ESTIMATION OF CARBON STOCKS IN *ACACIA-COMMIPHORA* WOODLANDS IN KITETO DISTRICT, TANZANIA

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ABSTRACT

Carbon stocks of *Acacia-Commiphora* woodlands was estimated using site specific biomass allometric models developed in Kimana Village, Kiteto District, Tanzania. Fifty sample trees covering a range of diameter at breast height (DBH) from 5.9 cm to 79.2 cm from 12 different tree species were destructively sampled to develop biomass and volume models. The sample trees included three dominant species namely *Commiphora africana*, *Balanites aegyptiaca*, and *Acacia tortilis*. Candidate non-linear models were fitted where DBH or combination of DBH and tree height (Ht) were used as predictor variables against separate tree components. Evaluation of model performance at the beginning was based on statistical significance of parameters: small root mean square error, higher R^2, and low mean prediction error. Final model selection was based on Akaike's Information Criterion, since the selected functions had different number of parameters. The developed models gave an option of using either DBH alone or in combination with Ht, depending on availability of inventory data and financial capability of the user since an additional variable has implication on inventory costs. The average basic density for tree species sampled ranged from 0.32 to 0.75 with an average of 0.59 g cm^{-3}. Forest inventory was carried out with 164 plots of 15m radius systematically laid out at sampling intensity of 0.75%. The number of tree stems per hectare was 971, basal area 5.96 m^2 ha^{-1} and volume 38.8 m^3 ha^{-1} with a carbon content of 21.96 t ha^{-1}. Carbon stock estimates computed from the developed biomass allometric equation with that derived from volume and basic density shows no significant difference for small to medium tree sizes. The developed models can be used in other woodlands with similar conditions and within DBH range of the sample trees.

DECLARATION

I, HARUNA LUGANGA, 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 nor being concurrently submitted in any other institution.

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The above declaration is confirmed by:

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Prof. S.M.S. Maliondo **Date**

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DEDICATION

This work is dedicated to my late young brother, Andrew Omary Luganga for his good wish to me during the whole period of the research. May Almighty God rest his soul in eternal peace. Amen!

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LIST OF ABBREVIATIONS AND SYMBOLS

AG	Aboveground biomass
AIC	Akaike's Information Criterion
BD	Basic Density
BEF	Biomass Expansion Factor
BG	Belowground biomass
C	Carbon
CO_2	Carbon dioxide
DBH	Diameter at Breast Height
FAO	Food and Agriculture Organization
G	Basal area per hectare
GHG	Greenhouse Gas
GPS	Global Positioning System
Ha	Hectare
Ht	Height
IPCC	Intergovernmental Panel on Climate Change
KINNAPA	Kibaya, Kimana, Njoro, Ndaleta, Namelek and Partimbo villages
MNRT	Ministry of Natural Resources and Tourism
MPE	Mean Prediction Error
N	Number of stems per hectare
NAFORMA	National Forestry Resources Monitoring and Assessment of Tanzania
R^2	Coefficient of determination
RCD	Root Collar Diameter

REDD	Reduced Emissions from Deforestation and Forest Degradation
REDD+	Reduced Emissions from Deforestation and forest Degradation plus the role of conservation, sustainable management of forests and Enhancement of forest Carbon stocks
RMSE	Root Mean Square Error
R/S	Root - Shoot ratio
SAS	Statistical Analysis System
T	Tonne
UNFCCC	United Nations Framework Convention on Climate Change
V	Volume

CHAPTER ONE

1.0 INTRODUCTION

Tanzania with a total area of 94.5 million hectares is endowed with various vegetation types of importance and unique values (FAO, 2007). About 48.1 million hectares of the total area of the mainland is forest land, out of which 91% are woodlands and the rest is forests (NAFORMA, 2014). Forests and woodlands provide a wide range of products and services such as food, water, medicine, woodfuel, biological diversity, carbon sequestration and raw materials to industries (Bond *et al*., 2009; Burges *et al*., 2010).

Inspite of having forest legislations and decentralised forest management in Tanzania, forest products and services are decreasing at alarming rate due to deforestation and forest degradation in both reserved and unreserved forests (Bromley and Idd, 2009). Deforestation and forest degradation have been going on for decades and are directly correlated with population growth and poverty in African countries (FAO, 2011). In Tanzania, the rate of deforestation is estimated at 403,000 ha per year (FAO, 2010). Such loss would otherwise have provided considerable amount of carbon sink if the forests were properly managed. Having a wide range of vegetation types which can potentially store and sequester considerable amounts of atmospheric carbon dioxide, Tanzania can mitigate the effect of greenhouse gases (GHG) and enhance livelihoods through the carbon market (Watkiss *et al.,* 2011).

Recognizing the crucial role of tropical forests as potential carbon sinks, a climate change mitigation and adaptation strategy to include Reduced Emissions from Deforestation and forest Degradation (REDD) is now being tested and debated by the United Nations Framework Convention on Climate Change (UNFCCC). The inclusion of REDD as a cost-effective option for mitigating GHGs emissions was first proposed by Papua New Guinea and Costa Rica (representing the Coalition of Rainforest Nations) during the 11^{th} UNFCCC annual meeting in Montreal, Canada in 2005 (UNFCCC, 2009). REDD as it is conceived would provide developing countries with incentives to reduce carbon emissions from forests. The scope of the REDD mechanism has broadened to REDD+ to accommodate different developing countries that are effectively protecting their forests through conservation, sustainable forest management, and enhancement of forest carbon stocks. The developing countries will be eligible for carbon payments under REDD+ on voluntary basis (Mukama *et al*., 2012).

1.1 Problem Statement and Justification

One of the large sources of uncertainty in estimates of carbon stocks in tropical forests is the lack of site specific models for converting tree dendrometric measurements to biomass estimates (Chave *et al*., 2005). Since tree allometry varies with forest types they belong to, allometric models need to be developed for different forest types (Burgess *et al*., 2010). Current available biomass models for Tanzania natural forest are localized to few forest types (Hofstad, 2005; *Mugasha et al*., 2013a) and most of them focus only on aboveground biomass (Brown, 1997).

Realizing these problems, Tanzania has now embarked to establish baseline information on carbon stocks through developing allometric equations for the main forest types (Mugasha *et al*., 2013a). There is neither biomass nor volume model for predicting carbon stocks in *Acacia-Commiphora* woodlands. Often, biomass has been derived from tree volume and wood basic density (Munishi and Shear, 2004). However, there is no conclusive evidence implemented to test the validity of this approach. In addition, assessment of carbon stocks in *Acacia-Commiphora* woodland for example by Anderson *et al*. (2012) used biomass equation developed in neighbouring country, Kenya. The use of site specific biomass equation for carbon stocks estimation, has been recommended in most literature since parameter estimates varies with species, stand age, site quality, climate and stocking of stands (Zianis and Mencuccini 2004; Návar-Cháidez, 2010).

The aim of this study was therefore to estimate carbon stock of *Acacia-Commiphora* woodlands using developed above and belowground biomass and volume allometric models. The study provides knowledge on the potential of *Acacia-Commiphora* woodland on the carbon storage.

1.2 Research Objectives

1.2.1 Overall objective

The overall objective of the research was to estimate carbon stocks in *Acacia-Commiphora* woodland as a potential carbon sink for mitigating carbon emissions and climate change through adoption of REDD+ in Kiteto district, Tanzania.

1.2.2 Specific objectives

i. To develop above and below ground biomass and volume allometric models for estimating carbon stocks in *Acacia-Commiphora* woodland;

ii. To determine wood basic density of sampled tree species in the *Acacia-Commiphora* woodland;

iii. To determine above and below ground carbon stocks in *Acacia-Commiphora* woodland; and

iv. To compare carbon stock estimates computed from the developed biomass allometric equation with those derived from volume and basic density.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Major Vegetation Types of Tanzania

In Tanzania, about one third of the land is occupied by different vegetation types (MNRT, 1998). More than 90% of the forest area is dominated by miombo woodlands, while the remaining areas comprise forest types like montane forests, lowland forests, mangrove forests and other woodlands like *Acacia-Commiphora* woodland. Each of the vegetation types has its own characteristics in terms of tree species composition, abundance, distribution and capacity to store carbon. *Acacia-Commiphora* woodland occupies most of the central and northern parts of Tanzania (Burgess *et al*., 2010).

2.2 *Acacia-Commiphora* Woodlands

In Tanzania, *Acacia-Commiphora* woodland is commonly found in Somalia-Masai phytochorion. These are deciduous bushland and thickets that form a climax vegetation type over the greater part of the Somalia-Masai region. They are characterized by dense bushland of 3 to 5 m tall with scattered emergent trees up to 9 m (Kindt *et al.,* 2011). The main canopy tree species are mostly multiple-stemmed trees or small trees that are branched near the base. In Tanzania the *Acacia-Commiphora* ecoregion includes most of the northern circuit National Parks (Serengeti, Mkomazi, Tarangire and Lake Manyara) and the central part (Burgess *et al*., 2010). This woodland is characterized by dominant tree and shrub plant species such as *Acacia tortilis*, A*cacia millifera*, *Commiphora africana, Commiphora abyssinica, Commiphora schimperi, Commiphora edulis, Commiphora campestris, Balanites aegyptiaca, Acalypha sp.*, *Aerva sp*, *Combretum sp.* and *Terminalia sp.* (Van Breugel *et al.,* 2011). The tree species have been traditionally used for fuel, fencing, medicine, beehives, carvings and most of them are highly palatable to livestock (Makonda and Ruffo, 2010).

2.3 Allometric Model for Estimating Volume and Carbon Stocks of Forests

Volume and carbon stocks in different vegetation types can be determined by using direct or indirect methods. In both methods, forest inventory information is necessary to provide measurable tree parameters. In addition to tree parameters, the direct method needs further information on weight of individual trees. Direct measurement of volume and carbon stocks on a large scale is destructive, tedious and time consuming but it has high precision (Salmaca, 2007; Ebuy *et al*., 2011; Henry *et al*., 2011). Indirect method for estimating volume and carbon stocks of forest involves the use of equations. Equations entail development of relationship of individual tree biomass and the easily accessible and measurable tree parameters such as diameter and height. Two forms of equations are commonly used; allometric equations or biomass expansion factors (Hewson *et al*., 2013). The scaling relationships by which the ratios between different aspects of tree size change when small and large trees of the same species are compared are generally known as allometric relations (Hairiah *et al.,* 2001).

The estimation of volume and biomass stocks through the use of allometric relations is basically a product of destructive sampling. In Tanzania, several previous studies (Malimbwi *et al.,* 1994; Chamshama *et al*., 2004; Mugasha *et al.*, 2013a) were done in developing biomass equations solely in miombo woodland. Assessment of carbon stocks in *Acacia-Commiphora* woodland has been done in Tanzania by Anderson *et* *al*., (2012) using biomass equation developed in the neighbouring country, Kenya. The use of site specific biomass equation for carbon stocks estimation has however been recommended by many researchers since parameter estimates vary with species, stand age, site quality, climate and stocking of stands (Zianis and Mencuccini 2004; Návar-Cháidez, 2010).

Biomass and its subsequent carbon stocks may also be estimated using forest inventory information such as wood merchantable volume. Estimates of biomass from merchantable volume and wood basic density generally require the application of a biomass expansion factor (BEF). BEFs are vaguely defined, some researchers define BEF as a ratio of aboveground biomass to stem biomass (Brown *et al*., 1989; Sanquetta *et al*., 2011), while others define it as a ratio of aboveground biomass to merchantable volume (Lehtonen *et al*., 2007; Návar- Cháidez, 2009; Petersson *et al*., 2012). According to Somogyi *et al*. (2008) and Hewson *et al*. (2013), BEFs are dimensionless hence in this study BEF will follow Brown *et al*. (1989) and Henry *et al*. (2010) definition as the ratio of individual tree aboveground biomass to the stem biomass. According to Hewson *et al*. (2013) BEFs are used for rough estimates of biomass using available forest inventory data when resources are not available to measure carbon stocks in forests. Moreover, Petersson *et al*. (2012) suggested that age dependent BEFs may be suitable alternatives for biomass estimation where representative biomass equations are not available.

This study was aimed at estimating carbon stocks from developed biomass allometric equations and compared them with the ones obtained from BEF.

2.4 Potential of Forests and Woodlands for Carbon Storage

Terrestrial ecosystems especially forests and woodlands have the greatest potential for mitigating atmospheric CO_2 emissions through conservation and management (Munishi and Shear, 2004). It is estimated that about 289 giga tonnes of carbon is stored in the world's forest biomass while 292 giga tonnes is stored in the soils (FAO, 2010). Forest and woodlands are important carbon sinks and sources containing majority of the above ground terrestrial organic carbon. International negotiations to limit GHGs emissions require understanding of the current and potential future role of forest carbon emissions and sequestration in both managed and unmanaged forests (Pan *et al*., 2011). Tanzania has reported an average carbon stock value of 60 t C ha^{-1} in living forest biomass (FAO, 2010), a national average that excludes other carbon pools such as soils, litter, and dead wood. A study in Mbulu District showed that *Acacia-Commiphora* woodlands can store up to 33.4 t C ha^{-1} (Anderson *et al.,* 2012) which is more or less the same as those of miombo woodland of 32.1 t C ha^{-1} as reported by Ryan *et al.* (2011) and 33 t C ha^{-1} by Malimbwi *et al.* (1994). Afromontane rain forest can store as much as 517 ± 17 t C ha^{-1} (Munishi and Shear, 2004), the amount which is by far higher than carbon stock in other forest types in Tanzania.

2.5 Drivers of Deforestation in *Acacia-Commiphora* Woodlands

In Tanzania deforestation is mostly pronounced in unprotected forests in village and general lands, as they are open access (FAO, 2006; Zahabu, 2008). Unprotected forests and woodlands are characterized among others, by insecure land tenure, shifting cultivation, illegal harvesting of wood fuel, poles and timber (Zahabu, 2008).

After biomass consumption for energy, the next important driver of deforestation is agricultural expansion and encroachment (Chiesa *et al*., 2009). This occurs primarily in the form of subsistence shifting cultivation. Land use change consisting of conversion from woodland to slash and burn agriculture is the main driver of deforestation in *Acacia-Commiphora* woodlands (Anderson *et al*., 2012). This land intrusion, conversion and resulting deforestation results into decline of carbon sinks. Anderson *et al*. (2012) showed that *Acacia-Commiphora* woodlands experience an average deforestation rate of 0.93% due to conversion and expansion of agriculture.

CHAPTER THREE

3.0 MATERIAL AND METHODS

3.1 Study Site

The study was carried out in Kimana Village, Kiteto District, Manyara Region in Tanzania. Kiteto District lies between latitude 4° 31’ and 6º 03’S and longitude 36° 15’ and 37° 25’E (Kiteto District Council, 2009). Kimana Village covers an area of about 55,194.76 ha which is dominated by Maasai Steppes (Olekao, 2011). In this vegetation, an estimated area of more than 2000 ha has been allocated for pastoral activities in Kimana Village. In this study a block of about 1500 ha which exclude grassland areas was delineated from the woodland.

The area has two rainy seasons: short rains start from October to December, and long rains from February/March to May. Average annual rainfall is 700 mm while the average annual temperature is 22 °C. The soil types are black cotton soil and clay sandy soil.

3.2 Data Collection

In this study, forest inventory data and data for development of allometric equations for prediction of tree volume and carbon stocks were collected.

3.2.1 Inventory data

3.2.1.1 Sample size determination

Boundary survey using GPS was carried out to delineate the study area. Base map of the study site (in Figure 1) showing the woodland boundary was drawn from coordinates using surveying and engineering application software (LISCAD 6.2). Coordinates from woodland boundary were used to determine the study site area using coordinate system conversion in Arc view 3.3 Software. The total number of sample plots was determined using the formula below;

$$N = \frac{T_A \, X \, S_i}{P_s X 100}$$

Where:

N	=	number of sample plots,
TA	=	total area of the forest,
Si	=	sampling intensity,
Ps	=	plot size.

A sampling intensity of 0.75%, with 164 main circular plots of 15m radius, was assumed enough to cover as much variation as possible in about 1500 ha of the delineated woodland.

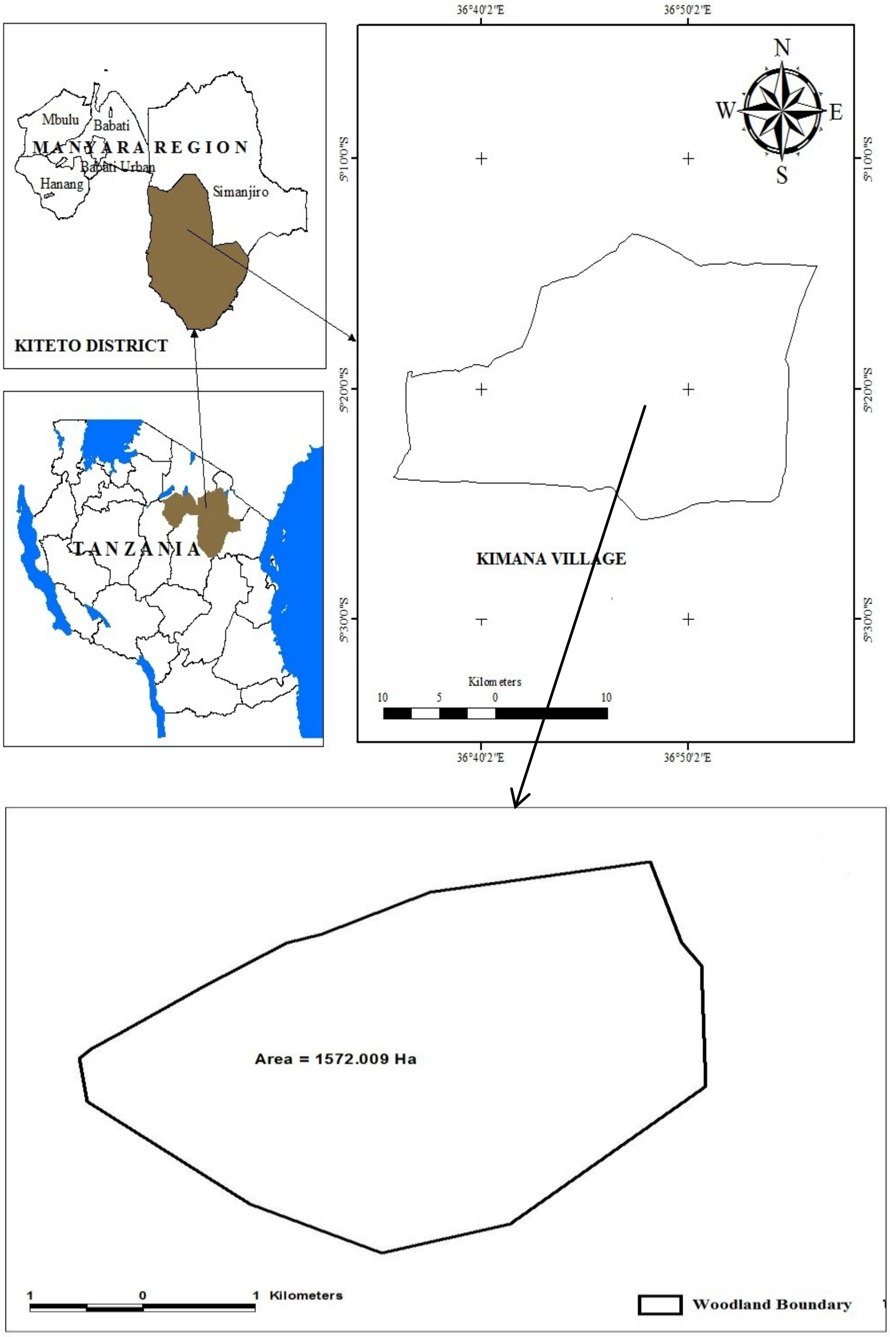

Figure 1: Map showing location of the study District, Village and site

3.2.1.2 Sampling design and plot layout

Systematic sampling design was employed in this study where temporary concentric circular sample plots of 2, 5, 10 and 15 m radii were laid out systematically along the transect at 200 m interval. The distance between transects was 400 m. The coordinates of each laid sample plot were generated by LISCAD software. The first plot was laid out randomly at half inter-plot distance from the forest boundary followed by systematic layout of other plots within the study site. The generated coordinates were used to trace the sample plots using GPS. A local botanist was involved in tree species identification. For specimens which proved difficult to identify in the field were collected for proper identification.

Within each sub-plot the following measurement were taken and recorded:-

i) Within 2 m radius; all trees with DBH ≥ 1 cm to < 5cm were recorded
ii) Within 5 m radius; all trees with DBH ≥ 5 cm to < 10cm were recorded
iii) Within 10 m radius; all trees with DBH ≥ 10 cm to < 20cm were recorded
iv) Within 15 m radius; all trees with DBH ≥ 20 cm were recorded

Three trees (small, medium and large size) were selected in each plot and measured for heights that were used to develop a height-diameter relationship for estimating Ht of other trees. The height-diameter model was fitted by weighted least square regression method using PROC NLIN procedure in SAS with a weight of DBH^{-1} to correct for heteroscedasticity (Picard *et al.,* 2012). The model is shown hereunder:

$\text{Height} = 1.3 + 1.0398\,\text{DBH}^{0.5899}$ (R^2 =0.77, RMSE=8.9, n=226)

Where; DBH is diameter at breast height, R^2 is coefficient of determination, RMSE is the root mean square error and n is number of sample trees.

3.2.2 Data for development of tree volume and biomass models

3.2.2.1 Tree selection

Trees from inventory data were grouped into eleven DBH classes i.e.0 - < 5 cm , 5-9.9 cm, 10 - 14.9 cm, 15 - 19.9 cm, 20 - 24.9 cm, 25 - 29.9 cm, 30 - 34.9 cm, 35 - 39.9 cm, 40 - 44.9 cm 45 - 49.9 cm and > 49.9 cm and their frequencies of distribution under each DBH class were determined. A total of 50 sample trees (Appendix 6) representing a range of diameter classes and tree species were purposively selected for destructive sampling for volume and both above and below ground biomass model development. Three dominant tree species namely; *Acacia tortilis, Commiphora africana* and *Balanites aegyptiaca* and other nine associated species that exhibit tree life form were included. Climbers were excluded since they need different modeling approach (Picard *et al.*, 2012). In the study site most of the tree species had small to medium sized DBH (1 to < 30 cm) as a result large trees mostly from *Acacia* species were included in the sample had an influence on the shape and trend of the regression curve. Most important is their huge contribution to carbon stocks (Zahabu, 2008).

3.2.2.2 Destructive sampling

The trees were measured for DBH using a tree calliper. The cut-off point between tree above and below ground biomass components was 15 cm height from the ground. Tree Ht was measured using Suunto hypsometer. For trees forking below 1.3 m from the ground level, each stem was measured and recorded separately, later the equivalent diameter of the forked tree was calculated following Snowdon *et al*. (2002) and Sawadogo *et al*. (2010) procedure as follows;

$$D = \sum_{i=1}^{n} (DBH^2)^{1/2}$$

Where; D is the equivalent diameter at breast height of the forked stems, DBH is the Diameter at breast height of the stems and n is the number of stems.

After felling, stem and branches were crosscut into billets ranging from 30 cm to 220 cm long that minimizes taper and convenient to weigh (Plate 1). Mid-diameter and length of each billet were measured for volume determination and then weighed to obtain the fresh weight data. Finally, each tree was arranged into the following sections:

- Stems $\geq$ 5 cm diameter,
- Branches < 5 cm diameter,
- Twigs < 2cm diameter and leaves and,
- Belowground component include roots, root crown and stump up to 15 cm from the ground level.

Total tree biomass and its subsequent carbon stocks is critical tool for understanding the potential of the woodlands in carbon sequestration. However, from utilization and marketing point of view, volume of stem and branches and biomass of stem, branches and leaves and twigs models are vital (Basuki *et al.*, 2009). In this type of vegetation type, trees are mostly used for beehives making, fuel wood and other end uses such as cuttings for live fences, hence minimum stem diameter for merchantable volume suitable for timber production was not considered.

For each tree section, a wood block of about 2 cm thick cut from bark to pith was taken. The fresh weight of each sample was determined using an electronic balance to the nearest +1 g, and then taken to laboratory to determine sample dry weight. Fresh weight for twigs containing leaves was also determined and samples collected for dry weight determination.

Plate 1: Crosscutting and measurement of billets (Photo: Fieldwork 2013)

For below ground sections (stump, root crown and roots), the sample trees were dug until all roots starting from the root crown were visible. Three roots from the root crown (largest, medium and the smallest in diameter) including their side roots were selected for excavation up to 1cm diameter, cleaned from soils and their diameter and weight determined. Other remaining roots from the root crown were only measured for diameter. Root crown including the stump were cleaned of soils and weighed to obtain fresh weight. Samples from the three sample roots, root crown and stump were extracted and measured for fresh weight and for biomass determination in the laboratory. Biomass of all unexcavated roots was estimated by using diameter-fresh weight relationship of excavated roots (see section 3.3.2). This was done with exception of *Balanites aegyptiaca*, in which the numerous fibrous roots were excavated together with the root crown (Plate 2) and tried to salvage as much broken roots as possible up to 1cm diameter.

Plate 2: Root excavation of *Balanites aegyptiaca* (Photo: Fieldwork 2013)

3.2.3 Laboratory procedures

3.2.3.1 Determination of sample dry weight

Samples from tree sections were taken to laboratory for oven drying to attain constant weight at 103 $\pm$ 2 °C for 7 to 10 days and their dry weight were recorded. For leaves and twigs, samples were oven-dried at 85°C for 4 days to constant weight to determine the oven dry weight.

3.2.3.2 Determination of wood basic density

In the laboratory, the wood blocks from the stem and branch billets were soaked in water for one week then measured for green weight using kitchen scale. Volume of each wood block was determined by water displacement method. A beaker of water was placed on a balance then the sample was suspended by needle clamped on a stand, then each sample was lowered into the beaker while being in no contact with the sides or bottom of the beaker. The weight in grams equals to the weight of the volume of water displaced of each sample was recorded. The blocks were then taken for oven drying to constant weight at 103 $\pm$ 2 ° C and their dry weight measured by using kitchen scale. After oven drying, wood basic densities were calculated using the formula:

$$\text{Wood basic density } (g/cm^3) = \frac{\text{oven dry weight (g)}}{\text{green volume } (cm^3)}$$

3.3 Data Analysis

Data analysis involved determination of tree volume and biomass, development of models and applying the selected models to the forest inventory data to estimate volume and biomass.

3.3.1 Determination of tree volume

Huber’s formula was employed to determine the volume of each billet from stems and branches (Philip, 1994). Total tree volume was calculated as the summation of individual stem and branches billet volumes.

3.3.2 Determination of wood biomass

The biomass ratios defined as the ratios of sample oven dry weight to sample green weight of the wood samples (Jayaraman, 1999; Picard *et al.,* 2012) were determined.

The biomass for each section (below ground, stem, branches and twigs and leaves) was obtained as a product of fresh weight and its corresponding biomass ratios *i.e.*

$$\text{Biomass (kg)} = \text{Green weight (kg)} \times \frac{\text{Sample dry weight (g)}}{\text{Sample green weight (g)}}$$

Since not all roots were measured for fresh weight in the field, fresh weight-diameter relationships were developed to estimate the fresh weight of the other roots. Because of the big difference in root architecture, tree species were divided into two dominant genera (*Acacia* and *Commiphora*), and other species were assigned to group with more or less the same root architecture as the two groups. *Balanites aegyptiaca* was excluded in root model development since their root biomass was estimated using different approach as stated earlier. The developed models are presented hereunder;

Acacia sp; $F = 0.2475D^{1.7212}$ (R^2 = 0.78, n = 69, RMSE = 5.1)

Commiphora sp; $F = 0.1923D^{1.6814}$ (R^2 = 0.73, n = 57, RMSE = 3.9)

Where: F is fresh weight of the root (kg) and D is root diameter at the base of root crown, $R^2$is the coefficient of determination, n is the number of sample roots and RMSE is the root mean square error (Kg).

The fresh weight estimated was then converted to biomass using the respective biomass ratio.

3.3.3 Development, selection and evaluation of biomass and volume models

Tree sections were first arranged within their respective components so as to have below ground, stems, branches and twigs and leaves biomass. Above ground biomass was obtained as summation of stem, branches and leaves and twigs components. For below ground component, biomass of sample and other roots were summed together with root crown and stump to obtain tree below ground biomass.

Tree components, above and belowground biomass allometric equations were fitted by least square method to obtain parameter estimates that best described the relationship between biomass or volume and DBH or combination of DBH and Ht using PROC NLIN of Statistical Analysis System (SAS) software.

The following general model forms were adopted and fitted for both biomass and volume:

$$Y = a.DBH^{b} \quad (1)$$

$$Y = a + b.DBH^{2} \quad (2)$$

$$Y = a.DBH^{b}.Ht^{c} \quad (3)$$

$$Y = \exp\left(a + b.\ln(Ht.DBH^{2})\right) \quad (4)$$

Where:

Y	=	biomass (kg) or Volume (m^3),
DBH	=	Diameter at breast height (m),
Ht	=	tree total height (m) and

a, b and c are regression coefficients.

Evaluation of model performance to select candidate model at the beginning was based on significance of parameters, high value of R^2, lower RMSE, mean prediction error (MPE), Percentage mean prediction error (MPE%) logical behavior of the models, and simplicity of the models. Candidate models with insignificant parameter(s) were omitted for the next steps in the evaluation. Selection of the final model was based on lower Akaike's Information Criterion (AIC) since the candidate model functions had unequal number of parameters (Chave *et al*., 2005; Picard *et al.,* 2012). Student t test was done for all best models to see whether the MPE% values were significantly different from zero (Mugasha *et al*., 2013a). For each tree section, two best models i.e. one with DBH only and another with combination of DBH and Ht were selected.

3.3.4 Computation of biomass expansion factor and root-shoot ratio

Other parameters such as root-to-shoot ratio (R/S) and biomass expansion factor (BEF) were also computed. R/S was computed as the ratio of tree belowground biomass to aboveground biomass, while BEF is the ratio of aboveground biomass to the stem biomass (Brown *et al*., 1989).

3.3.5 Computation of biomass, carbon stocks and stand volume

Best performing biomass equation with only DBH as independent variable was applied to each individual main tree component (above and belowground) within a plot to calculate total tree biomass in each plot. Biomass was converted into carbon by multiplying with a factor of 0.49 (Brown, 1997; Munishi and Shear 2004). Total tree carbon was aggregated for the whole plot and average of plot values were converted to per hectare basis that gives the carbon stock (tones ha^{-1}) of the woodlands. The distribution of carbon stock by DBH class and by dominant species was also determined. The same procedure was applied for estimation of average stand volume.

Wood basic density for sampled tree species and BEF were multiplied by volume estimates from total volume equation to provide estimation of biomass and its subsequent carbon stock. Biomass estimation using these parameters is given by a formula below;

$$AG = V * BD * BEF$$

Where; AG is the aboveground biomass,

V = total tree volume,

BD = Average tree basic density,

BEF = biomass expansion factor

The obtained biomass was converted to carbon as explained in the above section.

3.3.6 Comparison between the two approaches for carbon stock estimation

Carbon estimates based on BEF against carbon estimates based on biomass allometric equation were computed and compared using Z test in Microsoft Office Excel 2007.

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

Parameter estimates and model performance measures for both biomass and volume allometric models were estimated and presented in this chapter. In each component, at most two final selected models with either DBH only or with combination of DBH and Ht were selected and indicated with bolded font.

Carbon stock of the *Acacia-Commiphora* woodland was estimated using the final selected biomass allometric models with DBH alone as predictor variable. Results and discussion on tree basic density and model comparison were also presented. The following subsections give detailed results and its discussion.

4.1 Biomass Allometric Models

4.1.1 Leaves and twigs biomass models

Parameter estimates for leaves and twigs biomass models are presented in Table 1. Except for model 4, parameter estimates for all other models were significant and explained more than 50% variability of leaves and twigs biomass. Based on AIC, model 1 and 3 outperformed other models and therefore they were selected as final models. The R^2 ranges from 0.55 to 0.73 for models with DBH as the only predictor variable. When Ht was included in addition to DBH as predictor variables, the results showed slight improvement of R^2. Mugasha *et al*. (2013a) observed similar results in which biomass model for twigs involving DBH alone in miombo woodlands showed slight improvement when Ht was included in addition to DBH as predictor variable (i.e. R^2 increased from 0.68 to 0.69). On the other hand Grote (2002) showed that leaves and twigs biomass of spruce is poorly predicted from branch cross sectional area while Munishi *et a.l* (2010) observed the same component to be poorly predicted from DBH and Ht. The observed inconsistence regarding leaves and twigs biomass prediction based on diameter might be a function of site and growth conditions which affect their morphologies. The percentage MPE were non-significantly different from zero (P>0.05) for the final selected biomass model indicated by bolded font in Table 1. Model 3 was superior to model 1 due to its low AIC.

Table 1: Parameter estimates and performance criteria for leaves & twigs biomass models in *Acacia-Commiphora* woodland, Kiteto District

Model form	Parameter estimates			RMSE	R^2	%MPE	AIC
	a	*b*	*c*				
1	**2.2238**	**0.9893**		**21.2340**	**0.70**	**-1.977**	**449.413**
2	27.9763	0.0269		25.8324	0.55	-6.9E-15	469.015
3	**1.5346**	**0.6585**	**0.6697**	**20.0980**	**0.73**	**-1.758**	**444.862**
4	0.5656^{NS}	0.3987		20.1245	0.73		

RMSE=root mean square error (Kg), R^2=coefficient of determination, MPE=mean prediction error, AIC=Akaike's information criterion and a, b and c are regression coefficients and ^{NS} indicates non-significant parameter.

4.1.2 Branch biomass models

Parameter estimates and model performance measures for branch biomass models are presented in Table 2. Branch biomass was poorly predicted when model forms 1, 3 and 4 were fitted to data as shown by non-significant parameter estimates (P > 0.05). Models with non-significant parameters were excluded in model evaluation. In this component, only model form 2 showed significant parameter estimates and therefore selected as the final model. A similar trend was also reported by Munishi *et al*. (2010) in miombo woodlands and Sawadogo *et al*. (2010) in Sudanian savanna woodlands where DBH and Ht could not explain majority of the variation of branch biomass prediction. In another tree biomass study of *Pinus sylvestris* plantation, Xiao and Ceulemans (2004) showed that apart from tree DBH and Ht, branch biomass was well predicted by branch diameter and branch length as independent variables. It might be that DBH and Ht are not good predictors of branch biomass for *Acacia-Commiphora* trees due to large uncertainty of tree branches formation and sizes for the given tree DBH or Ht (Mugasha *et al*., 2013b).

Table 2: Parameter estimates and performance criteria for branch biomass models in *Acacia-Commiphora* woodland, Kiteto District

Model form	Parameter estimates *a*	*b*	*c*	RMSE	R^2	%MPE	AIC
1	0.7398^{NS}	1.1596		32.6971	0.33		
2	**13.6458**	**0.0192**		**34.0296**	**0.27**	**0.0192**	**496.575**
3	0.5613^{NS}	0.8423	0.608^{NS}	32.7951	0.33		
4	-0.5139^{NS}	0.4606		32.4669	0.33		

RMSE=root mean square error (Kg), R^2=coefficient of determination, MPE=mean prediction error, AIC=Akaike's information criterion and a, b and c are regression coefficients and ^{NS} indicates non-significant parameter.

4.1.3 Stem biomass models

Parameter estimates and model performance indicators for stem biomass models are presented in Table 3. All parameter estimates for stem biomass models were significant ($P < 0.05$) and the predictor variables were able to explain more than 95% variation. The stem biomass models based on DBH alone had a good fit (R^2 ranging between 0.97 and 0.98). When Ht was included the R^2 slightly increased to 0.99. The stem biomass models presented supports the findings of Malimbwi *et al.* (1994) and Chamshama *et al. (*2004) in miombo woodland in which addition of Ht as predictor variable lower RMSE and increased R^2. Moreover, Mugasha *et al.* (2013a) developed a set of non-linear functions for mixed species in miombo woodlands and DBH alone when was used as predictor variable accounted over 70% of the variation in stem biomass. When Ht was included, the models improved marginally by lowering RMSE and increased R^2, an observation which is consistent with the current study. The results in this study suggest that DBH and Ht are the main predictor variables for stem biomass. Among the selected models, the one with both DBH and Ht seemed to be superior compared to that with DBH alone because of its lower AIC. Though Ht measurement in closed canopy is very uncertain some researchers e.g. Chave *et al.* (2014) emphasized the inclusion of total tree height when available in estimation of biomass since it yields less biased estimates especially for very large trees.

Table 3: Parameter estimates and performance criteria for stem biomass models in *Acacia-Commiphora* woodland, Kiteto District

Mode l form	Parameter estimates			RMSE	R^2	%MPE	AIC
	a	*b*	*c*				
1	**0.0658**	**2.5177**		**74.8931**	**0.98**	**-1.665**	**575.459**
2	-117.8	0.6049		111.6	0.97	4.6E-14	615.381
3	**0.0279**	**2.2295**	**0.7911**	**60.5798**	**0.99**	**1.286**	**555.196**
4	-3.9366	0.2097		61.7716	0.99	2.610	556.197

RMSE=root mean square error (Kg), R^2=coefficient of determination, MPE=mean prediction error, AIC=Akaike's information criterion and a, b and c are regression coefficients.

4.1.4 Aboveground biomass models

Parameter estimates and model performance measures for aboveground biomass models are presented in Table 4. The final selected models with DBH only and combination of DBH and Ht were selected and are indicated with bolded font. This allows flexibility of using either of the two selected models depending on the desired precision, available data and financial capability. Based on lower AIC, model 3 was superior over the other.

Table 4: Parameter estimates and performance criteria for above ground biomass models in *Acacia-Commiphora* woodland, Kiteto District

Mode l form	Parameter estimates			RMSE	R^2	%MPE	AIC
	a	*b*	*c*				
1	**0.1879**	**2.2904**		**95.0958**	**0.98**	**-0.147**	**599.341**
2	-76.2149	0.6509		110.3	0.97	3.43E-14	614.191
3	**0.1050**	**2.0423**	**0.6205**	**83.7363**	**0.98**	**1.819**	**587.567**
4	-2.6226	0.9591		86.3693	0.98	-2.579	589.716

RMSE=root mean square error (Kg), R^2=coefficient of determination, MPE=mean prediction error, AIC=Akaike's information criterion and a,b and c are regression coefficients.

The biomass models based on DBH alone had a good fit (R^2 ranging between 0.97 and 0.98). High R^2 values signify that most of variation in biomass is strongly explained by the predictor variables (Overman *et al*., 1994).These results were consistent with previous study by Ryan *et al.* (2011) and Mugasha *et al.* (2013a) in which models with non-linear functions were developed for mixed species in miombo woodland and they used DBH alone which accounted about 90% of the variation in tree biomass. When Ht was included, the models improved marginally by lowering RMSE and increased R^2 an observation which is consistent with the current study. The results in this study suggest that DBH alone suffices to predict AG biomass for *Acacia-Commiphora* woodland. It is however recommended that the selected models with Ht included be applied when data on tree Ht are available or when the models are required to be applied beyond the modelling material (Mugasha *et al*., 2013a). Though DBH and Ht are the main biomass predictor variables, it has been recommended by some authors that inclusion of tree species specific density in modeling can improve biomass estimates (Chave *et al*., 2005; Henry *et al*., 2010; Chave *et al*., 2014).

4.1.5 Belowground biomass models

Parameter estimates and model performance measures for below ground biomass models are presented in Table 5. The below ground biomass models based on DBH alone and combination with Ht had a good fit (R^2 ranging between 0.92 and 0.96). All parameter estimates of the four candidate models were significant ($P < 0.05$). The models with both DBH and Ht had slight high R^2 compared to model with only DBH. These results were consistent with previously developed allometric models for mixed tree species of miombo woodland as reported by Malimbwi *et al.* (1994). Contrary to that, Mugasha *et al.* (2013a) developed a set of non-linear functions for mixed species in miombo woodland to estimate below ground biomass where addition of Ht to DBH as predictor variable did not show improvement in terms of R^2. This results suggest that DBH alone might be sufficient to predict below ground biomass as supported by Ryan *et al.* (2011).

Table 5: Parameter estimates and performance below ground biomass models in *Acacia-Commiphora* woodland, Kiteto District

Model form	Parameter estimates			RMSE	R^2	%MPE	AIC
	a	*b*	*c*				
1	**0.3867**	**1.6749**		**26.3282**	**0.94**	**-3.479**	**470.916**
2	14.0389	0.0974		30.3873	0.92	3.45E-16	485.255
3	0.2198	1.2669	0.8669	21.4688	0.96	-2.318	451.460
4	**-1.3847**	**0.6775**		**21.5111**	**0.96**	**-2.717**	**450.709**

RMSE=root mean square error (Kg), R^2=coefficient of determination, MPE=mean prediction error, AIC=Akaike's information criterion and a, b and c are regression coefficients

The ratios of belowground to aboveground biomass (root – shoot ratio) for the sampled tree species ranged from 0.13 to o.66 with an average of 0.28 as presented in appendix 6. The general trend of the root-shoot ratio (R/S) was that as the tree size increased the R/S decreased. The estimated average R/S value was small compared to miombo woodlands. Ryan (2011) and Mugasha *et al*. (2013a) observed average root-shoot ratio (R/S) of 0.42 and 0.40 respectively in miombo woodlands. Average root-shoot ratios have frequently been applied to estimate belowground biomass where only aboveground biomass data is available.

Biomass expansion factors (BEF) for the individual sampled trees ranged from 1.05 to 3.81 with an average of 1.77 are presented in Appendix 6. The general trend of the observed BEF was that, as the tree size (DBH) increased the BEF decreased. The observed average BEF was within the range to those reported by Brown *et al*. (1989) for tropical forest in African countries. Segura and Kannine, (2005) reported an average BEF 1.6 in tropical humid forest in Costa Rica which is small compared to that obtained in the current study. Many authors e.g. (Brown *et al*., 1989; Lehtonen *at al*., 2004; Soares, P. and Tomé, M. 2004) had pointed out that, variations of BEF's are mostly attributed by tree species, stand age and tree sizes.

4.2 Volume Allometric Models

4.2.1 Branch (< 5 cm $\geq$ 2cm) volume models

Parameter estimates and model performance measures for branches volume models are presented in Table 6. Coefficient of determination for tree branches volume models ranged between 0.19 and 0.27. Models 2 and 4 were significant in parameter estimates though small amount of variation were explained by the predictor variables. The low R^2 in both models indicated that there was a lot of uncertainty in tree branches volume and therefore DBH and Ht were not sufficiently able to explain large part of variation of branch volume. Other branch model forms were excluded from evaluation due to non-significant of parameter estimates (P > 0.05). The selected volume models are indicated in bold font. The percentage MPE were not significantly different from zero (P>0.05) for the final selected models. The most plausible explanation of low R^2 for branches is the fact that the demarcation point for branches relies only on size (minimum diameter) regardless of the position of the component which adds variability to the relationship between DBH and branches. However, a study by Chamshama *et al.* (2004) in miombo woodlands showed that branch biomass can be well predicted from DBH and Ht, as indicated by high R^2 and low standard error. This difference might be attributed by type of trees species composition in particular vegetation under study.

Table 6: Parameter estimates and performance criteria for branch volume models in *Acacia-Commiphora* woodland, Kiteto District

Model form	Parameter estimates			RMSE	R^2	%MPE	AIC
	a	b	c				
1	0.00209^{NS}	0.8811		0.0316	0.26		
2	**0.0205**	**0.000015**		**0.0330**	**0.19**	**-9.5E-13**	**-205.143**
3	0.00179^{NS}	0.6935^{NS}	0.355^{NS}	0.0319	0.26		
4	**-6.3194**	**0.3486**		**0.0315**	**0.27**	**-1.621**	**-209.840**

RMSE=root mean square error (m^2), R^2=coefficient of determination, MPE=mean prediction error, AIC=Akaike's information criterion and a, b and c are regression coefficients and ^{NS}indicates non-significant parameter.

4.2.2 Stem ($\geq$ 5 cm) volume models

Parameter estimates and model performance measures for stem volume models are presented in Table 7. The magnitude of explained variation of stem volume was found to be greater than 90% in all models. All models showed significant parameter estimates (P < 0.05). Model 3 was superior among others due to its lower AIC. The high R^2 is in line with previous studies by Chamshama *et al.* (2004) and Malimbwi *et al.* (1994) in which the use of DBH as predictor variable in estimating stem volume in miombo woodland provided a better fit. In addition, results by Malimbwi *et al*. (1994) showed improvement when Ht was combined with DBH in stem volume models.

Table 7: **Parameter estimates and performance criteria for stem volume models in *Acacia-Commiphora* woodland, Kiteto District**

Model form	**Parameter estimates** a	b	c	**RMSE**	**R^2**	**%MPE**	**AIC**
1	0.000148	2.3962		0.0687	0.99	-1.71	-131.914
2	**-0.1308**	**0.000807**		**0.1068**	**0.98**	**-7.8E-15**	**-136.356**
3	**0.000089**	**2.2036**	**0.5039**	**0.0560**	**0.99**	**0.197**	**-155.381**
4	-9.9416	1.0148		0.0676	0.99	2.711	-133.555

RMSE=root mean square error (m^2), R^2=coefficient of determination, MPE=mean prediction error, AIC=Akaike's information criterion and a,b and c are regression coefficients

4.2.3 Total tree (up to 2cm top diameter) volume models

Parameter estimates and model performance measures for total tree volume models are presented in Table 8 The magnitude of relationships between total tree volume and predictor variable(s) were positive, significant ($P < 0.05$) and high ($R2 > 90\%$) in all models. Model 3 was superior among others due to its lower AIC. The strong relationships between total tree volume and the predictor variable(s) in this study was also observed in previous studies by Malimbwi *et al*., (1994), Abbot *et al*. (1997) and Chamshama *et al.* (2004) in which the use of DBH alone or in combination with Ht as predictor variables in miombo woodland provided a better fit.

Table 8: Parameter estimates and performance criteria for total tree volume models in *Acacia-Commiphora* woodland, Kiteto District

Model form	Parameter estimates a	b	c	RMSE	R^2	%MPE	AIC
1	**0.000202**	**2.3269**		**0.0689**	**0.99**	**-1.352**	**-131.680**
2	-0.1139	0.000823		0.0983	0.98	3.6E-13	-96.150
3	**0.000133**	**2.1555**	**0.4352**	**0.0578**	**0.99**	**0.205**	**-152.222**
4	-9.5407	0.9807		0.0731	0.99	2.782	-125.774

RMSE=root mean square error (m^2), R^2=coefficient of determination, MPE=mean prediction error, AIC=Akaike's information criterion and, a, b and c are regression coefficients

4.3 Wood Basic Density of Sampled Trees

Wood basic densities of sampled tree species determined in this study are presented in Table 9. Basic densities of sampled tree species for stems ranged from 0.3 to 0.83 g cm^{-3} with *Acacia nilotica* species having the highest followed by *Acacia hockii* and *Balanites aegyptiaca* having average stem basic density of 0.83 g cm^{-3}, 0.8 $gcm^{-3}$and 0.73 gcm^{-3}, respectively. For branches, the basic density ranged from 0.33 to 0.77g cm^{-3} with an average of 0.58 g cm^{-3}. On average, roots had the lowest basic density of 0.55 g cm^{-3}. Among all sampled trees, *Commiphora* species had the lowest average stem basic density of 0.3 g cm^{-3}. Wood basic densities varied considerably with tree species. Moreover, wood basic density of most species from the study sites differed among the tree sections: it was higher at the stem than at the branch which was higher than roots.

The wood basic density information is a very important variable in addition to DBH to predict biomass (Chave *et al*., 2005). However, the lack of wood basic density information of most tree species in the tropics, impede the use of tree wood density to predict biomass. By providing wood basic densities, this study contributed additional information for particular sampled tree species. The average basic density of all sample trees found in the woodland was 0.59, which is in the range with some previous studies in miombo woodland and afromontane rainforest as reported by Malimbwi *et al*. (1994) and Munishi and Shear (2004), respectively. The average basic densities for the dominant tree species were 0.70 g cm^{-3}, 0.70 g cm^{-3} and 0.36 g cm^{-3} for *Acacia sp*., *Balanites sp*. and *Commiphora sp*., respectively. These values are in line with those in global wood density database which reported average tree density for *Acacia sp*. to range from 0.44 to 1.2 g cm^{-3} while *Balanites sp*. from 0.66 to 0.69 g cm^{-3} and 0.27 to 0.64 g cm^{-3} for *Commiphora sp*. in Africa and tropical countries (Zanne *et al*., 2009).

Table 9: Wood basic densities of sampled tree species from *Acacia-Commiphora* woodland in Kiteto District

Tree species		**Basic Density(gcm^{-3})**				
Local name	**Botanical name**	**Stem**	**Branch**	**Root**	**Tree Average**	**Species Average**
Mgungamaji	*Acacia sp.*	0.66	0.63	0.56	0.61	0.70
Oitii	*Acacia* sp.	0.81	0.77	0.65	0.74	0.70
Endempe	*Acacia hockii*	0.8	0.77	0.7	0.75	0.70
Kloriti	*Acacia nilotica*	0.83	0.67	0.72	0.74	0.70
Mgunga chuma	*Acacia tortilis*	0.77	0.64	0.62	0.67	0.70
Olog'oswa	*Balanites aegyptiaca*	0.73	0.67	0.71	0.70	0.70
Osilale	*Commiphor aafricana*	0.39	0.38	0.29	0.35	0.36
Lairupai	*Commiphora sp*	0.30	0.33	0.33	0.32	0.36
Hirihiri	*Commiphora sp*	0.41	0.40	0.41	0.40	0.36
Mtundulu	*Dichrostachys glomerata*	0.71	0.64	0.64	0.66	0.66
Mhunungu	*Zanthoxylum chalybeum*	0.68	0.68	0.54	0.63	0.63
Mnyangwe	*Ziziphus mucronata*	0.65	0.42	0.44	0.50	0.50
Average		**0.65**	**0.58**	**0.55**	**0.59**	**0.59**

4.4 Estimation of Biomass, Carbon Stocks and Stand Volume

Acacia-Commiphora woodland like other forest types can contribute to reduction in greenhouse gases emission through C sequestration process. Since in the past there was no allometric equation specifically for this biome for predicting biomass, this study takes advantage of the developed models to assess the contribution to offset carbon dioxide which indicates the potential for inclusion in the REDD+ mechanism. In addition, forest parameters that describe directly the forest health such as volume, basal area and stem density for each predetermined DBH classes have been presented in Table 10 and discussed.

The final selected allometric equation with DBH only as independent variable described in section 4.1 was employed for estimating above and belowground biomass. The second equation with DBH and Ht as predictor variables was not used in biomass estimation. This was done so as to avoid cumulative error in estimating Ht as recommended by Mugasha *et al*. (2013a) as only three sample trees were measured for height in each plot for developing height-diameter relationship. In addition, since there was no tree with DBH exceeding the size of modelling trees, I believe that this choice will not produce biased estimates.

Above and belowground biomass were 32.45 and 12.36 t ha^{-1}, respectively. The biomass obtained was converted to carbon using a factor of 0.49 (Brown, 1997; Munishi and Shear 2004) which gave 15.90 t ha^{-1}, and 6.06 t ha^{-1}for above and belowground carbon stocks, respectively.

The estimated total tree carbon stock of 33.4 t ha^{-1} reported by Anderson *et al*. (2012) in similar vegetation was higher than 21.96 t ha^{-1} obtained in the current study. The discrepancy may be due to the fact that Anderson *et al*. (2012) excluded heavily deforested area and used biomass models obtained from different sites in predicting biomass. Moreover, the low carbon stocks found in this study might be due to extreme encroachment for subsistence farming and harvesting of trees for wood fuel. The variation of carbon stocks has been recognized by different authors (Zianis and Mencuccini 2004; Návar-Cháidez, 2010) as a function of stand age, site quality, climate and stocking of stands among other factors.

The aboveground carbon stock in the woodland was lower than that of miombo woodland in protected areas as estimated by Chamshama *et al.* (2004), Munishi *et al.* (2010) and Ryan *et al.* (2011) of around 21.34, 19.2 and 21.2 t ha^{-1}, respectively. Chamshama *et al.* (2004) estimated carbon stocks in general land of miombo woodland to be in the range of 7.93 to 17.58 t ha^{-1} which is similar to the present study. However, the total carbon stocks reported in the current study could even be higher if other pools such as soil, litter and dead woods were included. Kirby and Potvin (2007) showed that pasture land can store up to 46 t C ha^{-1}when all pools are considered. According to MacDicken (1997), tree biomass is greatly affected by tree size, among others.

The model developed in this study was also used to predict the belowground biomass from the forest inventory data. The tree belowground carbon stock in the woodland was estimated to be 6.06 t C ha^{-1}, contributing 28% of total carbon stocks. This amount is in line with other results in different vegetation types in the tropics. Malimbwi *et al.* (1994) found that the root biomass percentage for miombo woodland in Tanzania was 20% of the total biomass. The lower contribution of belowground biomass found by Malimbwi *et al.* (1994) could be either attributed by the fact that small and fine roots were not included in their model or due to the actual difference of belowground biomass between miombo woodlands and that of *Acacia commiphora* woodland. However, similar forest types were found to have different level of belowground biomass in miombo woodland as observed by Ryan *et al*. (2011) in Mozambique and Mugasha *et al*. (2013a) in Tanzania.

Carbon stock of any forest which normally describes its forest health is affected by stand parameters such as stocking, basal area and volume (Terakunpisut *et al.*, 2007). Table 10 presents the relevant stand parameters for this study.

Table 10: Stand paremeters (N stems ha^{-1}, G m^{2} ha^{-1} V m^{3} ha^{-1}) and below (BGC) and above ground (AGC) carbon stocks (t C ha^{-1}) per DBH class in *Acacia-Commiphora* woodland, Kiteto District

DBH CLASS	N	G	V	BGC	AGC	TOTAL C
0-4.9	490	0.39	1.52	0.63	0.66	1.29
5-9.9	317	1.23	6.09	1.56	2.58	4.14
10-14.9	73	0.81	5.35	0.98	2.23	3.20
15-19.9	54	1.19	7.77	1.14	3.19	4.33
20-24.9	18	0.66	4.38	0.55	1.78	2.33
25-29.9	9	0.47	3.48	0.38	1.41	1.79
30-34.9	4	0.31	2.56	0.25	1.03	1.28
35-39.9	3	0.28	1.93	0.17	0.77	0.94
40-44.9	1	0.14	1.26	0.10	0.50	0.60
45-49.9	1	0.15	1.22	0.09	0.48	0.57
>49.9	1	0.33	3.24	0.21	1.27	1.48
TOTAL	971	5.96	38.8	6.06	15.9	21.96

Stand volume estimated using the selected allomeric equation with DBH only was 38.8 m^{3} ha^{-1} (Table 9). This volume was more or less the same as that of 43.9 reported by Chamshama *et al.* (2004) for miombo woodland in general land. However, in protected land miombo woodlands can have as much as 78 m^{3} ha^{-1} as reported by Zahabu, (2008). The low volume observed could be explained by large number of small trees (saplings and regenerants) which contributed very little. In addition, low architecture of *Acacia-Commiphora* vegetation (maximum Ht attained is and the spread of the crown is low) suggests that the tree have low volume than miombo trees. Hence, the observed low carbon stock in the woodland is associated with the low volume, among other factors. Anthropogenic activities may have significantly contributed to the current low volume in this woodland due to the presence of many regenerants and saplings which indicates extensive disturbances. Plate 3 shows that large areas of the study site have been and are still being cleared for cultivation (Plate 3). The presence of few big trees (Figure 2) especially the Acacia species indicated that large trees were harvested for charcoal making, as it was observed during field work. It is known that most of *Acacia* species have high calorific value (Malimbwi and Zahabu, 2008) making them suitable to harvesting for woodfuel.

Plate 3: The left photo shows destruction of carbon pools for cultivation, the right photo shows tree regeneration due to past disturbances in *Acacia-Commiphora* woodland in Kiteto District (Photo: Fieldwork 2013).

The DBH for all tree stems sampled in the woodland ranged from 1 to 66.8 cm. A total of 1569 tree stems from 21 species were found and recorded from the woodland. The stem density of the woodland with DBH $\geq$ 1cm was 971 trees stems ha^{-1} with a basal area of 5.96 m^2 ha^{-1}. High stem density in the woodland was observed in the three dominant species of *Commiphora africana* (334 N ha^{-1}), *Balanites aegyptiaca* (138 N ha^{-1}) and *Acacia tortilis* (71 N ha^{-1}) and these species accounted for about 56% of the total stand density. The distribution of the number of stems per hectare in each DBH classes followed the expected reversed J-shaped trend (Fig. 2). This indicates good forest regeneration and continuous recruitment trend. The estimated stems density in this study consisted of numerous young trees which contributed little to biomass and carbon stock. However, this indicated great potential for future sequestration if the forest will be better managed with minimal disturbance.

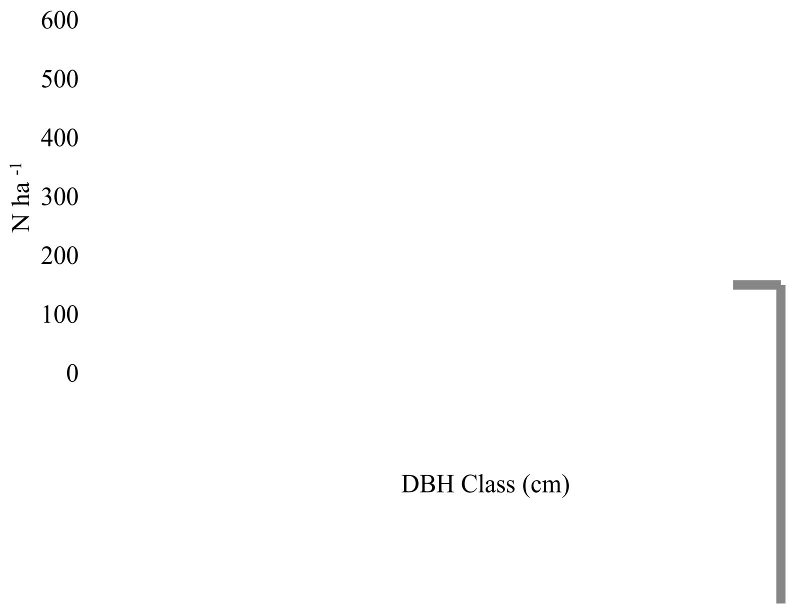

Figure 2: Stem density distribution in different DBH size classes in *Acacia-Commiphora* woodland in Kiteto District, Tanzania

4.4.1 Carbon storage in different DBH classes

Capacity of individual trees to store carbon varies with tree size (Terakunpisut *et al.,* 2007) which reflects stand volume and basal area and their contribution to overall forest varies due to difference in number of trees per ha represented in each diameter class (Mugasha *et al*., 2013b). In this study, trees were grouped in classes and their corresponding stand volume and basal area which affected carbon stocks are shown in Figure 5. The general trend was that, as the tree basal area and volume increased the carbon stocks also increased. The DBH class 15 - 19.9 cm contained most carbon (19.7%) of the total woodland followed by 5 - 9.9 cm (18.9%). The later DBH class had slightly large basal area of 1.23 $m^2 ha^{-1}$ with low carbon stocks compared to 1.19 $m^2 ha^{-1}$ that of the former DBH class with high carbon stocks. Apart from individual tree volume, the observed irregularity might be due to type and number of tree species contained in particular DBH class. Regenerants and saplings (DBH < 5 cm) contributed small amount of carbon stocks despite high number of stems due to their low volume. DBH class >49.9 cm with only one tree contributed significant amount of carbon stocks. The potential of big trees to carbon storage had also been revealed by many researchers (Zahabu, 2005; Mugasha *et al*., 2013a).

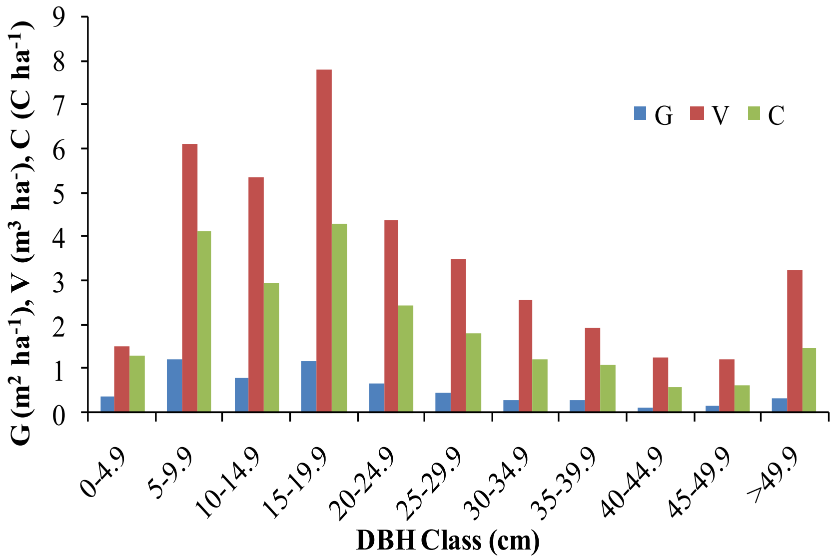

Figure 3: Basal area, volume and carbon stocks per hectare in different DBH size classes in *Acacia-Commiphora* woodland, Kiteto District

4.4.2 Contribution of dominant tree species to carbon stocks

Three tree species namely *Commiphora africana*, *Acacia tortilis* and *Balanites aegyptiaca* dominated the woodland and accounted for 68.7% of the total carbon stocks. The contribution of each tree species is presented in Figure 3.

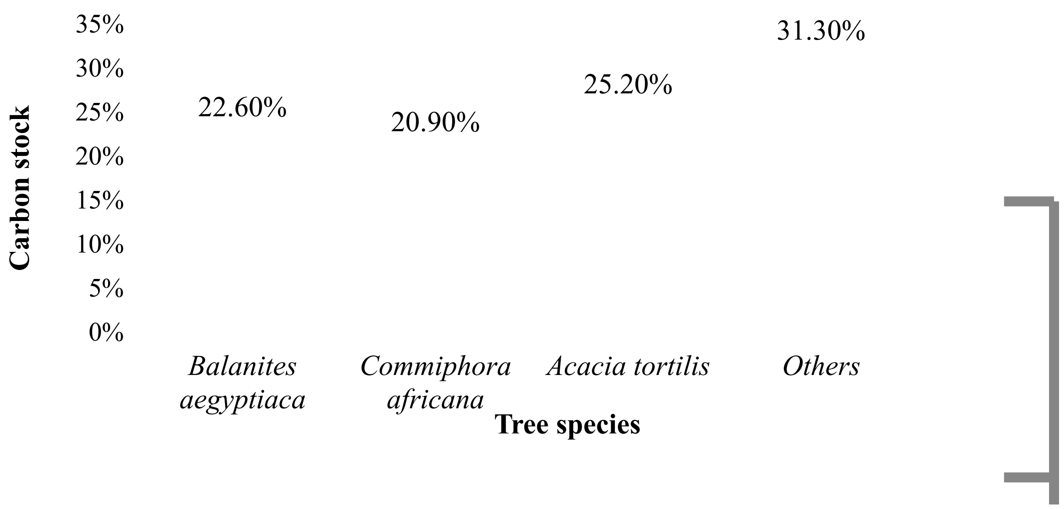

Figure 4: Contribution of the dominant tree species to carbon stock in *Acacia - Commiphora* woodland in Kiteto District.

The dominant species, namely; *Commiphora africana*, *Acacia tortilis* and *Balanites aegyptiaca* together contained 15.08 t C ha $^{-1}$ in the woodland and these three species accounted for 68.7 % of the total carbon stock. *Commiphora africana* was the most abundant species in terms of numbers (34%) but contributed only 20.9% of total carbon stock, an amount which was lower than 22.6% for *Balanites aegyptiaca* and 25.2% for *Acacia tortilis* which accounted for 14% and 7% of stem densities, respectively. *Acacia tortilis* had the highest biomass, but with relatively fewer stems, indicating that the majority were large trees. Apart from dominant tree species, other species together contributed 31.3% of the total carbon.

4.5 Comparison Between Two Approaches of Biomass Estimation

Two approaches for estimating biomass and their subsequent carbon stocks were compared. *Z*-test was used to compare means for predicted aboveground biomass of the two approaches. The equations for the two approaches are given hereunder;

Approach 1: $AG = 0.1879 \times DBH^{2.2904}$

Approach 2: $AG = V \times BD \times BEF$

Where;

AG is the aboveground biomass, DBH is the diameter at breast height, V is the summation of tree stem and branch volume, BD is the average tree basic density and BEF is the individual tree biomass expansion factor i.e. ratio of tree above ground biomass to stem biomass.

Z test revealed that there was no significant difference ($P > 0.05$) in predicted biomass when both approaches were employed. Graphical comparison between the two approaches is presented in Figure 5.

From the graph, it can be deduced that biomass of small to medium trees sizes are better predicted by either of the two approaches. But as the trees get larger in DBH, the second approach slightly overestimates predicted biomass, though not significantly ($P < 0.05$). The MPE% of the first approach is less compared to the second one though both are not significantly different from zero ($P < 0.05$) indicating non-significant overestimation of aboveground biomass by 0.15% and 4.14% for the first and second approach, respectively. This suggests that both approaches can be used on different occasions depending on the precision required. Biomass allometric equations are more precise in a sense that variables (DBH and Ht) are directly measured. In the other approach, variables like BEF and BD are estimated thus rendering uncertainity in computing biomass. Moreover, basic densities of all species in the woodland are not known and using sample tree basic densities may introduce errors. Overestimation of large trees was also observed by Soares and Tomé (2004) in plantation forest and suggested the use of age - dependent BEF's if allometric equations cannot be applied. Moroever, Petersson *et al*. (2012) cautioned on the use of BEF in estimating biomass as it may result into biased estimates and suggested to be used where biomass allometric models are absent.

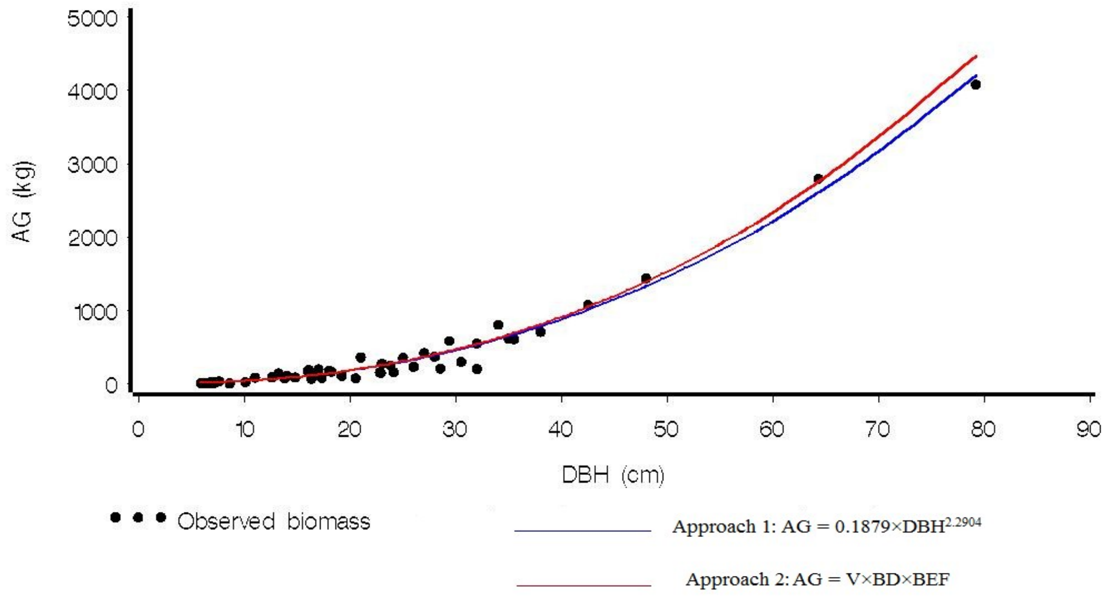

Figure 5: Comparison of aboveground biomass estimation over DBH between the two approaches for *Acacia-Commiphora* woodland, Kiteto District

CHAPTER FIVE

5.0 CONCLUSIONS AND RECOMMANDATIONS

5.1 CONCLUSIONS

In this study, models were developed using either DBH alone or combination of DBH and Ht and they both appeared to be useful for both volume and biomass prediction since most part of the variations were explained by predictor variables which are common recorded in forest inventories.

The observed average tree basic densities fall within the range of other forest and woodlands such as Miombo woodlands in Tanzania and other Africa and tropical countries at global level.

Although the observed carbon stock was much lower when compared to other protected forest/woodlands, the potential of carbon storage is still high enough for communities adjacent to these forest to benefit from REDD+.

Comparison between carbon stock estimates computed from the developed biomass allometric equations with those derived from volume and tree basic density showed that there was no significant difference between the two approaches. Both models can be used in different occasions depending on the desired precision.

5.2 RECOMMENDATIONS

The general recommendation is that since this study was conducted in village land with no any protection status, more studies are needed to cover variation in protected areas where this woodland is most predominant.

Since Models with both DBH and Ht did not show much improvement over the one with DBH alone and Ht measurement is very uncertain in most forests, it is recommended that the models with only DBH as predictor variable be used within the DBH range of the sampled trees in woodlands with similar conditions.

The basic densities determined for the sampled tree species will help improve the existing database. However, basic densities of other tree species associated with the woodlands needs to be explored since they had some contribution to carbon stocks.

Carbon stocks in the woodlands can be improved by attracting adjacent communities to participate in sustainable management through incentive based mechanism such as REDD+.

Biomass allometric equations are recommended for carbon stocks estimation since predictor variables such as DBH can be obtained or measured easily. Where biomass equations are not available, average tree basic density, stand volume and biomass expansion factors can be used to provide rough estimates of carbon stocks.

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APPENDICES

Appendix 1: Data sheet for forest inventory

Village: …………………… District: ………..…Date:…………………

Altitude ………… Eastings ………..….. Northings ……..……………...

Transect No. ……..…. Plot No: ……..

Tree no.	Local (tribe)/ botanical name	Dbh (cm)	Ht(m)

Appendix 2: Data sheet for aboveground destructively sampled trees

Date……………Tree No. ……..…. …..Local/Botanical name:……………….

Billet No.	Stems				Branches				Leaves& Twigs	
	Length (cm)	Mid Diameter (cm)	GW (Kg)	DW (Kg)	Length (cm)	Mid Diameter (cm)	GW (Kg)	DW (Kg)	GW (Kg)	DW (Kg)

Appendix 3: Datasheet for aboveground samples

Sample ID	Stems			Branches			Twigs and Leaves		
	Green Weight (Kg)	Dry Weight (Kg)	Biomass ratio	Green Weight (Kg)	Dry Weight (Kg)	Biomass ratio	Green Weight(Kg)	Dry Weight (Kg)	Biomass ratio
1									
2									
3									
4									
5									

Appendix 4: Datasheet for belowground destructively sampled trees

Tree No.	Root Crown		Largest root			Medium root			Smallest root		
	GW (Kg)	DW (Kg)	Diameter (cm)	GW (Kg)	DW (Kg)	Diameter (cm)	GW (Kg)	DW (Kg)	Diameter (cm)	GW (Kg)	DW (Kg)

Appendix 5: Datasheet for belowground samples

Sample ID	Root Crown		Largest root			Medium root			Smallest root		
	GW (Kg)	DW (Kg)	Diameter (cm)	GW (Kg)	DW (Kg)	Diameter (cm)	GW (Kg)	DW (Kg)	Diameter (cm)	GW (Kg)	DW (Kg)

Appendix 6: Data for destructively sampled trees summary

Tree No.	Local name	Botanical name	DBH	HT	Tree biomass(kg)				R/S	BEF	Tree volume(m^3)		Form factor
					Root	Stem	Branch	L&T			Stem	Branch	
1	Mgungachuma	*Acacia tortilis*	64.3	13.5	443.97	2428.9	241.0	128.3	0.159	1.15	3.071632	0.188208	1.34
2	Mpome	*Commiphora*	13.8	7.1	26.6	56.6	6.9	14.3	0.342	1.37	0.107128	0.009917	0.91
3	Mgungachuma	*Acacia tortilis*	16.4	6.1	34.9	59.2	14.5	62.3	0.257	2.30	0.094317	0.013886	1.19
4	Mnyangwe	*Ziziphus*	16.1	6.8	34.5	113.9	11.8	63.6	0.182	1.66	0.144336	0.168027	0.44
5	Olog'oswa	*Balanites*	23.8	5.3	95.5	130.1	46.4	78.1	0.375	1.96	0.166714	0.025216	1.23
6	Mpome	*Commiphora*	32	8.3	62.3	162.4	15.9	25.9	0.305	1.26	0.43253	0.021621	1.47
7	Mpome	*Commiphora*	24.1	6.2	36.2	120.4	14.6	23.1	0.229	1.31	0.312915	0.026626	0.83
8	Lairupai	*Commiphora sp*	8.6	4.7	2.28	4.4	1.6	3.9	0.232	2.26	0.01189	0.001138	2.10
9	Mhunungu	*Zanthoxylum*	27	8.6	125.1	282.7	50.4	90.6	0.295	1.50	0.341996	0.0341	1.31
10	Mgunga	*Acacia tortilis*	38	12.6	198.0	589.7	10.9	110.7	0.278	1.21	0.920410	0.019576	1.52
11	Mtunduru	*Dichrostachys*	12.6	7.3	33.7	39.8	14.7	38.2	0.364	2.33	0.035643	0.038877	1.22
12	Mtunduru	*Dichrostachys*	14	6.1	24.9	31.4	36.7	42.6	0.225	3.52	0.049578	0.044816	0.99
13	Lairupai	*Commiphora sp*	20.5	5.4	35.4	60.2	3.8	13.9	0.455	1.30	0.126375	0.007533	1.33
14	Lairupai	*Commiphora sp*	19.2	5.7	31.6	86.8	4.0	21.2	0.282	1.29	0.162859	0.008677	0.96

15	Olog'oswa	*Balanites*	12.6	5.7	15.1	46.6	3.6	42.6	0.163	1.99	0.039585	0.003891	1.63
16	hirihiri	*Commiphora sp*	26	7.3	43.5	177.9	20.9	36.9	0.185	1.33	0.298853	0.03497	1.16
17	Lairupai	*Commiphora sp*	10.1	4.2	7.2	16.7	3.4	4.9	0.287	1.50	0.025517	0.004978	1.10
18	Mgungachuma	*Acacia tortilis*	79.2	14.4	549.6	3904.3	29.7	149.0	0.135	1.05	5.229913	0.034527	1.35
19	Mgungamaji	*Acacia sp*	29.4	10.4	145.5	509.7	18.2	59.25	0.248	1.15	0.545660	0.003787	1.21
20	Mpome	*Commiphora*	22.8	5.9	49.1	106.9	7.0	45.9	0.307	1.50	0.215052	0.016693	1.04
21	hirihiri	*Commiphora sp*	16.3	7.7	13.2	52.7	5.7	14.2	0.182	1.38	0.111310	0.009636	1.33
22	Mgungamaji	*Acacia sp*	32	10.3	180.2	366.7	77.1	107.8	0.327	1.50	0.579811	0.090155	1.24
23	Mpome	*Commiphora*	28.5	7.3	87.4	171.8	8.2	31.4	0.413	1.23	0.430814	0.01972	1.03
24	Lairupai	*Commiphora sp*	6.7	3.9	2.2	3.1	1.0	3.7	0.282	2.56	0.007500	0.00147	1.53
25	Mpome	*Commiphora*	7	4.2	4.2	3.6	1.1	1.7	0.664	1.78	0.010553	0.002745	1.22
26	Olog'oswa	*Balanites*	6.3	4	2.5	4.1	1.3	6.2	0.213	2.81	0.005218	0.001184	1.95
27	Mgunga	*Acacia tortilis*	7.3	4.6	8.0	7.7	3.4	8.7	0.403	2.59	0.012571	0.003677	1.18
28	Mpome	*Commiphora*	6	4.4	3.6	3.3	1	2.8	0.509	2.16	0.002753	0.001798	2.73
29	hirihiri	*Commiphora sp*	5.9	3.9	4.2	3.4	4.4	3.9	0.359	3.44	0.005767	0.006277	0.89
30	Mtunduru	*Dichrostachys*	6.9	13	13.6	7.9	12.1	7.6	0.492	3.51	0.008961	0.010381	2.51
31	Mgungachuma	*Acacia tortilis*	35.5	12.2	219.2	494.8	54.8	62.7	0.358	1.24	0.808335	0.040462	1.42
32	Mgungamaji	*Acacia sp*	48	14.9	262.7	1294.3	32.1	115.5	0.182	1.11	1.823435	0.041963	1.45

33	Mgungamaji	*Acacia sp*	25	9.9	135.4	247.4	22.4	86.9	0.380	1.44	0.363975	0.014591	1.28
34	Mgungachuma	*Acacia tortilis*	42.5	12.6	218.4	931.9	33.8	110.9	0.203	1.16	1.292624	0.056692	1.32
35	Mpome	*Commiphora*	30.5	7.9	74.0	206.8	7.1	87.9	0.245	1.46	0.438304	0.027314	1.24
36	Mgungamaji	*Acacia sp*	34	11.8	176.2	608.1	98.1	102.4	0.218	1.33	0.764105	0.079599	1.27
37	hirihiri	*Commiphora sp*	28	5.8	84.9	315.5	32	24.8	0.228	1.18	0.577131	0.0595	0.56
38	Kloriti	*Acacia nilotica*	18	6.1	39.4	108.9	23.7	48.0	0.218	1.66	0.142800	0.025788	0.92
39	Mpome	*Commiphora*	22.9	7.4	53.3	106.4	19.5	24.5	0.355	1.41	0.202331	0.016578	1.39
40	Olog'oswa	*Balanites*	18.2	8.1	50.7	122.2	23.3	24.1	0.299	1.39	0.132326	0.022661	1.36
41	Olog'oswa	*Balanites*	23	7.3	45.0	230.8	16.0	29.7	0.163	1.20	0.285942	0.018748	1.00
42	Mgungachuma	*Acacia tortilis*	14.8	10.2	24.9	63.5	6.4	20.4	0.275	1.42	0.121649	0.01027	1.33
43	Mpome	*Commiphora*	17.3	6.1	23.9	46.3	15.4	21.2	0.289	1.79	0.102322	0.023514	1.14
44	Endempe	*Acacia hockii*	13.2	6.4	32.3	67.8	36.5	40.2	0.223	2.13	0.071565	0.030928	0.85
45	Oitii	*Acacia sp*	7.6	4.2	11.9	9.5	4.9	21.9	0.329	3.81	0.009782	0.00462	1.32
46	Endempe	*Acacia hockii*	11	6.4	13.7	36.4	16.2	32.0	0.161	2.33	0.030803	0.015851	1.30
47	Olog'oswa	*Balanites*	35	10.6	156.2	404.7	121.6	93.8	0.252	1.53	0.582911	0.062721	1.58
48	Oitii	*Acacia sp*	16	9.1	48.7	122.7	32.4	27.1	0.267	1.49	0.120127	0.029115	1.23
49	Endempe	*Acacia hockii*	17	8.2	48.1	106.8	47.7	47.3	0.238	1.89	0.127941	0.045925	1.07
50	Olog'oswa	*Balanites*	21	21	84	243.6	40	75.7	0.233	1.48	0.268425	0.040602	0.87