MODELS FOR ESTIMATING TREE VOLUME, ABOVE- AND BELOWGROUND BIOMASS FOR *ACACIA-COMMIPHORA* WOODLANDS IN SAME DISTRICT, TANZANIA

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ABSTRACT

Reduced Emissions from Deforestation and Degradation (REDD) framework demands measuring of carbon stock changes. In most cases, estimates of carbon stocks rely on volume and biomass estimation allometric models. Although species-specific and some generic models for biomass and volume estimation have been developed for some vegetation types such as Miombo woodlands, their use in *Acacia-Commiphora* woodlands in dry areas is questionable as they comprise short-height trees with small to medium tree diameters scattered from each other. This necessitates the need to develop robust generic allometric models that accounts for the heterogeneity of tree diversity in the *Acacia-Commiphora* woodlands in dry areas. Allometric models for volume and biomass estimation were developed by means of destructive sampling of 60 trees with *DBH* distribution ranging from 2.50 to 30.30 cm. Four different model forms were tested and the best model for estimating tree's section biomass and volume were selected based on the lowest values of Residual Standard Error (RSE) and Akaike Information Criterion (AIC). All selected models had their parameter estimates significantly different from zero ($P<0.01$). The best biomass and volume models were used to estimate total tree biomass (above- and belowground) and tree volume at plot level. The estimated total tree biomass and volume was 34.69 ± 2.42 t C/ha and 23.11 ± 1.64 m^3ha^{-1} respectively which is equivalent to carbon stock of 17.00 t C/ha. These estimates may be used to set a baseline for computation of carbon stock changes which are useful not only for sustainable management of the woodland but also for the implementation of $REDD^+$ policy.

DECLARATION

I, **Augustine Mathias**, do hereby declare to the Senate of Sokoine University of Agriculture that this dissertation is my own original work done within the period of registration and that it has neither been submitted nor being concurrently submitted in any other institution.

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DEDICATION

To my wife Namala, my sons Amedeo and Adeodatus, great inspirers of my heart and mind. You have so many wonderful experiences ahead of you. I am so proud of you all.

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LIST OF ABBREVIATIONS AND ACRONYMS

ABG	Aboveground biomass
AIC	Akaike Information Criterion
BGB	Belowground biomass
C	Carbon
cm	Centimeter
CO_2	Carbon dioxide gas
DBH	Diameter at Breast Height
E	East
FAO	Food and Agricultural Organization
GHGs	Green House Gases
ha	Hectare
Ht	Total tree height
IPCC	Intergovernmental Panel on Climate Change
kg	Kilograms
m.a.s.l	Mean average sea level
m	Meter
m^3	Meter cubic
mm	Millimeter
MNRT	Ministry of Natural Resources and Tourism
NAFORMA	National Forest Resources Monitoring and Assessment
R^2	Coefficient of Determination
RSE	Residual Standard Error
S	South
t/ha	Tons per hectare

URT	United Republic of Tanzania
^{0}	Degrees
^0C	Degrees centigrade
’	Minutes
’’	Seconds
$<$	Less than
$>$	Greater than
$\pm$	Plus or minus
%	Percentage
Σ	Summation

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background Information

Global greenhouse gases (GHGs) emissions from human activities have increased since pre-industrial times because emissions have been larger than removals (IPCC, 2007). Carbon dioxide gas (CO_2) has been the most GHG emitted to the atmosphere (Foster *et al*., 2007). According to IPCC (2007), the forest sector contributes about 20 % of the total GHGs emissions. The rise in GHGs accelerates climate change leading to challenges in mitigation processes. However, to reduce GHGs emissions, there should be accurate identification of GHGs emission levels across different sectors (Gibbs *et al*., 2007).

Mitigation of CO_2 emissions in the atmosphere has been the global agenda with mitigation options set from national to international levels (Pyo *et al*., 2012). These include multi-lateral agreement to limit CO_2 emissions under United Nations Framework on Convention of Climate Change's (UNFCCC) Kyoto Protocol with its Clean Development Mechanism (CDM) and Joint Implementation (JI) (Grace *et al.,* 2006; Petersson *et al*., 2012). However, CDM and JI excluded avoided deforestation for the 2008-2012 first commitment (Grace *et al.,* 2006; Gibbs *et al*., 2007; Macey *et al*., 2009). Deforestation and forest degradation are the main sources of GHGs in the tropics (Brown *et al*., 1989; UNFCCC, 2006). Recognizing the threats from deforestation and forest degradation, the UNFCCC's mitigation strategies were extended to include Reduced Emissions from Deforestation and forest Degradation (REDD) (Gibbs *et al*., 2007; Parker *et al*., 2009). Currently REDD also include forest conservation, sustainable management of forests and enhancement of forest carbon stocks ($REDD^+$) (Zahabu, 2012). REDD+ aims to provide financial incentives to forest-rich developing countries that can voluntarily reduce CO_2

emissions from deforestation and forest degradation, sustainably utilize and conserve forest and therefore enhance carbon stocks of their forests (Vieilledent *et al*., 2012). $REDD^+$ incentives are geared not only facilitate emission reductions in mitigating climate change but also conserve biodiversity and protect other ecosystem goods and services in developing countries (Zahabu, 2008). Despite the highest need of tree biomass estimation models for the preparedness of $REDD^+$ in developing countries, tree volume allometric models are still of important use in sustainable forest management (Comley and McGuinness, 2005; Mauya *et al.,* 2014; Masota *et al.,* 2014). Both forest biomass and volume estimates help to provide managerial information such as evaluation of growing stock and timber harvests that determines changes in ecosystem structure and functioning over the period of time.

Tanzania mainland has a total area of 88 025 028 hectares (ha) of land (URT, 2001; URT, 2003). According to MNRT (2015), the total forest area is estimated to be 48.1 million ha, which is 55% of the total land area of Tanzania mainland. Woodlands occupy 44.7 million ha of Tanzania's total land area or 92% of the total forest area (MNRT, 2015). Both forests and woodlands have a wide range of socio-economic and ecological values (Abdallah and Monela, 2007). They also serve as sources and sinks of the atmospheric CO_2 (Zahabu, 2012). Despite Tanzania's large forest coverage, the rate of annual loss in forest area is 403 000 ha (FAO, 2010). This remarkable loss in forest area would enhance livelihoods through carbon market if forest would have been sustainably managed.

1.2 Problem Statement and Justification

The $REDD^+$ incentives is a result-based mechanism (Zahabu, 2012) through which developing countries wishing to participate have to establish robust and transparent forest C Measurement, Reporting and Verification (MRV) systems (Breugel *et al*., 2011;

Vieilledent *et al*., 2012; Zahabu, 2012). This requires countries to assess their carbon baseline/reference levels (Henry *et al*., 2011). Forest Measurement, Reporting and Verification systems involving carbon stock estimation require tree allometric models for different vegetation types. Volume and biomass models for C stock estimation in some vegetation types have not been developed in developing countries (Chave *et al.,* 2005; Houghton, 2005). Biomass, volume and carbon quantities of trees vary with soil, elevation, climate and species (Chave *et al*., 2005; Vieilledent *et al.,* 2012; Mauya *et al.,* 2014). This means that the models ideally should be developed location-wise and species-wise for accurate and precise estimates (Williams *et al.,* 2008; Ryan *et al*., 2011; Breugel *et al*., 2011; Mauya *et al.,* 2014; Masota *et al.* 2014). However, in the tropics where there are many different species, generic tree biomass regression models are often used (Chave *et al*., 2005; Vieilledent *et al*., 2012).

Biomass and carbon can be assessed by direct or indirect methods. Direct methods are destructive which involve measuring tree biomass and volume directly by weighing trees in the field while indirect methods involve the use of easy measurable tree parameters like stem diameter at 1.3 m from the ground (*DBH*) and tree height (*Ht*) (Henry *et al*., 2010). Weighing trees in the field is the most accurate method of estimating tree biomass but extremely time consuming, destructive and costly.

In Tanzania development of biomass estimation models in natural forests is dated back to 1994 by Malimbwi *et al*. (1994) who developed tree volume and biomass allometric models for Miombo woodlands. Chamshama *et al*. (2004) also developed biomass and volume estimation models for this vegetation type at the same study site. Mugasha *et al.* (2013) developed allometric biomass estimation models for Miombo woodlands based on data from different parts of Tanzania. The study by Mauya *et al.* (2014) developed models for estimation of tree volume in Miombo woodlands of different parts of Tanzania. Also, the study by Masota *et al.* (2014) developed tree volume estimation models for single trees in tropical rain forests of Tanzania. Currently, ongoing studies sponsored by Climate Change Impacts Adaptation and Mitigation (CCIAM) programme for PhD and Masters Students aim to develop biomass and volume models for different vegetation types. In plantation forests species covered include *Pinus patula* in SAO Hill plantations and SUA Training Forest located at Olmotonyi, *Tectona grandis* in Longuza and Mtibwa Forest Plantations. In natural forests studies in progress cover Mangrove forests and *Acacia-Commiphora* of Kiteto District. Despite of the Same District's climatic, soil and environmental differences compared to Kiteto District, there is no biomass, volume models and carbon estimates in progress for *Acacia-Commiphora* species of Same District. This study aimed to developed volume, aboveground and belowground biomass estimation models for *Acacia-Commiphora* woodlands of Same District, Kilimanjaro region in Tanzania. The developed models are expected to play key role in estimating C stock to be used in among other applications the REDD+ implementation.

1.3 General Objective

The overall objective of this study was to develop above- and belowground biomass models, volume models and to estimate carbon stock for *Acacia-Commiphora* woodlands in Same District of Kilimanjaro region in Tanzania.

1.4 Specific Objectives

This study was built up by the following specific objectives:

(i) To develop above- and belowground biomass models for *Acacia-Commiphora* woodlands.

(ii) To develop volume models in *Acacia-Commiphora* woodlands.

(iii) To estimate volume, biomass and carbon stock of *Acacia-Commiphora* woodlands of Same Distict.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Acacia-Commiphora Woodlands

Acacia-Commiphora woodlands are dominated by mainly two thorn-bush genera of *Acacia* and *Commiphora*. A genus for *Acacia* is made up by mainly evergreen trees and shrubs in the family *Fabaceae* (Ross, 1981). They are native to tropical and subtropical regions of the world, particularly Australia and Africa (Hayward, 2004). Likewise the genus for *Commiphora* species is composed of most flowering plant in the family *Burseraceae*. The two genera are distributed in different parts of the world. In Tanzania *Acacia-Commiphora* species are widely distributed in different woodlands (NFP, 2001). They are distributed in the central and northern dry lowlands of Tanzania (URT, 2001) and fall mostly within the Somali-Masai phytochorion. *Acacia-Commiphora* woodlands in the northern part of Tanzania cover the Serengeti and Manyara area to Kilimanjaro (Marshall *et al*., 2012). The thorn-bushes range from east of Kilimanjaro to the coast of Tanga (URT 2001; URT, 2003). They dominate different ecological regions as they can sustain growth in semi-arid and arid dry areas with average of 800 mm of annual rainfall (Marshall *et al*., 2012).

2.2 The Role of Forests in Fixation of Carbon Dioxide

The world's forests store more than 650 billion tons of carbon where 44% are in the biomass, 11% in dead wood and litter, and 45% in the soil (FAO, 2010). According to DAFF (2008) Australia's commercial native forests, plantations and wood products sequestered a net amount of 56.5 million tons of CO_2 in 2005, thereby offsetting total GHG emissions by nearly 10% with native forests sequestering an equivalent of 5.5% of total emissions. Grace *et al*. (2006) indicates the mean C sequestration by savanna woodlands to be 7.2 ± 2.0 t C ha yr^{-1}. Also the study by Munishi *et al*. (2010) shows, that Miombo woodlands have the potential of sequestering an average amount of 19.12 t ha^{-1}. This indicates how worth forests play potential role in the fixation of CO_2. Thus forests and woodlands form a major component of the C reserves in the world's ecosystems and their role in mitigating climate change (Cairns *et al*., 1997; Henry *et al*., 2011; Kuyah et *al*., 2012 a, b; Mugasha *et al*., 2013).

2.3 Allometric Models for Tree Volume and Biomass Estimation

In forest management estimation of forest biomass and volume has been the tool for sustainable forest resources management (Zianis *et al*., 2005; Brandeis *et al*., 2006; Henry *et al*., 2011). Fuel wood management has motivated the need for tree biomass estimates whereas timber management has driven the need for tree volume estimates (Henry *et al*., 2011). Knowledge of a tree's mass or volume enables quantification of the ecosystem services it may provide (Snorrason *et al*., 2006; Robinson and Kile, 2007; Colgan *et al*., 2013), such as fuel wood, harvestable timber, fodder and more recently valuable information on the sequestration of GHGs (Munishi and Shear, 2004; Mugasha *et al.,* 2013). Thus, forest biomass or volume estimates provide managerial information on predicting changes in ecosystem structure and functioning over the period of time (Comley and McGuinness, 2005; Cole and Owel, 2006).

Determination of forest biomass or volume by non-destructive dendrometric measurements of tree such as stem diameter at breast height (*DBH*) and total tree height (*Ht*), are referred to as allometric approaches. Contrary, allometric models for tree biomass or volume estimates are developed by destructive sampling through measuring *DBH* and *Ht* of the sample trees, which are then felled and weighed to determine their dry weight. To develop allometric models, the relationship between tree's biomass and dendrometric measurement of the sampled tree is then established by regression methods. Such models have been developed at local level and at regional level and have been reported elsewhere in different parts of the world for different vegetation types (Brown 1997; Malimbwi *et al*., 1994; Chamshama *et al*., 2004; Chave *et al*., 2005, Zianis *et al*., 2005; Comley and McGuinness, 2005; Henry *et al*., 2011; Peterson *et al*., 2012; Mugasha *et al*., 2013; Mauya *et al.,* 2014).

However, majority of these studies are site specific and/or species specific and few of them have included tree belowground biomass (Cairns *et al.,* 1997; Henry *et al*., 2011; Kuyah *et al*., 2012 b; Mugasha *et al*., 2013). This means that, our knowledge on tree's belowground biomass (BGB) is limited when compared to their counterpart tree's aboveground biomass (AGB). In most cases, BGB biomass has been estimated as a function of AGB (Kuyah *et al*., 2012 b). In the absence of measured BGB values, many studies have revealed that the BGB constitutes a defined proportion of the AGB and the values ranges from 17% to 25% (Cairns *et al*., 1997; Kuyah *et al*., 2012 b) depending on such factors as nature of the plant, its root system and ecological conditions. Also, other studies have suggested the use of RS ratio in estimating BGB. Under this approach BGB is obtained as the product of AGB and the average RS ratio. However, the approach has been proved as not the best method for estimating tree belowground biomass (Mugasha *et al*., 2013).

2.4 Forest Carbon Stock Estimates

About 49% of the total tree biomass is assumed to be carbon (Munishi and Shear, 2005). Changes in biomass estimates enable a direct measurement of carbon sequestration or loss that can help validate carbon-cycle models (FAO, 2007). Analysing the potential of different ecosystems to sequester or store carbon provide understand of whether the corrective measures taken in land cover/land use changes and forest management are likely to create net C sources or sinks (Munishi and Shear 2004; Henry *et al*., 2011). Such assessments are also fundamental in quantifying pathways for ecosystem C fluxes and sequestration which are becoming of most use in abating climate change (Basuki *et al*., 2009). Since carbon estimates are of great use in C credits trading, the estimates help to develop the national emission baseline which is of fundamental use in carbon trading (Zahabu, 2012). Moreover, forest carbon estimates can be used by decision and policy makers when developing forest management plans and conservation policies.

CHAPTER THREE

3.0 METHODOLOGY

3.1 Description of the Study Area

Same District is located in the semi-arid plains of the Western Pare lowlands located between geographical coordinates; latitude $4^0$02'23'' to $4^0$37'12'' S and longitude $37^0$48'20'' to $38^0$04'16''E (Fig. 1). Rainfall distribution is bimodal, with an average annual rainfall ranging approximately from 400 to 600 mm. Mean temperatures range from 16^0C (July to August) to 32^0C (January). It is located at an elevation of 2133 m.a.s.l. Mkonga Forest Reserve (MFR) located 8 km away from Same District town centre along Moshi to Dar es Salaam road was selected as the study site. Mkonga Forest Reserve has a total area of 520 ha and was gazette in 1986. Mkonga Forest Reserve is an *Acacia-Commiphora* woodlands dominated with *Acacia* species like *A. tortilis*, *A. mellifera and A. nilotica. Commiphora* species include *C. africana, C. habessinica, C. schimperi, C. edulis* and *C. campestris*. Some associated species include *B. aegyptiaca and Cactus spp.*

3.2 Pilot Study

A pilot study was conducted within the study area aiming for collecting data for determination of tree variation within Mkonga Forest Reserve (MFR). By using relascope, 16 sweeps were randomly established within MFR. At each point, the relascope was used to determine Basal area (G) by using Basal Area Factor (BAF) of 1. Data collected in this exercise was used to calculate the variance (Pearson *et al.*, 2005) that was used to calculate the required number of plots. Number of plots was calculated by using the formula:

$$Number\ of\ plots\ (n) = \frac{t^2 \mathbf{CV}^2}{\mathbf{E}^2} \qquad (1)$$

Where: n = number of the required sampling units (plots) in the population; t = the sample statistic from the t-distribution for the 95% confidence level usually set at 2; CV = Coefficient of variation obtained from the standard deviation of the plot's basal area and E = allowable error or the desired half-width of the confidence interval. The number of plots at E of 10% was calculated to be 58 plots.

3.3 Plot Sampling, Forest Inventory and Tree Selection

Five line transects were established at systematic interval of 500 m and in each transect circular plots were established systematically at an interval of 200 m from one plot to another. Transect and plot distance was established based on the size of study area (See plot distribution pattern in Fig. 1). Circular plots with four concentric sub-plots of fixed area ranging from plot radius of 1 m (0.00 314 ha), 5 m (0.007 857 ha), 10 m (0.031 429 ha) to 15 m (0.0 707 ha) was used (NAFORMA, 2010). In each plot, tree numbers, stem numbers in case of forked trees and *DBH*. Tree height was measured for the largest, medium and smallest tree in each plot. In each sub-plot, trees were sampled and measured in the following manner: i) within 1 m radius: all trees with $DBH \geq 1$ cm were recorded; ii) within 5 m radius; all trees with $DBH \geq 5$ cm were recorded; iii) within 10 m radius; all trees with $DBH \geq 10$ cm were recorded; and iv) within 15 m radius; all trees with $DBH \geq$ 20 cm were recorded. Species botanical name or local name was recorded for each tree encountered in a plot.

3.4 Destructive Sampling for Biomass and Volume Estimation Models

To develop aboveground biomass (AGB), belowground biomass (BGB) and volume estimation models, trees were purposively selected for destructive sampling based on tree *DBH* classes and species dominance. Selection of sample trees was aimed at sampling a sufficient number of trees to represent different range of tree sizes and species to develop local biomass and volume allometric models (Snowdon *et al*., 2002; Breugel *et al*., 2011). A total of sixty trees distributed in 58 plots were sampled. Summary statistics of trees' parameters are presented in Table 1. To provide a spatial distribution; trees for destructive sampling were selected outside of the plot boundary especially for larger trees.

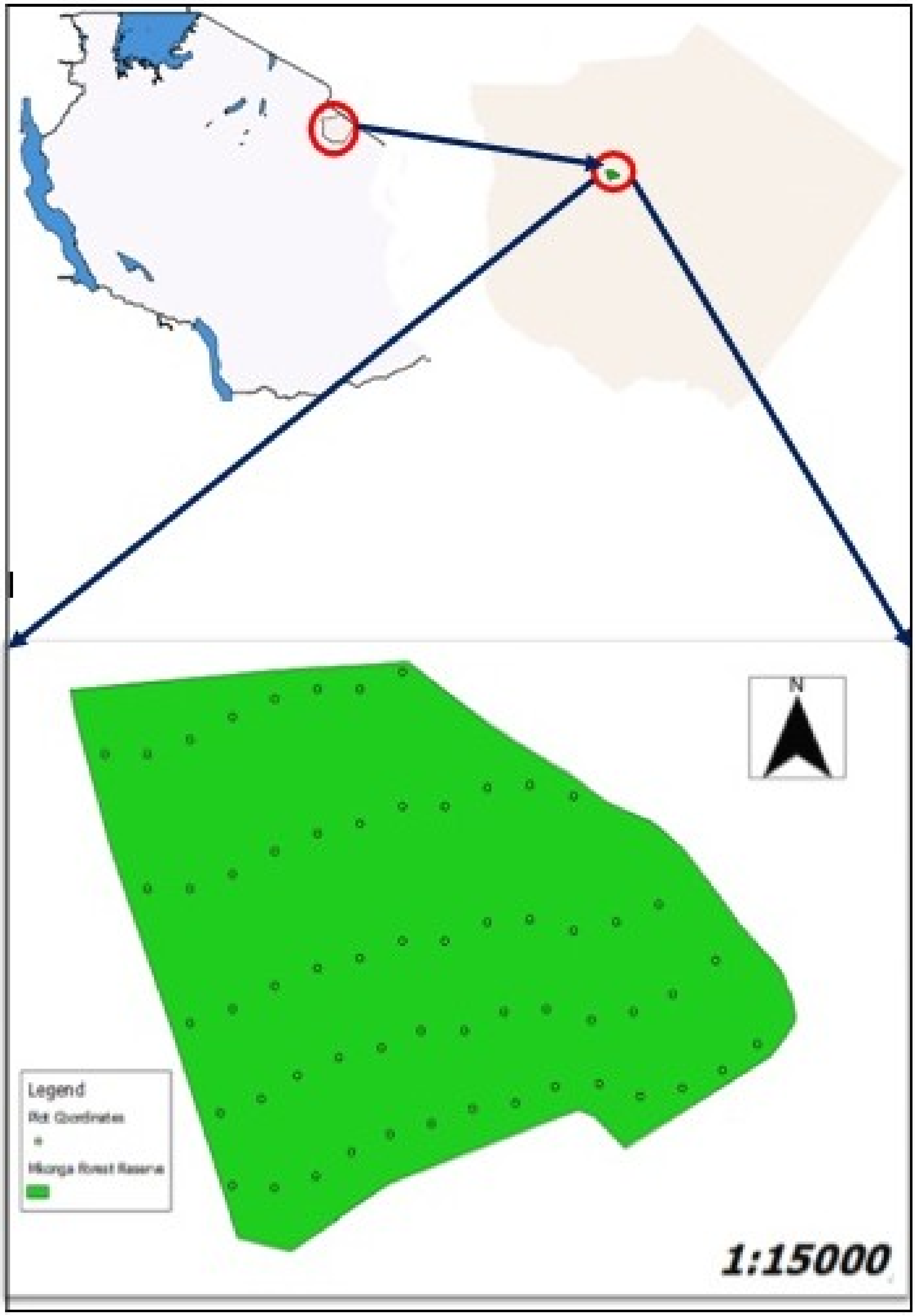

Figure 1: The map of Tanzania indicating enlarged map of Same District and enlarged map of Mkonga Forest Reserve showing the plot distribution

3.4.1 Destructive sampling for aboveground data

Trees selected for destructive sampling in each *DBH* class were measured for height and *DBH* at 1.3 m. After uprooting, the aboveground tree section were subdivided into main stem (up to a minimum diameter of 5 cm); by branches including tops (up to a minimum diameter of 2.5 cm); and twigs (with diameter < 2.5 cm). Stems and branches were further trimmed off into manageable billets length ranging from 1 to 2 m and then weighed for green weight. The green weight, diameter at (mid) and the length of each tree subsection were recorded in the field. Two or three small disk samples (depending on the stem length) from stem and branches, respectively, were cut and weighed for green weight. Disk samples from each aboveground tree section were labeled and stored for further laboratory analysis. Small branches with diameter less than 5 cm and twigs were tied into manageable bundles to determine their green weight.

3.4.2 Destructive sampling for belowground data

In Fig. 2 the sketch diagram of tree's belowground components is shown. To collect data from trees' belowground section; the soil were excavated until all main roots initiating from the root crown were visible. Then main roots (largest and medium) were fully excavated where possible to the minimum diameter corresponding to the branching diameter of smallest root. Smallest roots and side roots were traced to their minimum possible diameter. Smallest roots were measured for their branching diameter from the root crown. The largest and medium roots were measured for diameter at the branching point from their root crown and the cutting diameter that was comparable to the branching diameter of the smallest root. All roots initiating from the root crown were then removed and weighed to determine their green weight.

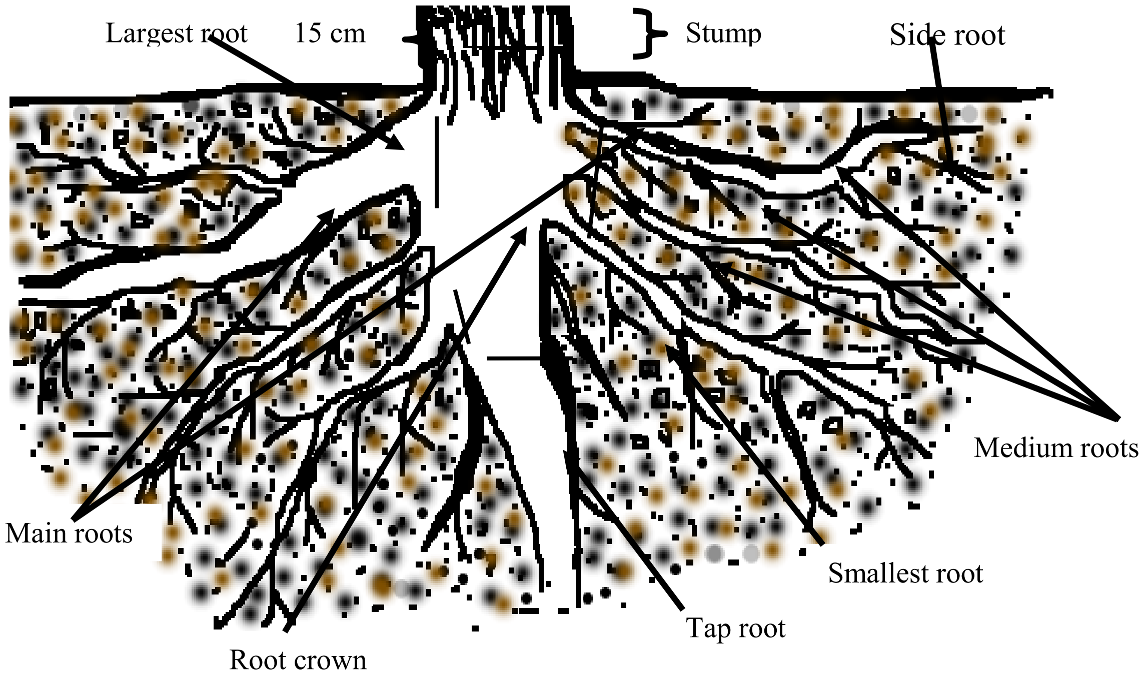

Figure 2: The sketch diagram of the tree's belowground components.

Then the root crown was separated from the tap root and then separated from aboveground tree component at 15 cm from the ground. The tap root was traced to the minimum diameter corresponding to the branching diameter of the largest root. The root crown was then weighed and its green weight was recorded. Before weighing belowground components were brushed to remove soil and rock particles (Snowdon *et al*., 2002). The remaining part of main roots (largest, tap root and medium) was estimated by using the dry weight of the smallest roots. Similarly, the remaining part of the crown was estimated by using data of the largest root. Small disk samples were taken from largest, medium and small root and one from the root crown. Disk samples were weighed for green weight, labelled and made ready for the laboratory procedures for determining their respective density and biomass ratio.

3.5 Laboratory Procedures

Disk samples from each tree section (roots, stems and branches) were soaked in water for the period of seven days until when their lumen were fully saturated up with water. Green volume of disk sample was obtained by means of water displacement (Williams *et al.,* 2008; Pyo *et al.,* 2012). Disk samples were oven dried at 110 ^{0}C for the period of 48 hrs and samples were weighed at the interval of time to determine whether they had attained constant weight (Mugasha *et al*., 2013). Thereafter, biomass ratio was calculated as: Biomass ratio = oven dry weight/Fresh weight.

3.6 Computation of Observed Biomass and Volume

The biomass in kg for each billet and each of the tied bundles was computed by multiplying green weight with its respective disk biomass ratio (Ryan *et al.,* 2011; Mugasha *et al*., 2013). Total AGB was computed as the sum of each aboveground tree component (stem, branch, and tied bundle of small branches and twigs). Biomass of unexcavated remaining part of the main and side roots were estimated by using nonlinear regression equations (cutting diameter & dry weight relations) (Snowdon *et al*., 2002, Mugasha *et al.,* 2013). Non-linear regression equations were formulated by using *"nls package in R Statistical Software"* and the best model was selected based on the lowest AIC values. Total BGB was computed as the sum of dry biomass of all main root, side root and root crown. Total tree biomass was calculated as the sum of total tree AGB and BGB. The volume of stem (up to diameter ≥ 5 cm) (Vs) and branches including tree tops (up to diameter ≥ 2.5 cm) (Vb) was computed by using Huber's formula (Abbot *et al*., 1997). Aboveground tree volume (*AGV*) was computed by summing individual tree volume component (Vs + Vb).

$$\text{Volume } (\mathrm{m}^3) = \frac{\pi \mathrm{d_m}^2 \mathrm{L}}{4} \quad \text{.......... (2)}$$

Where d_m is diameter at mid-length of log (m) and L is the length of the log (m).

Table 2 indicates the number of trees encountered during forest inventory in different *DBH* classes and the total number of trees destructively sampled in each *DBH* class.

Table 1: Statistical summary for tree parameters used in developing total tree biomass or volume estimation models

Tree parameter	Min.	Mean	Max.
Diameter at breast height (cm)	2.50	14.04	30.30
Height (m)	1.50	6.10	10.50
Total tree biomass (kg)	1.89	123.00	713.00
Tree aboveground biomass (kg)	1.14	101.20	609.60
Belowground dry biomass (kg)	0.33	21.23	116.20
Tree aboveground volume (m^3)	0.002	0.08	0.40

Table 2: Distribution, number of trees encountered in forest inventory for each *DBH* classes and the total number of trees destructively sampled per each *DBH* class.

Range of *DBH* Distribution	Number of trees	Trees selected for destructive sampling
1 – 5	82	8
6 - 10	201	13
11 – 15	209	16
16 – 20	116	13
21 – 25	31	7
26 – 30	8	3
30 >	1	0
Total	**648**	**60**

3.7 Model Development, Selection and Evaluation

3.7.1 Development of allometric models for biomass or volume estimation

To know the relationship between tree *DBH* and tree's different section's dry biomass, graphical/scatter plots were used. The plots indicated that the relationship between *DBH* and tree dry biomass were not linear (Fig. 3). Similar trends were observed by Braindeis *et al*. (2006); Zianis (2008); Litton and Kauffman (2008); Kuyah *et al*. (2012 a, b); Mugasha *et al.* (2013) and Fayolle *et al.* (2014). To assume linearity, tree data were log-transformed (Chave *et al.,* 2005; Fayolle *et al.,* 2014) and then log-transformed data were used to develop the models (Model form 1 - 4).

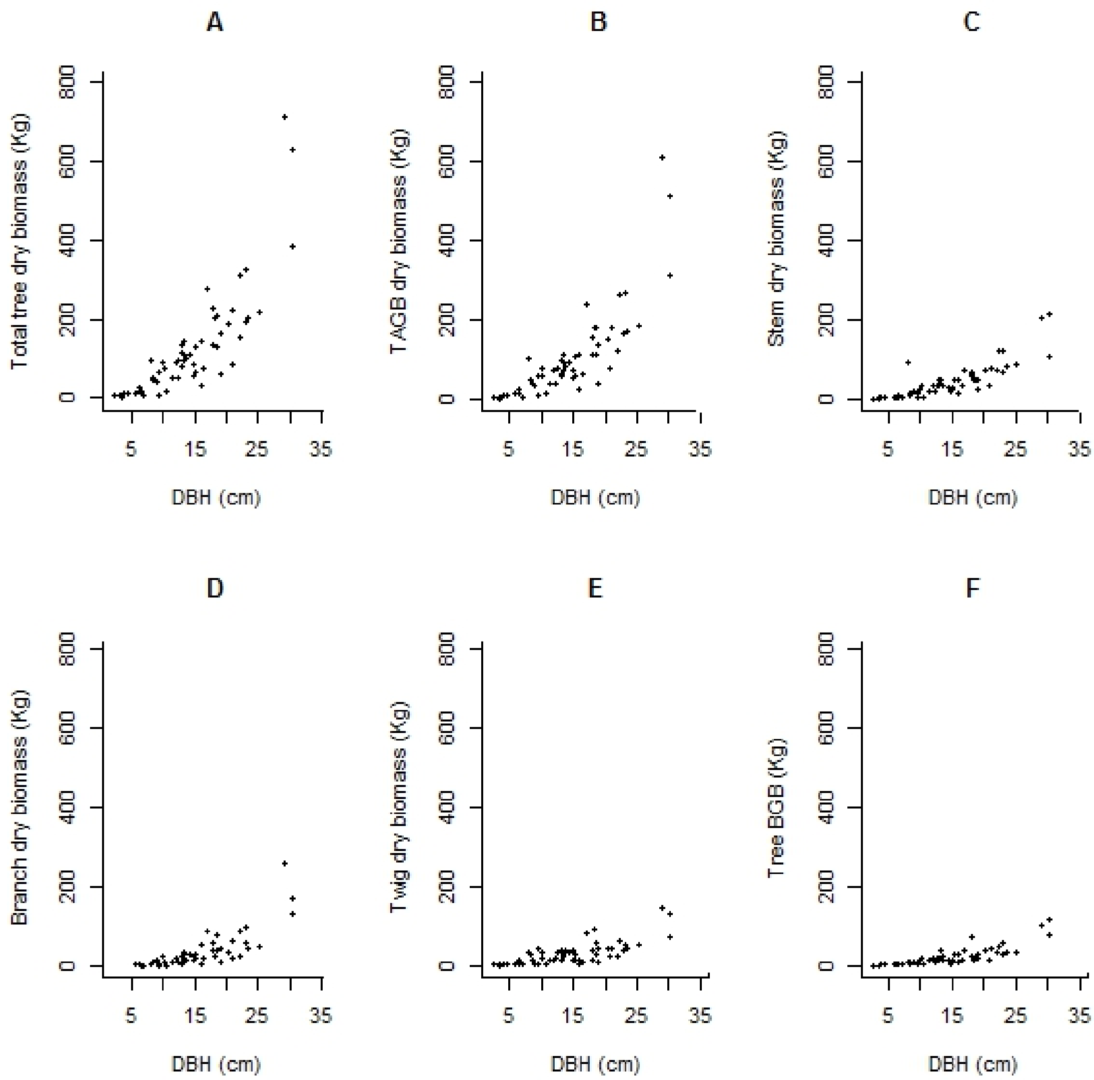

Figure 3: Graphical plots of the relationships between *DBH* and (A) total tree dry biomass, (B) tree aboveground biomass, (C) tree stem biomass, (D) branch biomass, (E) twig biomss and (F) belowground biomass.

Similarly, for volume estimation models graphical plots indicated that the relationship between different tree's section and DBH was non-linear (Fig. 4). The similar trend was observed by Khan and Faruque (2010), Mauya *et al.,* 2014 and Masota *et al.,* 2014. To assume linearity data were log-transformed prior linear.

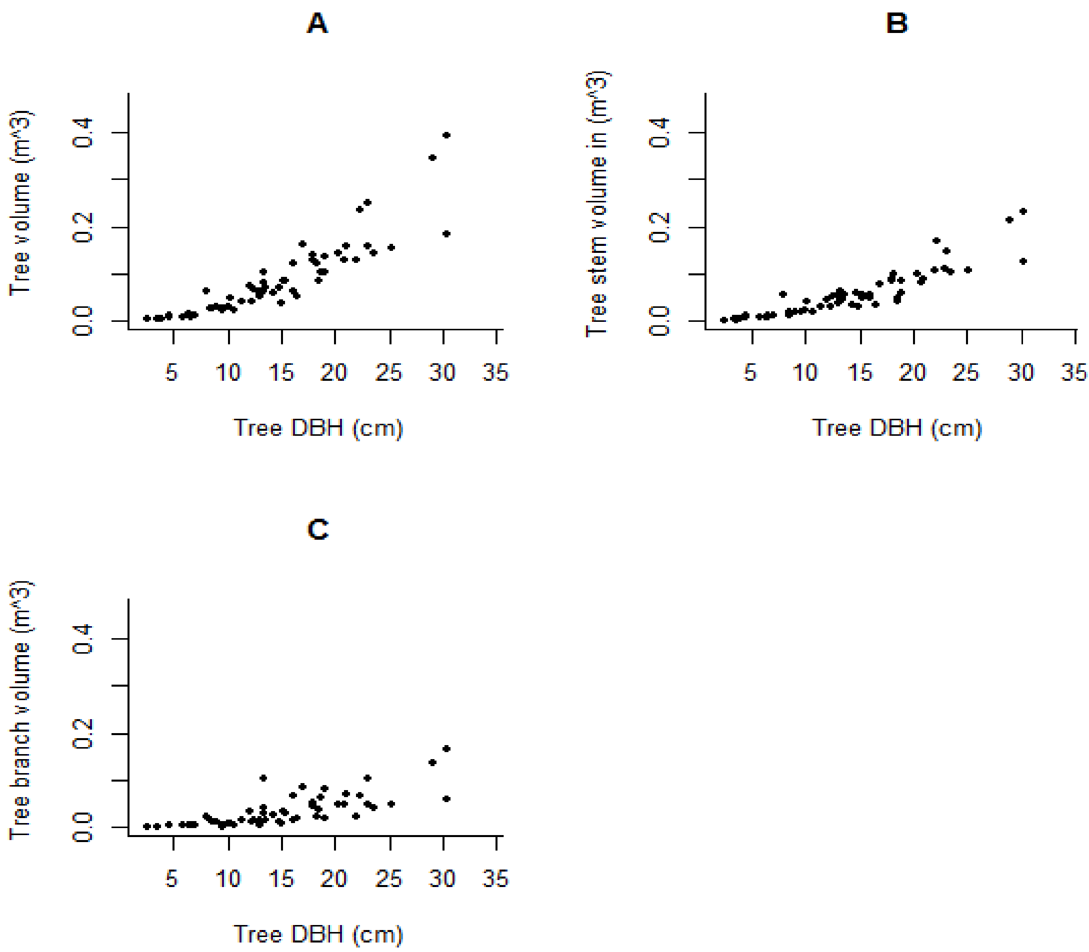

Figure 4: Graphical plots of the relationships between *DBH* (cm) and (A) total tree aboveground volume (m^3), (B) tree volume (m^3) and (C) tree branch volume (m^3).

Allometric models for total tree biomass, AGB, BGB, stem biomass and branch biomass using log-transformed variables were fitted to reduce heteroscedasticity (Ryan *et al*., 2011; Muthuri *et al*., 2011). For volume and biomass estimation models development, four different model forms for estimating aboveground tree volume, stem volume and branch volume were fitted. Biomass or volume estimation models were developed by fitting general models using 60 representative trees. Four different model forms for biomass and volume estimation equations fitted and tested are shown below:-

1. $Ln(Y) = a + b * Ln(D)$ ....*(Model form 1)*

2. $Ln(Y) = a + b * Ln(D^2)$ ....*(Model form 2)*

3. $Ln(Y) = a + b * Ln(D) + c * Ln(Ht)$ ....*(Model form 3)*

4. $Ln(Y) = a + b * ln(D^2 * Ht)$ ....*(Model form 4)*

Where Y = biomass (kg dry mass) or volume (m^3/tree), D = Diameter at breast height (cm); Ht = total tree height (m); a, b and c are regression coefficients.

3.7.1.1 Selecting the best model

The Goodness of fit was based on Akaike Information Criterion (AIC) (Chave *et al*., 2005; Ebuy *et al*., 2011; Alvarez *et al*., 2012; Kuyah *et al*., 2012a) and Residual Standard Error (RSE) (Chave *et al*., 2005). AIC is based on a penalized likelihood criterion that penalizes the model based on the number of parameters used in model fitting (Johnson and Omland, 2004). The AIC values were calculated as follows:-

$$AIC = -2\ln(L) + 2p \qquad (3)$$

Where, L is the likelihood of the fitted model and p is the total number of parameter in the model. The coefficient of determination (R^2) was reported in this study but was not used as the basis for model selection since AIC and RSE reported together provide sufficient information on the quality of model fit (Chave *et al*., 2005; Alvarez *et al*., 2012; Kuyah *et al*., 2012a; Fayolle *et al*., 2014). Regardless of AIC and RSE values, selected models should have their parameter estimates significant at probability level of 1%. The AIC and RSE values were directly calculated by using R-Software during linear regression procedures. Scatter plots of residuals versus measured biomass had to be equally distributed. Finally, best tree volume or biomass estimation models were selected based on their lowest prediction error or relative error (RE %) in estimating biomass or volume. The

RE was calculated using the equation adopted from Kuyah *et al*. (2012 a) as shown below:-

$$RE\% = \frac{\Sigma(Predicted\ biomass - Measured\ biomass)}{Measured\ biomass} * 100/n \ldots\ldots (4)$$

Where "n" is the number of observations.

3.7.2 Model prediction

Theoretically, log transformation of data causes biasness in the final biomass or volume predicted values and uncorrected values are expected to underestimate biomass values (Chave *et al.,* 2005; Alvarez *et al.,* 2012). A correction factor (CF) is required for the back logarithmic transformations when applied to generate biomass predictions. The CF is always a number greater than 1 and the greater the RSE the higher values of CF and the poorer the model performance in estimating biomass or volume values. Defined in equation (5) adopted from Chave *et al*. (2005; 2014), CF was calculated for all of the models developed for estimation of biomass or volume of different tree sections and the presented models already include the correction factor (Appendix B & C).

$$Correction\ Factor\ (CF) = exp(RSE^2/2) \ldots\ldots (5)$$

Where *RSE* is residual standard error of the model obtained from the linear regression outputs.

3.7.3 Testing the Applicability of the Existing Models

To know the applicability of the existing locally developed or regional models, AGB models developed by Mugasha *et al*. (2013) here referred Mugasha AGB and Chave *et al*. (2014) here referred Chave were used to test their applicability in *Acacia-Commiphora* woodlands. To estimate predicted biomass by Chave, the average basic wood density

(0.58) for African tropical tree species in Brown (1997) was used. The models used are shown below:-

1. Chave *et al.* (2014) $AGB = 0.0673 * (\rho D^2 Ht)^{0.976}$
2. Mugasha *et al.* (2013) $AGB = 0.0763 * dbh^{2.2046} * \mathrm{Ht}^{0.4918}$

Where; D is diameter at breast height (*DBH*), *Ht* is total tree height and ρ is basic wood density (BWD).

Likewise for volume models, the general volume model by Mauya *et al.* (2014) here referred Mauya and the volume by Malimbwi *et al.* (1994) here referred Malimbwi were used to test their applicability in *Acacia-Commiphora* woodlands. Mauya's model covered miombo woodlands from different parts of Tanzania and Malimbwi's model was developed from miombo woodlands of Kitulangaro forest reserve in Morogoro region. The models used are shown below:-

1. Mauya *et al.* (2014) $Volume = 0.00011 * DBH^{2.13300} Ht^{0.57580}$
2. Malimbwi *et al.* (1994) $Volume = 0.00010 * DBH^{2.0320} * Ht^{0.6600}$

3.8 Estimation of Volume, Biomass and Carbon Stock

The best models for total tree biomass and tree aboveground volume (AGV) estimation were used to compute the biomass (kg/tree) and volume (m^3) of all sampled trees from the forest inventory. Individual tree biomass and volume estimates were extrapolated to plot estimates by dividing individual tree estimates to respective plot area. Carbon stock was computed as 49% of the estimated biomass (Munishi and Shear, 2004). Estimates at the plot level were converted to per hectare basis by dividing with the area of each plot. The total estimated volume or biomass for the study area was determined by computing the average biomass or volume estimates at the plot level. Confidence interval of estimated volume or biomass was computed by formula adopted from Nickless *et al*. (2011) as shown below:-

$$Stand\ biomass\ or\ volume\ (kg\ or\ m^3/ha) = \Sigma Y/n_p \pm Z_{1-\alpha/2} * S_p/\sqrt{n_p - 1} \ldots\ldots (6)$$

Where Y is the sample plot biomass or volume, n_p is the number of sample plots and S_p is the standard deviation across the sample plots.

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

This study developed generic biomass and volume estimation models for estimating the standing stock of *Acacia-Commiphora* species in the dry woodlands of Same District. A total of sixty sample tree were destructively sampled. All of the developed linear regression models were statistically highly significant (P<0.01) and generally had a good fit. The residual plots for models were relativelly normally distributed. The present study is unique for tree volume and biomass estimates as most of the tree sizes in *Acacia-Commiphora* species of semi-arid region of Same District were included in model development (Table 1). The present study also developed specific models for the estimation of belowground biomass and total biomass of stems and branches. The two components have less been modelled independently in most of the studies. Also, the study covered a number of diversified tree species as sixty sample trees were destructively sampled from twelve different *Acacia-Commiphora* tree species where *Acacia tortilis* was the dominant species (Apendix A).

4.1 Biomass Models

4.1.1 Twigs biomass model

Twigs data from sixty sample trees were used to develop twigs biomass estimation models. Table 3 shows the twigs biomass models developed in this study. Model form 4 had the lowest AIC and RE% values and was selected as the best model in estimating twig biomass. The model has R^2 of 65.45 % which is in line with the R^2 (0.65) obtained by Niiyama *et al*. (2010) for leaf biomass model and very close to the reported R^2 of 68.0% for twig biomass estimation model by Mugasha *et al*. (2013) in the Miombo woodlands. The R^2 values obtained in the present study is lower to R^2 (0.74) reported by Braindeis *et* *al*. (2006) for leaf biomass estimation models in mixed dry forest species but very higher compared to the R^2 values ($R^2 = 0.40$) obtained by Mate *et al*. (2014) for predicting branch and twig biomass of *Afzelia quanzensis*. Also the lowest AIC value obtained in this study when tree height was included in model development is in with the study results by Mugasha *et al*. (2013). From the result, it is valid to conclude that twig biomass has a positive relationship (r = 0.66; P<0.01) with the parameter DBH^2H.

Table 3: Model parameters, selection and performance for estimating twig biomass.

Tree Component	Model form	Parameter estimates			RSE	AIC	R^2	CF	RE %
		a	*b*	*c*					
Twig biomass	1	-1.23**	1.62**		0.75	139.83	62.73	1.33	0.15
	2	-1.23**	0.81**		0.75	139.83	62.73	1.33	0.15
	3	-1.38**	1.08**	0.87*	0.73	136.84	65.70	1.30	0.32
	4	**1.38****	**0.62****		**0.73**	**135.27**	**65.45**	**1.29**	**0.11**

** Parameter estimate significant at 1% (p<0.01) level of significance *i.e* scaling factors *a, b* and *c* differ significantly from zero; * Parameter estimate not significant at 1% (p>0.01) level of significance.

4.1.2 Branch biomass models

Branch biomass estimation models were developed using only 42 trees with *DBH* greater or equal to 10 cm. This is similar as what was done by Mugasha *et al*. (2013) in developing branch biomass estimation model. Generally, branch biomass as the function of *DBH* only or the combination of *DBH* and *Ht* had poor relationship ($53<R^2<55\%$). Similar poor relationship between branch biomass and their predictor variables (*DBH* and/or *Ht*) compared to other tree sections was observed elsewhere (Dezzeo and Chaco´n, 2005; Mugasha *et al*., 2013; Yusuf *et al*., 2013; Mate *et al*., 2014). Model 4 had the lowest

AIC and RSE values of 101.40 and 0.78 respectively and was selected as the best model for branch biomass estimation.

Table 4: Models parameters, selection and performance for estimating branch biomass for trees with *DBH* ≥ 10 cm.

Tree Component	Model form	Parameter estimates			RSE	AIC	R^2	CF	RE %
		a	***b***	***c***					
Branch biomass	1	-4.77**	2.84**	-	0.79	103.66	52.66	1.37	0.33
	2	-4.77**	1.42**	-	0.79	103.66	52.66	1.37	0.33
	3	-5.55**	2.46**	0.96*	0.77	103.27	55.28	1.36	0.39
	4	**-5.62****	**1.17****	**-**	**0.78**	**101.40**	**55.15**	**1.35**	**0.36**

** Parameter estimate significant at 1% (p<0.01) level of significance *i.e* scaling factors *a, b* and *c* differ significantly from zero; * Parameter estimate not significant at 1% (p>0.01) level of significance.

4.1.3 Stem biomass models

Parameter estimates for stem biomass models are presented in Table 5. Model 3 had the lowest AIC and RSE values and was selected as the best models in estimating tree stem biomass. About 90.00 % (R^2 = 90.00; P<0.01) of the variability in stem biomass was explained by the predictor variables (*DBH* and *Ht*) as shown in Table 5. The R^2 observed in this study is in line with the R^2 values (ranging from 0.70 to 0.94) values reported by Yusuf *et al*. (2013) in models for estimating stem biomass of different *Acacia* species in Ethiopia. However, the R^2 is higher compared to the reported values by Mugasha *et al*. (2013) for stem biomass estimation with the value range from 0.68 to 0.80 for *DBH* only as independent variable and between 0.69 and 0.80 with both *DBH* and *Ht* as independent variables. The good fit of the selected model in the present study when compared to model form 1 and 2 concurs with what was observed by Guendehou *et al*. (2012) in developing stem biomass estimation model of selected tropical tree species in West Africa. This is contrary to Cienciala *et al*. (2013) who reported marginal improvement for some study site when *Ht* was used in model development while the other sites with the single predictor variable (*DBH*) had better performance compared to those with both *DBH* and *Ht*. Stem predicted biomass from all sample trees by the selected model constituted 67.20 % of the total observed biomass. This is in line with Nygard *et al*. (2004) who reported one third of the total fuel wood yield to be constituted by the trunk wood in the north Sudan savanna.

Table 5: Model parameters, selection and performance to estimate tree stem biomass.

Tree Component	Model Form	Parameter estimates			RSE	AIC	R^2	CF	RE %
		a	*b*	*c*					
Stem biomass	1	-2.35**	2.17**	-	0.54	99.35	85.59	1.15	0.14
	2	-2.35**	1.09**	-	0.54	99.35	85.59	1.15	0.14
	3	**-2.56****	**1.43****	**1.19****	**0.46**	**80.71**	**89.78**	**1.11**	**0.05**
	4	-2.55**	0.84**	-	0.46	80.87	89.41	1.11	0.07

** Parameter estimate significant at 1% ($p<0.01$) level of significance *i.e* scaling factors *a, b* and *c* differ significantly from zero; * Parameter estimate not significant at 1% ($p>0.01$) level of significance.

4.1.4 Biomass models for estimating total stem and branch biomass

Table 6 shows model parameters and the goodness of fit for different tree models developed to estimate trees' total branch and stem biomass. Model 4 had the lowest AIC and was selected accordingly. Generally, the fitted models to estimate total tree stem and branch biomass indicated the better performance judged by higher coefficient of determination (R^2) with the value range from 84.95 to 88.18%. Likewise, including height parameter in model development resulted to improvement of the model and such similar improvement in model fit when height is included is reported elsewhere (Malimbwi *et al.,* 1994; Mugasha *et al.,* 2013).

Table 6: Model parameters, selection and performance for estimating tree stem and branch biomass.

Tree Component	Model Form	Parameter estimates *a*	*b*	*c*	RSE	AIC	R^2	CF	RE %
Total Stem and branch biomass	1	-2.29**	2.33**	-	0.59	110.63	84. 95	1.19	0.14
	2	-2.29**	1.16**	-	0.59	110.63	84. 95	1.19	0.09
	3	-2.49**	1.63**	1.12**	0.53	98.16	88.18	1.15	0.04
	4	**-2.48****	**0.89****	**-**	**0.52**	**96.85**	**88.04**	**1.15**	**0.01**

** Parameter estimate significant at 1% ($p<0.01$) level of significance *i.e* scaling factors *a, b* and *c* differ significantly from zero; * Parameter estimate not significant at 1% ($p>0.01$) level of significance.

4.1.5 Aboveground biomass models

For aboveground biomass, Model form 4 gave the lowest AIC and RSE values (102.38 and 0.55) and was selected as the best model in estimating tree aboveground biomass (Table 7). The model indicated that 84% of the variability in aboveground biomass is explained by the predictor variable DBH^2H. This is slightly higher compared than the R^2 values (0.82) reported in Chaturvedi *et al.* (2012) for the similar model for tree biomass estimation in dry tropical species. The similar improvement in model fit when *Ht* was included in AGB model development was also observed by Segura *et al.* (2005) with the R^2 of 0.87. Similarly Guendehou *et al*. (2012) reported the improvement in model fit across all *Acacia* tree species under study when tree height was included in model development.

Table 7: Model parameters, selection criterion and performance for estimating total tree aboveground biomass.

Tree Component	Model form	Parameter estimates *a*	*b*	*c*	RSE	AIC	R^2	CF	RE %
AGB	1	-1.07**	2.03**		0.60	113.21	80.37	1.20	0.08
	2	-1.07**	1.01**		0.60	113.44	80.37	1.20	0.10
	3	-1.26**	1.37**	1.08**	0.55	103.35	83.89	1.16	0.04
	4	**-1.25****	**0.78****	**-**	**0.55**	**102.38**	**83.61**	**1.16**	**0.04**

** Parameter estimate significant at 1% (p<0.01) level of significance *i.e* scaling factors *a, b* and *c* differ significantly from zero; * Parameter estimate not significant at 1% (p>0.01) level of significance.

4.1.6 Belowground biomass models

Coefficient and model performance criteria are presented in Table 8. For Model 4, the combination of DBH^2 and *Ht* explained 85.34% of the variation in BGB and resulted to the lowest AIC and RSE values. The R^2 obtained in this study is slightly lower than the value reported by Mugasha *et al*. (2013) for the site specific models (ranging from 0.87 and 0.93). Models developed for estimating BGB had better model fit in terms RE % (0.07) when compared to their counterpart AGB estimation models. The four models developed had the RE% ranging from 0.05 to 0.00 indicating that any of the model can be used to estimate BGB since their RE% are within the acceptable limits. In the absence of *Ht* data model form 1 and 2 can be used to estimate BGB but if *Ht* data are available the present study recommends model form 4 to be preferred when estimating tree's belowground biomass.

Table 8: Model parameters, selection and performance to estimate belowground biomass.

Tree Component	Model form	Parameter estimates *a*	*b*	*c*	RSE	AIC	R^2	CF	RE %
BGB	1	-2.56**	2.00**		0.54	100.38	83.17	1.16	0.05
	2	-2.56**	1.00**		0.54	100.36	83.17	1.16	0.05
	3	-2.70**	1.50**	0.80**	0.51	94.11	85.33	1.14	0.01
	4	**-2.70****	**0.76****	**-**	**0.50**	**92.11**	**85.34**	**1.14**	**0.00**

** Parameter estimate significant at 1% ($p<0.01$) level of significance *i.e* scaling factors *a, b* and *c* differ significantly from zero; * Parameter estimate not significant at 1% ($p>0.01$) level of significance.

4.1.6.1 Root to shoot (RS) ratio

The computed RS ratio had the overall average value of 0.23 (Table 10). It can be observed that the RS obtained in this study had a slight variation across the *DBH* classes (Table 10). This concurs with what was reported by Niiyama *et al*. (2010). The overall RS obtained is slightly lower than the reported value of 0.26 by Cairns *et al*. (1997) ranging from 0.20 to 0.30. Also the RS ratio observed in this study is close to the range of RS ratio (0.27 to 0.58, with a mean of 0.42) reported by Ryan *et al*. (2011) which is in line with the average RS ratio by Mugasha *et al*. (2013), both of the two studies covered miombo woodlands. Such variations in RS ratio is attributed by many factors that include inherent species characteristics, site moisture, nutrient availability, regeneration strategies and completion for light as stipulated by Mokany *et al.* (2006).

4.1.7 Total tree biomass models

Table 9 shows parameter estimates and model performance criteria for total tree biomass estimation. Including tree height as the predictor variable improved the model fit. For example, including tree height in model development improved the model fit by reducing overestimation of the measured biomass from 0.09% to 0.03% (Table 9). This is similar as what was observed by Malimbwi *et al*. (1994) where including height in the polynomial equation improved the model fit by increasing the value of R^2 from 0.84 – 0.92 to 0.90 – 0.96. Model 4 gave the lowest AIC and RSE (94.74 and 0.52) and was selected as the best candidate model for estimating total tree biomass. The AIC and RSE values for all developed total tree biomass estimation models ranged from 106.45 to 94.74 and 0.57 to 0.52 respectively. This concurs with Cairns *et al*. (2003) found that biomass predictive models with predictor variable DBH^2H estimated biomass that was very close to the measured biomass (small RE %).

Table 9: Model parameters, selection and performance criteria to estimate total biomass.

Tree Component	Model form	Parameter estimates			RSE	AIC	R^2	CF	RE %
		a	*b*	*c*					
Total biomass	1	-0.85**	2.02**		0.57	106.45	81.99	1.18	0.09
	2	-0.85**	1.01**		0.57	106.43	81.99	1.18	0.09
	3	-1.03**	1.39**	1.01**	0.52	96.01	85.40	1.14	0.03
	4	**-1.02****	**0.78****	**-**	**0.52**	**94.74**	**85.18**	**1.14**	**0.03**

** Parameter estimate significant at 1% ($p<0.01$) level of significance *i.e* scaling factors *a, b* and *c* differ significantly from zero; * Parameter estimate not significant at 1% ($p>0.01$) level of significance.

4.1.8 Potential of previously developed biomass models

The performance of existing tree AGB estimation models were evaluated based on their small RE% in estimating tree aboveground biomass of 60 sample trees (Table 10). From Fig. 4 and Table 10 it was found that tree AGB estimation model developed in this study performed better in estimating tree AGB when compared to Mugasha and Chave's regional AGB estimation models. The model by Mugasha *et al*. (2013) significantly underestimated AGB by 0.16%. Chave's model underestimated AGB by 0.69% and the model was not statistically significant as indicated by the Student *t*-test ($p > 0.05$). The higher underestimation of the predicted biomass estimated by Chave's model is possibly due to the average density (0.58) for African tropical tree species since it is not known whether this value corresponds to the average real wood density values for the species under study. As *DBH* becomes larger (i.e 23 cm and above) Mugasha's model seems to perform better when compared to the other two models. The underestimation found from both of the two regional models justifies why models should be applied to their range and environmental conditions or vegetation types.

Table 10: Table to show variation of root/shoot ratio (RS) and comparison between existing AGB models with AGB model developed in this study based on their relative error % in estimating predicted biomass across *DBH* classes.

DDH class (cm)	N	RS	This study RE %	Mugasha RE %	Chave RE %
1 – 10	20	0.23	-0.65	-2.58	-3.35
11 – 20	30	0.24	0.38	-0.32	-1.40
21 – 30	10	0.21	-0.31	-0.15	-3.59
Overall	60	0.23	0.05	-0.16	-0.69

"N" represents number of observation

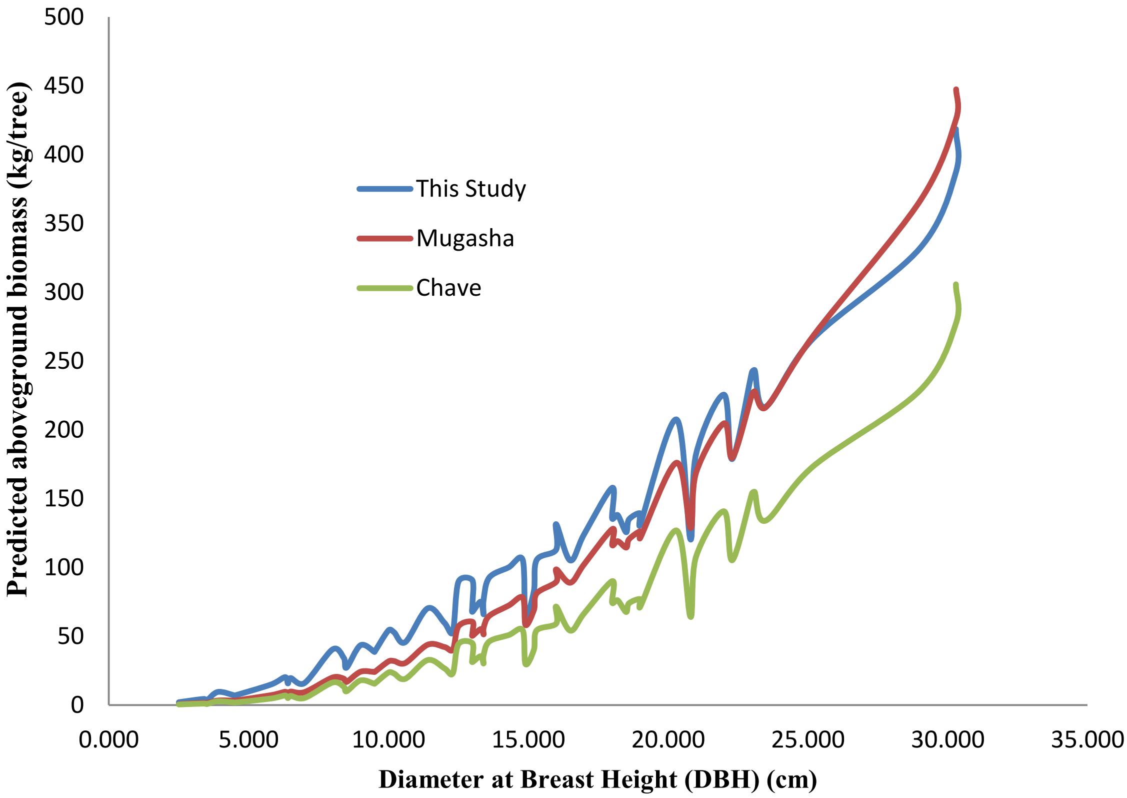

Figure 5: Comparison between the AGB model of this study and the existing AGB models.

4.2 Volume Allometric Models

Similar approach implemented in developing tree biomass estimation models was used to develop tree volume estimation models. This study developed allometric models to estimate the tree's branch volume, stem volume and total tree volume. Models were developed by using the relationship between the tree's section volume and the predictor variable *DBH*, DBH^2 and DBH^2H. Model 3 as the only additive model, was developed based on the predictor variable *DBH* and *Ht*. Including tree height as the predictor variable in estimating tree's component volume had slight variation in terms of RSE, R^2, and AIC values as compared to models with *DBH* only. This is similar as what was reported by Mauya *et al.* (2014).

4.2.1 Branch volume models

Contrary to the procedure adopted in developing branch biomass estimation model, models for estimating branch volume were developed by using the total number of sample trees. Similarly as observed in branch biomass models, the fit of branch volume models were not as good as the fit of stem and total volume models. The study by Mauya *et al.* (2014) and Masota *et al.* (2014) observed similar poor performance of branch volume models as compared to other tree components. Model form 4 had the lowest AIC values and was selected as the candidate model for estimating tree branch volume (Table 11). About 79.61% of the variability in branch biomass was explained by the predictor variable DBH^2H.

Table 11: Model parameters, selection criteria and performance to estimate tree branch volume (m^3/tree).

Tree Component	Model Form	Parameter estimates *a*	*b*	*c*	RSE	AIC	R^2	CF	RE %
Branch volume	1	-10.28**	2.38**	-	0.71	130.87	79.51	1.25	0.13
	2	-10.28**	1.19**		0.71	130.87	79.51	1.25	0.13
	3	-10.31**	2.07**	0.47*	0.71	131.45	80.00	1.25	0.14
	4	**-10.29****	**0.89****		**0.71**	**130.58**	**79.61**	**1.25**	**0.15**

** Parameter estimate significant at 1% ($p<0.01$) level of significance *i.e* scaling factors *a, b* and *c* differ significantly from zero; * Parameter estimate not significant at 1% ($p>0.01$) level of significance.

4.2.2 Stem volume models

For volume models of the stem, model form 4 had the lowest AIC values and was selected accordingly. As shown in Table 12, about 92.73% of the variation in stem volume was explained by the predictor variable DBH^2H. Also, the selected model had the lowest RE%

(0.04%) as compared to the other models. This concurs with what was observed by Ounekham (2009) who found that, the variable DBH^2H was highly significantly related to stem volume. Parameter estimates of the selected model were significantly different from zero ($p<0.01$). Model 3 its parameter estimate for the height variable was not statistically significant different from zero at the chosen level of probability and was not considered for estimating stem volume.

Table 12: Model parameters, selection criteria and performance to estimate stem volume (m^3/tree).

Tree Component	Model Form	Parameter estimates *a*	*b*	*c*	RSE	AIC	R^2	CF	RE %
Stem volume	1	-8.44**	2.01**	-	0.36	51.75	91.81	1.07	0.08
	2	-8.44**	1.00**		0.36	51.75	91.81	1.07	0.09
	3	-8.53**	1.67**	0.544*	0.34	45.07	92.91	1.06	0.05
	4	**-8.54****	**0.76****		**0.34**	**44.57**	**92.73**	**1.06**	**0.04**

** Parameter estimate significant at 1% ($p<0.01$) level of significance *i.e* scaling factors *a, b* and *c* differ significantly from zero; * Parameter estimate not significant at 1% ($p>0.01$) level of significance.

4.2.3 Total tree volume models

Parameter estimates and model performance criteria are as shown in Table 13. Model 3 had the lowest AIC values and was selected accordingly. Including height in model development, improved the model fit by reducing AIC and RSE from 45.22 to 39.30 and 0.34 to 0.32 respectively. High R^2 values ranging from 0.93 to 0.94 ascertains the goodness of fit of models. Braindeis *et al*. (2006) found that including tree height variable improved the model fit by increasing the value of R^2 from 97.08 to 99.16 in estimating total volume in Puerto Rican subtropical dry forests. Also, the highest R^2 obtained in this study is very close to the reported R^2 (ranging from 0.92 - 0.97) by Guendehou *et al.* (2012) for tropical tree species from West Africa. Model form 3 had the lowest values of AIC (39.30) and RSE (0.32) and was selected accordingly. The similar model form was judged to the best model in estimating tree total biomass by Masota *et al.* (2014). Also the model of this type, was found to be the best in category of models with both *DBH* and *Ht* by Mauya *et al.* (2014) for the general tree volume model in the study sites. Considering the AIC and R^2 values for the developed volume estimation models for different tree components, the model fit improved from branches to total tree volume models. Similar improvement in model fit was reported by Masota *et al.* (2014) when developing tree volume estimation models in the tropical rain forests in Tanzania.

Table 13: Model parameters, selection criteria and performance to estimate tree aboveground volume (AGV m^3/tree).

Tree Component	Model Form	Parameter estimates			RSE	AIC	R^2	CF	RE %
		a	***b***	***c***					
Total tree volume	1	-8.38**	2.13**	-	0.34	45.22	93.36	1.06	0.07
	2	-8.38**	1.06**		0.34	45.22	93.36	1.06	0.05
	3	**-8.46****	**1.82****	**0.49****	**0.32**	**39.30**	**94.19**	**1.05**	**0.05**
	4	-8.47**	0.81**	-	0.33	40.65	93.85	1.06	0.03

** Parameter estimate significant at 1% (p<0.01) level of significance *i.e* scaling factors *a, b* and *c* differ significantly from zero; * Parameter estimate not significant at 1% (p>0.01) level of significance.

4.2.4 Potential of previously developed volume models

The performance of existing tree volume estimation models were evaluated based on their small RE% in estimating tree volume of 60 sample trees (Table 14). From Fig. 5 and

Table 13 it can be observed that, volume estimation model developed in this study performed better in estimating tree volume compared to Mauya's and Malimbwi's volume models. The model by Malimbwi *et al*. (1994) significantly overestimated predicted volume by 2.00% while Mauya's model overestimated total tree volume by 5.04%. The test of statistical significance by using the Student *t*-test indicated that overestimation by Mauya's model was not statistically significant ($p > 0.05$). The overestimation of Mauya's Model in predicting volume could mainly be associated with the fact that the model was developed by wide range of tree *DBH* classes (1.20 cm to 95.00 cm) as compared to DBH classes (2.50 cm to 30.30 cm) used in this study simply because in *Acacia-Commiphora* species of dry areas it is rare to find large trees. The better performance of Malimbwi's models it is mainly due to the reason that most of tree *DBH* classes (9.30 cm to 43.00) used in model development where also included within tree sampling of the present study.

Table 14: Table to show the comparison between previously volume models with the volume model developed in this study based on their relative error % in estimating predicted volume across *DBH* classes.

DBH class (cm)	N	This study RE %	Mauya RE %	Malimbwi RE %
1 – 10	20	-0.20	0.21	-0.60
11 – 20	30	-0.01	1.22	0.33
21 – 30	10	0.75	7.43	3.70
Overall	60	0.27	5.04	2.00

"N" represents number of observerations

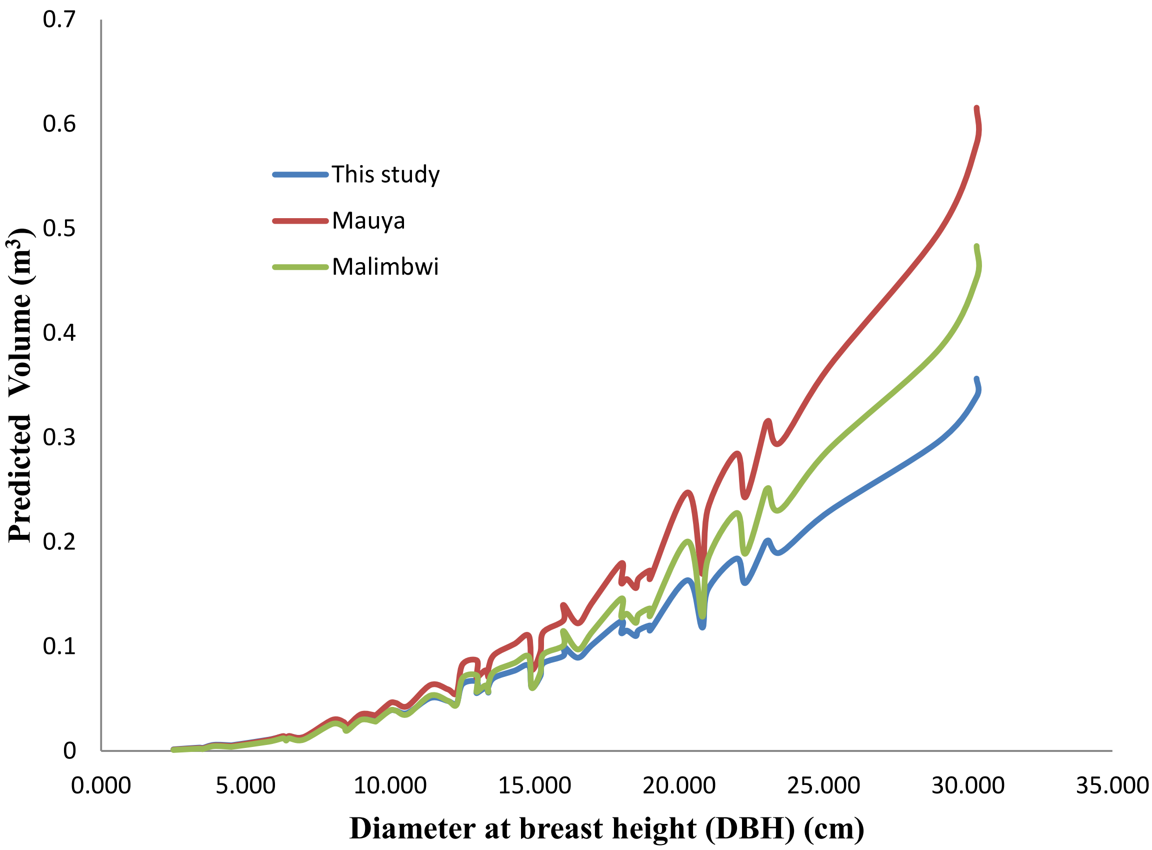

Figure 6: Comparison between the volume estimation model of this study and the existing volume models.

4.3 Forest Structure

Table 15 shows the statistics of the number of stems per hectare, basal area (m^2/ha), volume (m^2/ha), aboveground biomass, total biomass and average stand biomass estimates for different tree sections obtained in this study.

Table 15: Number of Stems (N) per hectare and Basal Area (G), Branch volume, Stem Volume, Total tree volume, Total biomass and average stand biomass estimates for different tree sections.

Stand parameter	Average plot estimate	Confidence interval
Number of stems per hectare (N)	870.24	91.31
Basal area (G) (m^2/ha)	5.53	0.39
Stand tree branch volume (m^3/ha)	7.91	0.57
Stand tree stem volume (m^3/ha)	15.88	1.12
Total tree volume (m^3/ha)	23.11	1.64
Twig biomass (t/ha)	10.24	0.73
Branch biomass (t/ha)	6.43	0.52
Total stem and branch biomass	18.03	1.30
Stem biomass (t/ha)	10.86	0.78
Aboveground biomass (t/ha)	28.66	2.03
Belowground biomass (t/ha)	5.96	0.42
Total tree biomass (t/ha)	34.69	2.42

4.3.1 Stem density and basal area estimates

The average number of stems per hectare (870.24 ± 91.31) obtained in this study (Table 15) is comparatively lower than the value (1376 ± 255) reported by Kaniki (2010) in Communal forest in Rombo District. Also, the number of stems per hectare observed in this study is comparatively higher than the reported value by Bernado (2009) for Acacia tree species under *'ngitili'* in Shinyanga region. However, the observed values in this study are within the range of stem density from 300 to 900 per hectare reported by

Timberlake *et al.* (2010) for higher stem densities in semi-arid dry forests. Similar studies from the related woodlands like Miombo woodlands from different parts have been reported slightly lower stem density per hectare ranging from 276 to 647 (Malimbwi *et al*., 1994; Njana, 2008; Shirima *et al.,* 2011; Kuyah *et al*., 2014; Alemu *et al.,* 2014).

The average basal area (5.53 ± 0.39 m^2/ha) obtained in this study is in line with the reported value of 5.22 m^2/ha but slightly higher than the basal area value (3.39 m^2 ha^{-1}) reported by Monela *et al.* (2005) for *Acacia* species in Shinyanga region. Kaniki (2010) reported the basal area with the value range from 2.60 ± 0.32 to 3.17 ± 0.45 m^2/ha for Communal and Private forests management respectively. Also, the basal area observed in this study is within the range of the basal area from 3.60 to 10.10 m^2/ha reported by Timberlake *et al.* (2010) in the Sudanian warm dry forests of western Africa. Alemu *et al.* (2014) reported the average basal area values of 9.33 m^2/ha of *Boswellia papyrifera* woodlands in north western lowlands of Ethiopia and the value is comparatively larger to observed values in this study. The differences in basal area estimates are more likely associated with different management strategies. For, example Mkonga Forest Reserve is managed by the Central Government since 1986 and since then there is minimal forest disturbances like charcoaling, livestock browsing and firewood extraction.

4.3.2 Total stand volume

The mean tree aboveground volume at the plot level was estimated to be 23.11 ± 1.64 m^3/ha (Table 15). The mean volume quantified in this study is comparatively higher than the reported value of 16.67 m^3/ha by Bernado (2009) for *Acacia* tree species under *'ngitili'* in Shinyanga Region. However, quantified volume in this study is comparatively lower than that of 43.90 m^3/ha reported by Chamshama *et al*. (2004) for the miombo woodlands of Tanzania. There are relatively few data from similar vegetation types against which the present study could make more comparison on the volume results. A number of studies on allometric models have been done in African savannas. However, most of them have reported the biomass of specific, individual species and few have considered the total biomass estimates rather than volume estimates.

4.3.3 Biomass and carbon stock estimation

The average biomass estimates for the total tree biomass was 34.69 ± 2.42 t/ha and AGB estimates was 28.66 ± 2.03 t/ha (Table 15). The AGB obtained in this study is slightly lower than the quantified biomass of 33 t/ha by Malimbwi *et al*. (1994) in Miombo woodlands of Kitulangalo Forest Reserves but higher than the biomass estimate value (25.4 t/ha) for *Acacia abyssinica* reported by Giday *et al*. (2013). Also the study by Colgan *et al*. (2013) estimated average plot biomass of 27.0 t/ha in the Savannah woodlands of Phalaborwa and Kruger National Park both of South Africa. Similar biomass estimates was obtained by Mate *et al*. (2014) in tree species of Mozambique Miombo woodlands. The AGB reported in this study is comparatively higher as compared to the value reported by Timberlake *et al.* (2010) with the ranging from 13 to 18 t/ha for Somali–Masai bush land.

The estimated average biomass in this study is equivalent to 17.00 t C/ha. The carbon estimate quantified in the present study is within the range reported by Shackleton and Scholes (2011) who quantified the carbon stock with the value range from 9.50 to 20.50 t C/ha. Also, Williams *et al*. (2008) reported carbon stocks in savannas of Mozambique with comparative figures from Zimbabwe, most of which fell in the range from 16 to 26 C/ha. However, The Carbon estimates obtained in this study is comparatively lower than the reported mean carbon density (23.40 ± 4.00 C/ha) by Shirima *et el*. (2011) in the Miombo woodlands in Tanzania's Eastern Arc Mountains.

4.3.4 The relationship between total stand volume and aboveground biomass

The higher value of AGB as compared to total volume values (Table 15) obtained in this study is mainly associated by the fact that volume models did not include twigs as compared to AGB models. As it can be observed in Table 15, stem and branch biomass in total contributes 18.03 t/ha which is 62.92% of the total aboveground biomass. This implies that twigs had much influence in the developed aboveground biomass estimation models since during data collection leaves and small branches (< 2.5cm) were grouped together as twigs. Higher value of AGB as compared to volume suggests that the wood density of studied species is above 1 g/cm^3, however, it should be noted that such higher value is because of the differences in modeling noted above. Thus, the present study provided good AGB estimates confined to branch and stems and this can be compared to total volume for a roughly wood density value of 0.78 g/cm^3.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

This study developed biomass and volume estimation models by using 60 sample trees selected to cover a wide range of tree sizes identified from *DBH* distribution during the forest inventory exercise. Biomass and volume models were developed by regressing tree's section biomass or volume and the predictor variable *DBH* and *Ht*. Including height parameter in model development improved the model fit throughout the fitted models for different tree sections. The predictor variable DBH^2H had lowest AIC values and highest positive relationship for most of the tree's section biomass and volume models. All of the selected models had good fit for predicting total tree biomass and tree section's biomass or volume since total variation explained by the relationship between dependent variables and predictor variables was at least 52 %. Generally, the biomass and volume models developed in this study provide a useful tool for biomass or volume estimation in *Acacia-Commiphora* of Same District and related sites. Belowground biomass models in this study provides the stepping stone when estimating tree's below- ground biomass since tree's below ground biomass is less studied for different vegetation type. Also the quantified biomass, volume and carbon stocks may set a baseline for calculating changes in carbon stocks over time that can be useful in implementing the $REDD^+$ policy in Tanzania.

5.2 Recommendations

For accurate tree volume, biomass and carbon estimates the use of locally developed generic models is important since most of the existing biomass or volume estimation models tended to significantly underestimate and overestimate biomass and volume estimates respectively. As observed by this study, that including tree height in biomass or volume estimation models had a significant improvement in the model fit so where there is no dense forest with closed canopies like in *Acacia-Commiphora* woodlands, this study recommends the use of tree height as the predictor variable in estimating tree volume or biomass. Similar studies have to be done for the same vegetation types from different parts of Tanzania so as to come up with the regional biomass or volume estimation models within *Acacia-Commiphora* tree species and shrubs of different environmental conditions.

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APPENDICES

A. List of sample tree species identified in their local and scientific names together with their tree diameter at breast height

B. (DBH), tree height (*Ht*) and measured biomass.

Tree number	Local name	Scientific name	DBH (cm)	Ht (m)	Measured Volume (m^3/tree)	Measured dry Stem and branch	Measured dry AGB (kg/tree)	Measured Dry total biomass (kg/tree)
1	Msusu	*Commiphora schimperi*	16.00	7.00	0.06	18.18	23.28	31.45
2	Mghaa	*Acacia tortilis*	13.00	8.00	0.06	52.43	64.4	134.51
3	Mghaa	*Acacia tortilis*	8.00	7.50	0.06	38.69	60.64	93.06
4	Mghaa	*Acacia tortilis*	18.00	8.50	0.14	121.29	156.77	226.53
5	Msusu	*Commiphora schimperi*	14.80	7.50	0.07	40.43	51.57	57.31
6	Kimodoa/Mnoa	*Acacia mellifera*	12.50	8.50	0.06	43.57	76	94.02
7	Mtundawe	*Pappea sp*	8.40	5.50	0.03	20.42	46.64	52.78
8	Mkoshi wa nd'ovu	*Acacia sp*	10.00	7.00	0.03	43.10	77.94	89.18
9	Mkoshi wa nd'ovu	*Acacia sp*	3.90	5.00	0.00	3.64	8.57	10.05
10	Mghaa	*Acacia tortilis*	13.00	6.00	0.06	44.16	59.63	79.23
11	Msusu	*Commiphora schimperi*	10.60	5.00	0.02	5.69	11.49	14.96

12	Mghaa	*Acacia tortilis*	29.30	9.50	0.18	236.30	310.58	385.59
13	Kiloriti/Mzameli	*Acacia nilotica*	6.50	4.50	0.01	4.33	11.74	14.41
14	Kiloriti/Mzameli	*Acacia nilotica*	19.00	6.50	0.14	93.59	135.93	165.63
15	Mponda	*Commiphora africana*	4.50	2.50	0.01	3.86	8.11	10.18
16	Msusu wa Mafuta	*Commiphora sp*	19.00	6.00	0.10	32.69	39.88	58.19
17	Mghaa	*Acacia tortilis*	29.00	8.50	0.35	462.66	609.59	713.02
18	Kiloriti/Mzameli	*Acacia nilotica*	18.20	7.00	0.12	86.34	178.77	201
19	Kimodoa/Mnoa	*Acacia mellifera*	18.60	6.50	0.10	126.18	181.15	205.59
20	Mkongori	*Unidentified*	13.40	5.00	0.06	48.23	69.71	93.08
21	Kimodoa/Mnoa	*Acacia mellifera*	16.50	6.00	0.05	52.49	62.91	75.48
22	Ulimbo	*Commiphora sp*	3.50	1.50	0.00	0.76	1.14	1.9
23	Mghaa	*Acacia tortilis*	16.00	8.50	0.12	100.98	112.39	141.39
24	Kimodoa/Mnoa	*Acacia mellifera*	17.00	7.00	0.16	157.07	237.83	276.63
25	Idudu	*Maerua triphylla*	13.30	6.00	0.10	77.21	110.01	145.82
26	Mghaa	*Acacia tortilis*	23.10	9.00	0.25	217.48	267.75	323.87
27	Kimodoa/Mnoa	*Acacia mellifera*	13.00	5.50	0.05	57.71	95.53	114.58
28	Mkonga	*Balanites aegyptiaca*	14.90	4.00	0.04	36.03	73.33	86.6
29	Msusu wa Maziwa	*Commiphora sp*	15.20	5.20	0.08	41.72	57.01	65.36
30	Mghaa	*Acacia tortilis*	10.20	6.50	0.05	40.76	57.58	74.03
31	Msusu wa	*Commiphora sp*	7.00	3.00	0.01	2.98	5.82	8.16

	Maziwa							
32	Kiloriti/Mzameli	*Acacia nilotica*	5.80	4.00	0.01	5.47	11.16	13.84
33	Msusu wa Maziwa	*Commiphora sp*	3.50	1.50	0.00	0.47	1.94	2.28
34	Kimodoa/ Mnoa	*Acacia mellifera*	15.30	7.00	0.08	76.55	104.68	130.57
35	Kimodoa/Mnoa	*Acacia mellifera*	13.60	7.50	0.07	45.91	83.71	97.48
36	Mghaa	*Acacia tortilis*	20.30	9.50	0.14	107.69	150.18	186.05
37	Mghaa	*Acacia tortilis*	30.30	10.50	0.39	381.27	513.02	629.24
38	Mghaa	*Acacia tortilis*	22.30	6.50	0.23	203.37	264.72	310.45
39	Kiloriti/Mzameli	*Acacia nilotica*	18.50	6.00	0.08	85.34	113.46	129.06
40	Kiloriti/Mzameli	*Acacia nilotica*	13.40	6.00	0.08	63.85	92.57	107.10
41	Kimodoa/Mnoa	*Acacia mellifera*	14.30	7.50	0.06	56.81	91.69	107.03
42	Kimodoa/Mnoa	*Acacia mellifera*	3.40	2.50	0.00	2.46	4.00	4.50
43	Msusu wa Mafuta	*Commiphora sp*	20.80	4.50	0.13	51.13	74.93	86.74
44	Mghaa	*Acacia tortilis*	11.40	7.50	0.04	28.07	40.04	52.23
45	Kiloriti/Mzameli	*Acacia nilotica*	12.30	4.50	0.04	22.70	39.59	50.07
46	Mghaa	*Acacia tortilis*	23.00	9.00	0.16	126.10	163.43	193.23
47	Mghaa	*Acacia tortilis*	9.00	6.50	0.03	28.82	33.04	41.91
48	Kimodoa/Mnoa	*Acacia mellifera*	8.50	4.00	0.03	23.40	38.22	43.97
49	Mghaa	*Acacia tortilis*	18.00	7.00	0.13	94.18	109.59	135.12
50	Mghaa	*Acacia tortilis*	23.50	7.50	0.14	123.95	167.67	202.86

51	Mkonga	*Balanites aegyptiaca*	9.50	5.00	0.02	16.80	59.70	67.26
52	Mdudu	*Boscia coriacea*	4.50	2.50	0.01	5.77	8.08	10.51
53	Mghaa	*Acacia tortilis*	12.00	5.50	0.07	55.23	70.60	89.34
54	Kimodoa/Mnoa	*Acacia mellifera*	6.40	3.50	0.01	11.87	23.08	27.55
55	Kimodoa/Mnoa	*Acacia mellifera*	2.50	1.80	0.00	1.72	5.97	7.10
56	Msusu wa Mafuta	*Commiphora sp*	9.50	5.00	0.02	4.44	6.37	7.73
57	Kimodoa/Mnoa	*Acacia mellifera*	6.30	5.00	0.01	9.27	13.52	15.73
58	Mghaa	*Acacia tortilis*	21.00	7.50	0.16	137.33	179.13	220.04
59	Mghaa	*Acacia tortilis*	22.00	9.00	0.13	97.34	119.21	153.03
60	Mghaa	*Acacia tortilis*	25.20	8.50	0.15	131.26	184.27	216.36
	TOTAL OBSERVED				**5.03**	**4309.58**	**6031.26**	**7381.97**

C. Models developed for estimating biomass of different tree sections indicated in non-linear formats.

Tree component	**Model form**	**Models with only *DBH* (CF included)**	**Model form**	**Models with both *DBH* and *Ht* (CF included)**
Total tree biomass	1	$\equiv 0.50280 * (DBH)^{2.018}$	3	$\equiv 0.40926 * (DBH^{1.389} * Ht^{1.011})$
	2	$\equiv 0.50283 * (DBH^2)^{1.009}$	**4**	$\boldsymbol{\equiv 0.41104 * (DBH^2 * Ht)^{0.775}}$
Tree aboveground biomass	1	$\equiv 0.40964 * (DBH)^{2.025}$	3	$\equiv 0.33054 * (DBH^{1.372} * Ht^{1.048})$
	2	$\equiv 0.40964 * (DBH^2)^{1.012}$	**4**	$\boldsymbol{\equiv 0.33285 * (DBH^2 * Ht)^{0.778}}$
Stem + Branch biomass	1	$\equiv 0.12050 * (DBH)^{2.327}$	3	$\equiv 0.09535 * (DBH^{1.630} * Ht^{1.120})$
	2	$\equiv 0.12050 * (DBH^2)^{1.164}$	**4**	$\boldsymbol{\equiv 0.09589 * (DBH^2 * Ht)^{0.893}}$
Stem biomass	1	$\equiv 0.10998 * (DBH)^{2.172}$	**3**	$\boldsymbol{\equiv 0.08565 * (DBH^{1.433} * Ht^{1.188})}$
	2	$\equiv 0.10998 * (DBH^2)^{1.086}$	4	$\equiv 0.08651 * (DBH^2 * Ht)^{0.837}$
Branch biomass DBH ≥ 10 cm	1	$\equiv 0.01163 * (DBH)^{2.837}$	3	$\equiv 0.00525 * (DBH^{2.461} * Ht^{0.957})$
	2	$\equiv 0.01163 * (DBH^2)^{1.3117}$	**4**	$\boldsymbol{\equiv 0.00489 * (DBH^2 * Ht)^{1.169}}$
Twig biomass	1	$\equiv 0.38750 * (DBH)^{1.620}$	3	$\equiv 0.25067 * (DBH^{1.078} Ht^{0.872})$
	2	$\equiv 0.38751 * (DBH^2)^{0.810}$	**4**	$\boldsymbol{\equiv 0.32715 * (DBH^2 Ht)^{0.624}}$
Belowground biomass	1	$\equiv 0.08973 * (DBH)^{1.999}$	3	$\equiv 0.07672 * (DBH^{1.503} Ht^{0.797})$
	2	$\equiv 0.08972 * (DBH^2)^{0.999}$	**4**	$\boldsymbol{\equiv 0.07655 * (DBH^2 Ht)^{0.763}}$

D. Models developed estimating volume of different tree sections indicated in non-linear formats.

Tree component	**Model form**	**Models with only *DBH* (CF included)**	**Model form**	**Models with both *DBH* and *Ht* (CF included)**
Total tree volume	1	$\equiv 0.000244 * (DBH)^{2.130}$	**3**	$\equiv \mathbf{0.000222} * (\boldsymbol{DBH}^{\mathbf{1.823}} * \boldsymbol{Ht}^{\mathbf{0.494}})$
	2	$\equiv 0.000244 * (DBH^2)^{1.063}$	4	$\equiv 0.000221 * (DBH^2 * Ht)^{0.805}$
Stem volume	1	$\equiv 0.000231 * (DBH)^{2.007}$	3	$\equiv 0.000208 * (DBH^{1.669} * Ht^{0.544})$
	2	$\equiv 0.000231 * (DBH^2)^{1.004}$	**4**	$\equiv \mathbf{0.000208} * (\boldsymbol{DBH}^{\mathbf{2}} * \boldsymbol{Ht})^{\mathbf{0.760}}$
Branch volume	1	$\equiv 0.00004435 * (DBH)^{2.380}$	3	$\equiv 0.0000426 * (DBH^{2.070} * Ht^{0.472})$
	2	$\equiv 0.0004435 * (DBH^2)^{1.190}$	**4**	$\equiv \mathbf{0.0000439} * (\boldsymbol{DBH}^{\mathbf{2}} * \boldsymbol{Ht})^{\mathbf{0.887}}$