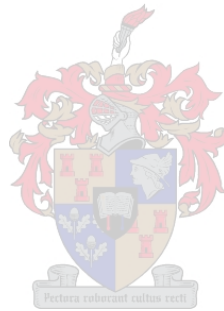


Estimating carbon sequestered in the *Cryptosepalum* forest in Mwinilunga District of North-western Province, Zambia

by
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*Thesis presented in partial fulfilment of the requirements for the degree
of Masters of Science in Forestry in the Faculty of AgriSciences at
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December 2017

Declaration

By submitting this thesis electronically, I declare that the entirety of the work contained therein is my own, original work, that I am the sole author thereof (save to the extent explicitly otherwise stated), that reproduction and publication thereof by Stellenbosch University will not infringe any third- party rights and that I have not previously in its entirety or in part submitted it for obtaining any qualification.

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Abstract

Cryptosepalum forests are an important part of the forest ecosystem in Mwinilunga district of the North-western Province, Zambia. Though they occupy only 3-5 % of the national total land area, their distribution at the local level, despite not being documented, is high. *Cryptosepalum* forests cover large areas in both the Mwinilunga and Solwezi districts in the North-western Province and parts of the Western Province, extending in to the border areas of Angola.

The estimation of carbon in the forest is currently an essential component in the implementation of emergent carbon credit market initiatives. The most important carbon credit market in Zambia is the United Nations Reducing Emissions from Deforestation and forest Degradation (UNREDD⁺) under the United Nations Framework Convention on Climate Change (UNFCCC, 1998). This necessitates the use of appropriate allometric models for accurate biomass prediction which are not readily available. The aim of this study was to develop site/species specific above-ground allometric models for the *Cryptosepalum* forests in the Mwinilunga district. The data was collected from one site namely *Kalemalema* in the Chiwoma area. It covers a wide range of tree sizes in terms of DBH and height i.e. 6.2–58.9 cm and 4.0–22.3 m, respectively. Above-ground biomass models were developed from 22 destructively sampled *Cryptosepalum* trees. The model fitting showed that large parts of the biomass variation ($R^2 = 57\%$) were explained by DBH and height. The inclusion of height increased the explanation of biomass variation from 44 to 57%. Therefore, it is recommended that height should be used as an additional independent variable. The species-specific model with the best fit is: Total Above-ground Biomass = $\ln(B) = \beta_0 * (\exp((\beta_1 * \ln(DBH)) + (\beta_2 * \ln(Ht))))$ (Where: $\beta_0 = 1.10349147$; $\beta_1 = 1.1157$; $\beta_2 = 0.01479$). When applying this model, biomass and carbon quantities for this forest type was estimated at 395.5 Mg ha⁻¹ and 197.8 Mg C ha⁻¹, respectively. When applying the root-to-shoot ratio of 1: 0.37, the Below-ground Biomass was estimated at 146.7 Mg ha⁻¹; resulting in an equivalent of 73.4 Mg C ha⁻¹ as Below-ground Carbon. This result compares favourably with the other studies for tropical evergreen forests in Africa. Therefore, it can be applied in the estimation of biomass and carbon for the *Cryptosepalum* forests in the Mwinilunga district under the UNREDD⁺ mechanism in Zambia.

Opsomming

Die *Cryptosepalum* bos is 'n belangrike deel van die ekosisteme in die Mwinilunga-distrik van die Noordwes Provinsie van Zambië. Hierdie bos-tipe beslaan slegs 3 tot 5% van die grondgebied van Zambië, maar dit kom wydverspreid voor op plaaslike vlak (alhoewel dit nie baie akkuraat gedokumenteer is nie). Dit dek groot dele in beide Mwinilunga en Solwezi distrikte in die Noordwes Provinsie asook dele van die Westelike Provinsie met verdere uitbreiding tot in die grensgebiede van Angola.

Die bepaling van koolstofinhoud van die bos is tans 'n noodsaaklike komponent vir die verkryging van koolstofkrediete in ontluikende markte. Die belangrikste koolstofkrediet mark in Zambië is UNREDD+ (Verenigde Nasies se vermindering van emissies deur ontbossing en bos aftakeling) onder die Verenigde Nasies se raamwerkkonvensie oor klimaatsverandering (UNFCCC). Die bepaling van koolstof steun op die akkurate voorspelling van biomassa deur die gebruik van toepaslike allometriese modelle wat nie gereedlik beskikbaar is nie. Die doel van hierdie studie was om bogrondse allometriese modelle te ontwikkel wat groeiplek- en spesie-spesifiek is vir die *Cryptosepalum* bos in die Mwinilunga Distrik. Data is versamel van een groeiplek genaamd Kalemalema in die Chiwoma gebied. Dit dek 'n wye verskeidenheid van boomgroottes in terme van DBH (deursnee op borshoogte) en boomhoogtes (van 6.2 tot 58.9 cm en 4.0 tot 22.3 m, onderskeidelik). Bogrondse biomassa modelle is ontwikkel uit destruktiewe monsters van 22 *Cryptosepalum* bome. Modelpassings het getoon dat groot dele van die variasie in biomassa ($R^2 = 57\%$) verklaar kan word deur DBH en hoogte. Die insluiting van die hoogte in die model het die hoeveelheid variasie in biomassa wat verklaar kan word in die model verhoog van 44 tot 57%. Daar word dus aanbeveel dat hoogte ook gebruik word as 'n onafhanklike veranderlike in die model. Die mees gepaste spesie-spesifieke model is: Totale bogrondse biomassa: $\ln(B) = \beta_0 * (\exp((\beta_1 * \ln(DBH) + (\beta_2 * \ln(Hoogte))))$ (Waar: $\beta_0 = 1.10349147$; $\beta_1 = 1,1157$; $\beta_2 = 0,01479$). Deur hierdie model is die hoeveelheid biomassa vir hierdie bostipe geskat op 395.5 Mg ha^{-1} en koolstofinhoud op $197.8 \text{ Mg C ha}^{-1}$. Deur die toepassing van die bogrondse : ondergrondse biomassa verhouding van 1 : 0.37, kan die ondergrondse biomassa geskat word op 146.7 Mg ha^{-1} ; dus ekwivalent aan $73.4 \text{ Mg C ha}^{-1}$ in wortelbiomassa. Hierdie resultaat vergelyk gunstig met ander studies vir tropiese immergroen woude in Afrika, en kan daarom gebruik word vir die skatting van biomassa en koolstof vir die *Cryptosepalum* bos in Mwinilunga Distrik onder die UNREDD+ voorskrifte in Zambië.

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Dedication

I dedicate this thesis to my:

Beloved wife: Doris Chimuka Kambayi, for taking care of the family while I was away;

Children: Zangi, Chisambo, Lushomo and Kisu;

Mother: Anna Sakuwaha;

Aunt: Rose Sakuwaha Mulambya;

Cousin: Esther Sakuwaha and niece: Kasamba Chimuka.

I love you, all.

Table of Contents

Declaration	i
Abstract	ii
Acknowledgements	iv
Dedication	v
Table of Contents	vi
List of Tables	x
List of Figures	xi
List of Acronyms	xii
Chapter 1: Background	1
1.1. Zambia.....	1
1.2. North – western Province	2
1.3. Mwinilunga District	3
1.4. Cryptosepalum Forests	5
1.4.1 Rationale for estimating carbon sequestered in the Cryptosepalum forests	6
1.5 Problem Statement	7
1.6 Study objective.....	8
1.7 Research question	8
Chapter 2: Literature Review	9
2.1 Allometry	9
2.1.1 Application of allometric biomass equations globally and in Africa.....	10
2.1.2 Difference between Miombo woodlands and Cryptosepalum forests	11
2.1.3 Pantropical vs. species – specific biomass estimation models.....	12
2.2 Forest inventories and biomass studies in Zambia.....	14
2.2.1 Early National / Regional Forest Inventories in Zambia	14
2.2.1 District Forest Inventories.....	15
2.2.2 National Wood Cover and Wood Biomass Inventories in Zambia.....	15
2.2.3 SADC Wood Energy Survey	15

2.2.4 Zambia Forestry Action Programme (ZFAP)	16
2.2.5 Food and Agriculture Organization (FAO) Global Forest Resource Assessment estimate..	17
2.2.6 Other Forest Inventories in Zambia (1990s – 2000s)	17
2.3 Review on Materials and Methods.....	19
2.3.1 Review on different Research Designs	19
2.3.2 Field Work (Including Measurements)	20
2.3.3 Effects of moderate thinning.....	21
2.3.4 Review of Laboratory Procedures.....	22
2.3.5 Data Analysis	22
Chapter 3: Materials and Methods	24
3.1 Study Area location and general description	24
3.1.1 Study Area Location	24
3.1.2 Climate.....	25
3.1.3 Vegetation	26
3.1.4 Soil Conditions.....	27
3.1.5 Biodiversity.....	27
3.1.6 Forest Land Use and Ecological Status.....	28
3.2 Methods.....	28
3.2.1 Field Work	28
3.2.2 Sampling	29
3.2.3 Surveying the Sample Plots	29
3.2.4 Acquiring tree data.....	30
3.3 Laboratory Work.....	33
3.3.1 Oven - drying	33
3.3.2 Wood density determination	33
3.4 Data analysis and modelling	34
3.4.1 Stand density (SD)	34
3.4.2 Assumptions.....	35

3.4.3 Model selection	35
3.4.4 Biomass estimation	35
3.4.5 Above–Ground Carbon (AGC).....	37
3.4.6 Below-Ground Biomass (BGB)	37
Chapter 4: Results.....	39
4.1 Basic Forest Information.....	39
4.1.1 Stand Characteristics.....	40
4.1.2 Diameter at Breast Height (DBH) distribution	41
4.2 Height vs. DBH models	41
4.3 Tree Component Biomass Models	44
4.3.1 Wood Density	45
4.3.2 Stem Biomass.....	46
4.3.3 Main Branch Base Biomass	47
4.3.4 Main Branch Biomass.....	47
4.3.5 Sub_branch model.....	48
4.3.6 Model for foliage biomass	51
4.4 Total Tree Biomass	55
4.4.1 Details of the best fitting model.....	57
4.4.2 Up-scaling of biomass and carbon from plot to hectare level.....	58
4.4.3 Comparison of tree biomass by component.....	59
4.5 Below Ground Biomass	60
Chapter 5: Discussion.....	61
5.1 Sample size	61
5.2 DBH distribution.....	61
5.3 Use of height as an independent variable.....	62
5.4 Use of wood density in the calculation of stem and main branch volume.....	63
5.4.1 Wood Density variability along the stem (butt–end, middle and top-end).....	63
5.4.2 Wood density as an independent variable.....	64

5.5 Collinearity.....	65
5.7 Biomass estimation by component	66
5.7.1 Stem wood biomass as % of total biomass	66
5.7.2 Branch wood biomass as % of total biomass.....	66
5.7.3 Foliage biomass as % of total biomass	67
5.8 Above – ground biomass distribution per DBH class.....	68
5.9 Comparison of <i>Cryptosepalum</i> AGB and AGC levels with other forests	69
5.10 Forest management implications	69
5.11 Recommendations.....	74
Chapter 6: Conclusion	75
Chapter 7: References	77
Chapter 8: Appendices	86

List of Tables

Table 3-1 Calculation of the mean R: S ratio using two similar woodland categories.....	37
Table 4-1: Variation in forest characteristics per plot.....	40
Table 4-2: Comparison of Height vs. DBH models.....	43
Table 4-3: Summary of mass, volume and wood density values.....	45
Table 4-4: ANOVA results on the difference in wood density as a result of disc position in the stem.	45
Table 4-5: Stem wood biomass per tree calculated as a product of mean wood density and volume	46
Table 4-6: Main Branch Base Biomass per each of the 22 trees	47
Table 4-7: The summary of the variation in main branch volume and main branch biomass per Tree	48
Table 4-8: The comparison of the two Sub-branch models	49
Table 4-9: Sub-branch biomass summary obtained using the model:	50
Table 4-10: Comparison of three tested foliage biomass models	53
Table 4-11: Comparison of total tree models tested	56
Table 4-12: Total Tree Biomass and Carbon estimates summarized in to quantity ha ⁻¹	59

List of Figures

Figure 1-1: The extent of open pit copper mining activities at Kalumbila Mine in NWP.....	3
Figure 1-2: Map of Zambia showing the extent of the <i>Cryptosepalum</i> forests (in deep green colour).	5
Figure 3-1: A <i>Cryptosepalum</i> forest stand in Kalemalema, Chiwoma area, Mwinilunga district....	24
Figure 3-2: Forest floor in a <i>Cryptosepalum</i> forest stand with mosses but little grass.....	27
Figure 3-3: Lay- out of subplots in one sample plot.	30
Figure 3-4: The tree components in to which a destructively sampled tree was divided.	32
Figure 3-5: Cutting of the 1 m billets and removal of discs (left) and separating foliage from the twigs (right).	32
Figure 3-6: Determination of volume of ‘wedges’ using the water displacement method.....	34
Figure 4-1: <i>Cryptosepalum exfoliatum</i> subsp. <i>pseudotaxus</i> trees in the centre towering over sub- dominant species.	39
Figure 4-2: A soil pit (left) showing sandy soils (right) in a sampled <i>Cryptosepalum</i> forest stand ..	40
Figure 4-3: Histogram showing DBH variation among all the 22 sampled trees in the 11 sample plots	41
Figure 4-4: Ht vs. DBH scatterplot (a) and regression model (b) showing 95% confidence and prediction intervals.....	44
Figure 4-5: Predicted vs. Observed Ht (a) and Residual vs. DBH plot (b) for Ht vs. DBH model. ..	44
Figure 4-6: Effect of position on Wood density	46
Figure 4-7: Scatterplot (a) and regression line (b) of sub branch model	50
Figure 4-8: The Residuals vs. Fitted plot of the model:.....	51
Figure 4-9: The scatterplot (a) and regression line (b) of the foliage model.	54
Figure 4-10: The Residuals vs. Diameter plot of the foliage model with the best fit.	54

List of Acronyms

AGB	Above-ground Biomass
ANOVA	Analysis of Variance
BGB	Below-ground Biomass
CBD	Convention on Biological Diversity
CH	Crown height
cm	Centimetre
DBH	Diameter at Breast Height
DRC	Democratic Republic of Congo
DSA	District Situation Analysis
ESP	Environmental Support Program
FAO	Food and Agriculture Organisation of the United Nations
FRMP	Forest Resource Management Project
GDP	Gross Domestic Product
GIS	Geographical Information System
GMA	Game Management Area
GRZ	Government of the Republic of Zambia
Ht	Height
ha	Hectare
ILUA	Integrated Land Use Assessment
IMF	International Monetary Fund
IPCC	Inter-governmental Panel on Climate Change
kg	Kilograms
m	Metre
Mg C ha ⁻¹	Carbon in tonnes per hectare
Mg ha ⁻¹	Biomass in tonnes per hectare
MRV	Monitoring Reporting and Verification
NWP	North-western Province
RMSE	Root Mean Square Error
RSE	Residual Standard Error
SADC	Southern African Development Community
SASSCAL	Southern African Science Service Centre for Adaptive Land Management
SNDP	Sixth National Development Plan
SOC	Soil Organic Carbon
TAGB	Total Above-ground Biomass
UN	United Nations
UNCED	United Nation Conference on Environment and Development
UNFCCC	United Nations Framework Convention on Climate Change
UNREDD	United Nations Reducing Emissions from Deforestation and forest Degradation
USD	United States Dollars
WD	Wood Density
ZFAP	Zambia Forestry Action Programme

Chapter 1: Background

1.1. Zambia

Zambia, a Sub-Saharan developing country, lies between 15° 00' South and 30° 00' East. The country borders with Democratic Republic of Congo (DRC) in the north, Angola in the west, Tanzania in the north east, Malawi and Mozambique in the east and, Botswana, Zimbabwe and Namibia in the south (Aregheore, 2015). Its capital city is Lusaka and has a forecast population for 2015 estimated at 16.2 million (World Bank Country Report, 2016). According to the same report, Zambia's Gross Domestic Product (GDP) in 2014 was USD 27.07 billion. The country is divided into 10 provinces namely the North-western, Western, Northern, Eastern, Central, Southern, Copperbelt, Luapula, Lusaka and Muchinga.

The country's forest cover estimated at about 49.9 million ha (66% of the total land cover), is still considered relatively good (Mukosha and Siampale, 2009). However, the country records one of the highest annual deforestation rates globally at 250 000 to 300 000 ha per year (Day *et al.*, 2014). Another source (Chundama, 2009), has indicated an annual deforestation rate three times higher than this, putting the figure around 900 000 ha per year. According to Chundama (2009), this is among the top 20 highest rates of deforestation in the world. The main deforestation drivers are clearing for agriculture, mining, infra-structure development (roads, dams, airports etc.) and settlement, logging and charcoal manufacturing (Vinya *et al.*, 2011; Day *et al.*, 2014). This high deforestation is associated with abject poverty rated at 60.5%, implying that 60.5% of Zambians survive on less than one United States Dollar (USD) per day (World Bank Country Report, 2016). Despite being listed among the top 10 copper producing countries in the world in 2014 (Williams, 2015), Zambia was ranked 139th out of 186 countries in terms of global GDP per capita by the International Monetary Fund (IMF) in the same year (O'Sullivan, 2015). The country is classified as least developed with an unemployment rate for a 15 – 24 years age bracket standing at 23% and GINI Index now rated at 57.5% (2010 Census Report, Zambia). Since the GINI Index shows inequality between the rich and the poor, this high percentage shows that, the gap between the rich and the poor is wide and that poverty is rising. Due to this high poverty level, over 70% of the rural population depends on the forest for their livelihood (Chundama, 2009), thus exerting huge pressure on the forest resource. In order to mitigate this, the government is focusing on diversifying the economy to reduce the dependency on mining, which is destructive to the environment, to tourism, manufacturing (value addition chains) and sustainable agriculture (including livestock, forestry and fisheries), according to the Sixth National Development Plan (SNDP) (GRZ 2011). With such a low GDP growth, the Government of the Republic of Zambia is currently unable to adequately provide funding for social

amenities, let alone environmental and natural resource management including forests (Appraisal Report: Decentralised Forestry related Natural Resource Management Programme, 2013). This necessitates the search for alternative forest financing regimes such as carbon trading in order to increase the money earned from natural forest ecosystems.

1.2. North – western Province

The North-western Province (NWP), one of the 10 provinces of Zambia, is composed of 11 districts namely, Mwinilunga, Chavuma, Kabompo, Zambezi, Kalumbila, Mushindamo, Manyinga, Ikeleng'i, Mufumbwe, Solwezi and Kasempa. Its provincial headquarters is situated in Solwezi; 612 km from the capital city, Lusaka.

According to Mukosha and Siampale (2009), NWP has the highest forest cover and therefore holds the largest amount of forest biomass in the country. This could be attributed to the fact that NWP has the lowest population density in the country, standing at 5.8 persons per km² (2010 Census Report), low levels of agricultural activity and a high mean annual rainfall (Aregheore, 2015). Nevertheless, the forest cover is being threatened by not only clearing for agricultural production and, local demand for both wood and non-wood forest products, but also mainly large- scale copper mining activities at mines such as Kansanshi, Lumwana and Kalumbila. The extent of large-scale mining, for instance, at Kalumbila in NWP is shown in Figure 1.1. The small-scale mining licenses in the province are numerous. Despite this mining investment, local people are still poverty-stricken. The official statistics show NWP to be among the poorest provinces in Zambia, with high rates of overall poverty and extreme poverty standing at 67.0% and 46.1%, respectively (2010 Census Report). The high poverty level leads to many people sorely depending on the forests as a source for their livelihood, especially shifting cultivation since the mainstay of the majority is peasant farming. This scenario makes alternative forest financing mechanisms such as carbon trading even more critical.



Figure 1-1: The extent of open pit copper mining activities at Kalumbila Mine in NWP

(Photo source: Kalumbila Mine website)

This mine is less than 100 km from the study site. Up to 7,000 ha of forest area was cleared (Day *et al.*, 2014) to pave way for not only actual copper mining activities but also mine infrastructure development including roads, aerodrome and dam; the dam is shown at top right corner of the image. Part of the area cleared was initially a forest reserve.

1.3. Mwinilunga District

According to Mwinilunga District Situation Analysis (DSA, 2012), Mwinilunga, one of the 11 districts in NWP, is located in the extreme north-western part of the province and covers an area of 18,763 km². It shares borders with the Kalumbila district in the east, the Mufumbwe and the Kabompo districts to the south, the Ikeleng'i district and the Democratic Republic of Congo (DRC) in the north and Angola to the west. The district's administrative centre is located 290 km and 872 km away from Solwezi (Provincial headquarters) and Lusaka (Capital city), respectively.

The Mwinilunga district falls within the high-altitude region, standing at average of 1 355 m above sea level (Mwinilunga district, DSA, 2012). According to the same report, the two major rivers namely Lunga and Kabompo have steep valleys in the southern part with characteristic river gorges.

The Mwinilunga district forms part of the high rainfall region of NWP (with mean annual rainfall of 1 386 mm) and has a long rainy season due to its proximity to the Equatorial region in the DRC. This area includes all major soil types, ranging from pure sand to clay. Due to high annual rainfall, which leads to heavy soil nutrients leaching, the predominantly sandy soils in the northern part are generally

acidic and infertile. The soils in the southern parts range from heavy sandy loam, sandy to clayey loam, and are less acidic. This zone is described as a cassava based traditional subsistence farming system; a form of shifting cultivation commonly known in Zambia as Chitemene. This is considered as one of the major causes of deforestation in the country (Chundama, 2009).

In terms of vegetation, the Mwinilunga district is exceptionally rich by Zambian standards and the number of woodland species is estimated at 950-1 000 (Mwinilunga district, DSA, 2012). The same report indicates that this species richness is attributed to the relatively high rainfall, long rainy season and diversity of soil types. The vegetation types for which the district is specially known are the wet forests (Miombo) since they contain tropical rain-forest elements, the higher rainfall Kalahari sand habitats (*Cryptosepalum* forests) and the watershed plains. The wet forest or Miombo woodlands on one hand cover the well- drained, strongly leached, acidic soils which might vary in texture from almost pure clay to almost pure sand. The dominant species are from the genera *Brachystegia*, *Julbernardia*, *Isoberlinia* and *Marquesia*. The species that are very prominent in the under storey are *Monotes* and *Uapaca*. On the other hand, the *Cryptosepalum* forests are found in the southern parts of the district with *Marquesia* forests being found around Lwau area and Chipya in the north-eastern part both lying on the Kalahari sands. The map showing the extent of *Cryptosepalum* forests in Zambia is shown in Figure 1. 2. The *Cryptosepalum* forests type (locally known as 'Mavunda'), dominated by tree species *Cryptosepalum exfoliatum* subsp. *pseudotaxus* (locally named 'Mukung'u) are a dry evergreen forest type which occurs exclusively on the higher-rainfall Kalahari sands.

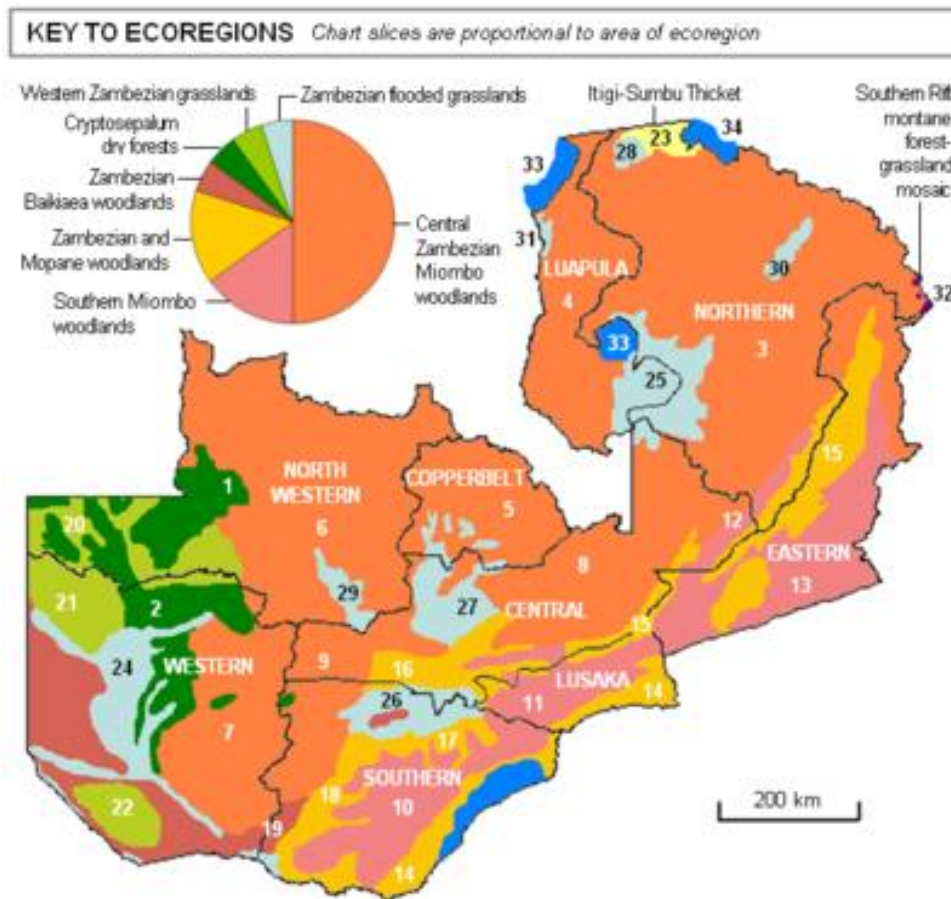


Figure 1-2: Map of Zambia showing the extent of the *Cryptosepalum* forests (in deep green colour).

Source: Fund and Hogan (2014).

1.4. *Cryptosepalum* Forests

According to Fund and Hogan (2014), the *Cryptosepalum* forests are sometimes referred to as Zambeian *Cryptosepalum* forests. These are said to be “dry” because they experience extensive seasonal dry periods, typically from May to October. This forest type is found at 1 100–1 200 m above sea level mainly in Zambia; covering 3-5 % of the country’s land area and is restricted to the North-western and the Western provinces of the country (Day *et al.*, 2014). The same forests are found in Angola, the DRC and Malawi; in the areas bordering with Zambia (Storrs, 1979). Although these forests are dry, they are evergreen in nature; they are said to be the largest area of tropical evergreen forests in Africa outside of the equatorial zone (Fund and Hogan, 2014). In NWP, these are confined to and drained by the Kabompo River and its tributaries, which forms part of the drainage basin of Upper Zambezi River. To the west, this area gives way to grassland where seasonal waterlogging suppresses tree growth. To the southwest lies the Barotse floodplain and to the north and the east, the eco-region gives way to the Miombo woodlands on soils containing higher nutrients. The *Cryptosepalum* forests represents a transition from Guineo-Congolian rainforests to Zambeian

woodlands. Hence, the forests are of moderate species richness, with a mixture of moist evergreen and woodland species. The dominant species is *Cryptosepalum exfoliatum* subsp. *pseudotaxus*. The extent of the *Cryptosepalum* forests is determined by the deep tertiary Kalahari sands of Aeolian origin, which are found under the eco-region (Fund and Hogan, 2014). This sand can reach more than 60 m in depth with high water tables (Fund and Hogan, 2014).

1.4.1 Rationale for estimating carbon sequestered in the *Cryptosepalum* forests

The Miombo woodlands, a semi-deciduous type of vegetation covering about 68.3 % of national forest area and 45.5 % of total land area, are the most dominant and economically important in Zambia (Day *et al.*, 2014). However, this study focuses on the *Cryptosepalum* forests, dry evergreen forests which accounts for 3-5 % of the national forest area (Fund and Hogan, 2014) for the following reasons:

- i. According to Day *et al.* (2014), Zambia is one of the nine pilot countries in the United Nations Collaborative Programme on Reduction of Emissions from Deforestation and Forest Degradation in Developing countries (UN-REDD⁺) and is currently at the first stage of REDD⁺ readiness. The country is earmarked to benefit from carbon trading; a forest self-financing mechanism where third world nations and their forest communities are compensated for preserving the forest. This mechanism requires up-to-date and credible estimates of carbon sequestration in the forests. Currently, these are not available for the *Cryptosepalum* forests. According to Integrated Land Use Assessment (ILUA I) (Mukosha and Siampale, 2009), Zambia is signatory to United Nations Conference on Environment and Development (UNCED) and Convention on Biological Diversity (CBD) agreements. Therefore, the country has a mandate to make available up-to-date and accurate information to key stakeholders, partners and the general public on changes in carbon stocks, forestry and natural resource management. Currently, the only information available is generalised for evergreen forests, which includes *Cryptosepalum* forests but offers no specific information on them as compared to adjacent forest types. Furthermore, the exercise for gathering this generalised data was undertaken at the national level; thus, the accuracy for specific forest types is quite low (Mukosha and Siampale, 2009). This study is poised to make a contribution to ILUA II (2010 – 2015) by providing forest specific carbon estimates and increase the chances of the *Cryptosepalum* forests to be considered for carbon trading under the UN-REDD⁺ mechanism.

- ii. According to Fund and Hogan (2014), this forest is said to grow on infertile Kalahari sand leading to little productive agricultural activities being undertaken in this area. The arable potential of the eco-region is equally low in the absence of substantial nutrient inputs into the system. This makes this forest type less attractive for small-scale agricultural activities and thus more suitable for carbon trading since the threat to clearing for agriculture is low. However, since the soils are of poor nutrient value, shifting cultivation (as destructive as this can be), may increase in the area. This may happen in an effort to increase agricultural production to meet food demand due to increased population resulting from mining activities amidst limited access to capital. The *Cryptosepalum* forests are without permanent surface water (Fund and Hogan, 2014). Therefore, this dry forest has remained relatively uninhabited by humans (fewer than five persons per km²), making the forest less prone to clearing for human settlement. Actually, wildlife habitat fragmentation and destruction have not yet occurred on a large scale and are unlikely to do so in the short term.
- iii. Since the forest is dense and evergreen, the undergrowth including grass is limited leading to insignificant disturbance by natural fire. Therefore, the threat of forest fires to carbon stocks managed in this area is negligible. Equally, native vegetation is difficult to clear making forest clearing limited.
- iv. Currently, the *Cryptosepalum exfoliatum* subsp. *pseudotaxus* is not an economically important timber species in Zambia. This implies that the threat to logging in mature stands is low.
- v. The forest covers part of West Lunga National Park and its surrounding Game Management Areas (GMAs) according to Fund and Hogan (2014). The same forest type also covers Lunda and Ndembo gazetted forest reserves. Therefore, the conservation efforts for the *Cryptosepalum* forests through carbon trading will have positive ripple effects on the management of the park, GMAs and the forest reserves.

1.5 Problem Statement

The *Cryptosepalum* forests are the largest evergreen forests outside of the Equatorial Rain Forest providing ecosystem services. These forests, therefore, have great potential to participate in carbon financing through Clean Development Mechanism under UN-REDD⁺. But, what is the accurate forest specific biomass and carbon stocking for the *Cryptosepalum* forests in the Mwinilunga district of the NWP? This information is not known because AGB estimation studies particular to these forests have not been undertaken. The national AGB estimated as being 108.2 Mg ha⁻¹ for all the evergreen forests in Zambia; a generalisation not specific to, but includes, the *Cryptosepalum*, the *Marquesia* and the

Parinari forests (Mukosha and Siampale, 2009). In addition, this national biomass estimation was done with high sampling error of 106.2 % (Mukosha and Siampale, 2009). Therefore, there is need to estimate the forest specific above-ground carbon content more accurately by determining its biomass if this forest is to be considered under the carbon financing initiative. The Below Ground Biomass (BGB) could then be estimated using the root: shoot (R: S) ratio (IPCC, 2006) as indicated by Mokany *et al.* (2006). Actually, the preparatory work for UNREDD⁺ implementation in Zambia, usually known as REDD⁺ readiness, is currently underway (Day *et al.*, 2014). Therefore, knowledge from this study could be useful in estimating above-ground carbon sequestered in, not only the *Cryptosepalum*, but also other natural forest stands in Zambia.

1.6 Study objective

The objective of this study is to develop a model for estimating the above-ground carbon content through the determination of the AGB in the *Cryptosepalum* forests in the Mwinilunga district.

1.7 Research question

This study will seek to answer the following question: What is the AGB estimate for this site using statistical models for upscaling?

Chapter 2: Literature Review

The estimation of biomass is a form of forest inventory; a process of quantifying (obtaining data on both quality and quantity) of vegetation biomass (Köhl *et al.*, 2006). This forms the basis for forest planning and forest policy formulation. Earlier concepts of sustainable forest management and forest inventory were focused primarily on timber production, but modern inventory concepts support a holistic view of forest ecosystems addressing multiple functions of forests including biomass. Biomass is defined as the living organic matter in plants that is produced by photosynthesis (Yuen *et al.*, 2016). This can be partitioned in to two components namely Above Ground Biomass (AGB) i.e. stem, branches, leaves, flowers and fruits above the soil surface and, Below Ground Biomass (BGB) i.e. root crowns, course roots and fine roots (Yuen *et al.*, 2016). Quantifying of vegetation biomass is needed in order to evaluate biological and economic productivity, fuel accumulation and nutrient allocation in the forest (du Toit *et al.*, 2014). Biomass studies have become crucial in the recent past arising from the need for determination of carbon sequestration in vegetation. Besides, the quest for understanding the impact of land cover changes and carbon fluxes has increased. The widespread interest in estimating biomass in tropical forests has increased with the advent of carbon accounting schemes such as UN-REDD⁺ (Yuen *et al.*, 2016). There are two ways used in determining carbon biomass; on one hand, biomass is determined directly from samples obtained from harvested trees through analytical means such as the use of carbon–nitrogen analyser. On the other hand, carbon can be calculated as a fraction of measured biomass (using ratios from 0.37 to 0.53) for various types of plants and trees (Yuen *et al.*, 2016). The preferred method for determining biomass is to destructively sample the plant, partition each by mass in to various constituent components (e.g. stem, branches, leaves, flowers, fruits, roots) and subsequently determine the carbon content of the various components using allometric relationships (Yuen *et al.*, 2016; Basuki *et al.*, 2009). According to Basuki *et al.* (2009), 50 % of biomass is made up of carbon.

2.1 Allometry

According to Yuen *et al.* (2016), the definition of allometry in biology was conceived as a study of how properties of an organism change with size-related traits. In other words, allometry designates the relative change of one biological trait ($\Delta Y/Y$) in relation to the relative change of a second one ($\Delta X/X$) (Sileshi, 2014). This, in tree biomass estimation, basically refers to mathematical equations relating biomass of an entire tree or individual tree components (e.g. stems, branches, leaves or roots) to one or more easily measured biophysical factors such as tree Diameter at Breast Height (DBH), tree height (Ht) or wood density (WD) (Basuki *et al.*, 2009; Paul *et al.*, 2016). Hence, one variable more difficult to measure e.g. biomass can be determined using another variable easier to measure

e.g. Diameter at Breast Height (DBH) (Picard *et al.*, 2015). The allometric scaling assumes a power function or is described by power laws because it is supported by the notion of growth as a multiplicative process (Picard *et al.*, 2015). According to Yuen *et al.* (2016) and Sileshi (2014), the power-law is sometimes referred to as law of simple allometry. In fact, the power-law relationships (with the function $-2/3$) were first recognised by Galton in 1879 (Yuen *et al.*, 2016). Huxley's book written in 1932, which described these relationships, was only published about half a century later and has been useful since. The power-law is one of the most commonly used forms of allometric equations in the calculation of biomass in Forestry. These laws are of the form:

$$Y = \alpha X^{\beta}$$

Equation 1

Where:

Y and X are the related variables

 α is the normalisation constant (Sileshi, 2014) β is the exponentOr its log form: $\ln(Y) = \ln(\beta_0) + \beta_1 (\ln X)$ (Sileshi, 2014);

Where:

Equation 2

Y = Biomass

X = DBH

 B_0 = intercept β_1 = exponent

The intercept (β_0) is hypothesized to be determined by several physiological and allocation traits of trees and thus can vary widely. The exponent (β_1), also called the allometric coefficient, can be perceived as a distribution coefficient for the growth resources between X and Y i.e. when X increases by 1%, Y increases by β %.

2.1.1 Application of allometric biomass equations globally and in Africa

Allometric equations have been used globally to estimate forest biomass (Basuki *et al.*, 2009). In Indonesia, for instance, biomass equations were used to determine biomass of moist tropical forests (Basuki *et al.*, 2009). In South East Asia, allometric models were used to determine the biomass of evergreen forests in Thailand (Yuen *et al.*, 2016) while a pantropical allometric model developed by Chave *et al.* (2005) was used to estimate biomass in moist tropical forests. This model was formulated

basing on the compilation of data since the 1950s from 27 study sites in America, Asia and Oceania. In Africa, an allometric model was developed using data collected from Central Africa (Ploton *et al.*, 2016) while another model was formulated for the Miombo forest in Tanzania (Mugasha *et al.*, 2013). Models can be applied either as generalized or site / species specific (Yuen *et al.*, 2016). On one hand, generalized models are in the form of multi-species equations for forests that have too many species to be sampled one by one; a good example is a tropical forest. On the other hand, site/species specific models are equations developed by sampling one particular species on a specific site (e.g. Magalhães and Seifert, 2015) or also across a spectrum of sites.

2.1.2 Difference between Miombo woodlands and *Cryptosepalum* forests

Species or site-specific biomass models are generally preferred over generalised ones. This is in line with observations made in studies such as Mugasha *et al.* (2013), Chave *et al.* (2014). This preference is due to inter-species and site characteristic variations that occur in many forest ecosystems particularly differences in allometry, architecture and wood density (Ngomanda *et al.*, 2013; Paul *et al.*, 2016). Intra-species AGB variations also exist among various sites due to differences in environmental conditions (including climate, soil, precipitation and topography) (Mugasha *et al.*, 2013). Due to these variations, the application of generalised or pantropical equations developed at locations that are different from that of application is limited even where the equation is species-specific (Yuen *et al.*, 2016). In Central Africa, for instance, the application of two above-ground models developed for Miombo woodlands (both using sample trees from the same site in the Morogoro region) in Tanzania to other Miombo forests in other regions within Tanzania is common (Mugasha *et al.*, 2013). This is because the number of allometric biomass models in existence for Sub-Saharan Africa is limited (Henry *et al.*, 2011) despite the fact that Miombo woodlands cover large areas in Africa; Miombo woodlands are found in south-eastern and central Africa and form a dominant vegetation type in Angola, Zambia, Tanzania, Malawi, and Zimbabwe (Mugasha *et al.*, 2013). The application of these models to other sites has been questionable given the differences that exist in climatic conditions, edaphic factors and topography. In addition, many biomass equations are basically ‘snapshots’ of biomass levels associated with a particular time of the year, e.g. wet or dry period, or periods when leaf shedding is or is not occurring. For instance, the use of equations developed during the period when trees were defoliated to one in which the trees are in full leaf may not be appropriate (Yuen *et al.*, 2016).

Due to the intra-species variation earlier alluded to, forests, including Miombo woodlands, are usually categorised in to dry, moist and wet. The genera that is dominant in these woodlands are *Brachystegia*, *Julbernardia* and *Isoberlinia* of the family *Fabaceae*, sub-family *Ceasalpinioideae*.

These genera are endemic to the Miombo eco-region. Despite their endemism and dominance, however, each of these genera contribution to numbers and biomass levels differently within and between communities (Frost, 1996). A scheme was proposed by Brown (1997) in which different allometric models could be used for different forests provided they fall in the same category of vegetation i.e. dry, moist and wet. In this case, a compromise is reached between variation in the environmental conditions and the availability of tree biophysical data; a major reason for generalisation. According to Chave *et al.* (2005), the wet forests are high rainfall lowland forests, which receive mean annual rainfall more than 3 500 mm and the moist forests have a marked dry season of 1- 4 months and they receive between 1 500 and 3 500 mm as mean annual rainfall. The third category namely the dry forests have a pronounced dry season during which the plants suffer serious water stresses for less than 5 months and the mean annual precipitation is less than 1 500 mm. In the dry Miombo, the above-ground woody biomass averages around 55 Mg ha⁻¹ whilst in the wet Miombo, 90 Mg ha⁻¹ is typical. It is believed that most of the tropical forest carbon sequestration takes place in moist tropical forests compared to the two other forest types (Chave *et al.*, 2014). Therefore, the generalisation of a model for all the Miombo woodlands is likely to result in over or under-estimation of the biomass levels. In any case, the *Cryptosepalum* forests are different from the Miombo woodlands. On one hand, the Miombo vegetation is described differently as semi-deciduous, semi- evergreen, drought deciduous or as simply deciduous. The *Miombo* forests are found mostly on clay soils (Lawton, 1964). The *Cryptosepalum* forests, on the other hand, are described as evergreen forests and mainly occurring on sandy soils (Lawton, 1964) despite both forest types being tropical. Consequently, if the generalisation of one model to all categories of the Miombo woodlands is debateable, how much more the generalisation of a model for the semi-deciduous Miombo woodland to the evergreen *Cryptosepalum* forests?

2.1.3 Pantropical vs. species – specific biomass estimation models

The generalisation of pantropical models is not the best option either because many of these were not only developed from small samples but also have narrow diameter ranges (Mugasha *et al.*, 2013; Paul *et al.*, 2016). Neither do the pantropical models always include twigs and branches, which means that these models are, more often than not, applied outside their valid data ranges. The way AGB is reported is also variable i.e. some researchers report woody biomass alone while others include foliage as part of woody biomass. Therefore, if one picks equations arbitrarily from existing literature and databases, the use of such models can result in unreliable estimation of forest biomass. This underscores the need to rigorously validate existing biomass models before such models are applied to local conditions (Sileshi, 2014). It is important to note that the formulation of the above-ground ‘global’ models for ‘dry forests’ was solely based on data collected from forests outside Africa (Chave

et al., 2005). There are no biomass models for the *Cryptosepalum* forests in Zambia except AGB models for the Miombo (Stromgaard, 1985; Chidumayo, 1990; Chidumayo, 2013). Although the number of sample trees used to develop the model by Stromgaard (1985) was comparatively large (i.e. 271), wet weight (kg/tree) was used as input variable instead of sample biomass. This means further data is required namely the dry to green (D: G) weight ratio of individual trees if the green biomass is to be converted into carbon (Mugasha *et al.*, 2013). The model formulated for the Miombo woodland in Zambia by Chidumayo (1990) was developed on trees with maximum DBH of 40-50 cm. Therefore, the application of this model on data with DBH higher than this range could lead to biased predictions. The maximum DBH for the data set used in this study was 58.9 cm. There has been emphasis in recent studies that pantropic allometric models may lead to the under-estimation of AGB of very large trees in areas where the trees are shorter but with large crowns (Chave *et al.*, 2014). The same authors point out that this is an issue because the large trees contribute a large fraction of the AGB stock in a tropical forest stand.

However, both the IPCC guidelines (IPCC, 2006) and the current standard operating procedures for carbon measurement such as described by Sileshi (2014) recommend the use of locally available generic equations. Species-specific models have been criticised in that they are generally based on small sample sizes due to the high cost of biomass measurement particularly of destructive sampling. The study by Chave *et al.*, (2014) analysed data obtained from globally distributed database of tree experiments involving destructive sampling in tropical forests, sub-tropical forests and savannah woodlands. Using the findings from the same study, the authors contend that, separate regression parameters for the dry, moist and wet vegetation types have not improved statistical performance of a biomass model. Thus, the models are consistent when applied to tropical, sub-tropical and savannah woodlands. The results of the same study show that once variation in diameter–height allometry is accounted for by using both DBH and Ht as independent variables, the pantropical AGB allometries are consistent across sites. This is with the view that the use of wood density in the model explains the variation in the growing conditions. Unfortunately, the IPCC guidelines (IPCC, 2006) and the current standard operating procedures for carbon measurement in Sileshi (2014) do not provide the guidance or standards for either selecting a model from the existing pool or developing a new one. As a result of this non-availability of guidelines, researchers involved in both the actual development and the application of biomass models are faced with a number of challenges. Firstly, a researcher that prefers using existing equations rather than developing new ones must also choose one among several equations that are available for one particular species. Sometimes, the sheer number of equations also makes the choice of biomass models from databases a daunting task (Sileshi, 2014). Secondly, a choice has to be made between species–specific and multi-species models. This problem

arises because there are inadequate species-specific equations for the species-rich tropical forests; thus, it is argued that the multi-species pan-tropical models are more appropriate (Chave *et al.*, 2005). Thirdly, a choice must be made between simple the bivariate power law (typical allometric) functions and models with multiple predictors. This challenge arises because the bivariate power-law models are believed to be too simple to deal with the complexity of tropical forest biomass. In addition, the increasing model complexity necessitates the use of large sample sizes and concurrent resource (time, labour) requirements.

Lastly, the many predictors with ill-understood relationships may result in uncertainty when developing new models with multiple predictors (Sileshi, 2014). The same author indicates that when constructing new models, the choice of predictors to be included in the final model is often challenging because the relationships among the many variables are not well understood. Although the generic models have a higher applicability and, consequently, are less costly, the site/species specific equations provide the most accurate biomass estimations within the data range of their formulation (Ngomanda *et al.*, 2014). However, the site/species specific equations are associated with uncertainty when used outside their calibration range (Paul *et al.*, 2016).

2.2 Forest inventories and biomass studies in Zambia

Forest inventories in general and biomass studies in particular have been conducted in Zambia. The outline of these exercises is as follows:

2.2.1 Early National / Regional Forest Inventories in Zambia

According to Mukosha and Siampale (2009), organized Forestry and forest management in Zambia began in 1930. The initial interest was in the establishment of plantations. This interest later moved to the measurement of indigenous forest resource productivity. The first attempt on forest inventory was done by the mines in the Copperbelt Province, to quantify available resources that could be used for refinery poles and mining structural timber.

Mukosha and Siampale (2009) also indicate that the first extensive regional forest inventory was done on the Copperbelt Province between 1942 and 1944. The same report adds that later a small-scale regional forest inventory was done in the Western Province between 1949 and 1951. This exercise targeted assessment of availability of sawn timber for concession harvesting for the Zambian Teak (*Baikiaea plurijuga*); the wood of this species was utilised for manufacturing railway sleepers for a railway company called Southern Africa Network (Mukosha and Siampale, 2009).

In both cases, neither carbon estimations through biomass calculations nor the use of allometric functions for the forest were involved.

2.2.1 District Forest Inventories

Mukosha and Siampale (2009) indicates that forest inventories became a district level activity during the decentralisation of the colonial administration (1952-1967). The inventories were recorded in voluminous so-called District Forest Management books. These books formed the baseline data for later inventories till 1967 when such inventories were suspended. Again, in these early stages, no efforts were made in estimating forest carbon through biomass calculations in general or estimations specific to the evergreen *Cryptosepalum* forests in the country.

2.2.2 National Wood Cover and Wood Biomass Inventories in Zambia

According to Mukosha and Siampale (2009), the first major assessment of the total woody biomass volume in Zambia was done in the mid-1980s under the National Wood Energy Consumption and Reserve Survey. The same authors indicate that this survey estimated the following as national figures:

- i. The total natural forest area for the country as 61.2 million ha.
- ii. The national forested and wooded area was 41.2–55.2 million ha.
- iii. The corresponding woody biomass volume (Growing Stock) was 3 000–4 100 million m³.

2.2.3 SADC Wood Energy Survey

The second survey of Zambia's woody biomass was completed in Holland as part of the Southern Africa Development Community (SADC) Wood Energy Study (Mukosha and Siampale, 2009). This assessment was based on satellite imagery analysis for the whole Southern African Development Community (SADC) countries. There was no reference made to the District Forest Management Books as database when making Zambia's estimates. The same report indicates that this study estimated Zambia's share of SADC woody biomass as follows:

- i. 2 600 million Mg; corresponding to 3 640 million m³ wood volume
- ii. An average basic woody density of 714 kg/m³ (this was an average of SADC trees)

This national estimate agrees with de Backer's study results of 1986 as cited by Mukosha and Siampale (2009). Although the national woody biomass was estimated at this stage, no carbon calculations were made.

Some work was done in Zambia on biomass estimation by Stromgaard (1985). This study was done in a small location in Kasama in the Northern Province for the Above-Ground Biomass (AGB) in the Miombo forests. In this study (Stromgaard, 1985), the researcher used Moisture Content to convert wet weight to dry matter; it is not clear whether any allometric functions were used. If they

were, these were for the Miombo and not for the evergreen *Cryptosepalum* forests. The results from Stromgaard's study (1985) show above ground fresh biomass of a Miombo stand (Undisturbed for 16 years) as 108 Mg ha⁻¹ or 48 Mg ha⁻¹ dry weight.

2.2.4 Zambia Forestry Action Programme (ZFAP)

Mukosha and Siampale (2009) also indicates that the third assessment was done in conjunction with the Zambia Forestry Action Programme (ZFAP, 1998). ZFAP (1998) used the District Forest Management Books as database besides other references with 30 years available information, including computer simulation to estimate Zambia's forest area; including growing and woody biomass stock (Alajarvi, 1996). Alajarvi's estimates were as follows:

- i. The total land area of forests and woodland in the country as 59.5 million ha
- ii. The total growing woody biomass stock estimate was at 4 202 million m³

The 59.5 million ha were divided into:

- i. Forested area estimated at 43.6 million ha
- ii. Scattered woodlands estimated at 15.9 million ha

In terms of estimated woody biomass growing stock, the following were estimates:

- i. In forested areas: 4 122 million m³
- ii. From scattered woodlands: 80 million m³

The fourth major estimate done for Zambia's forest was by the United Nations (UN) again through SADC. The Report of the 5th session of the UN Commission on Sustainable Development reports Zambia's forest cover to be 39 % or 29.4 million ha (Strid, 1997 as cited by Mukosha and Siampale, 2009). The difference between this estimate of 29.4 million ha by Strid (1997) and that of 59.5 million ha by Alajarvi (1996), a year earlier, is large. It is not clear what led to this disparity.

On the contrary, Chidumayo (1997) gives higher estimates for the Zambia's national forest cover than Strid (1997) for the same period as follows:

- i. Total forest area and Miombo woodlands at 44.0 million ha
- ii. Savannah woodland at 9.6 million ha

The above gives a total estimate for Zambia's national forest cover as 53.6 million ha. It is important to note that these estimates by Chidumayo (1997) were based on extrapolations from ZFAP estimates as pointed out by Mukosha and Siampale (2009).

2.2.5 Food and Agriculture Organization (FAO) Global Forest Resource Assessment estimate

FAO Global Forest Resource Assessment (2005) made its own estimate for Zambia. This was based on the District Forest Management Book as a database and small-scale satellite imagery. This FAO (2005) Forest Resource Assessment gives the estimate for forest cover as 31.2 million ha. This report gives no information on woody biomass resource either by volume or by dry weight.

2.2.6 Other Forest Inventories in Zambia (1990s – 2000s)

According to Mukosha and Siampale (2009), the major forest assessments done between 1990s and 2000s were as follows:

- i. The Provincial Forestry Action Plan (PFAP): This project's interest was in provincial level pilot collaborative forest management programmes. During this exercise, no district level inventories were done.
- ii. The Environmental Support Programme (ESP): This project conducted a forest inventory for Chibombo district alone aimed at enhancing revenue collection.
- iii. The Forestry Support Programme (SFP): Under this programme, a forest inventory was done from 2002 to 2004 using satellite imagery and also used Stratified Random Sampling System by province. This report indicated that the national forest area declined to 33.5 million ha. No lower level estimates were done such as provincial or district estimates. Since these were national estimates, it is advisable to take caution when referring to these statistics at lower levels such as provincial or district.
- iv. The Forest Resource Management Project (FRMP): This programme lasted from 2002 to 2008 and had provincial interest to establish effective pilot collaborative forest management programmes. This programme covered only two provinces in Zambia namely Luapula and NWP. Despite Mwinilunga being one of the operational districts in NWP under FRMP, no biomass estimates were done in the *Cryptosepalum* forests, either by using allometric functions or indeed by any other means.

The Mukosha and Siampale (2009) exercise included biomass estimation of the AGB and BGB generalised as evergreen forests in Zambia. The results from this study show national level statistics for evergreen forests to be as follows:

- i. AGB density is 108.2 Mg ha⁻¹
- ii. AGB is 88.6 million Mg
- iii. BGB is 17.7 million Mg

- iv. Total Biomass is 106.3 million Mg
- v. Dead Wood Biomass is 20.8 million Mg
- vi. Carbon Stock is 59.8 million Mg

Clearly, this was the first national assessment to include biomass for carbon estimation. This report provides an estimation of carbon contribution from evergreen forests to the national carbon budget at 2.1 %.

Nevertheless, it is important to note that these statistics are not specific to the *Cryptosepalum* but are for evergreen forests; a generalisation which includes three subtypes distributed as follows (Fanshawe, 1960; Lawton, 1964):

- i. *Cryptosepalum* forests: These are found on the Kalahari sands mainly in Mwinilunga and Solwezi districts in NWP and in some parts of Western Province. *Cryptosepalum exfoliatum* subsp. *pseudotaxus* is always dominant and may occur as pure in the canopy layer. *Guibourtia coleosperma* is rarely a co-dominant while sub-dominants include *Brachystegia spiciformis* and *Diospyros undabunda*. This forest is found in the Mwinilunga district and extends into the neighbouring Solwezi district of the North-western Province and part of the forest is found in the Western Province. In Mwinilunga, for instance, the part of forest (that was sampled) lies 24°11' East and 12° 26' South at an altitude of approximately 1 482 m with mean annual precipitation of 1 386 mm. Soils are described as very deep, almost sterile Kalahari sands which have been leached of all their bases.
- ii. *Marquesia acuminata* forests: These are found in the lake basins; mostly in the Kawambwa district of the Luapula Province. In this forest type, *Marquesia acuminata* is strongly dominant, almost pure. These forests are located in Mukabi Protected Forest Area (28° 52' East and 10° 28' South) at an altitude of approximately 1 300 m with soils that are said to be very deep sandy loams derived from granite (Lawton, 1964). The mean annual precipitation is 1 379 mm.
- iii. *Parinari – Syzygium* forests: These are normally found on the plateau; around the Ndola district in the Copperbelt Province. In these forests, *Parinari excelsa* and *Syzygium guineense* are dominant. This forest type occurs in three known sites namely Northrise, Chichele Forest Reserve and Ndola Sample Plots. Ndola is located 28° 38' East and 13° 0' South at an altitude of 1 270 m with mean annual precipitation of 1 233 mm. The soils here are characterised by very deep sandy clays derived from schists and quartzites of the Katanga series.

Despite all the above-mentioned forests being tropical evergreen, the fact that these forests have variations is obvious. Not only do the forests have different dominant species but the locations differ as well. In the case of the site conditions, there is a marked variation in terms of the environmental and climatic conditions. For example, while the *Cryptosepalum* forests are described as ‘dry’, the same cannot be said about the *Parinari–Syzygium* forests which may have riparian forest associations. Therefore, the generalisation of estimating biomass for evergreen forests as one category is quite debateable. Species-specific models should be applied if biomass estimation for the *Cryptosepalum* forests are to be accurate.

The latest study on biomass involving allometric functions and destructive sampling in Zambia, done by Chidumayo (Day *et al.*, 2014), estimated woody AGB loss for Miombo at 0.3–4.0 Mg ha⁻¹ year⁻¹. Although a large number of trees was used in the study (113) thereby benefiting modelling, this AGB study was carried out in one location only, namely the district in the Lusaka Province in central Zambia. This was specific to the Miombo forests and is not necessarily applicable to all forest types in Zambia (Chidumayo, 2013).

Therefore, no specific AGB allometric functions have been developed for the evergreen forests in general and the *Cryptosepalum forests* in particular in Zambia implying that there remains a gap in the knowledge relevant for the Monitoring, Reporting and Verification (MRV) for REDD⁺ in Zambia (Day *et al.*, 2014).

2.3 Review on Materials and Methods

2.3.1 Review on different Research Designs

In a study conducted in Zambia’s Miombo forest by Stromgaard (1985), 4 plots of 20 m x 20 m were used to collect tree measurements. Mukosha and Siampale (2009) used highly systematic sampling; there was no stratification used in establishing the main grid whose size was 1 km x 1 km. This grid size was large because this exercise was a national level assessment. Within each grid, 4 rectangular plots were established; each measuring 250 m x 20 m. These subplots were divided further in to subplot level 1 and subplot level 2. Though focused on Miombo woodlands, as this is the dominant and economically most important woodland, this process included a limited number of sampled tracts within other forest types as follows: Kalahari (20), Mopane (12), Munga (2) and closed forest, including evergreen (1). This is the reason why ILUA I (2005 – 2008), a process reported by Mukosha and Siampale (2009), has been criticised since it did not include adequate numbers of sampled tracts for some woodland types with low overall national coverage such as evergreen forests (Day *et al.*, 2014). However, it is hoped that an on-going exercise (ILUA II, 2011 – 2016) would involve stratified sampling of major forest types including closed forests such as evergreen forests.

In a study conducted in Miombo forests in Tanzania (Mugasha *et al.*, 2013) researchers used circular sample plots with 15 m radius at 4 different sites. In this case, 40 trees were sampled in each of the 4 sites.

A study conducted in Miombo forests in central Zambia by Chidumayo (2013), permanent sample plots of unknown size, established earlier, were used in collecting data at 5 sites. These plots were divided in to 8 subplots of the size 10 m x 20 m.

2.3.2 Field Work (Including Measurements)

The methods and measurement processes used in previous studies were as follows:

In the work done by Stromgaard (1985) for Zambian Miombo forests, the trees were mapped, identified by species name and, the height (Ht) and the diameter at breast height (DBH) measured before felling at 20 cm above the ground. Each individual sampled tree was then divided into stem, branches, twigs and leaves. The weight of leaves was taken first because leaves are most sensitive to moisture loss. This was followed by the weighing of the dead and the live branches. Then the larger bole was sawn into sections or billets and weighed. The study conducted by Chidumayo (2013) followed the same process.

In the nationwide work done in Zambia by Mukosha and Siampale (2009), the tree height (Ht) and the diameter at breast height (DBH) were measured. The AGB was calculated using existing expansion factors.

In the study conducted in Tanzania's Miombo forests by Mugasha *et al.* (2013), the tree height and DBH were measured before felling. This study used a destructive sampling method. For AGB, the tree bole was divided in to stem, main branches, sub branches, twigs and leaves. Except the leaves which were not included in the study, stem and the branches were cut in to billets of 1-2.5 m length, weighed for green weight and samples were collected. The twigs were put in bundles and weighed and small disc samples collected, labelled, measured and prepared for lab analysis.

For all the four studies reviewed here, only the study by Mugasha *et al.* (2013) in Tanzania used excavation method to achieve the BGB estimation. It is acknowledged that the BGB is problematic to measure in Zambian woodlands due to deep root systems (Day *et al.*, 2014).

The Intergovernmental Panel on Climate Change (IPCC) guidelines of 2006 (IPCC, 2006) define the five carbon pools as follows:

- i. Above-Ground Biomass (AGB): This includes all the biomass of living vegetation, both woody and herbaceous, above the soil including stems, stumps, branches, bark, seeds and foliage.

- ii. Below–Ground Biomass (BGB): This pool includes all the biomass of live roots. The fine roots of less than 2 mm diameter (suggestion only) are often excluded because these cannot be distinguished empirically from soil organic matter or litter.
- iii. Dead wood: This includes all the non-living woody biomass not contained in the litter; either standing, lying on the ground or found in the soil. The dead wood includes the wood lying on the surface, dead roots, and stumps larger than or equal to 10 cm in diameter (or in line with country specifications).
- iv. Litter: The litter pool includes all the non-living biomass with a size greater than the limit for soil organic matter (suggested 2 mm) and less than the minimum diameter chosen for dead wood (e.g. 10 cm), lying dead in various states of decomposition above or within the mineral or organic soil. This includes the litter layer as usually defined in soil typologies. The live fine roots above the mineral or organic soil (of less than the minimum diameter limit chosen for Below-Ground Biomass) are included in litter where they cannot be distinguished from it empirically.
- v. Soil Organic Carbon (SOC): This includes organic carbon in mineral soils to a specified depth chosen by the country and applied consistently through-out such measurements. The live and dead fine roots and dead organic matter within the soil that are less than the minimum diameter limit (suggested 2 mm) for roots and dead organic matter, are included with soil organic matter where they cannot be distinguished from it empirically. The default for soil depth is 30 cm, however, this sampling may result in disregard for some physical and chemical processes taking place at deeper soil layers and hence, 1m is strongly recommended (Mesa, 2015). Country-specific sampling depths may also be applied.

The same guidelines indicate the need to include all the five carbon pools if forest carbon is to be comprehensively estimated.

2.3.3 Effects of moderate thinning

The variation in AGB and the carbon distribution pattern in the previous studies conducted is most likely related to past disturbance history and age of the forests (Baishya *et al.*, 2009). While historical disturbance may influence removal of biomass from a forest, such disturbance or biomass removal does not always significantly influence AGB levels (Lung and Espira, 2015). This is because most biomass removal involves trees in small size classes which are insignificant contributors to the biomass (Lung and Espira, 2015). Both natural and anthropogenic processes that have influence on the presence and the health of large trees, will therefore have the greatest impact on the biomass (Lung and Espira, 2015). Thus, it is particularly important in forestry based carbon projects to pay special attention to activities which lead to the prevention or reduction of the loss of large trees such

as charcoal production and selective logging in order to maintain the carbon stock of a forest (Lung and Espira, 2015). Activities that limit subsistence use in terms of cutting small stems for construction and fuel wood might not have measurable immediate effects on carbon stocks (Lung and Espira, 2015). As observed by Geldenhuys (2015) regarding Miombo woodlands, pristine forests deny the local people the much-needed food and energy resources for various needs and means to generate financial resources to improve their living standards. Geldenhuys (2015) underscores the value of maintaining a balance between the environmental, social and economic benefits of managing the forests following a well-known concept of multi-purpose forestry, which provides different ecosystem services, which can be used to the global or local benefit (Mensah *et al.*, 2016). Doing so is most unlikely going to have negative impact on the financial outcomes associated with the generation and sale of the carbon credits (Lung and Espira, 2015). The moderate thinning of small sized trees rejuvenates the Miombo woodlands by opening the canopy (Geldenhuys, 2015). This could be applicable to the *Cryptosepalum* forests as well.

2.3.4 Review of Laboratory Procedures

The laboratory work done in the studies highlighted above was as follows:

In the work done by Stromgaard (1985), the literature does not clearly indicate how these samples were analysed, despite samples having been collected.

According to Mukosha and Siampale (2009), formulas were used to convert green weight to dry weight. Therefore, by implication, most likely no samples were analysed in the laboratory.

For the study conducted in Tanzania by Mugasha *et al.* (2013), all samples collected were oven-dried in laboratory at 70°C for at least 48 hrs and after that monitored for changes in weight with intervals of 6 hours until there was no change in weight.

In the study done by Chidumayo (2013), samples were taken to the laboratory for oven drying. The temperature used was 80°C for 72 hrs and then the samples were re-weighed in order to calculate the oven dry weight and the fresh weight ratios which were used to convert the fresh biomass to dry weight.

2.3.5 Data Analysis

The four studies reviewed above used different data analysis methods as indicated below:

In the study conducted by Stromgaard (1985), fresh weight figures were converted to dry matter using information on the Moisture Content of Miombo species.

On the other hand, Mukosha and Siampale (2009) used a programmed database to enter the tree data. Therefore, existing formulas and conversion factors were used to analyse the data and no allometric functions were developed in this exercise.

According to Mugasha *et al.* (2013), the work done in Tanzania's Miombo used allometric functions which were developed for both AGB and BGB. Regression analysis was used in processing the data. Similarly, the work done by Chidumayo (2013) used ANOVA and regression analysis to analyse the data. The allometric functions developed were for the AGB estimation and no BGB estimation was done.

Chapter 3: Materials and Methods

3.1 Study Area location and general description

3.1.1 Study Area Location

The study was conducted in an ‘open’ area of the *Cryptosepalum* forests in *Kalemalema* (Figure 3-1) in the Chiwoma area of the Mwinilunga district, North-western Province, Zambia as shown in Figure 3.2. In this case, ‘open’ means that the area is not a gazetted forest reserve but under the jurisdiction of the traditional leadership of His Royal Highness (HRH) Chief Chibwika of the Lunda speaking people.



Figure 3-1: A *Cryptosepalum* forest stand in *Kalemalema*, Chiwoma area, Mwinilunga district.



Figure 3-2 Map of NWP showing location of the study area in Mwinilunga district.

This figure shows the location of the study site only and not the shape of the forest sampled.

(Map source: Kalumbila Mine website)

3.1.2 Climate

According to DSA, Mwinilunga district (2012), Mwinilunga has a relatively a moderate climate that is determined by the humid Congo Air Mass and the Inter-Tropical Convergence Zone (ITCZ) that brings rain from October to April. It is characterised by two major seasons: cool and dry winters and wet and hot summers. According to Fund and Hogan (2014), the climate of the *Cryptosepalum* forests or eco-region is predominantly that of a tropical savannah.

Temperature

Mwinilunga district has an annual mean minimum temperature of 6°C in June to 15°C in September and October (DSA, Mwinilunga district, 2010). The authors report that the mean annual maximum is 28°C and varies from 24°C in June to 32°C in December while the annual mean temperature range is

17°C. However, Fund and Hogan (2014) provides the temperatures specific to the *Cryptosepalum* forests with mean annual temperatures of 20–22°C; the annual temperature range averaging approximately 8°C. The same source indicates the mean maximum and minimum temperatures for the *Cryptosepalum* forests as 28–30°C and 7–8°C, respectively.

Rainfall

The rains in Mwinilunga district usually begin in September and reach their maximum intensity between December and March (DSA, Mwinilunga district, 2010). The area has three seasons: a hot and dry season (ranging from August to October), a hot and wet season (from November to April) and a cool and dry season (from May to July) (DSA, Mwinilunga district, 2012).

Humidity

The mean annual relative humidity for Mwinilunga district is 68 % and varies from a monthly maximum of 84 % in December and January to a monthly minimum of 46 % in September (DSA, Mwinilunga district, 2012).

3.1.3 Vegetation

According to Day *et al.* (2014), the dry evergreen forests, including the *Cryptosepalum* forests, represent part of a floristic and physiognomic transition from the rainforest to woodlands. Therefore, many of the plant species are Afromontane linking species. However, they do not show the complex vertical structure found in the Afromontane and Afrotropical forests (Seifert *et al.*, 2014). The forest canopy rarely exceeds 25 m in height, except for a few emergents. Day *et al.* (2014) reports similar heights up to 27 m. In terms of species richness, this forest type is floristically poor, with a simpler structure than the rain forest. The dominant *Cryptosepalum exfoliatum* subsp. *pseudotaxus* is sometimes the only canopy species with *Guibourtia coleosperma* being often the co-dominant species (Fund & Hogan, 2014) similar to other dry Southern African woodlands with one dominant species, such as the Mecrusse in Mozambique (Matntilla and Timane, 2005; Magalhães and Seifert, 2015). Day *et al.*, (2014) describes these forest types as three storied with a dense shrub layer of 1.5–6.0 m high. The sub dominants are mainly *Brachystegia*, *Julbernardia* and *Isoberlinia* genera. Meanwhile, *Diospyros undabunda* is conspicuous where there is a dense thicket understory and epiphytic lichens are common. In this eco-region, little grass is found on the forest floor, which is predominantly covered in mosses in the denser forests as shown in Figure 3-1. After clearing, nearly impenetrable regeneration stages with numerous lianas, shrubs and small trees can develop in this forest, resulting

in sparse herbaceous undergrowth, which makes it difficult for the fires to penetrate. Therefore, fire is not an important disturbance factor in mature forest stands.



Figure 3-2: Forest floor in a *Cryptosepalum* forest stand with mosses but little grass

3.1.4 Soil Conditions

The Mwinilunga district has all major soil types, ranging from pure sand to clay (DSA, Mwinilunga district, 2010). Due to heavy soil nutrient leaching, the predominantly sandy soils in the northern part are generally acidic and infertile. The soils in the southern part, where the *Cryptosepalum* forests are located, range from heavy sandy loam, sandy loam to clayey, and are less acidic.

3.1.5 Biodiversity

The *Cryptosepalum* dry evergreen forests have a moderate species richness (Fund & Hogan, 2014). These forests, however, have flora and fauna that is distinctly different from surrounding eco-regions. As regards larger mammal fauna, the forests are a habitat for duikers (*Sylvicapra grimmia*), kudu (*Tragelaphus strepsiceros*) and African painted hunting dog (*Lycaon pictus*). These forests are used

as a safe retreat by elephants (*Loxodonta africana*) and buffalos (*Syncerus caffer*) from West Lunga National Park; forming a corridor between the park and habitats on the Angolan border. These forests include Game Management Areas (GMAs) to the east, north and west of the game park. In any case, due to their remoteness and impenetrability, the GMAs with *Cryptosepalum* forests are probably less heavily poached than other, more open reserves in more populated areas within Zambia.

3.1.6 Forest Land Use and Ecological Status

In general, the *Cryptosepalum* forests are still in a natural and undisturbed state (Fund & Hogan, 2014). Based on own observation, the forests are barely being exploited for domestic requirements such as building materials, timber, fuel wood and clearing for small-scale agricultural activities. Currently, the human disturbance is not severe and is limited to a few localized parts of the margins of these forests. Literature showing the extent of human disturbance on these forests in the North-Western Province is not available.

3.2 Methods

3.2.1 Field Work

The research data was collected from one study location in an open area namely *Kalemalema* in Chiwoma area of Mwinilunga district, North-western Province, Zambia. The following procedure was followed in line with recommendations made by Mukosha and Siampale (2009) as regards conducting effective inventories in the natural forests in Zambia:

Preparation for Field Work

The following activities were undertaken prior to field work:

- i. The research site was studied using maps
- ii. Logistical arrangements were made including transport and tools
- iii. Necessary approval was obtained from the Zambian Forestry Department, Zambian Police and traditional leaders.

Field Team Composition

The field team for this exercise was composed of the following:

- i. 1 Team leader
- ii. 1 Assistant Team leader
- iii. 2 enumerators

- iv. 4 workers (local people who did the field work including acting as guides, giving the local names of the trees, representing the community leadership and carrying the equipment)

3.2.2 Sampling

The sample plots were laid in the field as follows:

- i. Size and shape of each plot: Each of the square sample plots was 20 m x 20 m. While smaller sample plots are easier to collect data from, one requires a large number of such plots so that the sample area may be representative. Although the larger plots are more representative, data collection in such plots is quite difficult in dense forests with closed canopy due to poor visibility. Although, 20 m x 20 m plots are relatively small for woodland studies, these were deemed appropriate due to the fact that the sampled forest is dense and the canopy is closed. This is in line with observations made by Basuki *et al.* (2009).
- ii. Number of plots: 11 sample plots were established in the study area. Although limited, this number of sample plots was representative since, through personal observations, the forest in the area seemed relatively homogeneous as regards species composition and DBH distribution.
- iii. Spatial arrangement: the final decisions regarding the sampled forest and sample plot location were made in the field as, initially, the forest ear-marked as study site and the sample plots randomly located were too disturbed to be used for research purposes. A forest in which there was no evidence of disturbance, was selected instead.

3.2.3 Surveying the Sample Plots

The starting point for the measurements within plots was set in the South-western corner with all the sample plots having a North-South orientation as recommended by Condit (2008).

The procedure to establish permanent sample plots was as follows:

- i. Set out the sample plot with the distance of 20 m x 20 m. This was done by using a compass to measure the direction and a tape to measure the distance.
- ii. Each corner of the sample plot was marked with paint to indicate the end of the plot so that the paint could easily be seen whenever the team wanted to revisit the plot.
- iii. Establish nine (9) subplots of 5 m x 5 m using wooden pegs within each sample plot: these subplots are not permanent but used for tree enumeration only as shown in Figure 3.2.

GPS coordinates of the 11 plots are given in Appendix 1.

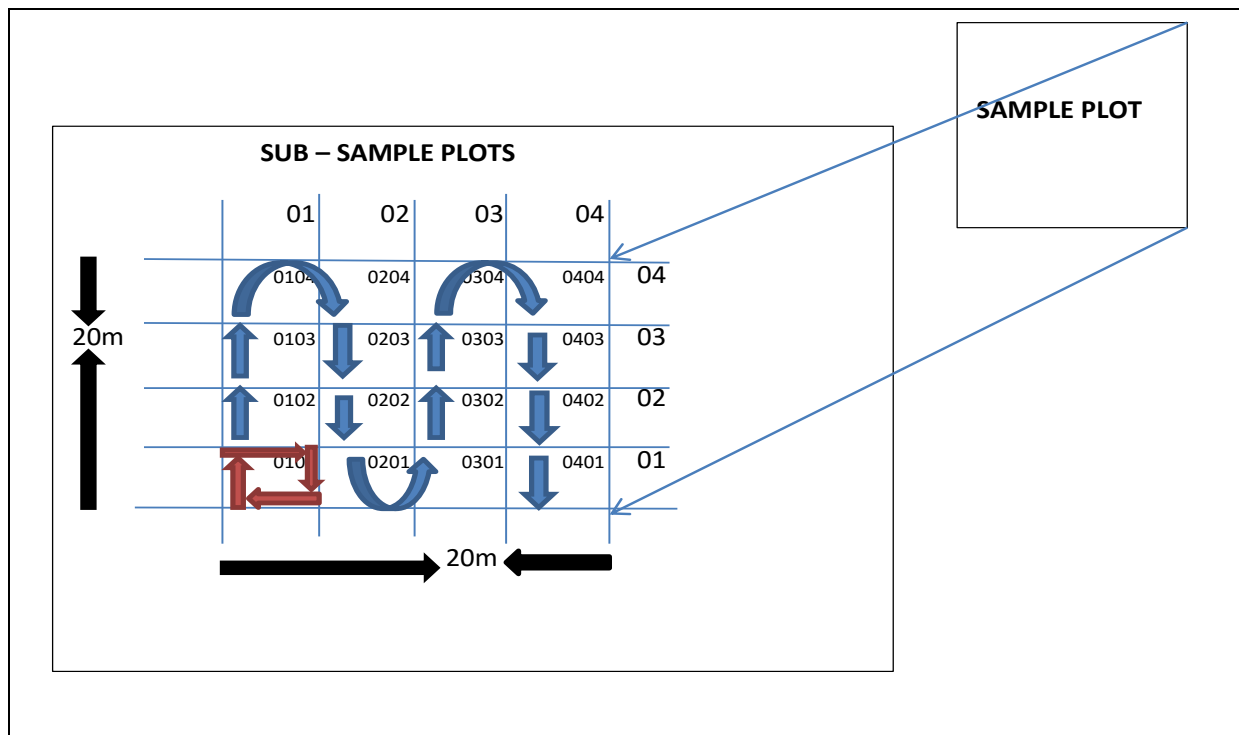


Figure 3-3: Lay- out of subplots in one sample plot.

The measurements commenced in the subplot coded '0101' at the South –west corner. Tree measurements were taken in clockwise direction as indicated by the red arrows. When measurements in subplot '0101' were completed, the enumerators then moved to the next subplot (0102); thereby following the subplots northwards as shown by the blue arrows. When the third subplot along this column (0103) is completed, the enumerators moved to the other columns as shown by the blue arrows until all the subplots were completed. The team then moved to the next sample plot. This was done to avoid double counting and ensure no target tree was left out in the inventory.

3.2.4 Acquiring tree data

Before destructive sampling, all *Cryptosepalum* trees in each plot were enumerated i.e. measurement of diameter at breast height (DBH) and height (Ht). The DBH was measured at 1.3 m above the ground using a diameter tape while Ht was measured using a Suunto Clinometer. A total of 22 trees (2 trees per plot) selected across all size classes were destructively sampled. After felling, all trees were measured again for DBH and length (L); this time crown height (CH) was also measured together with length (L) using the measuring tape. The L was measured in order to compare it with the Ht which was measured using the Suunto Clinometer. It was the Ht that was used in calculations and not the L since the upscaling models would use Ht. The trees were divided in to the following components as illustrated in Figure 3.3:

- i) Stem (from the stump to the beginning of the live crown; this being top-end)
- ii) Main-branch base (branching section found between the top end of stem and the main-branch)
- iii) Main-branch (from end of the main-branch base to diameter ≥ 8 cm)
- iv) Sub-branch and twigs (from diameter < 8 cm up to the twigs diameter ≥ 3 cm)
- v) Foliage

The tree components were sampled and the oven-dry weights obtained as follows:

Stem

The stem was divided in to 1 m sections; the length of the last section depended on the CH. Three (3) discs were removed from the stem (1 from the butt-end, 1 from middle and 1 from top-end) as shown in Figure 3.4. All the billets were measured for weight in the field using a crane digital scale.

Main-branch base

The length of both sides (left side and right side) of this section were measured using a tape. The diameters at the base of the section and at the beginning of the main branches were also measured.

Main-branch

All main-branches were counted and taking the top diameter of every main branch to be 8 cm, main-branch base diameters and lengths were measured. These parameters were necessary for the calculation of the volume.

Sub-branch

All the sub-branches on all the sampled trees were measured for base diameter using callipers and length using a measuring tape. Three (3) sub-branches per tree, including twigs, were destructively sampled. All the woody plant parts were cut and packed in sampled bags and their fresh weight was measured in the field using a digital scale.

Foliage

A foliage sub-sample from 4 (out of 22) trees was obtained due to defoliation in the forest at the time of sampling as a result of caterpillar infestation. This sub-sample from 4 trees was collected after the trees had recovered from the caterpillar infestation and were in full leaf. The leaves were separated from all sampled sub-branches and twigs (as shown in Figure 3.6) and packed in sample bags.

The discs, woody and the leaf samples obtained were weighed in the field using a digital scale; starting with the leaf samples because they are the most sensitive to dehydration. All the samples were then transported to the lab for oven drying.

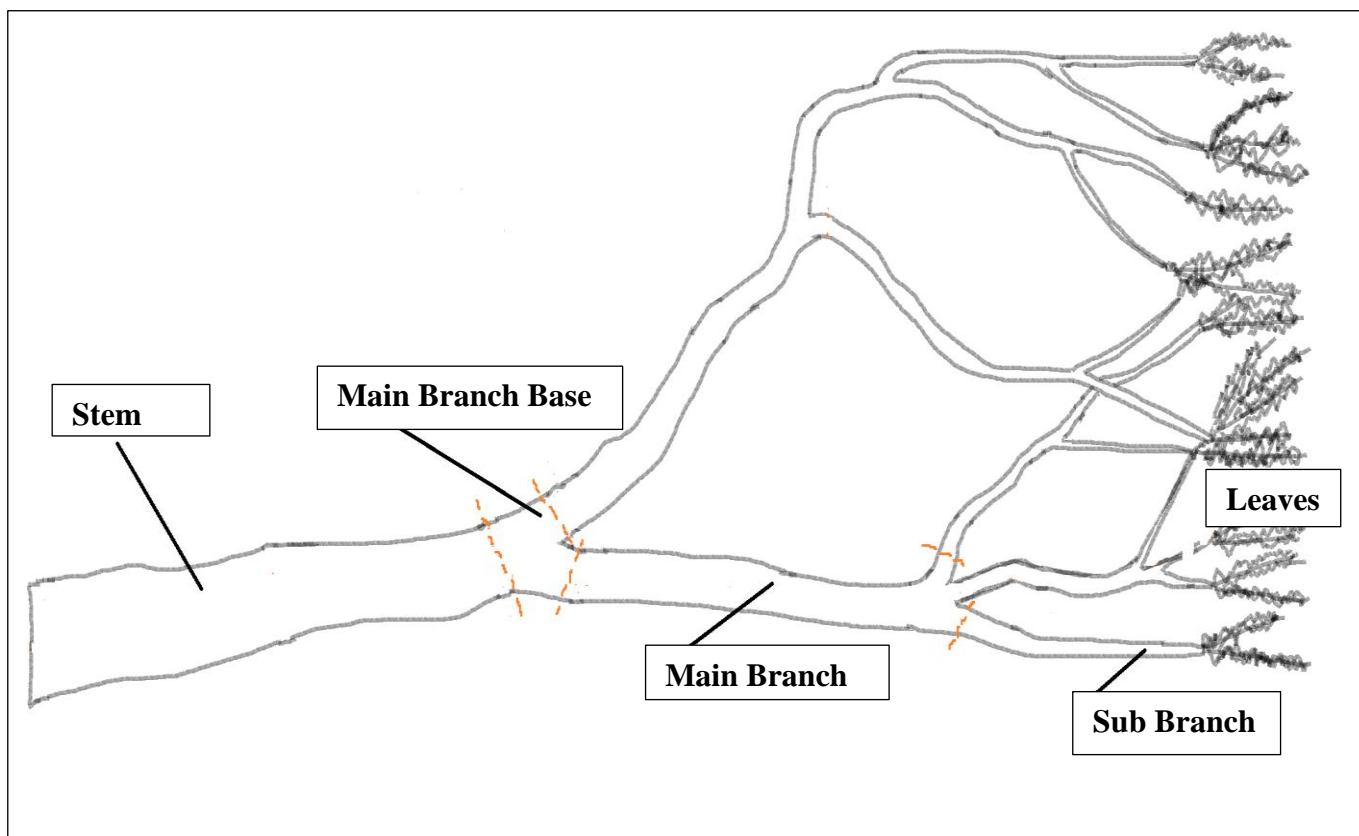


Figure 3-4: The tree components in to which a destructively sampled tree was divided.

The sub-branch component includes twigs i.e. sub- branches of diameter ≥ 3 cm.



Figure 3-5: Cutting of the 1 m billets and removal of discs (left) and separating foliage from the twigs (right).

Due to resource constraints (including budget, labour, time, facilities, tools and equipment), only the above-ground plant samples were collected for analysis in this study while BGB was estimated indirectly using the R: S ratio. Therefore, no samples from the BGB, dead wood, litter or SOC were collected for analysis.

3.3 Laboratory Work

3.3.1 Oven - drying

The plant samples were re-weighed at the lab to give a pre-oven drying mass. This was very helpful in confirming the correct field measurements of the samples. If the pre-oven mass was higher than the field measurements, then there was a good reason to suspect erroneous field measurements. The mean weight per disc sample reduced from 2.44 kg field measurement to a pre-oven weight of 2.18 kg representing a loss in moisture of 10.7 %. The mean weight per branch sample reduced from 2.23 kg field measurement to a pre-oven weight of 2.1 kg representing a loss in moisture of 5.8 %. The mean weight per leaf sample reduced from 0.8 kg field measurement to a pre-oven weight of 0.6 kg representing a loss in moisture of 26.8 %; giving the highest moisture loss among the tree components. The oven-drying was done at the Division of Forest Research in Kitwe; at both the lab at town office (for branches, sub-branches and foliage) and Riverside lab (for discs). All the samples were oven-dried at 102 \pm 3°C; leaf, branch and discs samples were dried using separate ovens. This is because of the different drying rates among leaf, branch and disc samples. The foliar samples took only 3 days; sub-branches took about 5 days while discs took up to 14 days, to attain constant mass. The samples were monitored twice daily. All the samples were removed from the ovens after reaching a constant mass.

3.3.2 Wood density determination

After the disc samples were oven-dry, 'wedges' were obtained from them as sub – samples. The oven-dry mass of the wedges was measured immediately after removal from the oven. The water displacement method was used to measure the volume (Osazuwa-Peters & Zanne, 2016). In this method, a bucket is filled with sufficient water and set on a digital scale; the mass of the bucket with water is set at zero. Before immersing in water, a wedge was attached to a long needle so thin that displacement by the needle's contact with water at the meniscus was insignificant. The mass reading on the digital scale (in kg) is equivalent to volume (dm³) since 1 dm³ equivalent to 1 litre weighs 1 kg. The measurement of volume, necessary for the basic density determination, is normally done before oven-drying. This is done to avoid shrinkage that results from oven-drying. The other disadvantage is that oven-dried samples absorb water during the volume determination resulting in erroneous measurements. In this study, the volume determination was done after oven-drying due to logistical limitations because of the study site being remotely located. However, the wedges were soaked in water for 14 days or more and were only removed for volume determination after reaching a constant mass; showing that the wedges had reached a water saturation point. In this case, the shrinkage due

to oven-drying was considered negligible. The determination of the volume using the water displacement method is shown in Figure 3.7



Figure 3-6: Determination of volume of 'wedges' using the water displacement method.

3.4 Data analysis and modelling

The tree sample data (stem, main branches, sub branches, twigs and leaves) was processed using the R Statistical Software (R Core Team, 2013). The models were formulated using regression analysis while the variation between and among groups was investigated through the Analysis of Variance (ANOVA). The graphs were developed using Sigma Plots Software (Version 10).

3.4.1 Stand density (SD)

The stand density, expressed as the number of stems per ha, of the forest was determined by the following formula:

$$SD = \text{Mean \# of stems} * 10\,000 / 400 \quad \text{Equation 1}$$

Where:

SD = Stand density (in stems ha⁻¹)

The factor of 10 000 / 400 is to upscale stems ha⁻¹ as the plot was 400 m²

3.4.2 Assumptions

The assumptions for all the data collected were as follows:

- i) Normality: This property was tested by visually assessing quantile-quantile plots in which normal distribution in the populations is confirmed when the plot approaches a straight line. In less-than-clear cases, normality was confirmed by conducting the Shapiro Wilk's test on the outcome variables (with the threshold of 0.05); outcomes with p-values <0.05 are significant, those >0.05 are not significant. The Null hypothesis for this test is that the data is obtained from a normally distributed population.
- ii) Homoscedasticity: This property was tested using 'Residual vs. Fitted' plot. The points for homoscedastic data are scattered randomly on the graph giving a 'sky-at-night' look.
- iii) Independence of errors was assumed.

3.4.3 Model selection

Models used by Basuki *et al.* (2009); Chave *et al.* (2014); Yuen *et al.* (2016) were considered as having high potential and were tested basing on two (2) model characteristics namely Root Mean Square Error (RMSE) and Adjusted R² and values. The Akaike Information Criterion (AIC) is a good model characteristic but was not used because the application of this model is specific to nested models.

3.4.4 Biomass estimation

Stem wood

The mass of each stem was obtained by using the following formula:

$$\text{Mass} = \text{Density} * \text{Volume} \quad \text{Equation 2}$$

The Volume of the stem was determined using the Smalian's formula:

$$\text{Volume} = \pi * L * ((D_1 + D_2)/8) \quad \text{Equation 3}$$

Where:

Density = Mean density of the 3 discs (butt-end, middle and the top-end) was applied to the main stem.

L = length of each stem

D₁ = Top diameter of each stem

D₂ = Base diameter of each stem

This was applied to sections of the stem for which upper, lower diameters and length were known.

Main branch base

The mass of each main branch base section was obtained by using formula:

Equation 2

Mass = Density * Volume (Density of the top disc was applied here)

The volume was determined using the Smalian's formula:

Equation 3

Volume = $\pi * L * ((D_1 + D_2)/8)$

Where:

L = Length of each section of the base

D₁ = Diameter at the top of each section

D₂ = Diameter at the base of each section; D₂ was calculated from the average of the top cross-sectional areas of the main branch base

Wood density used in the formulas above was determined by water displacement method as outlined in sub –section 3.3.2 above.

Allometric functions were developed with which sample biomass was up-scaled to whole tree, plot and stand.

Main branch

The mass of each main branch was obtained by using the formula:

Equation 2

Mass = Density * Volume

The volume was determined using the Smalian's formula:

Equation 3

Volume = $\pi * L * ((D_1 + D_2)/8)$

Where:

Density = Density of the top disc of the stem applied to the main branch

L = length of each main branch

D₁ = Top diameter of each main branch

D₂ = Base diameter of each main branch

Sub- branch

The mass of the sub-branch was estimated using a parsimonious log-transformed model:

$$\ln (B_{\text{Sub_branch}}) = \beta_0 + \beta_1 * \ln (D_{\text{Sub_branch}}) \quad \text{Model 2}$$

that was developed from destructively sampled sub- branch biomass and sub-branch diameter.

Foliage

Similarly, the foliage mass was estimated using a log-transformed model:

$$\ln (B_{\text{Foliage}}) = \beta_0 + \beta_1 * \ln (D_{\text{Sub_branch}}) \quad \text{Model 3}$$

fitted on destructively sampled sub-sample of foliage and branch diameters.

3.4.5 Above–Ground Carbon (AGC)

The AGC was quantified using the carbon fraction of 0.5 (Basuki *et al.*, 2009; IPCC, 2006; Lung & Espira., 2015).

3.4.6 Below-Ground Biomass (BGB)

The BGB was estimated from the AGB using the R: S ratio as provided by Mokany *et al.* (2006). The R: S ratio for this study was obtained by averaging the R: S ratios for two similar forest categories namely ‘tropical/sub–tropical/moist woodland’ and ‘tropical/subtropical/temperate dry woodland’. The ratios for the plantations could not be used because plantation forests are believed to have lower R: S ratios since most tree species are bred for aboveground production. The ratios for dry evergreen forests were not available. The procedure followed is shown in Table 3.1 below:

Table 3-1 Calculation of the mean R: S ratio using two similar woodland categories.

Category	R: S Ratio	Mean
Tropical/sub-tropical moist woodland	0.42	0.37
Tropical/sub-tropical/temperate dry woodland	0.32	

Equation 4

Where the Shoot biomass is considered as 1, Root biomass is estimated as 0.37.

$$\text{R: S ratio} = \text{BGB} / \text{AGB}$$

Where R: S ratio is the mean given in the table above i.e. 0.37;

$$(0.37) / 1 = (\text{BGB}) / \text{AGB}$$

Therefore, by cross-multiplication; $\text{BGB} = \text{AGB} * 0.37$ (kg). The amount of carbon is given as its equivalent.

Chapter 4: Results

4.1 Basic Forest Information

The *Cryptosepalum* forest stands in which our study was undertaken was found to be a dense three-storey vegetation type with a closed canopy. The dominant species in the forest in which plots were located is *Cryptosepalum exfoliatum* subsp. *pseudotaxus* but with *Guibourtia coleosperma* present as co-dominant and, *Brachystegia spiciformis* and *Isoberlinia angolensis* as sub-dominants. The understorey has species including *Diplorinchus condylocarpon*, *Combretum zeyheri*, *Combretum molle* and *Peltoforum africanum* while the forest floor has mainly mosses. The forest was found to have a clustering characteristic where *Cryptosepalum* sometimes may occur as pure stands with abundant climbers and lichens and, a few epiphytes. The *Cryptosepalum* is usually defoliated at the beginning of the rainy season each year by caterpillar but generally, the forest can be described as undisturbed as shown in the Figure 4-1. The soil is predominantly sandy as shown in Figure 4-2.

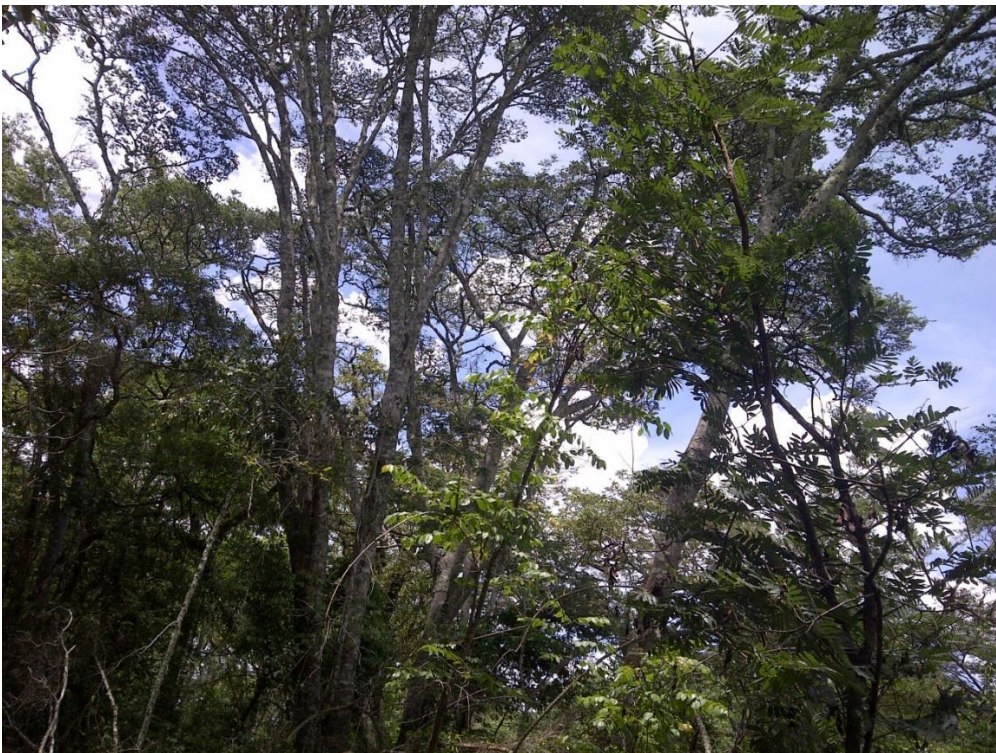


Figure 4-1: *Cryptosepalum exfoliatum* subsp. *pseudotaxus* trees in the centre towering over sub-dominant species.

In this forest, sub-dominants such as *Brachystegia spiciformis*, *Peltoforum africanum* and *Diplorinchus condylocarpon* are very common.



Figure 4-2: A soil pit (left) showing sandy soils (right) in a sampled *Cryptosepalum* forest stand

4.1.1 Stand Characteristics

This forest type showed high level of variation among sample plots in terms of height, DBH and stand density (stems ha⁻¹) (Table 4-1).

Table 4-1: Variation in forest characteristics per plot

Plot Number	Number of Trees Per Plot	Stand Density (Trees/ha)	Mean DBH Per Plot (cm)	Mean Height Per Plot (m)
1	20	500	16.9	11.2
2	10	250	28.7	16.4
3	15	375	24.1	17.4
4	20	500	22.5	14
5	12	300	34.1	17.3
6	15	375	24.4	15.8
7	11	275	22.9	15
8	17	425	22.4	14.9
9	12	300	21.7	15.2
10	15	375	16.1	11.7
11	14	350	27.8	17.4
Mean	15	365.9	23.8	15.1
Standard Error	1.01		2.3	1
Confidence Intervals			21.5 - 24.9	14.2 - 15.6

The variation in the number of trees per plot was evident. The range was 10-20 trees per plot with the difference between minimum and maximum being 100 %. The overall mean for all plots was 15 trees

per plot. The variation in mean DBH per plot was equally significant; ranging from 16.0 to 34.1 cm (about 100 %) with an overall mean of 23.8 cm. The mean height per plot showed lower variation with a range of 11.2 to 17.4 m with an overall mean of 15.1 m. The stand density varied from a minimum of 250 to a maximum of 500 and the mean estimated using pooled data from all plots was 366 (± 56) with Confidence Interval of 310 – 422 stems ha⁻¹.

4.1.2 Diameter at Breast Height (DBH) distribution

The DBH distribution is positively skewed whereby most of the trees are found in the 10-15 cm DBH size class with very few trees lying in DBH classes > 40 cm (Figure 4-3). Data was obtained from non-normally distributed population with Shapiro _Wilk test statistic = 0.95 and p-value = 1.679e-05).

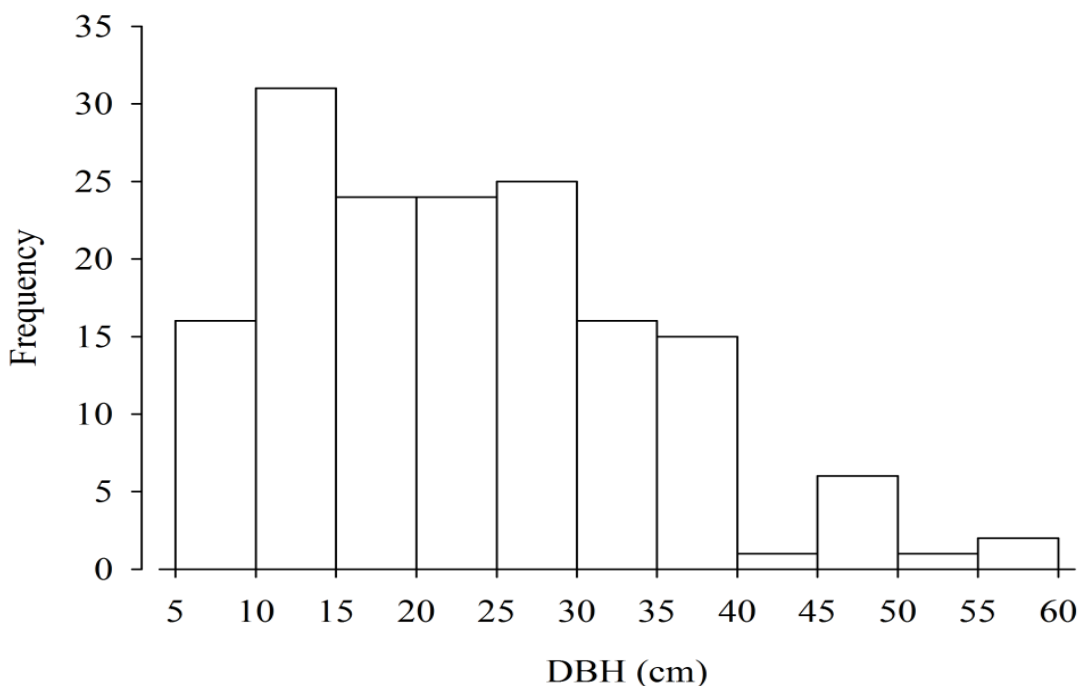


Figure 4-3: Histogram showing DBH variation among all the 22 sampled trees in the 11 sample plots

4.2 Height vs. DBH models

As expected, the DBH and height data exhibited non-normality (Shapiro-Wilk test statistic = 0.91812; p-value <0.001). Hence, a transformation was used. Of the two models tested, one model gave the best fit (Table 4-2) and this was of the form:

$$\ln(Ht) = \beta_0 + \beta_1 * (1/DBH) \quad \text{Model 1}$$

The linear transformation was adequate, with neither discernible trend in the residuals nor evidence of heteroscedasticity (Figures: 4-4 and 4-5).

Table 4-2: Comparison of Height vs. DBH models

Model	Predictors	Parameters	Estimates	SE	<i>n</i>	Parameter p-value	Adjusted R ² (%)	RSE	RMSE	Model p-value
1a: $\ln(\text{Ht}) = \beta_0 +$	Intercept	β_0	0.704	0.10		<0.001				
$\beta_1 * \ln(\text{DBH})$	$\ln(\text{DBH})$	β_1	0.639	0.03	159	<0.001	68.88	0.21	0.21	<0.001
1b: $\ln(\text{Ht}) = \beta_0 +$	Intercept	β_0	3.28	0.03		<0.001				
$\beta_1 * (1/\text{DBH})$	$1/\text{DBH}$	β_1	-11.702	0.49	159	<0.001	77.99	0.18	0.18	<0.001

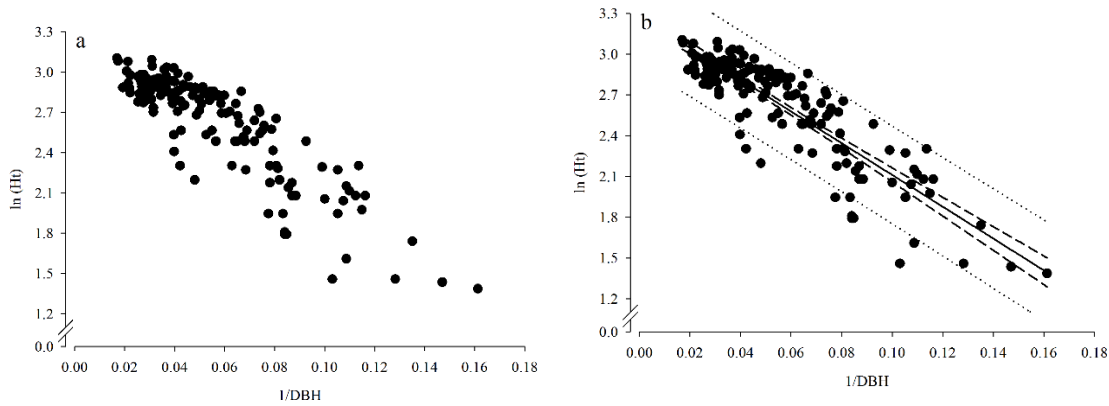


Figure 4-4: Ht vs. DBH scatterplot (a) and regression model (b) showing 95% confidence and prediction intervals.

This model is of the form:

$$\ln(Ht) = \beta_0 + \beta_1 * (1/DBH)$$

Model 1

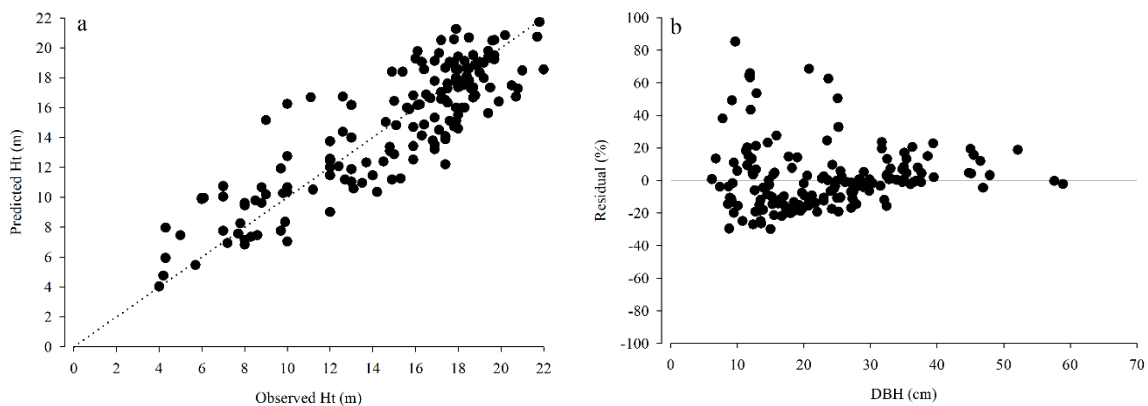


Figure 4-5: Predicted vs. Observed Ht (a) and Residual vs. DBH plot (b) for Ht vs. DBH model.

Both plots show a balanced model which is neither over-estimating nor under-estimating the dependent variable i.e. height.

4.3 Tree Component Biomass Models

Before a whole tree biomass model could be formulated, tree biomass estimation was done by component (stem, main branch base, main branch, sub-branch and foliage).

4.3.1 Wood Density

Since wood density is a necessary variable in the estimation of stem, main branch base and main branch, its calculations were done first. The density per disc was obtained by:

$$\text{Density} = \text{Mass} / \text{Volume.} \quad \text{Equation 2}$$

The mean wood density (for disc at butt-end, mid and top-end) of each sampled tree was obtained by dividing the mass by the volume of each ‘wedge’ sub-sample that was taken from disc samples. The variation in wood density per sampled tree is shown in Appendix 2. The summary of mean wood density, mass and volume per tree are shown in Table 4-3.

Table 4-3: Summary of mass, volume and wood density values.

Parameter	Mass (g)	Volume (cm ³)	Wood Density
Minimum	130.0	183.3	625.0
Median	264.6	385.0	697.5
Mean	290.0	417.5	701.8
Maximum	550.0	713.3	799.0
Standard Deviation	96.7	135.1	47.6
1st Quartile	231.7	340.8	675.5
3rd Quartile	319.2	465.0	732.2
Standard Error	20.6	28.8	10.2

The wood density varies from 625 to 799 kg/m³. The mean wood density for all sampled trees was 701.8 kg/m³ (± 10.2).

Position of the disc in the stem

The difference in wood density among discs due to the position in the stem (butt-end, mid and top-end) was investigated but was not statistically significant ($p= 0.979$) as shown in ANOVA Table 4-4. Its graphical representation is shown in Figure 4-6.

Table 4-4: ANOVA results on the difference in wood density as a result of disc position in the stem.

Statistic	<i>n</i>	Sum of Squares	Mean Squares	F-value	P-value
Position	3	0.00012	0.000058	0.022	0.979
Residuals	61	0.16045	0.002674		

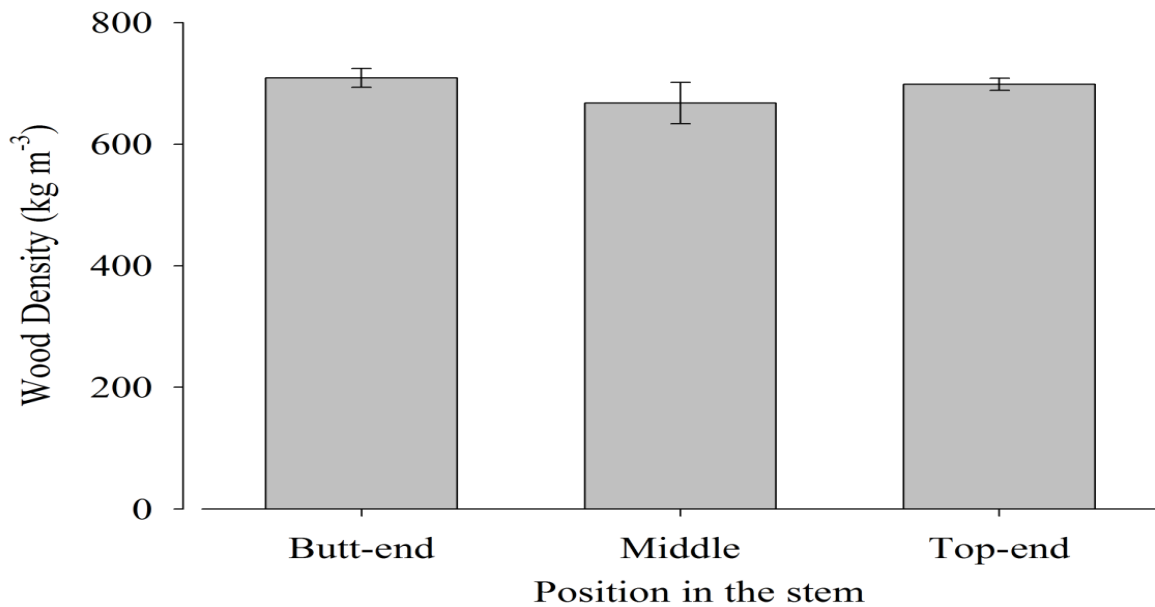


Figure 4-6: Effect of position on Wood density

The above figure shows only a slight variation in wood density among 3 positions in the stem. The mean wood density reduces slightly (but not statistically significant) from butt-end to middle section and increases again slightly to the top-end of the stem. The middle section has slightly higher within-variation than the rest.

4.3.2 Stem Biomass

The stem biomass per sampled tree was estimated using Mean Dry weight / Wet weight ratio of the discs applied to each billet. The biomass of the stem is a summation of the biomass of all billets per stem as shown in Appendix 3. The summary of stem biomass is given in Table 4-5.

Table 4-5: Stem wood biomass per tree calculated as a product of mean wood density and volume

Parameter	Stem Volume (cm ³)	Stem Wood Biomass(kg)
Minimum	0.05	31.6
Median	0.35	239.4
Mean	0.37	258.3
Maximum	0.71	442.8
Standard Deviation	0.16	108.76
1st Quartile	0.26	188.1
3rd Quartile	0.51	334.6
Standard Error	0.03	23.17

The stem wood biomass per tree varied from 31.6 to 442.8 kg. The mean stem wood biomass per tree for all sampled trees is 258.3 kg (\pm 23.17). The high variation in stem wood biomass quantity per individual tree is attributed to the high variation in the DBH class distribution and the difference in crown height (CH). For example, a tree with a DBH of 16 cm contains more stem biomass (up to 400 kg) because it has a higher CH of 8 m, hence a longer stem. Another tree with a larger DBH of 34 cm contains lower stem biomass (200 kg) since it has lower CH (around 3 m). This shows that there is a corresponding reduction in the stem biomass with a lower CH even if the DBH is higher.

4.3.3 Main Branch Base Biomass

Using the wood density of the top disc for each stem calculated in the procedure outlined in the Materials and Methods (Chapter 3), the main branch base biomass per tree was determined as a product of wood density (top disc wood density was applied) and the main branch base volume. Volume was estimated using the Smalian's formula as explained in the Materials and Methods (Chapter 3). The details of the biomass estimates for each section are given in Appendix 4. The summary of main branch base biomass for all 22 sampled trees is presented in Table 4-6.

Table 4-6: Main Branch Base Biomass per each of the 22 trees

Parameter	Main Branch Base Biomass(kg)
Minimum	<i>nil</i>
Median	7.62
Mean	7.62
Maximum	25.22
Standard Deviation	7.12
1st Quartile	1.75
3rd Quartile	10.22
Standard Error	1.52

The main branch base biomass varied from nil to 25.22 kg. The mean main branch base biomass for all sampled trees is 7.26 kg (\pm 1.52).

4.3.4 Main Branch Biomass

Using the top disc wood density for each stem (considered to be closest to the main branch and therefore more representative) as calculated in Sub-section 3.3 above, the biomass per main

branch was determined as the product of wood density and the main branch volume. The volume was estimated using the Smalian's formula as explained in the Materials and Methods (Chapter 3). The main branch biomass per tree is shown in Appendix 5. The summary of the main branch biomass for all the 22 sampled trees is presented in Table 4-7.

Table 4-7: The summary of the variation in main branch volume and main branch biomass per Tree

Parameter	Main Branch Volume (cm ³)	Main Branch Biomass (kg)
Minimum	<i>nil</i>	<i>nil</i>
Median	0.26	158.00
Mean	0.32	225.40
Maximum	1.10	867.10
Standard Deviation	0.31	256.90
1st Quartile	0.95	59.14
3rd Quartile	0.38	253.10
Standard Error	0.07	54.77

The main branch biomass per tree varied from nil to 867.1 kg. The mean main branch biomass for all sampled trees was 225.4 kg (\pm 54.77). The high variation in the main branch biomass is attributed to the variability in the crown architecture (heavy branching and the variation in CH because of either forking or trees having double leaders).

4.3.5 Sub_branch model

The sub-branch biomass was estimated using the model with the best fit namely the power model of the form:

$$\ln (B_{\text{Sub_branch}}) = \beta_0 + \beta_1 * \ln (D_{\text{Sub_branch}}) \quad \text{Model 2}$$

This model's comparison and model coefficient estimates are shown in Table 4-8. Model 2 in which diameter was log-transformed was the best-fitting model based on the criteria assessed as presented in Figures 4-7 and 4-8. The data that was analysed using this model was obtained from a population which was not normally distributed (Shapiro-Wilk = 0.9516, p-value = 0.01853). Few outliers (6) were found and deleted from the sub-branch data because it was clear that these outliers were as a consequence of measurement errors.

Table 4-8: The comparison of the two Sub-branch models

Model	Predictor	Parameter	Estimates	SE	<i>n</i>	Parameter p-value	Adjusted R ² (%)	RSE	RMSE	Model p-value
2a: $\ln(B_{\text{Sub_branch}}) = \beta_0 + \beta_1 * (D_{\text{Sub_branch}})$	Intercept	β_0	-0.3322	0.35		>0.05				
	Diameter	β_1	0.28121	0.06	56	<0.001	23.97	0.546	0.540	<0.001
2b: $\ln(B_{\text{Sub_branch}}) = \beta_0 + \beta_1 * \ln(D_{\text{Sub_branch}})$	Intercept	β_0	-1.252	0.55		<0.05				
	$\ln(D_{\text{Sub_branch}})$	β_1	1.466	0.33	56	<0.001	24.74	0.544	0.530	<0.001

The model 2b had the best fit and is of the form:

$$\ln(B_{\text{Sub_branch}}) = \beta_0 + \beta_1 * \ln(D_{\text{Sub_branch}})$$

Model 3

This is because this model had a higher Adjusted R² value and a lower RMSE value than the other.

The output of the sub-branch biomass estimation per sampled tree is presented in Appendix 6.

The summary of the sub-branch biomass estimation per tree for all 22 sampled trees is presented in Table 4-9.

Table 4-9: Sub-branch biomass summary obtained using the model:

$$\ln (B_{\text{Sub_branch}}) = \beta_0 + \beta_1 * \ln (D_{\text{Sub_branch}}) \quad \text{Model 2}$$

Parameter	Sub Branch Biomass (kg)
Minimum	11.40
Median	89.65
Mean	96.09
Maximum	214.60
Standard Deviation	62.70
1st Quartile	40.38
3rd Quartile	128.20
Standard Error	13.37

The sub_ branch biomass per tree varied from 11.4 to 214.6 kg. The mean sub branch biomass for all sampled trees is 96.09 kg (± 13.37).

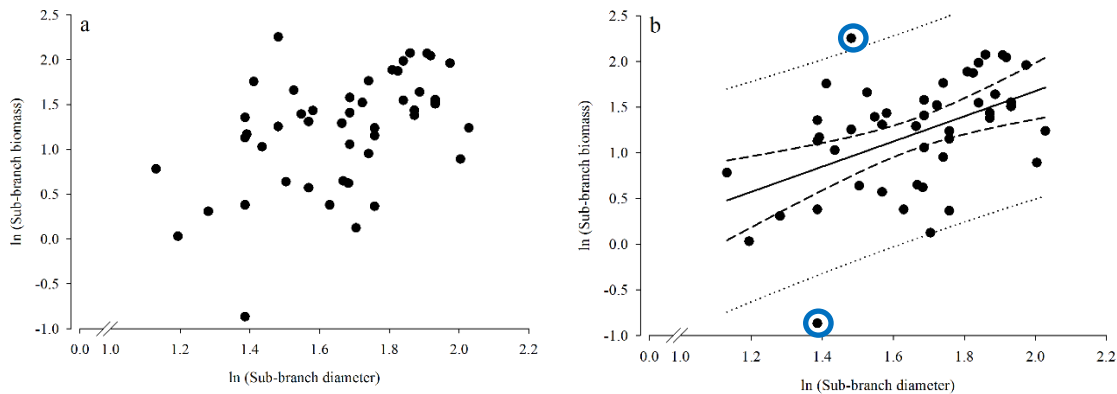


Figure 4-7: Scatterplot (a) and regression line (b) of sub branch model

The regression line shows outliers (circled in blue). This being a closed forest, the high variation in the sub-branch biomass is attributed to differences in crown architecture of the individual trees.

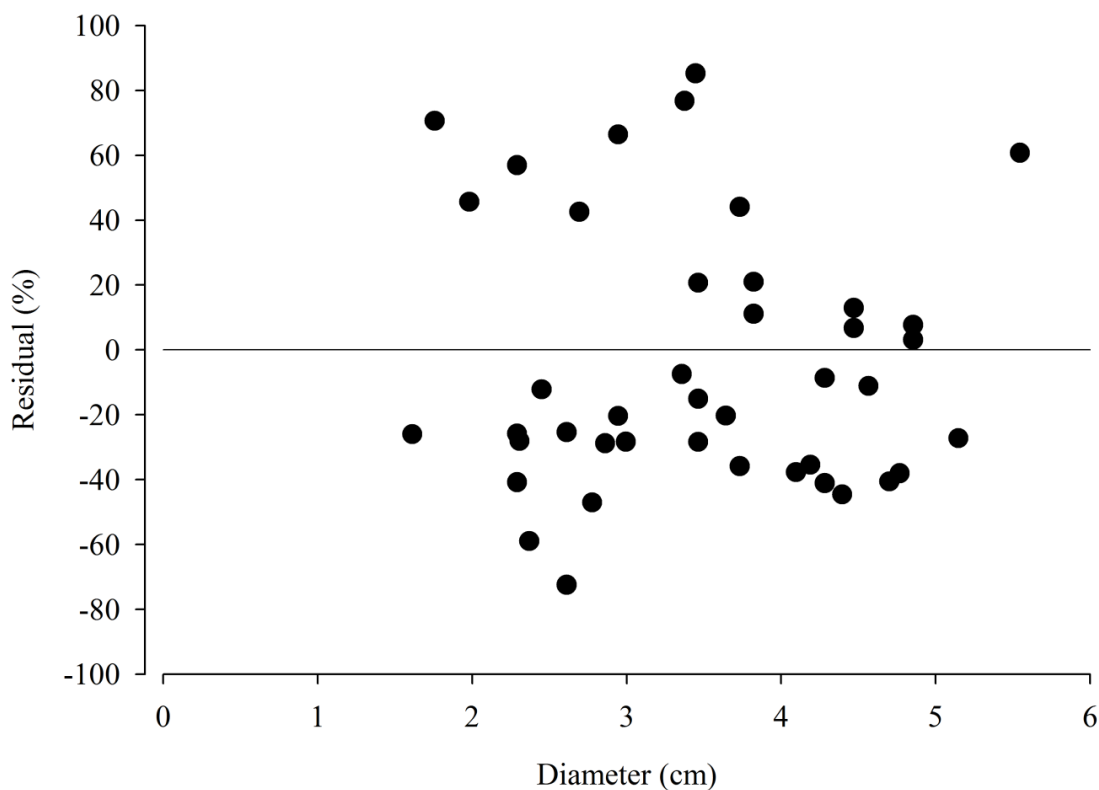


Figure 4-8: The Residuals vs. Fitted plot of the model:

Model 2

$$\ln (B_{\text{Sub_branch}}) = \beta_0 + \beta_1 * \ln (D_{\text{Sub_branch}})$$

The residual plot shows that the model is unbiased and is neither under-estimating nor over-estimating sub branch biomass.

4.3.6 Model for foliage biomass

Sampling for foliage biomass could only be done on a subset because all *Cryptosepalum* trees in the forest were defoliated by caterpillar when initial samples were collected. A sub-sample was collected 2 months later when the forest had recovered to full leaf. The level of foliage biomass for each of the 22 sampled trees estimated using the model from the sub-sample data is presented in Appendix 7.

The foliage biomass was estimated using the model with the best fit namely the power model of the form:

$$\ln (B_{\text{Foliage}}) = \beta_0 + \beta_1 * \ln (D_{\text{Sub_branch}})$$

Model 3

This model's comparison and model coefficient estimates are shown in Table 4-10. The linear transformation of the model is presented in Figures 4-9 and 4-10. The other model namely:

$$\ln (B_{\text{Foliage}}) = \beta_0 + \beta_1 * (D_{\text{Sub_branch}} + D^2_{\text{Sub_branch}})$$

was not considered because all the coefficient estimates, except the intercept (with p-value < 0.05), were statistically insignificant with p-value >0.05. The model using $\ln (D_{\text{Sub_branch}})$ had the best fit based on the criteria assessed (Table 10).

Table 4-10: Comparison of three tested foliage biomass models

Model	Predictors	Parameters	Estimates	SE	<i>n</i>	Parameter p-value	Adjusted R ² (%)	RSE	RMSE	Model p-value
3a: $\ln(B_{\text{Foliage}}) = \beta_0 + \beta_1 * (D_{\text{Sub_branch}})$	Intercept	β_0	-3.04	0.6	10	<0.001	44.53	0.4	0.366	<0.05
	$D_{\text{Sub_branch}}$	β_1	0.368	0.12		<0.05				
3b: $\ln(B_{\text{Foliage}}) = \beta_0 + \beta_1 * \ln(D_{\text{Sub_branch}})$	Intercept	β_0	-4.23	0.91	10	<0.001	48.52	0.39	0.352	<0.01
	$\ln(D_{\text{Sub_branch}})$	β_1	1.909	0.57		<0.01				
3c: $\ln(B_{\text{Foliage}}) = \beta_0 + \beta_1 * (D_{\text{Sub_branch}} + D_{\text{Sub_branch}}^2)$	Intercept	β_0	-2.51	1.39	9	>0.05	48.27	0.12	0.107	<0.05
	$D_{\text{Sub_branch}}$	β_1	1.045	0.56		>0.05				
	$D_{\text{Sub_branch}}^2$	β_2	-0.09	0.06		>0.05				

The model which had the best fit was of the form:

$$\ln(B_{\text{Foliage}}) = \beta_0 + \beta_1 * \ln(D_{\text{Sub_branch}})$$

Model 4

This is because it had a higher Adjusted R² value and a lower RMSE value than the other models.

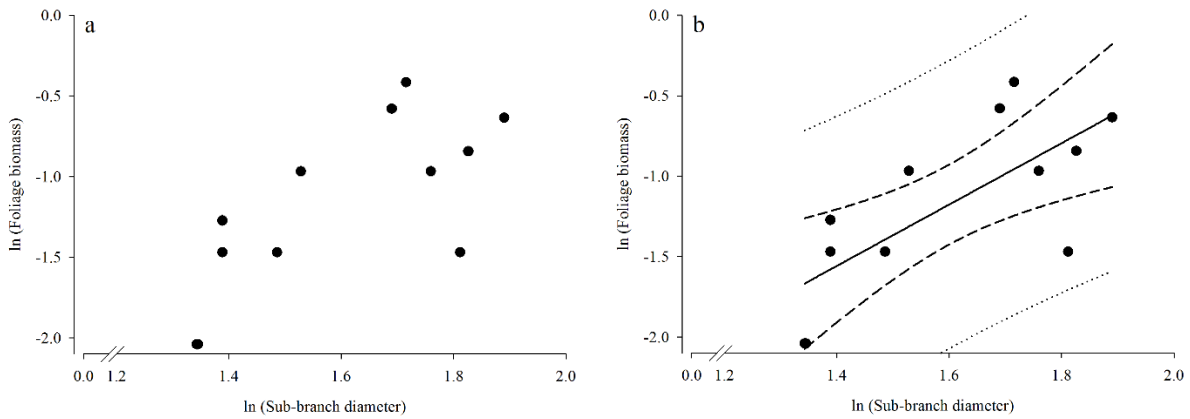


Figure 4-9: The scatterplot (a) and regression line (b) of the foliage model.

This is the model with the best fit showing 95% Confidence and prediction intervals. This is a balanced model in that it neither over-estimates nor underestimates the dependent variable namely foliage biomass. The small sample size ($n = 10$) is due to defoliation of the forest during the sampling.

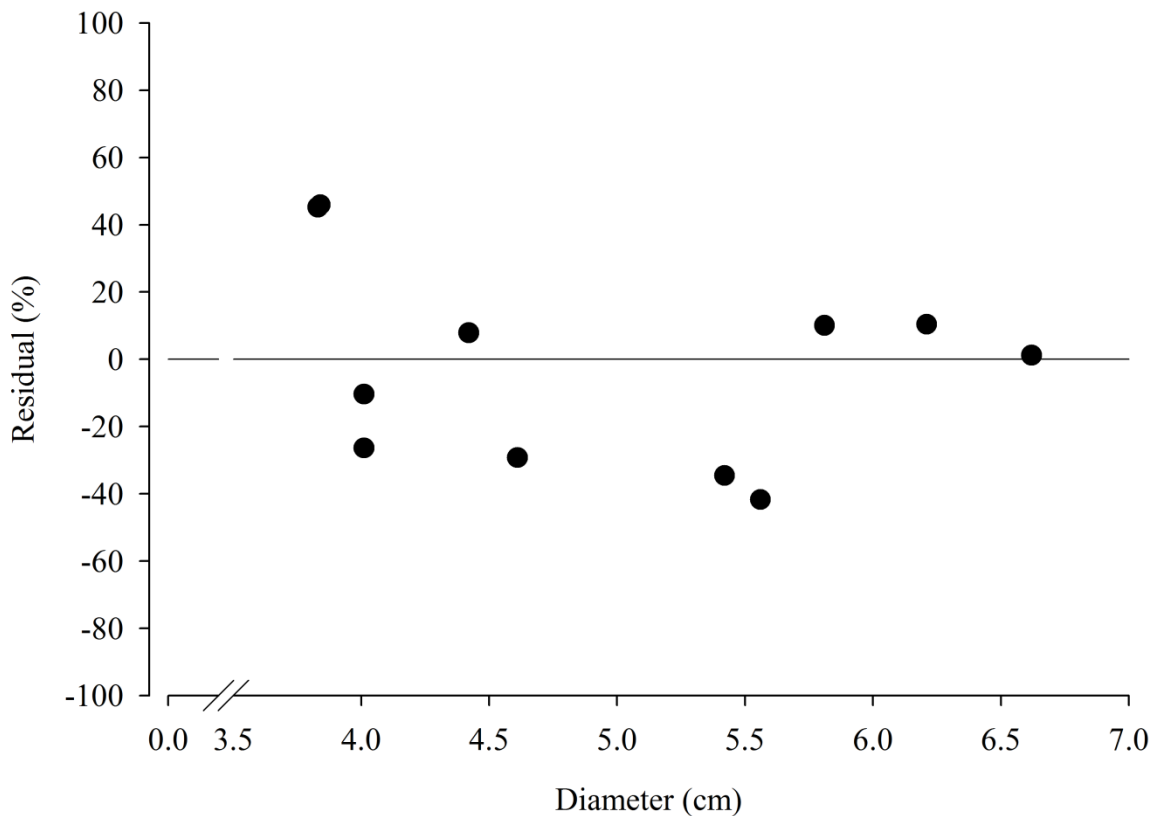


Figure 4-10: The Residuals vs. Diameter plot of the foliage model with the best fit.

The Residuals vs. Sub branch diameter plot shows that the model is balanced and does not underestimate or over-estimate the foliage biomass.

4.4 Total Tree Biomass

The data analysed for total AGB was obtained from summation of all tree component biomass values per tree as shown in Appendix 8. This data set shows that it was obtained from a normally distributed population as shown by the Shapiro Wilk's test result (p-value > 0.05).

All four models tested were found to be significant with p-values <0.01. Based on multiple estimates of model goodness-of-fit, the Schumacher-type model:

$$\ln (B_{\text{Total tree}}) = \beta_0 + \beta_1 * \ln (\text{DBH}) + \beta_2 * \ln (\text{Ht}) \quad \text{Model 4}$$

had the best estimates compared to the other models as shown in Table 4-11.

This model took into account the tree height and provided the model coefficient estimates given in Table 4-11 and the linear transformation shown in Figure 4-14.

This model was used to estimate the AGB of all trees for subsequent up-scaling.

Table 4-11: Comparison of total tree models tested

Model	Predictors	Parameters	Estimates	SE	<i>n</i>	Parameter p-value	Adjusted R ² (%)	RSE	RMSE	Model p-value
4a: $\ln(B_{\text{Total tree}}) = \beta_0 + \beta_1 * \text{DBH}$	Intercept	β_0	4.65	0.38	20	<0.001	44.06	0.51	0.48	<0.01
	DBH	β_1	0.06	0.01		<0.001				
4b: $\ln(B_{\text{Total tree}}) = \beta_0 + \beta_1 * \ln(\text{DBH})$	Intercept	β_0	1.79	1.05	20	>0.05	43.81	0.51	0.48	<0.01
	$\ln(\text{DBH})$	β_1	1.37	0.33		<0.001				
4c: $\ln(B_{\text{Total tree}}) = \beta_0 + \beta_1 * (\ln(\text{DBH}) + \beta_2 * \ln(\text{Ht}))$	Intercept	β_0	-0.72	1.32	19	>0.05	57.09	0.44	0.41	<0.01
	$\ln(\text{DBH})$	β_1	1.12	0.30		<0.01				
	$\ln(\text{Ht})$	β_2	1.19	0.45		<0.05				
4d: $\ln(B_{\text{Total tree}}) = \beta_0 + \beta_1 * ((\beta_2 * \text{DBH}^2 * (\beta_3 * \text{Ht}))$	Intercept	β_0	5.63	2.14	18	<0.05	54.22	0.46	0.42	<0.01
	DBH^2	β_1	-0.03	0.08		>0.05				
	Ht	β_2	-0.05	0.13		>0.05				
	$\text{DBH}^2 * \text{Ht}$	β_3	0	0.01		>0.05				

The model 4c had the best fit and is of the form:

Model 6

$$\ln(B_{\text{Total tree}}) = \beta_0 + \beta_1 * \ln(\text{DBH}) + \beta_2 * \ln(\text{Ht})$$

This is because it had the highest Adjusted R² and the lowest RMSE values than the other models. Although RMSE values were the same between 4c and 4d models, all coefficient estimates (except the intercept) in the 4d model were not significant (with p-values > 0.05).

4.4.1 Details of the best fitting model

The non-transformed model was of the form:

$$B_{\text{Total tree}} = \beta_0 + \beta_1 * (\text{DBH}) + \beta_2 * (\text{Ht})$$

Model 5

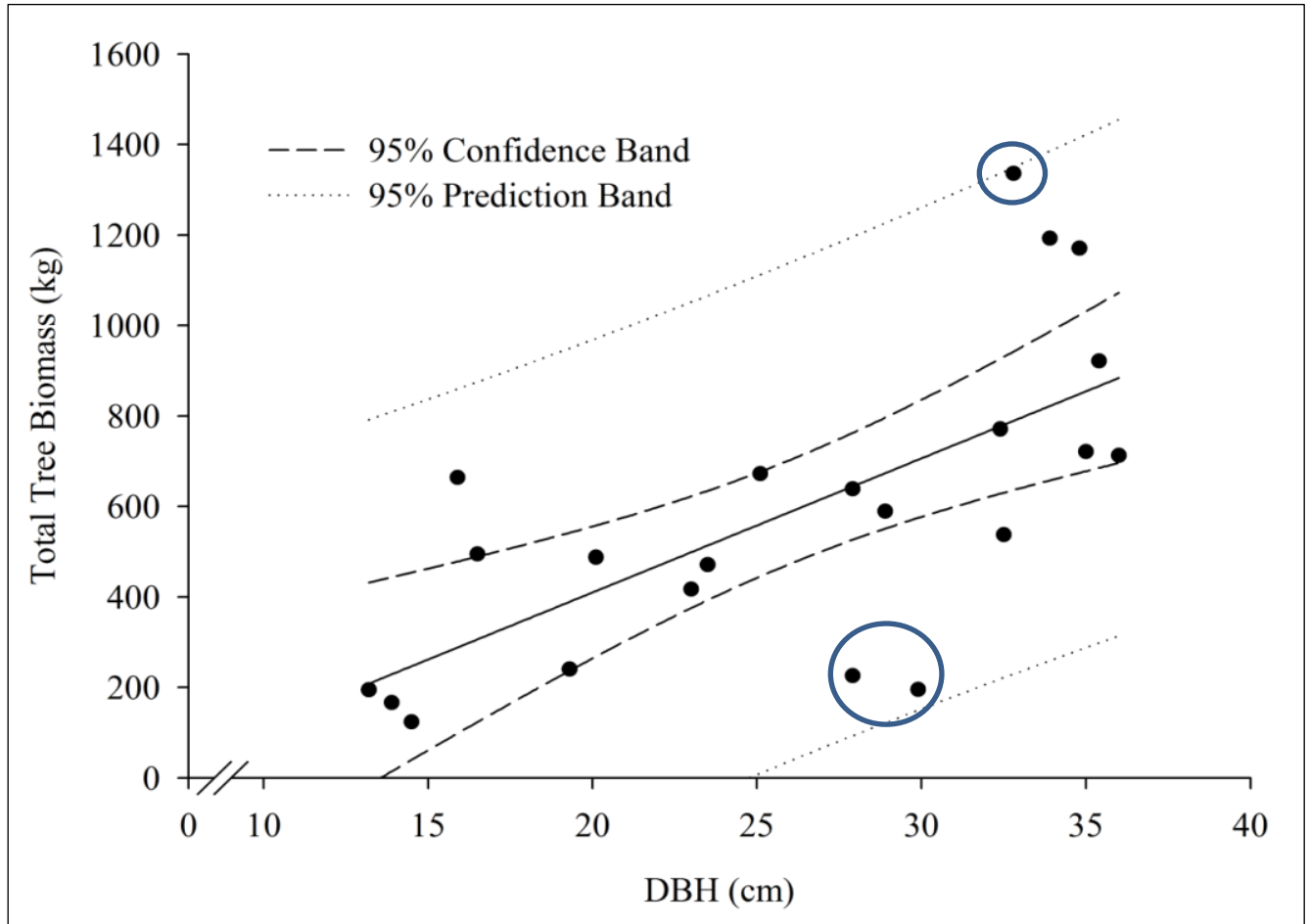


Figure 4-13: The regression of the non-transformed total tree biomass model.

This model shows 3 trees that are outliers (highlighted with a blue circle); hence the need for transformation. Two of these trees have medium sized DBH of 29.9 and 27.9 cm. Nevertheless, these have very low biomass levels of 196.8 and 226.7 Mg ha⁻¹, respectively. This is attributed to their low height of 8.8 and 11.1 m, respectively; compared to a sample mean height of 16.5 m. Actually, these are the 2 shortest sampled trees. To make the sample more representative, these 2 outliers were not deleted from the sample.

The log-transformed model was of the form:

$$\ln(B) = \beta_0 + \beta_1 * \ln(DBH) + \beta_2 * \ln(Ht)$$

Model 4

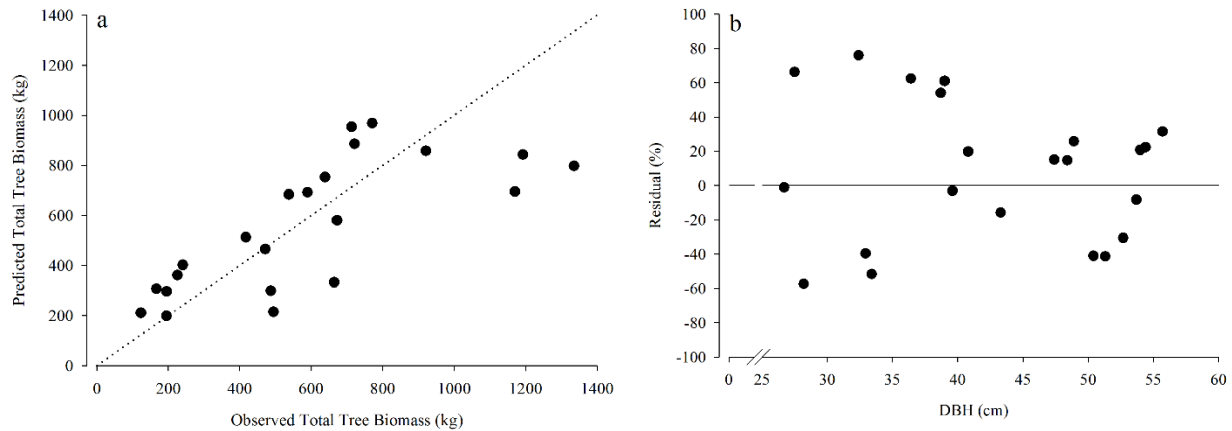


Figure 4-14: The Predicted vs. Observed (left) and the Residual vs. DBH (right) plots for the total tree model.

This is model 6c of the form:

$$\ln(B_{\text{Total tree}}) = \beta_0 + \beta_1 * \ln(DBH) + \beta_2 * \ln(Ht)$$

4.4.2 Up-scaling of biomass and carbon from plot to hectare level

Biomass per tree (as shown in Appendix 8) was up-scaled (as described in Chapter 3) to plot and hectare levels. The summary of biomass and carbon estimates ha^{-1} is shown in Table 4-12.

Table 4-12: Total Tree Biomass and Carbon estimates summarized in to quantity ha⁻¹

Plot Number	Biomass			Carbon
	Per Plot (kg)	Per ha (kg)	Mg ha ⁻¹	Mg C ha ⁻¹
1	10408.6	260215.2	260.2	130.1
2	14323.1	358078.5	358.1	179.1
3	19683.9	492096.6	492.1	246.1
4	20077.2	501929.6	501.9	251.0
5	22188.2	554703.9	554.7	277.4
6	17953.6	448839.1	448.8	224.4
7	10952.5	273812.7	273.8	136.9
8	17718.1	442953.4	443.0	221.5
9	12298.6	307464.0	307.5	153.8
10	9088.75	227218.9	227.2	113.6
11	19345.3	483633.0	483.6	241.8

Biomass and carbon levels for the sampled *Cryptosepalum* forest range from 227.2 to 554.7 Mg ha⁻¹ and 113.6 to 277.4 Mg C ha⁻¹ of biomass and carbon, respectively. The mean AGB estimate is 395.54 (\pm 68.61) Mg ha⁻¹ while the mean AGC quantity sequestered is estimated at 197.8 Mg C ha⁻¹.

4.4.3 Comparison of tree biomass by component

Biomass quantities for different tree components namely stem, main branch base, branch and foliage were compared as percentages of the total. The details of the variation in biomass by component (in %) are given in Appendix 9. A summary of tree component variation (in %) is shown in Figure 4-15.

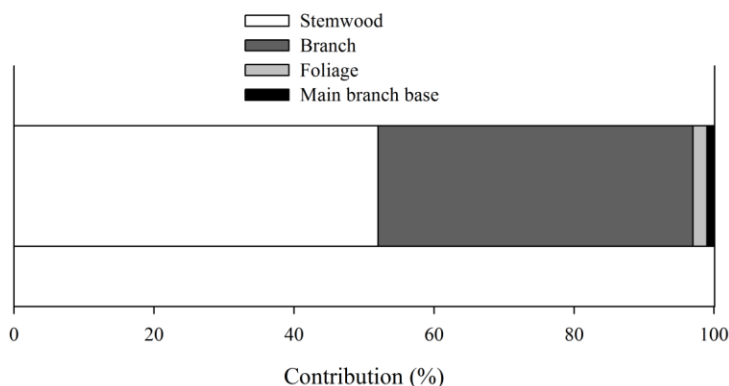


Figure 4-15: Comparison of tree component contribution to Total Above-Ground Biomass (%)

The smallest mean contribution to total tree biomass was from main branch base component at 1.0 % while the largest was from stem wood at 52 % followed by branch biomass at 45 %. The biomass from foliage represented 2 % of the total AGB of the tree and crown biomass (summation of branch and foliage) was estimated at 47 %.

4.5 Below Ground Biomass

Using the mean R: S ratio as calculated in Chapter 3 based on published values, the mean BGB (kg) quantity ha^{-1} was estimated from the mean AGB ha^{-1} as follows: Equation 6

$$\text{BGB} = 395\,540.43 * 0.371 \text{ (kg)}$$

$$\text{BGB} = 146\,745.5 \text{ kg}$$

$$\text{BGB} = 146.7 \text{ Mg } \text{ha}^{-1} \text{ (or } 73.4 \text{ Mg C } \text{ha}^{-1}\text{)}$$

Total biomass of the tree component of the sampled *Cryptosepalum* forest:

$$= \text{AGB} + \text{BGB}$$

$$= 395.5 + 146.7$$

$$= 542.2 \text{ Mg } \text{ha}^{-1}$$

Therefore, the quantity of Above-ground and Below-ground carbon sequestered in the tree component of the sampled *Cryptosepalum* forest:

$$= \text{AGC} + \text{BGC}$$

$$= 197.8 + 73.4$$

$$= 271.1 \text{ Mg C } \text{ha}^{-1}$$

Chapter 5: Discussion

5.1 Sample size

A total of 22 trees were destructively sampled for the current study with a consideration of the homogeneity of the study site and research limitations. Allometric studies have shown that, among other things, small sample sizes can lead to uncertainty associated with the allometric parameters when fitting models to parts of a dataset (Sileshi, 2014). Sample sizes of > 50 are often required in order to formulate each species-specific model (Chave *et al.*, 2004; Paul *et al.*, 2016). However, this is not necessarily always required. According to Yuen *et al.* (2016), case studies are on record where only 3-5 trees were sampled. In these cases, however, it is not clear whether this number was adequate to represent all the trees at the site. The destructive sampling of an appropriate number of trees that is representative of the full range of DBH classes present in an area is a prerequisite for the development of site or species-specific equations. On the contrary, Yuen *et al.* (2016) indicates that there is no consensus currently on the minimum number of trees that one should destructively sample. Roxburgh *et al.* (2015) advocates for at least 20-30 trees to be sampled in plantation forest biomass estimation. This author points out that sample numbers less than this may lead to higher model uncertainty despite individual allometric models having higher statistical significance. This is in line with the observation made by Chave *et al.* (2004) that tree-level errors average out in large plots. The number of trees used in this study (22) falls within this range.

5.2 DBH distribution

The DBH distribution of the sampled trees is positively skewed (Chapter 4, Figure 4-5 refers), with only a small number of large individuals in the forest. This reflects the characteristics of an indigenous forest naturally regenerating itself from seed (Swaine *et al.*, 1987) through active recruitment of younger trees that replace older trees dying of old age suggesting stability in size and age class distribution. This is typically found in native African forests and woodlands (Seifert *et al.*, 2011; Magalhães and Seifert., 2015). Continuous regeneration results in high variation in age; this is true especially for undisturbed forests (cases where human interference is very little or none at all) where the inverse J – shaped diameter distribution becomes apparent (Lykke, 1998). Since large trees contribute a bigger proportion of the AGB (Lung and Espira, 2015), the distribution of AGB across a sample plot is not normal (Chave *et al.*, 2004). Yuen *et al.* (2016) recommend destructively sampling an appropriate number of trees that represents the full range of

tree diameters and the distribution of trees in each diameter class. The same authors indicate that sampling should include both healthy and unhealthy individual trees.

Although large trees have higher biomass and consequently higher carbon content, smaller diameter trees have a greater potential for carbon sequestration because of a higher growth rate leading to increased photosynthesis (Lykke, 1998).

5.3 Use of height as an independent variable

In our study, both DBH and height emerged as independent variables. Literature indicates that the application of DBH alone is a good predictor of stem biomass (Ploton, 2016; Yuen *et al.*, 2016). The use of height to quantify stand carbon stocks can be avoided since its measurement is not only costly but also laborious, unless tree felling is involved (Chave *et al.*, 2005; Hunter *et al.*, 2013). Hunter *et al.* (2013) indicates that tree height can be difficult to measure even under the best field conditions possible. This is so because, besides field conditions, dense under-storey vegetation limits mobility while tall and closed canopies reduce visibility. Equally, height measurements are dependent on observer's experience, the type and quality of equipment used (Hunter *et al.*, 2013) and tree architecture (Basuki *et al.*, 2009). Clearly, tree height measurements in tropical forests have potentially large errors. From a prediction standpoint, the inclusion of height in the biomass model implies that any height measurement error will be propagated to the tree level and subsequently to the plot and stand levels (Seifert and Seifert, 2014; Picard *et al.*, 2015). Sometimes, such error propagation may be used as a caveat for using height as an independent variable. After all, height is no longer an independent variable in cases where it is estimated as a function of DBH and at the same time used in an equation which already has a diameter variable (Sileshi, 2014). Even if the inclusion of tree height slightly increases the explanation of the AGB variation (Mugasha *et al.*, 2013), this may lead to collinearity if necessary precaution is not taken (Picard *et al.*, 2015). It is thus recommended that models with DBH only, as an independent variable, be applied.

Nonetheless, other studies show that inclusion of tree height, as opposed to the use of DBH solely, significantly improves the prediction or estimation accuracy in tree biomass (Hunter *et al.*, 2013; Chave *et al.*, 2014; Yuen *et al.*, 2016). It is advisable to include height, although this might be a non-independent variable of vegetation characteristic, in order to account for the influence of all geographically-influenced growing conditions. Models with height are helpful in relating tree level biomass variations to stand level attributes including stand density, local competition, water

availability and nutrition (Picard *et al.*, 2015). The alternative to measuring all tree heights (in difficult circumstances) is to measure height for a well-distributed sample of about 100 trees per site whose mean can be applied in the modelling. In a case where this methodology has been used, up to 95% confidence intervals of transect biomass were constrained to within 4.5% on average when compared to reference values (Hunter *et al.*, 2013).

In this study, the inclusion of height in the power law biomass model for the full tree showed an improvement in the prediction resulting in a reduction of RMSE value from 0.48 to 0.41 as shown in Table 4-14 of Chapter 4. The adjusted R^2 value also improved from 0.44 to 0.57. This is in line with Chave *et al.* (2005) where it was observed that the application of height for the stand level estimates of biomass resulted in an error reduction from 19.5% to 12.8% across all forms of tropical forests and across continents. Essentially, the main effect of tree size on biomass was captured by DBH with height acting only as a correction factor (Picard *et al.*, 2015). This means that given two trees of the same DBH but different height, the two are expected to have different biomass quantities (Picard *et al.*, 2015); the one with bigger height has a higher quantity of biomass. Hence, height was used in this study as independent variable in order to account for specific differences in plant architecture as an effect of growing conditions. This is in line with what Paul *et al.* (2016) pointed out that it is beneficial to use height as an input variable in allometric models that include foliage biomass since foliage biomass is influenced by plant architecture.

5.4 Use of wood density in the calculation of stem and main branch volume

5.4.1 Wood Density variability along the stem (butt-end, middle and top-end)

There was a slight difference in the mean wood density for stem butt-end, middle and top-end for all the sampled trees with the mean of the three positions being 709 kg/m³, 668 kg/m³ and 699 kg/m³, respectively. Similar findings were made on drought tolerant eucalyptus in South Africa (Wessels *et al.* 2016; Lundqvist *et al.* 2017). It was slightly higher at the butt and top ends than the middle. This difference was not statistically significant with the ANOVA test on disc position giving a *p*-value of 0.98 (Chapter 4: Figure 4-6 refers). This is contrary to findings in other studies where wood density is said to vary with height (Seifert and Seifert, 2014; Paul *et al.*, 2016). For example, one author indicates that wood density is higher at the butt-end and breast height than at the top-end (Basuki *et al.*, 2009). It is not clear why wood density for the sampled *Cryptosepalum* forest is not statistically different along the stem. Published wood density studies on the

Cryptosepalum forests are currently not available. Nevertheless, the stem wood volume was calculated using the average of the values from the three positions. The main branch volume, on the other hand, was calculated using the top-end density of the main stem. This was with the view that the main stem top-end density is more representative to that of the main branch than the mean. The wood density of the sampled *Cryptosepalum* trees was estimated at 702 kg/m³; this is a higher density compared to other tropical African species with an average density of 500 kg/m³ (Reyes *et al.*, 1992). The wood density was used to convert volume to dry mass in line with other studies (Basuki *et al.*, 2009; Ploton *et al.*, 2016). This finding is potentially a very useful one; if *Cryptosepalum* as a species does not exhibit major up-the-stem density variations (this probably needs to be tested more rigorously), it would seem that taking a single DBH core would suffice for estimating whole tree density. As such, field sampling methods that include density (where useful) could be simplified with no loss of prediction accuracy.

5.4.2 Wood density as an independent variable

The wood density was not used as an independent variable in this study. However, other studies have used wood density in the models (Chave *et al.*, 2005; Basuki *et al.*, 2009; Lung and Espira, 2015; Picard *et al.*, 2015). It is important to note that whenever wood density is used in biomass models, it is preferred that these be measured on-site instead of depending on published data (Seifert and Seifert, 2014; Yuen *et al.*, 2016). This requires extra efforts and resources in order to measure the wood density of all the trees. As a result, wood densities from published databases are often used instead of making actual measurements *in situ*. Using pre-existing values of wood density from the literature or a database creates a source of uncertainty that can only be addressed by sampling at the site in question (Mugasha *et al.*, 2013; Yuen *et al.*, 2016).

Biomass studies conducted through destructive sampling indicate that wood density is an important variable in tree biomass predictions (Chave *et al.*, 2014). It is not advisable to use DBH as a predictor alone because the quantity of tree biomass is also affected by tree height and wood density (Chave *et al.*, 2005; Basuki *et al.*, 2009). The wood density is known to vary across different sites. For instance, wood density variation is so evident in a small geographical area whereby sites 1, 2 and 3 within Kwambonambi forest plantations in South Africa have their density estimated at 380, 411 and 462 kg/m³, respectively (Arbuthnot, 1991). Besides, wood density application is necessary in order to estimate the biomass of large trees whose biomass is more variable and has a

disproportionately large contribution to the forest biomass. In a study in East Kalimantan, Indonesia, for instance, results showed that trees with the largest diameters did not necessarily contain the highest biomass when wood density was taken into consideration due to the difference between individual trees in wood density (Yuen *et al.*, 2016). The same authors indicate that the inclusion of wood density is very important each time the stem biomass is calculated from stem volume. In some studies, wood density variations along the stem cannot be taken in to account because trees cannot be sampled destructively for many wood density samples. However, they provide an important factor at the species level. (Mensah *et al.* 2016).

However, in the current study the wood density was not used as an independent variable despite the fact that the stem biomass was calculated from stem volume. This was because, not only was the intra-tree variation statistically insignificant but all sample plots were located on the same site also. The application of wood density in biomass models is strongly recommended where models are formulated for data collected from different sites (Yuen *et al.*, 2016). This is so because wood density is strongly influenced by environmental factors (such as soil fertility, light availability, humidity, etc.), the climatic zone and the frequency of natural disturbances (Yuen *et al.*, 2016). This can be demonstrated by the fact that the same tree species growing on different sites can have different wood densities (Arbuthnot, 1991). Generally, wood density is only a valuable addition when, as a measurable and independent variable, it allows researchers to use a general model for forests with species and or sites where the wood density is known to vary. Therefore, the application of wood density in biomass models contributes towards reducing uncertainty arising from the variation among different sites.

5.5 Collinearity

Collinearity refers to a situation where changes in two (2) or more parameters (as the tree develops) are not independent of each other such as DBH and height (Picard *et al.*, 2015; Ploton *et al.*, 2016). In this study, collinearity was dealt with by adding height as a combined variable with DBH (i.e. D^2Ht) (Picard *et al.*, 2015). The testing of the variance inflation factor (VIF) for all the multiple regression models as recommended by Sileshi (2014) was not done because this study used simple models.

5.7 Biomass estimation by component

The biomass estimation for tree components was done separately for the stem, branch base, main-branches, sub-branches and foliage (Figure 3-4). This is in line with methods used in other studies (Parresol, 2001; Magalhães and Seifert, 2015). Each tree component is then compared to other components in this study (in terms of % contribution to the TAGB) and then to findings of previous studies. The high variation among tree components is due to the fact that the % biomass varies as a function of tree size; small trees have a large percentage of AGB in form of branches while large trees have a greater percentage of biomass in the stem. Consequently, the wider the DBH range, the higher the biomass variation among tree components.

5.7.1 Stem wood biomass as % of total biomass

The bulk of tree biomass estimated using allometric functions was found in the main stems and not in the branches and leaves. The stem wood biomass alone accounted for 17–94 % of the Total Above-Ground Biomass (TAGB) with a mean of 52 %. The high variation in stem wood biomass is due to differences in branching habits (crown architecture); given a tree with a double leader, the two large stems would be categorised as branches. The results obtained in this study are similar to the findings of a study conducted by Basuki *et al.* (2009) whereby main stem biomass contributed 45–90 % of TAGB with a mean of 67 %. Magalhães and Seifert (2015) report an average of 70% proportion of TAGB and 57% of the total biomass (above and below ground biomass) being attributed to the stem biomass for the dry Mecrusse woodlands in Mozambique. A study conducted in a moist tropical forest in the north-eastern part of Gabon found similar results where the stem wood biomass alone accounted for 66 % of the TAGB on average (Ngomanda *et al.*, 2013). Another study in the wet evergreen tropical forests in Ghana also had quite similar results in that the stem biomass alone accounted for 69 % of the TAGB (Henry *et al.*, 2010). The stem wood biomass is an important quantity because this component is the most merchantable and utilizable part in the forest industry. It follows that the carbon contained in the final wood products therefore remains stored for a long time and is not released into the atmosphere (Magalhães and Seifert, 2015). This is desirable for reducing the negative effects of climate change.

5.7.2 Branch wood biomass as % of total biomass

The branch wood biomass (main and sub-branches) accounted for 6–81 % of the TAGB with mean of 45 %. This result was higher than the findings made by Ngomanda *et al.* (2013) where branches

accounted for 28 % of TAGB. Another study in the wet evergreen tropical forests in Ghana also shows lower estimates in that branch biomass accounted for 27 % of the TAGB (Henry *et al.*, 2010). Paul *et al.* (2016) observed that the higher contribution of branch biomass to AGB is due to the plant architecture associated with the relatively heavy branches or small stems of high density. It was observed in this study that, due to competition, tree crown architecture was influenced by canopy opening; trees growing in the relatively less dense sections of the forest had the tendency to develop heavier branching than otherwise, since the forest is closed. This may partly contribute to this high branch biomass variation. The branch wood biomass is important in case the forest is harvested in a logging operation and the slash is left in the stump area. Since the forest is far from the villages, branch and foliage biomass components decompose in the field leading to a release of CO₂, though at a slower rate. This exacerbates the undesirable effects of climate change (Magalhães and Seifert, 2015).

5.7.3 Foliage biomass as % of total biomass

The contribution of leaf biomass to TAGB was in the range 1- 3 % with a mean of 2 %. This is in line with observations made by Chave *et al.* (2014) indicating that the leaf biomass usually contributes less than 5 % of TAGB. These results are similar to those obtained in a study conducted in a tropical moist forest in north-eastern Gabon by Ngomanda *et al.* (2013; article in press), where leaf biomass contributed 2 % to the TAGB.

The foliage biomass component is supposed to increase the level of TAGB in the *Cryptosepalum* forests over the deciduous Miombo woodlands by virtue of being evergreen. But the leaf biomass in this forest is ephemeral because this forest is defoliated at the beginning of the rainy season (August–October) every year by caterpillars most likely *Mylothris mavunda* (Cottrell & Loveridge, 1966). This defoliation led to a situation where it was only possible to collect a leaf sub-sample (4 out of 22 sampled trees) 2 months later than the scheduled sampling time. This sub-sample (18 % of the sample) is small and may not be representative of the leaf biomass in the population. Thus, separate biomass estimation equations for the ‘leaf-on’ and the ‘leaf-off’ conditions are required to estimate TAGB in this forest at different times of the year. However, it is important to note that the foliage biomass does not significantly affect the TAGB quantity. In an event that the forest is cleared in a ‘leaf-on’ condition for charcoal manufacturing or to pave way for agricultural or mining activities, this leaf biomass will be shed off and decompose releasing CO₂ in to the atmosphere (Magalhães and Seifert, 2015). This is undesirable as it contributes to Climate Change.

5.8 Above – ground biomass distribution per DBH class

The larger trees (of size from ≥ 70 cm DBH) store large amounts of biomass due to their high wood volumes and they account for more than 2/3 of sample-based pantropical variation in AGB (Slik *et al.*, 2013). In this study, the highest accumulation of biomass (66.9%) was observed in the middle DBH classes from ≥ 30.1 to 40 cm. The biomass accumulation in the DBH classes with smaller diameters from ≥ 5 – 20cm (15.1 %) was slightly less than that observed in the larger DBH classes from ≥ 40.1 to 60cm (18 %). This finding is in line with the observations made in other studies (Baishya *et al.*; 2009; Basuki *et al.*; 2009). The trees with DBH > 60 cm were not observed in this study. This could be attributed to high competition which results in to the death of some of the trees in order to create growing space for the remaining ones (Geldenhuys, 2015). Other studies indicate that the non-availability of trees with DBH > 60 cm could be attributed to the poor soils namely the Kalahari sands upon which this forest is growing as observed by Slik *et al.* (2013) that very poor soils can lead to stunted tree growth, suppressed maximum tree size and lowered AGB of large trees.

Studies have shown that matured tropical forests rich in AGB contain a large proportion of AGB in trees falling in the larger DBH category (Baishya *et al.*, 2009). According to Baishya *et al.* (2009), this higher proportion of AGB in the larger diameter classes signifies the important role this category of trees plays in carbon storage. Nevertheless, this does not underrate the role of smaller trees (<70cm DBH) in enhancing future carbon stock since they possess a unique carbon sequestration potential (Baishya *et al.*, 2009). Baishya *et al.* (2009) indicates that the mature forests do not add up any further biomass; this is because most parts of the gross primary productivity are consumed in respiration or converted to soil organic matter as litter with minimal net addition to AGB quantity. It is important to note that, even if these mature forests do not significantly add to carbon uptake, they play a critical role in regeneration and sustaining biodiversity (Baishya *et al.*, 2009). In terms of management, studies have shown that the larger trees, compared to smaller trees, may have higher vulnerability to changing climate potentially resulting in a decline in forest biomass storage (Slik *et al.*, 2013). A prolonged drought, for instance, may result in disproportionate increase in large tree mortality as compared to smaller DBH trees. Therefore, any impacts, either by global climate change or human disturbances such as logging, clearing to pave the way for agricultural activities or large-scale mining that reduce the abundance or persistence of these larger DBH trees, is likely to have measurable and large impacts on the forest AGB (Lung and Espira, 2015).

5.9 Comparison of *Cryptosepalum* AGB and AGC levels with other forests

The TAGB and AGC value for the sampled *Cryptosepalum* (closed canopy forest) for trees with a diameter ≥ 5 cm across all plots was estimated at 395.5 ± 68.6 Mg ha⁻¹ and 197.8 ± 84.17 Mg C ha⁻¹, respectively. This result is very similar to the value obtained for the African closed canopy forests done by Lewis *et al.* (2013) who estimated it at 395.7 Mg ha⁻¹. It also sits in almost the same range with the AGB values for the Amazonian forest estimated at 312 – 464 Mg ha⁻¹ (Lewis *et al.*, 2013). It is higher than the estimates for an African moist tropical forest observed by Lung and Espira (2015) i.e. 279 Mg ha⁻¹ and 260 Mg ha⁻¹ by Baishya *et al.* (2009). An estimate for the Miombo, a dry forest in Zambia, when categorized as semi-evergreen forest, found the AGB and the AGC to be at 93.1 Mg ha⁻¹ and 43.8 Mg C ha⁻¹, respectively (Day *et al.*, 2014). An estimation done by Mukosha and Siampale (2009) for the generalised evergreen forests in Zambia put the AGB at 108.2 Mg ha⁻¹. The estimate obtained in the current study is >200 % and > 300 % higher than that for the Miombo and generalised evergreen forests in Zambia, respectively. This higher AGB value for the sampled *Cryptosepalum* forest could be attributed to higher DBH of the biggest trees, the average species wood density and the stand density. This is in line with observations made by Lung and Espira (2015) that the DBH of largest trees, the mean species wood density and the stand density are the three most important forest stand variables influencing AGB. Taking wood density, for instance, the mean for the *Cryptosepalum* forest as estimated in this study is 700 kg/m³ while dominant species for the Miombo woodland such as *Brachystegia* have a mean of 520 kg/m³ (Reyes *et al.*, 1992). Equally, the stand density for the sampled *Cryptosepalum* forest as calculated in this study is 366 stems ha⁻¹ while that for the Miombo is at 231 stems ha⁻¹ (Mukosha and Siampale, 2009). It goes without saying that the *Cryptosepalum* forest stores substantially higher quantities of biomass and carbon stocks than some other dry tropical forests such the Miombo woodlands due to a higher mean wood density and stand density.

5.10 Forest management implications

Prior to this study, a major challenge for considering the *Cryptosepalum* forests in the REDD+ mechanism could have been the non-availability of species or forest-specific biomass estimation models. Henceforth, this is no longer the case. As alluded to in Chapter 1, Zambia as a developing country faces many environmental and socio-economic challenges. With a high poverty level of 60.5 %, a GINI Index of 57.5 % indicates that poverty levels are rising. With over 70 % of the rural population entirely depending on the forest for their livelihood, the threat from shifting cultivation

is likely to increase in the future, as limited access to farming inputs by peasant farmers gets worse. Though currently this not significant for the *Cryptosepalum* forests, there is high likelihood of pressure from shifting cultivation to increase as a function of population dynamics; the higher the population, the more the demand for food. With increased mining activities currently taking place in the North – western Province, forests are already being cleared to pave way for mining activities. Increased demand for domestic energy for miners' households could lead to a higher demand for charcoal; dual usage of both electricity and charcoal is a common practice in Zambia. This may result in an increased pressure on the forest due to charcoal manufacturing.

The *Cryptosepalum* forests, with an estimate of 542.2 Mg ha⁻¹ which is equivalent to 271.1 Mg C ha⁻¹, has great potential for carbon sequestration. This is because any moderate thinning done in this forest, thus opening the canopy, could result in small-diameter class trees developing in to large trees (Geldenhuys, 2015). Using the UNREDD⁺ mechanism, this forest could be managed for carbon sequestration so that the local community members can continue extracting forest produce for domestic use while benefiting financially through carbon trading. If the forest is left unmanaged, there is a high chance of losing it in the future. The following are the scenarios:

Table 5-1: Scenarios for *Kalemalema* forest as regards management of the forest for carbon sequestration

Scenarios /Variable	Best Case Scenario	Most Likely Scenario	Worst Case Scenarios	
			Scenario 1	Scenario 2
Management	Due to the very high potential for carbon sequestration, the <i>Cryptosepalum</i> forest in <i>Kalemalema</i> is put under management by using REDD ⁺ activities (≥ 271.1 Mg C ha ⁻¹ carbon sequestration function of the forest continues or increases)	The forest remains unmanaged and with open access to the public.	A concession is granted to a logging company (≥ 271.1 Mg C ha ⁻¹ carbon sequestration function of the forest ceases).	A Mining licence is issued to a mining company (≥ 271.1 Mg C ha ⁻¹ carbon sequestration function of the forest ceases).
Harvesting	Legal domestic extraction continues in form of moderate thinning for poles and fibre used in house construction. This is said to have virtually no negative effect on the growth rate of the forest and hence on carbon sequestration. If anything, thinning stimulates increase in DBH for remaining trees by opening the canopy, which might otherwise remain closed. This is in line with	The small-scale clearing for peasant farming and the extraction of domestic fuel wood and building materials such as poles, fibre etc. continues especially on the forest margins.	The forest is harvested during a logging operation.	The forest is cleared to pave way for mining.

	recommendations made by Geldenhuys (2015) in reference to a similar forest namely Miombo woodland.			
Multiple effects	This goes a long way in supporting conservation of not only the forests but also for the West Lunga National park and the surrounding GMAs.	The expansion of illegal domestic extraction of forest produce and forest utilisation threaten the ecosystem in West Lunga National Park and surrounding GMAs.	There is soil erosion leading to stream siltation	There is ecosystem destruction including loss of wild life habitat and siltation of streams due to soil erosion.
Benefit sharing	The local communities in general and the Community Resource Boards (CRBs) in particular participate in the initiative by applying lessons learnt from past wildlife Community Based Natural Resource Management (CBNRM) projects. The socio-economic benefits accrue to the local community leading to improved agricultural and livelihood service provision in the short term.	The local communities do not receive any compensation for avoided deforestation. The poverty levels remain high amidst increased population. The threat from logging, clearing for agricultural and mining activities or charcoal manufacturing remains minimal presently and in the near future. Nonetheless, the likelihood of this threat increasing in the distant future is eminent.	The branches and twigs (logging slash) are collected by community members for their domestic energy requirements.	Charcoal manufacturers obtain concessions to utilise the biomass after clearing.

Effects on climate change	In the long run, improved livelihood results in reduced poverty in the area. As a result of the reduced poverty, pressure on the forests is minimised whereby carbon sequestration in the forests continues; thus, mitigating the negative effects of Climate Change.	The carbon sequestration process continues in the forest.	271.1 Mg C ha ⁻¹ carbon sequestration function of the forest ceases, if the forest is clear-felled, or reduced significantly, where selective cutting is used. The wood products obtained from the timber remain a carbon sink but a huge amount of carbon gradually released in to atmosphere from combustion of fuel wood (logging slash) is significant.	≥ 197.8 Mg C ha ⁻¹ carbon sequestration function of the forest ceases as ≥ 542.2 Mg ha ⁻¹ (because other trees and plants species not included in this study exist in this forest as sub-dominants and under-storey species) of wood biomass is converted in to charcoal.
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5.11 Recommendations

- Given the high sequestration potential for the biomass and carbon, this forest should be put under management using the REDD⁺ mechanism. Through this initiative, the carbon stock will be conserved while benefits for the local communities are ensured.
- Future research in this forest that involves ‘leaf-on’ biomass estimation should be done when the forest is in full leaf (November–July). It is worth noting, however, that field activities should not be planned for the rainy season covering the period October–March. This is because it is strongly recommended that plant samples should not be collected after heavy rains; this affects their wet weight in the field.
- Standard forest tools and equipment should be used in height measurements and destructive sampling. For example, a chain saw is required not only for tree felling but also for removal of disc samples, if the disc samples are to be of the specific size.
- BGB and BGC estimated using the AGB and AGC is a step in the right direction. However, comprehensive carbon sequestration is complete only when other carbon pools are also estimated (IPCC, 2006) namely Soil Organic Carbon (SOC), Dead wood and litter. Future research efforts should include carbon estimation for these afore-mentioned pools.

Chapter 6: Conclusion

This study was aimed at estimating carbon sequestered in the *Cryptosepalum* forests of Mwinilunga district, North-western Province, Zambia. The study used a dataset from 22 destructively sampled *Cryptosepalum* trees with DBH and height ranges of 6.2–58.9 cm and 4.0–22.3 m, respectively. These DBH and height ranges are quite representative of the forest in this area. The best general model for estimating biomass for the sampled *Cryptosepalum* forest is:

$$\ln(B) = \beta_0 * (\exp((\beta_1 * \ln(DBH)) + (\beta_2 * \ln(Ht)))) \quad \text{Model 5}$$

Where:

$$\beta_0 = 1.10349147;$$

$$\beta_1 = 1.1157;$$

$$\beta_2 = 0.01479$$

When fitted, this model shows that a substantial part of the biomass variations ($R^2 = 57\%$) was explained by DBH and height. Since the inclusion of height in the model significantly increased the explanation of the biomass variation, it is better to apply the model with both DBH and height. This species-specific model can be used to complement the REDD⁺ activities (Chave *et al.*, 2014) currently being undertaken in Zambia by applying it to other *Cryptosepalum* forests within Mwinilunga district provided the tree sizes fall in the afore-mentioned model data range. The wood density was not used as an independent variable in the study. This is because wood density is usually applied in a mixed species model or when comparing more than one site as it is considered a good proxy indicator of site variations. But in this study, only one dominant species was considered and all the sample plots were located on the same site. Intra tree wood density variation was investigated and the effect of the position in the stem was found to be statistically insignificant. Therefore, future research in the *Cryptosepalum* forests need not collect more than one sample from each tree; one sample per tree adequately represents wood density in a particular tree. It is important to note, however, that the *Cryptosepalum* can be considered as a high-density wood with a density of 700 kg/m³.

Previous studies predicted the AGB and AGC as a generalization either for *Miombo* woodlands or evergreen forests in Zambia. The *Miombo* is a similar tropical but semi-deciduous woodland whose

dominant genera are *Brachystegia*, *Julbernardia* and *Isoberlinia*. The evergreen forests, besides the *Cryptosepalum* include the *Parinari–Syzygium* and *Marquesia acuminata*. Due to the differences in dominant species and sites, applying such estimates to the *Cryptosepalum* forests is not the best option. That is why species or forest-specific models are preferred. One model for the *Cryptosepalum* forests is developed and should be put to good use.

Chapter 7: References

- [FAO] Food and Agriculture Organisation of the United Nations. 2005. Global Forest Resources Assessment 2005: FAO Main Report. Rome. FAO.
- [GRZ] Government of the Republic of Zambia. 2012. District Situation Analysis (2012), Mwinilunga District Council. Mwinilunga. Zambia: GRZ.
- [GRZ] Government of the Republic of Zambia. 2010. District Situation Analysis (2010), Mwinilunga District Council. Mwinilunga. Zambia: GRZ.
- [GRZ] Government of the Republic of Zambia. 2010. Zambia Census of Population and Housing. Key Findings, Central Statistical Office, Lusaka, Zambia. GRZ.
- [GRZ] Government of the Republic of Zambia. 1998. Zambia Forestry Action Programme. Forestry Department: Ministry of Tourism, Land and Natural Resources. Retrieved from www.ministryoflands.gov.zm/index.php/forestry on 08.03.2015).
- [GRZ] Government of the Republic of Zambia. 2011. *Sixth National Development Plan 2011 - 2015*. Lusaka. Zambia: GRZ. Retrieved from: siteresources.worldbank.org/INTZAMBIA/Resources.
- [GRZ] Government of the Republic of Zambia. 2013. Appraisal Report: Decentralised Forestry Related Natural Resource Management Programme. Lusaka. Zambia: GRZ.
- [IPCC] Intergovernmental Panel on Climate Change. 2006. IPCC Guidelines for National Green House Gas Inventories. Introduction. Chapter 1, Volume 4. Agriculture, Forestry and Other Land Use: IPCC.
- [IPCC] Intergovernmental Panel on Climate Change. 2006. IPCC Guidelines for National Greenhouse Gas Inventories. Volume 4: Agriculture, Forestry and Other Land Use. Chapter 2. Generic Methodologies applicable to Multiple Land - Use Categories. IPCC.
- [IPCC] Intergovernmental Panel on Climate Change. 2006. IPCC Guidelines for National Greenhouse Gas Inventories. Volume 4: Agriculture, Forestry and Other Land Use. Chapter 4. Forest Land. IPCC.
- [UNFCCC] United Nations Framework Convention on Climate Change. 1998. Kyoto Protocol. United Nations. Retrieved from unfccc.int/resources/docs/convkp/kpeng.pdf: UNFCCC.

- Alarjavi (1996): Zambia Forestry Action Plan, Ministry of Environment and Natural Resources, Lusaka, Zambia.
- Arbuthnot, A.L. 1991. The influence of basic wood density of Eucalyptus on pulp and paper properties. In *Intensive Forestry: The role of Eucalyptus*. IUFRO Symposium. Proceedings vol.2. 2-6 September, Durban. South Africa.
- Aregheore, E.M. Country pasture and forage resource profiles. Retrieved from www.fao.org on 05/07/2015.
- Baishya, R; Karik, S.K and Upadhaya, K. 2009. Distribution pattern of above-ground biomass in natural and plantation forests of humid tropics in northeast India. *Tropical Ecology* 50 (2): 295–304.
- Basuki, T.M; van Laake, P.E; Skimore, A.K; Hussin, Y.A. 2009. Allometric equations for estimating the above-ground biomass in tropical lowland Dipterocarp forests. *Forest Ecology and management*. 257: 1684 – 1694.
- Brown, S. 1997. *Estimating Biomass and Biomass change of Tropical Forests: a Primer*. UN FAO Forestry Paper – 134. Rome: Food and Agriculture Organisation of the United Nations. Retrieved on 12.10.2016 from <http://www.fao.org/docrep/w4095e/w4095e00.htm>
- Chave, J; Andolo, C; Brown, S; Cairns, M.A; Chambers, J.Q; Eamus, D; Folster, H; Froward, F; Higuchi, N; Kira, T; Lescure, J.P; Nelson, B.W; Ogawa, H; Puig, H; Riera, B; Yamakura, T. 2005. Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia*. 145:87-99.
- Chave, J; Rejou – Mechain, M; Burquez, A; Chidumayo, E; Golgan, M.S; Delitti, W.B.C; Duque, A; Eid, T; Fearnside, P.M; Goodman, R.C; Henry, M; Yrizar, A.M; Mugasha, W.A; Landau, H.C.M; Mencuccini, M; Nelson, B.W; Ngomanda, A; Nogueira, E.M; Malavissi, E.O; Pelissier, R; Ploton, P; Ryan, C.M; Saldarriaga, J.G; and Vieilledent, G. 2014. Improved allometric models to estimate the above ground biomass of tropical trees. *Global Change Biology*. 20:3177 – 3190.

–

- Chave, J; Condit, R; Aguilar, S; Hernandez, A; Lao, S and Perez, R. 2004. Error propagation and scaling for tropical forest biomass estimates. The Royal Society. DOI 10.1098/rstb.2003.1425. Retrieved on 10.11.2016.
- Chidumayo, E. N. 2013. Forest Degradation and recovery in a Miombo woodland landscape in Zambia: 22 years of observations on permanent sample plots. *Forest Ecology and Management*. 291: 154 -161.
- Chidumayo, E. N. 1990. Above-ground Woody Biomass Structure and Productivity in Zambesian Woodland. *Forest Ecology and Management*. 36:33-46.
- Chidumayo, E. N. 1997. *Miombo Ecology and Management: An Introduction*. London. IT Publications (ITP) in association with Stockholm Environment Institute.
- Chundama, M. 2009. Preparing for REDD in dryland forests; investigating the options and potential synergy for REDD payments in the Miombo Eco-region. Zambia country study. International Institute for Environment and Development (IIED). London. UK.
- Condit, R. 2008. Methods for estimating above-ground biomass of forest and replacement vegetation in the tropics. Centre for Tropical Forest Science Research Manual, 73 pages. *Cryptosepalum exfoliatum*. Retrieved from https://en.wikipedia.org/wiki/Cryptosepalum_exfoliatum on 06 / 07/2015.
- Cottrell, C.B & Loveridge, J.P. 1966. Observations on the *Cryptosepalum* forests of the Mwinilunga District of Zambia. *Proceedings and Transactions of the Rhodesia Scientific Association* 51:1-44.
- Day, S.M; Gumbo, D; Moombe, K.B; Wijaya, A. and Sunderland T. 2014. Zambia Country Profile: Monitoring, Reporting and Verification for REDD+; CIFOR Occasional Paper 113, Bogor, Indonesia.
- Fanshawe, D.B. 1960. Evergreen forest relics in Northern Rhodesia. *Kirkia* 1: 20-24. National Herbarium and Botanic Garden Retrieved on 18.10.2016 from <http://www.jstor.org/stable/23500526>.
- Frost, P. 1996. The ecology of the Miombo woodlands. In Campbell, B (Ed); *The Miombo in transition: Woodlands and welfare in Africa*, pp 11-57. Centre for International Forestry Research, Bogor, Indonesia.

- Fund, W. and Hogan, C. 2014. Zambesian *Cryptosepalum* dry forest. Retrieved March, 2015 from <http://www.eoearth.org/view/article/51cdef4d7896bb431f69d7fe>.
- Geldenhuys, C.J. 2015. Ecological basis for integrated, multiple-use management of Mozambique forest and woodland areas. SESA Report to deal with REDD+. Report Number FW – 04/15.
- Goicoa, T; Militino, M.D and Ugarte, M.D (2011). Modelling above-ground tree biomass while achieving the additivity property. *Environmental Ecology Stat.* 18:367–384. DOI 10.1007/s 10651 – 010-0137-9. Retrieved on 23.11.2016.
- Henry, M; Picard, N; Trotta, C; Manlay, R.J; Valentini, R; Bernou, M and Sante-Andre, L. 2011. Estimating tree biomass of Sub-Saharan African forests: a review of available allometric equations. *Silva Fennica.* 45(3B): 477-569.
- Henry, M; Besnard, A; Asante, W.A; Eshun, J; Adu-Bredu, S; Valentini, R; Bernoux, Sante-Andre, L. 2010. Wood density, phytomass variations within and among trees, and allometric equations in a tropical rainforest of Africa. *Forest Ecology and Management* 260 (2010): 1375-1388.
- Hunter, M.O; Keller, M; Victoria, D and Morton, D.C. 2013. Tree height and tropical forest biomass estimation. *Biogeosciences.* 10: 8385 – 8399.
- Kohl, M; Magnussen, S.S and Marchetti, M. 2006. Sampling methods, Remote Sensing and GIS Multiresource forest Inventory. *Tropical Forestry.* ISBN: 3 – 540 – 32571 – 9. Springer.
- Lawton, R.M. 1964. The ecology of *Marquesia acuminata* (Gilg). RE.FR. Evergreen forest and the related *Chipya* vegetation types of North–eastern Rhodesia. *Journal of ecology.* 52(3): 467 – 479.
- Lewis, S.L; Sonké, B; Sunderland, T; Begne, S.K; Lopez-Gonzalez, G; Geertje van der Heijden, M.F; Phillips, O.L; Affum-Baffoe, K; Baker, T.R; Banin, L; Bastin, J; Beeckman, H; Boeckx, P; Bogaert, J; De Cannière, C; Chezeaux, E; Clark, C. J; Collins, M; Djangbletey, G; Djuikouo, M.N.K; Droissart, V; Doucet, J; Ewango, C.E.N; Fauset, S; Feldpausch, T.R; Foli, E.G; Gillet, J.F; Hamilton, C.A; Harris, D.J; Hart, T.B; de Haulleville, T; Hladik, A; Hufkens, K; Huygens, D; Jeanmart, P; Jeffery, K.J; Kearsley, E; Miguel, E; Leal, M.E; Lloyd, J; Lovett, J.C; Makana, J; Malhi, Y; Marshall, A.M; Ojo, L; Peh, K.S.H; Pickavance, G;

- Poulsen, J.R; Reitsma, J.M; Sheil, D; Simo, M; Steppe, K; Taedoumg, H.E; Talbot, J; Taplin, J.R.D; Taylor, D; Thomas,S.C; Toirambe, B; Verbeeck, H; Vleminckx, J; White, L.J.T; Willcock, S; Woell, H and Lise Zemagho, L.2013. Above-ground biomass and structure of 260 African tropical forests. *Biological sciences*. DOI: 10.1098 / rstb.2012.0295. Retrieved 11.10.2016.
- Lundqvist SO, Grahn T, Olsson L, Seifert T (2017). Comparison of wood, fibre and vessel properties of drought-tolerant eucalyptus in South Africa. Doi.10.2989/20702620.2016.1254910
- Lung, M and Espira, A. 2015. The influence of stand variables and human use on biomass and carbon stocks on African transitional forest: implications for forest carbon projects. *Forest Ecology and Management*. 351 (2015): 36-46
- Lykke, M, A. 1998. Assessment of species composition change in Savannah vegetation by means of woody plant size class distribution and local information; *Biodiversity and Conservation*. 7: 1261 – 1275.
- Magalhães, T.M and Seifert, T. 2015. Biomass modelling of *Androstachys Johnsonii* Prain: A comparison of three methods to enforce additivity. *International Journal of Forestry Research*. 2015: Article ID: 878402.
- Magalhães, T.M and Seifert, T (2015). Tree component biomass expansion and root-to-shoot ratio of Lebombo ironwood: measurement uncertainty. *Carbon balance and management*, 10:9 DOI: 10.1186/s 13021-015-0019-4
- Magalhães TM, Seifert T (2015). Estimates of Tree Biomass, and its uncertainties through Mean-of Ratios, Ratio-of-Means, and Regression Estimators in Double Sampling: A comparative Study of Mecrusse Woodlands. *American Journal of Agriculture and Forestry*, 3(3): 161-170
- Mensa S, Veldtman R, Seifert T: Allometric Models for Height and Aboveground Biomass of Dominant Tree Species In South African Mistbelt Forests. *Southern Forests* DOI.10.2989/20702620.2016

- Mesa, I. R (2015): Stochastic modelling of soil carbon stocks under different land uses: a case in South Africa. Master's thesis. Stellenbosch. Stellenbosch University.
- Mokany, K., Raison, R.J and Prokushkin, A.S. 2006. Critical analysis of root: shoot ratios in terrestrial biomes. *Global Change Biology*. 20: 84-86. Doi: 10.1111/j.1365-2486.2005.001043. Retrieved on 03.11.2015.
- Mugasha, W. A Eid, T; Bollandas, O. M; Malimbi, R.E; Chamshama, S. A. O; Zahabu, E and Katani, J. Z. 2013. Allometric models for prediction of above ground biomass and below ground biomass of trees in Miombo woodlands of Tanzania. *Forest Ecology and Management*.310:87-101.
- Mukosha, J and Siampale, A. 2009. Integrated Land Use Assessment Zambia (2005 - 2008). Lusaka, Zambia and Rome. Ministry of Tourism, Environment and Natural Resources and Forest Department, Government of the Republic of Zambia and the Food and Agriculture Organisation of the United Nations.
- Ngomanda, A; Obiang, N. L. E; Lebamba, J; Mavouroulou, Q.M; Gomat, H; Mankou, G.S; Loumeto, J; Iponga, D.M; Ditsouga, F.K; Koumba, R.Z; Bobé, K.H.B; Okouyi, C.M, Nyangadouma, R; Lépengué, N; Mbatchi, B; Picard, N. 2013. Site-specific versus pantropical allometric equations: Which option to estimate the biomass of a moist central African forest? Article in Press. *Forest Ecology and Management*.
- Osazuwa-Peters, O and Zanne, A.E. 2011. Wood density protocol. Prometheus Wiki. CSIRO. 1996-2013. Retrieved on 12.03.2016.
- O'Sullivan, A. List of countries by GDP (nominal) per capita. Retrieved from [https://en.wikipedia.org/wiki/List_of_Countries_by_GDP_\(nominal\)_per_capita](https://en.wikipedia.org/wiki/List_of_Countries_by_GDP_(nominal)_per_capita) on 06/07/2015
- Paressol, B.R. 2001. Additivity of non-linear biomass equations. *Canadian Journal of Forestry*.31: 865 – 878.
- Paul, K.I; Roxburgh, S; Chave, J; England, J.R; Zerihun, A; Specht, A; Lewis, T; Bennett, L; Baker, T.G; Adams, M.A; Huxtable, D; Montagu, K.D; Falster, D.S; Feller, M; Sochacki, S; Ritson, P; Bastin, G; Bartle, J; Wildy, D; Hobbs, T; Larmour, J.; Waterworth, R; Stewart, H.L; Johnson, J; Forrester, D.I; Applegate, G; Mendham, D; Bradford, M; O'grady, A; Green, D; Sudmeyer, R; Rance, S.J; Turner, J; Barton, C;

- Wenk, E; Grove, T; Attiwill, P.M; Pinkard, E; Butler, D; Brooksbank, K; Spencer, B; Snowdon, P; O'brien, N; Battaglia, M; Cameron, D.M; Hamilton, S; Authur, G and Singclair, J. 2016. Testing the generality of above-ground biomass allometry across plant functional types at the continental scale. *Global Change Biology*. 22: 2106-2124. Doi: 10. 1111/gcb.13201
- Picard, N; Rutishauser, E; Ploton, P; Ngomanda, A and Henry, M. 2015. Should tree biomass allometry be restricted to power models? *Forest Ecology and Management*. 353: 156-163.
- Ploton, P; Barbier, N; Momo, S.T; Rejou – Mechain, M; Basela, F.B; Chuyong, G; Dauby, G; Droissart, V; Fayolle, A; Goodman, R.C; Henry, M; Kamdem, N.G; Mukirania, J.K; Kenfack, D; Libalah, M; Ngomanda, A; Sonke, B; Texier, N; Thomas, D; Zebase, D; Couteron, P; Berger, U and Pelissier, R. 2016. Closing a gap in tropical forest biomass estimation: taking crown mass variation in to account in pan tropical allometries. *Biogeosciences*. 13: 1571 – 1585.
- R Core Team (2013) R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria. ISBN 3-900051-07. <http://www.r-project.org/contributors.html>.
- Reyes, G; Brown, S; Chapman, J; Lugo, A.E. 1992. Wood densities of tropical wood species. Technical Paper, SO–88; US Department of Agriculture, Forest Service, Rio Piedras, PR 00928–2500.
- Roxburgh, S.H; Paul, K.I; Clifford, D; England, J, R and Raison, R. J. 2015. Guidelines for constructing allometric models for the prediction of woody biomass: how many individuals to harvest? *Ecosphere*. 6 (3): 38
- Seifert T, du Toit B, Jooste GH, Seibold S, Durrheim G, Seydack A (2011). Towards an individual tree forest growth model for natural forests in South Africa: Testing competition indices to model individual tree diameter growth in Afro-temperate forests. 5th Natural forests and woodlands symposium, Richards Bay. South Africa, 10-14th April, 2011.
- Seifert, T and Seifert, S. 2014. Modelling and Simulation of tree biomass. In: Seifert, T (Ed.) *Bioenergy from Wood: Sustainable Production in the Tropics*. Springer.
- SigmaPlot (Systat Software), San Jose, CA

- Sileshi, W.G. 2014. A critical review of forest biomass estimation models, common mistakes and corrective measures. *Forest Ecology and Management*. 329: 237–254.
- Slik, J.W.F; Paoli, G; McGuire, K; Amaral, I; Barroso, J; Bastian M; Blanc, L; Bongers, F; Boundja, P; Clark C; Collins, M; Dauby, G; Ding, Y; Doucet, J; Eler, E; Ferreira, L; Fordshed, O; Fredriksson, G; Gillet, J; Harris, D; Leal, M; Laumonier, Y; Malhi, Y; Mansor, A; Martin, E; Miyamoto, K; Murakami, A.A; Hidetoshi, N; Nilus, R; Nurtjahya; Onrizal, O; Gutierrez, A. P; Permana, A; Poorters, L; Poulsen, J; Angulo, H. R; Reitsma, J; Rovero, F; Rozak, A; Sheil, D; Espejo, J.S; Silveira, M; Spironelo, W; ter Steege, Stevart, T; Aguilar, G.E.N; Sunderland, T; Suzuki, Eizi, Tang, J.W; Theilade, I; van der Heijden, G; van Valkenburg, J; Van Do, T; Vilanova, E; Voss, V; Wich, S; Woll, H, Yoneda, T; Zang, R, Zhang, M.G and Zweifel, N. 2013. Large trees drive above-ground biomass variation in moist lowland forests across the tropics. *Research Paper. Global Ecology and Biogeography*. 22: 1261–1271.
- Storrs, A.E.G. 1979. Know your trees: Some of the common trees in Zambia. Forest Department. Ndola. Zambia.
- Stromgaard, P.1985. Biomass, Growth and Burning of Woodland in a Shifting Cultivation Area of South Central Africa. *Forest Ecology and Management*, 12: 163 -178.
- Swaine, M.D; Hall, J.B and Alexander, I, J. 1987. The dynamics of Tree Populations in Tropical Forest. *Special Symposium Issue. Journal of Tropical Ecology*. 3(4): 331–345.
- Vinya, R., Syampungani, S., Kasumu, E.C., Monde, C. and Kasubika, R. (2011). *Preliminary Study on the Drivers of Deforestation and Potential for REDD+ in Zambia*. A Consultancy Report prepared for Forestry Department and FAO under the National UN - REDD+ Programme. Ministry of Lands & Natural Resources, Lusaka, Zambia.
- Wessels CB, Crafford PL, du Toit B, Grahn T, Johansson M, Lundqvist SO, Sall H, Seifert T (2016). Variation in physical and mechanical properties from three drought tolerant Eucalyptus species grown on the dry west coast of Southern Africa. *Eur.J.Wood Prod*. 74(44):563-575
- Williams, L. Copper's top 10 - Countries and Companies. Retrieved from [www.mineweb.com/news/base - metals - and - minerals/copper - top - 10 - countries – and - companies](http://www.mineweb.com/news/base-metals-and-minerals/copper-top-10-countries-and-companies) on 06/07/2015

www.worldbank.org/en/country/Zambia-Retrieved on 14.03.2016

Yuen, J.Q; Fung, T and Ziegler, A.D. 2016. Review of allometric equations for major land covers in S.E Asia. Uncertainty and implications for above- and below-ground carbon estimates. *Forest Ecology and Management*. 360: 323 – 340.

Chapter 8: Appendices

Appendix 1: GPS coordinates for all the 11 sample plots in *Kalemalema* forest

Plot Number	Longitude	Latitude
1	24°11'18.908"	12°26'36.772"
2	24°11'08.579"	12°25'14.133"
3	24°11'10.427"	12°25'09.823"
4	24°11'12.516"	12°25'03.316"
5	24°11'13.089"	12°24'57.682"
6	24°11'16.92"	12°26'26.316"
7	24°11'15.821"	12°26'25.601"
8	24°11'14.622"	12°26'24.224"
9	24°11'15.404"	12°26'22.581"
10	24°11'13.991"	12°26'20.632"
11	24°11'07.033"	12°25'13.762"

Appendix 2: Variation in mean Wood Density per sampled tree

Tree Number	Mean Mass (g)	Mean Volume (cm ³)	Mean Wood Density (kg/m ³)
1	130.0	183.3	733
2	283.3	400.0	708
3	358.3	476.7	742
4	228.3	320.0	708
5	275.0	393.3	691
6	241.7	350.0	680
7	328.3	520.0	626
8	225.0	326.7	697
9	258.3	370.0	698
10	291.7	430.0	672
11	275.0	376.7	730
12	266.7	350.0	758
13	250.0	340.0	737
14	438.3	673.3	650
15	550.0	713.3	783
16	262.5	395.0	674
17	408.3	596.7	682
18	250.0	343.3	728
19	200.0	250.0	799
20	441.7	636.7	694
21	200.0	320.0	625
22	216.7	420.0	625

Appendix 3: Variation in main stem biomass (Summation of biomass for billets) per tree

Tree Number	DBH (cm)	H (m)	Crown height (CH) in m	Stem Biomass Per Tree (kg)
1	27.9	11.1	4.27	209.8
2	25.1	18.2	7	270.7
3	15.9	17.5	9.2	392.5
4	28.9	18.5	11	413.3
5	32.4	22	10.1	333.1
6	19.3	17.1	13.4	176.4
7	27.9	20.5	9.7	442.8
8	36	19.7	9.3	242.1
9	23.5	16.1	5.3	119.4
10	32.5	16.4	9	389.1
11	35	19	9.5	408.2
12	13.2	13.5	9.4	167.7
13	29.9	8.8	5.8	184.0
14	35.4	18.3	6.6	335.1
15	33.9	18.78	3.3	203.7
16	14.5	13	1	31.6
17	23	17.8	4.51	236.8
18	34.8	15.6	5.5	303.8
19	32.8	18.5	10	273.6
20	13.9	18.5	2.2	128.8
21	20.1	12.84	7.76	200.5
22	16.5	11.7	6.6	220.1

Appendix 4: Variation in main branch base biomass estimated per tree.

Tree Number	DBH(cm)	Height (m)	Main Branch Base Biomass (kg)
1	27.9	11.1	<i>nil</i>
2	25.1	18.2	14.8
3	15.9	17.5	11.2
4	28.9	18.5	5.2
5	32.4	22.0	13.2
6	19.3	17.1	2.6
7	27.9	20.5	4.0
8	36.0	19.7	7.9
9	23.5	16.1	7.5
10	32.5	16.4	1.4
11	35.0	19.0	8.0
12	13.2	13.5	<i>nil</i>
13	29.9	8.8	<i>nil</i>
14	35.4	18.3	24.3
15	33.9	18.8	9.9
16	14.5	13.0	1.5
17	23.0	17.8	3.9
18	34.8	15.6	25.2
19	32.8	18.5	8.9
20	13.9	18.5	<i>nil</i>
21	20.1	12.8	7.7
22	16.5	11.7	10.3

Appendix 5: Variation in main branch biomass estimated per sampled tree.

Tree Number	Stem DBH (cm)	Tree height(m)	Branch Volume per Tree	Main Branch Biomass Per Tree (Kg)
1	27.9	11.1	<i>nil</i>	<i>nil</i>
2	25.1	18.2	0.46	317.99
3	15.9	17.5	0.25	174.39
4	28.9	18.5	0.26	94.83
5	32.4	22.0	0.37	254.23
6	19.3	17.1	0.04	30.30
7	27.9	20.5	0.18	72.26
8	36.0	19.7	0.38	249.60
9	23.5	16.1	0.30	211.63
10	32.5	16.4	0.14	92.89
11	35.0	19.0	0.29	211.91
12	13.2	13.5	<i>nil</i>	<i>nil</i>
13	29.9	8.8	<i>nil</i>	<i>nil</i>
14	35.4	18.3	0.57	366.63
15	33.9	18.8	0.95	867.07
16	14.5	13.0	0.08	54.76
17	23.0	17.8	0.16	111.69
18	34.8	15.6	0.94	690.30
19	32.8	18.5	1.06	838.80
20	13.9	18.5	0.01	3.64
21	20.1	12.8	0.26	165.43
22	16.5	11.7	0.24	150.62

Appendix 6: Variation in sub branch biomass per sampled tree.

Tree Number	<i>n</i>	Total Sub - branch Biomass Per Sampled Tree (kg)
1	2	15.6
2	14	68.8
3	14	86.1
4	15	76.2
5	36	170.4
6	9	31.0
7	31	115.7
8	62	213.4
9	32	132.4
10	15	54.1
11	18	93.1
12	8	27.0
13	2	11.4
14	45	195.2
15	18	112.0
16	7	35.8
17	15	64.8
18	27	151.2
19	47	214.6
20	10	34.3
21	22	96.9
22	24	113.8

Appendix 7: Variation in foliage biomass estimated per sampled tree.

Tree Number	Number of Sub-Branches Per Tree	Foliage Biomass Per Tree (Kg)
1	2	1.30
2	14	8.50
3	14	10.15
4	15	9.13
5	36	20.47
6	9	3.61
7	31	12.42
8	62	23.28
9	32	15.42
10	15	6.51
11	18	10.01
12	8	3.03
13	2	1.40
14	45	22.57
15	18	13.05
16	7	4.45
17	15	7.30
18	27	17.22
19	47	24.70
20	10	3.74
21	22	11.26
22	24	13.32

Appendix 8: Variation in Total Tree biomass data (used in the Total Tree Model) for biomass estimation for all trees

Tree Number	DBH	H	Total Tree Biomass
1	27.9	11.1	226.718
2	25.1	18.2	680.781
3	15.9	17.5	674.354
4	28.9	18.5	598.640
5	32.4	22	791.358
6	19.3	17.1	243.962
7	27.9	20.5	651.147
8	36	19.7	736.297
9	23.5	16.1	486.411
10	32.5	16.4	544.062
11	35	19	731.324
12	13.2	13.5	197.745
13	29.9	8.8	196.793
14	35.4	18.3	943.724
15	33.9	18.78	1205.706
16	14.5	13	128.045
17	23	17.8	424.451
18	34.8	15.6	1187.760
19	32.8	18.5	1360.476
20	13.9	18.5	170.473
21	20.1	12.84	498.646
22	16.5	11.7	508.050

Appendix 9: Variation in biomass by tree component

Tree Number	Biomass by Tree Component								Total Biomass Per Tree
	Stem		Symmetrical base		Branch		Foliage		
	Quantity	% of Total	Quantity	% of Total	Quantity	% of Total	Quantity	% of Total	
1	209.8	93	0.0	0	15.6	7	1.3	1	226.7
2	270.7	40	14.8	2	386.8	57	8.5	1	680.8
3	392.5	58	11.2	2	260.5	39	10.2	2	674.4
4	413.3	69	5.2	1	171.0	29	9.1	2	598.7
5	333.1	42	13.2	2	424.7	54	20.5	3	791.4
6	176.4	72	2.6	1	61.3	25	3.6	1	244.0
7	442.8	68	4.0	1	188.0	29	12.4	2	647.2
8	242.1	33	7.9	1	463.0	63	23.3	3	736.3
9	119.4	25	7.5	2	344.0	71	15.4	3	486.4
10	389.1	72	1.4	0	147.0	27	6.5	1	544.1
11	408.2	56	8.0	1	305.1	42	10.0	1	731.3
12	167.7	85	0.0	0	27.0	14	3.0	2	197.7
13	184.0	94	0.0	0	11.4	6	1.4	1	196.8
14	335.1	36	24.3	3	561.8	60	22.6	2	943.8
15	203.7	17	9.9	1	979.1	81	13.1	1	1205.7
16	31.6	25	1.5	1	90.6	71	4.5	3	128.1
17	236.8	56	3.9	1	176.5	42	7.3	2	424.5
18	303.8	26	25.2	2	841.5	71	17.2	1	1187.7
19	273.6	20	8.9	1	1053.4	77	24.7	2	1360.5
20	128.8	76	0.0	0	37.9	22	3.7	2	170.5
21	200.5	42	7.7	2	262.3	54	11.3	2	481.8
22	220.1	43	10.3	2	264.4	52	13.3	3	508.1
MEAN	258.3	52	7.6	1	321.5	45	11.0	2	598.5

