Hindawi
International Journal of Forestry Research
Volume 2018, Article ID 6495271, 14 pages
https://doi.org/10.1155/2018/6495271

Research Article

Allometric Equations for Estimating Silk Oak (*Grevillea robusta*) Biomass in Agricultural Landscapes of Maragua Subcounty, Kenya

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Received 23 April 2018; Revised 8 August 2018; Accepted 16 August 2018; Published 2 October 2018

Academic Editor: Scott D. Roberts

Grevillea robusta is widely interplanted with crops in Maragua subcounty, a practice that enhances biomass quantities in farmlands. However, quick tools for estimating biomass of such trees are lacking resulting in undervaluation of the farm product. This study sought to develop allometric equations for estimating tree biomass using diameter at breast height (DBH) and tree height as predictor variables. Tree biomass was computed using thirty-three (33) trees randomly selected from 12 one hectare plots established in each of the four agroecological zones (AEZs). DBH of all *Grevillea robusta* trees per plot was measured and three trees were selected for destructive sampling to cover the variety of tree sizes. Regression analysis was used to develop equations relating DBH/tree height to biomass based on linear, exponential, power, and polynomial functions. The polynomial and the power equations had the highest R^2, lowest SEE, and MRE values, while DBH was the most suitable parameter for estimating tree biomass. The tree stem, branches, foliage, and roots biomass comprised 56.89%, 14.11%, 6.67%, and 22.32% of the total tree biomass, respectively. The mean tree biomass density (12.430 ± 1.84 ton ha^{-1}) showed no significant difference ($p=0.09$) across AEZs implying no difference in *G. robusta* agroforestry stocks across the AEZ. The allometric equations will support marketing of tree products by farmers and therefore better conservation and management of the tree resource.

1. Introduction

Trees in agricultural ecosystems offset pressure on forest resources in conventional forests and therefore play a major role in sustaining the productivity of agricultural and forested landscapes. They are a source of livelihood for the rural communities providing wood and nonwood products like resin, honey, medicine, vegetables, among others and are also important in conservation of biological diversity, water, and soil conservation [1]. They represent a vital source of food for many of the world's poorest people, providing both stable and supplemental foods, fodder and fuel for lighting, and cooking and food processing. Besides, they are also important in biological diversity conservation and mitigating climate change through carbon sequestration [2].

Quantification of the amount of biomass and/or carbon stored in trees presently is an important component in the implementation of the emerging carbon credit such as Reducing Emissions from Deforestation and Degradation ($REDD^+$) [3]. Developing countries including Kenya can benefit from $REDD^+$ related mechanisms by providing accurate information about their forest and tree resources. REDD+ requires countries to establish measurement, reporting, and verification (MRV) methods [4]. This may consists of inventory of forests/trees in sampled plots and application of appropriate allometric equations to estimate biomass [2]. Biomass estimates eventually are converted into carbon and carbon dioxide (CO_2) equivalents.

Most of the small scale farmers in Maragua integrate trees (mainly *Grevillea robusta*) with crops in their farms.

The specific economic values of the trees planted in agricultural landscapes have not been fully explored. Since no marketing guidelines have been developed for the different tree products, prices of the products are normally determined by agreements between the seller and the buyer, and this varies from area to another, size of tree or product, and the targeted use of the product. In many cases, such negotiations do not favor the farmer and lowers the value of the tree, thus demotivating farmers from planting trees. A method that helps establish biomass stocks and provides accurate information about the available wood resources from this species would help in its management and conservation and would enhance the livelihoods of the farmers.

Some allometric equations have been developed to estimate tree biomass quantities using easily measurable parameters such as DBH and height [1–3]. Henry *et al.* [1] and Kuya *et al.* [5] constructed equations for estimating tree biomass in agricultural landscapes of western Kenya while Kinyanjui *et al.* [6] constructed an equation for inventory of the above ground biomass in the Mau Forest Ecosystem of Kenya. Mugo *et al.* [7] predicted stem diameter of open grown trees in western Kenya. Since tree allometry varies from site to site [8], such equations may not be appropriate for the conditions of Maragua subcounty in terms of agro ecological zonation and the purpose for which the trees are grown. Here, a variety of wood products are marketed for various uses including timber, firewood, pole wood, and fencing and some leaves have been used as livestock fodder. Hence, to meet the study area specific needs for tree products and tree components, it was necessary that equations for estimating *G. robusta* biomass quantities in the farming landscapes of Maragua subcounty are developed.

The purpose of this study was to develop equations relating tree biomass with easily measurable parameters of diameter at breast height (DBH) and height as a quick tool for valuation of tree products. The study also sought to assess variations of *G. robusta* biomass among agroecological zones of the study area as a basis for developing tree resource management plans.

2. Materials and Methods

2.1. Study Area. The study was done in Maragua subcounty of Murang'a county in central Kenya (Figure 1). The area covers 839 Km^2 [9], between longitude 36° 30′E and 37°30′E and latitude 00°30′S and 1°S. The study area consists of four upper midland agroecological zones (AEZ) as illustrated in Table 1. Such variations of altitude and climate are expected to influence allometry and also biomass productivity of *G. robusta* trees.

2.2. Physical and Topographic Features. The study area is a major source of numerous springs and rivers that drain into River Tana through rivers Maragua, Irati, Sabasaba, Kabuku, Makindi, Thuki, Thamuru, and Thika [9]. The geology of the subcounty consists of volcanic rocks of the Pleistocene age and basement system rock of Achaean type. Volcanic rocks occupy the western part of the county bordering the Aberdare ranges while rocks of the basement system are in the eastern part. Porous beds and disconformities within the volcanic rock system form important aquifers, collecting, and moving ground water, thus regulating water supply from wells and boreholes. In the study area Jaetzold *et al.* [10] classified and described soils in AEZ as shown in Table 2.

2.3. Land Use Activities. Farmers in the study area have actively adopted agroforestry [11]. Land use systems range from subsistence small holder farms to more cash crop oriented farms which relatively range from 1.5 to 2 acres. Woody vegetation forms part of the agricultural landscape which varies from single tree to small stands that consists of mainly exotic trees and isolated indigenous trees managed in different ways [11]. Trees are grown around the homesteads, in woodlots and croplands, and along farm boundaries. Githiomi *et al.* [11] further stated that trees and shrubs are grown around the homestead, in woodlots and cropland, and along farm boundaries and that woodlots are in small mono specific clusters of trees mainly in lower areas of the study area. According to Kuya *et al.* [5], such land use activities influence the biomass of agricultural landscapes in different ways depending on management activities.

2.4. Sampling Design. Stratified systematic sampling was used on a Geographical Information System (GIS) platform to select sampling sites in each of the AEZs. Each AEZ was divided into three equal polygons and the centre of each polygon was used as the reference data collection point (Figure 2). The position of the data collection point identified on the GIS map was recorded (Table 3), transferred into a GPS, and traced to the ground. The GPS readings were based on the UTM/UPS format in UTM zone 37S. A one hectare (100 x 100 m) plot was established at the reference point aligned to the North-South and East-West grids. All the *G. robusta* trees in the plot were recorded for diameter at 1.3 from the ground (DBH) and total height. Three *G. robusta* trees in each plot were selected for destructive sampling based on a proportional allocation among size classes identified in the plot.

2.5. Processing of Destructively Sampled Trees

2.5.1. Destructive Sampling. All the *G. robusta* trees selected for destructive sampling were categorized into DBH classes. The selected trees were uprooted onto tarpaulin sheets spread on felling direction (to avoid loss of foliage), leaves stripped off and debranched, and total tree length/height (HT) measured using a linear tape. Each of the trees was then divided into components (trunk, branches, foliage, and roots) and the trunk was cross cut to manageable sizes. The tree components were weighed in the field and their fresh weight was recorded. Samples were taken from the different components of the tree and their fresh weight was taken. The samples were subsequently oven-dried in the laboratory at 105°C as guided by [12].

Similarly the branches were trimmed, cross cut, and classified into four diameter classes as $0 < D < 2$ cm (Class

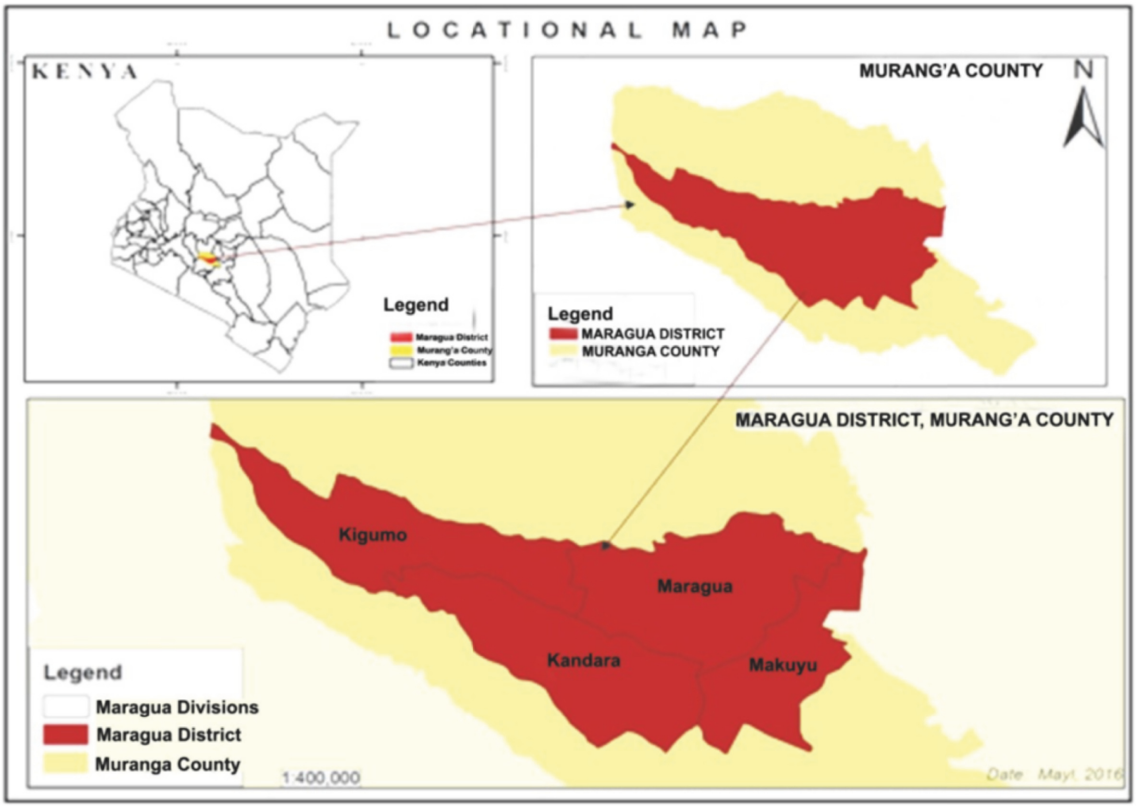

Figure 1: Study area. Showing the location on Kenyan map and within the Murang'a county.

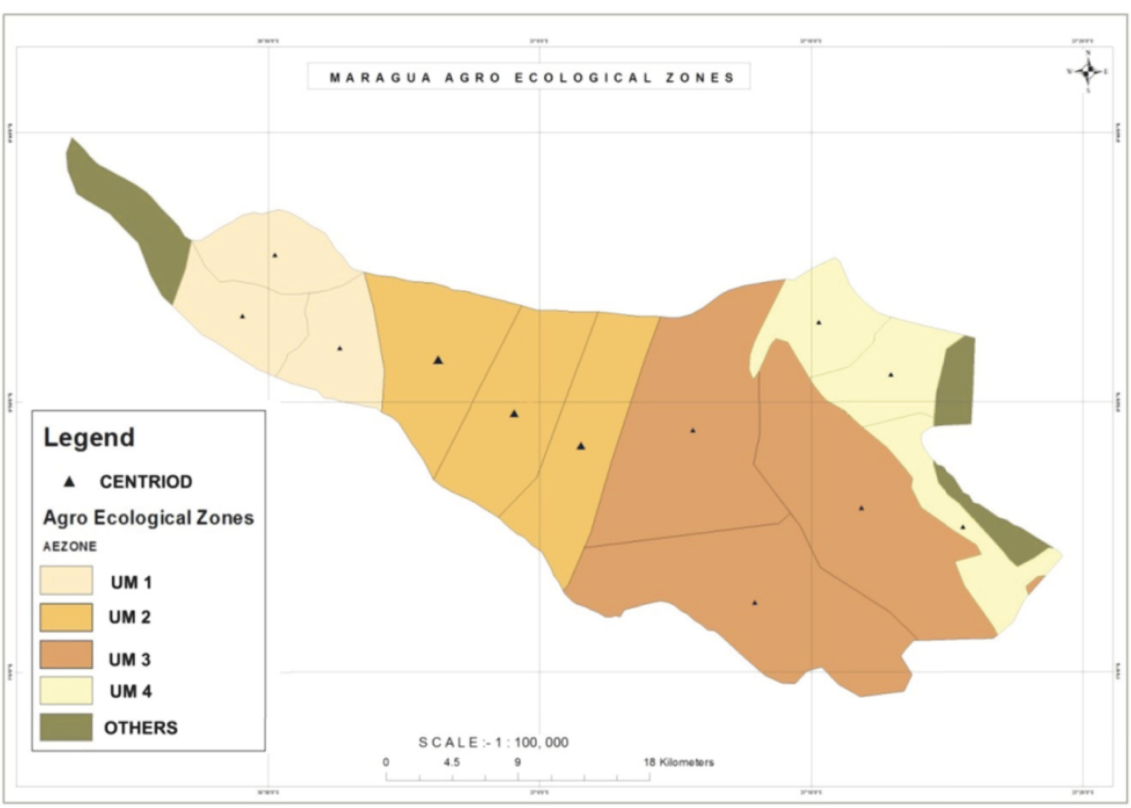

Figure 2: Maragua agroecological zones, showing polygons per zone and points for data collection.

Table 1: Biophysical and climatic conditions of Maragua subcounty (source [10]).

Attribute	Upper midland 1 (UM 1)	Upper midland 2 (UM 2)	Upper midland 3 (UM 3)	Upper midland 4 (UM 4)
Altitude range (m)	1730 - 2430	1500 – 1730	1340 – 1500	1060 - 1340
Mean annual Rainfall (mm)	2200	1537.5	955	970
Mean annual Temperature (°C)	18.4°C	19.3°C,	20.2	21.2

Table 2: Classification and description of soil in Maragua subcounty.

AEZ	Physiographic Lithology	Soil description
UM 1	MV2	Well drained, very deep, dark reddish to dark brown, very friable and smeary, clay loam to clay, with thick acid humic topsoil, in places shallow to moderately deep and rocky: Humic ANDOSOLS, partly lithic phase
UM 2	RB1	Well drained, extremely deep, dark reddish brown to dark brown, friable and slightly smeary clay with an acid humic topsoil: Ando-humic NITISOLS: with humic ANDOSOLS.
	RB2	well drained, extremely deep, dusky red to dark reddish brown, friable clay with an acid humic topsoil: humic NITISOL
UM 3	RB3	Well drained, extremely deep, dusky red to dark reddish brown friable clay; with inclusion of well drained, moderately deep, dark red to dark reddish brown, friable clay over rock, pisoferric or petroferric materials. Eutric NITISOLS: with nito-chromic CAMBISOLS and chromic ACRISOLS and LUVISOLS, partly lithic, pisoferric or petroferric phase
UM 4	LB1	Well drained, very deep, dark red, very friable clay: Nito-rhodic FERRALSOLS.

Table 3: Coordinates of data collection points for all the AEZs.

Agroecological Zone	Plot number	Eastings (m)	Nothings (m)
UM 4	1	305449.791	9900308.287
	2	301575.475	9908749.165
	3	297040.133	9914658.828
UM 3	1	290497.054	9896663.132
	2	298551.514	9903069.450
	3	289507.887	9901526.723
UM 2	1	281419.488	9909982.717
	2	276445.967	9904576.637
	3	268721.854	9911103.375
UM 1	1	263165.408	9896663.132
	2	259196.650	9918509.281
	3	256504.015	9914786.820

1), 2 ≤ D < 5 cm (Class 11), 5 ≤ D < 10 cm (Class 111), and D≥ 10 cm (Class IV) for easy of weighing. Their weights were taken for green weight to the nearest 0.1 kg. The heavier ones were measured as individual billets while the lighter ones were bundled together and weighed for their green weight. Aliquots were taken and labeled and their green weight was recorded to the nearest 0.01gm kept in bags and taken to the laboratory for oven-dry (105°C) weight measurement. The foliage was collected on to the tarpaulin sheet, bundled into gunny bags whose weights were known, and weighed to the nearest 0.1kg. Their green weights were calculated as the difference between the gross weight and the weight of the empty gunny bags and recorded. A sample of the foliage was taken from the combined mass of the foliage, weighed, recorded to the nearest 0.01gm, and oven-dried (70°C).

Excavation of the tree was done manually until all the roots were removed. The taproot was followed to its endpoint and root length recorded. Soil embedded in the stump joints and on root surface was removed by use of a brush and water. The roots were classified into size classes as (Class 1) 0 < D < 2 cm, (Class 11) 2 ≤ D < 10 cm, and (Class 111) D ≥10 cm for ease of weighing. Roots were weighed by size classes for green weight and recorded. An aliquot of each root size class was extracted and weighed for green weight, recorded, tagged, packaged, and taken to the laboratory to oven-dry at 105°C. In all the cases, the aliquots were left in the oven to dry and changes in dry weight were monitored on a daily basis until they reached a constant weight.

2.5.2. Biomass Measurement. The aliquot's green and oven-dry weights were used to get the dry-green weight ratios. These were subsequently used to convert the green weight of the tree component (trunks, branches, foliage, or roots) to dry weight, which is the component's biomass. The total aboveground (AGB) biomass was obtained by getting the sum of the biomass of the trunk, branches, and foliage. Similarly the total belowground (BGB) biomass was obtained by summing up all the dry weights of all the root sections of that given tree. Finally the total tree biomass (TTB) was obtained by adding up aboveground and belowground biomass. Scatter plots and function graphs were used in assessing the relationships between easily measurable variables of DBH and HT together with a combination of DBH and HT against total tree biomass and tree component biomass

2.5.3. Development of Biomass Equations. Thirty-three destructively sampled trees were used to develop the biomass estimation allometric equations. The measured predictor

Table 4: Biomass partitions (Kg) of each component and total tree biomass of sampled trees for every AEZ.

Zone	Stem	Branches	Foliage	AGB	BGB	TTB
UM 1	550.25	129.84	81.05	761.14	166.83	927.95
UM 2	1,011.10	218.45	87.36	1,316.91	372.56	1,689.47
UM 3	1,204.43	332.89	145.24	1,682.56	535.24	2,217.84
UM 4	838.14	213.13	109.07	1,160.84	339.87	1,500.61
Total	3,604.32	894.31	422.72	4,925.45	1,414.50	6,335.89

Table 5: Percentage contribution to total tree biomass among tree components in the different AEZ.

Zone	Stem	Branches	Foliage	AGB	BGB
UM 1	59.30	13.99	8.73	82.02	17.98
UM 2	59.85	12.93	5.17	77.95	22.05
UM 3	54.31	15.01	6.55	75.86	24.13
UM 4	55.85	14.20	7.27	77.36	22.65
Total	56.89	14.11	6.67	77.74	22.33

variables DBH, height (Ht), and product of DBH and HT (DBH∗Ht) for each of the destructively sampled trees were regressed to the dry weight (biomass) of the total tree biomass (TTB) or component biomass [(AGB), (BGB) branches biomass (BR), and foliage biomass (F)].

Scatter plots were used in illustrating the relationships between total tree and tree component biomass with the easily measurable variables. To derive the equation for each of the dependent variable (TTB, AGB, BGB, BR, and F) the regression functions (exponential, linear, polynomial, and power) were superimposed on the scatter plot graphs. The selection of the best fit equation was based on the lowest standard error of the estimate (SEE) which is the standard deviation of the residuals: the lowest residual mean error (RME) and the highest coefficient of determination (R^2).

2.5.4. Validation of Developed Allometric Equations. The mean differences between predicted and observed biomass were used to test the suitability of the equation. Simple linear regression analysis between observed and predicted values of the equations quantifies the tendency of residuals whereby R^2 and mean standard error (MSE) indicate the precision of the estimates. Residual plots were also used to assist in the evaluation of the equations. Bias% was computed as ((predicted biomass-measured biomass)/measured biomass)∗ 100 [13].

Finally the developed equation for total tree biomass was compared with several equations in similar management units but different geographical areas. The two sets of biomass values were subjected to a paired t test [14] to find if differences occur in each biomass estimate comparison.

3. Results

3.1. Preliminary Findings of the Dataset. A total of 1,090 trees were measured for DBH in the twelve (12) plots 222 in AEZ 1, 308 in AEZ2, 292 in AEZ 3, and 268 in AEZ 4. The values for DBH ranged from 1cm to 39.5cm with a mean of 11.08 cm in AEZ1, 11.51 cm in AEZ 2, 10.07 cm in AEZ 2, and 12.14 cm in AEZ 4. Height values ranged from 6.0m to 24.8m with a mean of 11.67m in AEZ 4, 13.32m in AEZ 3, 14.03m in AEZ 2, and 11.42m in AEZ 1. Out of the 1090 trees measured for DBH, 33 trees were destructively sampled for biomass measurements.

3.2. Percentage Contributions of Different Tree Components Biomass. The summary distribution of the total tree biomass and tree biomass components of the thirty-three destructively sampled trees of different sizes recorded in the study area are as shown in Tables 4 and 5. The total tree biomass (TTB) for the 33 trees was 6,335.89 kg distributed as follows: stem/trunk (56.89%), branches (14.11%), foliage (6.67%), and roots (22.33%). Thus aboveground biomass (AGB) comprised 77.74% while belowground biomass (BGB) was 22.33%. These are the proportions of biomass available for specific uses, e.g., timber (stem biomass), fuel wood (branches biomass), mulch/livestock feed/green manure (foliage biomass), and soil organic carbon services (roots).

The stem comprises the largest percentage of the total tree biomass (Table 5) while foliage has the least biomass contribution and this is in agreement with similar studies [1, 5, 15]. The 22.33% proportion of BGB is close to the IPCC default value for BGB which is taken as 24% [16]. The slight variations in allocation among AEZ could be a justification for development of very specific allometric equations for each of the AEZ. For example, the results indicated a slight increase in BGB/AGB ratio with altitude rise from UM1 (0.219) to UM4 (0.293). Such information on component ratios among *G. robusta* and which is based on tree allometry variations requires further research and supports its conservation and usage.

3.3. Illustrations of Biomass Estimation from Various Functions. Various functions were plotted and the biomass estimates done for each function. The goodness of fit in each regression was illustrated by the coefficient of determination (R^2 value) which explains how close the measured data are to

Table 6: Allometric equations for estimating various biomass using DBH.

Function	Equations	MRE	R^2	SEE
Exponential	$TTB = 10.91e^{0.150DBH}$	-29.10	0.84	4.57
Power	$TTB = 1.811DBH^{1.658}$	5.05	0.98	1.34
Polynomial	$TTB = 0.322DBBH^{2}+7.93DBH-19.26$	0.15	0.93	1.33
Linear	$TTB= 18.00DBH - 73.22$	0.07	0.91	1.52
Multiple	$TTB = 11.356DBH - 8.924HT + 0.536(DBH*HT) + 18.27$	-0.16	0.93	1.40
Exponential	$AGB=8.474e^{0.150DBH}$	-22.60	0.83	3.56
Power	$AGB=1.384DBH^{1.665}$	3.2	0.98	0.99
Linear	$AGB=13.99DBH - 56.96$	0.02	0.92	1.12
Polynomial	$AGB=0.248DBH^{2} + 6.243DBH - 15.45$	0.002	0.94	0.99
Multiple	$AGB=8.641DBH - 6.9HT + 0.424(DBH*HT) + 14.53$	0.06	0.90	1.98
Exponential	$BGB = 2.311e^{0151DBH}$	-5.13	0.82	1.04
Polynomial	$BGB = 0.074DBH^{2}+1.688DBH - 3.791$	0.10	0.82	0.50
Linear	$BGB = 4.013DBH - 16.24$	-0.01	0.81	0.53
Multiple	$BGB =2.713DBH - 2.028HT + 0.111(DBH*HT) +3.79$	0.10	0.82	0.51
Power	$BGB = 0.401DBH^{1.642}$	3.42	0.93	0.51

the fitted regression line [14]. These illustrations are shown in Figures 3, 4, and 5.

A comparison of functions for estimating TTB from DBH illustrates that the exponential function overestimates DBH for a tree of 35cm DBH. Though the other three functions have a near similar estimate, the R^2 values favor the power function ($R^2 = 0.97$) and the polynomial function ($R^2= 0.93$). Though the linear function gives relatives good R^2 value, foresters have disqualified linear relationships because they do not illustrate the ideal relationship between predictor variables and biomass or volume over a wide diameter size distribution [8, 16].

Estimation of total tree biomass from height varied greatly among functions making it difficult to select the ideal function. The R^2 values were also lower compared to those of using DBH as a predictor variable. The same trend was noted in estimating ABG from tree height. Noting that height measurement in forests is difficult and the fact that farmers sell trees while standing, the use of tree height may increase tree biomass or volume estimation costs, while not increasing accuracy of estimates. As such trials of height as a biomass-predictor variable were discarded in favor of DBH which is easy to measure and can be measured with high levels of accuracy [6, 8].

DBH gives a good estimate of AGB based on R^2 values with 0.98 for the power function and 0.94 for the polynomial function. Kuya [5] identified power functions as most ideal for estimating AGB in western Kenya while Henry et al. [1] preferred polynomial functions. It has been found that either of these functions is ideal based on the diameter size distribution [8]. Kuya [5] preferred power functions because of the large DBH size distribution which disqualifies polynomial functions which often have two turning points [14] and may not define the biomass-predictor relationship over a wide range of diameter sizes. In this case where *G. robusta* does not grow to large sizes in the study area, either a polynomial or a power function becomes ideal based on this criteria of choice.

3.4. Choice of Equation Based on Standard Error of Estimate and Mean Residual Error. Apart from the coefficient of determination, the standard error of estimate (SEE) and the mean residual error (MRE) have been used in choice of appropriate regression equations [14]. The SEE is a measure of the accuracy of predictions made with a regression line and the lower the value, the better the accuracy of an allometric equation [8]. Zar [14] also explains the mean residual error as another measure of the accuracy of a regression equation. Since residuals are differences between the data points and the regression line, the mean residual error refers to the error that is not explained by the regression line.

The choice of equation based on the three statistics is illustrated for the various biomass components in Table 6

Though linear functions had the least MRE for TTB and BGB, their previously described limitations [8, 14] disqualifies them. The polynomial functions have very small MRE values in all estimated biomass components of TTB (0.15kg), AGB (0.002Kg), and BGB (0.1Kg) illustrating their appropriateness based on this second selection criteria. Exponential functions have large mean bias in all functions and this further illustrates their inappropriateness in this selection. A bias of less than 5% of the total tree biomass is within acceptable range [16, 17] and would provide the farmers with the real value of the tree. In this case the polynomial function is very accurate with very minimal bias within the range of diameter sizes tested.

Based on the SEE, the polynomial function gave the lowest values at 1.33 for TTB, 0.99 for ABG, and 0.5 for BGB. This compared well with the power function which had 1.34 for TTB, 0.99 for AGB, and 0.51 for BGB. In this third selection criteria, the polynomial function again takes best preference.

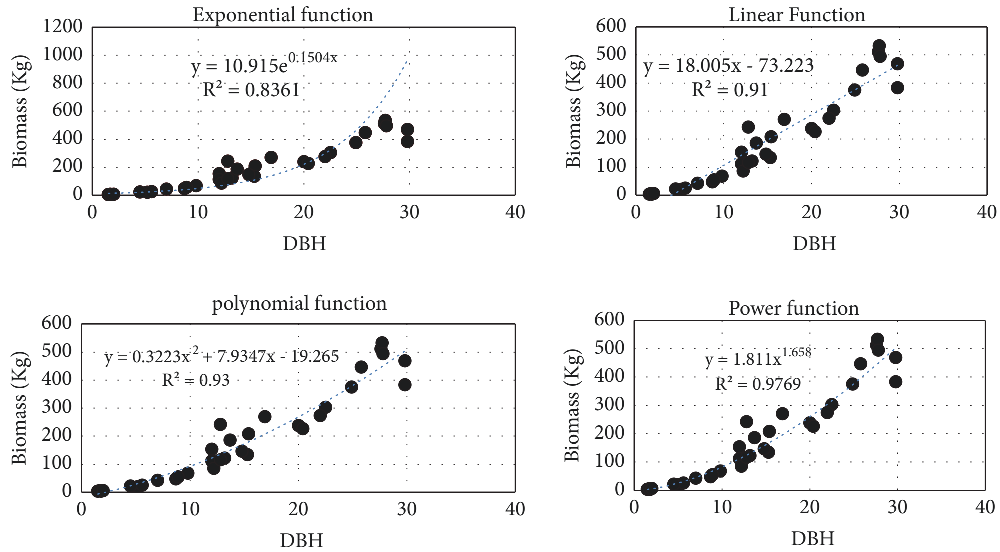

Figure 3: Comparison of functions for estimating total tree biomass from DBH.

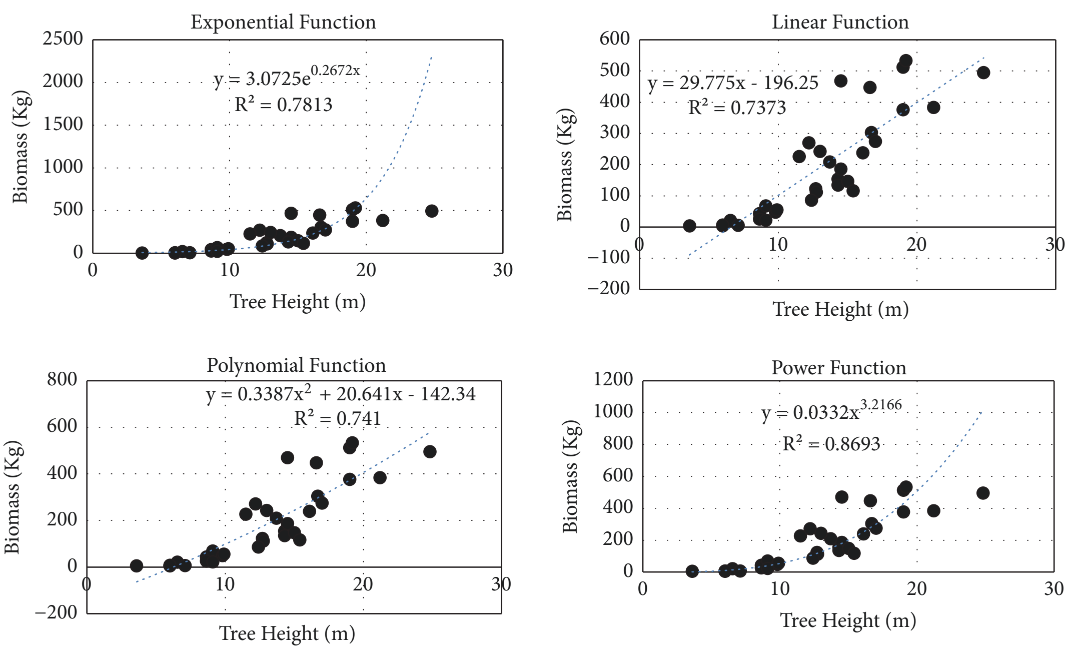

Figure 4: A comparison of functions for estimating total tree biomass from tree height.

Based on the statistics, Table 7 shows the list of preferred equations for estimating the different tree biomass components. Though all the preferred equations are polynomial functions, it should be noted that the power functions were the next best alternative and their application has already been illustrated for agroforestry species of western Kenya [5]. The limitation of two turning points observed in polynomial functions [14] may not apply in the study area where *G robusta* grows because the trees do not grow beyond the 40cm DBH size that was used in this study. It is however recommended that such equations should not be applied where trees of bigger sizes grow.

Table 7: A list of selected allometric equations for estimating biomass components.

Biomass component	Equations
Total Tree	$TTB = 0.322DBBH^2+7.93DBH-19.26$
Above ground	$AGB=0.248DBH^2 + 6.243DBH - 15.45$
Below ground	$BGB = 0.074DBH^2+1.688DBH - 3.791$
Branches	$BRA = 0.030DBH^2 + 1.574DBH - 4.984$
Foliage	$F = 0.04DBH^2 + 1.949DBH - 3.134$

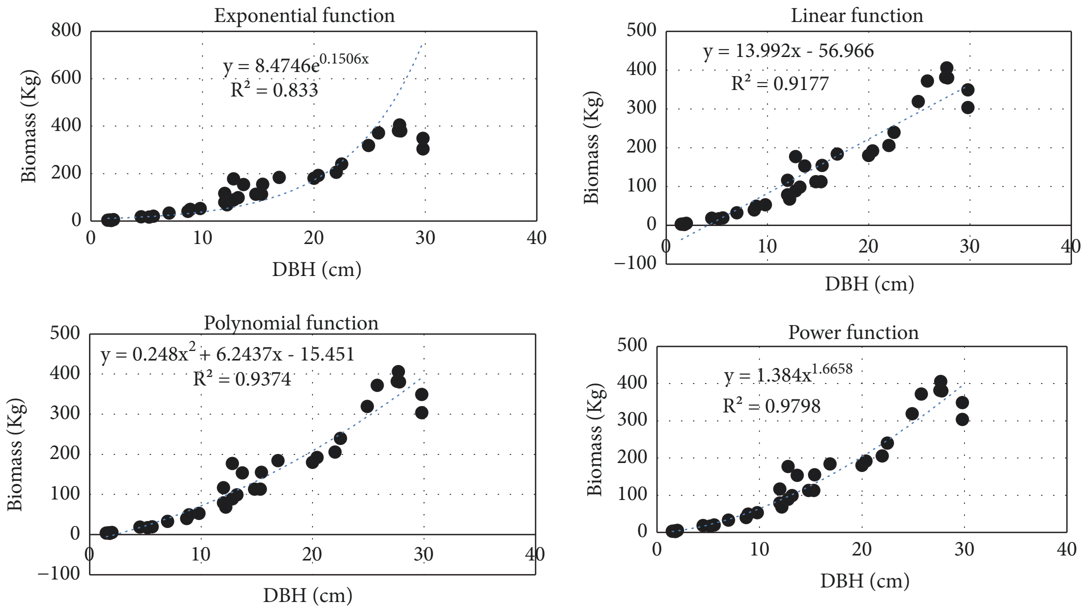

Figure 5: A comparison of functions for estimating above ground tree biomass from DBH.

Table 8: A validation of the equation with similar equations using the F values of the paired t-test.

Author	F calculated	F critical	Comments	Discussion
Kuya [5]	1.5375557	1.8283	There is no significant difference	The Kuya equation was developed in similar Agroforestry conditions but in a different AEZs of Kenya.
Henry [1]	0.817302	1.8283	There is no significant difference	The equation was developed for Agroforestry trees of Western Kenya in a different AEZ.
Benedicto [19]	2.070408	1.8408	There is a significant difference.	The equation was developed in Mexico. A totally different biome and may not be applicable in the study area.
Rurangwa [18]	1.118687	1.8408	There is no significant difference	Rurangwa developed this equation in Agroforestry trees of Ruanda which is within East Africa.

Table 9: Average biomass values per hectare in AEZs.

Component	Average biomass (Kg) per hectare			
	UM 1	UM 2	UM 3	UM 4
Foliage	922.128	874.343	724.966	788.837
Branches/foliage	1,964.818	1,849.623	1,533.623	1,668.739
Roots/belowground biomass	3,109.676	2,927.150	2,427.314	2,640.889
Stem/trunk	7,929.378	7,457.484	6,183.147	6,728.175
Total for tree	13,926.00	13,108.60	10,869.05	11,826.64

3.5. Validation of Developed Allometric Equations. Validation of the equations based on the bias of the equation in estimating specific diameter sizes is illustrated in residual plots used to assist in validation which are shown in Figure 6.

A second validation to compare biomass estimates from the preferred equation and that of similar studies shows that the developed equation compares well with other equations developed in agroforestry conditions of Kenya [1, 5] and Rwanda [18] but is not applicable in biomes far from the study area [19]. This finding illustrates that the process of destructive sampling to develop new allometric equations within a small geographical range may not enhance accuracy of estimates and an equation applicable in a similar land and tree management activity may as well be applicable in another one. The results are illustrated in Table 8.

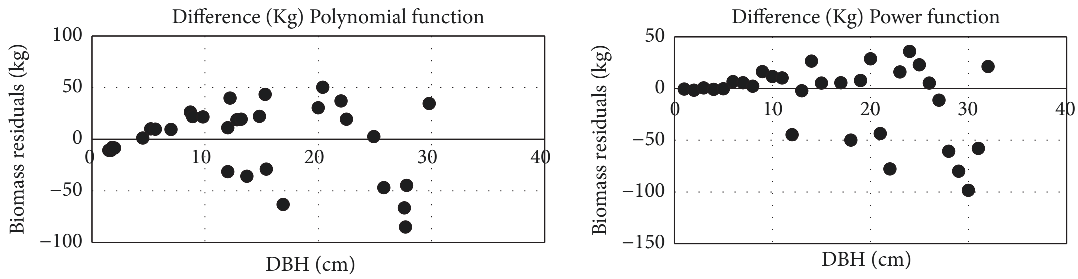

Figure 6: Residual scatter plots of total tree biomass using polynomial and power function for TTB.

Table 10: Total tree biomass and tree component biomass data of the 33 trees destructively sampled per every Agroecological Zone (AEZ).

AEZ	Tree No	DBH (cm)	Height (m)	Dry weights of biomass in kg					
				Stem	Branches	foliage	AGB	BGB	TTB
UM4	1	5.2	6.55	10.16	1.625	5.22	17.01	3.82	20.83
	2	1.5	3.6	1.55	0.644	1.02	3.31	0.801	4.01
	3	12	14.3	93.69	10.62	12.1	116.41	37.43	153.84
	4	13.2	12.7	70.22	11.08	17.49	98.79	23.46	122.25
	5	22.5	16.7	166.66	50.3	22.92	239.88	63.14	303.02
	6	29.8	14.5	247.52	80.42	21.27	349.21	119.55	468.76
	7V	1.8	6.0	1.65	0.33	0.662	2.64	1.461	4.10
	8V	13.7	14.5	112.22	26.61	14.64	153.47	32.42	185.89
	9V	20	16.1	134.87	31.5	13.75	180.12	57.79	237.91
UM3	10	12.0	12.75	59.01	6.88	13.14	79.03	32.4	111.43
	11	15.4	13.7	109.4	24.75	20.65	154.8	53.63	208.43
	12	7.0	8.65	20.38	5.0	7.5	32.88	9.83	42.71
	13	5.6	8.65	12.68	2.8	4.13	19.61	5.94	25.55
	14	27.6	19.0	270.53	92.98	17.97	381.48	130.37	511.85
	15	27.7	19.2	306.55	83.25	16.0	405.8	127.08	532.88
	16V	16.9	12.2	118.03	43.65	22.39	184.07	86.03	270.1
	17V	9.8	9.1	32.69	10.0	10.2	52.89	15.01	67.94
	18V	25.8	16.6	275.16	63.58	33.26	372.0	74.95	446.95
UM2	19	1.7	7.1	1.95	0.6	1.45	4.0	1.79	5.79
	20	8.7	9.8	24.98	6.43	8.75	40.16	7.86	48.02
	21	15.3	14.3	58.83	38.5	15.51	112.84	21.46	134.30
	22	14.8	15.0	69.63	32.71	10.46	112.8	33.99	146.79
	23V	12.2	12.4	40.63	13.93	13.5	68.06	17.75	85.81
	24V	12.8	15.4	62.94	19.15	7.0	89.09	27.26	116.35
	25	22.0	17.0	164.71	30.03	11.09	205.83	68.36	274.19
	26	29.8	21.2	259.8	33.2	10.89	303.89	79.34	383.23
	27V	27.8	24.8	327.63	43.9	8.71	380.24	114.75	494.99
UM1	28	2.0	6.0	3.21	0.94	1.19	5.34	1.01	6.35
	29	8.9	9.9	28.87	10.25	10.01	49.13	5.90	55.03
	30V	4.5	9.1	11.96	2.5	3.86	18.32	3.60	21.92
	31	12.8	13.0	114.66	31.50	31.22	177.38	65.22	242.6
	32	24.9	19.0	262.84	37.75	18.57	319.16	56.50	375.66
	33	20.4	11.5	128.71	46.9	16.2	191.81	34.60	226.41

Table 11: Allometric equations for estimating branch biomass using DBH.

Function	Equation	MRE	R^2	SEE
Exponential	$BR = 4.644e^{0.069Dbh}$	11.72	0.93	0.75
Logarithmic	$BR = 10.56\ln(DBH) + 1.534$	0.02	0.84	0.72
Polynomial	$\mathbf{BR = 0.077DBH^2 + 3.373DBH + 0.213}$	**- 4.53**	**0.99**	**0.58**
Linear	$BR = 0.941DBH + 13.24$	0.03	0.96	0.73
Power	$BR = 1.901DBH^{0.793}$	11.59	0.99	0.73s

Table 12: Allometric equations for estimating foliage using DBH.

Function	Equation	MRE	R^2	SEE
Exponential	$F = 4.795e^{0.045DBH}$	2.74	0.97	0.24
Logarithmic	$F = 3.62\ln(DBH) + 4.020$	0.02	0.84	0.22
Polynomial	$\mathbf{F = -0.031DBH^2 + 1.270DBH + 3.235}$	**-1.83**	**0.99**	**0.58**
Linear	$F = 0.295DBH + 8.452$	0.003	0.97	0.23
Power	$F = 2.213DBH^{0.596}$	-2.37	0.98	0.23

Table 13: Allometric equations for estimating TTB using HT.

Function	Equation	MRE	R^2	SEE
Exponential	$TTB = 3.090e^{0.266HT}$	-37.50	0.54	10.10
Logarithmic	$TTB = 315.7\ln(HT) - 597.3$	0.06	0.93	3.00
Polynomial	$\mathbf{TTB = -0.0409HT^2 + 18.63HT + 132.7}$	**0.21**	**0.99**	**2.52**
Linear	$TTB = 29.69HT - 198.0$	0.02	0,74	2.55
Power	$TTB = 0.401HT^{.1.642}$	-5.44	0.97	0.53

Table 14: Allometric equations for estimating AGB using HT.

Function	Equation	MRE	R^2	SEE
Exponential	$AGB = 2.454e^{0.263HT}$	-24.37	0.54	7.44
Logarithmic	$AGB = 240.1\ln(H) - 452.6$	0.084	0.93	2.48
Polynomial	$\mathbf{AGB = -0.312HT^2 + 14.11HT - 98.72}$	**0.24**	**0.99**	**2.10**
Linear	$AGB = 22.55HT - 148.50$	0.02	0.70	2.12
Power	$AGB = 0.027HT^{3.174}$	7.93	0.82	2.86

Table 15: Allometric equations for estimating BGB using HT.

Function	Equation	MRE	R^2	SEE
Exponential	$BGB = 0.631e^{0.269HT}$	-6.22	0.53	2.26
Logarithmic	$BGB = 70.7\ln(HT) - 133.3$	-0.04	0.93	0.79
Polynomial	$\mathbf{BGB = -0.067HT^2 + 4.781HT - 32.58}$	**0.15**	***1***	**0.71**
Linear	$BGB = 6.009HT - 43.45$	0.10	0.64	23.52
Power	$BGB = 0.006HT^{3.241}$	5.84	0.80	31.34

Table 16: Allometric equations for estimating TTB using combination of DBH and HT (DBH∗HT = P).

Function	Equation	MRE	R^2	SEE
Exponential	$TTB = 23.48e^{0.006P}$	-7.61	0.73	6.67
Logarithmic	$TTB = 107.7\ln(P) - 339.7$	0.002	0.72	2.85
Polynomial	$\mathbf{TTB = -0.000P^2 + 1.11P - 2.05}$	**-4.02**	***I***	**2.52**
Linear	$TTB = 0.829P - 0.929$	0.06	0.90	1.58
Power	$TTB = 0.395P^{1.125}$	2.15	0.98	2,68

Table 17: Allometric equations for estimating AGB using combination of DBH and HT (DBH∗HT = P).

Function	Equation	MRE	R^2	SEE
Exponential	$AGB = 18.26e^{0.0006P}$	-7.46	0.73	5.24
Logarithmic	$AGB = 82.22\ln(P) - 258.1$	-6.88	0.72	2.31
Polynomial	$\boldsymbol{AGB = -0.000P^2 + 0.829P - 16.09}$	**-2.9**	**1**	**1.85**
Linear	$AGB = 0.630P + 0.965$	0.19	0.86	1.46
Power	$AGB = 0.310P^{1.119}$	3.837	0.99	1.52

Table 18: Allometric equations for estimating BGB using combination of DBH and HT (DBH∗HT = P).

Function	Equation	MRE	R^2	SEE
Exponential	$BGB = 4.95e^{0.0006P}$	1.34	0.73	-1.45
Logarithmic	$BGB = 24.24\ln(P) - 76.22$	0.01	0.72	0.75
Polynomial	$\boldsymbol{BGB = -0.000P^2 + 0.255P - 5.495}$	**-1.01**	**1**	**0.69**
Linear	$BGB = 0.184P + 0.575$	0.07	0.78	0.75
Power	$BGB = 0.084P^{1.125}$	3.06	0.99	0.75

Table 19: Generated TTB from developed equation using DBH.

UM 1 DBH	GEN BIOM	UM 2 DBH	GEN. BIOM	UM 3 DBH	GEN BIOM	UM 4 DBH	GEN BIOM
12.8	129.5594	13.9	147.4242	18.6	233.6786	30.3	518.2414
2.4	4.18944	1	6.674	17	202.51	29.8	504.0422
1	6.674	9.2	77.25136	9.1	75.93304	1	6.674
1	6.674	1	6.674	18.8	237.7058	4.4	22.18384
4.4	22.18384	1	6.674	14.6	159.2514	26.5	414.892
15.4	173.205	13.5	140.826	18.5	231.676	1	6.674
16	183.976	1	6.674	2.5	5.02	1	6.674
10	88.06	16	183.976	16	183.976	1	6.674
10	88.06	3	9.282	19.4	249.9618	16	183.976
13	132.742	15.4	173.205	10.8	99.33456	18	221.772
12.8	129.5594	21.5	294.922	15.3	171.4354	13.5	140.826
20.9	281.7486	1.7	1.42064	12.8	129.5594	1	6.674
2.2	2.55016	12.2	120.1862	16.2	187.6246	14.8	162.6962
19	241.762	8	61.912	20.9	281.7486	17.5	212.05
2	0.94	8.76	71.50521	19	241.762	16	183.976
8.9	73.31824	13	132.742	2.2	2.55016	15	166.17
1.4	3.71576	1	6.674	7.8	59.45736	18.5	231.676
1.2	5.20944	1	6.674	5.2	30.19696	14	149.092
16.5	193.152	1	6.674	4.5	23.16	16.5	193.152
12.6	126.4058	1.5	2.958	4.5	23.16	12.6	126.4058
15.3	171.4354	1	6.674	2.4	4.18944	15.3	171.4354
13	132.742	2	0.94	4.2	20.25336	1	6.674
11.8	114.083	9.7	83.95216	5.1	29.16984	13	132.742
1.4	3.71576	9.6	82.59744	2.5	5.02	11.8	114.083
3.3	11.92656	12.2	120.1862	4.5	23.16	14.5	157.54
1.5	2.958	8.7	70.73256	5.4	32.27304	17.1	204.4034
2	0.94	8.3	65.64856	2.6	5.85784	1	6.674
1	6.674	10.9	100.7766	1	6.674	1	6.674
17.1	204.4034	6.8	47.62096	1	6.674	18	221.772
17.1	204.4034	6.9	48.77184	9	74.622	1	6.674

Table 19: Continued.

UM 1 DBH	GEN BIOM	UM 2 DBH	GEN. BIOM	UM 3 DBH	GEN BIOM	UM 4 DBH	GEN BIOM
9	74.622	2.9	8.41504	10.5	95.052	12.4	123.2814
11.4	108.0962	1	6.674	4.6	24.14344	11.4	108.0962
10.8	99.33456	5.1	29.16984	1	6.674	10.8	99.33456
11	102.226	11	102.226	1	6.674	9.3	78.57696
10.5	95.052	1	6.674	1	6.674	11.8	114.083
12	117.12	12	117.12	1	6.674	15.6	176.7662
7	49.93	10.4	93.63904	1	6.674	7	49.93
12.2	120.1862	5.2	30.19696	7	49.93	17.5	212.05
11.1	103.6826	11.1	103.6826	5.3	31.23136	14.4	155.8358
13	132.742	6.1	39.76864	1.3	4.46624	11.8	114.083
10	88.06	1	6.674	1.8	0.64104	10	88.06
12.8	129.5594	12.8	129.5594	1	6.674	13	132.742
20	262.48	6.8	47.62096	1	6.674	8	61.912
1	6.674	1	6.674	1	6.674	13.8	145.7638
10.4	93.63904	1	6.674	1	6.674	11.4	108.0962
14	149.092	1	6.674	9.8	85.31416	15.4	173.205
16	183.976	10.4	93.63904	1	6.674	8.4	66.90864
19.5	252.03	6.2	40.86856	1	6.674	7.8	59.45736
8.1	63.15024	9.5	81.25	2.8	7.55536	22.5	317.46
5.6	34.37824	8.5	68.176	4.9	27.13744	1	6.674
5.2	30.19696	6.5	44.212	4.2	20.25336	15.6	176.7662
10	88.06	8.1	63.15024	12.1	118.6494	1	6.674
13	132.742	1	6.674	8.7	70.73256	1	6.674
16.9	200.6238	1	6.674	5.6	34.37824	2.9	8.41504
21	283.926	8.2	64.39576	1	6.674	13.6	142.4646
21	283.926	5.7	35.44176	15	166.17	16.4	191.3022
13	132.742	1	6.674	20.2	266.711	1	6.674
3.9	17.41224	6	38.676	29.7	501.2242	1	6.674
17.3	208.2122	1	6.674	19.5	252.03	17	202.51
16	183.976	1	6.674	23	329.002	16	183.976
16	183.976	1	6.674	2.3	3.36616	18.7	235.6886
21	283.926	6.4	43.09024	18.3	227.6926	10.4	93.63904
18.7	235.6886	4.8	26.13216	12	117.12	12.2	120.1862
3.9	17.41224	1	6.674	5.4	32.27304	13	132.742
13.2	135.9538	1	6.674	13.2	135.9538	18	221.772
18	221.772	1	6.674	2	0.94	1	6.674
5.8	36.51256	1.5	2.958	1	6.674	1	6.674

3.6. Biomass Stocks among Agroecological Zones. Based on the allometric equations, the average TTB for *G. robusta* trees generated in each of the AEZ studied is as shown in Table 9. The TTB stock for each AEZ was 13. 926 $tonha^{-1}$, 13.109 $tonha^{-1}$, 10.869 $tonha^{-1}$, and 11.827 $tonha^{-1}$ in UM1, UM2, UM3, and UM4, respectively. Variability of tree biomass between the four agroecological zones showed no significant difference (p-value > 0.05) implying that though there could be a slight difference in the allometry of the tree species among AEZ, the total biomass does not vary. This also explains that the management of *G robusta* trees in the agricultural landscapes of the four AEZ does not differ and the farmers can form a marketing unit despite their different AEZ and their production quotas can be the same.

The average biomass stock of 12.43 ton/ha in the study compares well with the findings of Albrecht [20], 2-22 ton/ha, Henry [1], 9–11ton/ha, and Kuya [5], 16 ton/ha, all of which are for agricultural landscapes. This finding gives a better glimpse of the tree component in agricultural landscapes and is a good guide for the development of carbon stock factors in agricultural landscapes [21]. With this moderate stock, the farmers are able to practice agricultural activities while maintaining a tree cover in the farms which stabilizes the agricultural landscapes and reduces pressure for wood products from adjacent forests.

4. Conclusion and Recommendations

This study has developed a quick tool for estimating biomass from *G. robusta* trees in agricultural landscapes of Maragua county. The allometric equations allow better marketing of the trees and their components and will favor farmers who will get better value from their trees. The findings illustrate no much variations in stocking among the study strata and also comparing with studies in similar agricultural setups. Therefore the study illustrates the usability of general allometric equations which eliminate the expensive processes of destructive sampling. As such the developed equations are ideal for a wide range of application in areas of Kenya where *G. robusta* grows without any need to develop other equations.

The study identified only small sized *G. robusta* trees and the size limitation is influenced by their growth characteristics and the market conditions. The study proposes a validation of the allometric equations in cases where bigger sized trees exist. Similarly the small sample size used in this study may have not captured enough information on the allometry of the tree and a collation of this data and other existing datasets can help compare characteristics of allometry that may influence the equation used

Appendix

A.

See Table 10.

B.

See Tables 11, 12, 13, 14, 15, 16, 17, and 18.

C.

See Table 19.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Disclosure

The research was done as a part of a Master's thesis and was financed by the first author.

Conflicts of Interest

The authors have no conflicts of interest in the manuscripts and therefore do declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

The authors wish to acknowledge the Department of Natural Resources in Karatina University where the student is registered for providing supervision and guidelines. The authors would also like to thank Kenya Forest Service (KFS) authorities for giving a permission to conduct the study using their staff members and the farmers who allowed uprooting of trees in their farms.

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