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ABOVEGROUND BIOMASS AND CARBON STOCK OF USAMBARA TROPICAL RAINFORESTS IN TANZANIA

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ABSTRACT

Forest Above ground biomass (AGB) and carbon stock (AGC) estimation is important for carbon budget accounting, sustainable forest management as well as for understanding the role of forest ecosystem in the climate change mitigation. In the recent decade, there has been a growing global interest on quantifying AGB and AGC in the tropical countries. However, the information on AGB and AGC at local and subnational scales in most of the tropical forests is scattered and not consolidated. In this study, we reviewed the existing information on AGB and AGC for tropical rainforests of northern Tanzania. We used both data published in the peer-reviewed literature and data from unpublished sources provided by various sources.

Our results showed that, there are three types of data sources and methods used for estimation of AGB and AGC. These included, field, geographical information system and remote sensing. Of all the methods, field based method was applied to a large extent. The average reported minimum values of AGB and AGC are 177.00 Mg ha^{-1} and 88.5 Mg ha^{-1}, and the maximum average values are 872 Mg ha^{-1} and 436 Mg ha^{-1} respectively. Overall, the average values of AGB and AGC in the Usambara tropical mountain forests (UTMFs) are 351.08 Mg ha^{-1} and 175.54 Mg ha^{-1} respectively. Forest structure parameters, particularly tree sizes and number of tree stems, were the major structure parameters reported to affect the amount of AGB and AGC. To conclude, the study revealed that there is a progressive trend in the estimation of AGB and AGC in the UTMFs. However, more update and effective forest survey data and methods are needed particularly in west Usambara mountain forests block.

Key words: Above ground biomass and carbon stock, climate change, tropical rainforest.

BACKGROUND

Estimation of forest biomass and carbon stock is important for quantifying the roles of forests as carbon sources or sinks and for supporting sustainable forest management (Temesgen *et al.* 2015). In the recent decades, the concern about global climate change has even further highlighted the need to find efficient and more accurate ways of estimating and reporting forest biomass and carbon stocks at local, national, continental and global scales.

Tropical forests have drawn much attention given its capacity to store substantial amount of the world's carbon stocks, where approximately 55% of global terrestrial carbon, estimated at 471 ± 93 petagrams is stored in the tropical forests (Pan *et al.* 2011). In addition to their total carbon storage, tropical forests are also net carbon sinks (Lewis *et al.* 2013). As a consequence of their significant carbon storage and sink capacity, tropical forests are considered to play a critical role in climate change mitigation (Carrasco and Papworth 2014; Chazdon *et al.* 2016).

Despite their potential, tropical forests are threatened by deforestation and forest degradation, mainly caused by human induced activities such as timber and fuelwood extraction, conversion of the forest to other land uses such as agriculture farmland, oil and gas production, mining, and infrastructure development (Achard *et al.* 2002; Hansen *et al.* 2013). This has resulted to loss of biodiversity and increase in global carbon emissions as the major consequences (Sasaki *et al.* 2016). It is estimated that carbon emissions from tropical deforestation and degradation contribute about 8 to 15% of annual global anthropogenic carbon emissions (Houghton 2013; Chazdon *et al.* 2016). In view of this, the estimation of biomass and carbon stock is considered to be a critical step for development and implementation of mitigation strategies on reducing the negative impacts of greenhouse gases emissions in the tropical countries and globe at large.

Furthermore, the growing carbon trade and desire to mitigate carbon emissions through forest protection, has spawned a number of policies, programs, and legislative actions which needs estimations of biomass and carbon stock as the basis of their implementation strategies (Temesgen *et al.* 2015). One widely known forest based climate change mitigation strategy under the United Nations Convention on Climate Change (UNFCCC), is reducing emissions from deforestation and forest degradation (REDD+) (Angelsen 2017). This strategy or policy mechanism intends to combat climate change while enhancing forest protection by providing financial incentives for implementation of five REDD+ activities (UNFCCC, 2011, Petrokofsky *et al.* 2012) which include: (1) reducing emissions from deforestation, (2) reducing emissions from forest degradation, (3) conservation of forest carbon stocks, (4) sustainable management of forests, and (5) enhancement of forest carbon stocks. To assess outcome of the implementation of the REDD+ activities, implementers must create measurement, reporting and verification (MRV) schemes for carbon stocks and changes (Bos *et al.* 2019). Such schemes/systems are important for estimation and monitoring of carbon emission which is mathematically obtained as the product of activity data (AD) (i.e., area of forest changed into another type of land use) and Emission Factors (EF) (i.e., carbon stock change estimations per unit of activity (in carbon per hectare)). This has increased the number of projects and studies which have attempted to report biomass and carbon stock for different forests in the tropical countries at global and national scales (Le Quéré *et al.* 2014; Tyukavina *et al.*2015). For example, according to Romijn *et al.* (2015) the total tropical forest area that is monitored with good forest inventory data had increased from 38% in 2005 to 66% in 2015. However, there is still lack of harmonized and consolidated information on biomass and carbon stock at local and subnational scales, which may be due to variation in data sources, sampling design, estimation methods, scales of study areas, topography, forest types, elevation, level of anthropogenic pressures, and microclimate (Sun and Liu 2020). This may create challenges in reporting carbon emissions for the scale less than a nation. A typical example are tropical mountain forests where there is far less and scattered information on forest biomass and carbon stock, although their potential to store and sequester substantial amounts of carbon has been emphasized (e.g. Spracklen and Righelato 2014).

According to IPCC (2006), carbon emissions reporting requires estimation of Above-Ground Biomass (AGB); Below-Ground Biomass (BGB); deadwood; litter and soil organic matter. Of all the pools, AGB is considered to plays a key role in the development of REDD+ MRV system as well as in the sustainable forest management, because it can be recalculated to carbon data, and it is a major predictor variable for modelling the other four categories (Solberg *et al.* 2015). Additionally, AGB is identified as one of 54 Essential Climate Variables (ECVs) by the Global Climate Observing System (GCOS) because of its major role in the global carbon cycle (Santoro *et al.* 2020).

Thus, in this review, we summarized and synthesized Above ground biomass (AGB) and carbon (AGC) stock studies conducted in the Usambara tropical mountain forests (UTMFs) of Tanzania. The UTMFs are amongst the oldest and most biodiverse forests on Earth. They are a global priority for conservation and provide ecosystem services including carbon storage and sequestration. A number of AGB and AGC stock estimations have been reported by in situ studies conducted at different spatial scales in UTMFs. Yet to our understanding there is limited number of studies to date which have attempted to review and harmonize the AGB and AGC values reported in this biome. This study addresses this knowledge gap by enlightening the development status, state of art and research trends on AGB and AGC estimation as well as the factors affecting AGB and AGC distributions in the UTMFs.

The information on AGB and AGC presented in this review provides references for more accurate information in line with Tier 2 carbon estimation approach. More specifically, the paper aimed at 1) describing data sources, types for AGB and AGC estimation in UTMFs, 2) describing the state of art on AGB and AGC estimation methods in UTMFs, 3) summarizing and harmonizing the AGB and AGC estimates of UTMFs, and 4) reviewing factors affecting distribution of AGB and AGC in UTMFs.

METHODS

Study area

This review study focused on Usamabara Mountains Forests located in Lushoto, Korogwe, Mkinga and Muheza districts in Tanga region. The Usambara Mountains consists of two highlands blocks, the East Usambara Mountain Fiorests (EUMFs) which rises up to 1484 m and the West Usamabara Mountain Forests (WUMFs) which rise nearly to 2294 m (Platts *et al.* 2010). The two blocks are part of the widely known Eastern Arc Mountains (EAMs) which are group of isolated mountains stretching from Southeast Kenya to the Makambako Gap in Southcentral Tanzania (Figure 1). These blocks contain a large number of protected forests notably Nature and Forest Reserves which are also part of the World Database for Protected Areas (WDPA), managed by the United Nations Environment World Conservation Monitoring Centre (UNEP-WCMC). Figure 2 shows some of these forests in each block. Only forests with the GIS layers/polygons available in the WDPA and the Eastern Arc Conservation Endowment Fund (EAMCEF) website are shown in Figure 2.

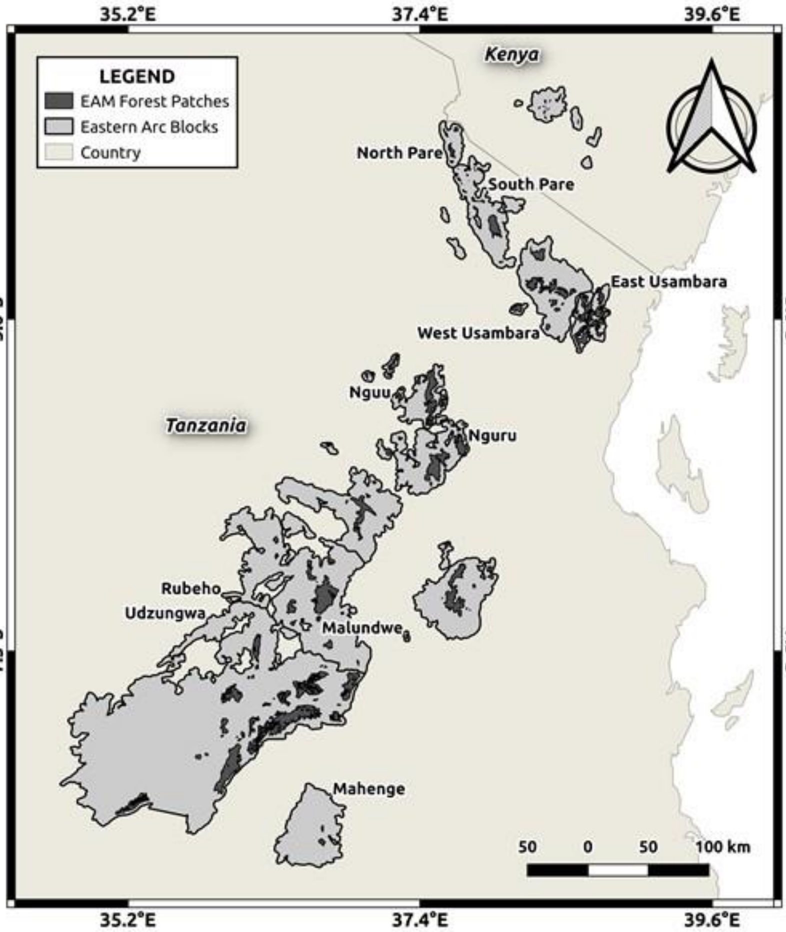

Figure 1. Eastern Arc Mountain Blocks

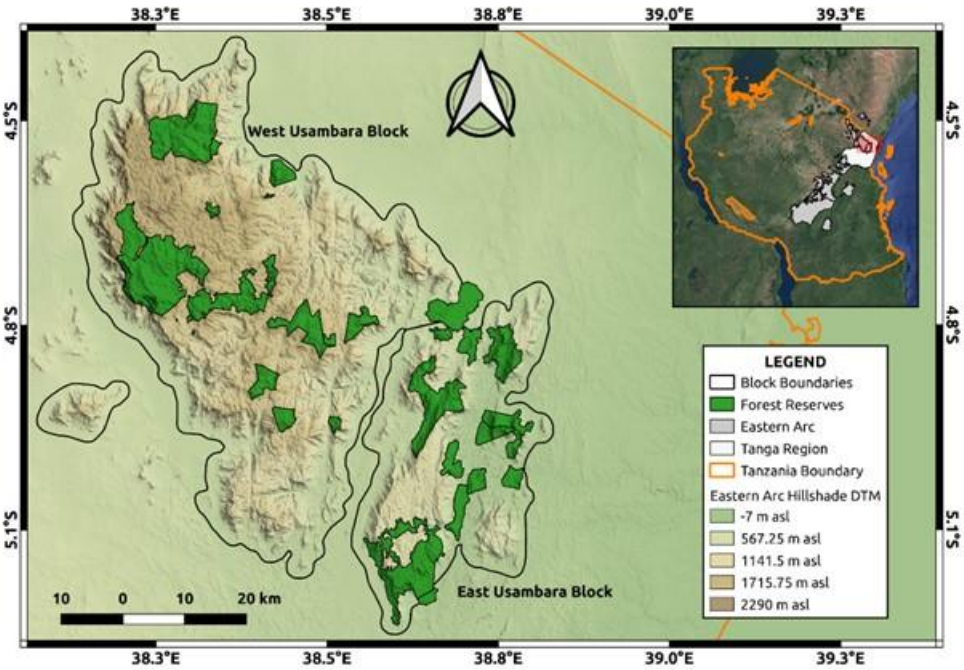

Figure 2. Forests in West and East Usambara mountains blocks

East Usambara Mountain Forests

The East Usambara Mountains fall within Muheza, Mkinga and Korogwe Districts in Tanga Region. They are situated within 40 km of the coastal town of Tanga, between 4º 48’ - 5 º 13’S and 38 º 32’- 38 º 48’E (Johansson *et al.* 1998). The rainfall distribution is bi-modal, peaking between March and May and between October and December. Rainfall is greatest at higher altitudes and in the south-east of the mountains, increasing from 1,200 mm annually in the foothills to over 2,300 mm at higher altitudes (Hamilton and Bensted-Smith 1989). The dry seasons are from June to August and January to March. In East Usambara there are two Nature Reserves (Amani and Nilo); eleven Forest Reserves (Bamba, Derema, Kambai, Kwamgumi, Segoma, Semdoe, Mtai, Mlinga, Manga, Mlungui, Longuza Teak plantation); four Village Forest Reserves (Kizee, Kizangata, Mfundia, Handei); and two private forests (Magoroto and Kwamtili). The total area is around 31,000 ha. The vegetation of these forests ranges from lowland areas at c.300 m on the eastern side, through sub montane forests to the montane forests. Tree species composition varies considerably, but species such as *Khaya anthotheca, Milicia excelsa* are found in the lowlands and others such as *Myrianthus holstii, Albizia gummifera, Allanblackia stuhlmannii* and *Newtonia buchananii* dominate at higher altitudes (URT 2010).

West Usamabara Mountain Forests

West Usambara Mountains are located in the Northern part of the Eastern Arc Mountains (4° 25'-5° 07' S and 38° 10'-38° 35' E) forming a large upland block covering 2200 km^2. The West Usambara Mountain Forests (WUMFs) are found mainly in Lushoto District, but a smaller area also occurs in Korogwe District. The climate in WUMFs is oceanic with bimodal rainfall, partly determined by their proximity to the Indian Ocean and the equator. Rainfall peaks in April and November. The mean annual rainfall maximum is 2,000 mm in the wettest areas, falling to less than 600 mm in the rain shadow areas (Lovett 1996). Temperatures are higher on the lower parts (25-27° C mean monthly) and lower on the plateau (13-18°C mean monthly). The minimum and maximum temperatures are 13°C and 27°C, respectively. Extreme temperatures (7°C during cold seasons and 30°C during hot seasons) have been recorded (Msuya and Kideghesho 2009). According to URT (2010). The WUMFs has one Nature Forest Reserve (Magamba); Twenty three Forest Reserves (Mkusu, Mzinga, Baga I, Baga II, Balangai, Ndelemai, Shagayu, Mweni-Gombero, Kisimagonja, Mahezangulu, Bumba Mavumbi, Kikongoloi, Manka, Bombo Makole, Kwebagu/Hebangwe, Kwenyashu, Shambalai, Mtumbi and Kitara ridge); and eleven Village Forest Reserves (Mzongoti, Chambogo, Kwamongo, Kifulio, Dindira, Shukilai, Sekigoto, Yumbu, Mazashai, Tanda, Deai). There is also one training forest under Sokoine University of Agriculture (Mazumbai) and two Private forests under management of tea estate (Ambangulu and Dindira Lutindi). These forests have vegetation types ranging from lowland, intermediate (sub-montane) to highland (montane) evergreen forests. Common trees are *Newtonia buchananii, Parinari excelsa, Albizia gummifera, Ocotea usambarensis* and *Allanblackia stuhlmannii.*

Data collection

Literature search and data compilation

We used both data published in the peer-reviewed literature and data from unpublished sources provided by various sources. Comprehensive literature search using Web of Science, Google Scholar databases, and Internet search via google chrome were used to extract peer reviewed studies related with AGB and AGC estimation in UTMFs. A substantial number of published studied and reports were obtained from EAMCEF website (http://www.easternarc.or.tz). Additionally, some of the existing data on tree diameter at breast height (*dbh*) and height (*ht*) were analyzed and their sources were cited and acknowledged. Credibility of the data were assessed based on the methodology of data collection and the obtained results in relation with the existing information. The detail of data collection is described below.

Data sources and types

Data sources in this study referred to the specific source, which reported the values of the AGB and AGC for the published and reported works. Likewise, for the cases of unpublished data this referred to the project, programme or institution, which supported the research work or provided the data to the authors. On the other hand, data types for published and existing data were categorized based on the definition by Lu *et al.* (2016) which were referred as field, remote sensing, and Geographical Information System (GIS) data.

State of art on biomass and carbon stock estimation methods

State of Art on the methods for estimation of AGB and AGC were grouped based on the data types described above. This included, field, GIS, remote sensing and combination of either field and remote sensing or field with GIS. Such description has been used by Lu, (2006); Lu *et al.* (2016); Wakawa (2016) for reviewing the state of art on the methods for forest biomass estimation in their studies.

Biomass and carbon stock

We extracted the AGB and AGC values from the texts, tables, and figures available in selected publications. Raw data available from a non-governmental conservation organization, Frontier Tanzania, (Doggart, 2000) and National Forest Resources Monitoring and Assessment (NAFORMA) (MNRT, 2015) programme were analyzed and generated the results which were used to present the AGB and AGC for specific forests. Sampling design and data collection procedures adopted by Frontier and NAFORMA are described in Frontier (2001), Vesa *et al.* (2010), MNRT (2015) and Mauya *et al.* (2019), while computations of the AGB and AGC is as explained below.

Computation of AGB and AGC

Single tree AGB for the raw data obtained from Frontier were computed using the allometric models by Masota *et al.* (2016). The single tree variables were then up scaled into per hectare values by dividing with the plot areas. AGC per ha were computed by multiplying AGB per ha with 0.50 following the procedure described by Smith *et al.* (2013). Moreover, AGB and AGC values for the specific forests located in both WUMFs were extracted from the countrywide plot values reported in the study by Mauya *et al.* (2019) computed from NAFORMA data. Plot values data from Frontier were further used to develop linear models for predicting AGB per ha using basal area per ha (BA) as input variable. This was done for the studies by Lovett (1996) at Kisimagonja Forest Reserve and by Nganyagwa (2014) at Mkusu Forest Reserve.

Factors affecting AGB and AGC distribution

It is well known that a number of factors affect spatial distribution of AGB and AGC in forest ecosystem (Imani *et al.* 2017). In this study, we reviewed reported factors intrinsic to the UTMFs and demonstrated how these factors may have caused variations of AGB and AGC among forests.

RESULTS

Data Sources and types

Based on the review, the key data sources used for AGB and AGC in the UTMFs are scientific publications and research reports. Comparing the two blocks, there were more studies reported from East Usambara Mountain forests as compared as to West Usambara Mountain forests (WUMFs). Majority of the reported studies are published between 1995 and 2015. The studies covered all the three basic data types commonly used in estimation of AGB and AGC (Table 1). These included; field (e.g. Munishi and Shear 2004, Masota *et al.* 2016) GIS (e.g. Marshall *et al.* 2012, Willcock *et* *al.* 2014, Hansen *et al.* 2015b) and remote sensing data (e.g. Hansen *et al.* 2015a, Hansen *et al.* 2015b, Mauya *et al.* 2015)

State of Art on methodology for estimating AGB and AGC

The state of art for AGB and AGC estimation using the three common datasets described above is described in the sub sections below and further presented in Table 1&2

Field based approaches

Field based methods had been used for estimation of AGB and AGC in UTMFs (Table 1). Destructive sampling method had been used to generate samples for development of AGB allometric models (Table 2). These models were developed by establishing a relationship between the tree AGB and the physical parameters of the trees. The reported AGB models in UTMFs used *dbh* only or *dbh* and *ht* or combination of *dbh*, *ht* and wood density (Table 2). Global AGB models were also used for estimation of the AGB and AGC by various authors (e.g. Marshall *et al.* 2012) in UTMFs, though use of local based models had been highly recommended by different scholars. Both local and regional models had been used to estimate AGB of the plot based measurements which involved *dbh* or *dbh* and *ht*. AGB models, which included total tree height, had been reported to have lower uncertainty as compared to those which do not include tree height. This is further demonstrated in Figure 3, where the models with *dbh* only seem to have larger predicted values over a given range of *dbh* as compared to the model with both *dbh* and *ht*. In this review, three Height–Diameter (*ht-dbh*) models (Table 2) developed in EUMFs were also reviewed and their performance is presented in Figure 4.

Table 1. Methods used for AGB and AGC estimation in UTMFs

Category	Methods	Number of studies	References
Field-based methods	Allometric equations	1	(Masota *et al.* 2016)
	Conversion from volume to AGB	1	(Munishi and Shear, 2004)
Remote sensing based methods	Optical remote sensing	1	(Willcock *et al.* 2014)
	Interferometric synthetic aperture radio detection and ranging (InSAR)	2	(Hansen *et al.* 2015b, Solberg *et al.* 2017)
	Airborne Laser Scanning (ALS)	3	(Hansen *et al.* 2015a, Hansen *et al.* 2015b, Mauya *et al.* 2015)
	Combination of InSAR and ALS	1	(Hansen *et al.* 2015b)
GIS-based	Methods based on ancillary data (e.g., Slope, soil, elevation and precipitation)	3	(Marshall *et al.* 2012, Willcock *et al.* 2014, Hansen *et al.* 2015b)

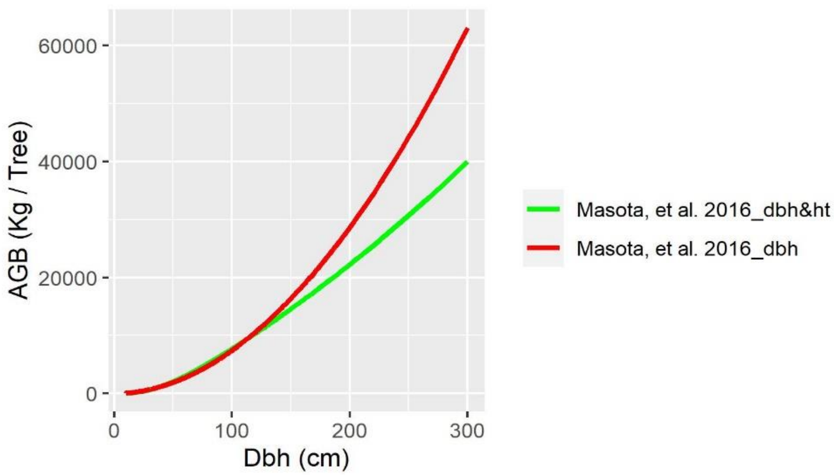

Figure. 3. Performance of AGB models with *dbh* only and *dbh* and *ht*

Table 2. Existing *ht* and AGB models in UMFs

Model component	n	Model	Source
H-D	751	$h = 1.3 + exp[7.0818 - 7.2141 \times dbh^{-0.1639}]$	(Mugasha *et al.* 2013)
	90	$h = 1.3 + 45.5103 \times [exp(-2.7163 \times exp(-0.0354 \times dbh))]$	(Mauya *et al.* 2015)
	1492	$1.3 + \frac{dbh^2}{(0.3376 + 0.9834 \times dbh^2)}$	(Hansen *et al.* 2015a)
AGB	60	$0.9635 \times dbh^{1.9440}$	(Masota *et al.* 2016)
	60	$0.4020 \times dbh^{1.4365} \times ht^{0.8613}$	

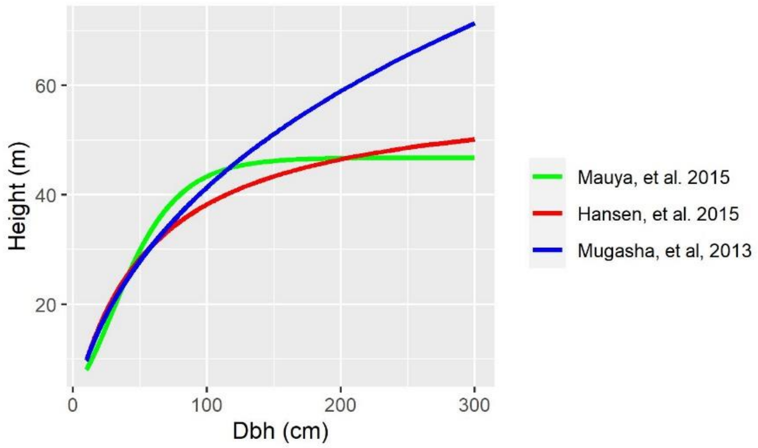

Figure. 4. A graph for tree *ht* over *dbh* based on the models developed for EUMTs

Systematic, random and double sampling for stratification with rectangular and circular plots of sizes ranging from 500 m^2 to 10,000 m^2 (i.e., 1 ha) have been adopted as sampling designs in the reviewed studies. Plot measurements involved trees with minimum *dbh* ranging from 5 cm to 10 cm for most of the reviewed AGB based studies. Estimation of the plot based estimates used area based approach where AGB and AGC of individual trees in the plot were up scaled into per ha basis by summing up all the trees in the plot and dividing by the plot area.

GIS and remote sensing based approaches

Three studies (Table 1) reported the use of Terrain Variables in the estimation of AGB and AGC. In the study by Marshall *et al.* (2012). AGC was modeled using a broad set of environmental, topographical and edaphic variables. Their results indicated that, climatic and topographical variables were more consistent predictors for AGC explaining for about 70% of the model variations. On the other hand, modelling and estimation of AGB using remotely sensing data had been reported in UTMFs. Three studies using wall-to-wall ALS data were reviewed. Results for the studies indicated that ALS had larger potential for AGB estimation in these types of forest with reasonable precision and accuracy. Area based approach (ABA) had been applied where statistical models relating AGB measured at the plot and ALS metrics were developed. The metrics, which were mostly selected in the reported studies, included parameters of the ALS height distribution such as the mean or percentiles and parameters related to the canopy density. Parametric statistical methods, particularly multiple linear regression was used for development of statistical models. Performance of the models were judged using *adjusted* -R^2 and RMSE. The reported results indicated R^2 ranging from 35% to 74% with RMSE values decreasing from 63.6 to 29.2 % (e.g. Mauya *et al.* 2015b).

Relative efficiency as the measure of the utility of ALS assisted inventory compared to field based estimates have been reported in the range of 1.7 to 7. (e.g. Hansen *et al.* 2015a; Mauya *et al.* 2015). Relative efficiency is equivalent to the factor by which sample sizes of field-based inventory would have to be increased to achieve the same precision using simple ALS assisted inventory. Plot size was reported as a major factor, which affect the precision of ALS, assisted Inventory.

Above ground biomass and carbon stock

Table 3 and Figure 5, summaries the AGB and AGC across different forests in EUMFs and WUMFs. Analysis based on the published and existing data indicated that, the average minimum values of AGB and AGC are 177.0 Mg ha^{-1} and 88.5 Mg ha^{-1} respectively. The maximum reported average values for AGB and AGC are 872 Mg ha^{-1} and 436 Mg ha^{-1}. Comparing the two blocks irrespective of the size of the forests and blocks, the highest average value AGB and AGC is reported in WUMFs particularly at Mazumbai and Kisima gonja, and the smallest average values is reported on the same block at Mkusu Forest Reserve. Overall, the average values of AGB and AGC in the UMFs are 351.08 Mg ha^{-1} and 175.54 Mg ha^{-1} respectively. Figure 5 prepared based of the Frontier datasets indicates that the spread of AGB and AGC values differs from one forest to another.

Factors affecting AGB and AGC estimates

Most of the reviewed studies indicated that AGB and AGC estimates in UTMFs varies with forest structure, selection of allometric models, field plot sizes, sampling intensity, topographical and environmental factors.

Forest structure

Forest structure parameters in particular tree sizes and number of tree stems were the major structure parameters reported to affect the distribution of AGB and AGC. Based on the reported studies, small size tree classes held most of the stems and small fraction of AGB/AGC. This is further demonstrated using Frontier datasets in Figure 6 & 7 where the class with dbh>=90 cm had larger mean values as compared to other classes.

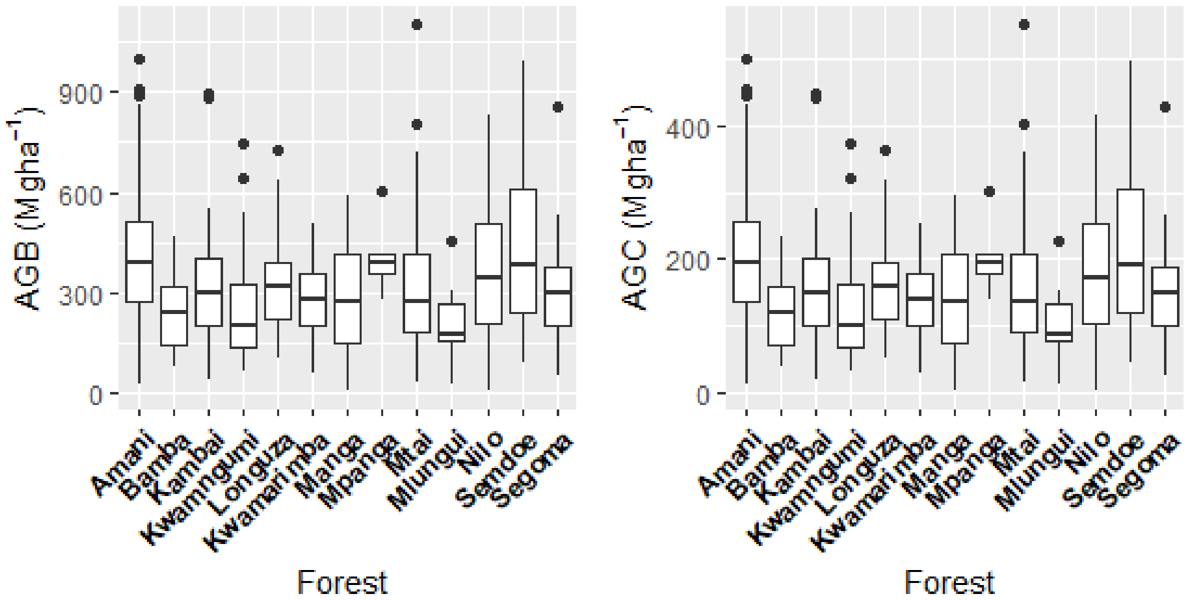

Figure 5. Box plots for the distribution of total plot based estimates of AGB and AGC for each of the forest of EUTMFs based on Frontier data. The high dots represent maximum value, the solid middle bar is the median value and lower dot is lower value.

Table 3. Block Name, Forest Name, Mean AGB and AGC ± Confidence Interval (CI) and source of information

Block	Forest Name	n	AGB (Mg ha $^{-1}$)	AGC (Mg ha $^{-1}$)	Source
EUMFs	Amani Nature Forest Reserve	173	461.9±31.9	230.95 ± 15.95	(Hansen *et al.* 2015a)
	Aman Nature Forest Reserve	168	407.12 ± 28.00	203.56 ±14.00	Frontier
	Bamba Ridge Forest Reserve	31	235.44 ± 37.79	117.72 ± 18.89	Frontier Data
	Kambai Forest Reserve	52	310.55 ± 44.78	155.28 ± 22.45	
	Kwamngumi Forest Reserve	47	257.40 ± 46.56	128.70± 23.28	
	Longuza Forest Reserve	18	332.40± 74.36	166.20 ± 37.18	
	Kwamarimba Forest Resrve	52	277.10±28.68	138.55 ± 14.34	
	Manga Forest Resrve	35	280.40 ±54.20	140.20 ± 27.10	
	Mpanga Forest Reserve	6	405.25 ±44.79	202.63 ± 43.90	
	Mtai Forest Reserve	99	314.77±37.94	157.39 ± 18.97	
	Mlungui Forest Reserve	8	209.73 ±89.75	104.86 ± 44.88	
	Nilo Forest Reserve	119	350.70±35.02	175.35 ± 17.51	
	Semdoe Forest Reserve	18	439.31 ±122.49	219.66 ± 61.25	
	Segoma Forest Reserve	50	305.86 ±39.85	152.93 ± 19.92	
WUMFs	Shagayu Forest Reserve		293±109	143.9	(Mbwambo *et al.* 2012)
	Shagayu Forest Reserve	10	353.4	176.7	NAFORMA Data
	Magamba Nature Forest Reserve		264.6	132.3	NAFORMA Data
	Mkusu Forest Reserves	30	177.00	88.5	Estimated from BA data reported by (Nganyagwa, 2014)
	Baga 1 Forest Reserve	8	389.2 ± 317	194.5 ± 158.5	NAFORMA Data
	Mazumbai and Kisima Gonja Forest Reserve	100	872 ± 28	436 ± 14	(Munishi and Shear, 2004)
	Kisima Gonja Forest Reserve		357.67 ± 219.24	178.83 109.62	Estimated from BA data reported by (Lovett 1996)
EUMFs and WUMFs	Amani Nature, Mazumbai, Baga 1, and Ambangulu	7	429±151	214.5±75.5	(Marshall *et al.*, 2012)

Allometric models

Two sets of models had been used for estimation of AGB i.e., models with *dbh* only and those which combine *dbh* and *ht*. Generally, the models which uses *dbh* as the only predictor variables have resulted into slightly larger estimates as compared to the models which combine both *dbh* and *ht* (e.g. Marshall *et al.* 2012). Furthermore, our review shows that allometric equations that are not specifically developed for UTMFs and by only including tree diameter, could over estimate AGB and hence be the major source of uncertainty in AGB and AGC estimation.

Field plot size

Field plot size had been reported as one of the key sampling parameters, which affects the precision estimates of AGB and AGC. Small field plot sizes were reported to have large variance as compared to larger plots. Figure 8, demonstrates this for the plot sizes ranging from 500 to 3000 m^2 based on the data from Mauya *et al.* (2015).

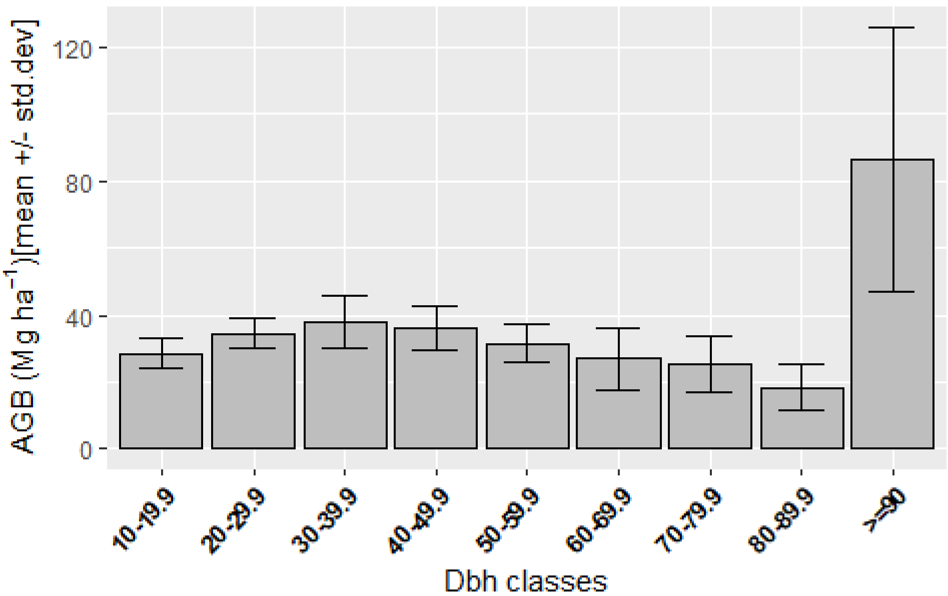

Figure 6. Error bars for the distribution of AGB across *dbh* classes based on Frontier data. The y-axis represents the Mean AGB ± standard deviation and the x-axis represent the *dbh* classes

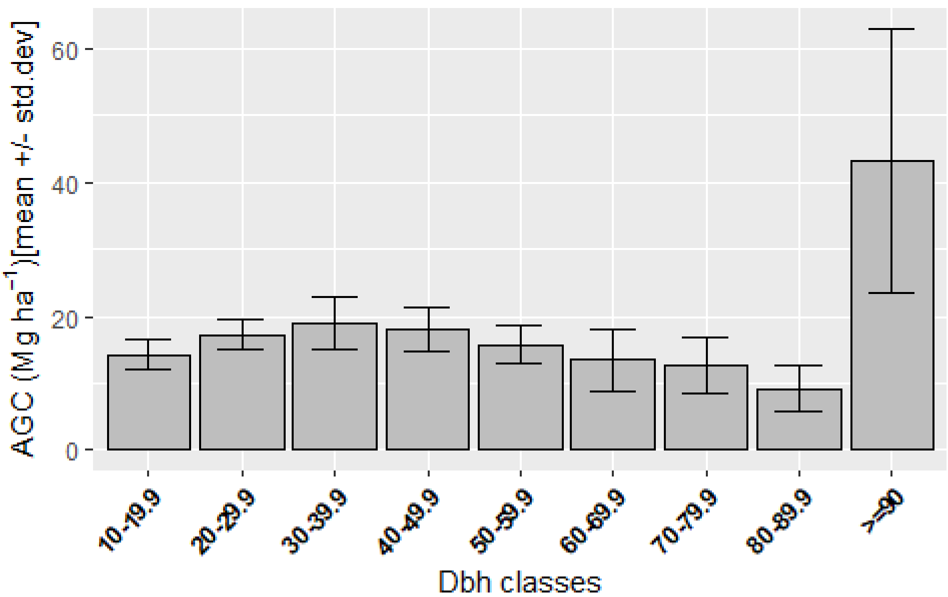

Figure 7. Error bars for the distribution of AGC across *dbh* classes based on Frontier data. The y-axis represents the Mean AGC ± standard deviation and the x-axis represent the *dbh* classes

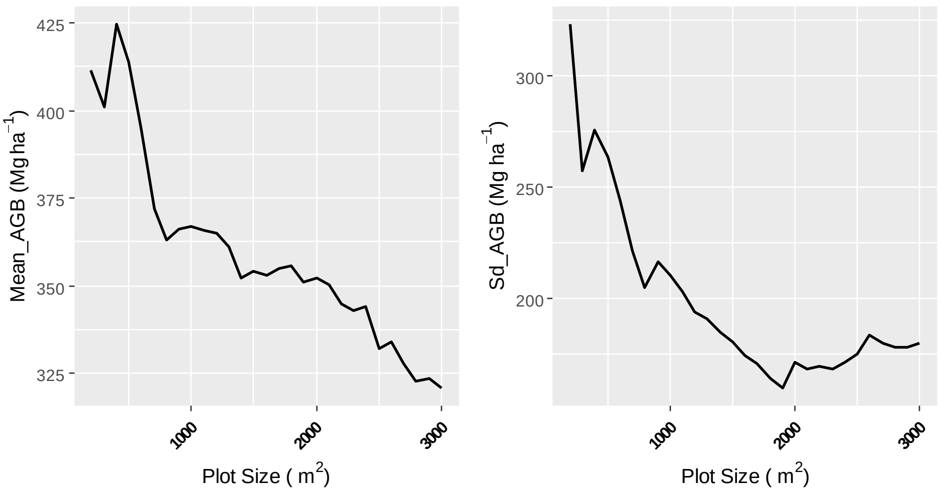

Figure 8. Mean and Standard Deviation of AGB estimates for different plot sizes

Topographical and environmental factors

Biophysical variables including slope, elevation and climate have been reported to strongly influence the distribution of AGB and AGC. For example, the study by Marshall *et al.* (2012) reported that Total AGC per plot was best modelled by physical variables slope, elevation and the presence/absence of elephants, by climate variable, and by soil pH. Physical variables were the strongest predictors, with slope and elevation explaining 63.7% of the variation in AGC.

DISCUSSION

Climate change mitigation schemes such as REDD+ need reliable, low-cost and repeatable estimates of biomass and carbon stock estimation as the basis for implementation and monitoring. To address this, various approaches for estimation of biomass and carbon stock had been devised and applied in different places across the tropical countries (Asrat *et al.* 2020). However, estimation of AGB and AGC is one among the complex and demanding processes in terms of time consumption, required equipment and financial resources (Petrokofsky *et al.* 2012, Temesgen *et al.* 2015, Masota *et al.* 2016). Therefore, whenever possible compilation and harmonization of the existing information on AGB and AGC is encouraged (e.g. Malhi *et al.* 2006, Henry *et al.* 2011, Gardon *et al.* 2020, Sun and Liu 2020). Such approach is compliant with IPCC Tier 2 accuracy level which encourages the use of forest volume or biomass values from existing forest inventories and/or ecological studies.

In this study, we reviewed AGB and AGC information existing in the UTMFs, which are one among the globally well-known tropical rainforests with both high biodiversity and carbon storage potentials (e.g. Munishi and Shear 2004; Marshall *et al.* 2012, Willcock *et al.* 2014). To our understanding, this is the first study to attempt to review AGB and AGC studies conducted in this biome. This study reviewed information and existing data from EUMFs and WUMFs. Approximately 1031 field plots were used to estimate AGB and AGC from various forests located in Usambara mountains. As such this study has generated a baseline information which can be used for reporting AGB and AGC values for the entire Usambara Mountain Forests as well as understanding the research trend on biomass and carbon estimation methods in the tropical rainforests.

The study has shown that AGB and AGC studies from the peer reviewed published studies had started to be reported since the year 2000 all the way to 2015. Most of the reported earlier studies (e.g. Lovett 1996, Tallents *et al.* 2005, Burgess *et al.* 2007), were focusing on the biodiversity survey under the support of various conservation projects since 1990s. These projects (e.g., Frontier Tanzania) generated a substantial amount of vegetation data (e.g. Doggart 2000) which were used in this study to compute AGB and AGC for the respective forests. Generally, our results showed that there is a progressive trend in the advancement of the methods for quantification of AGB and AGC, evolving from purely field to remotely sensed assisted forest inventory methods. This is partly because of the existing international and local initiatives to support the implementation of REDD+ projects as well as other initiatives intended for understanding of carbon potential of this important biome.

Field, GIS and remote sensing-based methods had been applied. In the context of field based methods both indirect and direct approaches had been applied. Indirect approach, involved the estimation of AGB as the product of volume over bark, Expansion Factor (EF) and Wood Density, and finally converting the value to AGC by multiplying with a factor of 0.5. Indirect method had been applied by Munishi and Shear (2004) in estimating AGB of WUMFs. Though the application of EF is not explicitly stated in the study by Munishi and Shear (2004). Since the application of the indirect biomass prediction method relies on BEFs not directly measured in ordinary forest inventories, the uncertainties in AGB estimation for this method, as compared to the direct method had been a concern of several authors Magalhães and Seifert (2015); Njana (2017). As such direct approach which involves the use of destructive sampling and allometric models is considered to be a more accurate compared to indirect approach (Njana 2017).

Allometric models using *dbh; dbh* and *height;* and *dbh, ht* and *wood density* have been developed for UTMFs by Masota *et al.* (2016), with sample datasets collected from EUMFs (ANR) and therefore they are more representative of the population of the trees of UTMFs. Use of these local based models as compared to the global models Chave *et al.* (2005) is highly recommended in the literatures in order to account for local based variations such as climate, soil, topography and tree species composition which affect the allometry and AGB distribution (Yuen *et al.* 2016). Use of local based models had further been emphasized as a best way of reducing uncertainty in AGB and AGC estimation (e.g. Van Breugel *et al.* 2011; Daba and Soromessa 2019). Models which incorporate *dbh* and *ht* or combination *dhh*, *ht* and *wood density* had been reported to have a better fit and lower uncertainty as compared to the models which include *dbh* only (Chave *et al.* 2005; Basuki *et al.* 2009; Feldpausch *et al.* 2011; Rutishauser *et al.* 2013). Among the reasons for such improvement is that; the relationships between AGB and tree attributes depend on factors such as site, successional status, ecological zone, forest type and management, which are highly explained by *ht-dbh* allometry. Thus, measurement and estimation of *ht* is important for obtaining accurate estimates in AGB. However, unlike *dbh* measurement, which is easy to measure with high accuracy in the field and available in the forest inventory databases, measurement of total tree *ht* is difficult and expensive, especially in the tropics. Therefore, to increase the cost-efficiency of the field work, it is a common procedure to measure *dbh* for all trees and *ht* for a subset of trees, called sample trees. The sample trees are then used to develop by *ht-dbh* models that can be used to predict *ht* of other trees with missing *ht* information. Such models are also important for growth and yield simulators which usually need information on tree height, either at the individual tree, plot, or stand level, to predict forest dynamics, dominant height, and site index. Our review showed that at total of three by *ht-dbh* models (e.g. Mugasha *et al.* 2013, Hansen *et al.* 2015a, Mauya *et al.* 2015) were reported from the UTMFs (Figure 4). Considering the performance of the models (Figure 4) and the size of the sample data as well as the geographical coverage, the model by (Hansen *et al.* 2015a) may be more considerable for height estimation in the UTMFs.07 However, the model does not have sample trees from WUMFs and thus consideration for developing model for WUMFs is important. Unlike other biomes in Tanzania and elsewhere, the presence of by *ht-dbh* and AGB allometric models have set a good basis for estimation of plot-based values on AGB and AGC, which are then used to calibrate other methods.

As stated above, GIS based methods had also been reported in UTMFs, where a broad set of the topographical and climatic variables were used to predict AGC. Though the authors did not present detailed model evaluation criteria that could be used to judge the potential gain of using this method relative to field-based methods, they have indicated that there is correlation between AGC and the respective variables. This implies that this method can further be tested and evaluated. However, according to Lu (2006) GIS based method should be used with caution especially when using environmental variables which are anticipated to have weak relationship with AGB. Thus, more in-depth studies are needed to explore potential of this method in UTMFs.

On the other hand, our study had revealed a well-documented technological advancement on application of remote sensing-based methods, particularly Airborne Laser Scanning (ALS). Overall, the findings of the studies by Hansen *et al.* (2015a); (Hansen *et al.* 2015b); Mauya *et al.*(2015) indicated that AGB could be modelled with ALS-derived metrics such as canopy height and canopy cover as explanatory variables with model performance similar to what has been reported in other tropical studies. Small plot sizes were reported to result in poorer models and therefore larger uncertainty of the final AGB estimates. Contribution of ALS data in improving the precision of AGB estimates was also demonstrated within a varying range of plot sizes. The Relative efficiency was > 1 (i.e., 1-7.7), indicating that ALS-assisted estimation was more efficient compared to pure field-based estimation. This implies that, to achieve similar precision of a pure field-based estimate relying on simple random sampling, would mean to increase the sample size for the field-based inventory by a factor equivalent to the value of RE, which would have a substantial effect on field inventory costs Mauya *et al.* (2015). In general, the gain in relative efficiency was more pronounced as plot size increased, suggesting that larger plots are more favorable when ALS data are used to assist in the estimation. Despite the potential of ALS assisted inventory in terms of technical efficiency, its use for operational purposes in Tanzania need economic considerations given the higher data acquisition costs as compared to other methods. In countries like Finland, Norway and Denmark ALS assisted inventory have simply turned out to be more cost–effective compared to other methods because of the higher labour costs (Kangas *et al.* 2018). In Tanzania labor costs are relatively lower compared to these countries and ALS acquisition costs are higher even in absolute terms. Therefore, consideration for assessing the applicability of open access remote sensing data, which have proved to have good performance for AGB estimation in other tropical forests, should be given priority as an opportunity for enhancing remotely sensed based forest inventory in Tanzania. More specifically the use of Sentinel 1, 2 and Landsat 8.

AGB and AGC estimates for UTMFs reported by different authors as well as those computed from the existing data in this study, indicated that mean AGB and AGC values ranged from 177.00 Mg ha^{-1} and 88.5 Mg ha^{-1} to 872 Mg ha^{-1} and 436 Mg ha^{-1}

respectively. These values are within those reported by Spracklen and Righelato (2014) for the world's tropical montane forests (i.e., AGB of 77-785 Mg ha^{-1}) as well as those of Lewis *et al.* (2013) which was estimated across 260 African tropical forests. The lower values reported in Mkusu Forest Reserve is because of the higher disturbance as compared other forests, which are dominated by relatively low frequency disturbance regimes over decades, allowing trees to grow large and contribute more to AGB and AGC. Forest structures in particularly tree sizes distribution in relation with AGB and AGC had been shown to be the key forest structure attribute which affects the distribution of AGB and AGC. Based on the Frontier data we showed that larger trees contribute more to AGB and AGC in these types of forests as compared to medium and small size trees (Figures 5&6). Similar findings had been reported by Slik *et al.* (2013), where they indicated that large trees (≥70 cm diameter at breast height (DBH) stored, on average, 25.1, 39.1 and 44.5% of above ground biomass (AGB) in South America, Southeast Asia and Africa, respectively, but represented only 1.5, 2.4 and 3.8% of trees >10 cm dbh. Climate, topography as well as estimation methods particularly the selection of allometric models are also reported to be the sources of spatial variations in AGB and AGC in the UTMFs. However further studies are recommended to investigate these factors using robust sample sizes which covers the substantial areas in the UTMFs.

CONCLUSION

To conclude, our study has provided the first extensive information on AGB and AGC for the UTMFs, which can be used to report forest carbon. As such, these forests remain to have higher AGB and AGC storage potential compared to other forests in Tanzania as long as their conservation status is not changed. Although there is a progressive trend in the estimation of AGB and AGC in the UTMFs, more update and effective forest survey data and methods are needed particularly in WUMFs. Potential use of open access remotely sensed data for estimation of AGB and AGC should further be investigated. Finally, the reporting of the total forest carbon will require information on other pools i.e., below ground biomass, litter, dead wood and soil, thus future studies should be encouraged to estimate biomass and carbon potential of these pools.

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