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Biomass Estimation Models for Cocoa (*Theobroma cacao*) Plantations in Ghana, West Africa

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Abstract

The role of cocoa systems for climate change mitigation and adaptation has increased substantially because of their capability to trap carbon dioxide from the atmosphere and deposited in the cocoa trees as carbon. Development of aboveground biomass (AGB) models for cocoa plantations is crucial for accurate estimation of carbon stocks in the cocoa systems, however, allometric models for estimating AGB for cocoa plantations remain a challenge for cocoa producing countries in Sub-Saharan Africa especially Ghana. The aim of this study is to develop allometric model that can be used for the estimation of AGB for cocoa plantations in Ghana, as well as West Africa. Destructive sampling was carried out on 110 cocoa trees obtained from the cocoa rehabilitation exercise for the development of the allometric models. Diameter at breast height (D), total tree height (H) and wood density (ρ) were used as predictors to develop seven models. The best model was selected based on coefficient of determination (R^2), index of agreement (I_A), root mean squared error (RMSE), bias (E%), mean absolute error (MAE) and corrected akaike information criterion (AIC_C) and percentage relative standard error (PRSE) of the estimated parameters. The selected model, which was the one with the predictors D and ρ, was given as; AGB = $0.7217\rho(D^2)^{0.921}$. It was compared with the Yuliasmara *et al.* (2009) cocoa model using equivalence test and paired sample t-test. The two models were found to be equivalent within ±10% of their mean predictions ($p < 0.0001$) for one-tailed tests for both lower and upper limits, while the paired sample t-test rejected the null hypothesis with mean difference of 14.16 kg between the two models. This study is significant because it has provided a model to estimate AGB for the cocoa plantations in Ghana which is very important for the Ghana Cocoa-Forest

REDD+ Programme and also can be used by other West African cocoa producing countries.

Keywords

Carbon Stocks, Diameter at Breast Height, Wood Density, Tree Height, Cocoa Landscape

1. Introduction

The world's foremost environmental issue is the climate change, which has a significant impact on both human activity and natural ecosystems (Watson *et al.*, 2002; Mohanty and Mohanty, 2009) [1] [2]. A significant amount of the world's carbon emissions come from fossil fuels and a sizeable portion comes from deforestation and forest degradation (Lu, 2006) [3]. Large amount of carbon is stored by natural forests and other woody vegetation in their sinks, which eventually help in climate change mitigation (Chave *et al.*, 2005) [4].

Ghana's main cash crop, cocoa (*Theobroma cacao*) contributes significantly to the economy of Ghana as it contributes about 25% of the country's gross domestic product through export and employ approximately 800,000 farming households (Peprah, 2015; Kolavalli and Vigneri, 2003) [5] [6]. Apart from the economic benefit, cocoa plantations also provide ecosystem services (Supriadi *et al.*, 2022) [7]. The role of cocoa systems for climate change mitigation and adaptation has increased substantially because of their capability to trap carbon dioxide from the atmosphere and deposited in the cocoa trees as carbon (Acheampong *et al.*, 2014) [8]. According to World Bank assessment with an estimated size of approximately 1.6 million hectares, cocoa farming in Ghana is one of the country's most important land uses (Ghana Investment plan for FIP, 2012) [9]. Based on this large area of cocoa plantations in Ghana, the cocoa sector could store large amount of carbon in cocoa trees, thereby reducing the concentration of greenhouse gases in the atmosphere (Askia *et al.*, 2016) [10]. In Ghana, cocoa farming has been known to be a key driver of deforestation, responsible for the loss of about 1.45 million hectares of the country's forest cover (Ashiagbor et 2020) [11]. The Ghana Cocoa-Forest REDD+ Programme (GCFRP) is a ground-breaking initiative with the purpose of alleviating Ghana's deforestation and forest degradation while simultaneously increasing sustainable cocoa production. The GCFRP's main goal is to combat deforestation and forest degradation, promoting climate-smart cocoa production which aims to create a number of opportunities for farmers' livelihoods and general well-being in the cocoa-producing regions of Ghana (GCFRP, 2016) [12]. For the GCFRP to realize its dual goals of increasing sustainable cocoa production and forest conservation, an accurate estimation of carbon stocks in cocoa agroforestry systems is essential. In this regard, estimation of carbon stocks in the cocoa trees is made possible with the use of cocoa allometric models.

Biomass and carbon stock estimation for tropical forests and other woody vegetation has attracted a lot of scientific interest lately as the change in biomass is viewed as a key factor in climate change (Basuki *et al.*, 2013) [13]. Accurate biomass and carbon estimations are hinged on allometric models, without these models carbon assessment cannot be successfully realized (Henry *et al.*, 2011; Adu-Bredu and Birigazzi, 2014) [14] [15]. These models serve as basic tools for assessing biomass based on a tree's diameter at breast height, total height and wood density, which are all readily observable quantities (Roxburgh *et al.*, 2015) [16]. Accurate estimations and analysis of biomass are essential steps in assessing carbon stocks and sequestration rates and evaluating potential effects of climate change (Temesgen *et al.*, 2015) [17]. Ghana is formulating Good Practice Guidance (GPG) to measure, track, and report on changes in carbon stocks and greenhouse gas emissions for Land Use, Land-Use Change, and Forestry (LULUCF) activities, which includes cocoa plantations (IPCC, 2003) [18]. Therefore there is the need to develop allometric models for accurate estimation of carbon stocks in the various ecosystems which includes the cocoa plantations in Ghana which has high potentials to sequestrate large amount of carbon from the atmosphere.

Some allometric models have been developed for estimation of AGB of cocoa such as; Smiley and Kroschel, 2008 [19]; Santhyami *et al.*, 2018 [20]; Yuliasmara *et al.*, 2009 [21], all these models from Indonesia and Somarriba *et al.*, 2013 [22] from Guatemala. Allometric models for estimating AGB for cocoa plantations remain a challenge for cocoa producing countries in Sub-Saharan Africa because quantification of AGB of cocoa is done using allometric equations developed outside the individual countries. Some studies used Chave *et al.* (2005) [4] allometric equation for estimation of AGB of cocoa in Central Cameroon (Saj *et al.* 2013) [23] and Chave *et al.* (2005) [4] model is to be used for moist and dry forest stands. Also others used Aabeyir *et al.*, (2020) [24] which is meant for Savannah woodlands was used to estimate plot level AGB of cocoa in southern Côte D'Ivoire (Kanmegne *et al.*, 2022) [25] and Torres *et al.*, (2014) [26] was used to quantify AGB of cocoa farms in Sefwi Juaboso of Ghana (Afele *et al.*, 2020) [27]. These models are usually limited in their uses by the diameter range used for the models standardization, the kind of tree species used to construct the models and the ecological zones under which these models were developed often limit the models applicability (Aabeyir *et al.*, 2020) [24]. In Ghana, cocoa is cultivated in nine out of the sixteen regions, which cover large land mass (Ayub, 2020) [28] but information on AGB of cocoa is scanty due to non-availability of local AGB allometric models for cocoa plantations. Right now, there is no local allometric model available to quantify AGB for the cocoa plantations in Ghana, where cocoa production significantly affects the AGB of the landscape. Hence, assessment of AGB for the cocoa plantations will require the use of models developed outside Ghana. However, a significant drawback of applying these equations is that they yield different outcomes when applied to places outside the locations in which they were developed (Chambers *et al.*, 2001; Zianis *et al.*, 2005) [29] [30], therefore there is the need to develop AGB cocoa allometric models in order to accurately estimate AGB of cocoa plantations in Ghana.

Hypothesis testing has been an essential tool in statistical analysis that is used to make decisions about a population based on sample data (Qualitygurus, 2023) [31]. It is used to determine the likelihood that a particular claim is true. Normally, there are two types of hypotheses used in hypothesis testing: the null hypothesis (Ho) and the alternative hypothesis (Ha) (Pereira and Leslie, 2009; Noonan, 2022) [32] [33]. Comparing means such as paired sample t-test is one of the common methods used in hypothesis testing (Qualitygurus, 2023) [31]. The paired sample t – test simply known as paired t-test is a statistical method used to determine whether the mean difference between 2 sets of observation is zero. If the p-value is less than the chosen significance level (e.g., 0.05), the null hypothesis is rejected in favour of alternative hypothesis (Jim, 2022) [34].

Equivalence testing has been one of the statistical methods used to demonstrate that something is close enough to the ideal to be acceptable (Pardo, 2014) [35]. Equivalence testing uses the same methodology as conventional hypothesis testing, but the null and alternate hypotheses are modified so that the null is that the systems are distinct (*i.e.*, the difference between them is large).This means that, if the difference between two methods is reasonably small, the null hypothesis is rejected in favour of the alternative. In conducting equivalence testing, the user must state an equivalence region which is the set of population mean differences that are deemed comparable to zero. (Dixon *et al.*, 2018) [36]. The two-one sided test of equivalence (TOST) is usually employed in equivalence testing because of its simplicity and widespread use in other scientific disciplines (Schuirmann, 1987) [37]. In the Two-One-Sided-Tests (TOST) method (Schuirmann, 1987) [37], the null hypothesis of non-equivalence, is divided into two one-sided null hypotheses Ha and Hb. A one-sided test at level α is used to evaluate each hypothesis, Ha and Hb. The null hypothesis is rejected at level α only if both one-sided null hypotheses (Ha and Hb) are rejected at level α, then the alternative hypothesis of equivalence is accepted (Dixon *et al.*, 2018; Aabeyir *et al.*, 2020) [24] [36].

The objectives of this study are to 1) develop allometric model to estimate AGB in the cocoa plantations of Ghana, and 2) evaluate if there is a major difference between the estimates of the best model developed under this study and the Yuliasmara *et al.* (2009) [21] cocoa model. This model was developed in Indonesia and was chosen for comparison because the model makes use of diameter at breast height (1.3 m) as its predictor which is the standard measurement of diameter while other cocoa allometric models like Smiley and Kroschel (2008) [19], Santhyami *et al.* (2018) [20], both from Indonesia and Somarriba *et al.* (2013) [22] from Guatemala make use of diameter measurement at 30 cm as predictor in their models.

2. Materials and Methods

2.1. Study Area

Juaboso and Bia West districts were chosen as the study area is in Ghana's cocoa landscape and are among the highest cocoa producing districts in the Western North region of Ghana and this region is the largest cocoa producing region in Ghana. The majority of inhabitants in these districts are involved in cocoa farming which employs about 70% of the population with nearly 26% of the working population is employed in the service sector, and the remaining 4% is in small-scale businesses (Ghana Statistical Service, 2014) [38].

Juaboso and Bia West districts (**Figure 1**) is located between latitude 6˚13'N to 6˚50'N and longitude 2˚40'W to 3˚16'W. It shares boundaries with Bia East, Asunafo North, Asunafo South, Sefwi Wiawso, Bodi, Suaman districts and Côte D'Ivoire. The study area covers an area of 2571.26 square kilometers. Cocoa is the major land-use system, which occupies greater percentage of the land in the area. Apart from cocoa farms, other land use which include food crop farms, fallowlands and other tree crops like oil palm, citrus and patchiness of grassland also occur with communities in relatively low lying areas. Within the study area is Krokosua Hills forest reserve, portion of Bia Tributaries North forest reserve and Bia National Park (game reserve) which also cover reasonable portion of the area (Ghana Statistical Service, 2014) [38].

With a mean annual temperature between 25.5˚C and 26.5˚C, the area has a tropical climate marked by warm temperatures. The annual rainfall levels are between the ranges of 1250 - 2000 mm with June and October as its peak months. The area is very undulating with the elevation of the terrain ranges between 137 - 594 m above mean sea level. The study area falls within Moist Evergreen, Moist Semideciduous North West and Moist Semideciduous South East subtypes ecological zones (Hall and Swaine, 1981) [39]. The soils are mainly Oxysols and Ochrosols (Anim-Kwapong and Frimpon, 2004) [40] with underlying Birimian and Hornblende parent rocks.

2.2. Destructive Sampling

Destructive sampling data collection was carried out between October 2019 and February 2021. The Ghana Cocoa Board is undertaking cocoa rehabilitation project in the Western North Region of Ghana, in which cocoa trees in farms infected with cocoa swollen shoot viral disease are cut and replanted. Advantage was taken of the rehabilitation exercise to select some cocoa trees for destructive sampling. In cocoa farms that have been earmarked for destruction, some healthy cocoa trees were selected for the study and the selection was done to cover a wider diameter class. The coordinates of the sampled cocoa trees were picked before they were felled and the felling was done close to the ground level.

The trees were destructively sampled from seven sites within three different ecological zones in the study area (**Table 1**). Total length of the felled tree was measured using linear tape and diametres were taken starting from the butt end of the main stem at 0.3 m, 1.0 m, 1.3 m, which is the diameter at breast height, 2.0 m, and thereafter at 2.0 m interval using diameter tape. The tree was stratified into the various organs of stem, branches and foliage. The respective organs were weighed with hanging scale, with the foliage being put into sack before being weighed. Disks samples were collected from the base, middle and the top of the stem and also from large branches for dry mass and wood density determination. The wood disk samples were taken close to the base, mid and top sections of both the stem and big branches. This is to capture the variation of the wood density along the trees, since density is typically greater at the base of the stem than at its top (Weber *et al.*, 2018) [41]. The disks were labelled, and their fresh masses determined using digital weighing scale and diameter at both ends as well as lengths were taken. These measurements were used to determine the disk sample green volumes. Foliage samples were also taken. The samples were taken to the laboratory for dry mass, as well as wood density determination. The destructive sampling processes are shown in **Appendix A**.

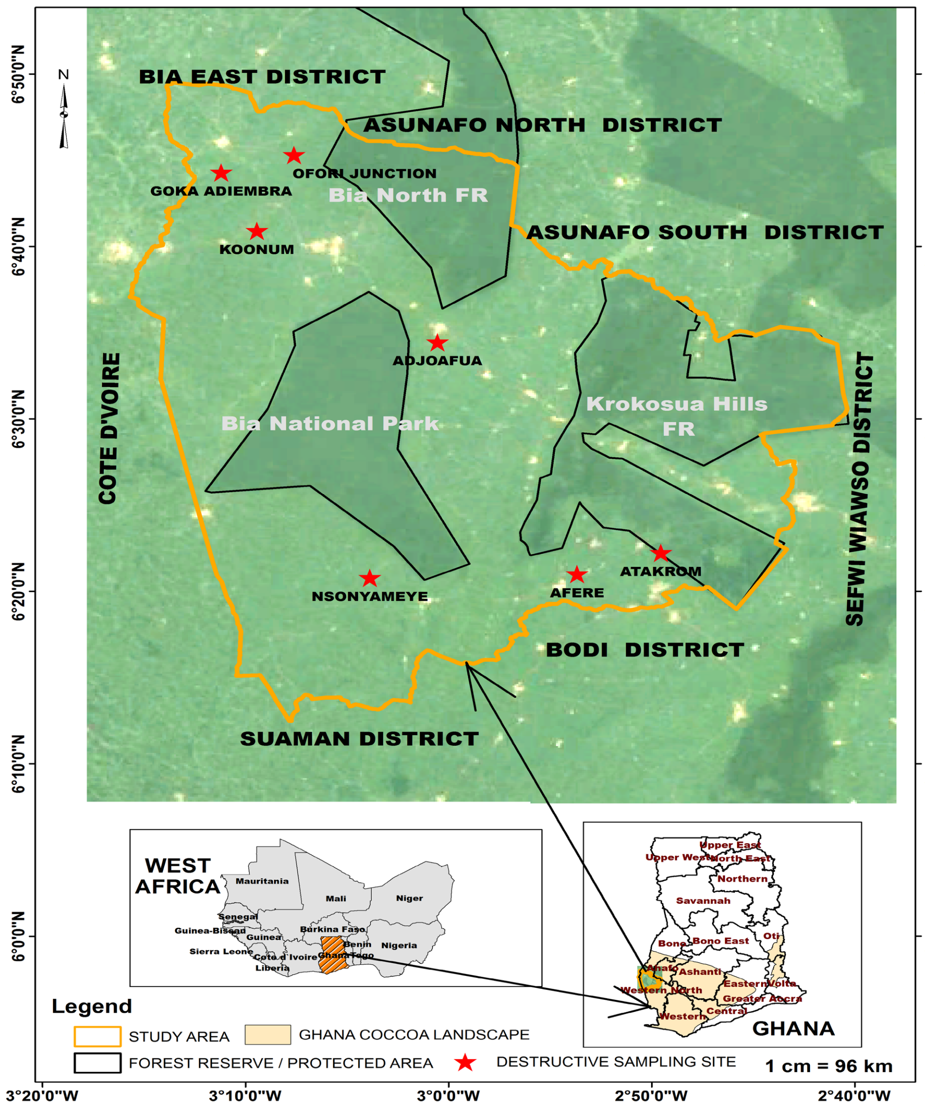

Figure 1. Map of the study area showing the cocoa mosaic landscape of Juaboso and Bia West districts of Ghana. The red star points are the destructive sampling sites (Image source: Landsat and Copernicus from goggle earth engine).

Table 1. Distribution of sampled cocoa trees per site and ecological zone.

	Ecological Zone			
Site	Moist Evergreen	Moist Semideciduous North West	Moist Semideciduous South East	**Total**
Adjoafua		10		10
Afere	40			40
Atakrom			10	10
Goka Adiembra		13		13
Koonum		6		6
Nsonyameye	5			5
Ofori Junction		26		26
Total	45	55	10	110

Few cocoa trees were obtained in the Moist Semideciduous South East ecological zone. As at the time of collecting destructive sampling data in this zone, only these cocoa trees which were in good conditions were available. The number of cocoa trees for the destructive sampling depends on availability of cocoa trees which have been earmarked for destruction with the consent of the farm owners.

2.3. Laboratory Work

The disk samples taken from the stems and branches were oven-dried to constant mass at 105˚C in the laboratory, according to Williamson and Wiemann's (2010) [42] recommendation that wood will release bound water at temperatures between 101˚C and 105˚C. The dry mass was determined with an electronic weighing scale. The leaves samples were put in envelopes, labelled and oven-dried to constant mass at 60˚C, and the dry mass determined using weighing scale.

2.4. Determination of the Phytomass for the Individual Cocoa Trees

The total dry mass of the various organs, namely stem, branch and foliage of each tree was determined from the total fresh mass and the sample dry to fresh mass ratio. The dry mass of an organ was therefore calculated as (Basuki *et al.*, 2022) [43] (Equation (1));

$$M_{\mathrm{TD}} = \frac{M_{\mathrm{DS}}}{M_{\mathrm{FS}}} \times M_{\mathrm{TF}}. \tag{1}$$

where M_{TD} is the dry mass of an organ, M_{DS} is the dry mass of the sample, M_{FS} is the fresh mass of the sample and M_{TF} is the total fresh mass of an organ. The total dry mass (phytomass) of a tree was obtained by the summation of the dry mass of the various organs (Kebede and Soromessa, 2018) [44] (Equation (2));

$$P_{\mathrm{M}} = M_{\mathrm{TDS}} + M_{\mathrm{TDB}} + {}_{T}M_{\mathrm{TDL}} \tag{2}$$

where P_M is the tree phytomass, M_{TDS} is the total dry mass for stem component, M_{TDB} is the total dry mass for branch component and M_{TDL} is the total dry mass for leaf component.

2.5. Wood Density Analysis

Green volume of the sample disks was calculated using truncated cone formula (Adu-Bredu *et al.*, 2008) [45] (Equation (3));

$$V_G = \frac{\pi L}{12}\left(D^2 + Dd + d^2\right) \tag{3}$$

where D and d are the diameter of the larger and smaller end of the disk, respectively, while L is the length of the disk. Wood density (ρ_d) of each disk sample was calculated from the dry mass (M_D) and the green volume (V_G) (Islam *et al.*, 2021) [46] (Equation (4));

$$\rho_d = \frac{M_D}{V_G}. \tag{4}$$

The wood density of each cocoa tree was computed using weighted average approach. The average wood density of the stem and branch for a tree was computed separately using Branch Mass Ratio (BMR) and Stem Mass Ratio (SMR) (Beck, 2018) [47] using Equations (5) and (6), respectively as;

$$\text{BMR} = \frac{\text{BM}}{\text{BM} + \text{SM}} \tag{5}$$

$$\text{SMR} = \frac{\text{SM}}{\text{BM} + \text{SM}} \tag{6}$$

where BM and SM is the total branch and stem dry mass, respectively. The weighted average wood density (ρ) for each cocoa tree was computed as (Ganti, 2023) [48] (Equation (7));

$$\rho = \left(\text{BMR} \times \rho_B\right) + \left(\text{SMR} \times \rho_S\right), \tag{7}$$

where ρ_B and ρ_S are the average density for the branch and stem disks, respectively.

2.6. Allometric Modelling Process

2.6.1. Model Fitting

The data used for the development of allometric models included diameter at breast height (D, cm), total tree height (H, m) and wood density (ρ, g·cm^{-3}) of 110 cocoa trees as control variables, and the corresponding phytomass as the response variable. Allometric models development and fitting can be done by using linear or nonlinear regression methods for estimating model parameters (Packard, 2013; Mascaro *et al.*, 2011) [49] [50]. Nonlinear regression method usually produces least model bias and error as well as good estimate of unknown parameters in a model with moderately small data set (Hui and Jackson, 2007) [51]. Nonlinear power function regression model constitutes the foundation of an allometric model, which uses diameter at breast height, full tree height and wood density as biomass predictors (Aabeyir *et al.*, 2020) [24].

In this study the model fitting was done using nonlinear power function model (Equation (8));

$$Y = aX^b \tag{8}$$

where a is non-zero coefficient ($a \neq 0$) and b is a real number. The selected model predictors and model parameters are significant because they constitute substantial source of error in biomass assessment (Djomo *et al.*, 2010; Sileshi, 2014) [52] [53].

In this study, seven different forms of allometric models were developed based on different combinations of the predictors; diameter at breast height (D, cm), height (H, m) and wood density (ρ, g·cm^{-3}) as D^2, $D^2\rho$, D^2H and $D^2\rho H$. These seven models were categorized into four based on the combinations of the predictors (**Table 2**).

Where a_1, a_2, a_3, a_4, a_5, a_6 and a_7 are allometric coefficients and b_1, b_2, b_3, b_4, b_5, b_6 and b_7 are allometric exponents. The models were parameterized using Statistical Analysis Software (SAS) SAS ONDEMAND FOR ACADEMICS.

2.6.2. Model Evaluation, Comparison and Selection

Model assessment was done using both graphical and statistical methods to evaluate the goodness-of-fit of the models because no single method is perfect (Hevia *et al.*, 2013; Tewari *et al.*, 2014) [54] [55].

The statistical methods used are efficiency-based and error–based measures to evaluate the models. The efficiency-based measures considered in this study include coefficient of determination (R^2) (Equation (9)) and index of agreement (I_A) (Equation (10)).

The error-based measures used include the root-mean-squared error (RMSE) (Equation (11)), bias (E%) (Equation (12)) and mean absolute error (MAE) (Equation (13)). The R^2 measures the total variation explained by the model. It provides a performance index for the model, with 1.0 denoting perfect fit and zero means no correlation (Hevia *et al.*, 2013; Soares and Tome, 2007) [54] [56].

Table 2. Model forms and combinations of predictors.

Category	Predictor(s)	Model label	Model form
I	D	M1	$a_1\left(D^2\right)^{b_1}$
II	D, H	M2	$a_2\left(D^2H\right)^{b_2}$
		M3	$a_3H\left(D^2\right)^{b_3}$
III	D, ρ	M4	$a_4\left(D^2\rho\right)^{b_4}$
		M5	$a_5\rho\left(D^2\right)^{b_5}$
IV	D, ρ, H	M6	$a_6\left(D^2\rho H\right)^{b_6}$
		M7	$a_7\rho\left(D^2H\right)^{b_7}$

The R^2 is calculated as (Mukuralinda *et al.*, 2021) [57] (Equation (9));

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n} \left(y_i - \bar{y}_i\right)^2} \tag{9}$$

The index of agreement (I_A) denotes the ratio of the mean square error to the potential error. The index of agreement range is similar to that of R^2 and lies between 0 indicating no correlation and 1 being perfect fit (Krause *et al.*, 2005) [58]. The I_A is defined as (Adhikary and Dash, 2017) [59] (Equation (10));

$$I_A = 1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n} \left(\left|\hat{y}_i - \bar{y}_i\right| + \left|y_i - \bar{y}_i\right|\right)^2} \tag{10}$$

The root mean squared error (RMSE) measures the average magnitude of prediction errors. Accurate predictions have RMSE value close to zero (Adhikary and Dash, 2017). The RMSE is calculated as (Stovall *et al.*, 2018) [60] (Equation (11));

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{N} \left(y_i - \hat{y}_i\right)^2} \tag{11}$$

Bias is a measure of systematic deviation of model predictions from observed data. Haung *et al.* (2003) [61] recommended that bias % < ±10% at 95% confidence level is acceptable. Bias (E%) is calculated as (Aabeyir *et al.*, 2020) [24] (Equation (12));

$$\text{E\%} = \frac{\sum_{i=1}^{N} \left(y_i - \hat{y}_i\right)}{\sum_{i=1}^{N} \hat{y}_i} \times 100 \tag{12}$$

Mean absolute error (MAE) is the average of all absolute errors. Reliable predictions have MAE value close to zero (Schneider and Xhafa, 2022) [62]. The formula for MAE is defined as (De Cáceres *et al.*, 2019) [63] (Equation (13));

$$\text{MAE} = \frac{1}{n} \sum \left|\hat{y}_i - y_i\right| \tag{13}$$

where y_i, $\hat{y}_i$ and $\bar{y}_i$ represent the measured, predicted and mean aboveground mass (AGM), respectively, whereas n is the sample size. Corrected Akaike Information Criterion (AIC_C) was used to compare and choose the best model from various models. Lower AIC_C scores are desirable and AIC_C punishes models that use more parameters. So if two models have the same AIC_C score, the one with fewer parameters will be regarded as the better model (Cai *et al.*, 2013; Migliavacca *et al.*, 2012) [64] [65]. AIC_C is calculated as (Aabeyir *et al.*, 2020) [24] (Equation (14));

$$\text{AIC}_\text{C} = n \log\left(\text{RMSE}^2\right) + 2k + \frac{2k(k+1)}{n-k-1} \tag{14}$$

where n is the sample size, k is the number of model input parameters and RMSE is the root mean squared error

The graphical evaluation was done by analysis of goodness-of-fit of the models by 1) plotting observed AGM against the predicted AGM of the best models in each category using linear regression method (Pineiro *et al.*, 2008) [66] and 2) examination of residual plots to assess the quality of the best models in each category. The Student's t-test of intercept equal to zero and a gradient of unity were used to assess the quality of the predictions (Adu-Bredu *et al.*, 2008) [24].

2.6.3. Model Validation

Validation of the models was done by assessing 1) the model parameters using Percentage Relative Standard Error (PRSE) method 2) Hypothesis testing by evaluating the mean difference of the observed against each of the predicted AGM of the seven models developed under this study 3) Equivalence testing of the predictions of best model with that of Yuliasmara *et al.* (2009) [21] model.

Percentage Relative Standard Error (PRSE) is measure of the reliability of the estimates of the parameters. A PRSE values less than 20% are recommended (Sileshi, 2014) [53]. Smaller PRSEs are indicative of more reliable results and larger one means less reliable results, and estimated as (Cabrera *et al.*, 2018) [67] (Equation (15));

$$\mathrm{PRSE} = \frac{\mathrm{SE}}{\theta} \times 100 \tag{15}$$

where θ the estimated parameter and SE is the corresponding standard error of the estimate.

The hypothesis testing to evaluate the mean difference of the observed and predicted AGM was done using the paired sample t-test. In this hypothesis testing, the null hypothesis (Ho) being tested is that the mean difference between the estimates of the observed against each of the predicted AGM of the seven models developed in this study is zero, with the alternative hypothesis (Ha) being that the mean difference is not zero (Majaski, 2023) [68] and stated below as:

$$\mathrm{Ho}: \mu_d = 0 \tag{16a}$$

$$\mathrm{Ha}: \mu_d \neq 0 \tag{16b}$$

The Two-One Sided Tests of equivalence (TOST) was used for the equivalence testing which compared the best model (M5) with Yuliasmara *et al.* (2009) (Y) [21] and Yuliasmara *et al.* (2009) [21] model is represented as (Equation (17))

$$\mathrm{AGB} = 0.1208 \times D^{1.98} \tag{17}$$

where D is diameter at breast height

With equivalence margin of ±10%, the mean of the predictions of the best model (M5) and Yuliasmara *et al.* (2009) (Y) [21], the equivalent bounds are represented as (Dixon *et al.*, 2018) [36];

$$\mu_{M5} / \mu_Y < 0.9 \tag{18a}$$

$$\mu_{M5} / \mu_Y > 1.1\,. \tag{18b}$$

Testing two one-sided hypotheses of Equations (18a) and (18b) and calculating D_{M5} as upper bound for each member and D_Y as the lower bound for each participant yields (Dixon *et al.*, 2018) [36];

$$D_{M5} = Y_{M5} - 0.9Y_Y \quad (19a)$$

$$D_Y = Y_{M5} - 1.11Y_Y \quad (19b)$$

where Y_{M5} is the value of prediction for model M5 and Y_Y is the value of prediction for Yuliasmara *et al.* (2009) [21] model. One-sample T-tests were performed using both D_{M5} and D_Y values.

In addition, hypothesis testing was done to assess the mean difference of the predictions of the best model (Model M5) in this study with the predictions of Yuliasmara *et al.* (2009) [21] model using paired sample t-test method. In this hypothesis testing, the null hypothesis (Ho) being tested is that the mean difference between the estimates of the best model (Model M5) and the predictions of Yuliasmara *et al.* (2009) [21] is zero, with the alternative hypothesis (Ha) being that the mean difference is not zero as stated in Equations (16a) and (16b).

3. Results

3.1. Dataset for Allometric Modelling

The dataset used for the allometric modelling include diameter at breast height (D, cm), total tree height (H, m) and wood density (ρ, g·cm^{-3}) (**Table 3**) and phytomass of 110 cocoa trees (**Table 4**) from seven sites in the study area.

The diameter at breast height (dbh) of 1.3 m aboveground of the destructively sampled cocoa trees ranged from 5.3 to 21.5 cm. The sampled trees were dominated by the 10 - 14.9 cm diameter class, followed in a decreasing order by the 15 - 19.9, 5 - 9.9 and above 20 cm diameter classes, with the proportion being 51.8, 29.1, 17.3 and 1.8%, respectively (**Table 3**). The total height ranged from 2.55 to 7.62 m. The bulk of the tree heights fall within 4 - 5.9 m, followed by the 6 - 7.9 and 2 - 3.9 m height class, with the distribution being 67.3, 18.2 and 14.5%, respectively. Wood density varied from 0.333 to 0.533 g·cm^{-3}. The bulk of the wood density was within the 0.40 - 0.49 range, followed by 0.30 to 0.39 and 0.50 to 0.59 g·cm^{-3}, with their proportion being 63.6, 33.6 and 2.7%, respectively.

The phytomass varies along the tree, with the stem having higher phytomass than the branches and leaves components as observed in **Table 4**.

Table 3. Class distribution of diameter at breast height, height and wood density for sampled cocoa trees.

Diameter Class (cm)	N	Height class(m)	N	Wood Density class (g·cm^{-3})	N
5 - 9.9	19	2 - 3.9	16	0.3 -0.39	37
10 - 14.9	57	4 - 5.9	74	0.4 - 0.49	70
15 - 19.9	32	6 - 7.9	20	0.5 - 0.59	3
20 - 24.9	2				
Total	110		110		110

Note: N is number of cocoa trees.

Table 4. Mean phytomass of sampled cocoa trees per site.

Site	*N*	Mass (kg)			
		Stem Mean ± SE	Branch Mean ± SE	Leaves Mean ± SE	Total Mean ± SE
Adjoafua	10	23.80 ± 1.92	18.88 ± 2.41	1.54 ± 0.34	44.12 ± 3.45
Goka Adiemra	13	31.73 ± 3.57	17.47 ± 2.89	1.34 ± 0.33	50.54 ± 4.23
Koonum	6	24.55 ± 4.54	5.01 ± 1.07	0.44 ± 0.18	30.01 ± 5.46
Ofori Junction	26	28.58 ± 2.12	17.83 ± 2.43	0.55 ± 0.16	46.96 ± 4.27
Afere	40	16.81 ± 2.02	9.32 ± 2.69	0.80 ± 0.16	19.23 ± 2.48
Nsonyameye	5	22.91 ± 4.23	16.38 ± 3.97	0.37 ± 0.06	39.66 ± 6.83
Atakrom	10	24.98 ± 3.02	18.45 ± 3.38	0.92 ± 0.20	44.35 ± 6.12
TOTAL	110				

3.2. Allometric Models Parameters

The models parameters based on different combination of the predictors is shown in Table 5.

3.3. Model Evaluation

3.3.1. Statistical Goodness-of-Fit of the Models

Statistical goodness-of-fit of the models based on coefficient of determination (R^2), index of agreement (I_A), root mean squared error (RMSE), bias (E%), mean absolute error (MAE) and Corrected akaike information criterion (AIC_C) are shown in Table 6.

For the efficiency-based measures; R^2 ranged from 70.8% to 84.9% with model M3 explained 70.8% of variation in AGB and model M5 had 84.9% of variability in AGB. The performance of model M4 is close to that of model M5 with R^2 of 84.8%, these two models use diameter and wood density as their predictors. The index of agreement, I_A, ranged from 85% for model M3 to 91% for model M5 while that of model M4 was 90%. The efficiency-based results revealed that models that used only diameter and wood density as their predictors (M4 and M5) performed better than those models without wood density, and also that of wood density with height.

For the error-based measures; RMSE has minimum value of 11.61 for model M5 and maximum of 12.91 for model M6 and model M4 with value of 11.62. The model bias(E%) reveals that models M1, M2, M4, M5, M6 and M7 under-predict the average AGB, while model M3 over-predict it. However all the seven models are accepted based on the criterion of Huang *et al.* (2003) [61] that bias of less than 10% is acceptable. The best model in terms of bias is M6, which has least bias% of −0.42%, and the worst is M3 with value of 3.2819%, nevertheless the difference between M6 and M1, M2, M4, M5 and M7 are very minimal.

The mean absolute error, MAE, ranged from 8.75 for model M5 to 10.34 for model M2, and model M4 had a value of 8.77. With respect to RMSE and MAE, models (M4 and M5) had the smallest errors and performed better than the rest of the models.

Table 5. Model results using different predictor(s) combinations.

Predictor(s)	Model label	Model Form	*a*	*b*	Model
D	M1	$a(D^2)^b$	0.2411	0.9586	$0.2411(D^2)^{0.959}$
D, H	M2	$a(D^2H)^b$	0.1938	0.7617	$0.1938(D^2H)^{0.762}$
	M3	$aH(D^2)^b$	0.0600	0.8995	$0.0600H(D^2)^{0.899}$
D, ρ	M4	$a(D^2\rho)^b$	0.6484	0.9296	$0.6484(D^2\rho)^{0.930}$
	M5	$a\rho(D^2)^b$	0.7217	0.9214	$0.7217\rho(D^2)^{0.921}$
D, ρ, H	M6	$a(D^2\rho H)^b$	0.3710	0.7675	$0.3710(D^2\rho H)^{0.767}$
	M7	$a\rho(D^2H)^b$	0.5412	0.7437	$0.5412\rho(D^2H)^{0.744}$

Table 6. Statistical goodness-of-fit of the models.

			Efficiency		Error			Comparison
Category	Modal Label	Model	R^2	I_A	RMSE	E (%)	MAE	AIC$_C$
1	M1	$AGB = 0.2411(D^2)^{0.959}$	0.821	0.89	12.14	−0.43	9.13	169.63
2	M2	$AGB = 0.1938(D^2H)^{0.762}$	0.744	0.86	13.49	−0.54	10.34	178.78
	M3	$AGB = 0.0600H(D^2)^{0.899}$	0.708	0.85	14.07	3.28	10.22	181.61
3	M4	$AGB = 0.6484(D^2\rho)^{0.930}$	0.848	0.90	11.62	−0.43	8.77	168.80
	M5	$AGB = 0.7217\rho(D^2)^{0.921}$	0.849	0.91	11.61	−0.47	8.75	168.77
4	M6	$AGB = 0.3710(D^2\rho H)^{0.767}$	0.778	0.87	12.91	−0.42	9.66	178.01
	M7	$AGB = 0.5412\rho(D^2H)^{0.744}$	0.783	0.88	12.81	−0.71	9.59	177.49

Corrected akaike information criterion (AIC$_C$) values ranged from 168.77 (M5) to 181.61 (M3) and this shows that M5 is the best performing model based on AIC$_C$. The AIC$_C$ values of models M4 and M5 are almost the same, however based on corrected akaike information criterion, if two models are being compared, the one with lower AIC$_C$ score is the best and will be regarded the better fit model (Cai *et al.*, 2013; Migliavacca *et al.*, 2012) [64] [65]. The R^2, I_A, RMSE and MAE within each category of the models were almost the same, but there are variations between the different categories. However, the bias (E%) values varies within the same category of the models as well as among the different categories. The AIC$_C$ values have small variations within the same category of the models with some difference between different categories.

3.3.2. Evaluation of Goodness-of-Fit of the Plots

The plot of observed AGB against predicted AGB of the models (Figure 2) is centred on models M1, M2, M5 and M7 which are the best models in each category based on AIC$_C$.

From Figure 2, the regression line is shown blue colour, the 95% confidence interval (CI) is in grey band and the prediction interval is the red dotted lines. From the graphs which are linear regression of observed AGB versus predicted AGB showed that all the four models exhibited heteroscedasticity.

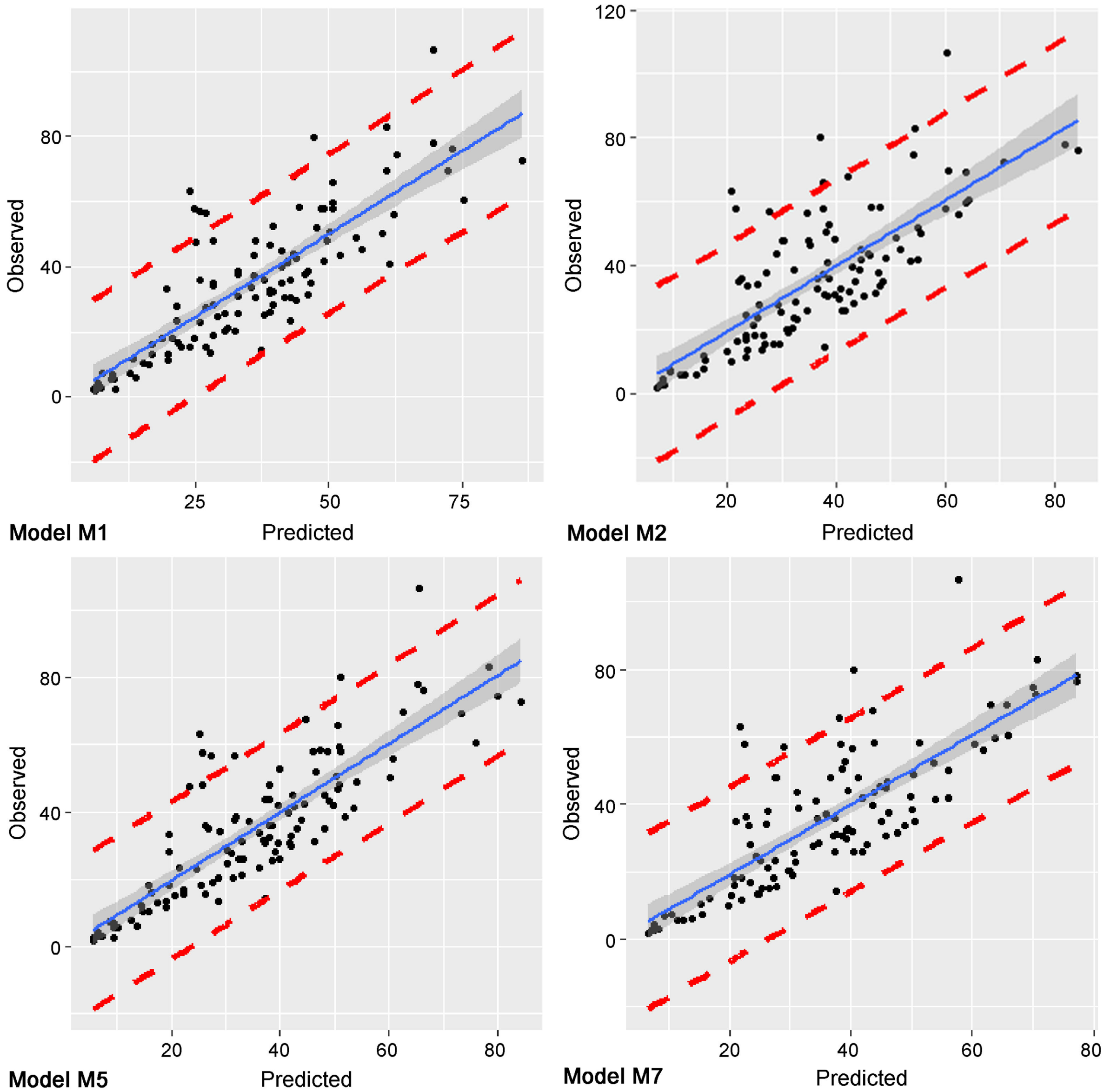

Figure 2. Relationship between observed AGB and predicted AGB.

Analysis of residuals is a key part of all statistical modelling and residual plots can be used to assess the quality of a model. Examining the histogram of the residuals of the models revealed that the distribution of the residuals exhibit the bell –shaped pattern of the normal distribution (Figure 3), this suggest that the models underlying assumptions have not been violated.

Plotting of standardized residuals against predicted AGB revealed that models M2, M5 and M7 revealed heteroscedasticity, while M1 exhibited homoscedasticity with one outlier point (Figure 4). Positive values for the standardized residual (on the y-axis) signify that the prediction was too low, and negative values indicate that the prediction was too high; 0 denotes the prediction was precisely correct. In practice, it is often considered any standardized residual with absolute value greater than 3 to be an outlier.

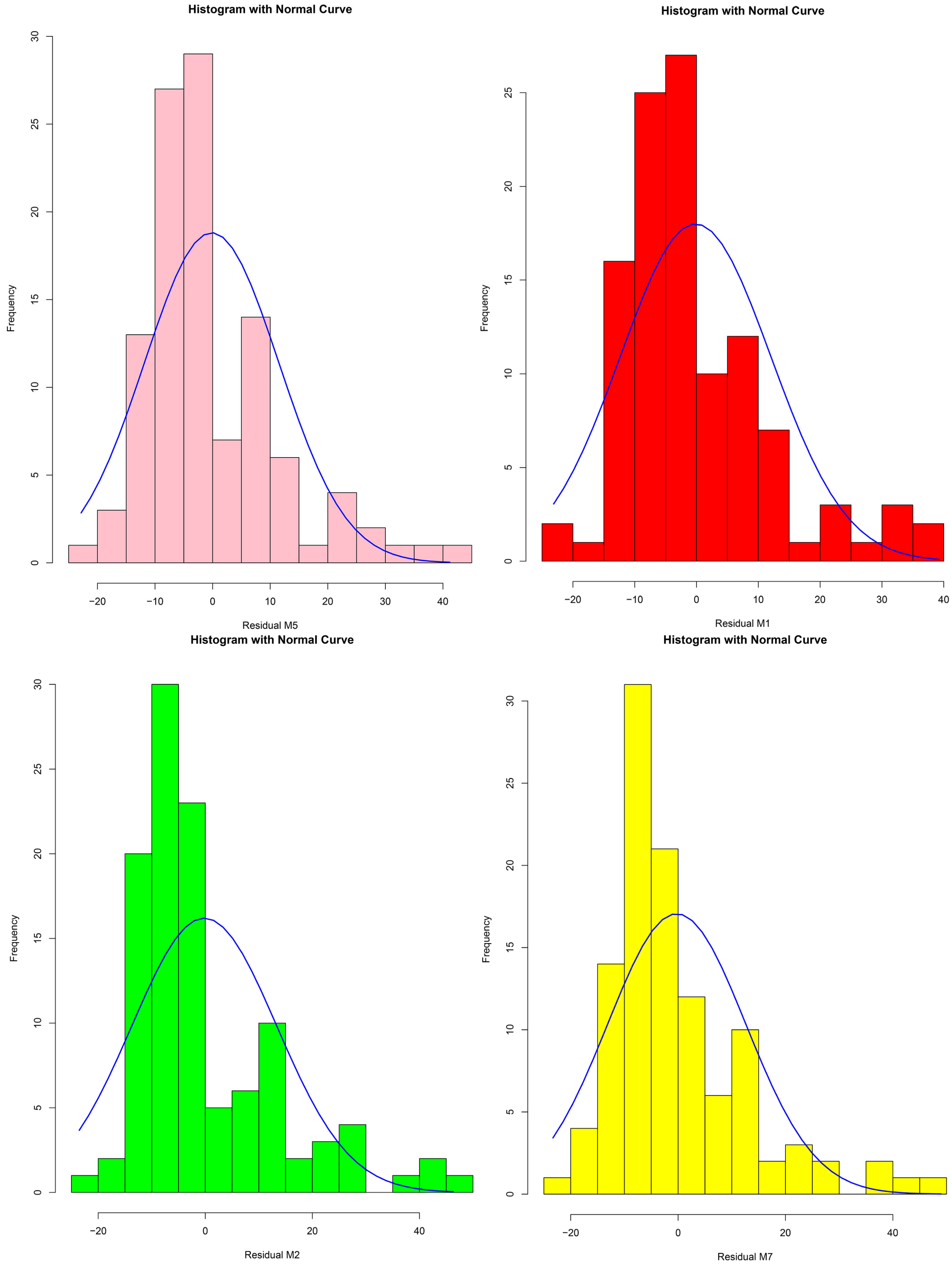

Figure 3. Histogram of residuals of the models.

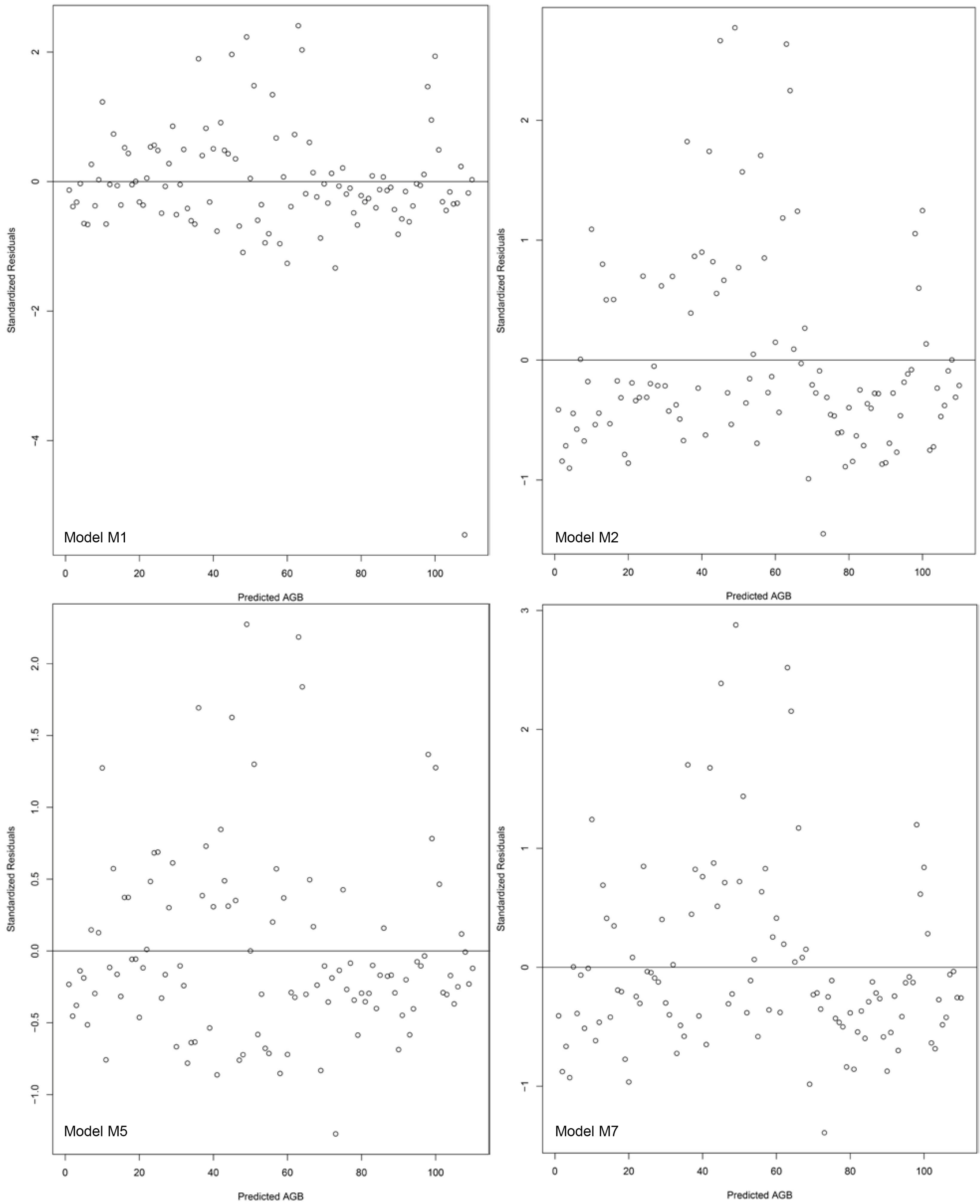

Figure 4. Standardized residuals versus predicted AGB of the models.

3.4. Model Validation

3.4.1. Percentage Relative Standard Error

The Percentage Relative Standard Error (PRSR) for the allometric coefficients

(a_i) and exponents (b_i) of the seven models are presented in Table 7.

The Percentage Relative Standard Error (PRSR) for the allometric coefficients ranged from 11.38% for M4 to 19.83% for M3 while PRSR values for allometric exponents varied from 7.59% to 10.29% for M4 and M3, respectively. All the PRSR values are less than maximum value of 20% which has been recommended for good model (Sileshi, 2014) [53]. This means that the model parameters are important in explaining the variability in AGB, suggesting that all the seven models are reliable and good in predicting AGB. The coefficient and exponent values were least in M4, which is made up diameter at breast height (D) and wood density (ρ). This implies that addition of wood density to diameter at breast height improved the model.

3.4.2. Paired Sample T-Test

The results of the observed and each of the predicted AGM of the seven models developed in this study using paired sample t-test is presented in Table 8.

Table 7. Percentage Relative Standard Error (PRSR) of parameters.

Model label	Model	PRSE Values (%)	
		Coefficient (a)	Exponent (b)
M1	$0.2411(D^2)^{0.959}$	14.68	8.16
M2	$0.1938(D^2H)^{0.762}$	19.30	9.35
M3	$0.0600H(D^2)^{0.899}$	19.83	10.29
M4	$0.6484(D^2\rho)^{0.930}$	11.38	7.59
M5	$0.7217\rho(D^2)^{0.921}$	13.36	8.16
M6	$0.3710(D^2\rho H)^{0.767}$	13.45	8.81
M7	$0.5412\rho(D^2H)^{0.744}$	18.14	9.26

Table 8. Paired sample t-test for observed and predicted AGM.

Model	Mean (SE)	Mean Diff	P value	95% CI
Observed	35.76 (2.03)	-	-	-
$0.2411(D^2)^{0.959}$	35.96 (1.64)	−0.20	0.8656	−2.13 to 2.52
$0.1938(D^2H)^{0.762}$	35.97 (1.53)	−0.21	0.8744	−2.37 to 2.79
$0.0600H(D^2)^{0.899}$	34.49 (1.74)	1.27	0.3498	−3.96 to 1.41
$0.6484(D^2\rho)^{0.930}$	35.94 (1.67)	−0.18	0.8759	−2.05 to 2.40
$0.7217\rho(D^2)^{0.921}$	35.81 (1.66)	−0.05	0.9671	−2.18 to 2.27
$0.3710(D^2\rho H)^{0.767}$	35.75 (1.58)	0.01	0.9903	−2.49 to 2.46
$0.5412\rho(D^2H)^{0.744}$	36.02 (1.57)	−0.26	0.8329	−2.19 to 2.71

Note: CI is Confidence Interval.

From the paired sample t-test results for the observed against each predicted AGM of the seven models developed in this study, all the p values of the seven models are greater than the standard significance level value of 0.05 *i.e.* $p > 0.05$. This means that there is no significant difference between the means of observed AGM and that of each of seven developed models, therefore the null hypothesis is accepted. Also, from the 95% Confidence Interval (CI), zero is included in the intervals of all the models. This specifies that there is no statistically meaningful difference between the means of the observed and each predicted AGM of the seven developed models. This indicates that the predictions by the models developed in this study are good and reliable.

3.4.3. Equivalence Testing of the Predictions of Model M5 with That of Yuliasmara *et al.* (2009) Model

The summary of the statistical results of Two-One Sided Tests (TOST) of equivalence between model M5 and Yuliasmara *et al.* (2009) model is shown in **Table 9**.

The p values of the two models is less than the standard significance level alpha value of 0.05, thus, $0.0001 < 0.05$, hence the two null hypotheses are rejected in favour of the alternative hypotheses. There is strong evidence to conclude that model M5 and Yuliasmara *et al.* (2009) [21] model are equivalent with respect to their AGB predictions.

3.4.4. Hypothesis Testing the Mean Difference in Predictions between Model M5 and Yuliasmara *et al.* (2009) Model Using Paired Sample T-Test

The hypothesis testing results of the mean difference of the predictions of model M5 and Yuliasmara *et al.* (2009) model using paired sample t-test is presented in **Table 10**.

Table 9. Results of TOST of equivalence between model M5 and Yuliasmara *et al.* (2009) model.

Statistic	Mean	Std Dev	Count	SE of Mean	DF	T Statistic	p value (One-Tailed)
DM5	16.60	8.41	110	0.80	109	20.70	<0.0001
DY	12.13	6.47	110	0.62	109	19.66	<0.0001

Note: DF is degree of freedom.

Table 10. Paired sample t-test results for model M5 and Yuliasmara *et al* (2009) model.

Model	Mean (kg)	Std Dev (kg)	SE (kg)	*N*	p value
Model M5	35.94	17.37	1.66		
Yuliasmara *et al* (2009)	21.78	10.41	0.99	110	<0.0001
Difference	14.16	6.96	0.67		

Note: Std. Dev is standard deviation, SE is standard error and N is the sample size.

The paired sample t-test results showed that the difference in means of the predictions (14.16 kg) of the two models was entirely different from zero at 95% confidence level. Also the P value is less than alpha value of 0.05, thus, $p < 0.05$, this provide enough evidence to reject the null hypothesis. This suggests that there is significant difference between the means of the two models and they are different models.

4. Discussion

4.1. Dataset for Allometric Modelling

The data used to develop the allometric models include diameter at breast height (D, cm), total tree height (H, m) and wood density (ρ, g·cm^{-3}) from three ecological zones in the study area. About 89% of cocoa trees used in developing the allometric models were within diameter at breast height class 10 - 14.9 cm and 15 - 19.9 cm with the rest within the classes 5 - 9.9 cm and 20 - 24.9 cm.). About 64% of the wood density was within the class 0.4 - 0.49 g·cm^{-3}, followed by 0.3 - 0.39 g·cm^{-3}, which constitute 33% and 0.5 - 0.59 g·cm^{-3} (3%). The highest wood density of 0.411 g·cm^{-3} was obtained in MSNW, the wood density in the ME and MSSE were similar, with their values being 0.395 and 0.394 g·cm^{-3}, respectively. The average wood density for cocoa in the study area is 0.40 g·cm^{-3} falls within the range of 0.35 to 0.45 g·cm^{-3} given by Romero (2018) [69] for Côte D'Ivoire. It did not deviate much from the value of 0.43 g·cm^{-3} for South America in global wood density database (Woodcock, 2000) [70]. It is not surprising that the average wood density is 0.40 g·cm^{-3}, because greater percentage (64%) of the wood density falls within the class 0.4 - 0.49 g·cm^{-3}. Also about 67% of the tree height was within the class 4 - 5.9 m and the remaining within the classes 2 - 3.9 m and 6 - 7.9 m making total of 33%.

4.2. Allometric Models Parameters

The accuracy of the models parameters contribute immensely to the predictions of the models and as such should be carefully examined, especially model M5 which has been chosen as the best model in this research. The allometric coefficient of the models in this study, which ranged from 0.0600 to 0.7437 with model M5 (0.7217), are higher than the one reported by Smiley and Kroschel (2008) [19] from Indonesia, which was 0.202.

The allometric exponents under this study varied from 0.7437 to 0.9586, with model M5 having a value of 0.9214, is lower that of Smiley and Kroschel (2008) [19] as 2.112. The variations could be due to differences in number of cocoa trees used in the allometric modelling. In this study the sample size was 110 while that used by that of Smiley and Kroschel (2008) [19] was 45 cocoa trees. Sample size affects model parameters because parameter estimates from small samples have high levels of uncertainty (Aabeyir *et al.*, 2020) [24]. The parameters of model M5 are more accurate than that of the model of Smiley and Kroschel (2008) [19], when taking into account the effects of sample size on model parameters.

4.3. Models Performance

Diameter at breast height (*D*) as a predictor is involved in all the seven models, with *D* alone (M1) explaining 82.07% of variations in *AGB*. This is anticipated because many researchers have revealed that stem diameter has been adequate biomass predictor (Henry *et al.*, 2011; Chave *et al.*, 2014) [14] [71]. Therefore, the diameter at breast height has always been the primary variable in linking tree characteristics to total aboveground biomass of trees, and it has a considerable impact on tree allometry.

The addition of wood density to diameter at breast height in category 3 models (M4 and M5) improved the AGB variability from 82.07% to 84.84% and 84.86% in M4 and M5, respectively. There is increase in R^2, it is consistent with the assertion that wood density is a key predictor of AGB (Djomo *et al.*, 2010; Chave *et al.*, 2014) [52] [71]. According to Dutcă (2019) [72], wood density truly explains variations in tree species multispecies allometric models.

Contrary, the inclusion of height to diameter at breast height as in the case of category 2 (M2 and M3), there is decrease in AGB variability from 82.07% to 74.35% and 70.75% in M2 and M3, respectively. The decrease in R^2 could be attributed to the extensive branching of the cocoa trees, which is a characteristic of tree crops. The fruit yield is of utmost importance in tree crops like cocoa. Trees height measurement are usually prone to errors on the field and this frequently leads to the elimination of tree height as a variable for predicting aboveground biomass of trees (Chenge, 2021) [73]. The addition of wood density and height to diameter at breast height, as in category 4 models ((M6 and M7), resulted in a decrease in R^2 from 82.07% to 77.76% and 78.34% in M6 and M7, respectively. The decrease in R^2 could be attributed to the inclusion of height predictor in the category 4 models. In terms of R^2, model M5 performed better than the other models in relation to AGB prediction.

Examining the histogram of the residuals of the models showed that the distribution of the residuals exhibited the bell –shaped pattern of the normal distribution (**Figure 3**), this suggest that the mean, median and mode are the same at the peak of the curve (Mcleod, 2019) [74]. The relationship between the observed and predicted *AGB* (**Figure 4**) as an evaluation of model predictions revealed that all the four models exhibit heteroscedasticity, and this is due to the residuals having unequal variance. Heteroscedasticity is usually unavoidable as the models take nonlinear power-law forms and unequal residual variance is accommodated when estimating model parameters (Dutcă *et al.*, 2022) [75].

The hypothesis testing of model M5 and Yuliasmara *et al.* (2009) [21] model using paired sample t-test and equivalence testing as means of validation came out with different conclusions. The paired sample t-test results showed that there is significant difference between the means of the predictions (14.16 kg) of the two models, while equivalence test revealed that model M5 and Yuliasmara *et al.*

(2009) [21] are equivalent within 10% of their mean predictions. The difference in the conclusions of the two tests can be attributed to the underlying principles of each test and the sample size as claimed by Yoo (2019) [76] that the null hypothesis will be more likely to be rejected as sample size grow due to rising z value. In this study, a sample size of 110 is adequate enough to support the assertion of Yoo (2019) [76]. This agrees with the results of the equivalence test under this study that Model M5 and Yuliasmara *et al.* (2009) [21] model are equivalent.

5. Conclusions

This study developed seven allometric models and compared them to find the best model among them to estimate AGB of cocoa trees in the cocoa landscape of Ghana. The best model was selected based on R^2, I_A, RMSE, bias (%), MAE and AIC_C values. The best performing model based on these metrics is AGB = $0.7217\rho(D^2)^{0.921}$ (model M5), which means that the model fitness is best when diameter at breast height combined with wood density.

The best model and that of Yuliasmara cocoa model were compared and found to be equivalent within ±10% of the means of their predictions, but the hypothesis testing using paired sample t-test results showed that there is significant difference between the means of the predictions of the two models. The best model developed under this study could be used to estimate AGB and quantify CO_2 emissions in cocoa plantations that are very important under the Ghana Cocoa-Forest REDD+ Programme (GCFRP) in the cocoa landscape of Ghana.

Credit Author Statement

This publication is an extract from PhD thesis of Emmanuel Donkor. Emmanuel Donkor drafted the manuscript, Stephen Adu-Bredu directed the field sampling and supervised the laboratory work, Yakubu Mohammed reviewed and edited the manuscript, Matthew Osei Jnr and Samuel A. Andam-Akorful reviewed and approved the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix A. Destructive Sampling Processes

Felling of cocoa tree

Cutting cocoa tree into stem and branches

Cutting stem into logs

Hanging stem logs onto scale

Weighing Branches

Plugging leaves into sack

Weighing fresh leaves

Weighing Disk sample

Weighing leaves sample