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STUMP DIAMETER: A POTENTIAL PREDICTOR OF REMOVED BIOMASS THROUGH TREE CUTTING

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ABSTRACT

Stump diameter (*SD*) has been rarely considered as an important tree parameter in forestry. It is until recently that *SD* has been found to be important predictor of tree diameter at breast height (*D*) and forest stand parameter such as volume and biomass. This study, developed *D-SD* relationships for nine different forest cover type in Tanzania mainland. A total of 32265 sample trees covering miombo woodlands, humid montane, lowland forests, bushlands, grasslands, mangroves, cultivated land, wetlands forests and plantations (*Pines* and *Eucalyptus* species) were used for fitting *D-SD* models. The findings revealed a linear relationship between *D* and *SD* for all forest covers. In addition, we found forest covers having similar *D-SD* allometry while others had unique *D-SD* allometry. This prompted fitting Generalised Linear Model where three forest cover groups were generated, i.e. group 1 (bushlands, woodlands, lowlands and grasslands); group 2 (mangroves, cultivated land, plantation and wetlands); and group 3 (humid montane). We fitted linear model to each forest cover group. Large variations in *D* were adequately explained by *SD* for each forest cover group. We further compared *AGB* values estimated from the measured *D* and estimated *D* from the *D-SD* equation. The estimated *AGB* from both approach did not differ significantly. We therefore, recommend the developed *D-SD* relationships models be applied to predict *D* of the missing trees for which their stumps still exist.

Keywords: Stump diameter, forest cover, Tanzania, biomass

INTRODUCTION

With a total of 48.1 million ha of forested land (54.4% of total land area; MNRT, 2015), Tanzania is among the highly forested country in Africa and its contribution to climate change mitigation cannot be underrated (Watson *et al.* 1996). Broadly, forested land in the country is comprised of forest and woodlands. Forests include montane, lowland, mangrove, and plantation forests, while woodlands include open and closed woodlands, and thickets. Woodlands occupy 44.7 million ha (~93.0% of the total forested land and 50.6% of total land area in Mainland Tanzania), followed by cultivated land (25.2%), bushland and grassland (16.6%) and forests (3.5%). However, the forests in the country are under threat. It is estimated that for the period between 2002 and 2013, the forest cover annual loss was estimated to be about 469,000 ha (URT 2007). The main drivers of deforestation have been identified to be expansion for farming and settlements. Another serious threat is forest degradation which takes place in fragmented manner (MNRT 2015). Selective cutting for fuelwoods and logging is reported to be the main drivers of forest degradation.

Notwithstanding, sustainable provision of goods and services from the forests requires effective forest management efforts. Credible forest management decisions rely on reliable information on extent and forest condition/structure. The most common practice to quantify forest quality and quantity is to carry out forest inventory by measuring tree dendrometric parameters. Dendrometric dimension of trees are highly correlated with other parameters which are expensive to measure directly, e.g., destructive sampling to acquire biomass and volume (Mugasha *et al*. 2013b). The magnitude of correlation varies from one set of dimensions to another. For decades, forester have utilized this relationships to estimate different tree attributes indirectly from other respective tree dimension (Chave *et al*. 2005, Feldpausch *et al*. 2010, Ledo *et al*. 2018, Mauya *et al*. 2014). Good examples are the estimation of total tree height (*H*) from tree diameter at breast height (*D*) (Feldpausch *et al*. 2010, Mugasha *et al*. 2013a), individual tree volume, above- and belowground biomass from D and/or H and /or basic wood density and/or crown diameter (Chamshama *et al*. 2004, Nogueira et al. 2008). It is unquestionable that *D* correlates strongly with biomass and volume than other dimensions, e.g. stump diameter (*SD*) (e.g. Malimbwi *et al*. 1994). However, *SD* is useful when *D* is not available specifically when estimating emission from tree cut using stump dimensions, i.e., *SD* and stump height (*SH*). This is possible when there is a regression equation relating *SD* and *D* measured from standing trees. Thus, the estimated *D* from *D-SD* relationship is applied to biomass/carbon and volume allometric equations to estimate emitted carbon and volume, respectively.

While deforestation is relatively easier to estimate, forest degradation is more challenging. Recently, Tanzania has engaged in developing Forest Reference Emission Level (URT 2017). Deforestation and conservation are the only REDD+ activities among the five activities, which has been included in the Tanzania FREL. Degradation has not been included due to inadequate data for establishing baseline and monitoring. Forest degradation is taking place all over the country in fragmented manner. Monitoring forest degradation by means of remote sense techniques poses a significant challenge since degraded forests frequently maintain a closed canopy (e.g., Miettinen *et al*. 2014). The main drivers of forest degradation are related to selective cutting such as extraction of wood fuel (charcoal and firewood), logging, grazing and wildfire. Nevertheless, techniques to estimate forest degradation need to be developed following stepwise approach. The approach which utilizes tree stumps left after selective tree cutting has been explored in this study. The advantage using tree stump is the fact that *SD* can easily be included as tree measured parameter during forest inventories as a means of assessing forest degradation. The approach is limited to the fact that the tree stumps have to remain in the field.

On the other hand, attempt to develop biomass and volume models which use *SD* as explanatory variable have been made for miombo woodlands in Tanzania (Malimbwi *et al*. 1994). It is apparent that such models are superior to models which utilize estimated *D* from *SD* since the former has no accumulation of error associated with a series of regression equations, e.g., from *SD* to *D* and from *D* to biomass. However, the developed biomass and volume models utilizing *SD* were developed from limited data and site which may not be adequate to cover tree biomass and volume variations at country level (Malimbwi *et al*. 1994). In addition, the precision of stand parameter estimates, e.g., biomass and volume per unit area, estimated from estimated *D* is not known. The accuracy of estimated stand parameters from estimated *D* will entirely depend on the magnitude of correlation between *SD* and *D*.

Therefore, this study intends to develop tool for estimating biomass of missing tree in a degraded or cleared forest which utilizes *SD* for main forest types in Tanzania. Specifically, this study aimed at 1) developing *D-SD* models for the main forest types; and 2) assessing the extent in which biomass estimated from measured *D* differ from biomass estimated from estimated *D*. This study utilized a network of plots established during the National Forest Inventory (NFI) commonly known as National Forest Resources Monitoring and Assessment (NAFORMA).

METHODOLOGY

Site Description

Data used in this study were obtained from a network of plots established by NAFORMA in Tanzania mainland. Data were collected over the entire Tanzania mainland covering all primary forest cover types. The country has a diverse climate with mean annual rainfall ranging from below 500 mm to over 2000 mm per annum. The rainfall for large parts of the country is bimodal with short rains from October-December and long rains from March to May. The biodiversity of forests in Tanzania mainland is high consisting over 10,000 plant species, hundreds of which are nationally endemic.

Woodlands and bushlands

The woodlands constitute the largest vegetation type in Tanzania Mainland, occupying about 44.7 million hectares which is equivalent to 93% of the entire forest area (MNRT 2015). The woodland has three subtypes: Closed (>40% canopy cover), Open (10-40% canopy cover) and Woodland with scattered cropland. The tree height ranges between 5 m and 20 m although occasionally being taller than 20 m. In term of amount of precipitation intercepted, miombo woodlands may be categorised into wet (>1000 mm) and dry woodlands (<1000 mm). Wet woodland is dominated by *Brachystegia*/*Julbernardia* sp. (Miombo woodland). Dry woodland is usually dominated by Vachellia species. Bushland differs from Woodland in two principal ways. Stature is less, rarely exceeding 5 m and normally between 1 m and 3 m in height. Single-stemmed plants are almost non-existent. The exception is when there are occasional trees termed as emergent. Bushland is fundamentally defined as being predominantly comprised of plants that are multi-stemmed from a single root base.

Humid montane and lowland forest

The humid montane and lowland forest occupy 995,000 ha and 1,656,500 ha, respectively in Tanzania Mainland which altogether is 5.5% of the countries forest area. These forests are characterized by high richness of flora and fauna and have high catchment values (Munishi and Shear 2004), thus, most of them are protected for soil, water and biodiversity conservation. Also, they are sources of timber and non-timber forest products, ecotourism potentials, carbon sinks and sources. Lowland forest is also known as coastal forest since large area of its forest is found along the coast of Tanzania Mainland and the remaining area in the inland (Binggeli 2001). Humid montane forests occur in wide elevation range covering extensive areas of the wetter eastern, southern and northern sides of the mountains in Tanzania Mainland (Munishi and Shear 2004).

Grassland

Grassland is another vegetation type possessing marked variety, with four sub-types (MNRT 2010). Open grassland is mostly confined, to the plains of the Serengeti, Masai Steppe, and to alpine areas of the Southern Highlands where exposure and edaphic conditions do not allow the natural development of anything more than a grass or herb. For the most part, this type occurs as its Sub-types in combination with either a limited Wooded or Bushed component, or with scattered subsistence cultivation. Wooded grassland and Bushed grassland both comprise of ground cover percent of trees or bushes below 10 percent of total. The grassland sub types are: Wooded grassland, Bushed grassland, Grassland with scattered cropland, and Open grassland.

Cultivated land

The Cultivated land is a type of land with four vegetation sub-types (MNRT, 2010). The physiognomy varies widely in accordance with the significance of the tree and crop component associated with each unit. The agroforestry systems which contain permanent tree crops (timber and fruit) that are mixed with permanent and annual agricultural crops (yam, beans, banana, coffee, etc.) such as the Chagga, Meru and Haya (Bukoba) home gardens are recognized as one vegetation sub-type. The tree crops (*Grevillea*, *Albizia*, Cordia, Citrus, *Acrocarpus*) which form the upper canopy act as shade to the lower canopy crops (banana, coffee, beans). Cultivation with herbaceous crops (e.g., maize, sorghum, millet, sugar cane, sisal, rice) where the tree component may be reduced to the occasional fruit tree or trees retained to demarcate field boundaries is a sub-type that approaches open grassland. At the other extreme, cultivation with pure woody crops of cashew, tea, coffee, mango, citrus, jackfruit and coconut are common and identifiable as a sub-type. The last vegetation sub-type is where the woody crops are mixed in varying proportions of fruit tree species such as mango, coconut, citrus and cashew.

Mangroves

Mangroves comprises of trees and shrubs which grow in or adjacent to the intertidal zone. They are found at tropical and sub-tropical latitudes, primarily along sheltered shorelines where freshwater (rainfall or river flow) dilutes the ocean, such as bays, estuaries, lagoons, backwaters, and rivers (up to the point where water remains saline). Mangroves are forests found in the tropical and subtropical coastlines between 30° south and north of equator (FAO, 2007). Within their latitudinal limits, mangrove distribution is largely influenced by temperature and moisture. Ideal conditions for growth include high humidity combined with freshwater input that provides silt and nutrients. In Africa, there are mangroves both at the western and eastern coasts. At the eastern coast of Africa, 14 mangrove species are growing naturally, and 10 among these are found in Tanzania Mainland. *Avicennia marina* (Forssk.) Vierh, *Sonneratia alba* J. Smith, and *Rhizophora mucronata* Lam. are the three most dominant mangrove species in Tanzania (Njana *et al*. 2016). Mangroves provide a range of goods (e.g., timber, poles, wood-fuel) and services (e.g., stabilization of the coastline and carbon sequestration).

Pine and Eucalyptus species

Pine and *Eucalyptus* species are among the planted exotic tree species in Tanzania mainland. Pines are native to the Northern hemisphere and in a few parts of the tropics in the Southern hemisphere. Pine species in Tanzania mainland include *Pinus patula*, *P. elliottii* and *P. caribaea*. These are the dominant species in most of the government and private plantations with about 78% of the total area planted and the remaining 22% is shared among hardwoods and other softwood species. *Eucalyptus* species are native to Australia, while a very small proportion are found in adjacent parts of New Guinea, Philippines, Timor and Indonesia (Brooker *et al*. 2000, Grubben 2004, Oballa *et a*l. 2010). In Tanzania mainland, the area under *Eucalyptus* species is estimated to be 25,000 ha (Munishi, 2007) of which 4,665 ha are grown by Government and the rest are grown by the private sector and small-scale farmers (Ngaga 2011). In Tanzania Mainland, *Eucalyptus* species were introduced in early 1890s with the aim of supplementing wood supplies from natural forests (Nshubemuki *et al*. 2001). The planted species include *E. saligna*, *E. grandis*, *E. camaldulensis*, *E. globulus*, *E. viminalis*, *E.*

citriodora, *E. regnans* and *E. microtheca* (Munishi 2007).

NAFORMA sampling design and field measurements

The sampling design applied by the NAFORMA was double-sampling for stratification which was designed based on a simulation study described by Tomppo et al. (2014). The first-phase sample consists of clusters of plots on a 5 × 5 km grid. The first-phase clusters were stratified based on predicted growing stock, time spent for cluster measurements and slope of the terrain. Altogether, the first-phase clusters that contain 6 to 10 plots were assigned to 18 pre-defined strata. The second-phase samples were systematically selected from the first phase sample, with different sampling intensities in each of the 18 strata following an optimal allocation procedure with cost functions tailored for each stratum (Tomppo et al. 2014). Greater sampling intensity was allocated to strata with large predicted growing stock and smaller sampling intensity to strata with small predicted growing stock. Only the clusters selected during the second phase of sampling were measured in the field. The distance between field plots within a cluster was 250 m, while the distance between clusters varies from 5 km to 45 km (Figure).

NAFORMA field plots were concentric plots which covered nine forest cover type, i.e. Bushland, cultivated lands, Grassland, Lowland, Mangrove, Montane, Plantation, Wetlands, and Woodland (MNRT 2015). For more details on the field measurements, we refer the readers to MNRT, (2010) and (2015).

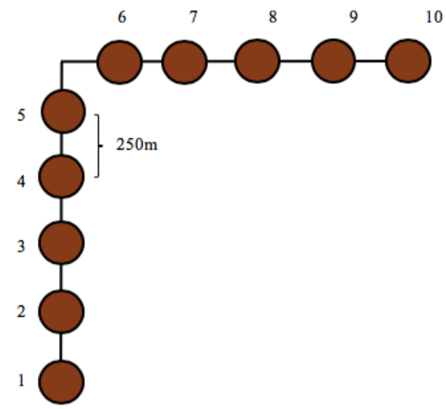

Figure 1. The NAFORMA cluster and plots layout (MNRT 2015). Data Exploration

Prior to model development, entire data were grouped into nine forest cover types in order to account for variations in *D-SD* relationship that might be attributed by forest cover differences. Exploration of *D-SD* data revealed that the number of stems per stumps affect the *D-SD* relationships. The difference was also apparent by inspecting scatter plots of all vegetation types (Figure). However, the number of stems above one did vary or make a definite pattern to separate them. Therefore, for each vegetation types, data set was separated into two, i.e., single stem and multi-stems. Later, it was realised that the data collection procedure for multi-stems was inappropriate, i.e., while each stem was measured for *D*, only one diameter measurement was taken at the base (*SD*). It would have been appropriate to measure the *SD* of each stem in a given stump. In that effect, observations with multi-stems were discarded in this analysis. Scatter plot of all cover types combined are presented in Figure .

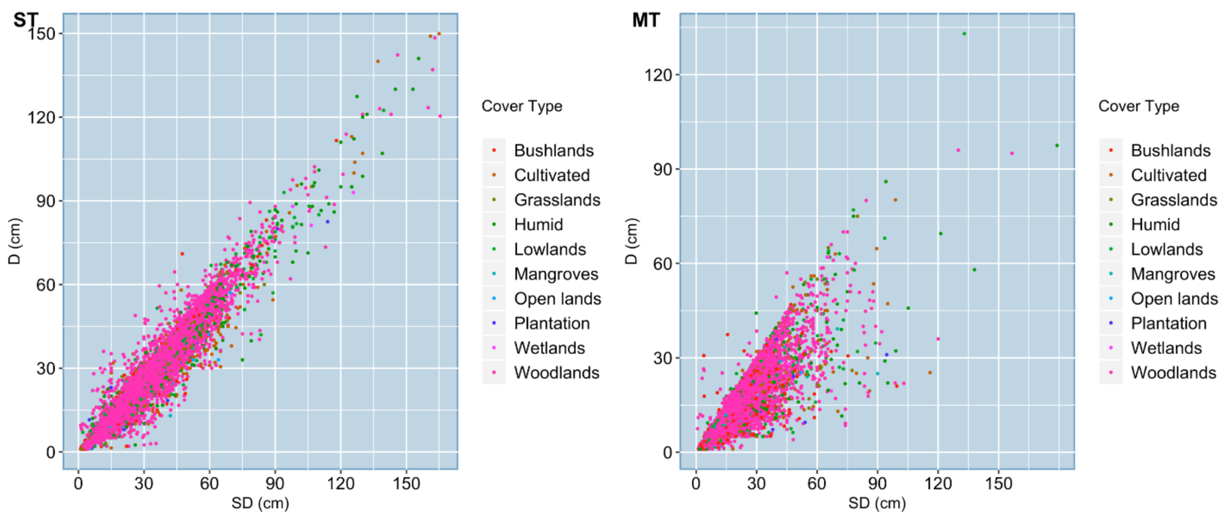

Figure 2. Scatter plots of single (ST) and multi-stems (MT) showing *D-SD* relationship for different forest cover type

Grouping Procedure and Modelling

Scatter plots revealed the liner relationship between *D* and *SD* (Figure 2; left panel). Visual analysis show that linear *D-SD* relationships of some cover types overlap. This necessitates to confirm the observed pattern statistically. A generalized Linear Model (1) Table ***1***. Intercepts present coefficient "*a*" and "*b*" of bushland cover type as a reference cover type in the GLM. Other coefficients present the differences between coefficient(s) of respective cover type from that of bushlands. When the *p*-value is less than 0.05, it implies that coefficient(s) of that respective cover is significantly different from that of bushlands. That is, the confidence intervals area of estimated *D* does not adequately overlap. The findings show that cultivated, mangroves, open were fitted to all data set combined by allowing coefficients, "*a*" and "*b*" to vary for each cover types. Plot and clusters were considered to be random effects.

$$D = a + b \times SD \quad (1)$$

The preliminary findings are shown in

lands, plantation and wetlands cover type differed significantly from other cover types (*p*-value < 0.05). At this point, one group thereafter referred as Group I was generated consisting of grasslands, bushland, miombo woodlands, and lowlands forest cover types. Other cover which was different were removed from the data set and combined, and GLM was fitted to ascertain whether there are cover types which have different *D-SD* relationships.

Table 1. Coefficients of the retained cover types and their significance (step 1)

Cover type	Coefficient symbol	Coefficient	SE	*p*-value	Coefficient symbol	Coefficient	SE	*p*-value
Bushlands	*a* (Intercept)	-0.7033	0.1271	0.0000	*b* (Intercept)	0.8641	0.0059	0.0000
Cultivated	*a*	0.0792	0.2241	0.7238	*b*	-0.0397	0.0077	0.0000
Grasslands	*a*	-0.0987	0.2577	0.7018	*b*	-0.0056	0.0105	0.5914
Humid	*a*	0.0537	0.1864	0.7734	*b*	-0.0158	0.0068	0.0203
Lowlands	*a*	0.1021	0.1852	0.5814	*b*	-0.0110	0.0073	0.1337
Mangroves	*a*	0.5022	0.4057	0.2158	*b*	-0.0556	0.0211	0.0085
Plantation	*a*	0.4220	0.3268	0.1967	*b*	-0.0345	0.0122	0.0047
Wetlands	*a*	0.9262	0.5478	0.0909	*b*	-0.0564	0.0159	0.0004
Woodlands	*a*	-0.2081	0.1324	0.1161	*b*	0.0045	0.0061	0.4531

Table **2** presents coefficients for the remaining covers types and their significance in respect to cultivated land cover type as reference cover. Except for humid (montane forests) cover, the estimated coefficients were not significantly different from cultivated cover's coefficients. Therefore, all the forest covers, were considered to have similar *D-SD* allometry and grouped in a single group thereafter referred as Group 2. Humid forest cover in this case was assigned to its own group (Group 3). Scatter plots showing the *D-SD* relationship for the emerged groups and the summary descriptive statistics of forest covers types and groups are shown in Figure 1 and Table 3, respective.

Table 2. Coefficients of the retained cover types and their significance (step 2)

Cover type	Coefficient symbol	Coefficient	SE	*p*-value	Coefficient symbol	Coefficient	SE	*p*-value
Cultivated	*a* (Intercept)	-0.5848	0.2443	0.0167	*b* (Intercept)	0.8235	0.0064	0.0000
Humid	*a*	-0.0999	0.3118	0.7486	*b*	0.0248	0.0077	0.0012
Mangroves	*a*	0.4245	0.5883	0.4706	*b*	-0.0132	0.0263	0.6154
Plantation	*a*	0.2825	0.4722	0.5497	*b*	0.0052	0.0155	0.7367
Wetlands	*a*	0.7451	0.7383	0.3130	*b*	-0.0157	0.0200	0.4341

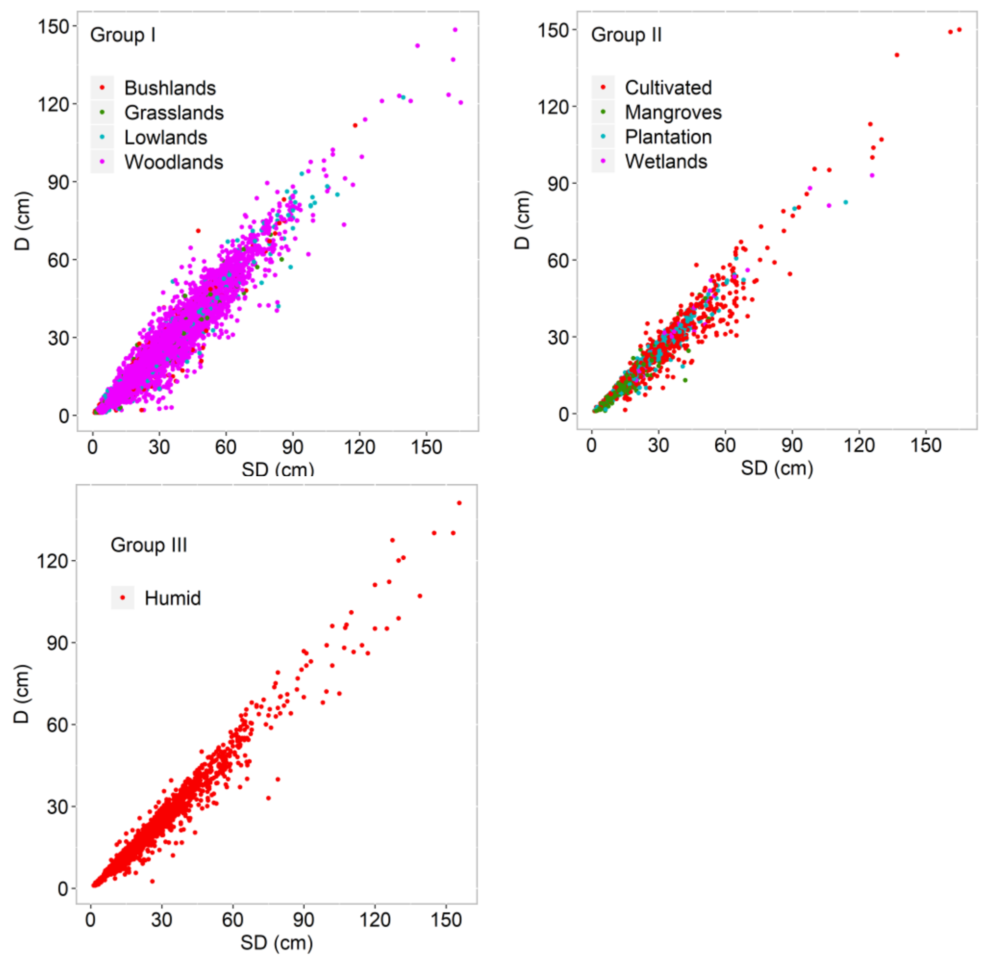

Figure 1. Diameter-stump diameter scatter plot

Table 3. Summary of descriptive statistics for forest cover and emerged groups

Group	Forest cover/Group	Diameter (cm) Mean	Max.	Min.	sd	Stump diameter (cm) Mean	Max.	Min.	sd	n
Forest cover	Bushlands	13.1	111.6	1	11.2	15.9	118.0	1.0	12.6	1493
	Cultivated	23.9	149.9	1	18.0	29.9	165.0	1.5	21.0	748
	Grasslands	17.8	69.5	1	11.7	21.7	85.0	1.5	13.3	623
	Humid	22.9	141.0	1	17.7	27.7	155.6	1.3	20.5	1650
	Lowlands	17.9	122.4	1	14.5	21.7	139.6	1.2	16.7	1535
	Mangroves	11.7	46.4	1	7.4	14.8	52.4	1.3	8.6	263
	Plantation	20.7	82.5	1.4	11.1	25.2	114.0	1.8	13.0	513
	Wetlands	23.7	93.0	2.2	17.3	29.1	125.8	3.5	21.1	82
	Woodlands	19.2	148.4	1	12.1	23.1	165.5	1.1	13.6	25358
Developed group	Group 1	18.8	148.4	1	12.3	22.7	165.5	1.0	13.8	29009
	Group 2	20.9	149.9	1	15.3	25.9	165.0	1.3	17.9	1606
	Group 3	22.9	141.0	1	17.7	27.7	155.6	1.3	20.5	1650
All		19.1	149.9	1.0	12.8	23.1	165.5	1.0	14.5	32265

Max= Maximum; Min= Minimum; sd= Standard Deviation.

Modelling

Since the *D-SD* relationship is linear, three linear model forms (2, 3, and 4) were fitted. NAFORMA data represent a hierarchical structure by which the field plots are nested within the clusters. In this case, linear Mixed Effect Modelling (LMM) approach is considered to be an ideal for development of predictive models that will account for dependence of the plots within the clusters (Pinheiro et al. 2007). Therefore, linear models consisting of two main parts, i.e., fixed and random effects were fitted. The fixed effects are common to all subjects, while random effect parameters are specific to each subject (in this case cluster ID) (Pinheiro et al. 2007). In this study, *SD* was used as the fixed effect and the cluster ID was accounting for random effect.

$$D = b \times SD \qquad (2)$$

$$D = a + b \times SD \qquad (3)$$

$$D = a + b \times SD + c \times SD^2 \qquad (4)$$

To account for variation (i.e., heteroscedasticity due to cluster) not accounted by the random effects, we also fitted the Mixed Effect Model (i.e., the random intercept model) with power variance function structure. In this case, we used the *varPower* function implemented in the *nlme* package (Pinheiro et al. 2007) of R software (R Core Team 2019). The models were fitted using Maximum Likelihood procedure, and compared with Mixed Effect Model, i.e., the random intercept model, using the likelihood ratio test to determine the effect of accounting heteroscedasticity using variance structure. Pseudo R-square (R^2) and Root Mean Square Error (RMSE) were computed for the best selected model in each cover type/group. The best models were selected based on lower Alkaike Information Criterion (AIC) and absence of non-significant coefficients.

Evaluation of Selected Models

The selected models were further assessed on percentage Mean Prediction Error (*E*%), at a group level and over forest cover types. Mean Prediction Error (*E*%) was computed using equation (5).

$$E\% = 100 \times \sum \left(\left(\frac{D - \hat{D}}{D} \right) \Big/ n \right) \qquad (5)$$

Where: *E*% is mean prediction error; *D* is measured diameter at breast height; $\hat{D}$ is estimated diameter at breast height; and *n* is number of observations in respective category.

Comparison of Estimated Biomass from Measured and Estimated Diameter

Aboveground biomass (AGB) from estimated *D* and *AGB* from measured *D* were evaluated by regressing *AGB* (from measured *D*; *y*-axis) as a function of *AGB* (from estimated *D*; *x*-axis) (Piñeiro et al. 2008). Ideally, if the two variable are equal, the linear relationship between AGB generated from two approaches must have a slope of 1 and intercept of zero (Gauch et al. 2003; Piñeiro et al. 2008). Biomass allometric models which utilize *D* alone have been developed for miombo woodlands (eq. 6; Mugasha et al. 2013b); lowland and humid forest (eq. 7; Mugasha et al. 2016); and mangroves (eq. 8; Njana et al. 2016). We applied the models to the NAFORMA data at plot level where *AGB* for trees which were measured for *D* and *SD* were estimated. To accomplish this, we first estimated *D* using selected *D-SD* models; and estimate individual trees *AGB* using estimated *D*. The next step was to estimate *AGB* using measured *D* as independent variable; and finally, compare *AGB* generated from estimated and measured *D*. We first compare the two *AGB* using coefficients (slope and intercept) of linear equation relating the two *AGBs*; and second, compare generated *AGB* from the two approaches per unit area.

$$\widehat{AGB} = 0.1027 \times D^{2.4798} \quad (6)$$

$$\widehat{AGB} = 0.6881 \times D^{1.93834} \quad (7)$$

$$\widehat{AGB} = 0.25128 \times D^{2.24034} \quad (8)$$

Where: $\widehat{AGB}$ is estimated biomass in kg; and *D* is estimated or measured diameter at breast height.

RESULTS

Model performance

Table **4** presents model's coefficients and performance. Models *SE* ranged from 2.62 to 3.28. Forest cover with lowest *SE* was group1 (Bushlands, Grasslands, Lowland, and Woodlands) while group 3 (humid) had highest model *SE*. Coefficient of determination (R^2) ranged from 0.90 to 0.95 where group 2 and 3 lower R^2 and higher *SE*. Except for group 2, coefficients "*c*" of model (3) was found insignificant. Based on lowest AIC, model (2) was selected for group 1 and 3 while for group 2, model 3 was selected.

Table 4. Model coefficients estimates and performance

Cover types	Model #	Model expression	Coefficients			Performance		
			a	*b*	*c*	SE	R^2	AIC
Group 1	1	$d = b \times sd$		0.8669		2.62	0.95	140372
	2	$d = a + b \times sd$	-0.8812	0.86696		2.62	0.95	140361
	3	$d = a + b \times sd + c \times sd^2$	-0.88733	0.8675	0.0000079^{ns}	2.62	0.95	140381
Group 2	1	$d = b \times sd$		0.81387		3.08	0.91	8747
	2	$d = a + b \times sd$	-0.37388	0.8184		3.08	0.92	8748
	3	$d = a + b \times sd + c \times sd^2$	0.5514	0.7578	0.000658	3.07	0.92	8735
Group 3	1	$d = b \times sd$		0.8477		3.28	0.90	8721
	2	$d = a + b \times sd$	-0.60796	0.8485		3.21	0.90	8720
	3	$d = a + b \times sd + c \times sd^2$	-0.32539	0.83003	0.00019^{ns}	3.28	0.90	8736

^{ns} Non-significant coefficients

Model evaluation

Result for selected group models prediction capabilities at forest cover level is shown **Table 5**. Selected model for group 1 had overall lower *E%* than other group models. The highest *E%* were found for group 3 followed by group 2. At forest cover level, Cultivated land, Mangroves (group 2) and humid montane (group 3) had higher *E%*.

Table 5. prediction capabilities of groups model to forest cover level

Group	Forest cover	*E%*	*p-value*
Group 1	Bushlands	1.98	0.2656
	Grasslands	-2.95	0.1149
	Lowlands	-0.12	0.5235
	Miombo woodlands	-1.92	0.1233
	All	-1.63	0.4587
Group 2	Cultivated	-7.54	0.1344
	Mangroves	-11.17	0.0698
	Plantation	-0.32	0.3589
	Wetlands	-1.39	0.7674
	All	-5.51	0.3341
Group 3	Humid/Montane	-6.72	0.7636

Comparison of Estimated Biomass from Measured and Estimated Diameter

Table 6 presents coefficients of linear regression equation relating estimated biomass from measured and estimated diameter (*D*). Based on *p*-value of the coefficients, intercepts for mangroves, lowland and humid montane were found to be highly non-significant (*p*-value <0.0001; intercept equal to zero) while for miombo woodland the *p*-value was found on the borderline. Slope for all cover was found to be around 1 and was highly significant.

Table 7 presents *AGB* per ha estimated from estimated *D* from *SD* and measured D. The *AGB* differences percentage ranged from 0.05% to 2.79%. Miombo woodlands and mangroves had highest *AGB* percentage differences (2.79% and 2.78%, respectively). Lowland and humid montane had relatively lower *AGB* percentage differences (0.05% and 1.31%, respectively).

Table 6. Coefficients of linear regression equation relating estimated biomass from measured and estimated diameter (D).

Forest cover	Coefficients		*P*-value
Miombo	Intercept	97.8469	0.045
	Slope	1.0033	<0.0001
Mangroves	Intercept	5.1513	0.945
	Slope	1.0248	<0.0001
Lowland	Intercept	10.5525	0.83
	Slope	0.9969	<0.0001
Humid montane	Intercept	-53.2113	0.456
	Slope	1.0216	<0.0001

Table 7. *AGB* per ha estimated from estimated *D* and measured *D*

Forest cover	*AGB* estimated from estimated *D* (tones/ha)	*AGB* estimated from measured *D* (tones/ha)	Difference (tones/ha)	Difference in percentage (%)
Miombo	8.30 ± 0.23	8.54 ± 0.24	0.24	2.79
Lowland	10.97 ±1.10	10.96 ± 1.12	-0.005	-0.05
Mangroves	4.86 ± 1.22	5.00 ± 1.45	0.14	2.78
Humid	22.27 ± 2.24	22.56 ± 2.32	0.29	1.31

DISCUSION

The *D-SD* allometry for different forest covers portrayed similarity as a result three groups were formed using GLM approach (e.g., Liao 2013), i.e. Group 1 (Miombo woodlands, lowland forest, bushlands and grasslands); Group 2 (cultivated, mangroves, wetlands and plantation); and Group 3 consisting of only humid montane forest. Similarity and significant coefficients differences among forest cover types assured the necessity for grouping.

While it is difficult to explain the *D-SD* relationship similarity of some forest cover types, there are possible explanations for some groups. Group 1 consists of forest cover which overlap and therefore tree species found in one forest cover also are present in other forest cover. For example, the most distinctive feature which differentiate lowland forest from Miombo woodlands is the elevation, i.e. lowland forest are mainly found close to the coast while Miombo woodlands are dominate most area inland (e.g., Mugasha *et a*l. 2016). Moreover, Group 3 which has only humid montane forest consist of buttressed tree species which are not found in other forest cover type categories (Park 2002). Buttressed tree species are likely to affect the *D-SD* relationships in different way which separate humid montane forest cover from others. This is further confirmed by the large value of humid forest cover model standard error compared to other groups. On the other hand, Group 2 consist of forest cover with multiple features. For example, the fact that cultivated land is widely distributed in other forest cover and mixed with the planted trees on farm. This also apply to forest plantation. Although, mangroves are only situated in the coast where fresh water mixes with salt ocean water, mangrove environment is highly dynamic and harsh and mangrove species are variously adapted to cope with these environmental conditions which may result to broad range of mangrove tree species with different *D-SD* allometry (Njana *et al*. 2016, Selvam ed 2007).

The findings revealed that large variation in *D* (>90%) were able to be explained by *SD*. There are quite few studies which have explored relationship between *D* and *SD*. The explained variation in *D* explained by *SD* is comparable with the findings reported by Bylin (1982) for the 15 southern species in the United States. He found coefficient of determination (R^2) to range from 70% to 96%. Group 2 and 3 had relatively lower R^2 and higher *SE*. This is in line with the actual tree stem characteristics in forest covers found in these forest cover as explained before, i.e. existence of buttressed trees in humid montane forests (Masota *et al*. 2016); existence of cultivated land in difference forest cover types (MNRT 2015); and peculiar stem characteristics of mangrove tree species (Njana *et al*. 2016, Selvam ed 2007).

The prediction error (*E*%) were not significantly different from zero (*p*-value >0.05). The study revealed similar trends displayed by R^2 (lower) and *SE* (higher) for group 2 and 3, *E*% for forest covers in these groups were relatively higher which may be explained by the fact described above. Nevertheless, since the E% where in most cases lower than 10% (e.g., Mugasha *et al*. 2013), the group models are able to predict *D* of its respective forest cover types with appropriate accuracy.

For all tested forest cover, *AGB* generated from measured *D* and estimated *D* did not differ significantly. Slopes and intercept generated by regression equations were 1 and 0, respectively suggesting that the two value of *AGB* were statistically the same (Gauch *et a*l. 2003, Piñeiro *et al*. 2008). Furthermore, the difference between *AGB* estimated from measured and estimated *D* per unit area were very small ranging from 0.05% to 2.79%. This imply that *D* estimated from *SD* can adequately estimate *D* which in turn can be applied to estimate other forest stand parameters (Bylin 1982b). This is apparently a step forward toward developing robust tool essential for estimating forest degradation.

CONCLUSION

The *D-SD* relationship models were developed with comprehensive data set collected from NFI covering main forest types in Tanzania Mainland. The findings show the linear relationship between *D* and *SD*. In addition, we found that some forest covers have similar *D-SD* allometry while other are unique allometry as a result three main groups were generated using generalised linear modelling approach, i.e. group 1 (bushlands, woodlands, lowlands and grasslands); group 2 (mangroves, cultivated land, plantation and wetlands); and group 3 (humid montane). For each group, large variations in *D* were adequately explained by *SD*. The *AGB* estimated by measured *D* and estimated *D* did not any noticeable differences. This is apparently a step forward toward developing robust tool essential for estimating forest degradation. We therefore, recommend the models be applied when predicting *D* of the missing trees for which their stump still exist.

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