

# Development of Stem Volume Equation for Urban Trees of Abomey-Calavi in Southern Benin (West Africa)

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**Abstract:** Information on growing stock is important for understanding health assessment, environmental analysis, carbon storage estimation, and economic analysis of urban forest. The stand volume estimation enables the calculation of ecosystemic services value and growth stock of urban forests. However, most of volume models fitted for multiple species in tropical forests may not be suitable for urban trees. This study was conducted to develop generic volume models for urban trees in Abomey-Calavi at the southern Benin. A total of 1608 trees belonging to 80 plant species were measured for their diameter at breast height (DBH), stem height (h) and stem volume using non-destructive sampling methods. Using a nonlinear procedure, six volume models were constructed. Cross validation and Fit statistics like standard error of estimate (SEE), relative absolute error (RAE), root mean square error (RMSE), fit index (FI), Akaike information criterion (AIC) and Willmott's agreement index (dw) were used to evaluate the efficiency and stability of different models. The six generic volume models developed in this study included both diameter and height. These models exhibited an absence of multicollinearity, with normal and homoscedastic residuals. Furthermore, they show high efficiency (IF > 0.997) and reduce of prediction errors (RMSE: 0.05388–0.06629 m<sup>3</sup>; RAE: 0.05186–0.06952), which ensuring stability in the estimates. However, the Model II was the best for predicting the stem volume of urban tree according to evaluation statistics and rank analysis. The models developed can provide stem volumes prediction with accurate estimations. Though, stem heights should be systematically measured. These models can contribute to assess the productivity of urban forests in order to pursue their sustainable management and planning.

**Keywords:** Stem Volume Equation, Urban Forest, Forest Productivity, Sustainable Management, Benin

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## 1. Introduction

The cities are facing challenges in preserving and sustaining urban forest. Rapid population growth and urban sprawling tend to eclipse the importance of plant species in the South Sahara cities' development plan. These phenomenon deeply modified the urban ecosystem, which cannot satisfy the well-being of city dwellers.

Urban greening needs better data for describing its structure and functions [1-3]. An inventory is an important step in understanding the composition, structure and growing stock of urban forest. Information on growing stock is essential for understanding health assessment, environmental

analysis, carbon storage estimation, and economic analysis of urban forest [4, 5]. However, much more information is needed to begin managing the urban forest in a sustainable way, and to guide forest managers. Quantitative information about trees, area coverage and distribution are required to evaluate the function of urban forest in supporting the resilience of urban ecosystem [3]. Volume equations are among other commonly used for this purpose [6, 7]. According to Avery and Burkhart [8], volume equations are used to estimate average content of standing trees of various sizes and species. The development of effective and accurate volume model is essential for urban forest managers and planners. Modeling is good tools for decision making

regarding the complexity of urban ecosystem.

Volume models are various mathematical statements applied to quantify tree and stand volume for forest management planning [9, 10]. These models are often used to estimate the volumes of other standing trees which cannot be over emphasized. Therefore, the prediction of volume models are required to be very accurate, flexible and valid [11]. Volume is easily estimated from direct measurable tree dimensions [12]. Trees diameter, height and forms are main variable in stand volume assessment [13]. The range, extent and availability of these variable are important for volume estimate reliability [12, 14].

Recent research works use allometric equations constructed from easily measurable tree parameters (diameter, height and forms) to estimate individual tree and stand volume [12, 15, 16]. Thus, generalized allometric models are fitted for multiple species in tropical forests, and they are usually employed to evaluate timber volume in various countries [17, 18]. Although, these models give out useful volume estimation insights into most or wider forest management applications [10], they may not be suitable for urban trees [19-21]. Indeed, there are big differences between growth environment in urban and natural forest [5]. Trees in urban areas allocated proportionately more resources to stem and canopy growth rather than height growth [22]. Which gave them more different conformations than forest trees forms [21]. It is then evident to develop new local volume models for urban trees [23].

In Benin, tree volume models are generally constructed for plantation forest [24] and natural forest species [25-27]. On this fact, the development of volume models for urban forest become an imperative. Using data from field inventory (tree height, diameter and form), timber volume has been estimated with non-destructive felling methods. Current and accurate stand volume estimation enables the calculation of ecosystemic services value and growth stock of urban forest. It make managers understanding of forest productivity and give a basis for planning sustainable forest management [28]. The aim of this research is to develop generic volume allometric models for urban trees in order to apprehend the regulation function of urban flora notably its productivity and potential of carbon storage for the cities in southern Benin.

## 2. Material and Methods

### 2.1. Study Area

Abomey-Calavi city ( $6^{\circ}20' - 6^{\circ}35'30''\text{N}$ ,  $2^{\circ}13' - 2^{\circ}24'30''\text{E}$ ) is located in the Guineo-Congolese zone of southern Benin. The climate is sub-tropical with four distinct seasons throughout the year (Two wet and two dry seasons). The site is characterized by a bimodal precipitation distribution. March and July receive higher rainfall, while September–November receive less rainfall. The mean annual rainfall and temperature recorded were 1277.67mm (1982–2018) and  $27.59^{\circ}\text{C}$  (1982–2018), respectively. The Soils are mainly ferrallitic on loose clayey sediment of continental terminal, on sandstone and

colluvial materials. These climatic and pedological conditions are favorable for plant species establishment in the city. The urban area of Abomey-Calavi district covers 257.11 km<sup>2</sup> presently. The population density is 1443.30 persons per km<sup>2</sup> with an average annual growth rate of 4.97% [29]. This rapid population growth rate is a challenges in preserving and sustaining urban forest.

### 2.2. Data Collection

The data was collected using stratified random sampling approach [30, 31]. The inventory of urban trees was done in square sample plots of one-hectare size to assess stem volume. One hundred and sixteen (116) plots were prospected in whole stand. The free version of Mobil Topographer 9.3.2 and QField 1.5.3 were utilized for location and moving in the sample plots area, respectively.

A non-destructive method was used to measure all living tree species during the inventory process [24, 32]. It is an alternative method for obtaining tree volume data without cutting down or cause physical damage to the trees [33, 34]. In each plot, the following variables were measured on the trees: (1) diameter at breast height outside bark ( $dbh \geq 5\text{ cm}$ ); (2) stem height (height measured at the ground level to the crown base). The diameter at breast height was measured at 30 cm above the buttresses, if present [35]. All trees were also counted and identified at species level. The measurements of diameter were made using diameter tape whereas those of the heights were done using an optical clinometer (Brunton Sum 360LA).

After the inventory process, trees for consecutive diameter measured along the stem, were selected proportionally to species frequency in a plot. However, hollow trees and trees with a broken top were not taken into account [24, 27]. A total of 1608 trees belonging to 80 plant species were considered to quantifying the stem volume (Table 1). Three segments were considered during the measurement of diameter along the bole (base segment, intermediate and upper). At the base segment of the tree (from ground level to 0.3 m), the first three measurements were of the constant length of 0.1 m. In the following segment (0.3–1.3 m height), five measurements were made at 0.20 m interval. The upper section started at 1.30 m above the ground, here, the diameter outside bark was measured at 1 m interval up to the maximum height measurable using a ladder and climbing techniques [32]. These measurements were considered to describe tree profile in the lower section in which taper changes so rapidly low on the bole [36].

According to the global form of trees inventoried, the volume of each tree was estimated with three equations. The volume of bottom section was obtained using the formula for truncated Neloid [37], and then Smalian's formula was used to compute the volume to the following section (0.3–1.3 m height) of the tree. For the top stem section (up to 1.3 m height), truncated cone formula was used to calculate its volume [16, 25]. The volume of the different sections were summed up to calculate the stem volume [38, 39].

**Table 1.** Descriptive statistics of urban trees observed data.

Statistics	DBH (cm)	Height (m)	Volume (m <sup>3</sup> )
Model fitting dataset (80% of observed data)			
No. Of observation	1286	1286	1286
Minimum (Min)	6.3636	1.300	0.0266
Maximum (Max)	222.7272	10.8012	22.1585
Mean	27.7359	3.6241	0.4964
Standard-Deviation	21.5612	1.9353	1.2125
Model validation dataset (20% of observed data)			
No. Of observation	322	322	322
Minimum (Min)	6.3636	1.3	0.0276
Maximum (Max)	197.2727	8.3846	16.4342
Mean	28.3061	3.5820	0.4999
Standard-Deviation	21.5666	1.8789	1.2048

### 2.3. Data Analysis

To fit and test the possibility of a generic volume equation for the whole city, seventy-four models (8 single-predictor models and 66 two-predictor models) had been constituted from several models commonly published in forestry literatures [5, 6, 38, 40-43]. These models were fitted in their nonlinear form to predict stem volume [43-45]. Only, those which were successfully satisfied the assumptions underlying nonlinear regression models were considered in this paper (Table 2).

**Table 2.** Models for stem volume predictions of urban trees.

Models	Volume model
I	$V = \beta_0 * DBH^{\beta_1} + \beta_2 * (DBH^{\beta_3} * h) + \varepsilon_i$
II	$V = \beta_0 * DBH^{\beta_1} + \beta_2 * (DBH^{\beta_3} * h^{\beta_4}) + \varepsilon_i$
III	$V = \beta_0 * DBH + \beta_1 * DBH^2 + \beta_2 * (DBH^{\beta_3} * h) + \varepsilon_i$
IV	$V = \beta_0 + \beta_1 * DBH^2 + \beta_2 * h + \beta_3 * (DBH^2 * h) + \varepsilon_i$
V	$V = \beta_0 * DBH + \beta_1 * h + \beta_2 * (DBH^{\beta_3} * h) + \varepsilon_i$
VI	$V = \beta_0 + \beta_1 * DBH^2 + \beta_2 * h + \beta_3 * (DBH^2 * h^{\beta_4}) + \varepsilon_i$

$V$  : over-bark stem volume (in m<sup>3</sup>), DBH: diameter at breast height (in cm), h: stem height (in m),  $\varepsilon_i$ : random error, and  $\beta_0, \beta_1, \beta_2, \beta_3$  and  $\beta_4$  are parameters to be estimated from the data.

Exploratory data analysis was carried out to identify the dispersion and distribution of the variable used for modeling. The presence of heteroscedasticity was checked by visual inspection of the standardized residuals plots and tested using White-Pagan's general test [44] at  $\alpha=0.05$ . The multicollinearity was assessed in the model by condition number (CN). CN is calculated as the square root of the ratio between the maximum and minimum eigenvalue of the correlation matrix [46]. The collinearity associated problems was considered when CN value was greater than  $\sqrt{1000}$  [47].

To account the heteroscedasticity in the model, the nonlinear generalized least squares function (gnls) in the R package [48] was used with the argument "weights=varPower()". This argument was added to the model to describe the within group heteroscedasticity. Which

allowed to give an unbiased estimates of the model parameters. When the gnls function had not satisfied model assumption, nonlinear boxcox transformation was done through "boxcox.nls()" in the R package nlwr. To assess whether or not the residuals are normally distributed, the Shapiro-Wilk's normality test was used at 0.05 level significance [49]. The significance of regression coefficients ( $\beta_i$ ) was tested against zero using t-test ( $\alpha=0.05$ ).

### 2.4. Model Evaluation and Validation

To assess the performance of the models, five goodness-of-fit statistics were computed using the formulation presented by [49-51] (Table 3): standard error of estimate (SEE), relative absolute Error (RAE), root mean square error (RMSE), fit index (FI) and Akaike information criterion (AIC).

**Table 3.** Parameters used to assess the performance of volume models.

Evaluation statistics	Equations
Standard error of estimate (SEE)	$SEE = \sqrt{\frac{1}{n-k} \sum_{i=1}^n (V_i - \hat{V}_i)^2}$
Relative Absolute Error (RAE)	$RAE = \frac{\frac{1}{n} \sum_{i=1}^n  V_i - \hat{V}_i }{\frac{1}{n} \sum_{i=1}^n  V_i - \bar{V} }$
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (V_i - \hat{V}_i)^2}$
Fit index (FI)	$FI = 1 - \frac{\sum_{i=1}^n (V_i - \hat{V}_i)^2}{\sum_{i=1}^n (V_i - \bar{V})^2}$
Agreement index (dw)	$dw = 1 - \frac{\sum_{i=1}^n (V_i - \hat{V}_i)^2}{\sum_{i=1}^n ( \hat{V}_i - \bar{V}  +  V_i - \bar{V} )^2}$
Akaike's Information Criterion	$-2\log(L) + 2(p + 1)$

$V_i$  : over-bark stem volume of  $i^{th}$  tree,  $\bar{V}$  : mean over-bark stem volume of the trees,  $\hat{V}_i$  : predicted over-bark stem volume of  $i^{th}$  tree,  $n$ : number of observations, L: maximum likelihood of the model [49], p: parameters of the model

The best model was identified using rank analysis [46, 52]. The specific and relative position of each model were gotten by the method proposed by Poudel and Cao [53]. The relative rank of the model  $i$  was defined in Equation (1). In this ranking system, 1 and  $m$  indicate the best and the worst model respectively. It was applied to SEE, RAE, RMSE, FI and AIC statistics for stem volume to calculate average rank of each model.

$$R_i = 1 + \frac{(m-1)(S_i - S_{\min})}{S_{\max} - S_{\min}} \quad (1)$$

Where  $R_i$  is the relative rank of model  $i$  ( $i=1, 2, 3, \dots, m$ ),  $S_i$  is the goodness-of-fit statistics produced by model  $i$ ,  $S_{\min}$  is the minimum value of  $S_i$ , and  $S_{\max}$  is the maximum value of  $S_i$ .

The graphical analysis of residuals for the selected model was made using a scatterplots and a quantile-quantile plots at 95% probability. A scatterplots of standardized residuals and fitted values allowed to explore how better the model estimated the observed data. However, quantile-quantile plots was used to compare residuals to theoretical quantiles. Cross-validation approach was used as an additional criterion for validating the selected model [32, 53, 54]. All field data were randomly split into two subsets (calibrating set and validating set). The calibrating set comprised 80% of data (1286 trees). It was used to construct the models. The validating set comprised 20% of tree data (322 trees). This set was used to test the models [39, 55, 56]. The train dataset was used for model estimation at 1,000 times. For each iteration, RMSE, RAE, FI and AIC were computed. At the end of process, the mean of each parameter was reported with 95% confidence interval. To identify an eventual prediction bias for the best model, the relation between observed and predicted stem volumes was graphically represented on the original scale [32]. Moreover, agreement index (dw) of Willmott [57]

was also calculated to verify agreement among observed and predicted values for the selected models [50]. This index is ranged from 0 to 1, where the value close to 1 indicates perfect agreement between pairs of values [32]. The measured and predicted volumes were also compared using a paired student t-test at 5% of significance level [43].

All computations and analyzes were performed using the statistical software R [48].

### 3. Results

#### 3.1. Development of Volumetric Models

The six adjusted volumetric models included tree diameter, stem height and interaction terms as predictor variables. All of them presented significant regression coefficients at 1% level (Table 4). The standard errors for each of the coefficients vary from model to model. The lowest standard error was noticed for  $\beta_3$  in Model IV whereas the maximum standard error was for  $\beta_1$  in Model I. The values of condition number (CN: 3.238 - 17.195) of these models were less than  $\sqrt{1000}$ . The residuals of each model were normally distributed (Shapiro-Wilk's normality test: p-value > 0.001) without heteroscedasticity (White-Pagan's general test: p-value > 0.001).

**Table 4.** Statistical parameters of stem volumes fitted models. Standard error of estimated parameters in bracket; level of significance: \*\*\* (p-value < 0.001).

Models	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$
I	$V = \hat{\beta}_0 * DBH + \hat{\beta}_1 * \left( DBH^{\hat{\beta}_3} * h \right)$				
	3.090717e-3*** (8.036395e-5)	1.18101*** (1.064057e-2)	2.683241e-5*** (1.600893e-6)	2.18684*** (1.548498e-2)	-
II	$V = \hat{\beta}_0 * DBH + \hat{\beta}_1 * \left( DBH^{\hat{\beta}_3} * h^{\hat{\beta}_4} \right)$				
	3.333772e-3*** (1.197466e-4)	1.13612*** (2.057014e-2)	3.297694e-5*** (3.873651e-6)	2.173432*** (1.571985e-2)	0.9307291*** (2.894055e-2)
III	$V = \hat{\beta}_0 * DBH + \hat{\beta}_1 * DBH^2 + \hat{\beta}_2 * \left( DBH^{\hat{\beta}_3} * h \right)$				
	4.054806e-3*** (4.243279e-5)	5.293607e-5*** (3.176334e-6)	3.406283e-5*** (1.514866e-6)	2.117552*** (1.187489e-2)	-
IV	$V = \hat{\beta}_0 + \hat{\beta}_1 * DBH^2 + \hat{\beta}_2 * h + \hat{\beta}_3 * \left( DBH^2 * h \right)$				
	0.02945628*** (1.1237e-3)	1.514673e-4*** (3.61876e-6)	-1.204299e-3*** (4.681679e-4)	5.307427e-5*** (1.029161e-6)	-
V	$V = \hat{\beta}_0 * DBH + \hat{\beta}_1 * h + \hat{\beta}_2 * \left( DBH^{\hat{\beta}_3} * h \right)$				
	5.096067e-3*** (5.024491e-5)	-2.950904e-3*** (2.324569e-4)	3.917498e-5*** (1.668212e-6)	2.1192*** (1.102899e-2)	-
VI	$V = \hat{\beta}_0 + \hat{\beta}_1 * DBH^2 + \hat{\beta}_2 * h + \hat{\beta}_3 * \left( DBH^2 * h^{\hat{\beta}_4} \right)$				
	0.0302293*** (1.210197e-3)	1.35515e-4*** (1.32413e-5)	-1.518597e-3*** (4.987545e-4)	6.350504e-5*** (8.71704e-6)	0.929278*** (5.38234e-2)

$\hat{\beta}_i$ : estimates value of regression coefficient

#### 3.2. Models Accuracy and Reliability

The performance of the models was evaluated using five fit

statistics (Table 5). Among the different models, the SEE was ranged from 0.05398 to 0.06639 with a difference of 0.0124 m<sup>3</sup>. The Model II having the best value and the Model III the poorest (Table 5). Concerning the RMSE distribution, Model

III had the highest value ( $RMSE=0.06629 \text{ m}^3$ ), whereas the Model II had the lowest ( $RMSE=0.05388 \text{ m}^3$ ). The difference in RMSE among models was  $0.01241 \text{ m}^3$ . The Models II and I allowed more accurate prediction for stem volume than the others. The value of fit index (FI: 0.9970–0.9980) revealed that the six constructed models were quasi perfect. For this statistic, Model II (FI=0.9980) and Model I (FI=0.9979) performed well with a difference of 1‰ on the others. They were followed by the Models V and IV. For the Models VI and III, the FI values were around 0.9970. The Relative Absolute Error were closer to zero (RAE: 0.0519–0.0695). The

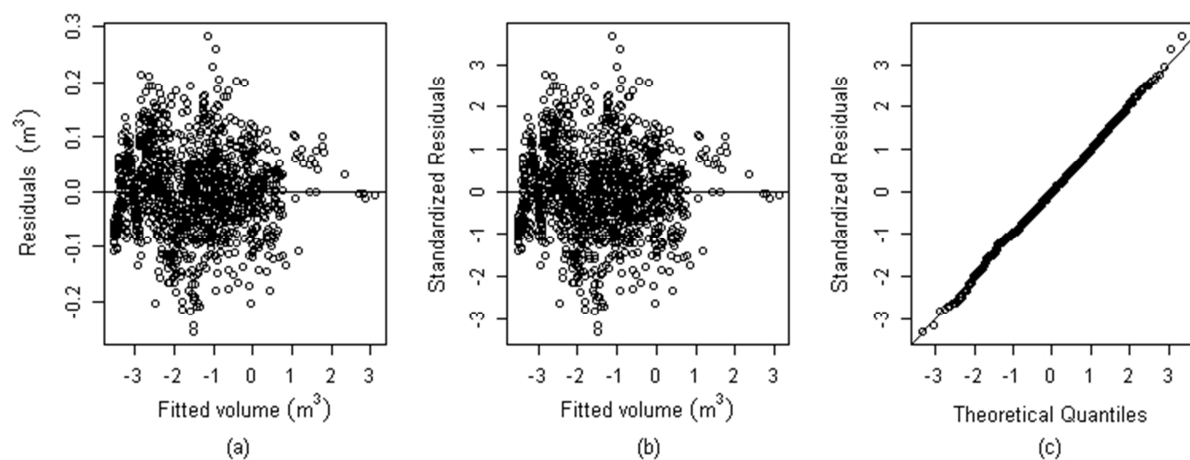
difference in RAE among models was 0.01766, which indicated a better performance of the models. A lower value was obtained in Model II while the higher value was noted in Model VI. Regarding the AIC value, Model II presented better performance with the lowest AIC (-3851.324) while the Model III exhibited the highest value ( $AIC=-3320.347$ ; Table 5). During the model ranking process, higher values of the average rank of the five fit statistics is an indication of a poor model. Based on a result, the best model was found to be Model II (Av.Rank=1), whereas Model VI (Av.Rank=5.932) was the poorest (Table 5).

**Table 5.** The indices of goodness-of-fit of six volumetric models: SEE: Standard error of estimate, RMSE: Root Mean Square Error, RAE: Relative Absolute Error, FI: Fit index, AIC: Akaike's Information Criterion. The best model is bolded.

Models	SEE	RMSE	RAE	FI	AIC	Av.Rank	CN
I	0.05559	0.05551	0.05255	0.99790	-3776.824	1.402	3.357
II	0.05398	0.05388	0.05186	0.99802	-3851.324	1.000	3.686
III	0.06639	0.06629	0.05597	0.99701	-3320.347	5.041	17.195
IV	0.06404	0.06394	0.06782	0.99722	-3412.989	4.647	12.923
V	0.06132	0.06123	0.05660	0.99745	-3524.531	3.039	3.238
VI	0.06633	0.06620	0.06952	0.99702	-3321.585	5.932	13.715

The graphic presentation of residuals plots against predicted stem volume indicated no identifiable trend of scatter-plots (Figure 1a). There were also no heteroscedacity problems (Figure 1b). The selected models presented uniform residual distributions over the range of predicted volume. These residuals were adequate for theoretical normal

distribution (Figure 1c). The standardized residuals values higher than -3 and 3 indicated sight presence of discrepant observations. However, these observations had a small contribution to the estimates and, represented real values of the sampled populations. Furthermore, they were kept in the analysis process.



**Figure 1.** Scatterplots of residuals against fitted values (a), scatterplots of standardized residuals against fitted values (b), and normal Q-Q plot (c) for the best-fitted stem volume model.

The cross validation process had provided satisfactory statistical results. The RMSE was ranged from  $0.05221 \text{ m}^3$  (Model II) to  $0.06586 \text{ m}^3$  (Model VI). It was 0.48% to 3.20% lower than the initial values of table 6. The value of RAE varied from 0.05286 (Model II) to 0.07172 (Model VI). The fit index exhibited a value higher than 0.995 for all models, indicating a good prediction of stem volume. The six models were perfect to predict accurately the stem volume, but Models II and I performed better. The agreement index showed the values closest to 1 (dw: 0.9992–0.9995). So, observed and predicted stem volume were very similar through the models (Table 6). The scatterplot of observed and

predicted stem volume for the best model revealed a good distribution of point around the reference line (Figure 2).

**Table 6.** Cross validation fit statistics of six volumetric models. The best model is bolded.

Models	RMSE	RAE	FI	AIC	dw
I	0.05488	0.05364	0.99656	-762.298	0.9994
II	0.05221	0.05286	0.99681	-785.903	0.9995
III	0.06416	0.05706	0.99571	-685.351	0.9993
IV	0.06330	0.07021	0.99532	-685.249	0.9993
V	0.06093	0.05763	0.99589	-706.170	0.9993
VI	0.06586	0.07172	0.99511	-662.678	0.9992

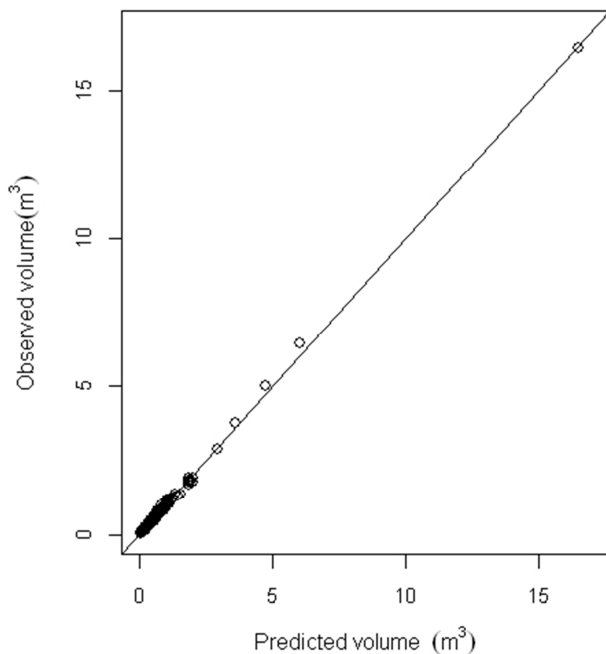
The mean difference between observed and predicted stem volume was ranged from  $-0.01929 \text{ m}^3$  (Model VI) to  $0.00594 \text{ m}^3$  (Model V). It was very close to zero for Model II. The standard error of mean difference was slightly higher for the Models IV, V and VI than the others. There are lower range between min and max predicted value among models (Table

7). However, the range of predicted values performed by Model II was the closest to the initial ones in table 1. The comparison of these observed and predicted volumes using a paired student t-test ( $\alpha=0.05$ ) indicated that the difference between the two volumes was non-significant (Table 7).

**Table 7.** Results of paired t-test for estimated and predicted stem volume. Standard error of mean difference in bracket; Min and Max: Minimum and maximum of predicted stem volume.

Models	Mean	t-value	P-value	Min	Max
I	-0.00342 (0.0410)	-0.0382	0.9695 <sup>ns</sup>	0.02949	14.81107
II	0.00041 (0.0513)	0.0039	0.9969 <sup>ns</sup>	0.02964	16.50293
III	0.00354 (0.0479)	0.0339	0.9729 <sup>ns</sup>	0.03018	16.9771
IV	-0.01843 (0.0607)	-0.1759	0.8604 <sup>ns</sup>	0.03682	17.83857
V	0.00594 (0.0744)	0.0557	0.9556 <sup>ns</sup>	0.03097	14.59825
VI	-0.01929 (0.0767)	-0.1637	0.8700 <sup>ns</sup>	0.03702	16.9371

ns: non significant (p-value>0.05)



**Figure 2.** Scatterplots of observed against predicted tree volume for best-fitted stem volume model. The finest line corresponding to a ratio of 1:1 (reference line).

## 4. Discussion

The volume models of this study are new for the urban forests of Benin. These models can provide an accurate estimates of stem volume of these forests in southern Benin. Environmental heterogeneity of the city have an influence on the diversity, composition and structure of urban flora. In this sense, providing the regression models capable to determine forest production based on estimated timber volume is fundamental. [54, 58]. The six models selected from de 74 ones initially established were double-entry models. They integrated systematically interaction terms as predictor variable, and presented the best statistical performance for predicting stem volume. This highlight the main role of interaction terms in stem volume estimation. This quality was

due to the relative homogeneity of stem volume and its allometric attributes which, were easily described by tree diameter and height [32, 59]. This pint of view was reinforced by the most accurate models of tree volume cited in the forest literature [4, 12, 23, 34, 44, 60, 61]. The models of Schumacher-Hall and Spurr which are based on the interaction terms, were widely used to predict most accurately tree volume prediction in tropical and subtropical regions [12, 24, 27, 32, 54] Although, the use of height to estimate volume and biomass in tropical forests engender a controversy due to measurement difficulties in dense forests [59, 62], the situation in urban area is different. In urban area, environmental heterogeneity, forests management practices, presence of several isolate and large trees and, a wide range of heights for the same diameter range increased the variability of allometric relationships [60, 63, 64]. Therefore, the use of height became necessary for accurate prediction of tree volume. At city scale, height measurement can be easier by training. Moreover, the production of an adequate local allometric relationship could be an alternative way to estimate tree height [62]. Tree height measurement can also be improved by using LIDAR sensor fine-scale data [65, 66]. The importance of diameter-height relationship in the accurate estimation of tree volume [32, 54] and biomass [24, 63, 67, 68] oblige to think about the development of web or mobile applications capable to facilitate the measurement of height with more accuracy.

Regarding the fit statistics, the generic volume models (I to VI) developed in this study show high efficiency ( $IF > 0.997$ ) and stability (lower standard error for estimates). The prediction errors (RMSE, RAE) are much reduced which ensuring better estimates. This result is globally comparable to other studies [32, 44, 54-61]. These models have done a high explications of observed data and return the most accurate estimates. However, the Model II is considered as the best for predicting the stem volume of urban tree based on the evaluation statistics and rank analysis. Our results confirm that stem heights should be systematically measured in order to improve stem volume estimation [61]. The quality of the models validate the suitability of nonlinear models for volume

estimation in tropical ecosystem [18].

Cross validation process reveal a better predictive capabilities of the stem volume models developed in this study. The mean difference between observed and predicted stem volume for Model II is very close to zero, which show the quality of this model for predicting accurately the stem volume of urban tree.

## 5. Conclusions

Base on the regression methods assumptions, the stem volume models constructed in this study were validated. The six generics models provided an accurate estimates with valid confidence intervals. An interaction terms are key predictor in the models. Which, highlight the importance of height for predicting stem volume (with bark) in urban forest. Depending on fit statistics and cross validation process results, the models are efficiency and performed well for predicting stem volume. However, the rank analysis indicated Model II as the best. Therefore, applying this volume model can help to understand accurately urban forest growing stock. These models represented a valuable contribution to forest managers. They can be used to develop decision support tools to sustain urban forestry decision making. Further researches should elucidate the influence of stem form in model accuracy and, the prediction performance of models cross city strata and phyto-districts. It would be worthwhile to compare these volume models to species-specific ones at a city scale.

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