0.93)	2.406 (0.50)		0.623	1.211	14	2.081	48.941	0.000

<b>Trunks</b>	<b>SS</b>	$\ln(B)=a+b\ln(D)+c\ln(H)$	-3.832 (1.57)	0.065 (0.71)	4.192 (2.42)	0.840	0.378	7	1.074	10.333	0.01
	<b>HGS</b>	$\ln(B)=a+b\ln(D)+c\ln(H)$	-2.641 (0.94)	3.270 (0.57)	1.871 (1.23)	0.952	0.372	7	1.071	10.102	0.001
	<b>Global</b>	$\ln(B)=a+b\ln(D)+c\ln(H)$	-2.068 (0.84)	2.224 (0.39)	-0.958 (0.92)	0.789	0.654	14	1.238	31.486	0.000
<b>Aboveground biomass</b>	<b>SS</b>	$\ln(B)=a+b\ln(D^2H)$	-3.633 (2.40)			0.628	0.607	7	0.529 (0.15)	16.522	0.02
	<b>HGS</b>	$\ln(B)=a+b\ln(D)$	-3.916 (0.30)	2.982 (0.17)		0.979	0.291	7	1.043	6.271	0.000
	<b>Global</b>	$\ln(B)=a+b\ln(D)$	-2.340 (0.60)	2.117 (0.32)		0.760	0.777	14	1.352	36.512	0.000
<b>Belowground biomass</b>	<b>Global</b>	$\ln(B)=a+b\ln(D)$	-6.426 (0.47)	2.182 (0.30)		0.880	0.719		1.294	21.140	0.000

Biomass (B), diameter at breast height (D), height (H), Coefficient of regression model (a, b and c), specimen number (N), coefficient of determination adjusted ( $R^2_{adj}$ ), correction factor (CF), residual standard error (RSE) and Akaike information criteria (AIC).

#### 4. Discussion

The significant and positive diameter-height relationship corroborates those reported by Mamadou [59] on 574 individuals of 8 species from the Ngaoundere savannas ( $R^2=0.5063$ ) and by Halilou [60] on 96 individuals belonging to 16 species from the Ngaoundere savannas. ( $R^2=0.4956$ ). The diameter-height relationship is also a good indicator of the ecological growth conditions of a species [56]. The choice of the mathematical model to adjust the parameters must be carefully considered in the estimation of the biomass of woody plants [61]. Leaf biomass, branch biomass, trunk biomass, total aboveground biomass (AGB) and belowground biomass (BGB) of individuals were calculated using the power model. This mathematical model has been widely used in the literature for predicting the standing biomass of woody species in Europe [48] and in Africa [45,61,62,63]. The allometric models developed vary from one compartment to another and even from one area to another. This variation would be linked to the variation in biomass observed between the different parts of the species Ganame et al. [61]. The sample size was small at 14 individuals. Indeed, the sample size in the development of allometric models is variable in the literature and takes into account the availability of resources (individuals) and the time allocated to the study Tchindebe et al. [64]. Some predictive allometric equations of biomass have been constructed from different numbers of individuals depending on the ecosystem: 26 trees in the forest zone of Benin by Guendehou et al. [65], 20 trees in the wooded savannah of the Sudanian zone of Senegal by Mbow et al. 2014 [66], 38 trees in the Sahelian zone in Senegal by Thiam et al. [67], 20 trees in the Sudano-Sahelian savannas of Cameroon by Tchindébé et al. [40]. However, this number of individuals is equal to that used by Manzo et al. [68] in *Faidherbia albida* agrosystems in Aguié, Niger.

Allometric models developed with diameter (D) as the only explanatory variable were the most effective in predicting branch biomass, aboveground biomass of individuals from High guinea savannas, global as well as belowground biomass. Numerous studies have shown that the DBH is the most commonly used explanatory variable for predicting the biomass of different compartments of woody species [24,45,69]. Indeed, DBH can be easily measured in the field with more precision than other dendrometric parameters. In addition, this variable is still available in inventory data Ganame et al [61]. However, linear models with DBH as the sole predictor predict leaf biomass the least in this study. The leaves are the most consumed component of *M.oleifera* [6,70,71]. This heavy use explains its abusive exploitation, making the individuals less and less healthy. Haoua et al. [72] showed that anthropogenic activities are major causes of the decrease in biomass of the most exploited parts of a woody plant. Ducta et al. [73] report the influence of sample quality on the models. In this case, it significantly influenced the establishment and choice of the leaf model. The incorporation of height as a second variable in addition to DBH was therefore necessary to improve the prediction of leaf biomass. The  $\ln(B)=a+b\ln(D^2H)$  and  $\ln(B)=a+b\ln(D)+c\ln(H)$  models better predict the biomass of other compartments and zones. Including height as a secondary variable contributes in some cases to the improvement of the model fit. Studies have reported that using DBH as a sole predictor of biomass underestimates [74] or overestimates tree biomass [75,76]. Other studies have recommended adding a second and/or third variable to the DBH to improve the accuracy of biomass estimation [77,78]. In

addition, some authors like Picard et al. [41], Ngomanda et al. [79] and Sawadogo et al. [80] have found that the inclusion of tree height as an integrated or secondary independent variable can improve model performance with the advantage of increasing the applicability of the equations at larger scales. Although obtaining tree height in forest inventories is not an easy task [81], incorporating the height parameter is known to significantly improve tree biomass [82,83]. Biomass prediction models vary across different tree compartments. The results of this study are similar to those obtained by Djomo et al. [26], Ganame et al. [61], Sawadogo et al. [80], Dimobe et al. [84] and Traore et al. [85] who all showed variation in the allometric equations depending on the parts of the tree. These models (except those of the trunk) for the same species, also vary according to the climatic zones.

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## 5. Conclusion

This study established mono-specific allometric equations to predict the biomass of leaves, branches, trunks, roots, above-ground and below-ground biomass of *Moringa oleifera* in the Sudano-Sahelian zone as well as the High guinean savannahs of Cameroon. The three models opposite were tested:  $\ln(B) = a + b \cdot \ln(D)$ ,  $\ln(B) = a + b \cdot \ln(D^2H)$  and  $\ln(B) = a + b \cdot \ln(D) + c \cdot \ln(H)$ . Tree biomass allocation varies between compartments and sites of *M. oleifera*. The DBH as a single variable proved to be the best predictor of the global biomass of the branches, above-ground biomass of the HSGs and global as well as the below-ground biomass. However, the incorporation of height as a second predictor variable improved the performance of predicting the biomass of other compartments in their respective areas. Thus, the best models for the prediction of aboveground biomass of *M. oleifera* are  $-3.653 - 0.250 \ln D + 5.119 \ln H$  (Sudano-Sahelian),  $-3.916 + 2.982 \ln D$  (High guinean savannahs),  $-2.340 + 2.117 \ln D$  (Global) and finally for the roots  $-6.426 + 2.182 \ln D$ . The results of this study provide a reliable and rapid contribution to the assessment of the biomass and carbon stock of *M. oleifera* in agroforestry systems under the ecological conditions of Cameroon.

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