

ALLOMETRIC EQUATIONS FOR ESTIMATION OF ABOVE-GROUND BIOMASS IN COMMUNITY-MANAGED SECONDARY MIOMBO FORESTS OF THE LAKE CHILWA BASIN

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Accurate estimation of above-ground biomass (AGB) is essential for assessing carbon stocks and forming climate change mitigation strategies, especially in tropical ecosystems. This study developed site-specific allometric equations for estimating above-ground biomass in community-managed secondary miombo forests of the Lake Chilwa Basin, Malawi. Using destructive sampling of 58 trees across multiple plots, diameter at breast height ($D_{1.3}$), total height (H_t), and crown diameter (C_d) were measured. Trees were oven-dried in parts (trunk, branches, foliage), and their dry weights summed. The relationship between dry weight and dendrometric variables ($D_{1.3}$, H_t , C_d) was analysed using Nonlinear Least Squares regression to derive four models with different variable combinations. Model performance was evaluated using adjusted R^2 , RMSE, Furnival Index, PRESS, and absolute mean deviation (AMD). The most robust model (Y_{11}), incorporating $D_{1.3}$, H_t , and C_d , explained 88.9% of biomass variability. Comparisons with commonly used generalised models revealed significant biases ($P < 0.01$), due to site-specific factors such as species composition and tree size range. While some regional models performed better, their applicability was still limited. These findings underscore the need for localised models to improve biomass estimation accuracy. The developed models provide practical tools for forest managers in the Lake Chilwa basin and similar ecological zones.

Keywords: Allometric equation, above-ground biomass, Lake Chilwa Basin, secondary miombo forest

INTRODUCTION

Accurate estimation of above-ground biomass (AGB) is fundamental for quantifying forest carbon stocks, understanding carbon dynamics, and supporting climate change mitigation policies, particularly in tropical and sub-tropical forest ecosystems (Brahma et al. 2021). Secondary forests—defined as naturally or assisted-regenerating vegetation on previously disturbed or cleared land—are increasingly important for sequestering atmospheric carbon, restoring biodiversity, and sustaining ecosystem functions (Chazdon 2014). These forests frequently occupy abandoned agricultural land or degraded landscapes and are central to contemporary ecological restoration efforts.

In sub-Saharan Africa, many forested landscapes are managed through decentralised systems. Community-managed forests, often referred to as Village Forest Areas (VFAs), involve local communities in the stewardship of forest resources, including their protection,

restoration, and sustainable use (FAO 2016). These participatory governance models have shown promise in enhancing forest condition while supporting rural livelihoods.

The Lake Chilwa Basin, located in southeastern Malawi and extending into western Mozambique, is an ecologically and socio-economically significant transboundary landscape. The basin includes Lake Chilwa, Malawi's second-largest lake and a designated Ramsar site of international importance due to its biodiversity, extensive wetlands, and critical role as a habitat for migratory birds. The basin supports diverse livelihoods through agriculture, fishing, and forest product use, and is a priority area for sustainable development and regional environmental cooperation.

Surrounding the basin are extensive Miombo woodlands, a tropical deciduous forest type dominated by species in the genera *Brachystegia*, *Julbernardia*, and *Isoberlinia* (Frost 1996). These

woodlands span much of southern and eastern Africa and are vital for fuelwood, timber, non-timber forest products, and carbon storage. In both Malawi and Mozambique, community-managed secondary Miombo forests are playing a growing role in climate adaptation, land restoration, and rural energy provision.

Despite their importance, estimating biomass in these landscapes remains challenging due to ecological heterogeneity, variable disturbance histories, and the limited availability of site-specific data. Widely used allometric models, such as those developed by Brown (1997) and Chave et al. (2005), were primarily based on data from mature, undisturbed tropical forests with large trees. When applied to secondary or degraded forests, these models often yield biased estimates (Basuki et al. 2009, Beets et al. 2012, Kachamba et al. 2016). Additionally, research has demonstrated that allometric relationships vary significantly with forest structure, species composition, and management history (Cairns et al. 2003, Clark et al. 2001, Kebede & Soromessa 2018), highlighting the limitations of generalised models.

In Malawi, existing biomass studies have largely focused on primary Miombo woodlands, with little attention given to secondary forests under community management. No published

studies to date have developed biomass models specifically for secondary Miombo forests in the transboundary Lake Chilwa Basin, despite the growing importance of such data for REDD+ programs and carbon accounting initiatives (Kamaljit et al. 2023).

This study addresses this knowledge gap by developing and validating site-specific allometric equations for estimating above-ground biomass in community-managed secondary Miombo forests within the Lake Chilwa Basin. The models were derived using locally collected dendrometric data, and their performance was evaluated against existing generalised equations. The results aim to improve biomass estimation accuracy and inform forest management, carbon assessments, and climate finance initiatives in similar ecological zones.

METHODOLOGY

Study area and study sites

The study was conducted in the Lake Chilwa Basin, a transboundary landscape situated in southeastern Malawi and western Mozambique, covering approximately 8350 km², with 2700 km² area falling within Mozambique (Sagona 2013) (Figure 1). Elevations range from 627 m to 1050

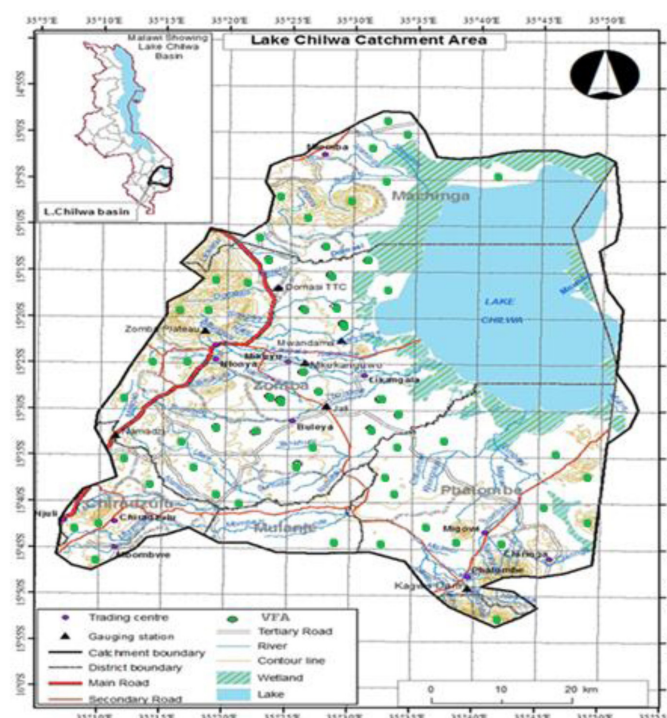


Figure 1 Map of the study area in Malawi and specific study sites (VFAs)

m above sea level, and the region experiences a subtropical climate with mean annual rainfall between 800 mm and 1200 mm (Zomba District Assembly 2009).

The study area is primarily savannah, turning into moderate wetlands towards Lake Chilwa. The vegetation is dominated by Miombo woodland, composed primarily of tree genera such as *Brachystegia*, *Julbernardia*, and *Isoberlinia* (Frost 1996). These woodlands are characterised by deciduous tree species and a pronounced dry season. Study sites were located in secondary Miombo forests, specifically within community-managed areas known locally as Village Forest Areas (VFAs), which are governed by local communities. These forests have undergone various degrees of degradation and natural regeneration.

Forest inventory

Initially, a pilot inventory was conducted. The initial inventory involved the establishment and measurement of 10 semi-permanent sample plots, each measuring 10 m × 10 m, strategically placed across representative forest areas within the basin. The primary purpose of this preliminary survey was to collect baseline data on tree diameter distribution and other key forest characteristics to estimate the required sample size for the full inventory.

Specifically, the coefficient of variation in diameter class frequencies from these 10 plots was used in a standard sample size formula (Pearson et al. 2005) to calculate the total number of plots needed to achieve a 95% confidence level with 10% precision in estimating the diameter class distribution.

Final inventory followed the pilot inventory. In contrast, the final inventory involved the full deployment of this statistically determined number of plots across the basin. These plots were also semi-permanent and followed the same 10 m × 10 m square layout, but they were more randomly distributed over a larger area to capture the full spatial and structural variability of the forests. The final inventory provided a more robust dataset for analysing forest structure, assessing resource conditions, and informing destructive sampling (collecting data for biomass models), which followed.

All trees in each plot, were assessed for

diameter at breast height ($D_{1.3}$ = 1.3 m from the ground); height (H_t); and crown diameter (C_d). Crown diameter was measured in meters (m) as the average horizontal projection of the crown in the north-south and east-west orientations. Diameter ($D_{1.3}$) was measured in centimeters (cm) using standard diameter tapes. Total tree height (H_t) was measured in meters (m) using height sticks/rods.

Destructive biomass data

Destructive sampling was used for the collection of data for the development of allometric equations. In total, 58 trees were felled, out of which 46 were used for the development of allometric equations and the remainder were for testing the models. The study used diameter class-based multi-stage sampling. Thus, the contribution of each diameter class was proportional to its dominance in the study area. In each plot, trees were selected randomly by using numbered tags that were fixed on each tree during inventory.

Selected trees were felled and divided into component parts, namely the trunk, branches, and foliage. The trunks and branches were cut into smaller logs that would easily fit into the ovens. On the site, foliage was carefully plucked and packed into plastic bags. The parts of each tree were labelled with codes to ease identification. Then the component parts were oven dried to constant weight (approximately zero moisture content). The leaves and twigs were oven-dried at $70 \pm 2^\circ\text{C}$ and woody samples at $105 \pm 2^\circ\text{C}$ (Tomczak et al. 2022). The dry mass of the component parts of each tree were then weighed and summed up to determine the biomass content of each tree.

Table 1 highlights the structure of the forests in the study area based on diameter class and species composition per diameter class. This informed the destructive sampling design.

Data analysis

Firstly, the relationships between dependent (above-ground biomass) and explanatory variables were tested using simple linear regression. The explanatory variables were diameter at breast height ($D_{1.3}$), tree total height (H_t), and crown (C_d).

Table 1 Forest structure by diameter class and species

Diameter class (cm)	Proportion (%)	Species distribution per diameter class (%)
5.0–6.9	31	6 % <i>Ochna swainfurtheriana</i> , 12 % <i>Lannea discolor</i> , 12 % <i>Diplorhynchus condylocarpon</i> , 18 % <i>Uapaca kirkiana</i> , 6 % <i>Brachystegia manga</i> , 12 % <i>Brachystegia spiciformis</i> , 6 % <i>Pterocarpus angolensis</i> , 12 % <i>Bauhinia petersiana</i> , 6 % <i>Brachystegia utilis</i> , 6 % <i>Raurea orientalis</i> , 6 % <i>Dispyros krkiii</i> , 6 % <i>Anona senegalensis</i>
7.0–8.9	45	4 % <i>Ochna swainfurtheriana</i> , 12 % <i>Lannea discolor</i> , 4 % <i>Diplorhynchus condylocarpon</i> , 20 % <i>Uapaca kirkiana</i> , 8 % <i>Brachystegia spiciformis</i> , 8 % <i>Pterocarpus angolensis</i> , 4 % <i>Bauhinia petersiana</i> , 20 % <i>Brachystegia utilis</i> , 8 % <i>Anona senegalensis</i> , 4 % <i>Dalbergia nitidula</i> , 4 % <i>Dispyros krkiii</i> , 4 % <i>Burkea africana</i> , 4 % <i>Raurea orientalis</i>
9.0–10.9	14	13 % <i>Uapaca kirkiana</i> , 37 % <i>Brachystegia spiciformis</i> , 25 % <i>Brachystegia utilis</i> , 25 % <i>Brachystegia manga</i>
≥11	10	17 % <i>Uapaca nitida</i> , 17 % <i>Brachystegia spiciformis</i> , 49 % <i>Brachystegia utilis</i> , 17 % <i>Azanza garkana</i>

Table 2 The most commonly used models in Malawi which were tested

ID	Model	Reference
Y ₁	$B_{ag} = 0.0267D^{2.5996}$	Grace et al. (2007)
Y ₂	$B_{ag} = \exp(-2.134 + 2.53 \ln D)$	Brown (1997)
Y ₃	$B_{ag} = 3.01D - 7.48$	Chidumayo (1997)
Y ₄	$B_{ag} = \exp(2.516 \ln(D) - 2.462)$	Malimbwi et al. (1994)
Y ₅	$\ln(B_{ag}) = -1.232 + 2.178 \ln D$	Basuki et al. (2009)
Y ₆	$0.21691 \times D^{2.318391}$	Kachamba et al. (2016)
Y ₇	$0.103685 \times D^{1.921719} \times H^{0.844561}$	Kachamba et al. (2016)

D_{1.3} is diameter at 1.3m above ground and H_t is total tree height

Nonlinear Least-Squares (NLS) regression analyses were conducted to investigate and model the relationship between a response variable - above ground biomass (B_{ag}) and one or more predictors – diameter at breast height ($D_{1.3}$), total height (H_t), and crown diameter (C_d). For the developed models, evaluation of the best-fit models was based on correction factor (CF), the coefficient of adjusted determination (R^2), and the root mean square error (RMSE) of the fitted equation. All models were computed using the MINITAB 19 statistical package.

The models developed in this study were also compared with commonly used generalized models in Malawi (Table 2). Evaluation of the predictive power of the models was tested using the criteria of the model's biological logic, the Furnival index (FI) for comparing models with different dependent variables; the PRESS statistic that requires fitting of the P parameter model to each of N different data sets (Picard et

al. 2012); the Absolute Mean Deviation (AMD) and; the root mean square error (RMSE). The best-fit model should have the lowest FI, PRESS statistic, AMD and RMSE.

Mean biomass estimates for training data were compared among the models using the analysis of variance (ANOVA). Post-hoc tests were conducted using Tukey's multiple comparison test.

RESULTS AND DISCUSSION

Development of allometric equations for above-ground biomass estimation

The correlation between predictors and response is a useful tool in establishing the true relationship between two variables. In forestry, correlation can be used to link difficult-to-measure variables, such as volume, biomass or carbon, to easy-to-measure tree characteristics,

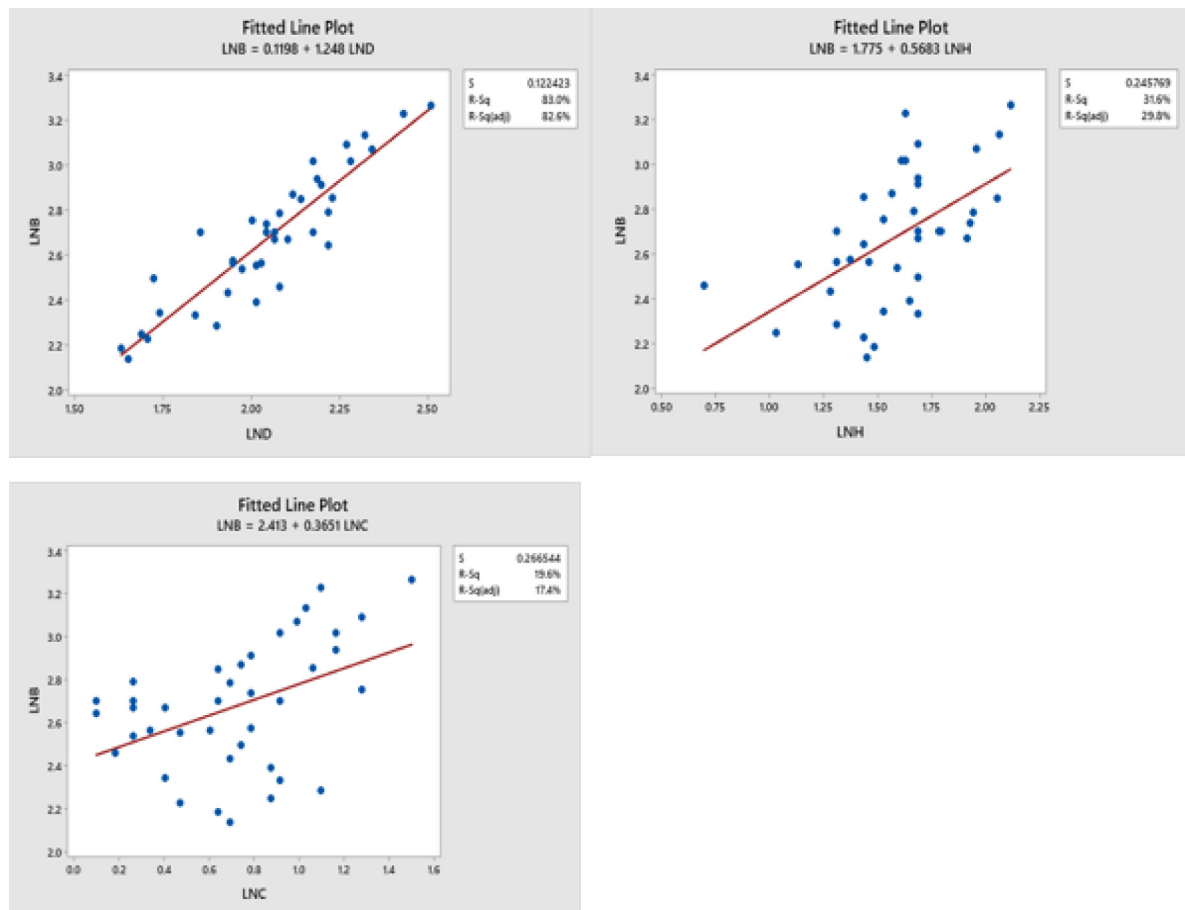


Figure 2 Relationships between AGB and three dendrometric variables

such as diameter or height, for example, with statistically determined parameters. Chave et al. (2005) suggest that the key variables to be measured to assess the biomass are tree diameter at breast height, tree height, and wood density. This is because diameter and height are commonly used in the mathematical formulas for volume calculation, hence easy to understand. Wood density and crown width/area are also very important as they differ a lot among tree genera and species (Picard et al. 2012).

In this study, the relationship between above-ground biomass (B_{ag}) and predictors was initially tested using simple linear regression. The predictors were diameter at breast height ($D_{1.3}$), total tree height (H_t), and crown diameter (C_d).

Figure 2 indicates that diameter at breast height ($D_{1.3}$) accounted for the greatest proportion of variance in above-ground biomass (B_{ag}), with a coefficient of determination (R^2) of 83.0%, followed by total tree height (H_t) and crown diameter (C_d), which explained 31.6%

and 19.6% of the variance, respectively.

The findings align with the conclusions of several previous studies that have emphasized the predictive capacity of these variables in forest biomass estimation (Chave et al. 2005, Basuki et al. 2009, Diomé et al. 2010, Henry et al. 2011, Pilli et al. 2006). Notably, Henry et al. (2011) reported that 63% of the biomass models developed for biomass estimation in the sub-Saharan forests utilised $D_{1.3}$ as a sole predictor variable. However, to improve precision, more combinations of predictors are often used for biomass predictions.

Table 3 shows the results of the four developed allometric equations for estimation of above-ground biomass for community-managed secondary miombo forests of Lake Chirwa Basin. The models (Y_8 , Y_9 , Y_{10} , and Y_{11}) estimate biomass basing on $D_{1.3}$ alone; $D_{1.3}$ and H_t (height); $D_{1.3}$ and C_d (crown diameter) and; $D_{1.3}$, H_t , and C_d , respectively. Model Y_8 shows that B_{ag} is estimated with $\text{adj. } R^2 = 81.6 \pm 0.8344\%$, $P < 0.001$. On the other hand, Y_{11} accounts for $88.9 \pm 0.681\%$.

Table 3 The four biomass allometric equations developed in this study

Code	Model	RMSE	CF	R ² (Adj)
Y ₈	$\ln(B_{ag}) = 0.41391 + \ln D^{1.13754}$	0.8344	1.008	81.6
Y ₉	$\ln(B_{ag}) = -0.623128 + \ln D^{1.07815} + \ln H^{0.276845}$	0.7588	1.007	86.1
Y ₁₀	$\ln(B_{ag}) = -0.507231 + \ln D^{1.11982} + \ln C^{0.107978}$	0.7105	1.006	86.5
Y ₁₁	$\ln(B_{ag}) = -1.55052 + \ln D^{1.07957} + \ln H^{0.210328} + \ln C^{0.0878105}$	0.681	1.005	88.9

B_{ag} = Biomass above ground; $D_{1.3}$ = diameter at breast height (1.3 m from ground); H_t = total tree height; C_d = crown diameter.

The selection of predictor variables in this study was guided by both empirical relationships and the practical qualities that define effective allometric equations, especially from the perspective of end users such as forest managers, carbon stock assessors, and policymakers. Good allometric equations must strike a balance between accuracy, simplicity, cost-effectiveness, transferability, and field applicability (Chave et al. 2014, Picard et al. 2012, Sileshi 2014). These qualities were prioritised in the model development process to ensure the equations could be used reliably in resource-limited contexts.

Diameter at breast height ($D_{1.3}$) was selected as the primary predictor due to its high explanatory power ($R^2 = 83\%$ in this study), ease of measurement, and consistent use in forest inventory protocols. As Picard et al. (2012) and Litton & Kauffman (2008) noted diameter at breast height can be measured with minimal error ($\approx 3\%$) using simple tools such as a diameter tape, making it superior to more complex or equipment-intensive variables. In contrast, tree height often has measurement errors ranging between 10–15%, is labor-intensive to collect in closed-canopy environments, and is typically recorded only for a subsample of trees in national forest inventories. Similarly, crown diameter, although informative about tree architecture and competitive space (Feldpausch et al. 2011, Jucker et al. 2017), is not commonly recorded due to field measurement constraints.

Model Y₈ relies solely on diameter at breast height ($D_{1.3}$) and is the most straightforward and practical. It is particularly suitable for large-scale forest inventories, REDD+ MRV systems, and rapid biomass assessments in

developing countries, where resources, time, or technical capacity for measuring additional variables are constrained (Brown 1997, Chave et al. 2005, Lumbres & Jin Lee 2013). Because diameter at breast height ($D_{1.3}$) is a universally measured and low-error variable, equation Y₈ is especially useful in operational forestry, ecological monitoring, and community-based inventory systems where data consistency and field simplicity are paramount. Despite being the least statistically precise (Adj. $R^2 = 81.6\%$), its usability is unmatched, justifying its inclusion in this suite of models.

Model Y₉ incorporates tree height which improves biomass estimation accuracy because height integrates stand structure and vertical growth, especially in multi-layered or heterogeneous canopies (Chave et al. 2014, Feldpausch et al. 2012). This model is most suitable for projects where height data are available from sample plots, remote sensing (e.g., LiDAR), or advanced forest inventory methods. It bridges practicality and improved accuracy and is recommended for biomass projects at research or national reporting levels where tree height can be feasibly collected.

Model Y₁₀ includes crown diameter which enhances the model's ability to capture variation in tree biomass arising from crown expansion and architecture (Poorter et al. 2015, Jucker et al. 2017). This model becomes particularly valuable in forest types where tree growth forms are irregular or where crown competition influences biomass accumulation (e.g., open-canopy woodlands or disturbed forests). While crown measurement is not routinely included in national inventories, it is increasingly accessible via drone imagery or high-resolution aerial photography, which makes this model

suitable for technology-assisted surveys and studies focused on tree architecture or species competition.

Model Y₁₁ combines all three predictors and represents the best statistical performance (Adj. $R^2 = 88.9\%$, lowest RMSE). It is recommended in research, carbon accounting, and ecological modeling settings where comprehensive and accurate biomass estimation is needed, and where all predictor variables can be reliably collected. It is ideal for landscape-level studies, biomass mapping, or calibration of remote sensing algorithms. Given its superior fit, it should be the model of choice when field conditions or remote sensing data allow for the collection of both height and crown diameter in addition to diameter at breast height ($D_{1.3}$).

Although wood density is a well-recognized determinant of biomass and is frequently recommended in pan-tropical models (Chave et al. 2005, Reyes et al. 1992), it was deliberately excluded from the models in this study. This decision reflects real-world limitations in Sub-Saharan African contexts, particularly Malawi, where species-level wood density data are sparse, inconsistent, or unavailable. Furthermore, intra- and inter-species variability in wood density is often substantial (Litton & Kauffman 2008),

which can introduce bias if general or averaged values are used (Fayolle et al. 2013). Using models based solely on measurable structural variables avoids these pitfalls and enhances model applicability.

In order to enhance the statistical robustness of the developed allometric models, this study deliberately employed distinct predictor variables across different model formulations, rather than relying on multiple transformations of a single variable. This approach was adopted to mitigate the risk of multicollinearity—a common statistical concern in allometric biomass modeling that can inflate standard errors and distort parameter estimates. As highlighted by Henry et al. (2011) and Zuur et al. (2010), multicollinearity not only undermines the reliability of regression coefficients but also complicates the interpretation of variable importance within a model. By using unique, biologically relevant variables such as diameter at breast height, total tree height, and crown diameter, this study ensured a more stable and interpretable model structure that aligns with best practices in ecological modeling.

Figure 3 suggests a reasonable linear relationship and equal variance of the error terms.

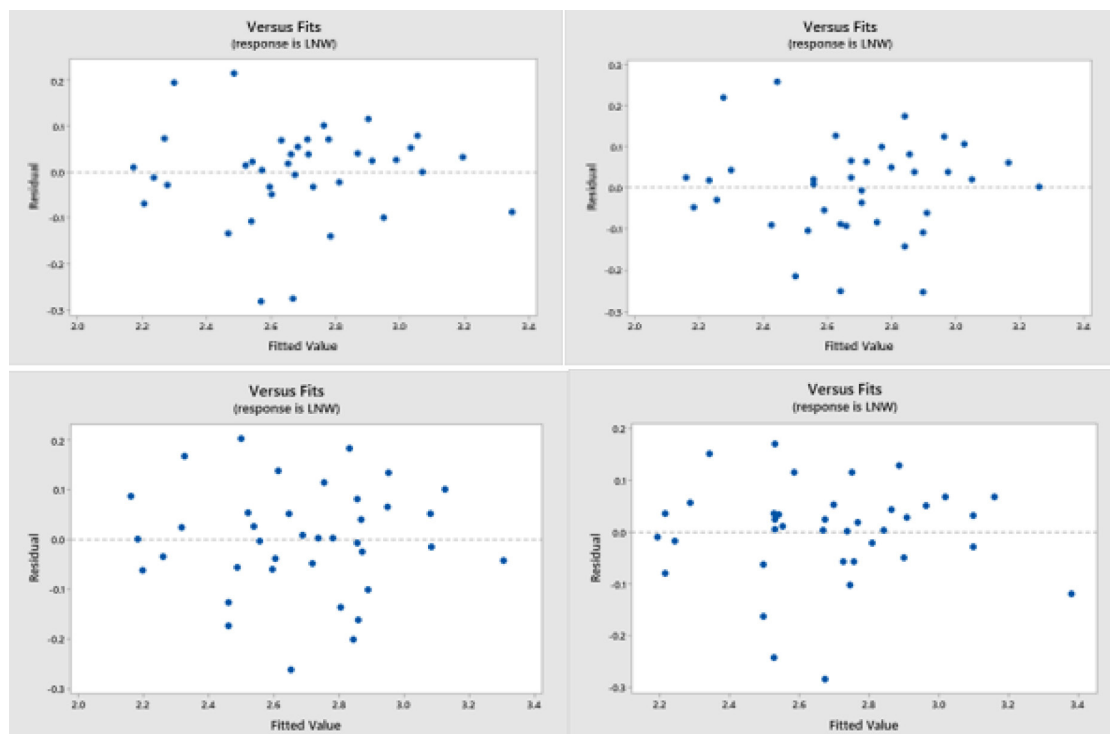


Figure 3 Residual versus Fits plots

Plots of residual against fits of all models showed reasonable linearity; no discernible pattern, below and above the zero (0), signifying consistency of variance over classes of the predictor variables (Figure 3). This signifies that all models developed in this study are reliable.

Comparing developed models against commonly used models in Malawi

In Malawi, several allometric equations are commonly used to estimate above-ground biomass (AGB), including both pan-tropical and regionally calibrated models. These models are summarized in Table 2 and include those developed by Brown (1997), Chave et al. (2005), Basuki et al. (2009), Grace et al. (2007), and Kachamba et al. (2016). In order to evaluate their applicability to the Lake Chilwa Basin, the study conducted a comparative evaluation based on fit statistics and the models' performance when applied to the local training dataset.

Fit and evaluation statistics of the developed and allometric equations commonly used in Malawi are presented in Table 4. Results show that FI ranged from -9.7443 to 0.6766. The highest FI was observed in the model Y_5 and the lowest AMD, was also observed in model Y_{11} . For RMSE, the values ranged from 0.6810 to 6.9232. The bias ranged from -6.0059 to 4.1918. The highest PRESS statistic value was observed in model Y_6 while Y_{11} showed the lowest.

The generalised allometry for tropical forests,

the model developed by Grace et al. (2007) and two (2) models developed by Kachamba et al. (2016) were completely incongruent. The models recorded high FI and RMSE, and AMD values over 0.5 times the 95% CI of the observed mean. The PRESS statistic of these models was very high. This implies that these models cannot be used in Lake Chilwa Basin or any areas with similar characteristics.

Models developed by Chidumayo (1997) and Malimbwi (1994) showed relatively better predictive power. FI, RMSE, AMD and PRESS statistics were within reasonable ranges. However, the fit statistics of these models were not as good as for the models developed in this study. While these models can be used in the study area or any area with similar characteristics, larger deviations from the mean should be expected.

Furthermore, the results showed that all developed models have good predictive powers. This signifies that all the equations developed in this study may assist forest managers in acquiring a more credible and accurate above-ground biomass estimation for secondary forests in the Lake Chilwa Basin in Malawi and Mozambique. However, where resources and conditions permit, model Y_{11} is the most recommended model as it is the strongest model.

Figure 4 shows the comparisons of the means of observed biomass against predictions by generalized models and locally developed models on the training dataset.

Table 4 Fit and evaluation statistics of all allometric equations

MODEL	FI	RMSE	AMD	PRESS	Rank
Y_1	0.3916	9.0106	4.1918	18.5441	7
Y_2	0.6662	12.7802	4.2159	28.051	8
Y_3	0.1073	2.3249	0.9562	1.4428	5
Y_4	0.2347	5.5017	1.4059	4.0625	6
Y_5	0.9232	15.615	6.0059	47.9309	11
Y_6	0.8744	13.973	5.8974	48.5783	10
Y_7	0.6875	12.886	4.3247	42.3814	9
Y_8	0.0781	0.8344	0.6406	0.6962	4
Y_9	0.0682	0.7588	0.5944	0.5758	3
Y_{10}	0.0588	0.7105	0.589	0.5048	2
Y_{11}	0.0522	0.681	0.5581	0.4638	1

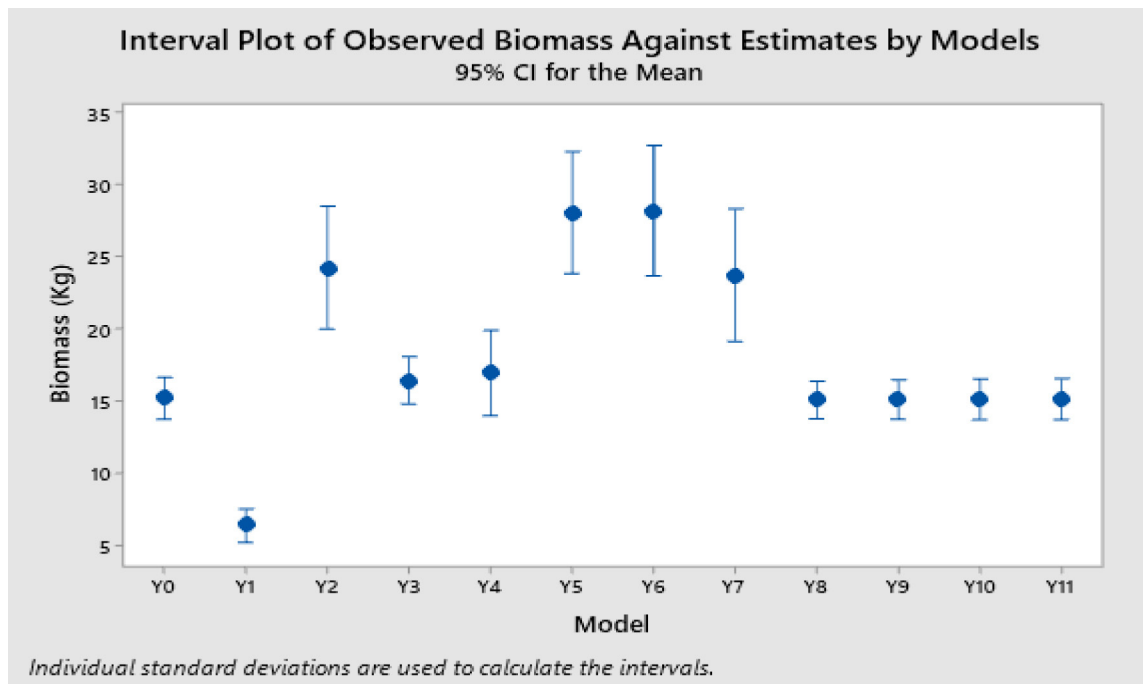


Figure 4 Mean carbon estimates for models against observed mean

Figure 4 compares the observed mean above-ground biomass (Y_0), the mean biomass estimates derived from generalized allometric equations (Y_1 , Y_7), and estimates from local allometric equations developed in this study (Y_8 , Y_{11}). Among the generalised models, Y_1 significantly underestimated biomass relative to observed values ($P < 0.05$), while equations Y_2 , Y_5 , Y_6 and Y_7 overestimated biomass significantly ($P < 0.05$). In contrast, models Y_3 and Y_4 produced estimates that were not statistically different from the observed mean, indicating acceptable predictive performance. The performance of the developed models (Y_8 , Y_{11}) suggests improved alignment with site-specific forest structure compared to generalised equations.

Table 5 for Tukey's multiple comparison tests shows that the observed mean (Y_0) and projected means by models Y_3 , Y_4 , Y_8 , Y_9 , Y_{10} , and Y_{11} , are not statistically different. Models Y_1 , Y_2 , Y_5 , Y_6 and Y_7 are different from all the model array.

Results revealed significant discrepancies ($P < 0.001$) between the AGB estimates from these generalised or regional models and those generated by the locally developed equations (Figures 4 and 5). Notably, the pan-tropical models by Brown (1997) and Basuki et al. (2009), as well as the Malawian miombo woodland models by Kachamba et al. (2016), consistently overestimated biomass in the study

area. In contrast, the model developed by Grace et al. (2007) for the N'hambita community in Mozambique significantly underestimated biomass. These findings align with observations by Beets et al. (2012) and Sileshi (2014), who reported that generalized allometric equations often yield biased predictions when transferred to new ecological settings.

Several factors may explain the observed bias in these generalized models. First, they were largely developed using tree samples with a wide diameter range—often from 5 cm up to 160 cm DBH (Chave et al. 2005, Basuki et al. 2009). In contrast, the current study focused on secondary forests with a narrower diameter distribution, predominantly between 5 and 12 cm. Because larger trees disproportionately influence mean biomass values in general models, their use in smaller-statured forests leads to systematic overestimation. Second, many of these generalized models were derived from primary or protected forest areas, which typically have higher biomass accumulation and different structural characteristics compared to degraded or recovering secondary forests (Lumbres & Jin Lee 2013). These differences in forest structure, stem form factor, and species composition contribute significantly to the misalignment of model outputs with local conditions.

Table 5 Tukey's multiple comparison tests of the model estimates

Model	N	Mean	St Dev	95% CI	Grouping
Y ₆	39	28.13	13.93	(25.33, 30.93)	A
Y ₅	39	28.00	12.99	(25.20, 30.79)	A
Y ₂	39	24.20	13.12	(21.40, 26.99)	A
Y ₇	39	23.66	14.14	(20.87, 26.46)	A
Y ₄	39	16.91	9.12	(14.12, 19.71)	B
Y ₃	39	16.384	5.054	(13.587, 19.181)	B
Y ₀	39	15.158	4.511	(12.361, 17.954)	B
Y ₁₁	39	15.104	4.387	(12.308, 17.901)	B
Y ₁₀	39	15.092	4.337	(12.295, 17.888)	B
Y ₉	39	15.073	4.159	(12.276, 17.870)	B
Y ₈	39	15.046	4.011	(12.249, 17.843)	B
Y ₁	39	6.342	3.539	(3.546, 9.139)	C

Means with similar letters denote that biomass estimates are similar.

The underperformance of the Kachamba et al. (2016) models is particularly noteworthy, given that they were developed for Malawian miombo woodlands. However, their calibration data included larger trees and more mature forest stands than those found in the Lake Chilwa Basin. The secondary forests in this study are in various stages of regrowth and are characterised by smaller, more slender stems. Thus, despite being country-specific, the Kachamba models overestimated AGB because they reflect biomass dynamics in a structurally different forest context. This finding emphasizes that even within a single country, ecological variability must be accounted for when selecting biomass estimation models.

In contrast, the models developed by Chidumayo (1994) and Malimbwi (1997), though older, performed reasonably well. This may be attributed to the similarity in forest conditions and diameter ranges used in their development. For example, the Chidumayo (1994) model was specifically derived from miombo woodlands with trees in the 6–10 cm DBH range, closely matching the structure of the forests examined in this study. This underlines the importance of diameter class matching between model calibration data and application contexts, a principle increasingly emphasised in

recent biomass modeling literature (Chave et al. 2014, Goodman et al. 2014).

These results carry important implications for forest carbon accounting, REDD+ MRV systems, and forest management in Malawi. The findings reinforce the need for site-specific model calibration and validation, even when national models exist. Relying on generalised equations without ground-truthing can lead to systematic biases, misinformed policy decisions, and misallocation of carbon credits or conservation resources. Therefore, for landscapes like the Lake Chilwa Basin—characterised by secondary, degraded, or regenerating forests—locally calibrated equations, such as those developed in this study, provide more accurate, reliable, and ecologically meaningful biomass estimates.

CONCLUSIONS AND RECOMMENDATIONS

This study developed and evaluated four allometric equations for estimating above-ground biomass (AGB) in community-managed Miombo forests within the Lake Chilwa Basin in Malawi. All four models demonstrated acceptable predictive accuracy and consistency, affirming the hypothesis that locally developed,

site-specific equations provide more reliable AGB estimates than generalised models.

Among the models, predictive performance improved with the inclusion of additional variables—specifically, total tree height and crown diameter—supporting the hypothesis that multi-variable models yield greater precision. Nonetheless, the model based solely on diameter at breast height ($D_{1.3}$) remains valuable for its operational simplicity and cost-effectiveness in resource-limited settings.

The comparative analysis further demonstrated that generalised allometric models exhibited significant biases when applied outside their calibration domains. These findings substantiate concerns about the transferability of biomass models across ecologically diverse regions. Thus, the results support the conclusion that model selection must be informed by ecological context, species composition, and stand structure.

In light of these findings, the study recommends the development and adoption of site-specific allometric models tailored to the ecological and silvicultural characteristics of distinct forest zones in Malawi. The use of the silvicultural guidebook of Malawi can facilitate this process by guiding the delineation of biomass models according to silvicultural zones and land use systems. This zonal modeling approach is essential to improve the accuracy of biomass assessments and to inform sustainable forest management and REDD+ initiatives in the region.

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