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Spatial Variation in Tree Density and Estimated Aboveground Carbon Stocks in Southern Africa

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Abstract: Variability in woody plant species, vegetation assemblages and anthropogenic activities derails the efforts to have common approaches for estimating biomass and carbon stocks in Africa. In order to suggest management options, it is important to understand the vegetation dynamics and the major drivers governing the observed conditions. This study uses data from 29 *sentinel* landscapes (4640 plots) across the southern Africa. We used T-Square distance method to sample trees. Allometric models were used to estimate aboveground tree biomass from which aboveground biomass carbon stock (AGBCS) was derived for each site. Results show average tree density of 502 trees$\cdot$ ha^{-1} with semi-arid areas having the highest (682 trees$\cdot$ ha^{-1}) and arid regions the lowest (393 trees$\cdot$ ha^{-1}). The overall AGBCS was 56.4 Mg$\cdot$ ha^{-1}. However, significant site to site variability existed across the region. Over 60 fold differences were noted between the lowest AGBCS (2.2 Mg$\cdot$ ha^{-1}) in the Musungwa plains of Zambia and the highest (138.1 Mg$\cdot$ ha^{-1}) in the scrublands of Kenilworth in Zimbabwe. Semi-arid and humid sites had higher carbon stocks than sites in sub-humid and arid regions. Anthropogenic activities also influenced the observed carbon stocks. Repeated measurements would reveal future trends in tree cover and carbon stocks across different systems.

Keywords: biomass; allometry; anthropogenic disturbance; sentinel landscapes; carbon stock; southern Africa

1. Introduction

Woody plants in forests, croplands and rangelands of southern Africa play crucial socio-economic and ecological functions [1,2]. In addition to being a larger pool of terrestrial carbon sink, biomass is the chief source of energy for more than 80% of the population and replenishes soil fertility in traditional farming systems [3]. However, the functions of tree and plants are challenged due to various natural and anthropogenic disturbances. In addition to ecological limits, woody biomass stocks vary across landscapes as a result of land cover and land use changes associated with anthropogenic activities [4,5]. In order to suggest management options, it is important to understand the biomass and carbon stock dynamics and the major drivers governing the observed condition.

Different approaches have been used to estimate carbon stock and understand drivers of biomass distribution and extraction [6–8]. The T-square method, as used in ecological surveys and lately in health, is more robust in estimating populations [9,10]. The errors associated with sample size and topographic differences can be resolved by estimating distribution and density at larger landscape/stand level [6]. The recent approach of using sentinel sites, which are representative landscapes geo-referenced for spatial and temporal change detection facilitate baseline analysis and monitoring [11,12]. Sentinel landscapes are designed to have hierarchical organization so that variability within and between different spatial scales can be assessed [12,13].

The appropriate approach to estimate aboveground biomass and derive associated aboveground biomass carbon stock (AGBCS) is through on-site destructive sampling, which is not only time-consuming but also not suitable for diverse tropical systems and wide geographical areas [14]. In situations where destructive sampling is not feasible, it may be possible to use allometric equations developed for similar site and environmental conditions to estimate AGBCS [7,14,15]. At present, there are several equations developed using data from similar/same ecoregions at stand, forest, national, eco-regional and global levels. The use of inventory data at national and regional scale is, however, challenging due to unjustified selection of appropriate biomass estimation or allometric equations [6]. It is thus paramount to select equations that are developed for and based on similar ecological conditions and tree stands. Through the use of Akaike information criteria (AIC) and Root Mean Square Error (RMSE), it will be possible to evaluate the explanatory power of the equations selected and decide whether they can be a good approximation to the area of interest [15].

The objective of this study was therefore to build an approach and construct a baseline for estimating tree density and carbon stocks across different sites and eco-zones of Southern Africa. The specific objectives are to (1) adapt distance methods for unbiased estimation of tree density at landscape level, (2) estimate aboveground biomass and carbon stocks for plots and sentinel sites using models selected by information criteria, and (3) determine variability in tree density, measured height and diameter, and estimated biomass carbon stocks within and across sentinel sites. Understanding spatial variability of carbon stock across land use and eco-zones can play a crucial role in the design of management strategies. This can also facilitate "carbon-saving" credit schemes and provide necessary incentives.

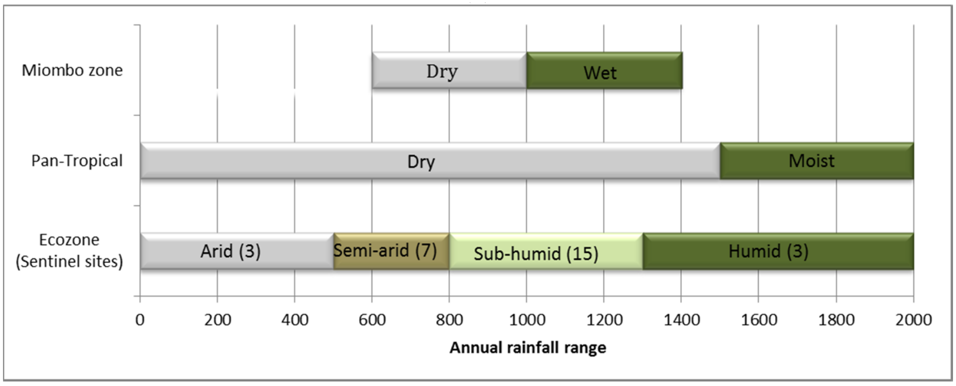
2. Materials and Methods

2.1. Description of the Study Area

The study covered 29 sentinel sites located in Angola, Botswana, Malawi, Mozambique, Zambia, and Zimbabwe covering four eco-zones; *i.e.*, arid, semi-arid, and sub-humid to humid climate (Figure 1a,b and Table 1). The eco-zones defined by the quotient between yearly positive precipitation and yearly positive temperature were used as primary clustering units as they show the bio-climatic gradient [16].

(**a**)

Figure 1. *Cont.*



(**b**)

Figure 1. (**a**) Location of the sampling sites in Southern Africa and (**b**) description of areas with respect to miombo, pantoropical and ecozones.

Table 1. Distribution of the sites, vegetation types and ecological zones with corresponding Koppen–Geiger (R) and pan-tropical (PT) climatic zones.

Location	Site Name	Major Woody Vegetation Composition	R	PT
Angola	Bimbe	Re-growth fallow; sparse remnant trees on farmland	Sub-humid	Dry
	Luimbale	Re-growth fallow, sparse remnant trees on farmland and old-growth on hill tops	Sub-humid	Dry
	Mucope	Regrowth Mopane woodland with open canopy used chiefly for grazing	Semi-arid	Dry
	Sanza-pombo	Tall grass (>1.5 m) with scattered trees	Humid	Moist
Botswana	Gumare	Old-growth *Terminalia* spp.	Arid	Dry
	Paje	Old-growth *Terminalia*; mopane and Acacia	Arid	Dry
	Shoshong	Re-growth fallow; remnant trees on farmland; and old-growth along valleys and hilltops	Arid	Dry
Malawi	Golomoti	Miombo remnant trees on escarpment and re-growth on farmland and old-growth; mopane & acacia re-growth & remnants on cropland in the plain	Semi-arid	Dry
	Kandeau	Remnant trees, exotic fruit and firewood trees on farmland and homesteads	Sub-humid	Dry
	Linthipe	Remnant native trees, exotic fruit and firewood trees on farmland and homesteads	Sub-humid	Dry
	Nambuma	Remnant native trees, exotic fruit and firewood trees on farmland and homesteads	Sub-humid	Dry
	Nkhata Bay	Rubber plantation; old and re-growth miombo and fruit trees	Humid	Moist
	Nsipe	Remnant trees on farmland, fallow and old-growth on hills	Sub-humid	Dry
	Thuchila	Exotic fruit and firewood trees on homesteads and along streams and roads	Sub-humid	Dry
Mozambique	Chica	Re-growth fallows, remnant trees and cashewnut on farmland	Sub-humid	Dry
	Chiculecule	Thorny thickets on west and miombo on east (mainly re-growth fallow and remnants on farmland)	Arid	Dry
	Furanungo	Old-growth on cluster 4; re-growth fallow; and remnants on farmland	Sub-humid	Dry
	Ihansunghe	Dense old-growth mangrove lowland; coconut & mangoes on farmland	Humid	Moist
	Macasangila	Heavily cut coppice shoots; with intact woodland in cluster 4	Sub-humid	Dry
	Martinho	A few patches of re-growth woodland; and treeless farmland	Semi-arid	Dry
	Massuque	Old-growth miombo closed canopy	Semi-arid	Dry

Table 1. *Cont.*

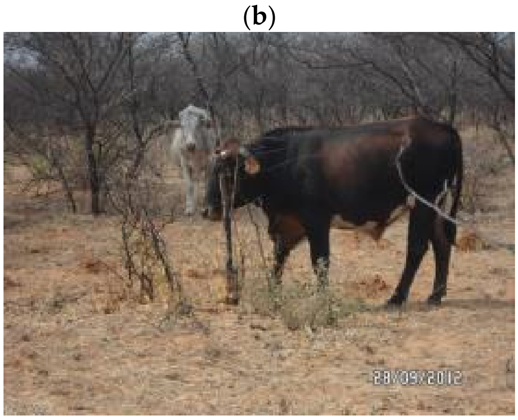
Location	Site Name	Major Woody Vegetation Composition	R	PT
Zambia	Budula	Remnant trees on cropland; and old-growth untilled areas and hills	Sub-humid	Dry
	Chilende	Old-growth miombo	Sub-humid	Dry
	Fisenge	Patches of old-growth miombo; remnant trees on farmland	Sub-humid	Dry
	Monga	Old-growth miombo on steep slopes; re-growth and remnant trees on farmland	Sub-humid	Dry
	Musungwa	Palm and mango trees on southern tip; greater part is flood plain and grassland	Sub-humid	Dry
Zimbabwe	Chikumbakwe	Scattered trees and shrubs on farmland; re-growth miombo; waterlogged grasslands	Semi-arid	Dry
	Gambissa	Old-growth *D. cinerea* thickets; miombo and mopane	Semi-arid	Dry
	Kenilworth	Miombo old-growth; *D. cinerea* thickets re-growth fallow and remnant trees on farmland	Semi-arid	Dry

The sampled areas fall within the Zambezian phytochoria in Southern Africa [17] with dominant woody vegetation assemblages including not only the *miombo, Burkea/Terminalia/Combretum*, *Mopane* woodlands (Plates 1a,b,f respectively), and *Acacia/Combretum*, but also the transition to the *Guinea-Congolia* in the west and *Zanzibar-Inhambane* to the east. Areas under cultivated and left fallow contained a mixture or predominance of exotic fruit and firewood species. Cocoa and palm trees were found along water fringes of Inhambane in Mozambique (Plate 1g) and Musungwa in Zambia (Plate 1h) sites, respectively (Table 1). A few sampling points in Nkhatabay, Malawi, were within a plantation of rubber trees, *Hevea brasiliensis*.

(**a**)

(**b**)

(**c**)



(**d**)

Plate 1. *Cont.*

(**e**)

(**f**)

(**g**)

(**h**)

Plate 1. Tree and stand structure in varied land cover and use types (**a**) Miombo woodland at Massuque in Mozambique; (**b**) Terminalia woodland in arid zone at Gumare in Botswana; (**c**) trees on farm (scattered trees in intensively cropped areas at Linthipe in Malawi; (**d**) burnt and respouting trees with intensively grazed dry grass at Paje in Botswana; (**e**) intensively cultivated plains and forested hills at Luimbale in Angola; (**f**) intact mopane woodlands in semi-arid zone at Kenilworth in Zimbabwe; (**g**) mangroves with salt pans in depressions and trees on raised areas at Inhassunge in Mozambique; and (**h**) Dauwn palm on edge of Kafue river flood plain at Musungwa in Zambia.

2.2. Sampling Strategy and Data Collection

This study applied the Africa Soil Information Service (AfSIS) sampling protocol where the sub-Saharan African continent is stratified according to the Koppen-Geiger climatic zones [18,19]. Additional sites of the CGAIR Drylands (CRP1.1) and the Africa Research in Sustainable Intensification for the Next Generation (Africa RISING) Programs were also included following similar sampling framework. Extensive data were collected from 4640 plots in the 29 sentinel sites (Table 1) covering a total area of 290,000 ha.

In all of the 29 sites, we employed the Land Degradation Surveillance Framework (LDSF) in which sample points are selected using hierarchical stratified random sampling [20]. The LDSF was designed to have sentinel sites of 10,000 ha as sampling framework. The sentinel site was stratified into 16 clusters of 100 ha. Within each cluster, 10 plots of 0.1 ha were randomly located (Figure 2a). The plot was further divided into four subplots of 0.01 ha as sampling units (Figure 2b). Tree related measurements were done at the sub-plot level.

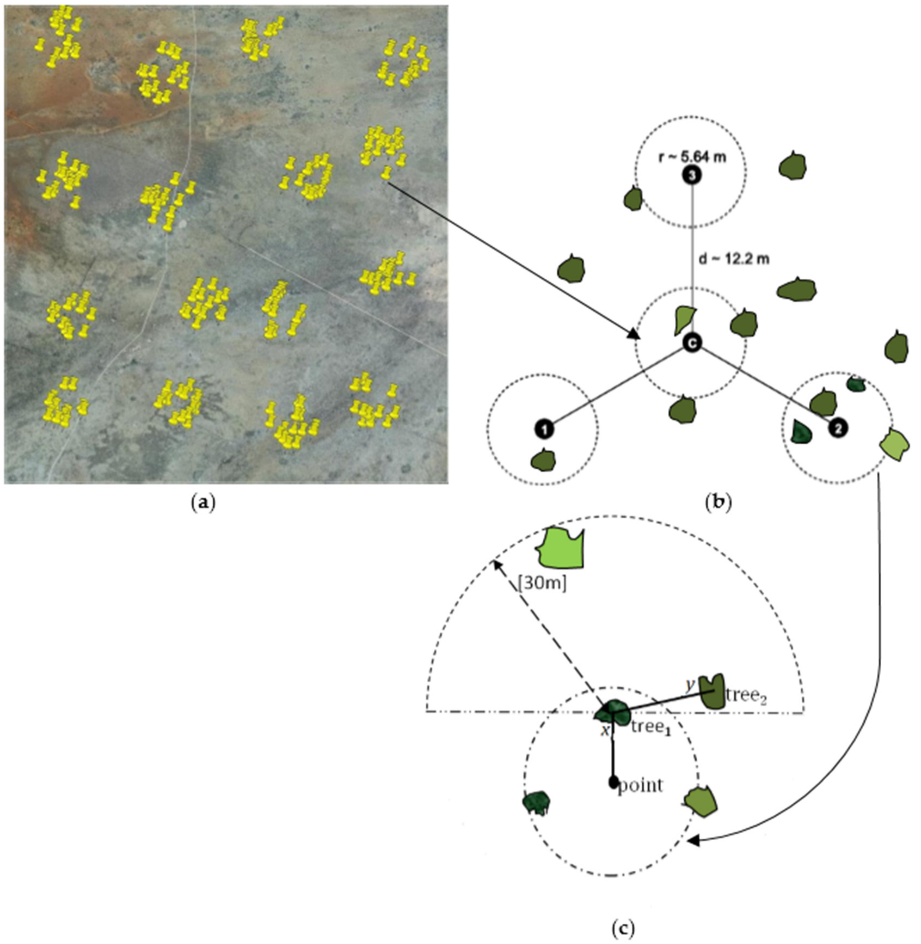


Figure 2. (**a**) Hierarchical sampling of plots (individual icons) in 16 clusters within the 10 by 10 km sentinel site (**b**) sampling subplots layout and (**c**) the T-square method employed to measure tree attributes for each subplot. NB: subplots c1 and c2 are non-vacant; c3 is vacant; and c1 could have tree 1 but no tree 2 within a 30 m radius (see Section 2.3 for details).

Global Positioning System was used to navigate to sentinel sites-clusters-plots-subplots. The central position of the plot (referred as the central subplot, *c*) was marked (Figure 2a). From the center-point of this subplot, a distance of 12.2 m was measured to the upper slope position using measuring tape and the center of the next subplot was marked as subplot 2. Subplots 3 and 4 were located by offsetting 120 and 240 degrees from subplot 2, respectively. The radius of each subplot was 5.64 m, which approximately gives 0.01 ha area.

Sampling of individual trees for measurement was done using the T-square method [21]. The T-square has an advantage over other widely used distance or point-centered methods to estimate density for populations where individuals (trees) are randomly distributed in a study area [21,22]. Using the T-square method, the "*point to tree*$_1$" distance (x_i) was measured from the center of a subplot to the nearest tree. From the first tree observed (tree$_1$), a "*tree*$_1$ *to tree*$_2$" distance (y_i) was then measured to the nearest neighbor in the direction away from and perpendicular to the line "point to tree$_1$" (Figure 2c). The angle of measurement was constrained to lie in the hemisphere with search diameter of 30m, the average distance between nearest neighboring trees expected in randomly distributed tree population in farmlands [23]. For *tree*$_2$, diameter at 1.3 m height (D) and height (*h)* are measured using a measuring tape and clinometer, respectively.

For biomass estimation, woody plants with height of 3 m or more were considered as they are assumed to contain the greater portion of aboveground biomass carbon [5]. These tree stands also escape fire die back and are generally conserved by farmers while those below than 3 m and herbaceous plants are prone to destruction by fires and more likely cleared in cultivated areas [1].

In each plot, the degree of disturbance due to agriculture, cutting trees, grazing, fire, erosion, alien vegetation, *etc.* was assessed visually and through interviews with plot owners on a scale of 0 to 3 representing none to high impact following the procedures in the LDSF protocol [20]. The probability of a plot experiencing a given form of disturbance was estimated for each site (based on 160 plots per site) using a logistic regression model. For this purpose, estimates of the linear predictors (on the logit scale) and odd ratios were obtained for sites within each eco-zone separately. Predicted probabilities of each disturbance variable were then calculated from the odds ratios for each site within an eco-region.

2.3. Tree Density Estimation Using the T-Square Method

Most national forest inventories estimate tree density by counting the total number of trees and adjusting for the size of the area considered [24]. However, in our study sites, as is the case in most tropical grasslands, tree distribution is sporadic and sparse in agricultural areas and semiarid zones, thereby having vacant subplots where no measurements were made. Estimating tree density by relating the number of trees encountered with the area of plot/subplot could thus over or under-estimate tree density and carbon stock. In order to avoid that, the search areas were not restricted to the small plot area and adjustments were made to make sure that the calculated density was based on vacant and non-vacant plots/subplots.

To deal with errors associated with plot sizes, we estimate density and biomass at cluster level to increase the degrees of freedom (especially for sparsely populated areas), thereby having an unbiased estimate [9]. In a cluster, the unbiased mean search area (assuming there are no vacant subplots) occupied by nearest tree for the distance point to tree$_1$ is:

$$A_x = \frac{\pi \sum_1^m \sum_1^n {x_{ij}}^2}{n\,(nm-1)}, \tag{1}$$

where m is the number of points (plots) in a cluster; i a particular plot; n is the number of subplots, j being a subplot, x_{ij} is the distances as described in the previous section. The corresponding unbiased estimate of density δ, as demonstrated by Mitchell [22] is the reciprocal of the search area given by:

$$\delta_x = \frac{n\,(nm-1)}{\pi \sum_1^m \sum_1^n {x_{ij}}^2}. \tag{2}$$

Similarly, the search area for the next nearest tree to a neighbor in the semi-circle is calculated as:

$$\frac{1}{2} A_y = \frac{\pi \sum_1^m \sum_1^n {y_{ij}}^2}{2n\,(nm-1)}, \tag{3}$$

where y_{ij} is the distance. Tree density within the corresponding search areas is given by:

$$\delta_y = \frac{2n\,(nm-1)}{\pi \sum_1^m \sum_1^n {y_{ij}}^2}. \tag{4}$$

The combined density that is robust to non-random pattern is [21]:

$$\delta_{xy} = \sqrt{\delta_x \delta_y}. \tag{5}$$

The quations described above assume that all subplots contain trees but as discussed earlier, the sampled areas have vacant subplots. The absolute density should thus be corrected for vacant subplots for both the first and second trees. To achieve this, we first estimated the density of non-vacant subplots using:

$$\delta_{xy(mn-m_0)} = \sqrt{\frac{(nm-m_0-1)_x * (nm-m_0-1)_y}{(\pi \sum_{mn=1}^{nm-m_0} x_i) * \; (\pi \sum_{mn=1}^{nm-m_0} y_i)}}, \tag{6}$$

where m_o denote number of vacant subplots. To correct for the bias, we employ the correction factor (CF) following Warde and Petranka [25] and derived as:

$$\delta_{xy_c} = \sqrt{\frac{(nm - m_0)_x \,(nm - m_0)_y}{(\pi \sum_{mn=1}^{nm-m_0} x_i)\,(\pi \sum_{mn=1}^{nm-m_0} y_i)}}\; CF. \tag{7}$$

CF values were obtained from the *CF* table corresponding to proportion of vacant quarters (VQ), using:

$$\mathrm{VQ} = \frac{m_{o_x} \, * \, m_{o_y}}{nm_x nm_y}. \tag{8}$$

2.4. Estimating Variation in Tree Density, Height and Diameter

Variations in tree density, height and diameter were estimated using generalized linear mixed model to account for the hierarchical nature of the sampling. The first step involved analysis of variation across eco-zones (fixed effects). Here, a random intercept with site as the subject was specified as the random effect. The random statement in the model specifies that the linear predictor contains an intercept term that randomly varies at the level of the "study site" effect. The second step involved analysis of site effects (entered as fixed effects) within each eco-zone. In this case, a random intercept was introduced with clusters as a subject in the model in order to estimate the 95% confidence intervals (95% CI) correctly. Statistical inference was based on the means and their 95% CI.

2.5. Estimation of Aboveground Biomass (AGB) and Carbon Stocks

Tree biomass was estimated using existing multispecies biomass estimation models developed for each zone (Table 2). Some models such as the ones developed by Chave *et al.* [14] though robust for pan-tropical vegetation; they use default values for wood specific gravity and could not be applied to our dataset as it captured some species whose wood specific gravity are not yet determined. AGB was predicted using measured diameter as an input variable in each model. The predictive performance of each model was then compared and the best approximating model selected for each zone. Variations in estimated AGB across sites in the same eco-zone were estimated using linear mixed model. For each eco-zone, countries were entered as fixed effects and a random intercept with plots as subjects were entered as random effects in the mixed effects model. The best model was considered the one that gave the lowest AIC, narrow confidence intervals, and lower root mean square error (RMSE) [15]. Tree biomass was estimated using the best performed model. Stand biomass (per hectare) was then estimated by aggregating cluster level data since density adjusted for vacant subplots was aggregated at cluster level.

Table 2. Selected equations used to estimate aboveground biomass (AGB (kg· tree^{-1})) in the study area.

Source	Equation	Eco-Region	Rainfall (mm/Year)	
Arid and Semi-Arid				
Mugasha *et al.* [26] $_a$	AGB = exp(−2.2453 + 2.4735ln(D)	Dry miombo Tanzania	6–1000	(9)
Chidumayo [27] $_a$	AGB = 0.0446D$^{2.765}$	Dry miombo Zambia	850–940	(10)
Chidumayo [27] $_b$	AGB = 2.5553ln(D) − 2.5265	Dry miombo Zambia	850–940	(11)
Ryan *et al.* [28]	lnAGB = 2.601log(D) − 3.62	Dry miombo Mozambique	520–1120	(12)
Sub-Humid				
Kuyah *et al.* [29]	AGB = 0.0905D$^{2.4718}$	Savanah: Markhamia, Eucalyptus, Acacia	1000–1300	(13)
Brown *et al.* [30] $_a$	AGB = 34.4703 − 8.0671D + 0.6589D^2	Tropical dry	<1500	(14)
Mugasha *et al.* [26] $_b$	AGB = exp(−1.6557 + 2.3427ln(D)	Wet miombo Tanzania	1000–1400	(15)
Humid				
Mugasha *et al.* [26] $_b$	AGB = exp(−1.6557 + 2.3427ln(D)	Wet miombo Tanzania	1000–1400	(16)
Brown *et al.* [28] $_b$	AGB = exp(−2.4090 + 0.9522ln(D^{2}hρ))	Tropical moist	>1500	(17)

Subscript letters ($_{a,\,b}$) denote different models by the same author the same year.

Aboveground biomass carbon stocks (AGBCS) were estimated from AGB using the equation [31]:

$$AGBCS = AGB * 0.47 \quad (18)$$

Several studies have shown that the carbon fraction approximates between 0.47 and 0.50 of the total biomass [31–34]. Although Clark and Kellner [6] suggest to use species/stand specific values, it is a daunting task considering the varied species combinations encountered in the tropics [7]. Moreover, the aggregated range at stand level will not be very different from current widely used values obtained from meta-analyses of species specific values in the regions. In this study, we used 0.47, which is considered standard and is widely used to estimate AGBCS from AGB data for carbon trade in the tropics [31,32].

To assess the overall validity of the approach and thus show the level of confidence in both accuracy and precision of the results, we compared the estimates against biomass and carbon stock values obtained using destructive sampling in the region.

3. Results

3.1. Tree Density, Height and Diameter

Of the total 18,560 sampled subplots, 49.6% had at least a tree within 5.64 m radius while the search for the next tree within the 30 m radius hemisphere captured 47.4% of the trees (Table 3). The proportion of vacant subplots was 52.6%. Chilende in Zambia had the highest presence of trees (with 93.4% of the subplots having trees) whereas Musungwa (Zambia) had the least (0.03%). In most sites, there was high likelihood of finding the second tree from the first, except for Malawian sites of Golomoti, Kandeau, Linthipe and Nsipe where trees were more scattered.

Table 3. Summary of presence of trees, distribution (search area, SA) in the study area.

			Subplot (Number)		SA (m^2)			
Eco-Zone	**Country**	**Sentinel Site**	**$Tree_1$**	**$Tree_2$**	**$Tree_1$**	**SD**	**$Tree_2$**	**SD**
		Grand-average	**324**	**313**	**34.2**	**87.3**	**66.7**	**116.5**
Semi-arid		Sub-average	299	292	54.7	276.2	80.3	136.2
	Botswana	Gumare	456	451	31.3	24.3	44.8	67.0
	Botswana	Paje	179	162	40.9	28.6	115.4	189.4
	Botswana	Shoshog	156	152	124.1	1027.7	106.7	167.6
	Mozambique	Chiculecule	404	402	22.4	24.2	54.2	120.7
Semi-arid		Sub-average	399	387	26.9	23.7	53.1	104.3
	Angola	Mucope	517	516	25.9	24.3	38.3	88.2
	Malawi	Golomoti	232	161	29.9	25.3	79.2	178.0
	Mozambique	Martinho	283	277	34.8	25.8	99.3	161.4
	Mozambique	Massugue	532	531	24.6	22.2	34.2	54.3
	Zimbabwe	Chikumbakwa	174	170	29.7	26.4	67.9	146.6
	Zimbabwe	Gambissa	502	500	19.5	20.1	22.8	43.8
	Zimbabwe	Kenilworth	553	552	23.5	21.7	29.9	58.1
Sub-humid		Sub-average	286	266	31.0	24.8	85.5	140.9
	Angola	Bimbe	299	289	32.8	27.2	78.1	141.8
	Angola	Luimbale	402	400	25.6	24.6	43.6	100.9
	Malawi	Kandeau	162	97	35.8	23.3	187.9	280.0
	Malawi	Linthipe	117	55	41.2	27.1	125.0	169.4
	Malawi	Nambuma	152	139	46.9	27.2	221.1	274.9
	Malawi	Nsipe	226	138	36.8	27.7	85.0	165.3
	Malawi	Thuchila	92	79	33.1	26.6	108.4	189.0
	Mozambique	Chica_b	420	416	21.8	23.0	43.7	100.5
	Mozambique	Furancungo	268	249	28.3	25.9	43.9	87.1
	Mozambique	Macssangila	293	290	25.7	25.1	62.0	124.7
	Zambia	Budula Silya	395	392	22.1	21.9	34.8	81.0
	Zambia	Chilende	599	599	22.7	21.3	27.1	32.8
	Zambia	Fisenge	305	299	23.2	23.3	49.9	121.2
	Zambia	Monga	534	533	23.9	21.9	33.5	66.2
	Zambia	Musungwa	20	17	45.1	26.3	138.1	179.0
Humid		Sub-average	314	309	24.3	24.7	48.1	84.5
	Angola	Sanza Pombo	425	421	23.4	23.6	41.7	85.5
	Malawi	Nkhata Bay	266	256	24.2	24.9	37.5	67.1
	Mozambique	Ihassunge	251	249	25.3	25.6	65.0	100.8

Average search area from center to $tree_1$ was 34.2 ± 87.2 m^2 and from $tree_1$ to $tree_2$ was 66.7 ± 116.5 m^2 (Table 3). The search area between the first and the second trees was wider (indicating sparse tree populations) in arid areas compared to the humid zones. Nambuma, Kandeu, and Linthipe in Malawi (Plate 1c), Musungwa in Zambia (Plate 1h), and Paje in Botswana had sparse populations. Woodlands at Gambisa in Zimbabwe, Chilende in Zambia, Kenilworth in Zimbabwe, Massuque in Mozambique, Mucope in Angola and Gumare in Botswana had clustered tree distributions as indicated by almost similar search areas for $tree_1$ and $tree_2$.

Tree density varied significantly across sites (Figure 3, Table 4) and eco-zones. The average tree density (adjusted for vacant subplots) was 502 trees· ha^{-1} with semi-arid regions having higher density of 682 trees· ha^{-1} followed by humid zone (584 trees· ha^{-1}) while the arid regions had the least with 393 trees· ha^{-1}. Musungwa in Zambia had the least tree density of 23 trees· ha^{-1} while Kenilworth in Zimbabwe had the highest of 1293 trees· ha^{-1}. Gambisa in Zimbabwe had more vacant subplots such that the adjusted density was 1107 trees· ha^{-1} (47% of the unadjusted). At Furancungo (Mozambique), the adjusted density was 25% of the density for non-vacant subplots. The sparsely populated areas include Musungwa (Zambia) with adjusted density of 80% and the four Malawian sites (Linthipe, Nambuma, Thuchila and Kandeau) with adjusted density of less than 20% of the non-vacant density.

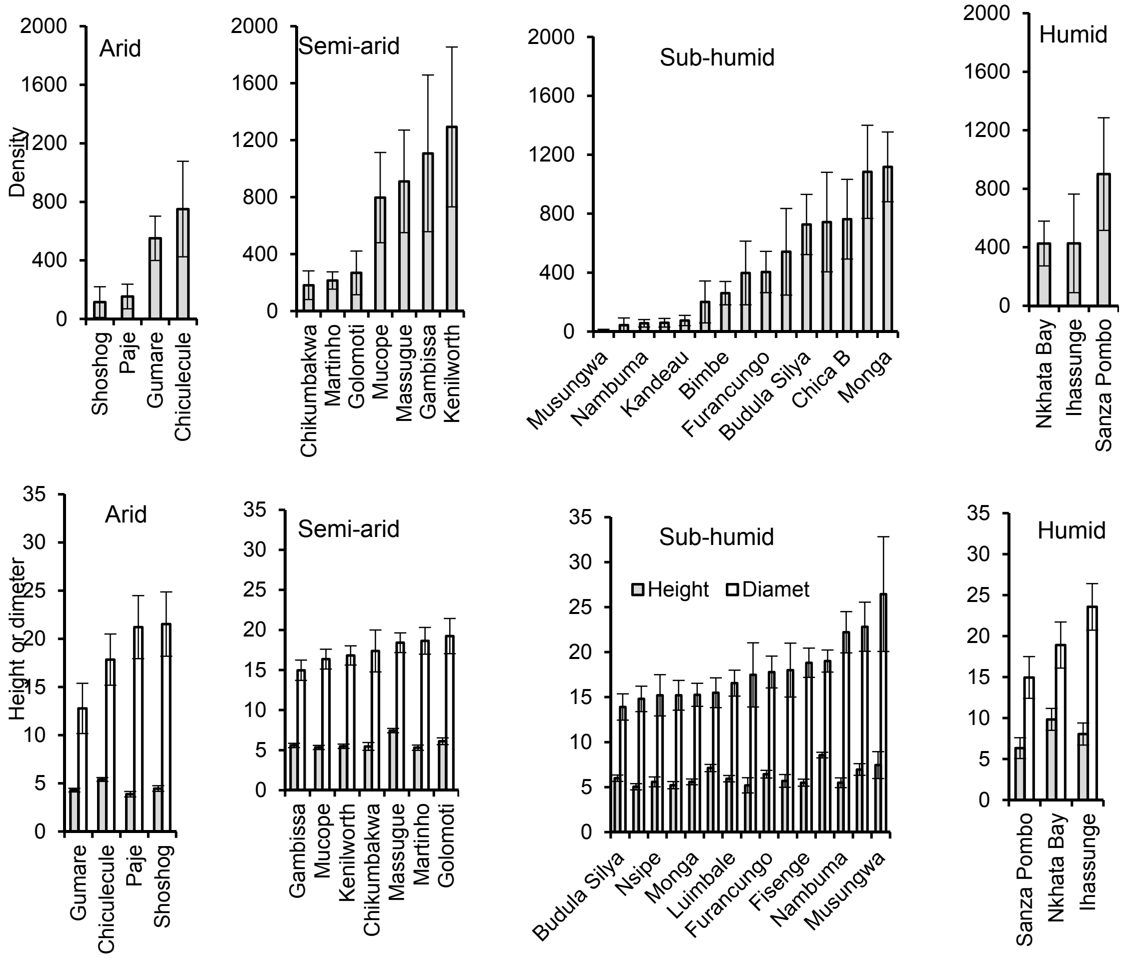


Figure 3. Variation in tree density (in ha^{-1}) (**top panel**); total height (in m) and diameter at breast height (D in cm) (**bottom panel**) across eco-zones and sites. Vertical bars represent 95% confidence intervals.

The average tree height significantly varied across sites and eco-zones (Figure 3, Table 4). Sites in humid areas had taller trees (mean 7.7 m) while those in arid areas tend to be significantly shorter (mean 4.6 m) than those in all other eco-zones. The average tree diameter also varied across sites and eco-zones (Figure 3, Table 4). Remnant trees in cultivated and drier areas had larger diameters than dense re-growth saplings in semi-arid and arid areas. Generally larger tree diameters were found in humid zones compared to the other eco-zones. However, the 95% CL does not indicate significant differences between eco-zones. With fewer trees, Musungwa in Zambia had relatively large diameter trees averaging 27.2 ± 18.0 cm. In this site, the trees are well preserved under co-management arrangement between the local community and Zambia Wildlife Authority since it is within the buffer zone of Kafue National Park. The arid areas, despite having shorter trees, tend to have larger diameter trees. Most trees in the area were coppice re-growth of multiple stems from single stump. The dominantly cultivated area of Nambuma (Malawi) had fewer and large diameter trees averaging 21.46 ± 20.6 cm. The sites with smallest diameter trees include Nsipe (Malawi), Gumare (Botswana) and Furancungo (Mozambique) with average diameters of 12.01 cm, 12.88 cm and 13.67 cm, respectively.

Table 4. Tree density (unadjusted and adjusted for vacant subplots), total height and diameter at breast height. Figures in parenthesis are 95% confidence intervals of means.

Eco-zone	Country	Sentinel Site	Unadjusted Density	Density Adjusted for Vacant	Height (m)	Diameter$_{1.3}$ (cm)
Arid	Botswana	Shoshog	467	115 (9.7–220.4)	4.5 (4.2–4.7)	21.5 (18.2–24.9)
	Botswana	Paje	1026	153.2 (69–238)	3.9 (3.6–4.2)	21.2 (17.9–24.5)
	Mozambique	Chiculecule	1440	751 (424–1077)	5.4 (5.2–5.6)	17.8 (15.2–20.5)
	Botswana	Gumare	1123	551 (400–703)	4.3 (4.1–4.5)	12.8 (10.2–15.4)
		Mean	1014	393 (240–545)	4.6 (4.4–4.9)	16.9 (15.9–17.9)
Semi-arid	Zimbabwe	Chikumbakwa	905	181 (81–281)	5.5 (5.0–6.0)	17.4 (14.8–20.0)
	Mozambique	Massugue	1392	911 (550–1271)	7.4 (7.2–7.7)	18.4 (17.2–19.6)
	Mozambique	Martinho	691	215 (154–276)	5.3 (5.0–5.6)	18.6 (17.0–20.3)
	Zimbabwe	Kenilworth	1756	1293 (732–1854)	5.5 (5.2–5.7)	16.8 (15.6–18.0)
	Malawi	Golomoti	1348	268 (115–422)	6.1 (5.7–6.5)	19.2 (17.0–21.4)
	Angola	Mucope	1471	797 (480–1114)	5.3 (5.1–5.6)	16.4 (15.1–17.6)
	Zimbabwe	Gambissa	2374	1107 (557–1657)	5.6 (5.3–5.9)	15.0 (15.0–16.2)
		Mean	1420	682 (566–797)	5.9 (5.7–6.1)	17.1 (16.4–17.8)
Sub-humid	Malawi	Nambuma	355	56 (30–82)	5.5 (4.9–6.0)	22.2 (19.9–24.5)
	Malawi	Kandeau	734	75 (40–111)	7.0 (6.3–7.6)	22.8 (20.1–25.6)
	Zambia	Musungwa	282	7 (0–15)	7.4 (6.0–8.9)	26.4 (20.1–32.8)
	Zambia	Fisenge	1440	542 (248–836)	5.5 (5.1–5.9)	18.8 (17.2–20.4)
	Malawi	Thuchila	690	60 (31–89)	5.7 (5.0–6.4)	18.0 (15.0–21.0)
	Malawi	Linthipe	342	43 (−6–93)	5.2 (4.4–6.0)	17.5 (13.9–21.0)
	Mozambique	Chica_b	1394	762 (492–1033)	5.0 (4.7–5.4)	14.8 (13.4–16.2)
	Malawi	Nsipe	1045	201 (58–343)	5.6 (5.0–6.1)	15.2 (12.9–17.5)
	Mozambique	Furancungo	1667	404 (263–544)	6.4 (6.0–6.9)	17.8 (16.0–19.6)
	Zambia	Chilende	1638	1084 (767–1401)	8.6 (8.3–8.9)	19.0 (17.8–20.2)
	Mozambique	Macssangila	1039	397 (181–613)	7.1 (6.7–7.5)	15.5 (13.8–17.1)
	Zambia	Budula Silya	1541	726 (522–9310	6.0 (5.6–6.3)	13.9 (12.4–15.4)
	Angola	Luimbale	1369	743 (405–1081)	5.9 (5.6–6.3)	16.6 (15.1–18.0)
	Zambia	Monga	1502	1118 (881–1355)	5.6 (5.3–5.9)	15.3 (14.0–16.5)
	Angola	Bimbe	760	261 (182–340)	5.2 (4.8–5.6)	15.2 (13.5–16.9)
		Mean	1053	432 (353–511)	6.2 (6.0–6.4)	16.8 (16.2–17.5)
Humid	Mozambique	Ihassunge	1062	427 (90–764)	8.0 (6.7–9.4)	23.6 (20.7–26.4)
	Malawi	Nkhata Bay	1433	426 (90–764)	9.8 (8.5–11.2)	18.9 (16.1–21.7)
	Angola	Sanza Pombo	1370	900 (515–1285)	6.3 (5.1–7.6)	15.0 (12.4–17.5)
		Mean	1288	584 (408–760)	7.7 (7.4–7.9)	17.8 (16.8–18.9)
		Grand mean	1194	502 (445–559)	6.1 (6.0–6.2)	17.0 (16.7–17.3)

3.2. Tree Biomass and Carbon Stocks

Among the various set of models used (Table 2), models by Ryan *et al.* [28], Kuyah *et al.* [29] and Mugasha *et al.* [26] best approximated aboveground biomass and carbon stock for the arid and semi-arid; sub-humid; and humid eco-zones, respectively (Table 5). The results show that the region contains considerable amount of aboveground biomass and carbon stocks at both tree and stand levels (Table 4). Individual tree biomass averaged 329.6 kg· tree^{-1} with humid zone having trees with more biomass (409.3 kg· tree^{-1}) followed by arid zone. The sub-humid zone had the lowest biomass (238.4 kg· tree^{-1}). The arid and semi-arid zones had the largest variability indicated by large standard errors.

Trees with lower biomass were observed in newly cultivated areas of Bimbe in Angola, Budula-Siliya in Zambia and at Gumare in the arid zone of Botswana. Sites with higher variability in biomass carbon contents include Chikumbakwa and Chiculecule (Mozambique) and Gumare (Botswana) while those with low variability include Musungwa (Zambia), Luimbale (Angola) and Furancungo (Mozambique).

Table 5. Mean tree biomass estimates (kg· tree^{-1}) with lower and upper 95% confidence limits (95% CL). The best approximating model identified using Akaike Information Criterion (AIC) and Root Mean Square Error (RMSE) are shaded. The mean estimate is the weighted average for a particular model on individual tree basis.

Ecoregion	Model	Country	Mean (kg· tree^{-1})	95% CL	AIC	RMSE
Arid and semi-arid	Mugasha *et al.* [26] $_a$	Angola	253.1	109.7–396.4	59275	28.3
		Botswana	270.6	150.4–390.9		22.2
		Mozambique	545.5	381.5–709.5		15.0
		Zambia	189.0	50.2–327.8		36.7
		Zimbabwe	255.8	156.2–355.5		19.5
	Chidumayo [27] $_a$	Angola	313.4	38.1–588.6	63620	43.9
		Botswana	341.2	109.4–573.0		34.0
		Mozambique	865.3	551.0–1179.7		18.2
		Zambia	221.1	−45.3–487.5		60.3
		Zimbabwe	340.0	147.1–533.0		28.4
	Chidumayo [27] $_b$ linear	Angola	257.9	92.5–423.3	60218	32.1
		Botswana	277.2	138.3–416.1		25.1
		Mozambique	594.1	405.0–783.1		15.9
		Zambia	189.6	29.5–349.6		42.3
		Zimbabwe	265.0	149.7–380.3		21.8
	Ryan *et al.* [28]	Angola	102.3	32.0–172.5	54428	34.4
		Botswana	110.2	51.2–169.3		26.8
		Mozambique	244.7	164.4–325.0		16.4
		Zambia	74.5	6.5–142.5		45.7
		Zimbabwe	106.2	57.1–155.3		23.1
Sub-humid	Kuyah *et al.* [29]	Angola	126.7	80.7–172.6	69731	18.2
		Malawi	271.6	224.3–319.0		8.7
		Mozambique	202.3	173.7–230.9		7.1
		Zambia	179.6	146.0–213.1		9.4
		Zimbabwe	313.3	155.0–471.7		25.3
	Brown [30] $_a$	Angola	142.1	87.0–197.2	71344	19.4
		Malawi	314.0	257.2–370.8		9.1
		Mozambique	231.8	197.6–266.1		7.4
		Zambia	204.2	164.0–244.5		9.9
		Zimbabwe	361.2	171.4–550.9		26.3
	Mugasha *et al.* [26] $_b$	Angola	215.6	129.5–301.8	75332	20.0
		Malawi	483.2	394.4–572.0		9.2
		Mozambique	355.4	301.7–409.0		7.6
		Zambia	311.9	248.9–374.8		10.1
		Zimbabwe	554.9	258.1–851.8		26.8
Humid	Mugasha *et al.* [26] $_b$	Angola	213.4	89.8–337.0	15562	28.7
		Malawi	404.1	265.6–542.5		17.0
		Mozambique	614.5	472.3–756.7		11.5
	Brown [30] $_b$	Angola	255.6	78.4–432.9	16226	34.3
		Malawi	505.3	307.1–703.5		19.4
		Mozambique	802.4	599.0–1005.7		12.6

Subscript letters ($_{a,\,b}$) denote different models by the same author the same year.

The stand AGB estimated using the individual tree and density adjusted for non-vacant subplots was 119.9 Mg· ha^{-1} constituting carbon stocks of 56.4 Mg· ha^{-1} (Table 6). Semi-arid and humid zones had higher carbon stocks (72 Mg· ha^{-1}) compared to sub-humid region (34.3 Mg· ha^{-1}). At site level, higher carbon stocks were recorded in the semi-arid regions of Kenilworth and Gambisa (both in Zimbabwe) and Massuque (in Mozambique), arid area of Chiculecule (Mozambique) and sub-humid area of Chilende (Zambia). Sites in sub-humid regions of Linthipe, Thuchila, Nambuma, Kandeu and Nsipe (all in Malawi), Musungwa (Zambia) and Bimbe (Angola) had relatively lower carbon stocks.

Table 6. Estimated aboveground tree biomass (Kg· tree^{-1}) and stand biomass (Mg· ha^{-1}) and their 95% confidence limits (95% CL) and carbon stocks (Mg· ha^{-1}) at the sites in southern Africa.

Zone	Country	Site	Tree Biomass	95% CL	Stand Biomass	95% CL	Carbon Stock
Arid	Mozambique	Chiculecule	541.6	198.4–716.7	225.7	101.0–289.3	106.1
	Botswana	Gumare	153.3	108.2–176.3	79.9	47.6–96.4	37.6
	Botswana	Shoshog	406.9	282.4–470.4	45.6	18.5–59.4	21.4
	Botswana	Paje	468.0	318.8–544.1	42.9	25.1–52.0	20.1
		Mean	392.4	227.0–476.8	98.5	47.9–124.3	46.3
Semi-arid	Zimbabwe	Kenilworth	240.9	190.9–266.4	293.8	210.3–336.4	138.1
	Mozambique	Massugue	220.8	165.7–248.9	228.6	159.8–263.7	107.5
	Zimbabwe	Gambissa	180.3	138.0–201.9	227	148.4–267.1	106.7
	Angola	Mucope	252.6	198.1–280.4	172.8	130.8–194.2	81.2
	Zimbabwe	Chikumbakwa	553.4	−7.6–839.6	66	12.7–93.2	32.0
	Malawi	Golomoti	252.0	135.2–311.6	48.8	10.2–68.5	23.0
	Mozambique	Martinho	249.2	168.4–290.4	47.3	5.4–68.7	22.1
		Mean	278.5	141.3–348.5	154.9	96.9–184.5	72.8
Sub-humid	Zambia	Chilende	187.7	158.7–202.5	248.2	178.4–283.8	116.6
	Zambia	Monga	173.6	141.3–190.1	190.4	146.3–212.9	89.5
	Mozambique	Chica_b	181.7	121.9–212.2	147.6	22.9–211.2	69.4
	Zambia	Fisenge	251.3	160.7–297.5	105.2	73.8–121.2	49.4
	Angola	Luimbale	138.1	115.0–149.9	92.9	54.5–112.5	43.7
	Zambia	Budula Silya	112.0	87.9–124.3	70.9	52.3–80.4	33.3
	Mozambique	Furancungo	176.1	135.5–196.8	60.1	35.8–72.5	28.3
	Mozambique	Macssangila	166.6	99.0–201.1	57.3	27.3–72.6	26.9
	Angola	Bimbe	110.6	85.9–123.2	29.7	16.6–36.4	14.0
	Malawi	Nsipe	183.5	96.5–227.9	27.4	11.5–35.5	12.9
	Malawi	Kandeau	330.8	204.4–395.3	21.8	−16.6–41.4	10.2
	Malawi	Nambuma	398.4	110.1–545.5	18	6.0–24.1	8.5
	Malawi	Thuchila	292.7	151.6–364.7	14.1	4.9–18.8	6.6
	Malawi	Linthipe	196.7	65.4–263.7	7.7	2.0–10.6	3.6
	Zambia	Musungwa	675.9	188.6–924.5	4.8	−23.0–19.0	2.2
		Mean	238.4	128.2–294.6	73.1	39.6–90.2	34.3
Humid	Malawi	Nkhata Bay	396.7	300.5–445.8	165.7	55.4–222.0	77.9
	Angola	Sanza Pombo	213.2	164.4–238.1	164.9	95.5–200.3	77.5
	Mozambique	Ihassunge	617.9	442.1–707.6	128.7	61.7–162.9	60.5
		Mean	409.3	302.5–463.8	153.1	70.8–195.1	72.0
Overall mean			329.6	199.7–395.9	119.9	63.8–148.5	56.4

4. Discussion

This study has revealed high variability in tree density, biomass and carbon stocks across land uses and eco-zones in southern Africa. Areas with high levels of anthropogenic disturbance (e.g., many in Malawi) appear to have the lowest tree densities and biomass carbon while undisturbed woodlands and some grazing areas showed dense tree cover and carbon stock (Table 7).

Table 7. Ecological zones (according to Koppen–Geiger) of the study sites and major sources of disturbance. The probability of a plot experiencing disturbance due to agricultural activities, cutting trees, grazing, fire, erosion and alien species are shown under each category.

Eco-Zone	Country	Site Name	Agriculture	Cutting	Grazing	Fire	Erosion	Aliens
Arid	Botswana	Gumare	0.000	0.000	0.994	0.469	0.500	0.000
		Paje	0.138	0.000	0.000	0.238	0.438	0.000
		Shoshong	0.125	0.275	0.931	0.038	0.481	0.000
	Mozambique	Chiculecule	0.638	0.631	0.238	0.250	0.425	0.100
		p value	***	***	***	***	NS	NA
Semi-arid	Mozambique	Martinho	0.531	0.569	0.106	0.456	0.581	0.106
		Massuque	0.025	0.000	0.650	0.437	0.506	0.000
	Zimbabwe	Chikumbakwe	0.250	0.450	0.863	0.431	0.381	0.013
		Gambissa	0.213	0.188	0.963	0.469	0.688	0.000
		Kenilworth	0.150	0.000	0.869	0.594	0.681	0.000
	Angola	Mucope	0.300	0.094	0.981	0.075	0.481	0.000
	Malawi	Golomoti	0.394	0.444	0.119	0.800	0.550	0.000
		p value	***	***	***	***	***	NA
Sub-humid	Angola	Bimbe	0.381	0.306	0.006	0.681	0.806	0.006
		Luimbale	0.381	0.256	0.038	0.438	0.781	0.000
	Malawi	Kandeau	0.438	0.263	0.106	0.700	0.669	0.000
		Linthipe	0.450	0.094	0.156	0.625	0.219	0.000
		Nambuma	0.469	0.900	0.113	0.050	0.594	0.000
		Nsipe	0.394	0.356	0.144	0.806	0.763	0.000
		Thuchila	0.088	0.969	0.081	0.150	0.431	0.013
	Mozambique	Chica	0.606	0.500	0.013	0.400	0.756	0.125
		Furanungo	0.413	0.281	0.013	0.825	0.750	0.000
		Macasangila	0.706	0.481	0.000	0.538	0.656	0.050
	Zambia	Budula	0.518	0.388	0.394	0.431	0.831	0.000
		Chilende	0.006	0.000	0.025	0.450	0.544	0.000
		Fisenge	0.431	0.594	0.094	0.388	0.388	0.013
		Monga	0.413	0.181	0.713	0.444	0.894	0.000
		Musungwa	0.019	0.031	0.000	0.900	0.281	0.000
		p value	***	***	***	***	***	NA
Humid	Angola	Sanzapombo	0.125	0.113	0.081	0.800	0.756	0.000
	Malawi	NkhataBay	0.481	0.700	0.156	0.644	0.494	0.006
	Mozambique	Ihansunge	0.263	0.750	0.006	0.231	0.438	0.175
		p value	***	***	**	***	***	NA

p values show significance of differences between sites (** $p = 0.05$; *** $p < 0.001$ and NS $p > 0.05$). NA means that maximum likelihood estimates do not exist due to lack of convergence.

Except few sites with higher estimates, the majority of the AGB values in this study are within the range of estimates obtained in other studies from tropical dry to moist forests. A review by Gibbs *et al.* [35] also established that sub-Saharan Africa's open, closed and tropical seasonal forest contains carbon stock ranging from 17 to 152 Mg· ha^{-1}. The wide variability in carbon stock could be a reflection of differences in topography, climate and land use regimes across those different systems.

Generally, biomass carbon stocks in humid and sub-humid areas were affected by intense cultivation and wood fuel extraction whereas bush fires destroy trees in semi-arid and arid zones. Fire has a long history in the evolution of southern African savanna ecosystems and there exists some degree of fire dependency for the growth, production, regeneration and coexistence of herbaceous and woody savanna vegetation [17]. However, humans have altered the intensity and timing of fire over time, and anthropogenic activity is one of the main causes of fires [36]. For example, the current distribution of *miombo* woodland, the principal vegetation type in the Zambezian savanna zone, is believed to reflect the history of anthropogenic fire utilization in the region [17].

In closed undisturbed forests, regional trends in rainfall and topography are the prime determinants of woody biomass carbon stock [4,37]. Olson *et al.* [38] found carbon stocks of 120, 105, and 72 Mg· ha^{-1} for tropical rain, moist and dry forests, respectively. A similar gradient was captured by Intergovernmental Panel on Climate Change (IPCC) [31] where Africa's tropical wet forest had higher carbon stocks (145.7 Mg· ha^{-1}) followed by woodlands with short season (122.2 Mg· ha^{-1}), woodlands with short dry season (57.81 Mg· ha^{-1}) and drier areas with 33.84 Mg· ha^{-1}.

At stand level, woody biomass follows a gradient along successions following disturbance [39]. Disturbance regimes including conversion of forests to agricultural production, fires, wood extraction and grazing exert local to regional impact on tree biomass as reflected in the variability of biomass/carbon stocks estimates within eco-zones and countries [27]. In this study, the intensively cultivated sub-humid areas of Malawi had consistently lower biomass estimates compared to arid areas under moderate cultivation and intense grazing in Botswana (Table 4). This could be linked to disturbance probabilities (Table 1) where sites in Botswana have lower cutting and agricultural incidence compared to those of Malawi. National carbon estimates reviewed by Gibbs *et al.* [35] based on studies conducted between 1983 and 2007 shows varied carbon stocks among four countries as follows: Angola (59.44 with range 28.53–94.39), Zambia (53.4 with range 19.64–92.86), Mozambique (49.6 with range 24.16–65.39) and Malawi (2.86 with range 1.61–4.16), which generally agreed with the estimates in this study.

The carbon stocks found in this study in undisturbed and disturbed woodlands and croplands are within the ranges estimated previously in the region. Kuyah *et al.* [29] recorded carbon stocks of 0.8–22 Mg· ha^{-1} in croplands and disturbed woodlands of Malawi. Ribeiro [40] found carbon stocks of 19 Mg· ha^{-1} in undisturbed miombo woodland within Niassa Forest Reserve in northern Mozambique. Several studies in miombo woodlands of eastern Arc Mountains and Kitulango Forest both in Tanzania found carbon estimates within the rage of 15.5–80 Mg· ha^{-1} [41–43]. The study by Chidumayo [27] in miombo of Zambia found carbon gradients in spatial (adjacent re-growth and old-growth) and temporal (1990–2012) scales. He established that the re-growth experienced minimal disturbance and had increased carbon stock from 3.8 Mg· ha^{-1} at eight years in 1990 to 16.0 Mg· ha^{-1} in 2012. On the other hand, an old-growth that experienced moderate disturbance had its carbon stock decreased from 47.0 to 35.3 Mg· ha^{-1}. These trends are primarily a result of woodland management and utilization regimes by local communities and are supported by the observation by Chidumayo [44]. Chidumayo noted that many interacting land use factors have shaped regeneration and regrowth of miombo woodlands. In the arid areas, the woodlands are preserved because other vegetation types cannot be supported by the little rains received [37].

Socio-cultural factors also influence biomass within ecological zones with Paje (Botswana) having lower biomass due to scorching bush fires whereas woodlands of Shoshong (Botswana) are traditionally protected. The mangroves of coastal Mozambique are also conserved by local communities without formal institutions and contain considerable biomass stocks. The results from this study are consistent with estimates by Fatoyinbo *et al.* [45] who found 67 Mg· ha^{-1} carbon stocks in mangroves of Inhambane along the central-southern coastlines of Mozambique. The Inhassunge site is generally located below sea level, water floods the coastal lines and valleys form a network of rivers that flow upland during lunar tide and towards the ocean when the water recedes. Woodlands have formed natural bands and are conserved by local communities (Plate 1g). Other studies in the region show that beliefs, taboos and tradition are among the driving forces shaping use and management of tree/forest resources [46,47].

Overall, biomass carbon stocks followed the gradient in ecological and anthropogenic disturbance regimes, hence the need for different management approaches specific to the zone or site(s). Being the first regional study across a range of eco-zones and land cover/use types, the approach and estimates can serve as a baseline and used for future monitoring of carbon stock and income generation through "carbon trade". This will add to the pool of information required to enhance negotiation capacity of governments, private sector and communities involved REDD+ and voluntary carbon markets.

5. Conclusions

Tropical forests have great potential for mitigating global warming due to atmospheric CO_2 emissions. The miombo dominated woodlands in Southern Africa are also major sources of livelihoods.

However, their potential is impaired by deforestation and forest degradation, which contribute about one fifth of total anthropogenic CO_2 emissions. Restoring landscapes and proper management of forest resources are necessary to tackle problems of climate change and global warming. Carbon sequestration incentives require that initial carbon storage is established and the role of projects in tackling atmospheric emission verified. Understanding spatial variability of carbon stock across land use and eco-zones can play a crucial role in the design of management strategies. This can also facilitate "carbon-saving" credit schemes and provide necessary incentives. However, developing countries face measurement challenges due to diversity in vegetation species, inaccessibility and limited resources.

The paper reports the estimate of biomass and carbon stock from land degradation surveillance of randomly selected 4640 plots across six countries of Southern Africa (Angola, Botswana, Malawi, Mozambique, Zambia, and Zimbabwe). Generalised allometric equations for tree species in different vegetation types and climate zones were used to estimate aboveground biomass based on which carbon stock was estimated. The study estimated average aboveground tree density of 502 trees$\cdot$ ha^{-1} and carbon stock of 56.4 Mg$\cdot$ ha^{-1}. There were however wide site to site variability in both biomass and carbon stock due to a combination of natural and anthropogenic processes. Areas with high levels of anthropogenic disturbance (e.g., many in Malawi) appear to have the lowest tree densities and biomass carbon while undisturbed woodlands and some grazing areas showed dense tree cover and carbon stock. Given the extent and variability of woody carbon stocks in the region, there is a huge capacity for the ecosystem to store carbon if properly managed. Managing the carbon stock in this extensive carbon rich ecosystem can also contribute to global initiatives in combating global warming. Financial incentive designed to ensure proper management of the woodland and forest ecosystem can contribute to the creation of considerable carbon sink contributing to the REDD+ initiatives in developing regions.

The data for this study is based on large number of plots distributed across diverse ecological and land use systems. Moreover, the study captured diverse ecosystem ranging from xeric shrublands to dense humid forests along latitudinal and altitudinal gradients using consistent methods. The estimated aboveground biomass and carbon stock can thus form a baseline against which future trends can be compared for monitoring and impact assessment. Despite the fact that the estimates reported in this study are based on allometric models that are suited to corresponding agro-ecological zones and/or tree species, it will be necessary to test the results using measured biomass and carbon values.

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Abbreviations

The following abbreviations are used in this manuscript:

AGB	aboveground biomass
AGBC	aboveground biomass carbon
AGBCS	aboveground biomass carbon stock
AfSIS	Africa Soil Information Service
AIC	akaike information criterion
LDSF	land degaradation surveillance framework
REDD+	Reducing Emmisions from Degradation and Forest Degradation
RISING	research in sustainable intensification for the next gerneration

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