Biomass Modelling of Selected Drought Tolerant Eucalypt Species in South Africa

by

Darius Phiri

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Supervisor: Prof. Thomas Seifert
Co-supervisor: Pierre Ackerman

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Dedications

To my beloved late father and mother, only God can repay you for helping me reach this far.

TABLE OF CONTENTS

Declaration i

Abstract ii

Acknowledgements iii

Dedications vi

Table of contents vii

List of Figures xii

List of Tables xv

List of Abbreviations xvi

Chapter 1 : INTRODUCTION 1

1.1. Background 1

1.2. Problem Statement 4

1.3. Objectives of the study 4

1.3.1. Main objective 4

1.3.2. Specific objectives 4

1.3.3. Research questions 5

1.4. Rationale of the study 5

1.5. Thesis Structure 6

Chapter 2 : LITERATURE REVIEW 7

2.1. Forest models: Importance and use 7

2.2. Forest Biomass 7

2.2.1. Methods of biomass assessment 8

2.3. Biomass tree components 9

2.3.1. Branches 9

2.3.2. Foliage 11

2.3.3. Stem wood 11

2.3.4. Bark 12
2.4. Drying of Biomass samples 12
2.5. Sampling and Upscaling of biomass 12
2.6. Additivity in biomass models 14
2.6.1. SUR and NSUR 14
2.6.2. Compositional models 15
2.7. Goodness of fit for regression models 15
2.8. Back transformation bias correction 17
2.9. Error propagation 18
2.10. Review of existing biomass models 19
2.11. Forests and arid climatic conditions in South Africa 24
2.12. The genus *Eucalyptus* 26
2.12.1. Physiognomic and morphology of *Eucalyptus* 27
2.12.2. Silvicultural characteristics of *Eucalyptus* 27
2.13. *Eucalyptus cladocalyx* 28
2.13.1. Occurrence and Ecology 29
2.13.2. Morphology of *E. cladocalyx* 30
2.13.3. *E. cladocalyx* in South Africa 30
2.13.4. Uses of *Eucalyptus cladocalyx* 31
2.13.5. Potentialities of *Eucalyptus cladocalyx* in arid regions 32
2.14. *Eucalyptus gomphocephala* 32
2.14.1. Occurrence and Ecology 33
2.14.2. Morphology of *Eucalyptus gomphocephala* 33
2.14.3. *E. gomphocephala* in South Africa 34
2.14.4. Uses of *E. gomphocephala* 34
2.14.5. Potentialities of *E. gomphocephala* in arid regions 34

2.15. *E. grandis x camaldulensis* (Hybrid) 35
2.15.1. *E. camaldulensis* 35
2.15.2. *E. grandis* 36
Chapter 3 : MATERIALS AND METHODS 39
3.1. Study sites 39
3.1.1. Location 39
3.1.2. Climate and natural vegetation 40
3.1.3. Soil type and land use 41
3.1.4. Description of the trials at the study sites 42
3.2. Methods 43
3.2.1. Tree selection 43
3.2.2. Biomass sampling 44
3.2.3. Laboratory procedures 47
3.2.3.1. Drying series of sub-sample 48
3.2.4. Up-scaling Procedure 49
3.3. Data analysis 50
3.3.1. Seemingly unrelated regression 50
3.3.2. Error propagation 50
3.3.3. Assumptions in biomass modelling 51
3.3.4. Goodness of fit 51
3.3.5. Back transformation correction 52
3.3.6. Data analysis for drying series 52
Chapter 4 : RESULTS 53
4.1. Sampled trees 53
4.1.1. Distribution of sampled trees 53
4.1.2. Height Model 54

4.1.3. Volume Models....55
4.2. Upscaling models....57
4.2.1. Pooled crown model....57
4.2.2. *E. cladocalyx* crown models....60
4.2.3. *E. gomphocephala* crown biomass model....63
4.2.4. *E. grandis x camaldulensis* crown biomass model....66
4.2.5. Density determination....69
4.3. Biomass models....72
4.3.1. Pooled biomass models....72
4.3.2. *E. cladocalyx* biomass models....76
4.3.3. *E. gomphocephala* biomass models....79
4.3.4. *E. grandis x camaldulensis* biomass models....82
4.4. Propagated error....85
4.5. Drying series....87
4.5.1. Discs....87
4.5.2. Bark....89
4.5.3. Branches....90
4.5.4. Foliage biomass change....91
Chapter 5 : DISCUSSION OF RESULTS....94
5.1. Distribution of sampled tree....94
5.1.1. Diameter height Model....94
5.1.2. Volume Models....95
5.2. Upscaling models....95
5. 2.1. Pooled crown model....95
5. 2.2. Eucalypts species crown biomass model....96
5.3. Density determination....97

5.4. Biomass models....97
5.4.1. Pooled biomass Model....97
5.4.2. Individual eucalypt species biomass models....98
5.5. Propagated error....100
5.6. Drying series....101
Chapter 6 : CONCLUSION AND RECOMMENDATIONS....103
6.1. Conclusion....103
6.2. Recommendations....105
References....106
Appendix I....113
Appendix II....115

List of Figures

Figure 1.1: Distribution of forest plantations and indigenous forests in South Africa (De Beer, 2010) 3
Figure 2.1: Above and belowground biomass components (Seifert & Seifert, 2013) 10
Figure 2.2: Biomass upscaling steps involved in forest stand (Ackerman *et al.*, 2012) 13
Figure 2.3: Example a biomass regression (Ackerman *et al.*, 2012) 18
Figure 2.4: Map of rainfall pattern in South Africa (Shulze, 2007) 25
Figure 2.5: Distribution of *Eucalyptus spp* in the world (Brooker, 1990) 26
Figure 2.6: *E.cladocalyx* at the study site in the western coast of South Africa at the age of 20 years 30
Figure 2.7: *E. gomphocephala* on the study site in the western coast of South Africa at 20 years 33
Figure 2.8: Foliage for *E. grandis x camaldulensis* at the study site in the western coast of South Africa 36
Figure 2.9: Stem for *E. grandis x camaldulensis* at the study area in the west coast of South Africa 37
Figure 3.1: Location of study sites and other experimental site in Western Cape (du Toit *et al.*, 2012) 39
Figure 3.2: Typical natural vegetation of the study sites 40
Figure 3.3: Dry sand soils on the west coast of South Africa 41
Figure 3.4: *Eucalyptus* species on the experimental plot on the west coast of South Africa at 20 years of age 43
Figure 3.5: Points for disc removal on sampled trees 44
Figure 3.6: Sampled tree after felling at the study site 45
Figure 3.7: Biomass samples packed in plastic bags for transportation to the laboratory 46
Figure 3.8: Oven drying and weighing of biomass samples in the laboratory 47
Figure 3.9: CT-scanning density determination equipment and method (Holger Roth, GE Systems) 48
Figure 4.1: Diameter distribution of the sampled eucalypt trees for the biomass study 53
Figure 4.2: Dbh and height relationship of the three tree species 54
Figure 4.3: Height and diameter predicted vs. residual plots 55
Figure 4.4: Dbh and volume distribution of sampled trees 56

Figure 4.5: Volume and dbh model predicted values vs. Residuals for model 4.4 57
Figure 4.6: Pooled branch biomass and diameter relationship 58
Figure 4.7: Branch biomass model predicted values vs. residuals for Model 4.13 60
Figure 4.8: *E.cladocalyx* biomass and branch diameter relationship.....61
Figure 4.9: *E. cladocalyx* foliage biomass model predicted values vs. residuals for Model 4.16.....62
Figure 4.10: Branches and foliage biomass relationship with branch diameter for *E.gomphocephala*.....64
Figure 4.11: *E.gomphocephala* foliage biomass model predicted values vs. residuals plots ..65
Figure 4.12: The relationship between branch biomass and branch diameter.....67
Figure 4.13: *E. grandis x camaldulensis* foliage biomass model predicted values vs. residuals plots.....68
Figure 4.14: Images from the CT –scanner in ImageJ.....70
Figure 4.15: Results on average grey value in ImageJ 70
Figure 4.16: Example of a calibration linear equation for wood density based on grey values 71
Figure 4.17: CT –scanning density classes for the three *Eucalyptus* species 72
Figure 4.18: Percentage of different biomass components for the pooled data with standard deviation in error bars 73
Figure 4.19: Development of different biomass components over the dbh for a pooled model 74
Figure 4.20: Pooled systems of equations predicted vs. residual plots.....76
Figure 4.21: Percentage of biomass components towards total biomass.....77
Figure 4.22: *E.cladocalyx* systems of equations predicted vs. residual plots 79
Figure 4.23: Percentage aboveground biomass components for *E. gomphocephala* 80
Figure 4.24: *E. gomphocephala* system of equations predicted vs. residual plots 82
Figure 4.25: Percentage of biomass components for *E. grandis x camaldulensis* with standard deviation in error bars 83
Figure 4.26: *E. grandis x camaldulensis* systems of equations predicted vs. residual plots ...85
Figure 4.27: Distribution of Error propagated during sampling and regression.....86
Figure 4.28: Disc biomass percentage change trends 87
Figure 4.29: Disc biomass percentage change at different drying temperatures 88
Figure 4.30: Bark biomass change and standard deviation as error bars.....89

Figure 4.31: Bark biomass percentage change on different drying temperatures.....90
Figure 4.32: Branch biomass percentage change trends.....91
Figure 4.33: Foliage biomass change with change in temperature.....92

List of Tables

Table 2.1: Formula to determine volume of a stem sections (logs) 11
Table 2.2: Existing *Eucalyptus* biomass model from South Africa and other countries (Ackerman *et al*., 2012) 23
Table 2.3: Key site requirements of commercial *Eucalyptus* species and hybrids (Louw & Smith, 2012) 28
Table 2.4: Density of selected *Eucalyptus* wood species (McMahon *et al*., 2010) 32
Table 3.1: Area allocated to various land use in the Western Cape (Botman, 2010) 42
Table 3.2: Selected *Eucalyptus* trees used in the study 44
Table 4.1: Diameter height Models 54
Table 4.2: Volume models with parameters p-values in brackets 56
Table 4.3: Pooled crown foliage and branch models 59
Table 4.4: Biomass models for crown components for *E.cladocalyx* 63
Table 4.5: *E.gomphocephala* crown component biomass models 66
Table 4.6: *E.grandis x camaldulensis* crown component biomass models 69
Table 4.7: SUR systems of equations for Pooled data 74
Table 4.8: Systems of equations for *E.cladocalyx* biomass models 78
Table 4.9: Systems of equations for *E. gomphocephala* 81
Table 4.10: Systems of equations for *E. grandis x camaldulensis* 84
Table 4.11: Component of error propagation in biomass modelling 86
Table 4.12: Parameter and model statistics for the biomass drying model at different temperatures. 88
Table 4.13: Anova Table for drying series of the four biomass components 93

List of Abbreviations

AIC	Akaike Information Criteria
ANOVA	Analysis of Variance
CRBD	Completely Randomized Block Design
DAFF	Department of Agriculture, Forestry and Fisheries
DBH	Diameter at Breast Height (1.3m from the ground)
DIRAP	Dry land Industry and Rural Afforestation Project
DRC	Democratic Republic of Congo
FAO	Food and Agriculture Organization
GDP	Gross domestic product
KZN	KwaZulu-Natal
NSUR	Non-linear Seemingly Unrelated Regressions
NTFP	Non-Timber Forest Products
REDD	Reducing Emissions from Deforestation and Forest Degradation
SUR	Seemingly unrelated regression
SUR	Seemingly Unrelated Regressions
UNFCC	United Nations Forum on Climate Change
UNFCCC	United Nations Framework Convention on Climate Change

Chapter 1 : INTRODUCTION

1.1. Background

Climate change and the emphasis on renewable energy as an alternative for fossil fuel have made plant biomass to be considered as an important alternative energy source. Samalca (2007) pointed out that the entire forest ecosystem stores about 80% of aboveground carbon and 40% of the belowground carbon. Forests reduce the amount of carbon in the atmosphere predominantly in four ways; (1) storage of carbon in the biosphere, (2) storage of carbon in forest products, (3) use of wood as a product instead of other products that cost more in carbon during the production process, and (4) replacing of fossil fuels by renewable energy (Ross, 2004; Botman, 2010). The Department of Minerals and Energy (2003) reported that 14% of the world energy is in the form of bioenergy of which 38% is used in developing and emerging economies, such as South Africa.

Biomass is commonly sourced from existing plantations established for the production of timber or pulp wood. Besides these plantations, biomass is also obtained from other plantations established specifically for biofuel production (Botman, 2010). Ackerman *et al.* (2012) referred to the importance of forest residues as a vital source of biomass especially after harvesting operations. Thus branches, foliage and bark contribute to available biomass. Further consideration on sources of biomass showed that invasive species are an important source of forest biomass (Kitenge, 2011). Although alternative sources of biomass exist, forest plantations have remained the major source of biomass especially in South African context.

The Department of Fisheries and Forest (DAFF) (2011) indicated that forest plantations cover 1.1% of South African land area of which Mpumalanga has the largest plantation area of 40.8%, followed by KwaZulu-Natal (KZN) with 39.6%, Limpopo 4.6% and the Western Cape has the smallest plantation area of 3.9% (Figure 1.1). The majority of these plantations are stocked with pines - 51%; eucalypts - 40.4 %, wattle - 8.2%, and other species - 0.4% (Forestry South Africa, 2010; De Beer, 2012; DAFF, 2011; Louw & Smith, 2012).

Besides biomass production, De Beer (2012) reported that forests plantations have multiple contributions to the country's economy, for instance, in 2008/9 the forest sector in South Africa contributed about R20 376 million to the Gross Domestic Products (GDP) which

translated to about 1.2% of the GDP. Furthermore, about 77 000 people are employed in the forest sector in South Africa of which the majority are from rural communities (De Beer, 2012).

The overall envisaged contribution of the forest sector to the nation is to achieve social, economic and ecosystem sustainability. However, due to limited land available and suitable for afforestation; the expected goals have not been achieved due to South Africa being identified as a water scarce country (Magumba 1998; Ham & Theron, 2001; Botman, 2010). The Western Cape is not an exception with regards to water constraints where rainfall is below average (Section 2.11 and 3.1.3) occurring during winter when vegetative growth is minimal. Van Wyk *et al*. (2001) also argued that afforestation programmes have diminished because of lack of suitable land while the existing land is being prioritised for agricultural purposes. Nevertheless, Seifert (2012) proposed three strategies for increasing forest ecosystem services while alleviating poverty for rural communities; (1) increasing competitiveness in the existing plantation and sawmill to secure jobs, (2) plantation establishment for rural communities who participate in value addition process on the forest side, and (3) mobilisation of small grower woodlots for farmers.

The philosophy of establishing woodlots as a solution to the potential shortage of forest products is feasible because it does not have high demanding prerequisites such as larger pieces of land and access to substantial capital (Magumba, 1998; van Wyk *et al*., 2001). However, due to the nature of the arid climatic conditions experienced in large parts of South Africa, drought tolerant species are needed for the establishment of woodlots on marginal sites.

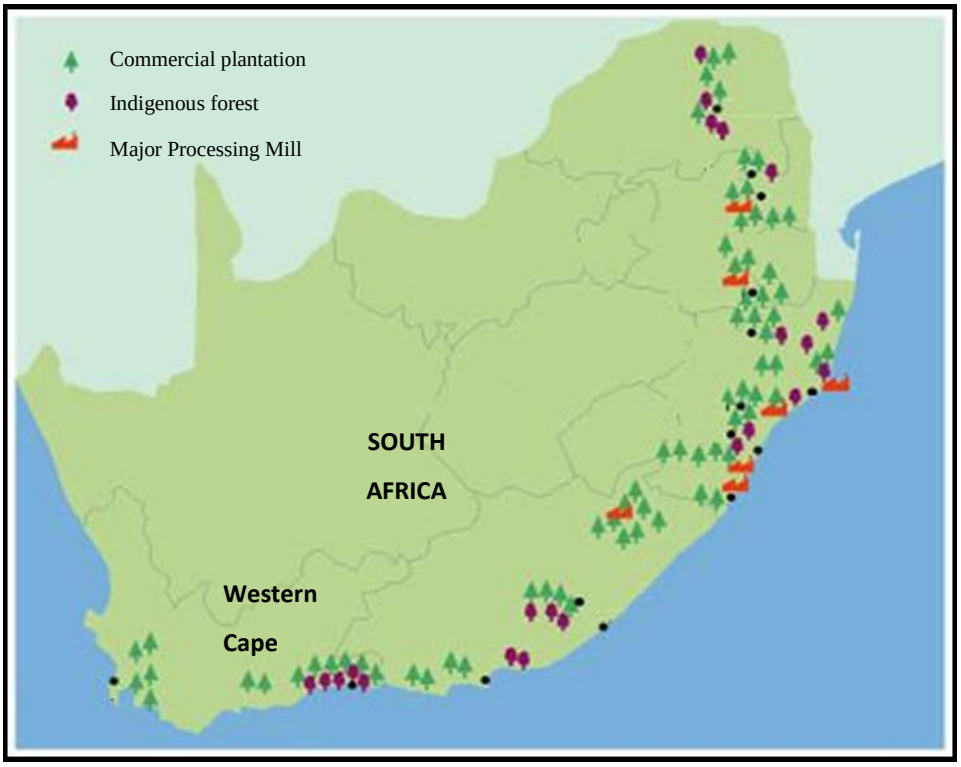


Figure 1.1: Distribution of forest plantations and indigenous forests in South Africa (De Beer, 2010)

As a driver for woodlot establishment in the Western Cape region, related climatic conditions of Australia and Israel were taken into account (Magumba, 1998). Species which were drought tolerant in the native environment in Australia were expected to be suited to dry areas of South Africa. This led to the establishment of several experimental plots along the West Coast of South Africa (van Wyk *et al.*, 2001).

The West Coast trials were established in 1991 with eucalypt hybrids and genetically pure *Eucalyptus* species from Australia, Morocco and Israel, which included *E. gomphocephala* and *E. cladocalyx* as explained in Section 3.1.4 of Chapter 3. Results of the trials showed that under correct silvicutural and management practices, some selected species perform better in the arid regions of South Africa. The genetic stock from Australia, which comprised *E. gomphocephala* and *E. cladocalyx* proved to be the best performing species while the hybrid *E. grandis x camaldulensis* performed comparatively well (van Wyk *et al.*, 2001; Magumba, 1998; Botman, 2010). In order to gain further understanding on these drought tolerant species (*E. gomphocephala*, *E. cladocalyx* and *E. grandis x camaldulensis*), the study in this thesis developed biomass models of each of these species for use as preliminary models in biomass resource assessment and its related management.

1.2. Problem Statement

The decline in availability of forests products, especially fuel wood and sawn timber from indigenous sources and existing plantations has necessitated the establishment of woodlots in rural communities. This is to meet the ever rising demand while maintaining the existing forests which have been subject to exploitation pressure from adjacent communities. Although woodlots potentially provide a promising solution to this problem, there is need to planting fast growing species, such as eucalypts species, which can survive in arid region, especially the west coasts of South Africa where the average rainfall is below 400 mm per annum and occurs in winter (Figure 2.4). Growing trees under these adverse climatic conditions require information not only on the establishment and growth but also on timber yield. However, such information is currently lacking, especially biomass models and other biomass characteristics. For these reasons, preliminary biomass models for the three eucalypt species (*E. gomphocephala*, *E. cladocalyx* and *E. grandis x camaldulensis*) need to be developed.

1.3. Objectives of the study

1.3.1. Main objective

The main objective of this study was to develop biomass models for the selected drought tolerant eucalypt species.

1.3.2. Specific objectives

The specific objectives of the study were to:

1. Formulate models for each species using different statistical methods to ensure additivity of biomass components.
2. Selecting the most suitable modelling method for each species.
3. Compare two density determination methods through displacement and CT-scanning.
4. Assess the variation in amounts of biomass when dried at different temperatures (lower than the standard drying temperature of 105 ˚C).
5. Assess the error-propagation pattern when upscaling with the biomass models.

1.3.3. Research questions

The objectives were met through the following research questions:

1. Does the formulated model follow the general additivity properties?
2. How do biomass components of leaves, bark, stem wood and branches vary between species?
3. How big are the biomass (dry weight) variations for different biomass components when dried at different temperatures?
4. Are there species specific differences in the drying pattern?
5. Does the displacement method underestimate or overestimate wood basic density as compared to the CT-scanning method of determining basic densities?
6. What is the size of the propagated error?

1.4. Rationale of the study

Forest ecosystems are complex because of the dynamics and interactions among biotic and abiotic factors within an ecosystem. Due to this complexity, the need for specific quantitative and qualitative information is essential in order to manage the forest sustainably (Samalca, 2007). Sustainable management of forest resources demands a deeper understanding of ecosystem functions which require supportive tools for forest management decisions. Among many options for forest management tools, forest models are vital. Forest models represent the dynamics of the forest ecosystem in different aspects such as mortality, growth and productivity (van Laar & Akça, 1997; Subasinghe, 2008; Bettiger *et al.*, 2009). However, models to represent different dynamics and interactions are lacking and most often have limitations.

The lack and limitation of models affect the efficiency in the management of forest resources. Subasinghe (2008) explained that forests established for the production of substantial amounts of ecosystem services[1] need large amount of information and models for effective management and planning. *Eucalyptus* species growing on the dry west coast of South Africa

[1] Ecosystems services are tangible and intangible products which a realised from the forest which include wood products, employment, carbon sequestration and many others.

equally need management tools in order to monitor amongst others, biomass products. As motioned in Section 1.1, increased expectations in renewable energy, sustainable use of forest resources and carbon sequestration has brought about an increase on the demand of biomass models (Salis *et al*., 2006; Fehrmann & Kleinn, 2006; Bettinger, 2009; FAO, 2012).

Particular attention should be paid to species that can withstand adverse conditions such as aridity because these species often offer the only supply of biomass in those areas and are important in supplying other ecosystem services. Therefore, this study focused on biomass modelling of the selected *Eucalyptus* species (*E. gomphocephala*, *E. cladocalyx* and *E. grandis x camaldulensis*). Models parameterised in the present study will contribute towards developing biomass assessment (quantification) methods, and identifying other biomass attributes of these species. Thus, these models will be useful in inventories especially in the carbon offsetting potential of forest plantations under similar environmental conditions. In addition, the formulated models can be included in bioenergy resource quantification and carbon sequestration programs such as Reducing Emissions from Deforestation and Forest Degradation (REDD) as suggested in FAO (2012) and Samalca (2007). Finally, the results from this study will be vital in determining the feasibility of establishing small scale woodlots for timber and biomass production.

1.5. Thesis Structure

This thesis comprises six chapters. Chapter 1 has given an introduction to the context of the study. Chapter 2 focuses on a comprehensive literature study on different theoretic aspects of biomass modelling. A detailed description of the study sites, material and methods are presented in Chapter 3 while the results are given and discussed in Chapter 4 and Chapter 5, respectively. Conclusion and recommendations are provided in Chapter 6. Relevant data sheets used during data collection have been included in the appendix.

Chapter 2 : LITERATURE REVIEW

2.1. Forest models: Importance and use

Sustainable management of forest resources requires supportive information because it is a dynamic process in which variables defining it change over time (Subasinghe, 2008). Saint-André *et al*. (2004) pointed out that forest models are now widely used in forestry and agroforestry in order to simulate the dynamic nature of the forests. These models have the same basic objective; i.e., mimicking key variables that are difficult to measure with conventional methods (Salmaca, 2007; Seifert & Seifert, 2013).

Vanclay (1994) defines forest models as an abstract representation of natural dynamics of a forest, which include aspects of growth, mortality and other changes. Forest models are considered to be an important tool for sustainable forest management, requiring detailed information on tree growth, forest dynamics and ecosystem services. Some of the common ecosystem services are carbon sequestration and bioenergy production which directly relate to biomass and biomass models (Davis & Johnson, 1982; Philip, 1994; Bettiger *et al.*, 2009; Baishya & Barik, 2011).

2.2. Forest Biomass

Several studies on climate change have indicated that forest ecosystems play a major role in carbon sequestration and storage. Carbon from the atmosphere is taken up by vegetation during photosynthesis and stored as plant biomass as part of the carbon cycle process (Samalca, 2007). Forest ecosystems store about 80% of all aboveground and 40% of all belowground terrestrial organic carbon (Baney *et al*., 1978; Montagu *et al*., 2005; Samalca, 2007; Litton, 2008). Consequently, the United Nations Forum on Climate Change (UNFCC) through Kyoto Protocol under Article 3.3 recognised the important role that forests play in carbon sequestration (Samalca, 2007; FAO, 2012; Zeng & Tang, 2012).

In order for the forest to significantly contribute towards the process of carbon sequestration, sustainable management strategies are needed to maintain existing forests and not expose them to unnatural disturbances (Samalca, 2007). FAO (2012) reported that human influence on forests through land use conversion contributes to the loss of forests, especially in Africa. This loss of forest affects the carbon balance as the trees undergo decomposition which releases carbon to the atmosphere. It is these carbon dynamics which call for assessment of

present and future biomass quantities as it directly translates to carbon[2] (Samalca, 2007). With the increased emphasis on ecosystem services, quantification of carbon by determining the amount of biomass available has also increased because both carbon and biomass are important components of ecosystem services (Chidumayo, 1990; Litton, 2008).

Zeng and Tang (2012) argued that because of global climate change and the importance of carbon sequestration, it is necessary to add forest biomass estimation to national forest resource monitoring inventories. Thus, efficient and effective methods of biomass assessment have to be continuously developed. Parresol (1999) pointed out that assessment of biomass is important for two major reasons; (1) resource use, and (2) environmental management. In addition, the determination of quantities of biofuel available has become another important topic in the field of renewable energy. Samalca (2007) stated that biomass plays a dual role in greenhouse gas mitigation as related to the objectives of the United Nations Framework Convention on Climate Change (UNFCCC); (1) as an energy source to substitute fossil fuels; and (2) as carbon storage. Besides these two aspects, in environmental management, biomass is used as an indicator of the growth of forest ecosystems. Therefore, knowledge on biomass loss or accumulation over time is important (FAO, 1997; Subasinghe, 2008; Bettiger *et al.*, 2009).

2.2.1. Methods of biomass assessment

Samalca (2007) introduced three approaches to biomass assessment which includes; field measurement, Geographic Information System (GIS) and remote sensing. The field measurement approach was found to be more accurate when compared to the other two approaches. However, the field approach involves extensive fieldwork at potentially high cost. In nearly all the above approaches, ground data is needed for validating. This implies that it is equally important to have field measurements for both remote sensing and GIS based methods for the purpose of validation. The most common predictive parameters measured during field work are diameter at breast height dbh (height of 1.3m), height (h) and crown

[2] The amount of carbon is calculated by multiplying biomass by 0.5.

dimensions (Philip, 1994; Parresol, 1999; van Laar & Akça; 1997; Samalca, 2007; Seifert & Seifert 2013).

Field measurement for biomass sampling includes the following two methods; (1) destructive, and (2) non-destructive (Samalca, 2007). The destructive method is mostly used in tree biomass sampling in which selected trees are felled and necessary variables (dbh, h, component masses) are measured. The mass of a tree is measured by weighing or sampling of individual tree components. Sampling of tree components is usually preferred for big trees because the total weight method is expensive and time consuming (Seifert & Seifert, 2013). Parresol (1999) and Carvalho *et al*. (2003) reported that the total weighing method is not only time consuming and expensive but less accurate. Furthermore, sampling of components has been improved by including regression in sampling. For example, Seifert and Seifert (2013) recommended this method of sampling as it provides detailed compositional biomass data for individual trees.

A non-destructive sampling procedure does not require trees to be felled for measurement. Stem volume is assessed along the stem by a tree climber and wood density measurements are taken by core sampling. In order to obtain branch data, diameters of branches are measured while climbing the trees with certain branch samples cut off for volume and biomass determination (Samalca, 2007; Seifert, personal communication).

2.3. Biomass tree components

2.3.1. Branches

An efficient way of sampling branches involves a two phase sampling procedure (Seifert & Seifert, 2013). In the first phase, diameters at the base of all the branches (preferably 4 to 5 cm from the main stem) are measured. It is from these branches that a sub-sample is drawn at random to estimate biomass through oven-drying. The estimated biomass from the sampled branches is then regressed against the branch diameter or basal area in the second phase. Other predictor variables such as branch heights have been used successfully as well (Seifert & Seifert, 2013). Van Laar and Akça (1997) showed that a considerable increase on R^2 can be attained by adding branch height as a predictor variable. Although these variables can be used, only a slight improvement on the model is attained. Therefore, branch diameter or branch basal areas still remain the most important independent variables (Chiyenda & Kazoka, 1984; Samalca, 2007).

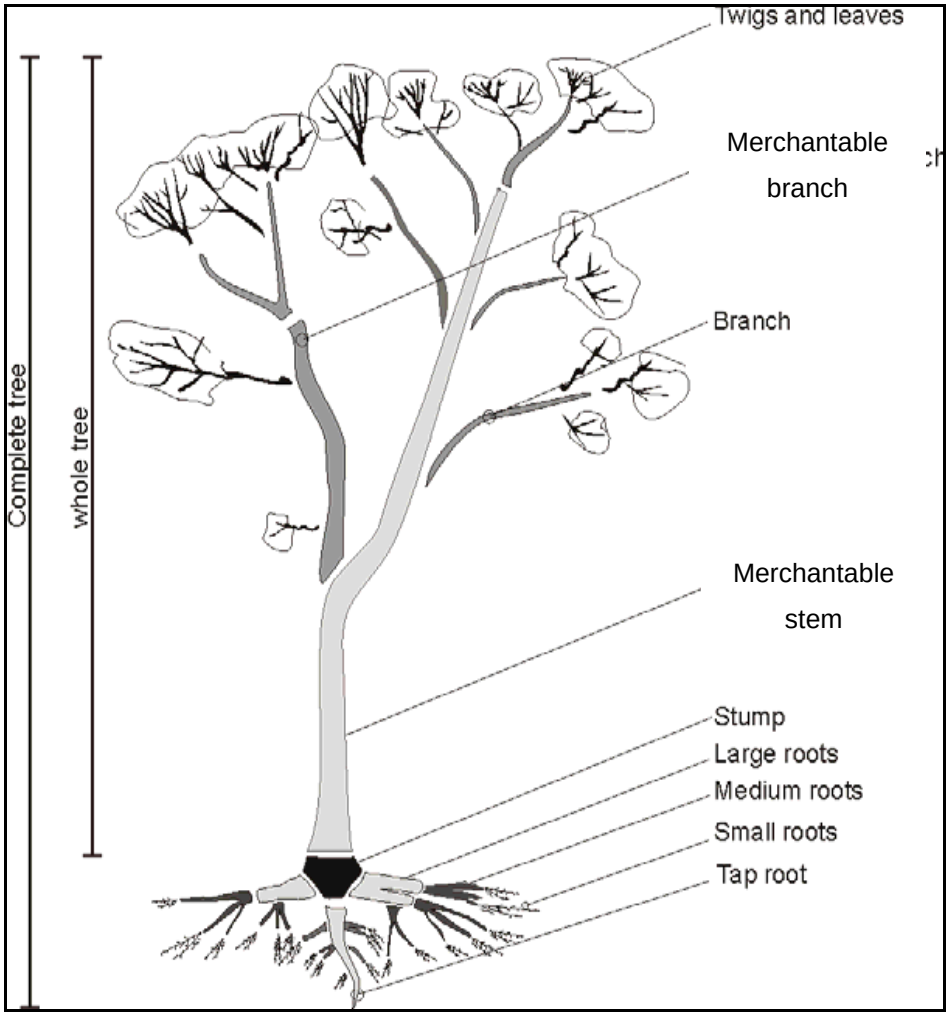


Figure 2.1: Above and belowground biomass components (Seifert & Seifert, 2013)

Montagu *et al*. (2005) proposed a different sampling method for estimating branch biomass. A representative sub-sample is collected from the branches, which is then oven dried from which the ratio of oven-dry biomass to green biomass is derived. It is important to note that in the method proposed by Seifert and Seifert (2013), dry masses are used directly in regressions. In this method however, the ratio between dry mass to green mass is used to determine the branch biomass. Mutakela (2009) cautioned that it is important to measure the ratios of the live and dead branches separately because these give different masses as a result of variation in moisture content. Van Laar and Akça (1997) reported a ratio of 0.45 and 0.8 moisture content for dead and live branches respectively hence indicating the variability on weight.

2.3.2. Foliage

Unlike smaller trees, where foliage is measured together with other components during total weighing, bigger trees demand foliage sampling. A number of branches of the total branches (preferably 25%) are sampled (van Laar & Akça, 1997). In two separate studies by Mutangu *et al*. (2005) and Litton (2008) five branches per tree were sampled for foliage. It is from these branches that foliage is separated and oven dried until a constant mass is attained (Montagu *et al*., 2005; van Laar & Akça, 2007; Litton, 2008). During the analysis, foliage biomass from trees of the same species is regressed with the diameter or basal area of the respective branches in order to increase the size of the sample (Saint-André *et al*., 2004).

2.3.3. Stem wood

Biomass determination for stem wood is typically done in two phases; (1) Volume determination, and (2) disc measurements in which density is calculated. Volume of the felled tree is determined using the Smalian's formula (Table 2.1). In some cases Newton's formula is used (Table 2.1) (Philip, 1994; Jayaraman, 1999). During Phase 2, discs are cut from the stem and separated from the bark. The discs are then oven dried and the ratio of oven-dry weight to green weight assessment is determined. Basic density is then derived for the discs, which is attributed to the respective stem section and biomass is finally determined by the product of basic density and volume (Montagu *et al.*, 2005; Ackerman *et al.*, 2012; Seifert & Seifert, 2013).

Table 2.1: Formula to determine volume of a stem sections (logs)

No.	Name	Formula
1.	Smalian's formula	$V= \frac{\pi L(d1^2+d2^2)}{8}$
2.	Huber's Formula	$V=\frac{\pi L dm^2}{4}$
3.	Newton's Formula	$V= \frac{\pi L(d1^2+4d^2m+d2^2)}{24}$

Note: d_1 is diameter at base of the log, d_m is diameter of the log at mid length of log, d_2 is diameter at top of log, L is length of the log and V is the volume of the log

2.3.4. Bark

In the same way as stem biomass determination (Section 2.3.3), the collected discs are also considered for the bark density measurement. Bark thickness is measured from four directions of the disc at 90 º for volume under bark (V.u.b) and volume over bark (V.o.b) determination. Furthermore, the wood to bark ratio and respective densities are derived. In another alternative method recommended by Saint-André *et al*. (2004), the bark is removed from the disc and density measurements are carried out directly. The preliminary measurements usually requires oven-drying of biomass.

2.4. Drying of Biomass samples

The standard drying temperature in biomass studies is usually 105 ºC or 103 ± 2 °C (Ackerman *et al*., 2012; Seifert & Seifert, 2013). However, literature shows that different drying temperatures between 60 and 105 ºC have been used in cases where other chemical properties are the focus of the analysis. Saint-André *et al*. (2004) and Montagu *et al*. (2005) reported using 60 ºC in separate biomass studies while Cunia and Briggs (1985) used 65 ºC. In a study carried out on dry Miombo woodlands, Grundy (1995) used the standard biomass drying temperature of 105 ºC. FAO (2012) recommended drying biomass components at different temperature, thus foliage can be dried at 70 ºC, flowers and fruits at 65 ºC, while stem wood and branches were recommended to be dried at the standard biomass drying temperature of 105 ºC. Seifert and Seifert (2013) pointed out that lower drying temperatures are employed in biomass studies in order to prevent some chemical components (nutrients) such as volatile nitrogen and sulphur from escaping. The loss of such elements at high drying temperature has been associated to the reduction of biomass by 2 to 3 % in *Pinus patula* (Forrest, 1968; Barney *et al*., 1978). Seifert and Müller-Starck (2009) reported similar results in a study on Norway spruce. When the cones were dried at 38 ºC, biomass reduced to 84%, at 60 ºC it reduced to 80% and at 105 ºC it reduced to 78% of the fresh weight. Once biomass samples are dried at lower temperatures than the standard (105 ºC), the resulting biomass is usually overestimated since the water which is still bound in the biomass components is weighed as part of dry mass (Ackerman *et al*., 2012; Seifert & Seifert, 2013).

2.5. Sampling and Upscaling of biomass

Biomass determination for a stand usually employs sampling. FAO (2012) pointed out that sampling need to take into account stand specifics such as site and stand density which

cannot be noticed if the entire forest stand biomass was determined. In order to attain this, biomass is usually modelled at the individual tree level. Seifert and Seifert (2013) explained that biomass modelling for bioenergy purposes is typically an upscaling process and includes two steps; (1) from samples to an individual tree, and (2) from the tree to stand level (Figure 2.2).

There are a number of methods used to determine the amount of biomass for individual trees and forest stands. Seifert and Seifert (2013) suggest three methods; (1) bulk sampling method, (2) fresh weight sampling, and (3) sampling with regression. Bulk sampling is applied in short rotation biomass plantations in which all sampled trees are cut and chipped. The fresh weight for the chips is determined before drying while the oven-dry mass is determined after drying. The fresh weight sampling method involves determining the full fresh weight of the entire tree. This is followed by selecting a representative sample which is then oven dried and the ratio of dry: fresh weight is determined to finally convert the measured fresh mass to dry mass. This method, while very useful for smaller trees, has disadvantages in bigger trees, in particular when many different biomass components should be assessed (Seifert & Seifert, 2013). Employing sampling with the regression approach requires a sub sample of branches, foliage and stem to be collected, which is then oven-dried. In the next step, regression models are constructed for scaling up to the entire tree. FAO (2012) and Ackerman *et al.* (2012) indicated that sampling with regression is the most commonly used method since it provided detailed compositional biomass data for individual trees.

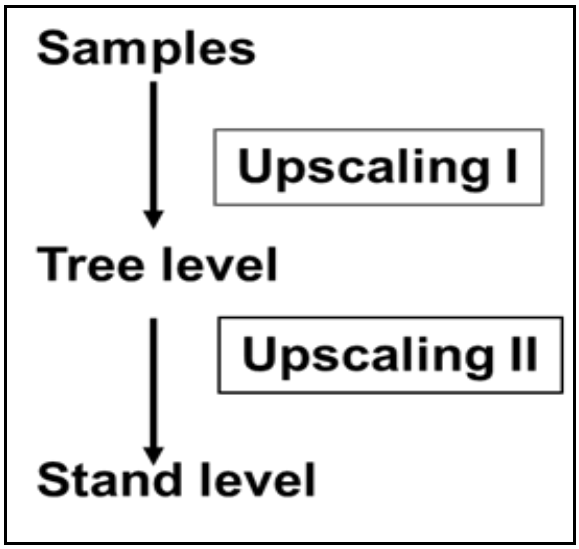


Figure 2.2: Biomass upscaling steps involved in forest stand (Ackerman *et al.*, 2012)

2.6. Additivity in biomass models

Additivity refers to the concept that the sum of the biomass components (stem wood, bark, foliage, branches) estimates should equal the total biomass obtained from the total biomass model. Parresol (2001) and Saint André *et al*. (2004) explained that the additivity property assures harmonised regression functions which are consistent with each other.

Van Laar and Akça (2007) explained that proper inventory depends on reliable and additive component estimates because it shows an exact relationship between the components and total biomass. Furthermore, studies of ecosystem productivity, energy flow, and nutrient flow often break down biomass into component parts hence additivity is required (Chayenda & Kozak, 1984; Cunia & Briggs, 1985).

There are a number of statistical procedures which were successfully used to attain the additive property in biomass modelling. These methods are Nonlinear Seemingly Unrelated Regressions (NSUR), Seeming Related Regression (SUR) and Isometric Log Ratio (ILR) Composition models (Parresol 1999; Parresol 2001; Seifert & Seifert, 2013). Saint André *et al.* (2004) explained that SUR is a reliable method in the study of above and belowground biomass while IRL composition models are commonly used in geochemical studies which require high precision. Common methods which strive to satisfy additivity as proposed by Parresol (2001) are discussed in Section 2.6.1 and Section 2.6.2.

2.6.1. SUR and NSUR

SUR is a method of joining all components and the total tree biomass model by taking into account contemporaneous correlations and introducing restrictions on a set of regression equations (Srivastava & Gile, 1987; Cadavez & Henningsen, 2011; Goicoa *et al.*, 2011). Non-linear models with multiplicative errors have been used widely to model biomass as it can be transformed into linear model by logarithmic transformation. Saint-André *et al.* (2004) explained that as a result of the additivity restriction, the inherent model for the total tree cannot be linearized. In order to take this problem into account, a more flexible procedure for non-linear functions that attempts to achieve additivity while taking into account non-independence correlation is usually employed. This method is called NSUR.

Goicoa *et al.* (2011) explained that joint general linear models can be divided into three groups. The first group called NSUR model where a number of nonlinear model are grouped together and the error term in the common allometric model is additive. In Nonlinear

Seemingly Unrelated Regressions Log transformed (NSURLOG) models, the allometric models have a multiplicative error. The logarithmic transformation leads to two linear regressions, nevertheless, the equation for the total cannot be linearized. Another group of regressions includes squares of explanatory variables, in which the weights are the same in all the equations, thus additivity property is automatically satisfied because the explanatory variables are the same (Parresol, 1999).

2.6.2. Compositional models

Composition data analysis uses ILR transformation models and was first applied to tree biomass in Seifert and Seifert (2013). In this method, the elements of the composition are non-negative and sum up to a unity. In this case, data is restricted to non-negative quantities such as weights, counts and areas which are scaled to a total of the components. Buccutied and Pawlowsky-Glahn (2006) explained that the simplest example of a composition scenario is as follows: The total of the two components can be taken as one unity and the difference between the unit and one of the components is just one minus the first component. Although this method has not been extensively used in biomass modelling, it is commonly used in geochemical analysis. Thomas and Aitchison (2010) used ILR transformation method to model sandstone composition and the resulting models were highly significant and additivity was satisfied.

2.7. Goodness of fit for regression models

A number of measures for goodness of fit and comparing alternatives between different models have been recommended by Parresol (1999). Some of these methods are; Coefficient of determination (R^2), Fit index (FI) which is more like R^2, standard error of estimates (se), Coefficient of variation (CV), Furnival's index (I) and relative standard error S (%).

FI is similar to R^2, the bigger the value of FI the better the model. To obtain the FI value, the total sum of squares (TSS) and the residual sum of squares (RSS) are calculated and the FI is found by subtracting the ratio from one (Equation 1).

$$FI = 1 - (RSS / TSS) \quad (1)$$

Where:

FI = Fit index

TSS = Total sum of squares

RSS = Residual sum of squares

Another measure of goodness of fit is the se which uses the actual units of measurements. Saint-André *et al.* (2004) and FAO (2012) highlighted that when the value for se is small compared to the value from other models, it means the model has a good fit. It is usually calculated as shown in Equation 2.

$$se = \sqrt{RSS/(n - P)} \quad (2)$$

Where:

se = Standard error

RSS = Residual sum of square

P = number of model parameters

n = sample size

Besides the FI and se of estimate, Parresol (1999) also recommended the CV to be used as a measure of goodness of fit. CV is one of the measures for making quick comparisons between models and is expressed in percentage form. Equation 3 shows the formula for calculating CV.

$$CV = (se / x)\ 100 \quad (3)$$

Where:

CV = Coefficient of Variation

se =Standard error

x = mean

Another common measure of goodness of fit, which is also used in model selection, is I. This measure was proposed by Furnival in 1961 based on the normal likelihood functions (Parresol, 1999; Saint-André *et al*., 2004). When testing equations, the large value of I indicates a poor fit while the smaller value indicate a better fit (Parresol, 1999). The general formula for I is as shown in Equation 4.

$$I = [f'(Y)] - x\ RMSE \quad (4)$$

Where:

I = Furnival's Index

Y = mean

RMSE = Root mean square error

Other measures of goodness of fit are: percentage standard error S (%), the percentage error (Pe), and the Akaike Information Criterion (AIC). S (%) is applied by calculating the residuals in relation to the predicted values. This statistic indicates the size of error as a percentage of the mean of the distribution of the predictor valuable. Parresol (1999) stated that if the value of S (%) is close to zero, then the precision of the model is high.

Pe is a precision index, which uses a Chi-square test. For instance, the value of Pe can be used to represent the relative difference in percentage of estimate of tree or component weight to its true value. This statistic computes the value of Pe that would be necessary to assure non-significance Chi-square test (Parresol, 1999).

The AIC is a common measure for comparing models and is used in selecting the best fitted model. The smaller AIC value indicates a better fit for the model. AIC takes into account the number of parameters in the model when comparing different models and thus ensures parsimony in model selection (Parresol, 1999; Ott *et al*., 2001)

2.8. Back transformation bias correction

Regression analysis is the most widely used method for estimation of biomass in forest stands. Sprugel (1983) and Smith (1993) pointed out that the standard least squares techniques are commonly used in fitting regression lines with different parameters. The resulting equations or models can either be linear or nonlinear. Nonlinear correlations of variables are often logarithmically transformed to attain the linearity while satisfying the assumptions of homoscedasticity (Figure 2.3).

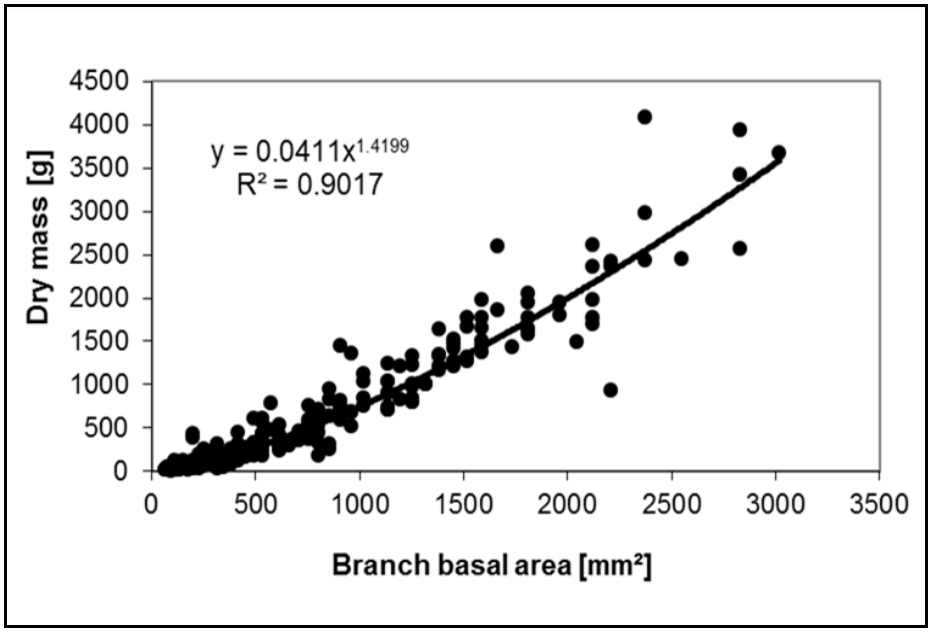


Figure 2.3: Example a biomass regression (Ackerman *et al.*, 2012)

A large amount of literature has been built on how to comply with various assumptions, especially when data transformations are involved prior to the fitting procedure. Baldwin (1986) explained that most biological data, such as dimensions of organisms, logarithm transformation should be undertaken prior to the testing of hypothesis on regression analysis since it reduces the heteroscedasticity. Seifert and Seifert (2013) compared the results of ln-transformed regression after back transformation with and without a bias correct factor. This example clearly demonstrated the necessity for a back transformation bias correction in order to obtain unbiased results. The reason is that the antilogarithms of values from the logarithm regression results in biased estimates. As a result of this biasness, a method shown in Section 3.3.5 has been developed for the corrections of error in biomass inventories.

2.9. Error propagation

Samalca (2007) pointed out that forest inventories are an efficient way of assessing carbon stocks and emission through deforestation. However, biomass assessments procedures are not free from errors. In order to make correct inferences about long term dynamics in biomass stocks, it is important to understand the uncertainties (errors) associated with the biomass estimation. Three sources of errors were cited in Samalca (2007) and Chave *et al.* (2004); (1) measurement errors (2) error due to choice of allometric model, and (3) sampling errors. Efforts to reduce these errors during inventory have been made by using random sampling but this does not guarantee unbiased estimates (van Laar & Akça, 1997; Segura, 2005).

Samalca (2007) explained that in most cases random sampling designs for forest inventories consist of two phases. During the first phase, a relatively large sample of trees is selected in which different tree parameters are measured. It is important to note that during the first phase, trees are not measured for biomass but for the common parameters such as dbh and h. A relatively small sample (ideally a sub-sample of the first sample) is taken in the second phase of which biomass is determined. The biomass is estimated for the bigger stand in an upscaling process from a regression based relation of biomass and auxiliary variables such as dbh and h. This estimation is made with an assumption that the trees sampled for biomass are representative for the trees in the larger sample. The process can be referred to as an upscaling procedure because a number of steps are involved in estimation to a stand level (Ackerman *et al*., 2012; Seifert & Seifert, 2013).

In the upscaling procedure, two types of errors are prominent; errors due to the random selection of the trees in Phase 1 and error due to sampling in Phase 2. Errors in Phase one is largely affected by the sampling design used, sample size, type of estimator used and the inherent variation between the sampled trees (Seifert & Seifert, 2013). Errors due to sampling in the second phase involve regressions (Samalca, 2007). The magnitude of the error is mainly affected by the sampling design, the sample size, the estimation procedure and the variation of the biomass value of the regression function. The combination of the two errors in the two phases gives a value for the total error propagated. Samalca (2007) based on the works of Cunia (1986), proposed a procedure for determining the error propagated (Equation 6).

$$S^2 = S^2_{(x)} + S^2_{(y)} \qquad (6)$$

Where:

S^2= Total variance

$S^2_{(X)}$ = variance associated with sampling

S^2 (y) = variance associated with regression

2.10. Review of existing biomass models

A substantial number of studies have been conducted in developing allometric equations to predict different parameters such as volume and biomass. The majority of these models use variables such as dbh, h, d^2h and crown dimensions as predicting parameters (van Zyl, 2005;

Samalca, 2007; Subasinghe, 2008; Ackerman *et al*., 2012). In addition to these parameters, Parresol (2001) indicated that diameter at the base of live crowns proved to be one of the best predictor variables. However, this parameter was not significant in other independent studies as reported in Samalca (2007).

In regression analysis, the parameters of the models are estimated typically by least squares method with some additional assumptions that should be satisfied. The main assumptions for regressions are that residuals of the model must be independent, a constant variance (homoscedasticity) should exist and residuals should be normally distributed (Jayaraman, 1999; Parresol, 2001; Goicoa *et al*., 2011).

Samalca (2007) revealed that the simplest form of biomass predicting models that can be formulated is the simple linear model which is fitted using simple least squares estimation procedure (Equation 7). Parresol (1999) stated that linear regression models exhibit heteroscedasticity in most biomass studies because of the increasing dimensions of trees with age. Thus, the variance increases with the increase in dbh and h. In such a case, either weighted least square estimation or logarithmic transformation (Section 2.8) procedure is applied to solve the problem of heteroscedasticity. The general form of a linear model is shown in Equation 7. Saint-André *et al.* (2004) and Samalca (2007) pointed out that an addition of more independent variables (Equation 8) can improve the model significantly. For example, Grundy (1995) used dbh as predictor variables in the biomass study on the Miombo woodland in which an addition of h and age significantly improved the model fit.

Simple linear regression

$$Y\ (\text{biomass}) = b_0 + b_1\ (X_1) + \varepsilon \qquad (7)$$

Multiple linear regressions

$$Y\ (\text{biomass}) = b_0 + b_1\ (X_1) + b_i x_i + \varepsilon \qquad (8)$$

Where:

b_0, b_i= estimated parameters

x= independent variable

ε= error

The most commonly used biomass models are nonlinear (power function) models based on the allometric theory (Samalca, 2007). A review of 65 tree species models of North America

reported in Samalca (2007) indicated that all the models were nonlinear. The popularity of nonlinear biomass models is attributed to the good fit exhibited by these models on biological data (Crow & Schlaegel, 1988; van Zyl, 2005; FAO, 2012). In order to simplify these models, linearization using logarithm transformation on both the left and right hand side of the equation is employed (Equation 10). Parresol (1999) explained that the transformed model parameters can easily be estimated by the least square method and the model is simple to interpret, however, this causes a problem of biased back transformed biomass values if uncorrected as explained earlier in Section 2.8.

Nonlinear model:

$$Y\ (\text{biomass}) = b_0\ (X_1)^{n}\varepsilon \qquad (9)$$

Logarithm transformed model:

$$\ln Y\ (\text{biomass}) = \ln\ (b_0) + b_1\ \ln(X_1) + \ln\ \varepsilon \qquad (10)$$

Where:

b_0, b_1 = estimated parameters

X = independent variable

ε = error

2.10.1. Biomass models used in South Africa

Diverse biomass models exist for the prediction of biomass of different species in South Africa. A critical review on biomass models in South Africa in Ackerman *et al*. (2012) showed that a substantial number of biomass models exist for pines and eucalypts. However, models applicable at a national scale and a regional level do not exist. In addition, the review indicates a clear lack of biomass information on most productive hybrids especially in a South African context. Subsequently, the majority of the models were classified as preliminary models because they are formulated based on a small number of trees and the drying temperature in most cases is lower than the standard drying temperature of 105 °C. As a result of the small sample and lower drying temperature, existing models need to be tested and validated before use (Seifert & Seifert, 2013).

A number of eucalypt models have been developed for local forests and forests in other countries with climates conditions related to South Africa. In South African context,

numerous authors have reported a number of models with dbh, h and d^2h as independent variables (Table 2.2). For instance, models on *E. smithii*, *E. nitens* and *E. grandis* have been formulated for forest plantations in Mpumalanga and KZN (Herbert, 2003; Dovey, 2009). These models were based on drying temperature lower than the standard biomass drying temperature (105 °C). As a result, these models overestimate biomass quantities (Forrest, 1968; Barney *et al.*, 1978; van Laar & Akça, 2007; Seifert & Seifert, 2013).

Models applicable to eucalypt in South African Mediterranean region have been parameterised in other countries such as Chile and Israel. Zohar and Karschon (1984) reported models formulated on *E. camaldulensis* plantation of dry areas of Israel (Table 2.2). Israel experiences climate conditions (Mediterranean) which is related to the study sites in the present study (van Wyk *et al.*, 2001; Botman, 2010). Furthermore, in Chile, biomass models were formulated for *E. nitens* with the drying temperature of 70 °C (Ackerman *et al*., 2012). Table 2.2 summarises some of the existing eucalypt biomass models.

Table 2.2: Existing *Eucalyptus* biomass model from South Africa and other countries (Ackerman *et al.*, 2012)

Species	Component (Kg)	Formula	Age	Dry temp	Location
A. *E. smithii*	Leaves	$y=-0.4622 + 0.0445(dbh)^2$	4yrs	70 °C	Mpumalanga South Africa.
	Branches	$y=-0.4622 + 0.1294(dbh)^2$			
	Bark	$y=-0.0859 +0.0239(dbh)^2$			
	Stem	$y=-0.5217 + 0.1286(dbh)^2$			
B. *E.camaldulensis*	Bark	$\ln y =-1.769+0.808\ln(dbh^2h)$	4-35yrs	70 °C	Israel
	Twigs	$\ln y =-1.068+0.599\ln(dbh^2h)$			
	Leaves	$\ln y =1.420+0.651\ln(dbh^2h)$			
	stem	$\ln y =-1.668+0.599\ln(dbh^2h)$			
	Total tree	$\ln y =-0.990+0.830\ln(dbh^2h)$			
C. *E. nitens*	Branches	$Y=-0.6819 +0.0770*(dbh)^3$	5yrs	75°C	Mpumalanga South Africa
	Leaves	$Y=-0.2147 + 0.0371(dbh)^4$			
	Stemwood	$Y=-0.5847 + 0.1683*(dbh)^6$			
	Bark	$Y=0.0967 + 0.0248*(dbh)^5$			
D. *E.nitens*	Branches	$\ln Y= -11.07 + 2.033\ln(dbh^2)$	15yrs	75°C	Central Chile
	Stemwood	$\ln Y= -4.56+1.037\ln(dbh^2h)$			
	Bark	$\ln Y= -8.33 +1.1987n(dbh^2h)$			
	leaves	$\ln(y)=-0.4622 + 0.045(dbh^2h)$			
	Total tree	$\ln(Y)= -4.833+1.083\ln(dbh^2h)$			
E. *E. grandis*	Stem	$Y=450*0.02volume(m^3)$	6-12yrs	70°C	KwaZulu-Natal South Africa
	bark	$Y=0.12*timber\ volume(m^3)$			
	Branch	$Y=0.12*timber\ volume$			
	Leaves	$Y=0.09*timber\ Volume(m^3)$			

Species	Component (Kg)	Formula	Age	Dry temp	Location
F. Eucalypt (Hybrids)	Leaves	$Y=(-0.9335- 0.5551Age +0.3147Age^2) +(0.3145 - 0.1059Age) Circ_{1.30m} + 0.0007208Cir_{1.30m}$	1.2-7yrs	60°C	Congo (Pointe-Noire)
	Branches	$y=-0.2051 - 0.8321Age + 0.1729Cir_{1.30m} + 0.00003Age2Cir_{1.30m}$			
	Bark	$Y=-0.089 + (0.001896 + 0.000113Age)Cir_{1.30m}$			

2.11. Forests and arid climatic conditions in South Africa

South Africa is a semi-arid country with an average rainfall below 450 mm. Poynton (1979) reported that 65% of the country receives 500 mm per annum which is acceptable for dry land farming (Figure 2.4). However, the rainfall is very unevenly distributed within South Africa. About 21% of the country receives less than 250 mm rainfall per annum which cannot support agriculture and forestry activities (Botman, 2010). Large portions of South Africa receiving below average rainfall are located in the Western Cape Province in which rainfall is received during winter (van Wyk *et al*., 2001). Figure 2.4 shows the rainfall distribution in South Africa.

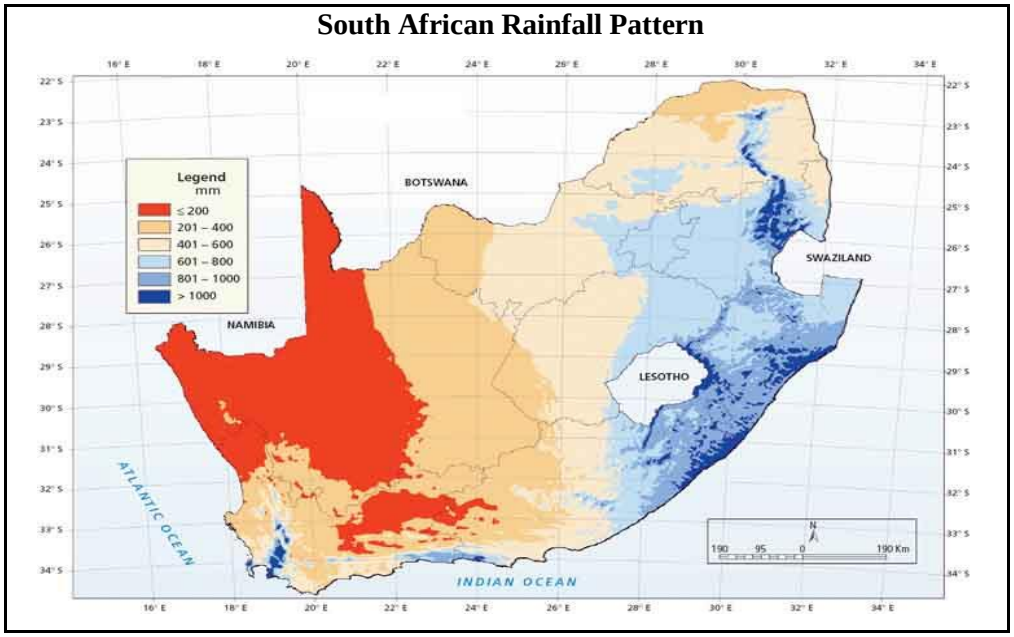


Figure 2.4: Map of rainfall pattern in South Africa (Shulze, 2007)

Van Wyk *et al.* (2001) pointed out that drought tolerant species growing on marginal sites are a timely solution, especially with the increased demand on land. This could facilitate the establishment of woodlots and consequently increase the supply of forest products (van Wyk *et al.*, 2001; Magumba, 1998). Equation 11 and 12 shows models developed to predict diameter and height at a specific age on the dry west coast of South Africa (Van Wyk *et al.*, 2001).

$$dbh = -22.462 - 124.1476.age + 124.1476.\ln(age) \quad (11)$$

$$h = -22.45 + 1215.419.age - 9.013.age^2 \quad (12)$$

Where:

dbh = diameter at breast height

h= height

The ever rising demand for ecosystem services has indicated that an increase in the supply of forest product is essential in order to meet the demand (Louw & Smith, 2012). For instance, the sustainable annual allowable cut in South Africa is 19 million fresh tons against a demand of 22 million tons per year. Moreover, the current projection for the next 30 years indicates that the demand will reach 28 tons per year (De Beer, 2012). With this case at hand, van Wyk *et al*. (2001) recommended that one of the solutions is to intensify plantation establishment programs by using drought tolerant species.

2.12. The genus *Eucalyptus*

The genus *Eucalyptus* comprises in excess of 400 species of which more than half are sub species, which include hybrids (Poynton, 1979). Nearly all *Eucalyptus* is endemic to Australia and Tasmania (Figure 2.5). However, very few commercially important species are found as indigenous in New Guinea and islands in Indonesia. Brooker (1990) explained that in Australia and Tasmania, *Eucalyptus* account for almost 95% of the flora of the native vegetation. Most of these species are found to be located south of latitude 7 ºN to 43 ºS and from sea level to 1800 m above sea level (Florence, 1996). The *Eucalyptus* species are adapted to a wide range of climatic conditions which are specific to each species.

Poynton (1979) explained that it is expected that different species vary in yield when grown in distinct region especially under very diverse climatic conditions. Thus, species of the genus *Eucalyptus* can be found from the warm tropics to a cold snow line and from summer to winter rainfall areas. This range of mean annual precipitation in the habitats where eucalypts grow is from 250 mm to more than 3000 mm, covering various biomes from rainforest to arid regions (Brooke, 1990; Florence, 1996).

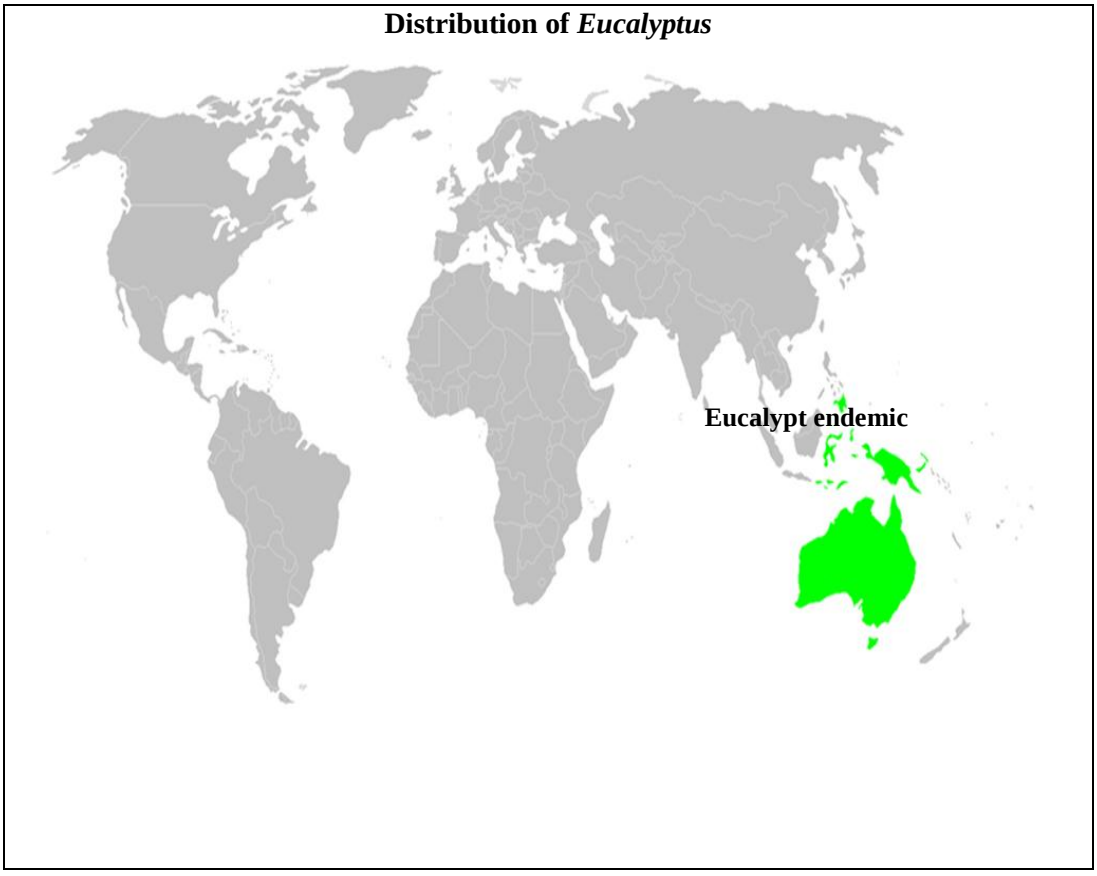


Figure 2.5: Distribution of *Eucalyptus spp* in the world (Brooker, 1990)

2.12.1. Physiognomic and morphology of *Eucalyptus*

Generally the *Eucalyptus spp* are monoecious and evergreen plants ranging in stature and habit from erect forest trees with clear bole to branched shrubs (Brooke, 1990). Florence (1996) explained that eucalypts have well developed roots systems which grow deep and spread widely as compared to other tree species. Many eucalypts, when young, produce an efficient storage and protective organ called lignotuber which has its origins in regions of meristematic tissue present in the axil of cotyledons or of the first few pairs of leaves (Poynton, 1979).

2.12.2. Silvicultural characteristics of *Eucalyptus*

Eucalypts have attributes which make it exceptional among the exotic tree species. The most outstanding attributes from a Silvicultural point of view are; exceptional vigour, remarkable capacity to survive under adverse environmental conditions and the extraordinary speed of recovery after experiencing a disturbance to growth such as forest fires (Florence, 1996). Poynton (1979) explained that sustained vigorous growth of *Eucalyptus* as a genus can be ascribed largely to having shoots capable of rapid and continuous development.

The ability of eucalypts and many other trees to survive and regrow after forest fires, drought or damage has been attributed to the presence of lignotubers, which help in the development of shoots in the juvenile phase of the tree (Poynton, 1979). In addition, eucalypts seed freely, and those that do not form a lignotuber often produce and extraordinary abundance of seed in case the parent trees die (Brooke, 1990; Florence 1996). These seeds grow into resilient seedlings with an ability to survive in conditions where they are exposed to intense competition by bigger trees. Generally, most eucalypts coppice strongly but certain non-lignotuber forming, thin baked species are regarded as poor coppicers (Poynton, 1979).

The eucalypts rooting system is another important aspect, which contributes greatly to the survival in harsh conditions. The roots of large eucalypts have been traced horizontally for a distance of more than 21 m in clay soils and 37 m in sandy soils (Poynton, 1979). In the later soils, the roots penetrate the soil to a depth of about 30 to 40% of the corresponding tree height at the age of 5 years (Florence, 1996). As a result of these different characteristics among the species, eucalypt varies in the ability to resistance drought and frosts (Table 2.3). Apart from withstanding drought conditions (Table 2.3), eucalypts also perform considerably well in salt coastal areas (Magumba, 1998; Hengari, 2008).

Table 2.3: Key site requirements of commercial *Eucalyptus* species and hybrids (Louw & Smith, 2012)

Species	MAT(°C) Range		Max Jan Temp (°C)	Frost Resist	Snow Resist	Soil Drainage	Comments
	MIN	MAX					
E.grandis	16.5	20.5	29.0	N	N	I	High susceptible termites
E. badjesis	14.5	17.0	26.5	H	M	G	Susceptible to snout beetles, *Phytophthora*
E.benthamii	14.5	18.0	26.5	S	L	I-M	Susceptible to snout beetle, competitive on rocky/stone sites
E.elata	15.0	18.0	27.0	M	L-M	G	High susceptible to termites, beetles
E.grandis x camaldulensis	18.0	22.0	31.0	L	N	I-M	Broad site adaptation, modest yield
E.grandis x nitens	15.0	17.5	27.0	H	N	VG-I	High leaf area index, die back on drought sites

Key:

Frost Resistance: Nil (N), Light (L), moderate (M), high (H)
Snow Resistance: Nil (N), Light (L), moderate (M), high (H)
Soil drainage: Poor (P), moderate (M), imperfect (I), Good (G)

2.13. *Eucalyptus cladocalyx*

E. cladocalyx is commonly called Sugar Gum and belongs to family *Myrtaceae*. *E. cladocalyx* produces cream white flowers in summer and its old bark is smooth and grey in colour (Poynton, 1979). The taxonomy for *E. cladocalyx* in line with Florence (1996) is summarised as follows:

Kingdom	Plantae (Plants)
Sub kingdom	Tracheobionta (Vascular plants)
Super division	Spermatophyta (Seed plants)
Division	Magnoliophytta (Flowering plants)
Class	Magnoliopsida (Dicotyledons)
Subclass	Rosidae
Order	Myrtales
Family	*Myrtaceae*
Genus	*Eucalyptus* (gum)
Species	*Eucalyptus cladocalyx* (Sugar gum)

2.13.1. Occurrence and Ecology

E. cladocalyx (Figure 2.6) is endemic in South Australia and very limitedly distributed in region of Spencer Gulf and the Kangaroo Island. Brooker (1990) explained that it attains its best development in the Southern Flinders Range and North Coast of Kangaroo Island, but it does not usually grow into a big tree on the eastern side of the Eyre Peninsula. In these regions, climate is temperate and humid to sub humid, summer is hot and dry while the winters are mild to cool and fairly wet. Temperatures in summer often exceed 38 ºC while in winter the temperature can fall below 10 ºC. Minimum rainfall is usually around 380 mm and the maximum rainfall being 600 mm per annum with occasional droughts (Poynton, 1979; Florence, 1996).

Figure 2.6: *E.cladocalyx* at the study site in the western coast of South Africa at the age of 20 years

2.13.2. Morphology of *E. cladocalyx*

E. cladocalyx is a medium sized tree, growing to a height of up to 37 m and a diameter of between 90 and 180 cm under favourable conditions. However, Florence (1996) explained that on poor soils and in dry localities, it often reaches no more than one third of the optimal size. In favourable conditions, it develops into a well-shaped tree with straight trunk that is free of branches while in poor conditions it is usually stunted. It generally has an open crown with foliage massed at the bent ends of the branches to produce an umbrella like canopy (Poynton, 1979; Brooker, 1990; Florence, 1998).

2.13.3. *E. cladocalyx* in South Africa

E. cladocalyx has been planted in South Africa for the supply of utility grade timber, shelter, shade and for ornamental purposes. It grows rapidly and thrives in warm dry conditions. Poynton (1979) and Magumba (1998) explained that this specie has been widely planted in

the Western Cape Province. Despite its early introduction; it has not played a significant role in afforestation program for many years (van Wyk *et al.*, 2001).

Nevertheless, *E. cladocalyx* was planted in the western coast area because of its corresponding geographic conditions with the winter rain areas of Australia. *E. cladocalyx* thrives best in a warm climate; however, it is not well suited to either subtropical and frost conditions. Poynton (1979) confirmed the later argument by stating that it has a great ability to withstand drought conditions but is sensitive to frost, especially when the trees are still young. Hengari (2008) reported that in coastal areas it may be affected by sea breeze while young, though it stands storm wind and hot dry winds during mature stage.

One of the key merits of this species is its ability to grow on less fertile soils. *E. cladocalyx* produces utilisable timber crop on marginal sites where other eucalypts do not succeed, particularly in the winter rainfall areas (Jacobs, 1979; van Wyk *et al.*, 2001). However, its performance declines especially towards mountainous areas where soils are shallower, sandy and extremely deficient in nutrients (Poynton, 1979).

E. cladocalyx responds well to early and heavy thinning until the age of five years. It generally has a fairly compact, dense crown though with time the head becomes open and spreading. On poor sites the trees assume a more stunted branch habit, however; in favourable conditions it produces moderate straight trunk free of branches (Florence, 1996). Apart from performing well in marginal environmental conditions, *E. cladocalyx* is also free from serious diseases and pests under climatic conditions where it is best suited. Nevertheless, it is attacked by *Phoracantha semipunctata* (Poynton, 1979) which induces bark cracks down to the cambium in stands grown in the Western Cape (Seifert, personal information).

2.13.4. Uses of *Eucalyptus cladocalyx*

The heartwood is different from the whitish sapwood and sometimes has a particularly attractive dark brown colour. The species has a high wood density (see Table 2.4) of above 650 kg/m^3 with favourable mechanical properties (Florence, 1996; Botman, 2010). Although the heart wood is resistant to decay, it can be attacked by some insects. As a result of all these good properties, it is suitable for heavy construction, high class joinery and railway sleepers. In rural communities, it is used as firewood (Poynton, 1979; Jacobs, 1979; Florence, 1996). The tree flowers regularly between September and March, and yields an abundance of nectar

for honey production; however, it does not rate highly as a source of pollen (Poynton, 1979; Florence, 1996).

Table 2.4: Density of selected *Eucalyptus* wood species (McMahon *et al*., 2010)

No.	Species	Green density kg/m^3	Air dried density kg/m^3	Basic density kg/m^3
1	*E. cladocalyx*	1200	800	750
2	*E. camaldulensis*	1130	800	650
3	*E. grandis*	950	630	510
4	*E. gomphocephala*	1250	1030	840

2.13.5. Potentialities of *E. cladocalyx* in arid regions

E. cladocalyx has proven to grow better than most *Eucalyptus* species on poor, salt and skeletal soils in winter rainfall areas, where its wood is used for poles, fuel and other purposes in rural communities (Poynton, 1979). Florence, 1996 stated that this species is important in those environmentally marginalised areas as it has potential for afforestation. Its excellent honey potential and the fact that the leaves are browsed by horses, cattle and sheep make it an ideal tree for small scale forestry.

2.14. *E. gomphocephala*

E. gomphocephala is also known as Tuart (Barber *et al*., 2003). It has dense foliage, white cream flowers and a grey structured bark (Figure 2.7). The fruits are narrow, cup shaped and 13 to 25 mm long (Poynton, 1979).

Figure 2.7: *E. gomphocephala* on the study site in the western coast of South Africa at 20 years

2.14.1. Occurrence and Ecology

E. gomphocephala is found naturally in Western Australia and has limited distribution on the sandy plains in the eastern coast belt. The climate is temperate and humid with a mean minimum and maximum temperature for the warmest and coolest months respectively that vary from 25 to 29 ºC; and from 4 to 7 ºC. Average rainfall is between 760 mm and 1020 mm per annum while the mean monthly temperature in summer does not exceed 25 ºC (Poynton, 1979; van Wyk *et al*., 2001).

2.14.2. Morphology of *E. gomphocephala*

E. gomphocephala is a tree of medium to large size, reaching height of 24 to 46 m and a diameter of 90 to 240 cm in most places except in the northern Australia where it grows no taller than 12 m (Florence, 1996). It forms a short erect straight trunk which accounts for half

its overall height and a well-developed and a fairly dense crown supported by large and spread branches. Van Wyk *et al.* (2001) stated that *E. gomphocephala* regenerates readily from coppice, but is usually crooked or forked under South African environmental conditions. The species yields one of the strongest and most durable of the Australian timbers (Poynton, 1979).

2.14.3. *E. gomphocephala* in South Africa

E. gomphocephala has been grown in South African coastal district of Western Cape for shelter and general amenity purposes (van Wyk *et al*., 2001). Its introduction in South Africa can be traced back to 1895 (Poynton, 1979). This species of *Eucalyptus* has shown vigour in its performance in the winter rainfall areas of the western coastal areas. Furthermore, *E. gomphocephala* has proved outstanding on salt soils and in semi-arid region (Jacobs, 1979; Magumba, 1998; Hengari, 2008).

2.14.4. Uses of *E. gomphocephala*

The heartwood of *E. gomphocephala* ranges in colour from pale brown to almost oak with a whitish sapwood. Florence (1996) reported that timber from *E. gomphocephala* is exceedingly heavy, having a density of 850 kg/m³ (Table 2.4). Consequently, the timber is strong and hard. Although it is hard on the plane, it takes a good and smooth finish in furniture. Besides being used in the furniture industry, this timber is used in heavy construction, framing, for railway sleepers and fencing. Brooker (1990) added that *E. gomphocephala* flowers regularly from December to April and yields both nectar and pollen in moderate quantities hence it is good for honey production. This species produces high grade honey even though its pollen is considered to be of low quality. The tree is wind firm and has been recommended to be planted in dry wind areas, especially in areas with winter rainfall (Poynton, 1979; Hengari, 2008).

2.14.5. Potentialities of *E. gomphocephala* in arid regions

E. gomphocephala is not popular as a plantation species in South Africa and other countries. However, Barber *et al*. (2003) indicated that there is a decline in the number of *E. gomphocephala* trees both in its native environment and were it is planted as an exotic tree. This trend has been attributed to excessive exploitation of *E. gomphocephala* for timber. Furthermore, in plantation establishment, this species is less preferred because of its relative

slow growth and mediocre form (Poynton, 1979). It is however, suitable for tall shelterbelts, particularly at the coast, and can be used for stabilisation of coastal sandy soils. The major advantage of *E. gomphocephala* is its ability to grow in dry winter areas as possible woodlot species with a potential source of many forest products (van Wyk *et al.*, 2001; du Toit, 2003; Botman, 2010).

2.15. *E. grandis x camaldulensis* (Hybrid)

In order to meet the ever rising demand for forest products, tree breeders have been working on combining different genetic stocks to form hybrids. Hybridisation is done in tree improvement programs that target favourable traits such as the enhanced growth rate, product quality, and resistance to drought and diseases (Poynton, 1979; Magumba, 1998; Hengari, 2008). *E. grandis x camaldulensis* clones were among the first eucalypt hybrids grown on a commercial basis in Australia (Florence, 1996). This hybrid is mostly used in afforestation programs because of its ability to grow fast in water scarce areas. Furthermore, *E. grandis x camaldulensis* produces a straight trunk, which makes it attractive for sawmilling (van Wyk *et al.*, 2001). *E. grandis x camaldulensis* is a hybrid of *E. grandis* and *E. camaldulensis,* hence it is important to separately consider the attributes of each parent tree.

2.15.1. *E. camaldulensis*

2.15.1.1. Characteristics of *E.camaldulensis*

E. camaldulensis is fast growing, and usually reaches 40 to 45 m in height depending on its location. Florence (1996) and van Wyk *et al.* (2001) explained that *E. camaldulensis* is the most wide spread eucalypt in Australia and is commonly found along waterways. Tree form is straight under favourable conditions; however, the species can develop twisted branches in drier conditions (Poynton, 1979).

In South Africa, *E. camaldulensis* is grown in semi-arid zones and is adapted to different types of soils. In a provenance trial at Lake Albacutya in Victoria, it proved superior in areas with rainfall of 350 mm per year (Jacobs, 1979). Apart from this species growing fast in arid regions, it is also salt tolerant hence making it possible to grow in arid salt regions (Magumba, 1998; Hengari, 2008).

Figure 2.8: Foliage for *E. grandis x camaldulensis* at the study site in the western coast of South Africa

2.15.1.2. Utility of *E. camaldulensis*

The utility of timber from *E. camaldulensis* tree is determined by the quality of the sapwood and the heartwood. Usually the sapwood is greyish in colour and 5 to 8 cm wide while the heart wood is orange or deep red. The heart wood has high density of over 650 kg/m^3 making it heavy hence the wood is strong and hard but moderately stiff (Poynton, 1979; Magumba, 1998). Furthermore, the wood is characterised by a finer texture and an attractive figure (appearance) than with most eucalypt species. In addition to timber, the tree yields a lot of pollen as it flowers regularly between October and March (Poynton, 1979; Florence, 1996).

2.15.2. *E. grandis*

2.15.2.1. Characteristics of *E. grandis*

E. grandis grow as a straight and tall forest tree, reaching heights of 50 m. The annual rainfall in its natural habitat varies from 1100 to 3500 mm with mean maximum and minimum

temperatures range from 29 to 35 °C and 11 to 20 °C from warmest and coolest months respectively (Poynton, 1979; Brooker, 1990). *E. grandis* is the dominant tree of wet forests in Australia and is popular because of its straight trunk. Consequently, it is in high demand for timber and pulp. It has been grown as an exotic tree in the plantations of Brazil and southern Africa. However, it faces challenges in many locations such as Namibia and desert areas were rainfall is minimal, which has been resolved through hybridisation with drought tolerant species like *E. camaldulensis* (Poynton, 1979; van Wyk *et al*., 2001; Hengari, 2008).

Figure 2.9: Stem for *E. grandis x camaldulensis* at the study area in the west coast of South Africa

2.15.2.2. Potentiality of *E. grandis x camaldulensis*

Considering the combined characteristic of the hybrid, a trial on the western coast of South Africa selected *E. grandis x camaldulensis* as a possible candidate for arid regions. The resultant growth rate of many of the hybrid families was unexpected as the parent species originated from summer rainfall regions (Wyk *et al.* 2001). The yield of the best *E. grandis x camaldulensis* would have been equivalent to the best performing species (*E. gomphocephala*

and *E. cladocalyx*) if the survival was equally good. This hybrid was selected as it would provide a combination of straight stems and fast growing trees that can survive in arid conditions of the west coast (Magumba, 1998).

Chapter 3 : MATERIALS AND METHODS

3.1. Study sites

3.1.1. Location

The study sites are located on the western Atlantic coastline of South Africa in Western Cape Province (Figure 3.1). The actual study sites are Pampoenvlei farm, Chemfos and Coetzenburg. Pampoenvlei is located at 33° 29' S and 18° 23' E, Chemfos is at 32°57' S and 18°26' E while Coetzenburg is situated in Stellenbosch at 33°57' S and 18°52' E (Botman, 2010; du Toit, Botman & Kunneke, 2012).

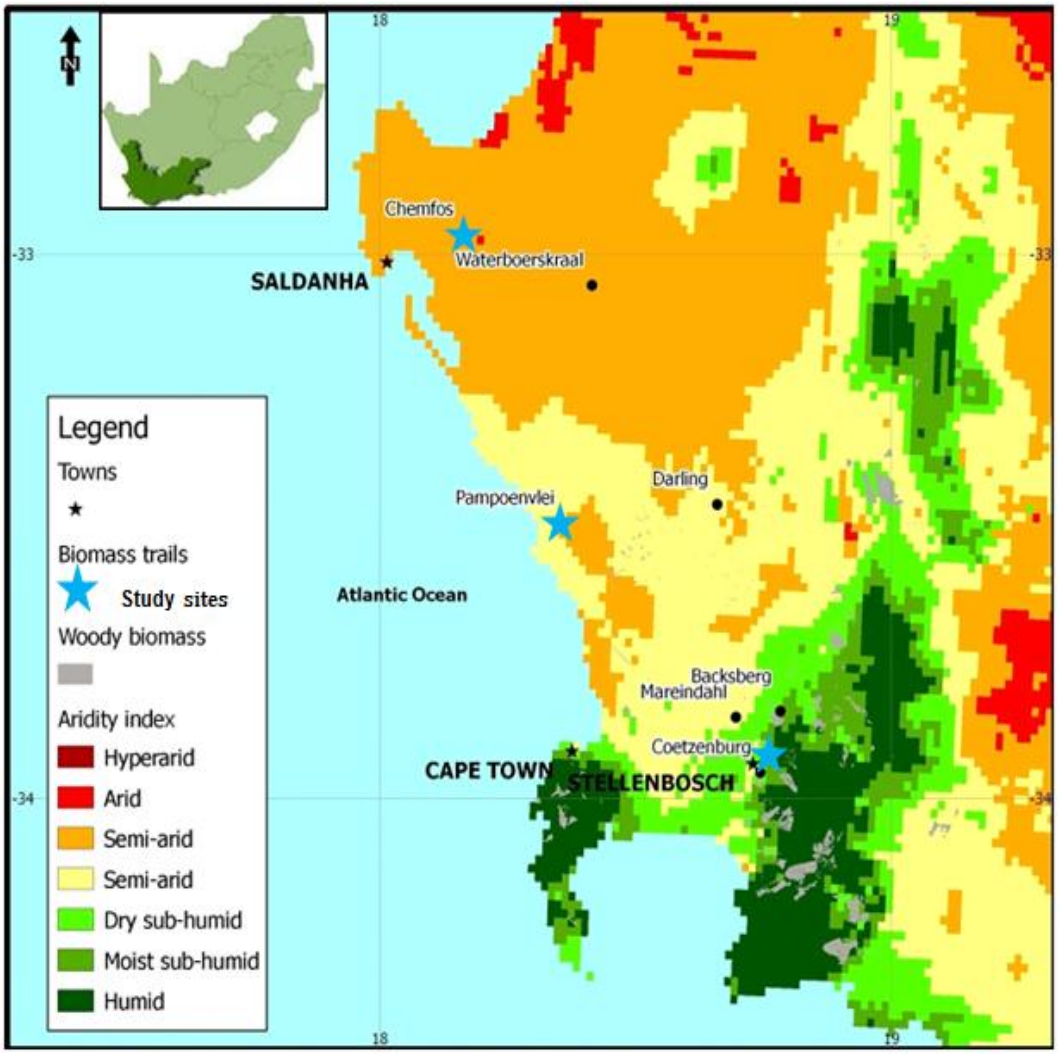


Figure 3.1: Location of study sites and other experimental site in Western Cape (du Toit *et al.*, 2012)

3.1.2. Climate and natural vegetation

The three study sites (Pampoenvlei, Chemfos and Coetzenburg) experience Mediterranean type of climate with winter rainfall and dry hot summer months. Botman (2010) indicated that Pampoenvlei and Chemfos are classified as a semi-arid area with winter rainfall of less than 400 mm (Figure 2.4) received between May and August. Temperature ranges between 7 ºC to more than 35 ºC with an Aridity Index[3] (AI) between 0.20 and 0.50 (du Toit *et al*., 2012). Furthermore, Coetzenburg is classifieds as dry sub-humid area because the area is not as dry as the other two sites (Pampoenvlei and Chemfos) (van Wyk *et al.*, 2001; Botman, 2010).

Natural vegetation covering the study sites is collectively called Fynbos (Magumba, 1998). Fynbos is the term used to describe the indigenous vegetation of the Western Cape which is dominated by sclerophyllous scrubs up to 3 m in height. Acocks (1953) identified two types of Fynbos; (1) Coastal Fynbos, and (1) Coastal Renosterveld. The major botanic families in these two botanic groups are *Proteaceae* and *Restionaceae* respectively.

Figure 3.2: Typical natural vegetation of the study sites

[3] Aridity Index (AI) is the ration between precipitation and potential evapotranspiration hence being dimensionless ($AI = P/E_p$).

3.1.3. Soil type and land use

The terrain at two of the study sites is almost flat with slopes of less than 3%, while Coetzenburg is located near more hilly terrain having a less gentle slope (Botman, 2010). Soils at these sites have been classified under South African Soil Classification System (SASCS) as Lamotte, Constantia, Fernwood and Kroonstad, which support normal rooting system (Magumba, 1998; van Wyk *et al.*, 2001). During winter, water tables can be found to be between 2 to 3 m from the soil surface (Botman, 2010).

Figure 3.3: Dry sand soils on the west coast of South Africa

Although these sites receive low rainfall, the areas are successfully used for agricultural purposes (Table 3.1). As a result of the high demand for agriculture land, only marginal sites and grasslands are left for potential plantations and woodlot establishment. Thus most woodlots have been established on marginal[4] land which cannot support agriculture crop production because of poor soil fertility, shallow depth, poor drainage and unsuitable chemical properties (van Wyk *et al*., 2001; Botman, 2010).

[4] Site quality is one of the most important aspects in plantation establishment apart from aspects such as species choice, accessibility and location as it determines the quality of the products.

Table 3.1: Area allocated to various land use in the Western Cape (Botman, 2010)

Land use	Area (ha)
Cultivated	2 256 270
Degraded	305 578
Grassland	120 878
Thicket and Bush land	653 527
Indigenous Forest	62 430
Woodland	2
Exotic Plantations	107 661
Scrubland	9 199 979
Water body	47 376

3.1.4. Description of the trials at the study sites

Studies on the performance of different drought tolerant tree species in arid region of Western Cape started in 1991 under the Dry-land Industry and Rural Afforestation Project (DIRAP). After considering the performance of selected *Eucalyptus* species in other Mediterranean regions of the world, it was assumed that these *Eucalyptus* species would perform well if not better in similar environmental conditions in South Africa. The then Faculty of Forestry at the University of Stellenbosch initiated the project and trials were established in the winter of 1991 (Figure 3.4). The trials included 50 seedlings spaced at 5 m x 2 m laid in a completely randomised block design (CRBD) with five replications in three blocks (Magumba, 1998; van Wyk *et al*., 2001).

Figure 3.4: *Eucalyptus* species on the experimental plot on the west coast of South Africa at 20 years of age

Performance assessment of these tree species was carried out by taking into consideration the survival, height and diameter growth. After planting the seedlings, measurements were taken at ages one, three and six years. Forest mensuration and statistical methods of analysis were used in understanding the performance of the trial using dbh and height. Based on results of the trial, *E. gomphocephala*, *E. cladocalyx* and a hybrid *E. grandis x camaldulensis* performed better than the other species (van Wyk *et al*., 2001).

3.2. Tree sampling methods

3.2.1. Tree selection

Tree sampling for the study was done at the study sites described in Section 3.1. Selection of trees depended on the species and size of the tree, and was restricted to a relatively small number of trees. This restriction was to conserve the continuation of growth of the remaining trees on the experiment plots, as the study employed a destructive approach. In order to cover the existing range of potentially harvestable tree sizes, trees were sampled in three groups; (1) small (dbh < 21 cm), (2) medium (dbh of 21 to 30 cm), and (3) large (dbh > 30 cm). A total of 33 trees were sampled with 14 trees from the Pampoenvlei farm, 14 tree from

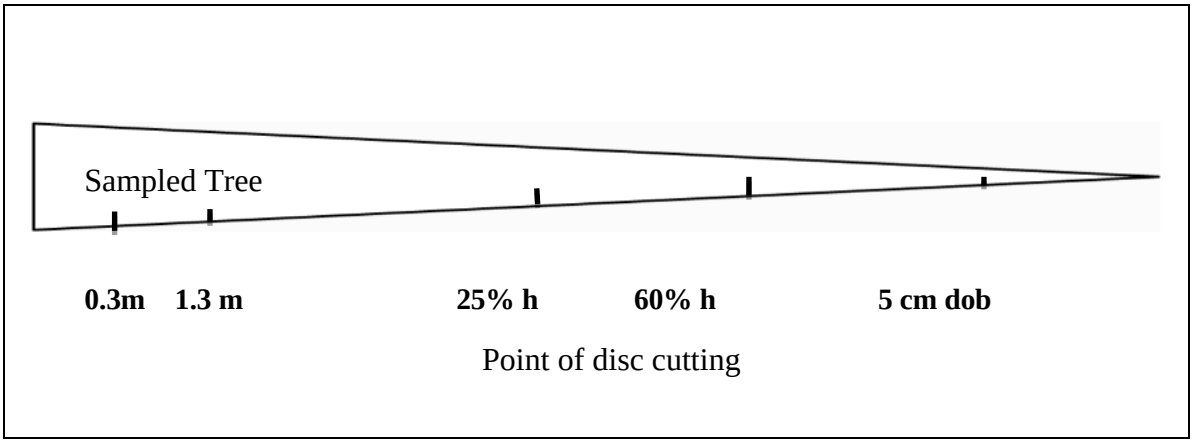
Chemfos, and five additional small trees from Coetzenburg (Table 3.2). The smaller trees consolidated the even distribution of dbh and height of the sample.

Table 3.2: Selected *Eucalyptus* trees used in the study

Species	Site	Age (years)	Number of Trees
E. cladocalyx	Pampoenvlei farm	20	5
	Chemfos	20	4
E. gomphocephala	Pampoenvlei farm	20	5
	Chemfos	20	4
	Coetzenburg	5	5
E. grandis x camaldulensis	Pampoenvlei farm	20	5
	Chemfos	20	5
Total			**33**

3.2.2. Biomass sampling

Prior to felling, dbh (diameter at height of 1.3 m), tree height, crown height, and crown diameter were measured and recorded for each tree. The selected trees were felled using chain saws and the stems were marked at five points for discs cutting (Figure 3.5). In order to reconstruct volume, the stem diameter was measured at every one meter point along the tree height until the diameter over bark was 5 cm.



Note: h is total tree height in meters; dob is diameter over bark

Figure 3.5: Points for disc removal on sampled trees

3.2.2.1. Discs and bark sampling

In order to estimate the wood and bark density distribution along the stem, discs were cut at marked points using Chainsaws (Figure 3.5). The thickness of all the discs was measured to be 5 cm. Diameters under bark and over bark was also measured at four directions at 90 ° on all the discs in order to calculate the bark volume. Tree numbers, types of species and trees sizes were marked on upper surfaces of the discs for identification. This followed by putting the disc in plastic bags (Figure 3.7) in order to avoid excessive loss of moisture during transportation to the laboratory. Figure 3.6 shows measurements on a sampled tree after felling.

Figure 3.6: Sampled tree after felling at the study site

3.2.2.2. Branches sampling

Five branches per tree were randomly sampled following a range of diameters along the stem to avoid sampling branches of almost the same size. The diameters of the sampled branches were measured using a vernier calliper and recorded on a data sheet (Appendix I). The

selected branches were cut and packed in plastic bags (Figure 3.7) for biomass upscaling. The diameters of all the dead and live branches on the sampled trees were measured. This was followed by transportation of the samples to the laboratory for drying (Section 3.2.3).

3.2.2.3. Foliage sampling

Foliage (leaves and fruits) were collected for the complete analysis of aboveground biomass for each of the five sampled branches. Prior to drying, leaves and fruits were separated from the branches and packed in separate paper bags while the diameter of the particular branch from which the leaves were collected was recorded in order to be used during regressing. For the purposes of identification; species name, tree number and tree size were marked on the paper bag. At this point, foliage was ready for drying in the ovens.

Figure 3.7: Biomass samples packed in plastic bags for transportation to the laboratory

3.2.3. Laboratory procedures

Water displacement on the fresh discs was carried out for the purpose of volume determination with and without the bark as proposed in Seifert and Seifert (2013). The discs and the bark were separated using knives and totally submerged in a water basin while taking the weight on a scale in grams following Archimedean principle[5] of water displacement. The basic principle of the displacement method is that the weight in grams equals volume in cm^3. The resulting volume and dry mass was used for the calculation of basic density.

All the samples were put in separately marked paper bags before drying. Drying of these samples was carry out in the oven at 60 °C for 48 hours in order to reach a constant weight. It is important to note that the volume and dry mass of both the bark and the discs was used to calculate basic density as illustrated in Equation 13 and 14 of Section 3.2.7.2.

Figure 3.8: Oven drying and weighing of biomass samples in the laboratory

[5]Archimedes' principle, a law of physics, which indicate that the upward that is exerted on a body immersed in a fluid is equal to the weight of the fluid that the body displaces.

3.2.3.1. Drying series of sub-sample

The Initial samples were dried at 60 ºC to minimise the loss of volatile nitrogen components since further analysis on nutritional levels was planned on the same samples. To obtain compatibility of this biomass study to other studies, a sub-sample of 40 samples (10 for leaves, 10 for bark, 10 discs and 10 for the branches) was selected from the sample for further drying at different temperatures in a drying series. The sub sample was dried at 60 °C, 65°C, 80 °C, 90 °C and 105 °C to a constant weight for 48 hours while the dry weight was determined for each drying temperature.

3.2.3.2. Density analysis using CT-scanning method

X-ray based CT-scanning was used for alternative density determination in order to validate the accuracy of the density. The samples (discs) were placed on a rotating stage, and about 2000 to 3000 two dimension (2D) images were acquired at various angles around the object as it rotated (Figure 3.9). The images were then reconstructed to form a tomogram in three dimensions (3D) and stored in form of slice images and image stacks as suggested by du Plessis and Seifert (2012).

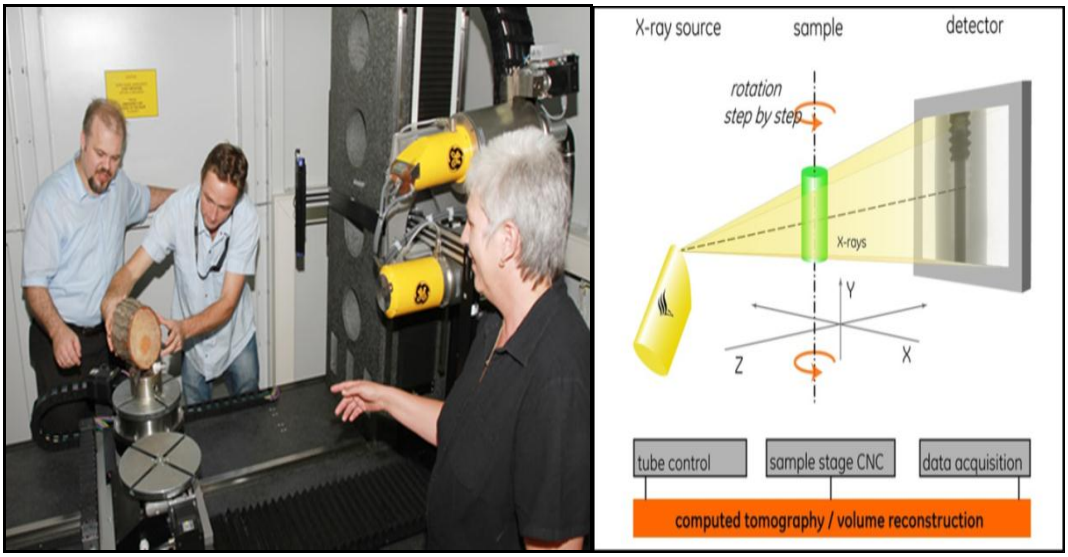


Figure 3.9: CT-scanning density determination equipment and method (Holger Roth, GE Systems)

The X-ray attenuation is represented as grey values in the visual CT image. These values were regressed to the absolute material density in the calibration procedure. Further analysis on average grey values was done with the image analysis software ImageJ (Collins, 2007). This was followed by density calibration curves construction based on 13 known wood

densities. It was these density curves, which were used to predict unknown densities for the samples as indicated in Section 4.2.5.

3.2.4. Up-scaling Procedure

Upscaling is a procedure of building up biomass quantities from the field samples to the individual tree and stand level (Seifert & Seifert, 2013). The upscaling of the crown and stem was carried out separately. The crown included the foliage and branches while the stem included the stem wood and the bark. Section 3.2.7.1 and 3.2.7.2 presents how upscaling was done for the two parts.

3.2.7.1. Upscaling of branch and leaf biomass with a regression approach

The diameters of all the branches on the same tree were recorded as well as the distance from the bottom of the tree at the insertion with the stem. Biomass for sample branches and leaves were then pooled across the sampled trees of one species and used in fitting allometric models. Branch diameters and branch basal area were used as independent variables to simulate biomass. These allometric equations were subsequently used in determining the biomass of all the other branches and foliage for each tree during upscaling.

3.2.7.2. Upscaling wood stem and bark based on a geometric approach

The stem volume was reconstructed geometrically using Smalian's formula (Equation 13) for the entire stem with diameter taken at both ends of a meter section as explained in Section 3.2.2. Diameter over and under bark were used to calculate the ratio of the bark to the stem volume in percentage. These respective volumes of each section were then multiplied with basic density values for wood and bark (Equation 14). This process of upscaling resulted in obtaining the total mass for all the biomass components hence obtaining the total biomass for each individual tree.

Smalian's formula: $V = \frac{\pi L(d1^2 + d2^2)}{8}$ (13)

$$\text{Biomass} = V \times r0 \quad (14)$$

Where:

V = volume

r0 = basic density

d_1= diameter at the bottom end of a stem section

d_2= diameter at the upper end of the stem section

l = stem length

3.3. Data analysis

Data analysis focused on parameterising of biomass models that ensure additivity. Furthermore, analysis was conducted on variations of oven-dry weight (biomass) at different drying temperatures. Statistical analysis was done in R statistical software (R Core Team, 2013) using a package called "`Systemfit`" (Henningsen & Hamann, 2013). The principle method used was a multivariate regression that estimates all biomass components simultaneously to ensure that biomass add up to the total and thus ensuring additivity (Seifert & Seifert, 2013). Additivity of the biomass components was attained by joint regression using a Seemingly Unrelated Regression (SUR) approach (Parresol, 1999).

3.3.1. Seemingly unrelated regression

In biomass modelling a frequently desired feature is that the individual biomass components are summing up to the total biomass as predicted by a model for the all the components at once, which is called additivity. In order to attain this condition, many methods have been proposed and used (Seifert & Seifert, 2013). Parresol (1999) proposed a method called NSUR and SUR, which takes into account the contemporaneous correlations between the variables of the different components. The method results in a higher efficiency of estimation (Parresol, 1999; Ackerman *et al*., 2012).

3.3.2. Error propagation

Biomass assessment methods produce a propagated error which needs to be quantified. In this study, error propagation was partitioned into sampling error and error due to regression (Equation 15) as proposed in Cunia (1979) and Samalca (2007).

$$S^2 = S^2_{(x)} + S^2_{(y)} \quad (15)$$

Where:

S^2 = Total variance

$S^2_{(x)}$ = variance associated with sampling

$S^2_{(y)}$ = variance associated with regression

3.3.3. Assumptions in biomass modelling

The following assumptions need to be tested in regression analysis; (1) homoscedasticity, (2) additivity, (3) normal distribution of residuals, and (4) independence of data (Ott *et al*., 2001; Schabenberger & Pierce, 2002). Homoscedasticity is a condition of uniform variances tested on residuals plotted against the predicted values. In most cases, the variance changes along with the independent variable which is called heteroscedasticity and is a violation of regression assumptions (Ackerman *et al*., 2012; Seifert & Seifert, 2013) and in this study it was minimised through logarithmical (ln) transformation of the data and using weighted linear models. Biomass component models also demands that the additivity assumption to be attained. In order to achieve this, the SUR models will be used as suggested in Parresol (1999). Normal distribution of the residuals, i.e., the probability distribution characterised by a bell shape, will be tested by Shapiro-Wilk test (Ott *et al*., 2001; Chamber & Hand, 2008). Furthermore, independence of the data ensures that the data is not in clusters, and is managed by using reliable sampling methods (Seifert & Seifert, 2013).

3.3.4. Goodness of fit

To select the best model, different measures of goodness of fit will be used. The best models for this study will be selected by; coefficient of determination (R^2), Standard error (se) (Equation 16) in form of Mean Standard Error (MSE) and Root Mean Standard Error (RMSE), and Akaike Information Criteria (AIC).

$$se = \sqrt{RSS/(n-P)} \quad (16)$$

Where:

se = Standard error of estimate

RSS = Residue sun of square

P = number of parameters in the model

n = sample size

3.3.5. Back transformation correction

To make linear models the data will be logarithmically (ln) transformed. It has been observed that when data is log transformation, biased estimated values are obtained after back transformation (Seifert and Seifert, 2013). In order to avoid this, all the transformed models will be subject to bias correction, which is variance, divided by two (Equation 17)) as suggested by Baskerville (1972).

$$\text{Biomass} = \exp\left(b_0 + b_1\,(\text{dbh}) + {}^{\alpha^2}/_{2}\right) \qquad (17)$$

Where:

b_0, b_1 = are coefficients,

dbh = the diameter at breast height (1.3m) in cm

α^2 = variance

3.3.6. Data analysis for drying series

The effect of increasing drying temperature on biomass was initially assessed using scatter plots to visualise trends in the data. A further analysis on the total percentage change on oven dry weight (biomass) from the lowest temperature to the highest temperature were compared amongst the samples using analysis of variance (ANOVA). In cases where there was a strong correlation between increase in temperature and weight percentage change, simple linear regression models were formulated. It is important to note that the reference point of 100% was based on drying temperature of 105 ˚C.

Chapter 4 : RESULTS

4.1. SAMPLED TREES

4.1.1. Distribution of sampled trees

Mean dbh of the three eucalypt species was 25.08 cm while it ranged from 7.2 to 37.1 cm (Figure 4.1). The standard deviation for the dbh distribution over all selected eucalypt species was ± 7.88 cm.

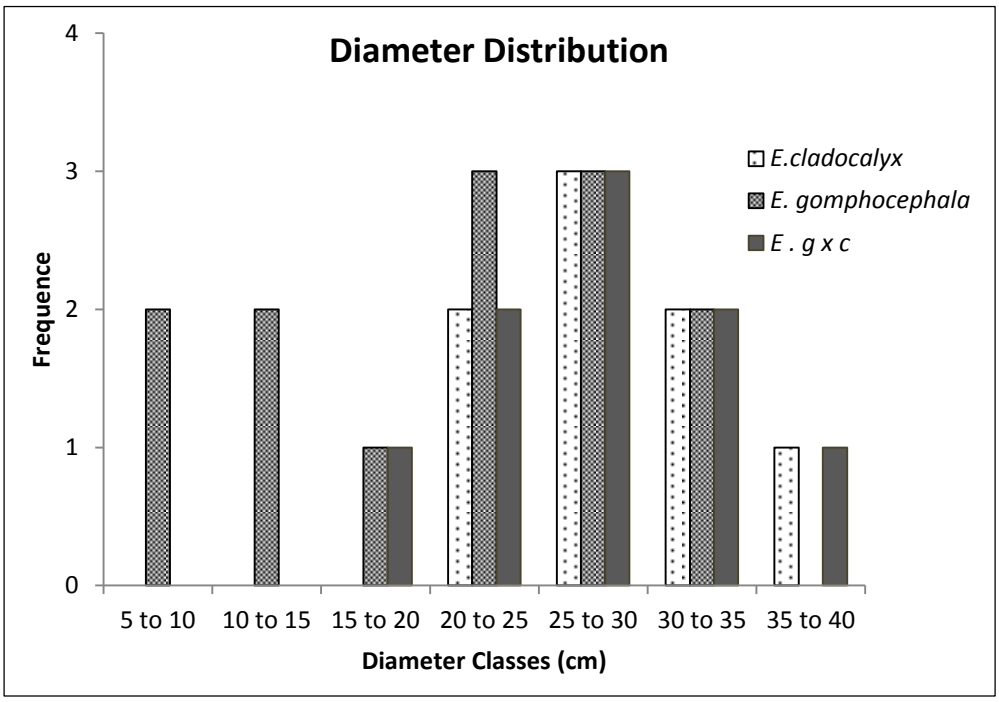


Figure 4.1: Diameter distribution of the sampled eucalypt trees for the biomass study

Mean height was 14.26 m while its range was from 7.8 to 19.4 m (Figure 4.2) with a standard deviation of ± 3.01 m. There was a strong correlation between height and dbh as indicated by Pearson's products moments correlation value of 0.76 with a smaller p-value ($p = 0.0018$) indicating that the correlation is significantly different from zero.

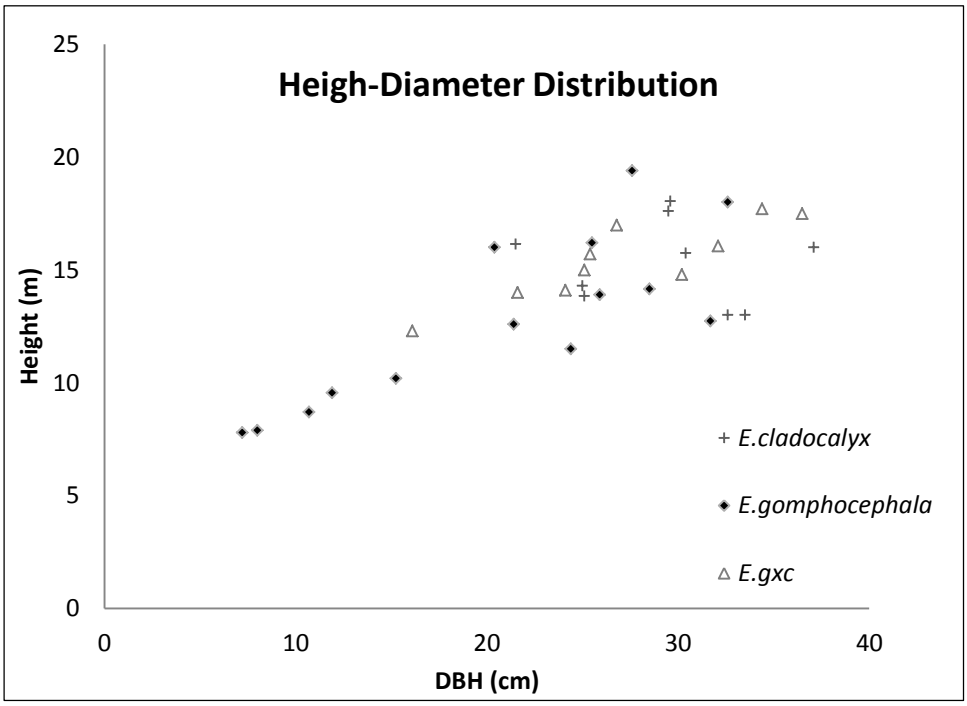


Figure 4.2: Dbh and height relationship of the three tree species

4.1.2. Height Model

Two models were formulated to predict height; not all the models were significant. The transformed model (Model 4.2 in Table 4.1) had a coefficient of determination (R^2) of 0.72 while the untransformed Model (Model 4.1) had R^2 of 0.57. Table 4.1 shows the details of all the estimated parameters for the two height models.

Table 4.1: Diameter height Models

Model	Dependent variable	Independent variable	Parameter estimate and the p-values		R^2	Model p-value
			b_0	b_1		
4.1	h	dbh	6.94 (1.29e-06)	0.29 (2.28e-07)	0.57	0.654
4.2	ln(h)	1/(dbh)	2.99 (2e-16)	-7.60 (3.50e-10)	0.72	2.6e-10

Note: h is tree height and dbh is diameter at breast height

The p-value of Model 4.1 was not significant ($p > 0.05$) while that for Model 4.2 was highly significant ($p < 0.05$). Predicted values for Model 4.2 were plotted against the residuals; the plots did not show a clear pattern (Figure 4.2) indicating that the residuals were

homoscedastic. The normality assumption of the models was determined by using Shapiro-Wilk test on the residuals, which indicated a large p-value ($p > 0.05$). With this larger p-value for Shapiro-Wilk test, it can be assumed that the normality assumption was attained.

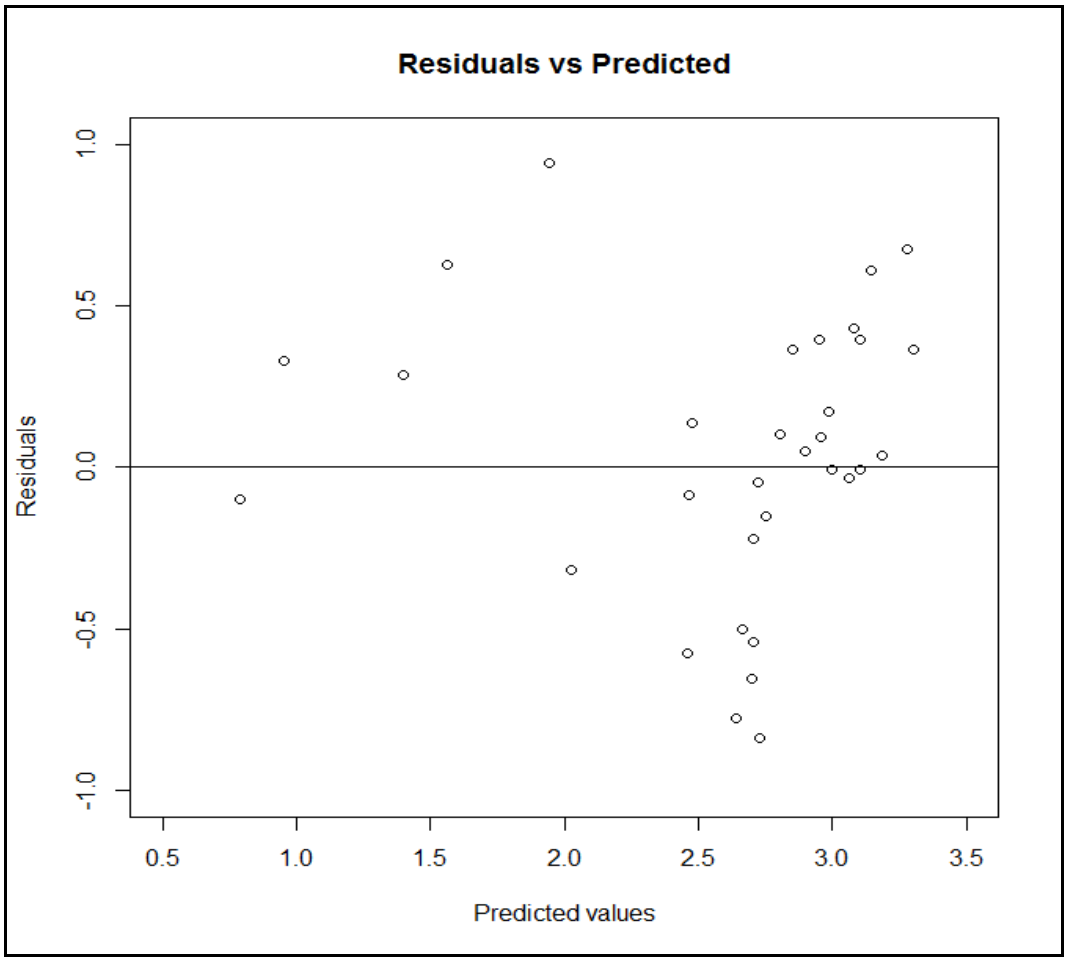


Figure 4.3: Height and diameter predicted vs. residual plots

4.1.3. Volume Models

Three models were parameterised for volume prediction. The first model (Model 4.3) had dbh as the only predictor variable; the second model (Model 4.4) was a transformed model based on dbh and h while the third model (Model 4.5) had d^2h and h as predictor variable (Table 4.2). Figure 4.3 shows the empirically measured distribution of dbh and volume of the trees.

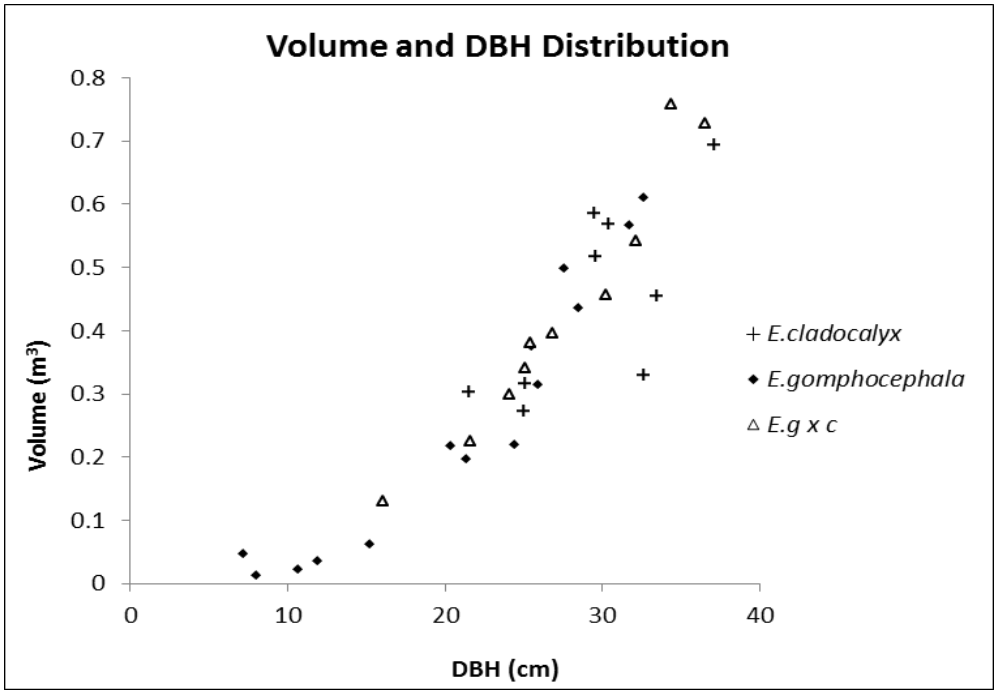


Figure 4.4: Dbh and volume distribution of sampled trees

All the three formulated models for predicting volume were significant (p-value < 0.05); however, the intercept and h for Model 4.5 were not significant as indicated in Table 4.2. Model 4.4 had the highest R^2 value of 0.94 while Model 4.5 had the lowest R^2 value of 0.85.

Table 4.2: Volume models with parameters p-values in brackets

Model	Dependent variable	Independent variable	Parameter estimates and their p-values			R^2	Model p-values
			b_0	b_1	b_2		
4.3	Volume	dbh	-0.25 (213e-6)	0.02 (1.01e-14)		0.91	0.002
4.4	ln(Volume)	ln(dbh), ln(h)	-10.29 (2.12e-14)	1.69 (1.12e-8)	1.38 (0.001)	0.94	2e-16
4.5	Volume	(d^2h),h	-4.5e-5 (0.366)	3.04e-05 (1.52e-14)	5.91e-3 (0.204)	0.85	0.001

The plot for residuals against predicted values for Model 4.4 did not show a clear pattern indicating that the uniformity of the residuals was maintained (Figure 4.5). Therefore, Model 4.4 was chosen as the best model for volume prediction.

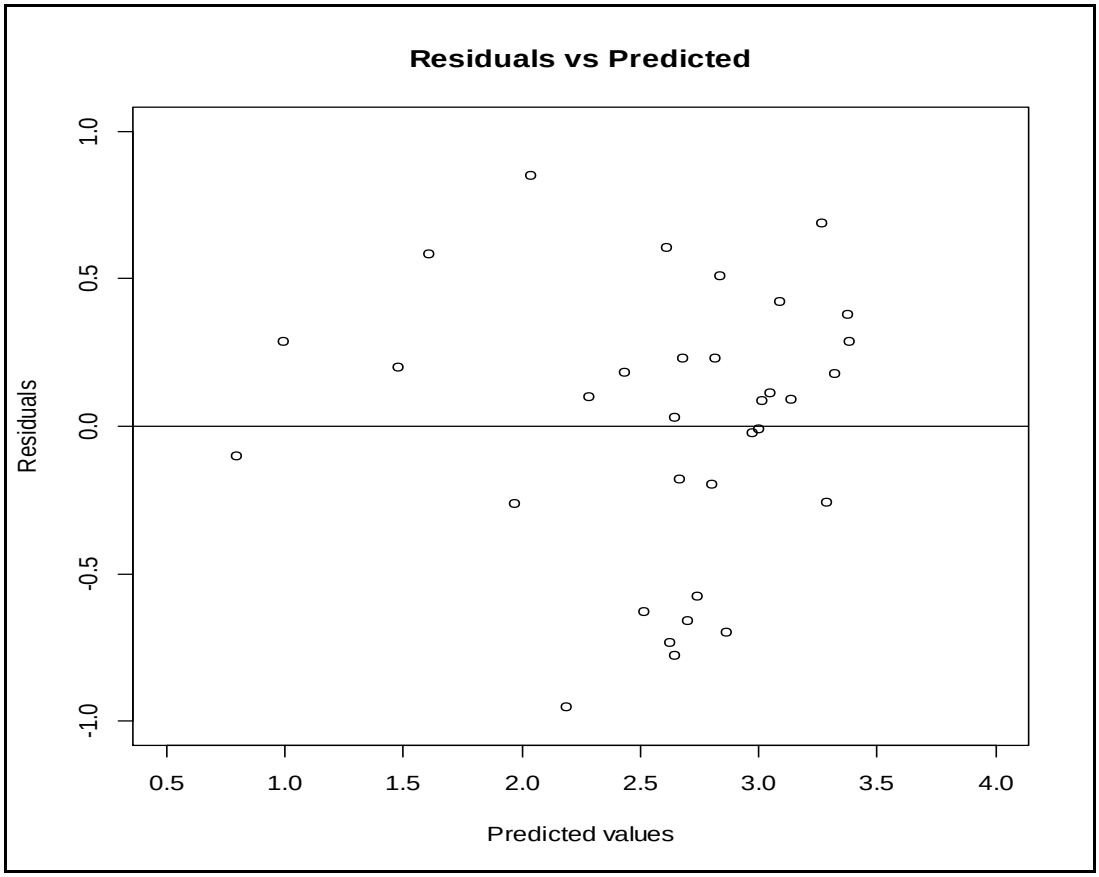


Figure 4.5: Volume and dbh model predicted values vs. Residuals for model 4.4

4.2. UPSCALING MODELS

4.2.1. Pooled crown model

4.2.1.1. Pooled foliage model

Models for predicting foliage biomass for all the branches were fitted using branch diameters (d) and branch basal area (ba) as independent variables[6]. Models with one predictor variable (Models 4.7, 4.8 and 4.9) and a two predictor variable model (Model 4.6) were parameterised. Model 4.9 was a logarithmically (ln) transformed model of branch diameter (d). Figure 4.6 shows the relationship between biomass and branch diameters.

[6] Independent variable represents the input or predicting parameter which the dependent variable is the output or response.

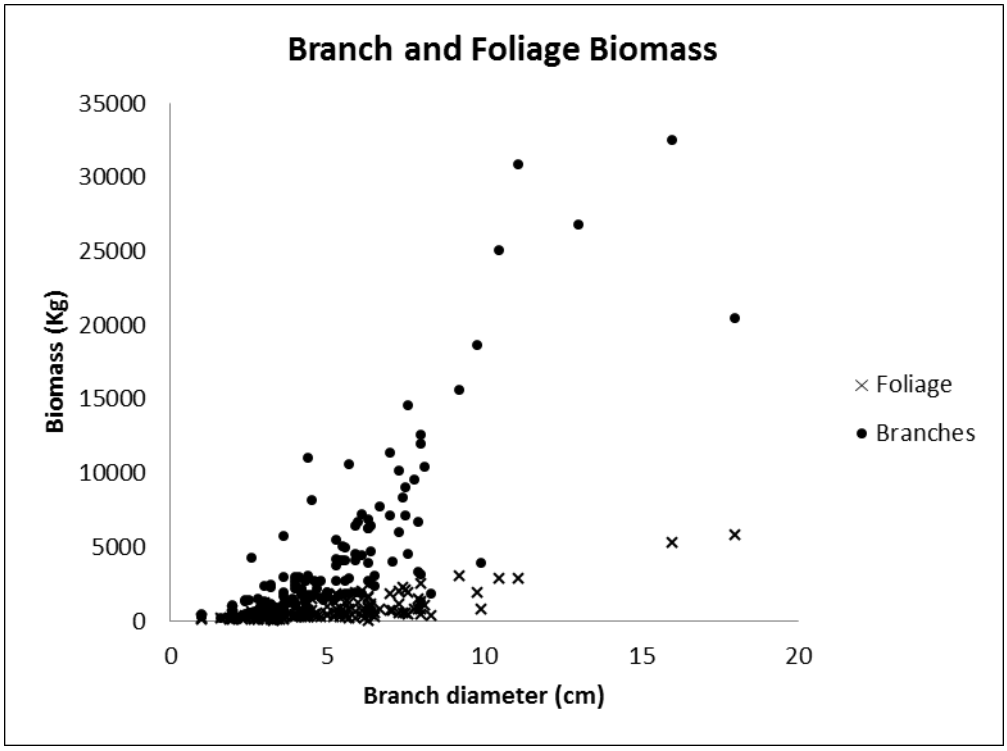


Figure 4.6: Pooled branch biomass and diameter relationship

Assessment of the significance of the parameters of the foliage models showed that Model 4.6 had only one parameter (ba) significant while intercept and d were not significant ($p > 0.05$). Model 4.8, which had the highest R^2 of 0.70 and all its estimated parameters significant ($p < 0.05$), was the best fitting model (Table 4.3). Furthermore, the residuals against predicted values plot did not indicate a clear noticeable pattern.

Table 4.3: Pooled crown foliage and branch models

	Model	Dependent variable	Independent variable	Parameter estimate with there p-values in brackets			R^2
				b_0	b_1	b_2	
Foliage	4.6	F_{bm}	ba, d	153.35 (0.061)	2355456.5 (0.002)	-2.01 (0.123)	0.69
	4.7	F_{bm}	d	-556.16 (0.003)	257.55 (352e-7)		0.61
	4.8	F_{bm}	ba	147.34 (0.001)	233874.16 (232e-5)		0.70
	4.9	$\ln(F_{bm})$	ln(d)	1.777 (0.004)	1.341 (145e-5)		0.40
Branches	4.10	Bbm	ba, d	-2230.3 (0.012)	790206.17 (312e-3)	850.3 (0.294)	0.69
	4.11	B_{bm}	d	-4635.4 (345e-4)	1731 (0.003)		0.67
	4.12	B_{bm}	ba	299.0 (0.214)	1459157.5 (0.003)		0.68
	4.13	$\ln(B_{bm})$	ln(d)	2.05 (256e-4)	10.53 (0.001)		0.71

Note: F_{bm} is foliage biomass, B_{bm} is branch biomass, ba is basal area, and d is branch diameter

4.2.1.2. Pooled branch model

Four models were formulated so that the best model could be selected for predicting branch biomass. Model 4.13 [ln (B_{bm}) = 2.05 + 1.96ln (d)] was considered the best fitting model because all the parameters were significant and it had the highest R^2 value of 0.71 (Table 4.3). The residual against predicted values plots for Model 4.8 in Figure 4.7 was consistent on a range of predicted values indicating the homoscedasticity of the residuals.

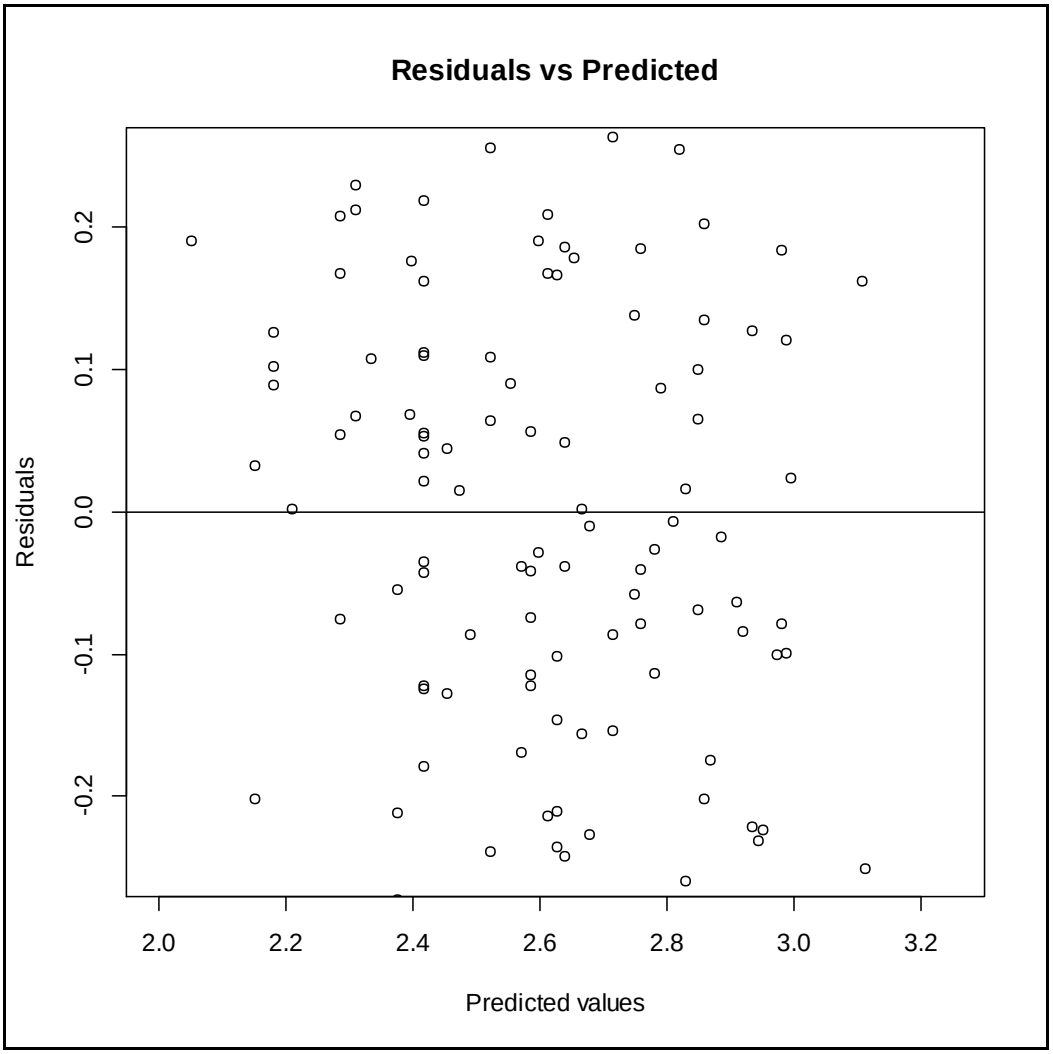


Figure 4.7: Branch biomass model predicted values vs. residuals for Model 4.13

4.2.2. *E. cladocalyx* crown models

There is a strong correlation between diameter and biomass (r = 0.84) and p-value of 0.002. The p-value showed that the correlation was significant different from zero. Basal area and total branch biomass relationship were strong with a high value of r (r = 0.93) and a smaller p-value ($p < 0.05$). Figure 4.8 shows the relationship between branch biomass and branch diameters.

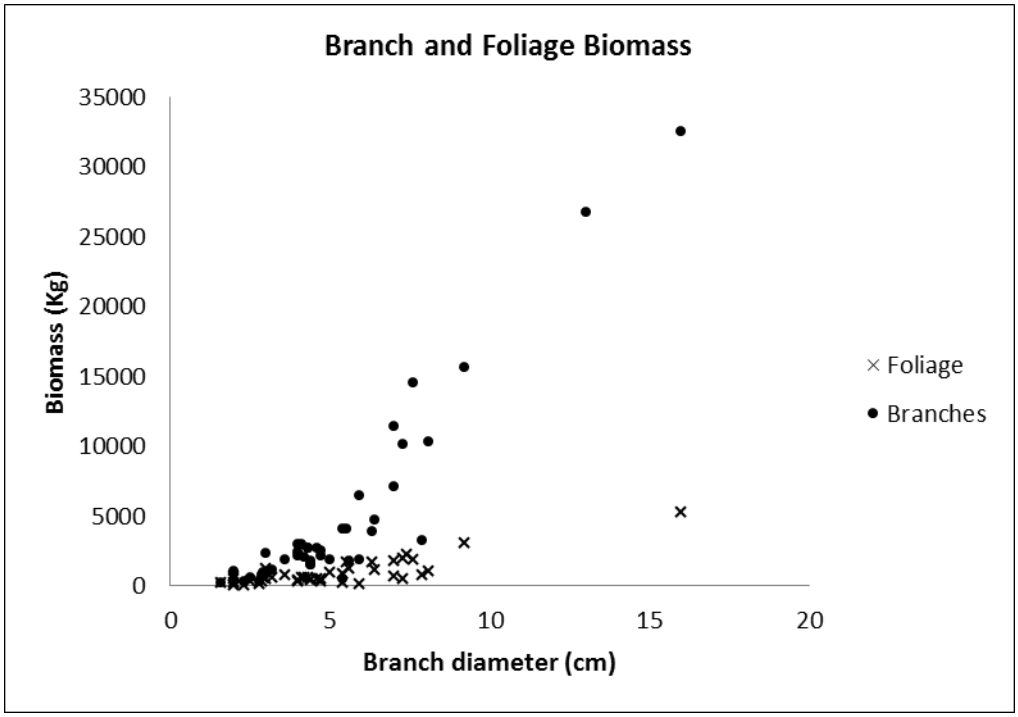


Figure 4.8: *E.cladocalyx* biomass and branch diameter relationship

4.2.2.1. *E. cladocalyx* foliage models

To predict the foliage biomass for *E. cladocalyx*, four models (Model 4.14, 4.15, 4.16 and 4.17) were parameterised using ba and d as predictor variable as shown in Table 4.4. Model 4.14 and 4.15 had R^2 of 0.77; Model 4.15 had R^2 of 0.71 while Model 4.17 had the lowest R^2 value of 0.49. Three models (4.15, 4.16 and 4.17) had all the estimated parameter significant; however, not all the estimated parameters were significant for Model 4.14 as shown in Table 4.4. The plots for residuals against predicted values for the finally chosen Model 4.16 had no clear pattern indicating the uniformity in the residuals hence homoscedasticity of the residuals (Figure 4.9).

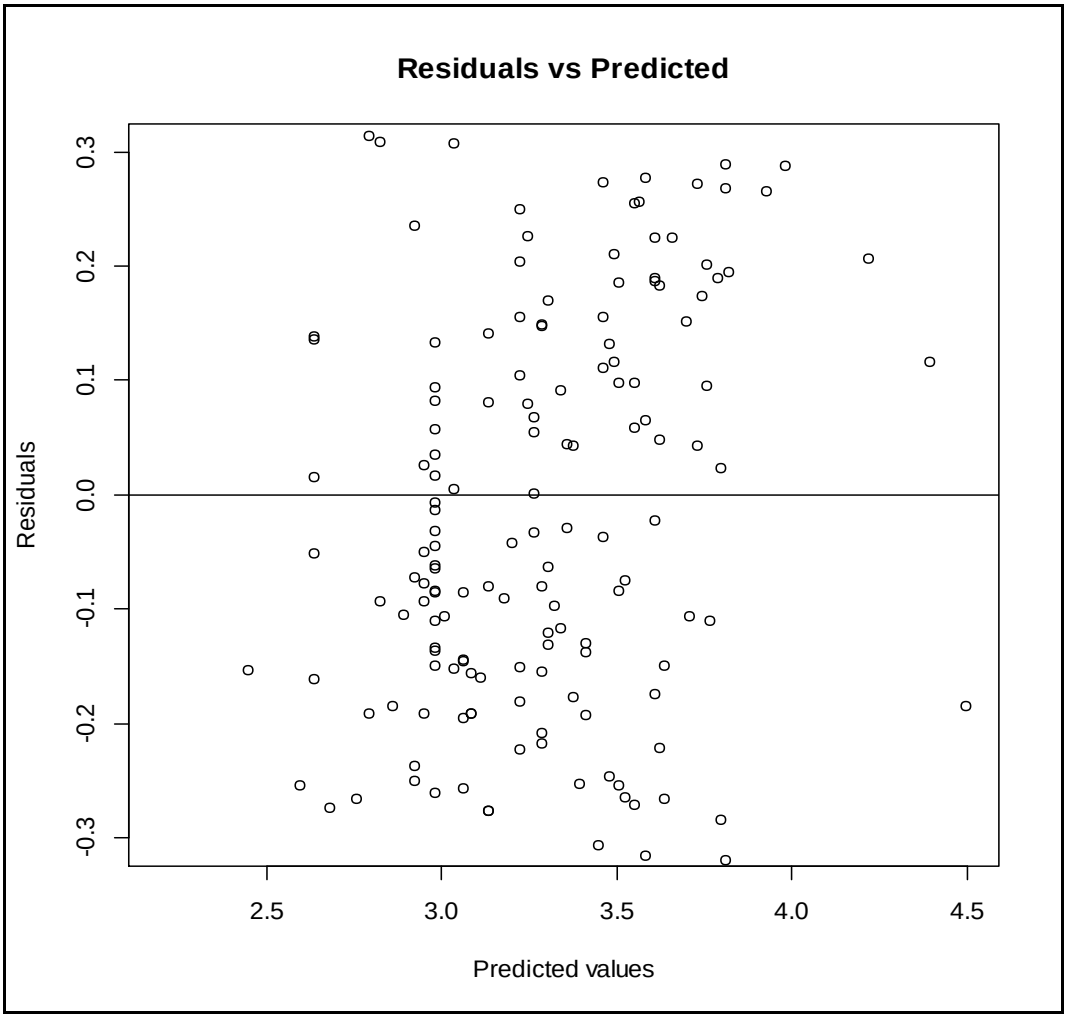


Figure 4.9: *E. cladocalyx* foliage biomass model predicted values vs. residuals for Model 4.16

4.2.2.2. *E. cladocalyx* Branches

Four models were formulated to predict branch biomass for *E. cladocalyx* from which the best model was selected (Table 4.4). All the models were significant, however, only Model 4.18 had all its estimated parameters significant different from zero (p-values < 0.05). Model 4.18 and 4.20 had the highest value of R^2 of 0.91 while Model 4.21 had the lowest R^2 of 0.81. In this case, Model 4.18 was the best model for predicting *E. cladocalyx* branch biomass since it was the only model with all the estimated parameters significant.

Table 4.4: Biomass models for crown components for *E.cladocalyx*

	Model	Dependent variable	Independent variable	Parameter estimate with p-values in brackets			R^2
				b_0	b_1	b_2	
Foliage	4.14	F_{bm}	ba, d	108.20 (0.057)	222913.15 (0.001)	48.07 (0.345)	0.77
	4.15	F_{bm}	d	-600.80 (564e-4)	301.95 (0.003)		0.71
	4.16	F_{bm}	ba	254.59 (0.001)	260150.49 (741e-4)		0.77
	4.17	$\ln(F_{bm})$	ln(d)	1.8671 (0.041)	1.3956 (0.001)		0.49
Branches	4.18	Bbm	ba, d	-1403.3 (0.001)	1490683.5 (231e-5)	408.8 (0.002)	0.91
	4.19	B_{bm}	d	-6414.8 (0.023)	2177.4 (0.111)		0.84
	4.20	B_{bm}	ba	-163.5 (0.004)	802792.3 (0.105)		0.91
	4.21	$\ln(B_{bm})$	ln(d)	1.95 (2.134)	2.14 (267e-4)		0.81

Note: F_{bm} is foliage biomass, B_{bm} is branch biomass, ba is basal area and d is branch diameter

4.2.3. *E. gomphocephala* crown biomass model

The scatter plot for *E. gomphocephala* crown biomass showed a strong relationship between biomass and branch diameter. Figure 4.10 shows that the branch biomass was high for each particular diameter as compared to the foliage biomass. R values of 0.79 and 0.83 were calculated for foliage and branches biomass respectively with a small p-value ($p < 0.05$) for both foliage and branches.

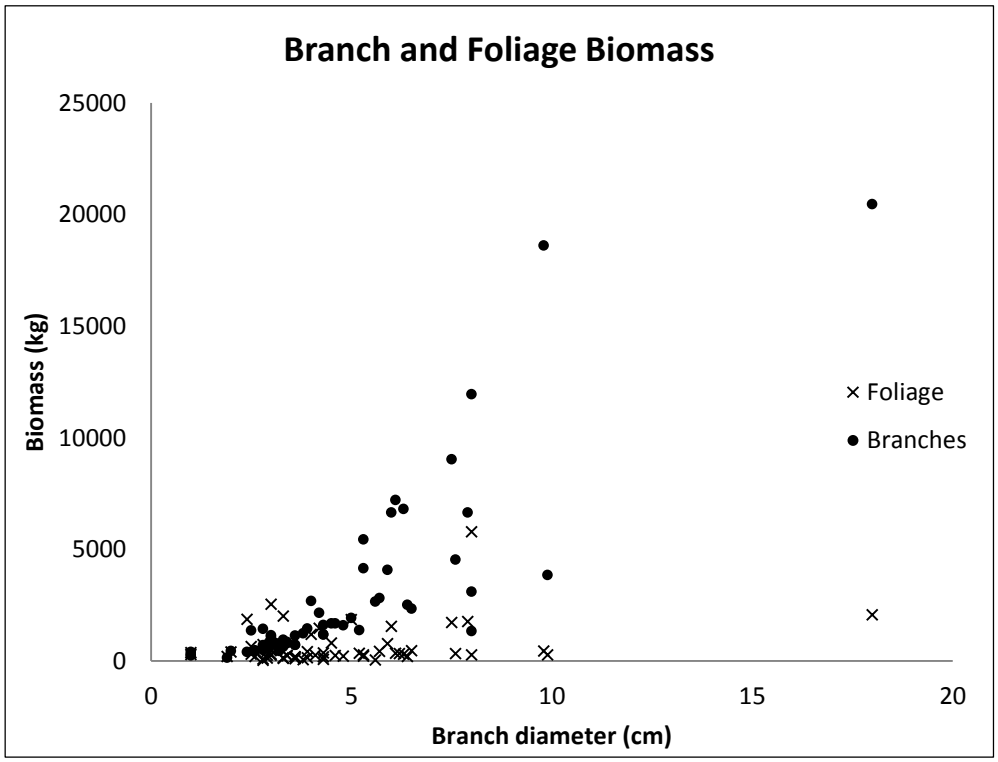


Figure 4.10: Branches and foliage biomass relationship with branch diameter for *E.gomphocephala*

4.2.3.1. *E. gomphocephala* foliage models

Four models were formulated to predict foliage biomass from which the best fitting model was selected. Model 4.23, 4.24 and 4.25 had all the estimated parameters[7] significant (p-value < 0.05). All the models were significant with a small p-value ($p < 0.05$), and Model 4.25 [In (F_{bm}) = 1.59 + 1.55 ln (d)] was a better model since it had the highest R^2 (0.72) value and all its parameters significant (Table 4.5). The residuals against predicted plots confirmed the homoscedasticity of the variance as there was no clear pattern on the plot in Figure 4.11.

[7] Estimate parameters refer to the intercept (a) and the partial slopes (b_1, b_2, b_3) of the regression.

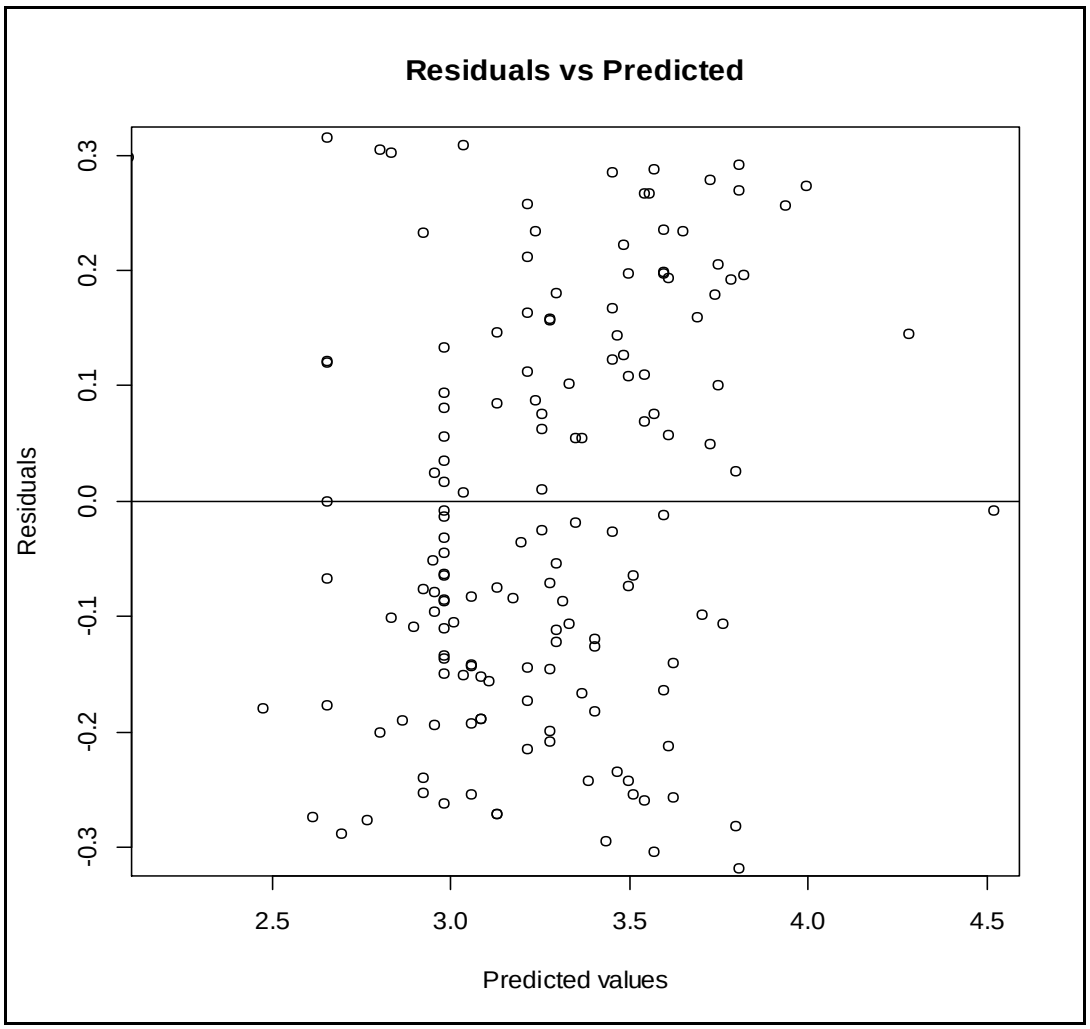


Figure 4.11: *E.gomphocephala* foliage biomass model predicted values vs. residuals plots

4.2.3.2. *E. gomphocephala* branch models

Four models were formulated for the prediction of *E. gomphocephala* branch biomass. Only Model 4.29 had all estimated parameters significant from zero (p-value < 0.05) with R^2 of 0.78 while Model 4.28 had the lowest R^2 of 0.67. All the models (Model 4.26, 4.37, 4.28 and 4.29) were significant with small p-values ($p < 0.05$). In this case model 4.29 is the best fitting model having all its estimated parameters significant and the highest R^2 (Table 4.5).

Table 4.5: *E.gomphocephala* crown component biomass models

	Model	Dependent variable	Independent variable	Parameter estimate with p-values in brackets			R^2
				b_0	b_1	b_2	
Foliage	4.22	F_{bm}	ba, d	75.57 (0.001)	198632.93 (214e-5)	27.20 (0.421)	0.71
	4.23	F_{bm}	d	-598.39 (0.021)	268.12 (0.001)		0.63
	4.24	F_{bm}	ba	158.25 (0.003)	218108.01 (364e-4)		0.71
	4.25	$\ln(F_{bm})$	ln(d)	1.59 (0.004)	1.55 (0.014)		0.72
Branches	4.26	Bbm	ba, d	-1832.8 (0.013)	322730.9 (231e-7)	832.8 (0.154)	0.72
	4.27	B_{bm}	d	-2885.2 (0.345)	1219.31 (0.012)		0.71
	4.28	B_{bm}	ba	634.1 (0.011)	924392.2 (0.341)		0.67
	4.29	$\ln(B_{bm})$	ln(d)	1.92 (0.001)	2.02 (0.003)		0.78

4.2.4. *E. grandis x camaldulensis* crown biomass model

Crown biomass for *E.grandis x camaldulensis* was predicted by models parameterised using the linear relationship between branch biomass, ba and d. Figure 4.12 shows the strong positive relationship between diameter and biomass. The value of r for foliage biomass and branch diameter was 0.72 while whole stem biomass and branch diameter had 0.83 as correlation coefficients which were all significant ($p < 0.05$).

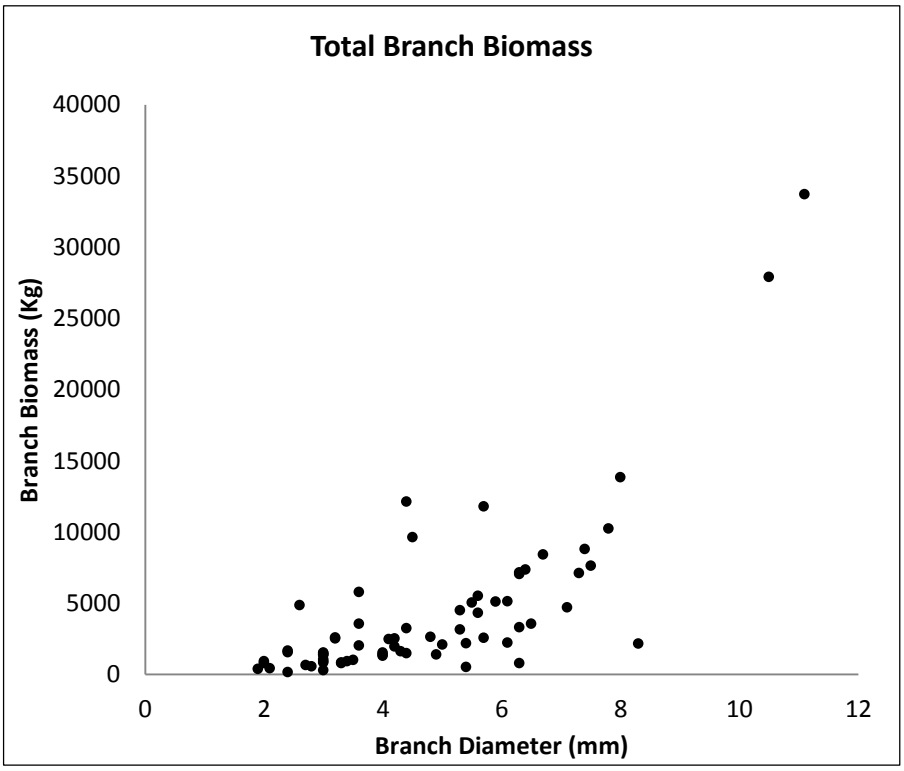


Figure 4.12: The relationship between branch biomass and branch diameter

4.2.4.1. *E. grandis x camaldulensis* foliage biomass models

Four models were fitted on the data for *E. grandis x camaldulensis* from which the best model was selected. All the models had all the estimated parameters significant with a small p-value ($p < 0.05$); Model 4.30 was the best model since it had the highest R^2 value of 0.65 while Model 4.33 had the lowest R^2 of 0.35 (Table 4.6). Figure 4.13 show the residuals plotted against predicted values for the best model confirming the homoscedasticity of the residuals since there was no clear pattern.

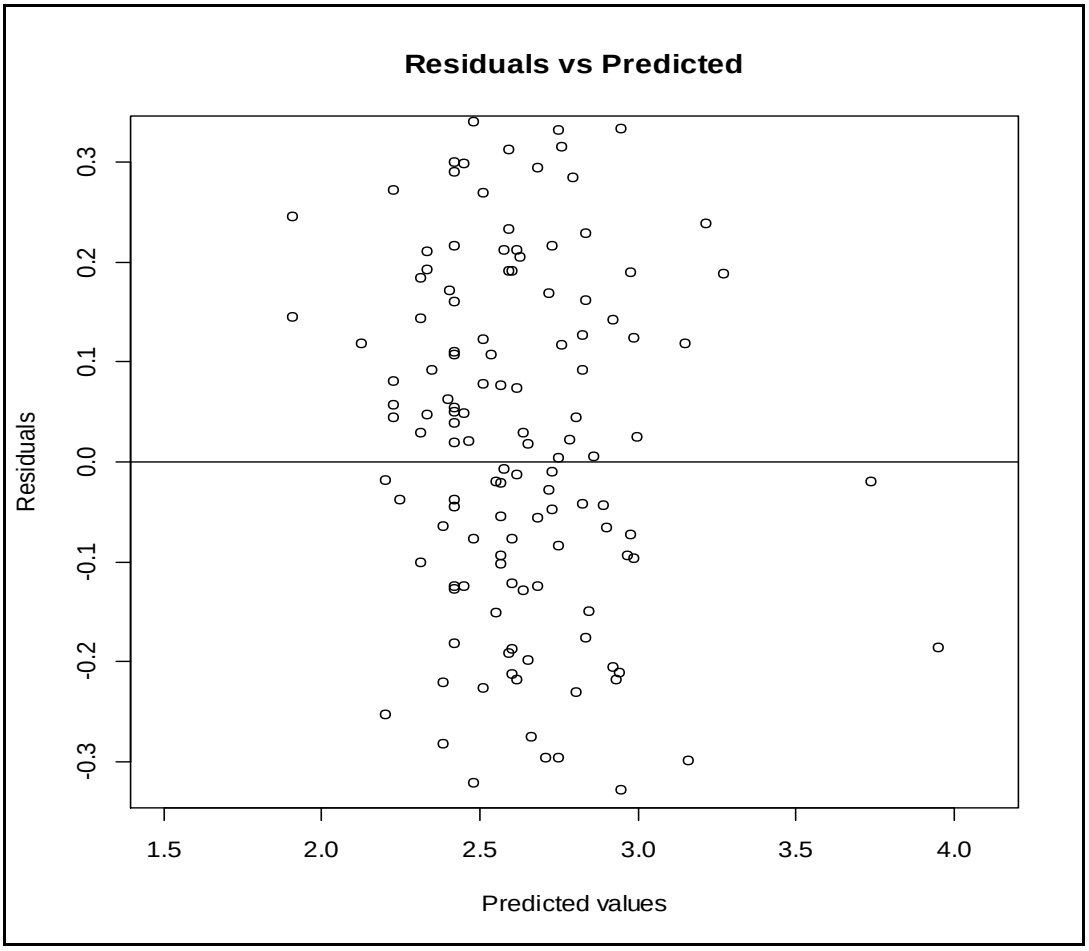


Figure 4.13: *E. grandis x camaldulensis* foliage biomass model predicted values vs. residuals plots

4.2.4.2. *E. grandis x camaldulensis* Branch biomass

All the parameterised models for *E. grandis x camaldulensis* branch biomass models had all the estimated parameters significant (p-value < 0.05) except for Model 4.35. Model 4.34 had the highest R^2 value of 0.76 (Table 4.6) and the residual against predicted values did not show a clear noticeable pattern. In this case, Model 4.34 can be referred to as the best fitting model.

Table 4.6: *E.grandis x camaldulensis* crown component biomass models

	Model	Dependent variable	Independent variable	Parameter estimate with p-values			R^2
				b_0	b_1	b_2	
Foliage	4.30	F_{bm}	ba, d	-621.5 (0.004)	455575.3 (213e-6)	216.57 (0.012)	0.65
	4.31	F_{bm}	d	-337.8 (0.001)	185.75 (0.012)		0.51
	4.32	F_{bm}	ba	76.28 (314e-7)	224039.4 (0.003)		0.62
	4.33	$ln(F_{bm})$	ln(d)	1.78 (0.012)	1.25l (0.012)		0.35
Branches	4.34	Bbm	ba, d	-6203 (0.002)	5473513 (212e-5)	2893.4 (0.001)	0.76
	4.35	B_{bm}	d	-5455 (0.123)	1952 (0.001)		0.56
	4.36	B_{bm}	ba	-1138 (0.004)	2387697 (256e-8)		0.69
	4.37	$ln(B_{bm})$	ln(d)	2.03 (0.001)	2.01 (0.041)		0.60

Note: F_{bm} is foliage biomass, B_{bm} is branch biomass, ba is basal area and d is branch diameter

4.2.5. Density determination

The mean density of the pooled samples was 620.65 kg/m^3 for displacement and 810.24 kg/m^3 for CT-scanning. From Shapiro-Wilk test and Bartlett test, both the displacement and CT-scan densities were normally distributed and homoscedastic with larger p-values ($p > 0.05$). The two independent sample t-tests indicated a smaller p-value of 0.001 ($p < 0.05$) showing that the density from displacement method was significant different from that from the CT-scanner. In the present study, densities from the CT-scanning were adopted for further biomass calculation because these values were in line with the values in literature (Botman, 2010; McMahon *et al.*, 2010). Figure 4.14 and 4.15 shows an example of a scan and results from ImageJ respectively.

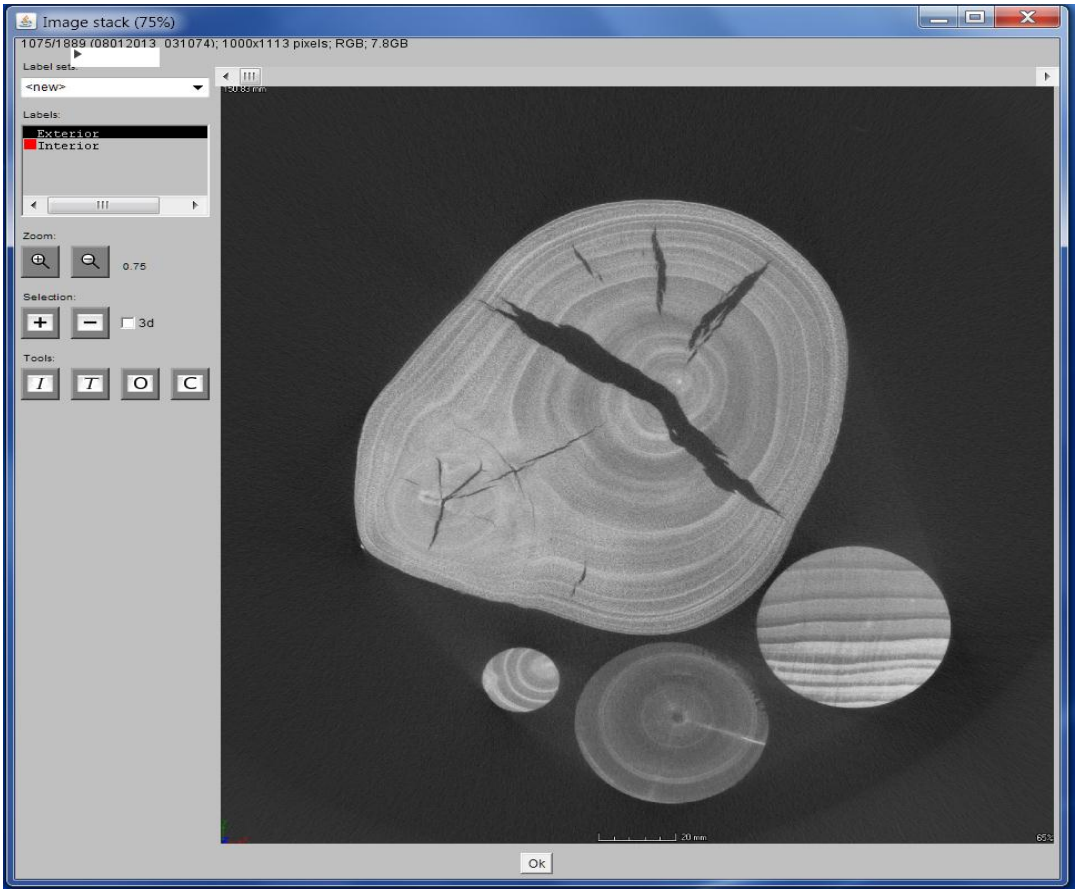


Figure 4.14: Images from the CT –scanner in ImageJ

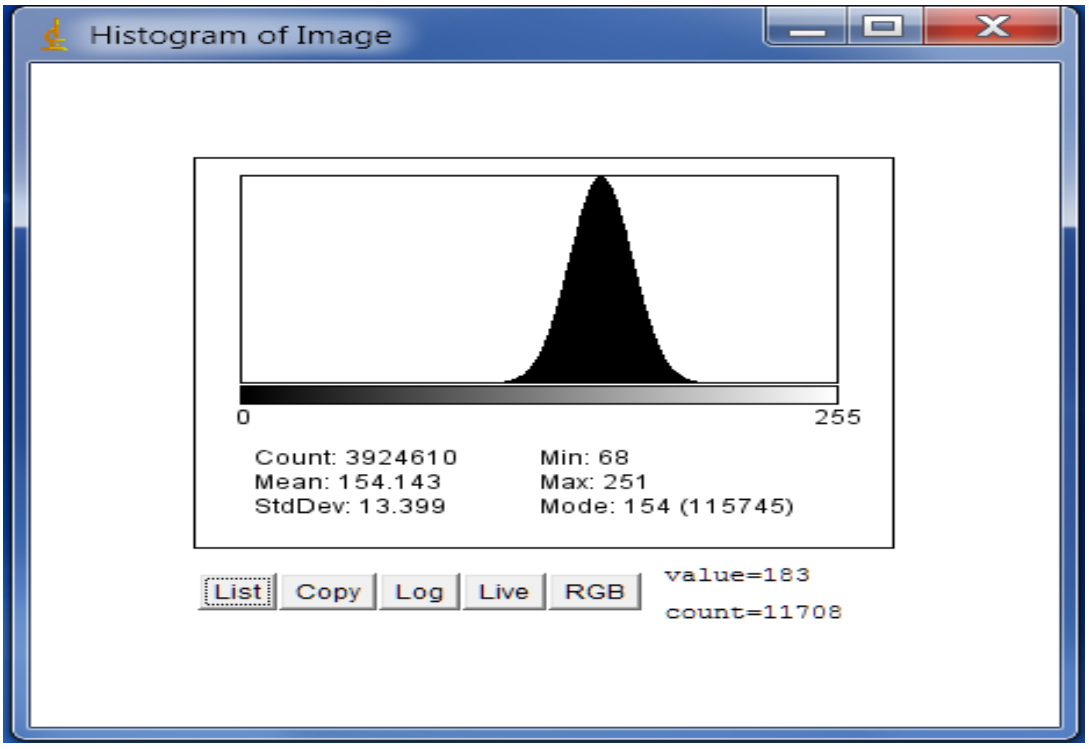


Figure 4.15: Results on average grey value in ImageJ

Linear equations of the form "r0 = a + b (grey value)" with an R^2 between 0.74 and 0.96 were obtained during the calibration process and used as calibration function to estimate the true density from the grey values. Figure 4.16 shows an example of a linear equation for calibration samples.

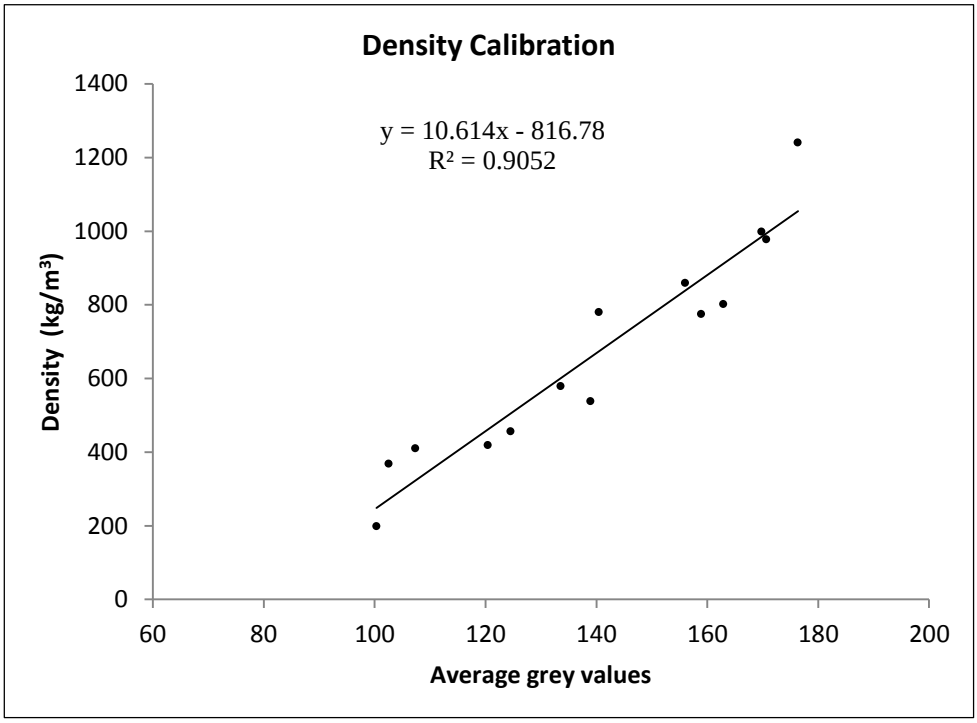


Figure 4.16: Example of a calibration linear equation for wood density based on grey values

The comparison of density from the CT-scanner among the three species (*E. gomphocephala*, *E. cladocalyx* and *E. grandis x camaldulensis*) showed that *E. cladocalyx* had the highest mean density of 856.53 kg/m^3, *E. gomphocephala* had 830.63 kg/m^3 and the lowest mean density was found for *E. grandis x camaldulensis* of 797.08 kg/m^3. Figure 4.17 shows the density classes of the three tree species.

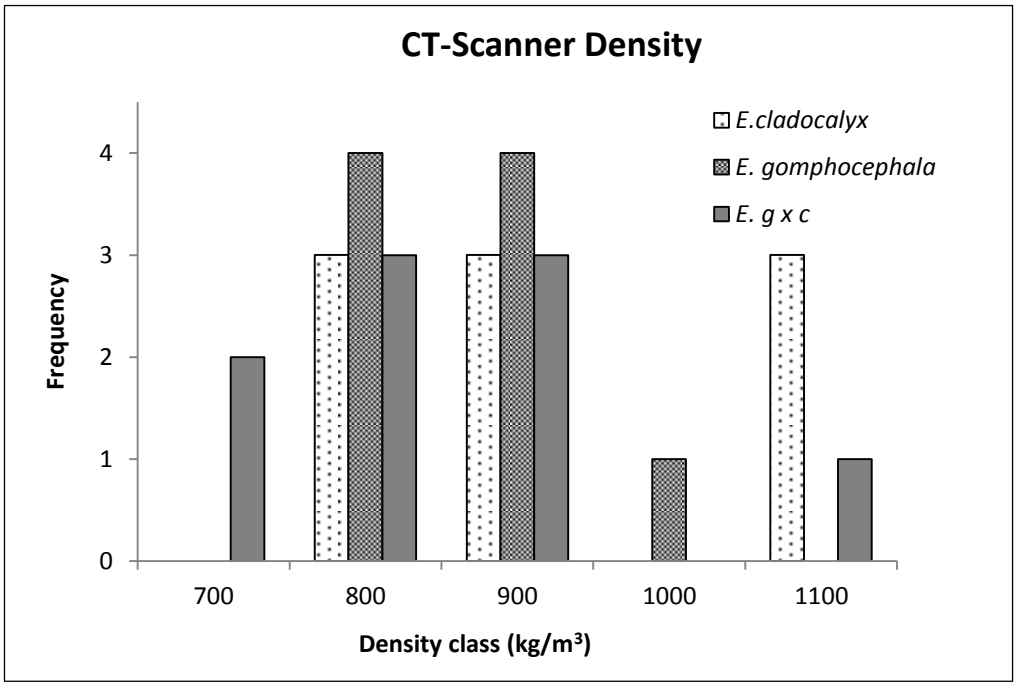


Figure 4.17: CT –scanning density classes for the three *Eucalyptus* species

4.3. BIOMASS MODELS

4.3.1. Pooled biomass models

The mean stem biomass on pooled data was 234.6 kg; bark biomass had 26.502 kg as the mean while foliage had the lowest mean biomass of 17.6 kg. Stem biomass had the highest maximum biomass of 466.3 kg while foliage had the lowest maximum biomass as compared to other components (stem, bark and branches).

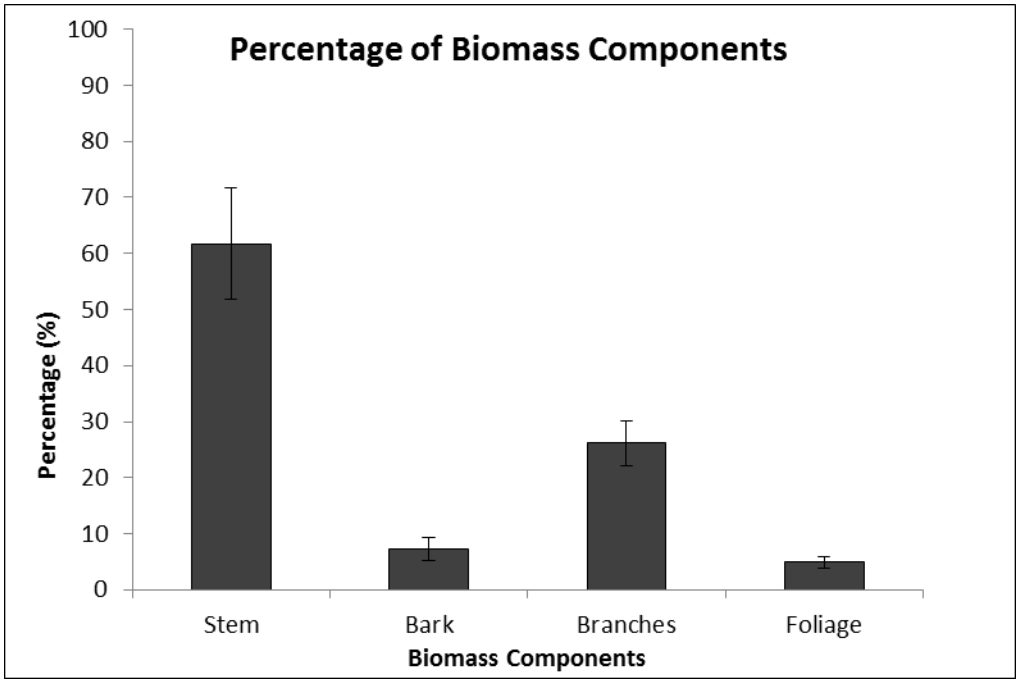


Figure 4.18: Percentage of different biomass components for the pooled data with standard deviation in error bars

A nonlinear relationship was found between dbh and all four components (Figure 4.19). Pearson's moment correlation indicated smaller p-values ($p < 0.05$) for all the components. The relationship between total biomass and dbh was the strongest with a high value of r of 0.94 while that for foliage was relatively weak ($r = 0.63$).

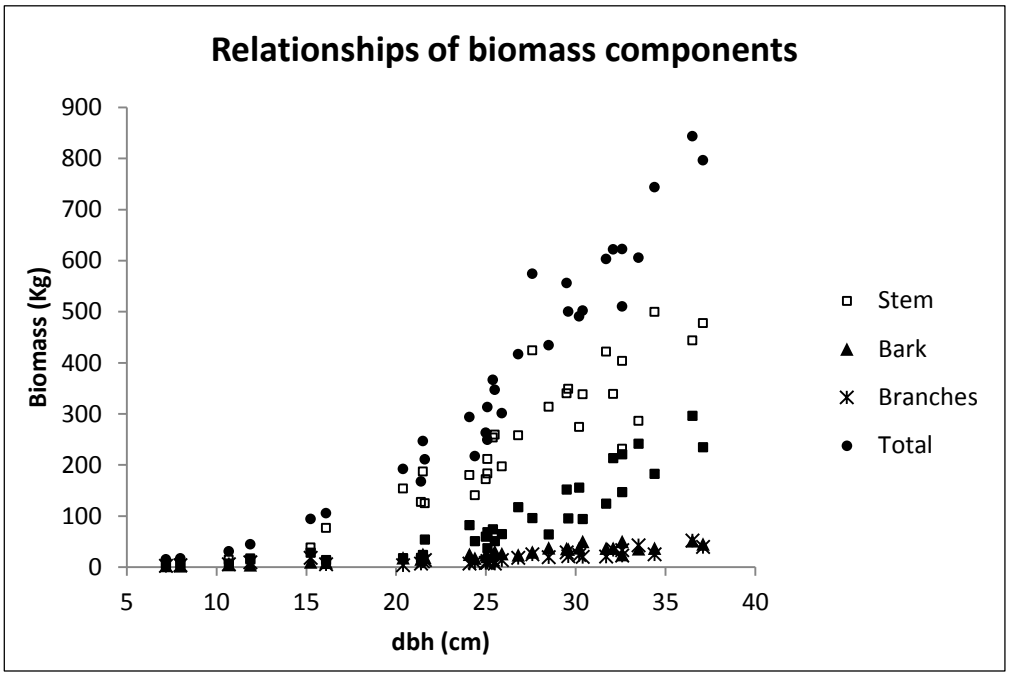


Figure 4.19: Development of different biomass components over the dbh for a pooled model

Four models were parameterised to predict biomass for the components (foliage, bark, branches and stem wood) for the pooled data set and an additional model for predicting total biomass was parameterised with an aim of attaining additivity[8] (Table 4.7). Separate models were parameterised on different components from which the best fitting model was selected. The selection of the best model combination considered the significant (p-value < 0.05) of the estimate parameter, R^2, MSE and RMSE of the models. The system of equations showed that the stem biomass model (Model 4.38) fitted the data better than the other component models. Model 4.38 had the highest R^2 of 0.96 with the lowest MSE and RMSE of 0.009 and 0.094 respectively. The foliage model was the least well-fitting model because of its largest MSE and RMSE of 0.234 and 0.484 respectively. Furthermore, the foliage model (Model 4.40) had the lowest value of R^2 (R^2 = 0.05). All estimated parameters were significant for all models Table 4.7

Table 4.7: SUR systems of equations for Pooled data

[8] Additivity is attained when biomass predicted for the four components (bark, foliage, branches and stem wood) is the same as for the biomass predicted by total model.

Model	Dependent variable	Independent variable	Parameter estimate and their p-values			R^2	RMSE
			b_0	b_1	b_2		
4.38	ln(Total)	ln(dbh), ln(h)	-3.35 (2.2e-2)	2.16 (2.2e-2)	0.80 (1.8e-5)	0.96	0.094
4.39	ln(Bark)	ln(d^2h)	-3.49 (4.5e-10)	0.73 (2.2e-2)		0.91	0.248
4.40	ln(Foliage)	ln(dbh)	-2.36 (0.0026)	1.58 (1.7e-8)		0.64	0.484
4.41	ln(Branch)	ln(d^2h), ln(h)	-3.62 (3.2e-05)	1.47 (6.9e-2)	-2.07 (0.064)	0.88	0.412
4.42	ln(Stem)	ln(dbh), ln(h)	-5.59 (2.22e-4)	2.16 (2.2e-3)	1.45 (4.7e-8)	0.98	0.155

The results from Shapiro-Wilk test on normality showed large p-values ($p > 0.05$) indicating that the residuals were normally distributed for all the models. The homoscedasticity assumption was assessed by plotting the predicted values against the residuals. Figure 4.19 shows the residuals plots from different biomass components models. Generally, all the plots did not show a clear noticeable pattern thus satisfying the assumption of homoscedasticity.

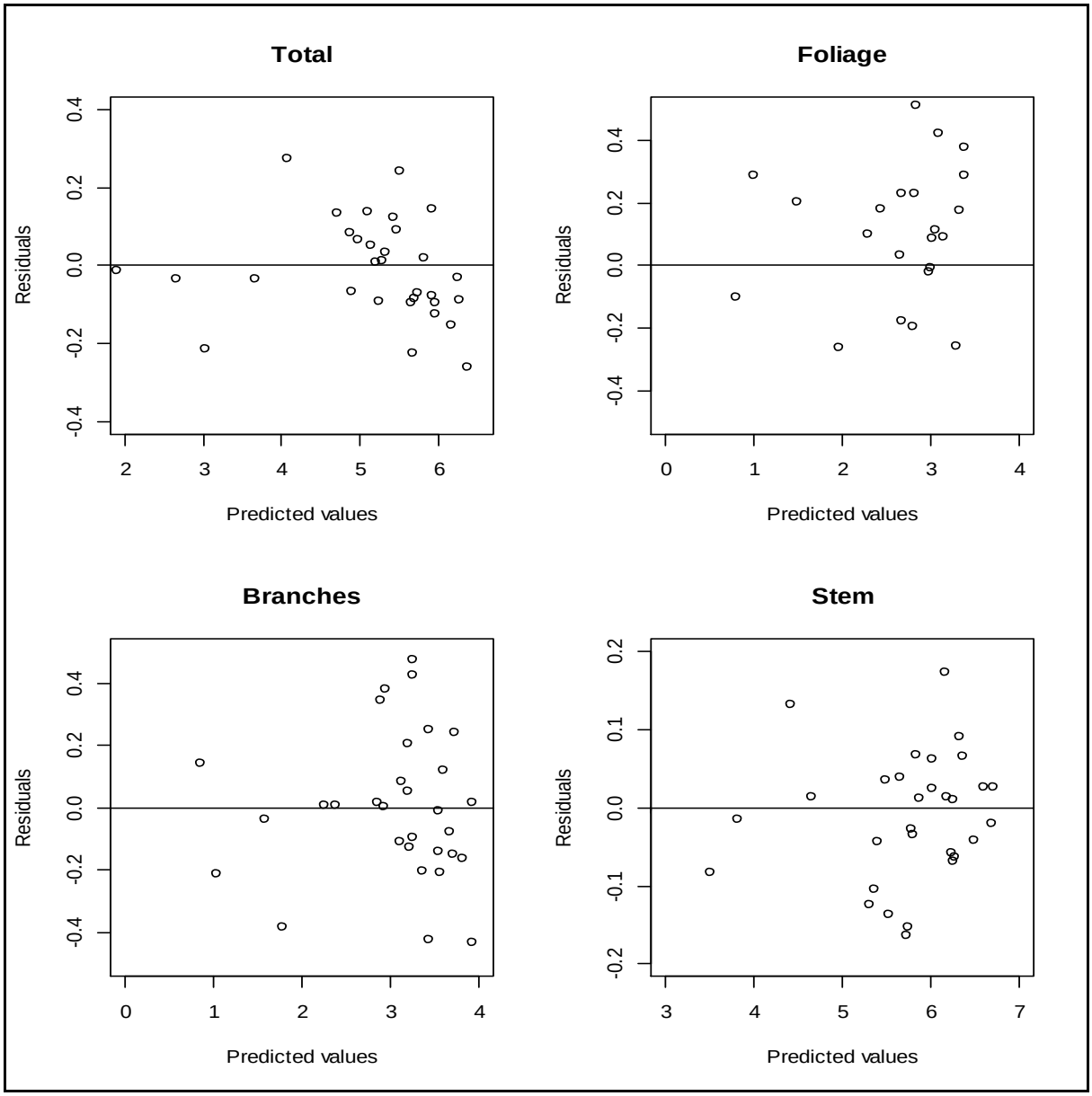


Figure 4.20: Pooled systems of equations predicted vs. residual plots

4.3.2. *E. cladocalyx* biomass models

E. cladocalyx stem biomass contributed 61%, branches 28%, bark 6% while foliage contributed 5% towards the total biomass (Figure 4.21).

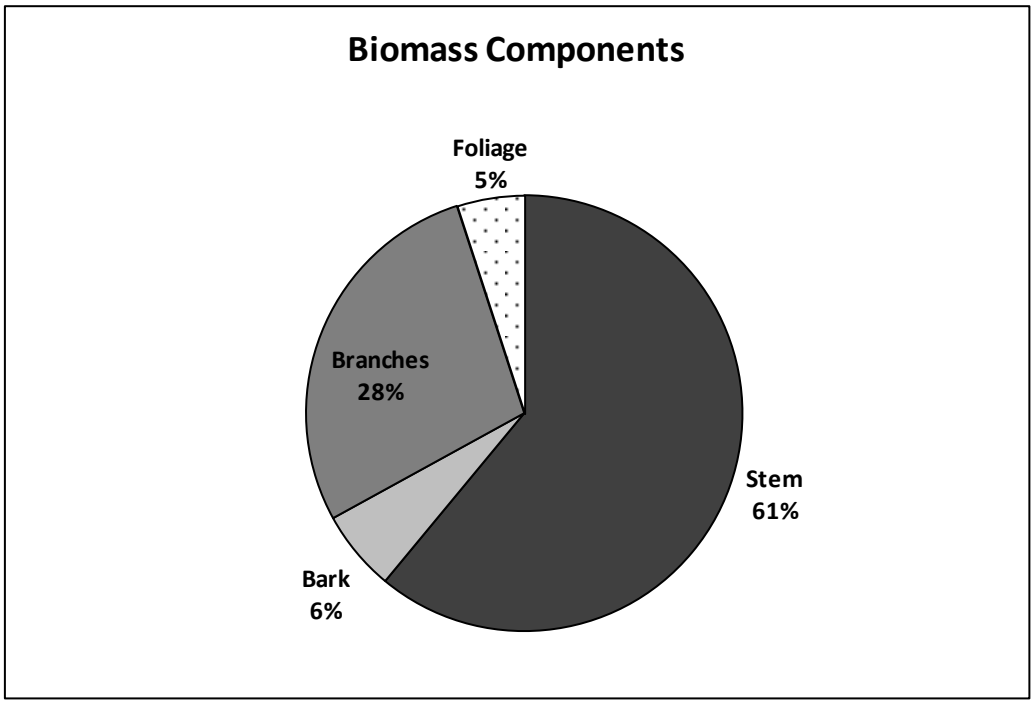


Figure 4.21: Percentage of biomass components towards total biomass

Five models were formulated as a system of equations to predict the biomass of each component of *E. cladocalyx* while achieving additivity of the total biomass (Table 4.8). Model 4.43, Model 4.44 and Model 4.47 had two predictor variables, which were all significant (p-values < 0.05). Model 4.60 had R^2 of 0.50; Model 4.62 had R^2 value of 0.75 while Model 4.43 had R^2 of 0.96. The model predicting total biomass (Model 4.43) had RMSE of 0.094 while Model 4.44 had the highest RMSE of 0.886. In this system of equations for *E. cladocalyx,* stem model (Model 4.47) fitted the data better than the other component models as indicated by the high values of R^2 and lower RMSE.

Table 4.8: Systems of equations for *E.cladocalyx* biomass models

Model	Dependent variable	Independent variable	Parameter estimate and their p-values			R^2	RMSE
			b_0	b_1	b_2		
4.43	In(Total)	ln(dbh), ln(h)	-4.014 (0.003)	2.33 (4.2e-5)	0.82 (0.001)	0.96	0.094
4.44	ln(Bark)	ln(d^2h), ln(h)	2.81 (0.021)	0.23 (0.05)	-0.59 (0.047)	0.50	0.886
4.45	ln(Foliage)	ln(dbh)	-8.58 (0.0026)	3.45 (0.002)		0.77	0.326
4.46	ln(Branches)	ln(d^2h)	-14.96 (0.009)	2.07 (0.002)		0.75	0.447
4.47	ln(Stem)	ln(dbh), ln(h)	-4.73 (0.002)	1.802 (5.5e-4)	1.57 (0.004)	0.95	0.085

The Shapiro-Wilk normality test on the residuals resulted in a large p-values ($p > 0.05$) indicating that the normality assumption is satisfied on all the models. The plots for the residual against predicted values had no visible pattern indicating that the homoscedasticity assumption was satisfied (Figure 4.22).

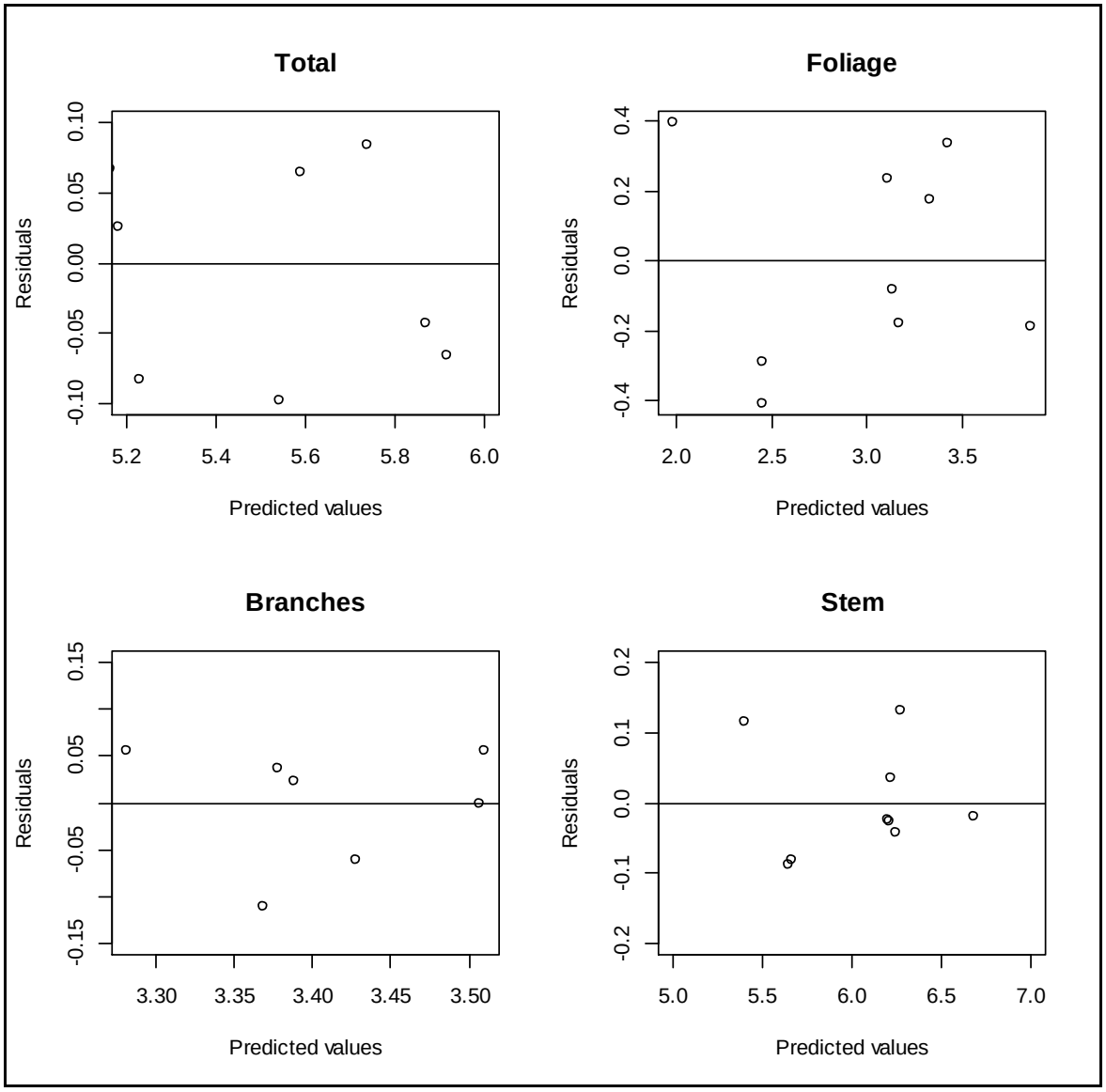


Figure 4.22: *E.cladocalyx* systems of equations predicted vs. residual plots

4.3.3. *E. gomphocephala* biomass models

Figure 4.23 shows the proportions of the different biomass components of the total biomass for *E. gomphocephala*. Stem biomass was 48% of the total biomass, bark was 5%, and foliage was 4% while the branches were 43%. Prior to model formulations, the relationship between the independent parameters and biomass was accessed. The value of r between total biomass and dbh was 0.94 while that between total biomass and height was 0.73. These relationships were significant with smaller p-values ($p < 0.05$).

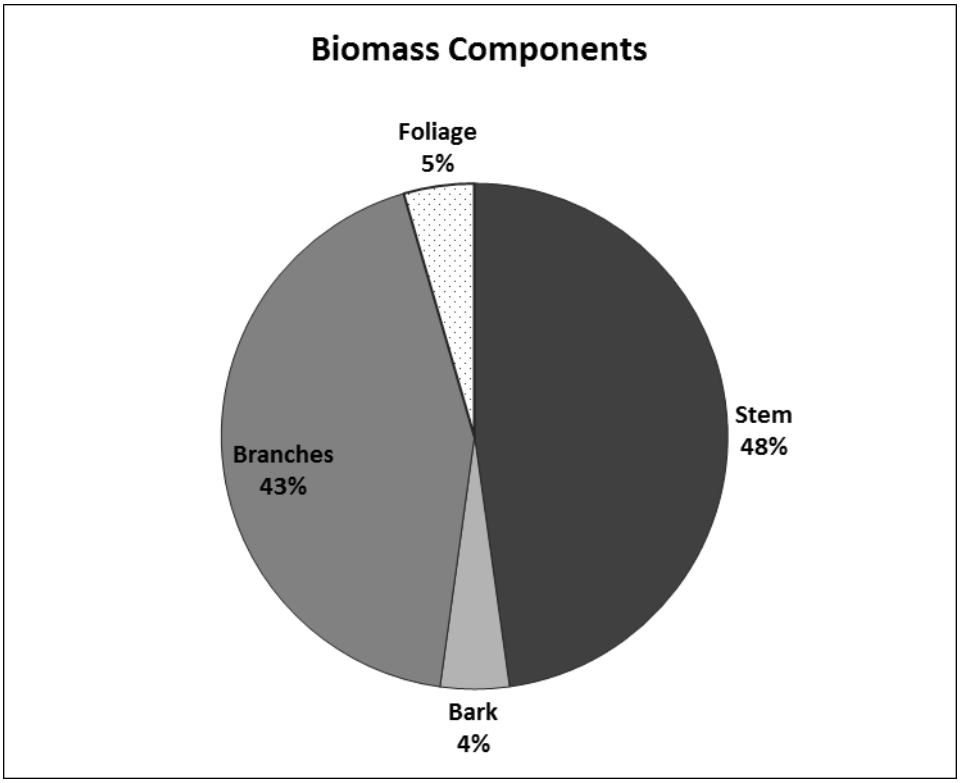


Figure 4.23: Percentage aboveground biomass components for *E. gomphocephala*

A system of five models was parameterised for the biomass components of *E. gomphocephala*. Model 4.48 was formulated to predict the total biomass directly while the other four models (Model 4.49, 4.50, 4.51 and 4.52) were parameterised to predict biomass for the components. Model 4.48 had two predictor variables while the other four models had only one predictor variable. All the estimated parameters shown in Table 4.9 were significant ($p < 0.05$). Model 4.50 had the lowest R^2 of 0.60 while Model 4.48 had the highest R^2 of 0.98. The lowest value of RMSE was 0.07 for Model 4.48 while the largest RMSE value was for Model 4.51 which was 0.34 (Table 4.9).

Table 4.9: Systems of equations for *E. gomphocephala*

Model	Dependent variable	Independent variable	Parameter estimate and their p-values			R^2	RMSE
			b_0	b_1	b_2		
4.48	ln(Total)	ln(dbh), ln(h)	-1.156 (1.07e-6)	1.89 (4.2e-5)	0.75 (0.001)	0.98	0.070
4.49	ln(Bark)	ln(d^2h)	-1.21 (0.037)	1.99 (0.002)		0.78	0.26
4.50	ln(Foliage)	ln(dbh)	-0.68 (00.027)	1.44 (0.016)		0.60	0.27
4.51	ln(Branch)	ln(d^2h)	-4.40 (0.0001)	5.85 (4.5e-6)		0.84	0.34
4.52	ln(Stem)	ln(dbh)	-0.91 (0.0034)	1.902 (4.5e-4)		0.85	0.19

The assumption of normality far all the models was tested using the Shapiro-Wilk test on the residuals, the result showed larger p-values ($p < 0.05$) indicating that the data was not different from the normal distribution. Furthermore, homoscedasticity was assessed by plotting the residuals against the predicted values. Figure 4.24 had no visible pattern indicating that the residuals were almost the same across the data.

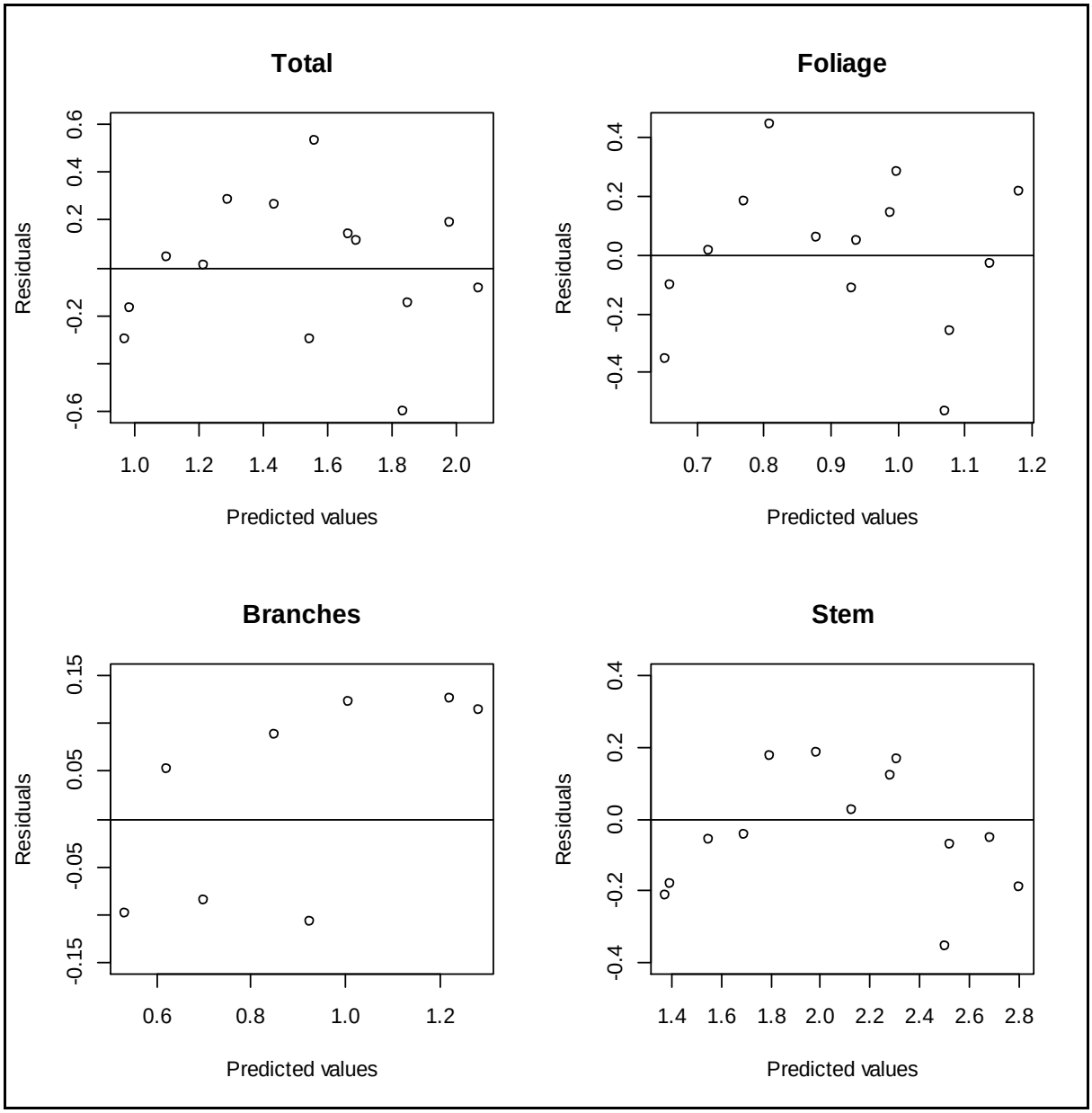


Figure 4.24: *E. gomphocephala* system of equations predicted vs. residual plots

4.3.4. *E. grandis x camaldulensis* biomass models

Figure 4.25 shows the biomass components of *E. grandis x camaldulensis*. Branch biomass had the highest mean biomass followed by stem biomass while foliage had the lowest mean biomass. The relationship between total biomass and dbh was evaluated by the value of r which was 0.96 and significant (p-value < 0.05) indicating that there is a strong positive correlation between total biomass and dbh.

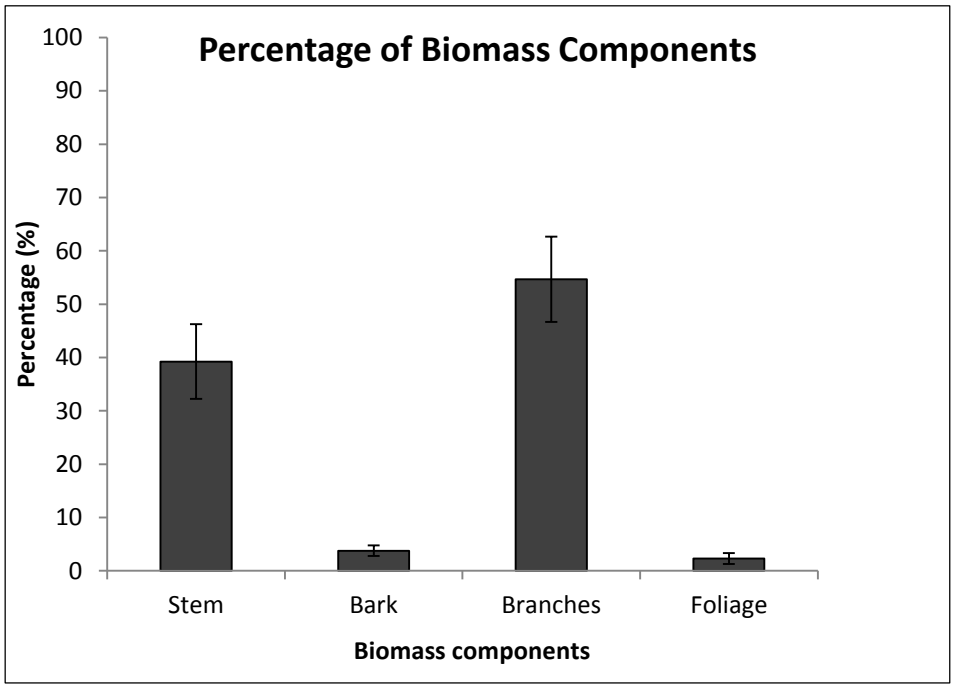


Figure 4.25: Percentage of biomass components for *E. grandis x camaldulensis* with standard deviation in error bars

Five models were formulated to predict the biomass of the components for *E. grandis x camaldulensis* as shown in Table 4.10. Model 4.53 and 4.57 had two predicting variables while the other models (Model 4.54, 4.55 and 4.56) had only one predicting variable. Model 4.53 had the highest value of R^2 of 0.98 while Model 4.55 (foliage model) had the lowest value of R^2 of 0.79. The RMSE of Model 4.53 was 0.038 which was the lowest while Model 4.55 had the highest RMSE value of 0.33.

Table 4.10: Systems of equations for *E. grandis x camaldulensis*

Model	Dependent variable	Independent variable	Parameter estimate and their p-values			R^2	RMSE
			b_0	b_1	b_2		
4.53	ln(Total)	ln(dbh), ln(h)	-3.49 (2.9e-5)	2.22 (2.19e-7)	0.79 (1.3e-4)	0.98	0.038
4.54	ln(Bark)	$\ln(d^2h)$	-3.41 (0.0006)	0.72 (0.002)		0.93	0.12
4.55	ln(Foliage)	ln(dbh)	-0.68 (00.027)	1.44 (0.016)		0.79	0.33
4.56	ln(Branch)	$\ln(d^2h)$	-8.94 (3.1e-6)	1.45 (1.3e-6)		0.95	0.20
4.57	ln(Stem)	ln(dbh), ln(h)	-3.86 (0.0034)	1.73 (4.5e-4)	1.33 (0.008)	0.97	0.097

The normality assumption was tested on the residuals of the models using Shapiro-Wilk test which indicated large p-values ($p > 0.05$) indicating that the normality assumption was satisfied. Homoscedasticity for all the models was verified by plotting the residuals against predicted values. There was no clear pattern indicating that the homoscedasticity assumption was attained (Figure 4.26).

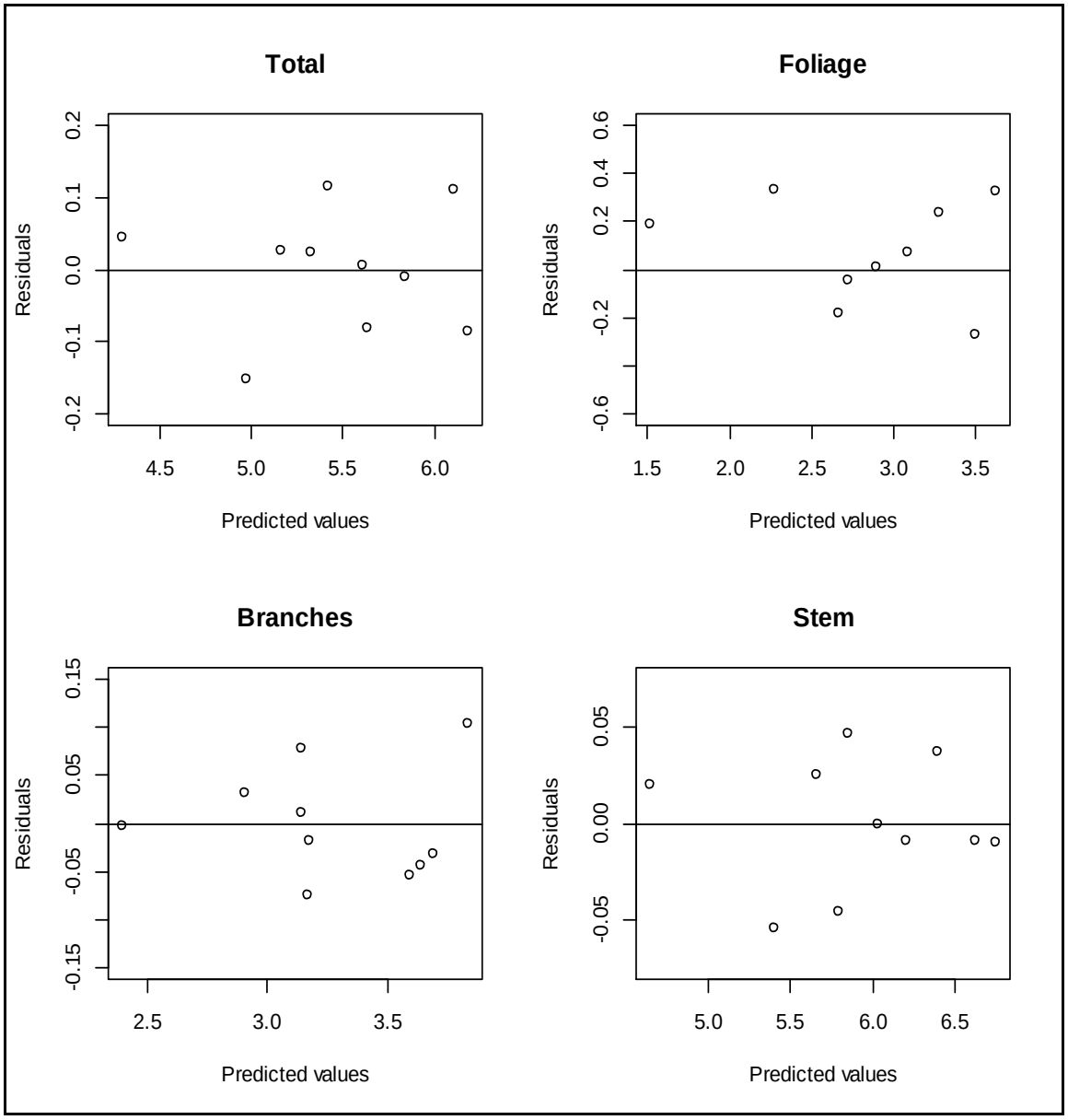


Figure 4.26: *E. grandis x camaldulensis* systems of equations predicted vs. residual plots

4.4. PROPAGATED ERROR

Two sources of error in the biomass upscaling procedure were considered in the study; (1) sampling error, and (2) error due to regression. The results indicated that the Upscaling 1 which involved the building up of the different components to a tree level had a slightly larger contribution to the total error. Upscaling 1 contributed 51% of the total error while the error due to regression (Upscaling 2) contributed 49% of the error. Figure 4.27 shows the contribution by the two upscaling stages to the total error propagated.

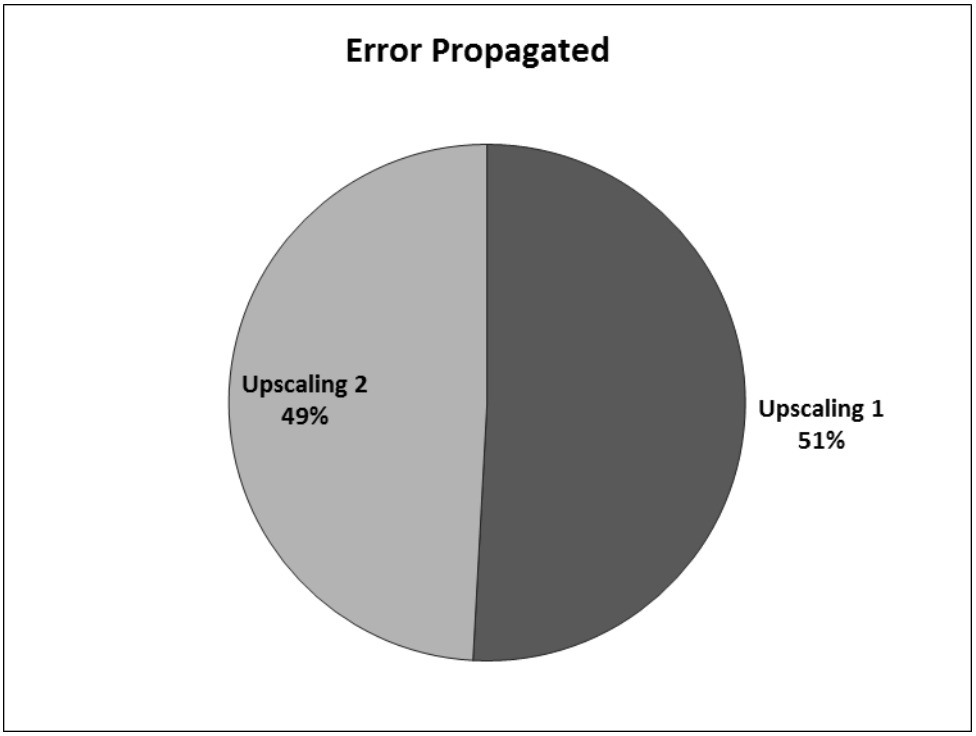


Figure 4.27: Distribution of Error propagated during sampling and regression

The mean percentage error propagated was 2.63% per tree. Upscaling 1 contributed 1.34% of the total error while Upscaling 2 which was as a result of error due to regressions amounted to 1.29%. This implies that, Upscaling 1 and Upscaling 2 contributed 51% and 49% of the total error as indicated in Figure 4.27 and Table 4.11.

Table 4.11: Component of error propagation in biomass modelling

Source of Error	Components	Regression	Total
All tree in kg	163.87	158.37	322.24
Per Tree in kg	4.965	4.79	9.76
Percentage (%)	1.34	1.29	2.63

4.5. DRYING SERIES

4.5.1. Discs

During the drying series, changes were detected on weight of all the species. On average, weight for discs reduced to 94% when the temperature was raised from 60 to 105 ºC. *E. cladocalyx* and *E. gomphocephala* weight reduced to 94% while *E. grandis x camaldulensis* had the highest percentage reduction as the final biomass was 93%. The drying trend showed that, the highest percentage change (4%) on weight occurred when the temperature was raised from 65 to 80 ºC. The drying pattern showed a gradual increase on percentage change for all the species and a steady drop after temperature was increased further than 90 ºC (Figure 4.28).

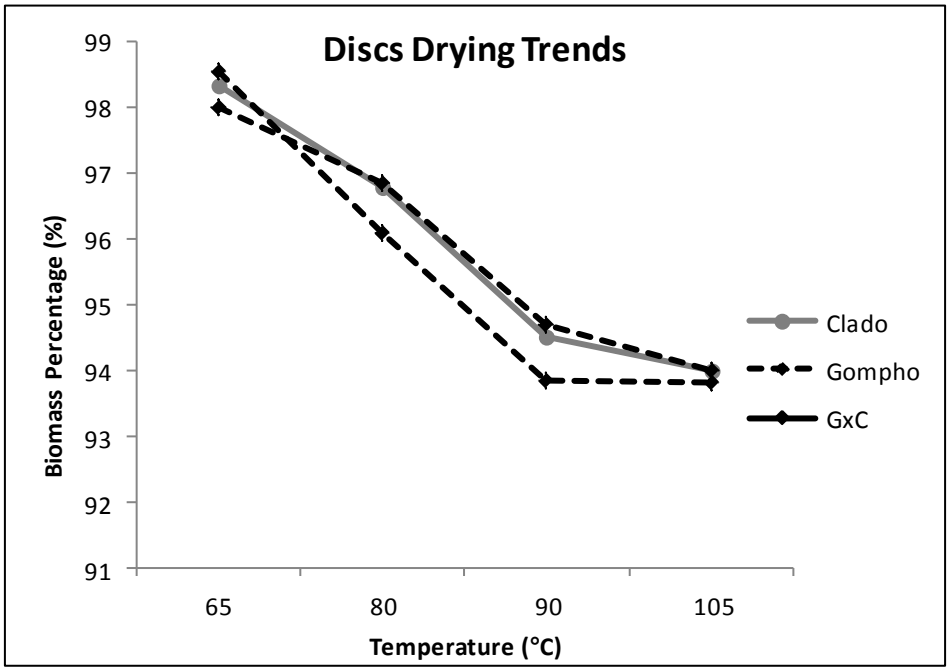


Figure 4.28: Disc biomass percentage change trends

4.5.1.1. Discs Model for biomass change

There was a strong negative linear relationship between drying temperature and discs weight percentage change (r = -0.94). As a result of this strong relationship between temperature and biomass change, a model was established to predict the biomass at a specific drying temperature. The model was statistically significant in its intercept and predictor variable (p-value < 0.05) and had R^2 value of 0.89. A Shapiro-Wilk test (test value of 0.074) indicated

that the biomass values were not significantly different from normal hence being normally distributed. The formulated model (Model 4.58) is shown in Table 4.12.

Table 4.12: Parameter and model statistics for the biomass drying model at different temperatures.

Model	Dependable variable	Independent variable	Parameter estimate		R^2	Model p-value
			Parameter			
			b_0	b_1		
4.58	Biomass Percentage (Bm %)	Drying Temperature (dt)	105.441 (4.05e-16)	-0.114 (4.65e-06)	0.89	0.0018

Further analysis was carried out on variation on weight change between species using ANOVA with species and temperature as factors. The results indicated a significant difference of temperature on a 0.05 significance level (p-value = 0.0463) while species interaction was not significant. Bonferroni post-hoc analysis was conducted to check which pairs of temperature gave a different weight change. The results from pairwise comparison indicated that 90 ºC and 105 ºC did not differ while 60 ºC and 80 ºC were different from the rest (Figure 4.29).

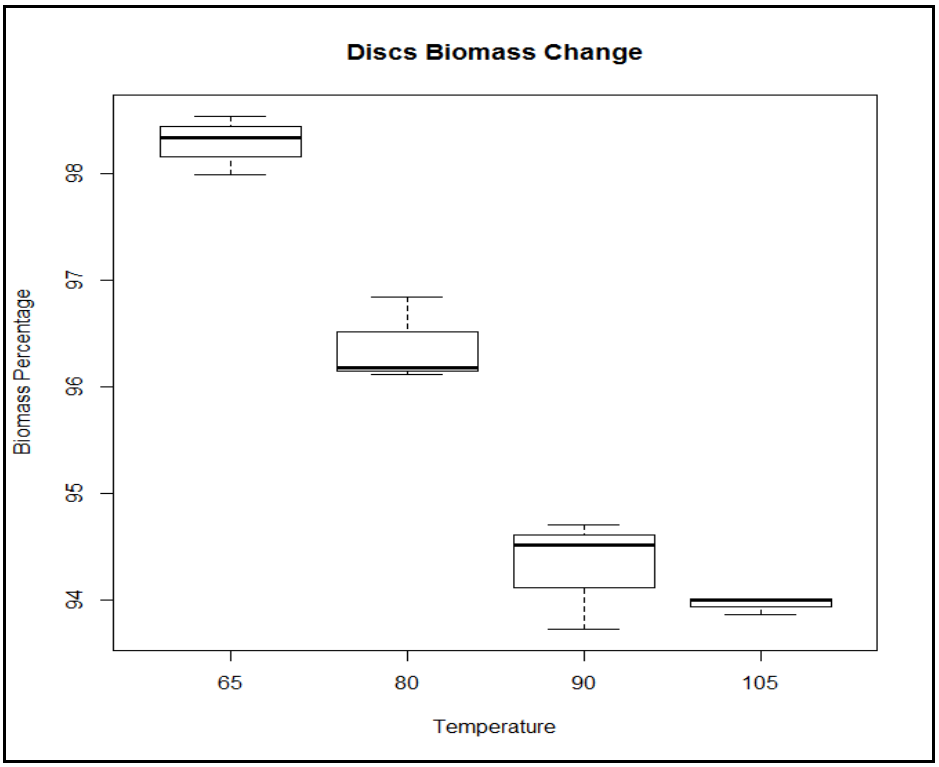


Figure 4.29: Disc biomass percentage change at different drying temperatures

4.5.2. BARK

Bark weight on average changed to 96% for all the species with the largest percentage change of (3%) when drying from 60 to 80 ºC. *E. gomphocephala* had the highest percentage drop on biomass to 94.33% followed by *E. grandis x camaldulensis* to 95.51% while *E. cladocalyx* had the lowest drop on biomass to 97.2%. Figure 4.30 shows the percentage weight at different drying temperatures for each species.

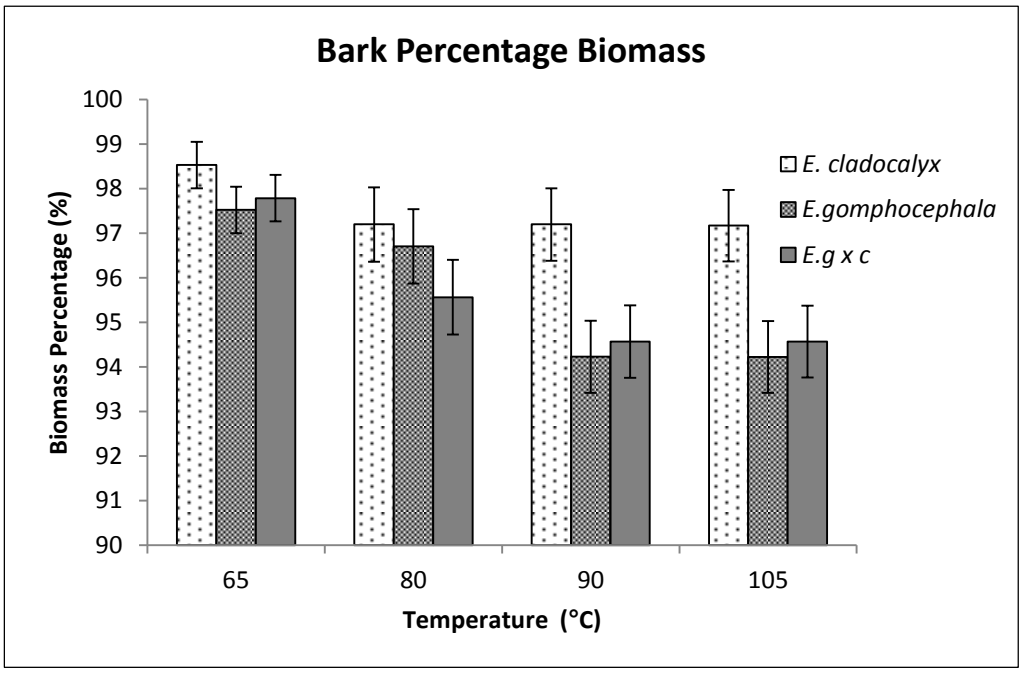


Figure 4.30: Bark biomass change and standard deviation as error bars

The ANOVA results showed that the weight change was not different at any particular temperature. Table 4.13 indicated a large p-value of 0.979 on the different drying temperature. The result on the different species showed similar results as the p-value for the species was also large (p-value = 0.65). Figure 4.31 shows the mean different changes in weight with temperature and species.

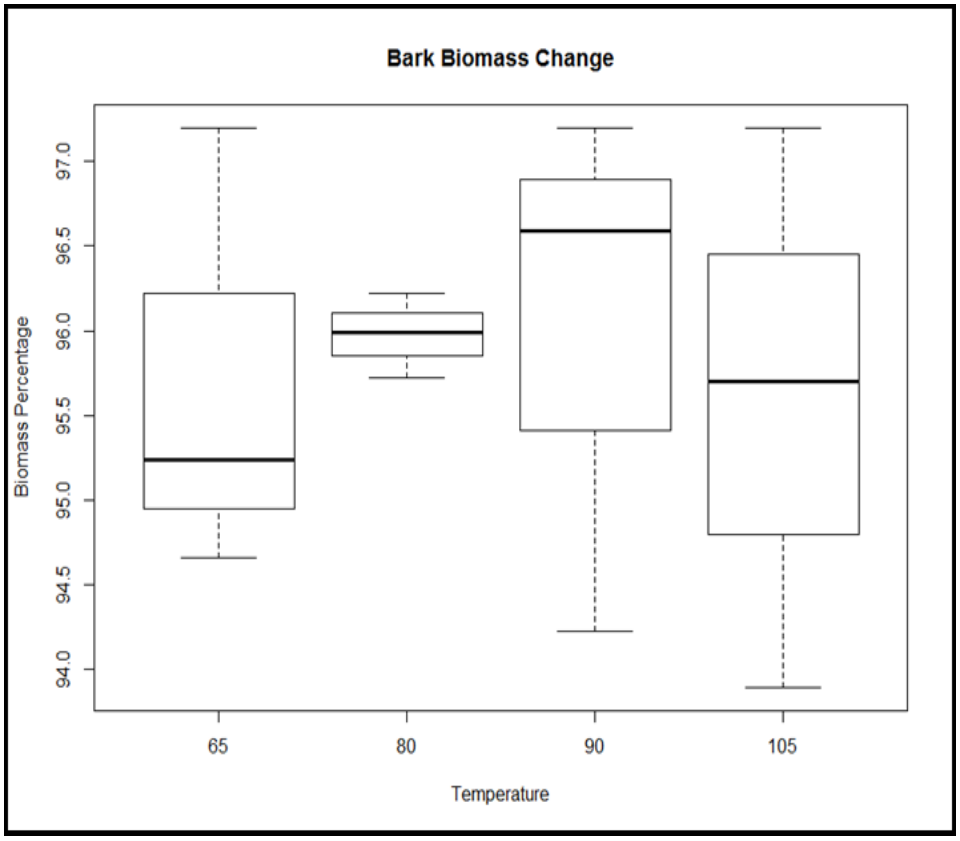


Figure 4.31: Bark biomass percentage change on different drying temperatures

4.5.3. Branches

The average absolute weight change for all the species after drying from 60 to 105 ºC was 97.84%. *E. grandis x camaldulensis* had the highest change in which weight dropped to 96.49%, *E. gomphocephala* to 97.94% and *E. cladocalyx* to only 99.07%. The highest change of 1.07% occurred between 60 and 65 ºC. The profiles on the changes of weight with temperature are as shown in Figure 4.32.

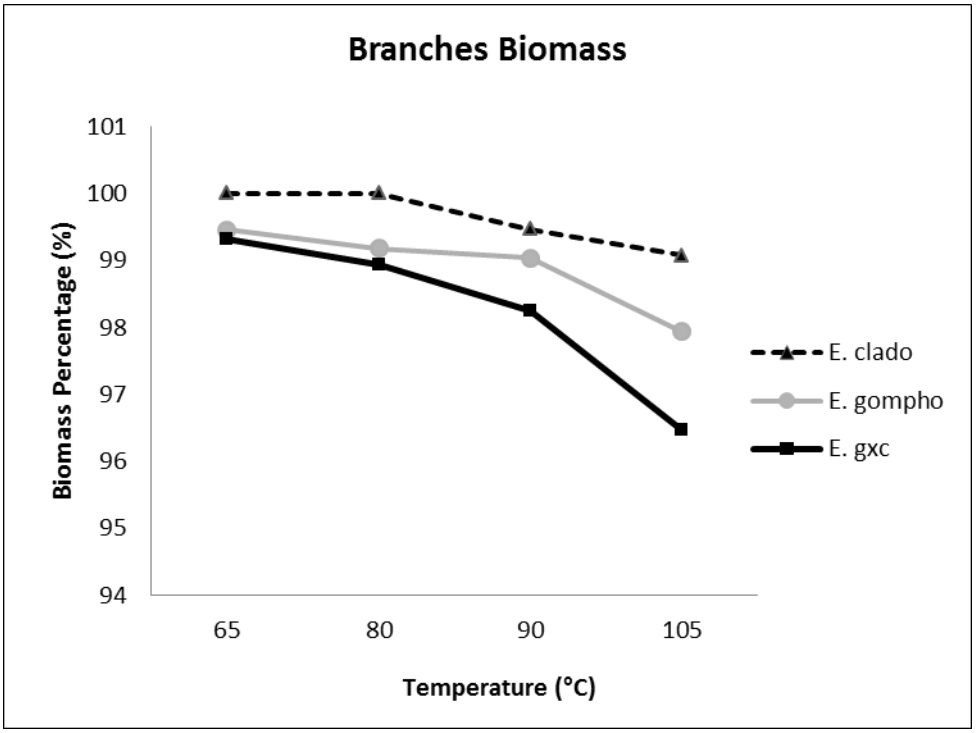


Figure 4.32: Branch biomass percentage change trends

When weight at different drying temperature was compared statistically, ANOVA results indicated a p-value of 0.033 while when the weight change was compared among the species, a p-value of 0.0212 was calculated. These values where all smaller than the significance level of 0.05 showing that there is a significant difference when biomass is dried at different temperature on the branches.

4.5.4. Foliage biomass change

Mean foliage biomass for all the species after drying from 60 to 105 ºC was 98.63%. This translates to less than 2% reduction in the amount of biomass on all the species. *E. grandis x camaldulensis* had the highest change of weight reducing to 97.9%. The highest weight change occurred when the temperature was increased from 60 to 65 ºC. Figure 4.33 shows the changes in foliage weight at different drying temperatures.

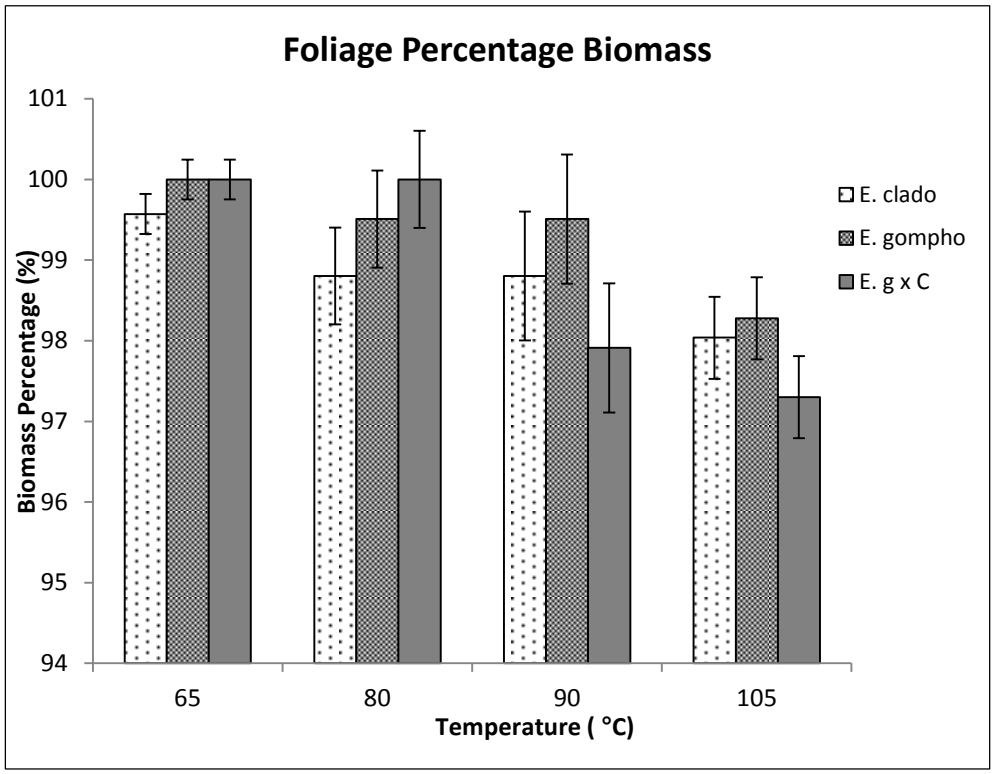


Figure 4.33: Foliage biomass change with change in temperature

When weights under different drying temperatures were statistically compared, the results from the ANOVA (Table 4.13) indicated a p-value of 0.3667. This result showed that there is no significant difference on weight for the leaves with an increase on drying temperature. Table 4.13 summarises the results from ANOVA on the four biomass components.

Table 4.13: Anova Table for drying series of the four biomass components

Component	Parameter	Sum Sq	Mean Sq.	F-value	p-value
Disc	Temperature	1.57262	1.57262	5.5694	0.04631*
	Species	0.11435	0.05718	0.2025	0.82205
	Temperature*Species	0.18211	0.09106	0.3225	0.73617
Bark	Temperature	7.73	7.73	7.6948	0.97923
	Species	0.2687	0.1344	0.1338	0.87734
	Temperature*Species	0.8827	0.4413	0.4393	0.66365
Branches	Temperature	0.02905	0.02905	0.3172	0.0333*
	Species	0.84073	0.42037	4.5908	0.0212*
	Temperature*Species	0.10466	0.05233	0.5715	0.59266
Leaves	Temperature	0.8221	0.82207	0.9526	0.3667
	Species	0.8998	0.4499	0.5214	0.6183
	Temperature*Species	0.2669	0.13343	0.1546	0.8601

Chapter 5 : DISCUSSION OF RESULTS

5.1. DISTRIBUTION OF SAMPLED TREE

Tree sampling in the present study was carried out following an even distribution of diameter classes. The diameter distribution in Figure 4.1 indicates that most of the trees were between the diameters of 20 and 35 cm. Saint-André *et al*. (2004) and Samalca (2007) recommended an even distribution of diameter classes where small and big diameter trees should be included in biomass studies in order to maximise the representation of models. Thus, smaller trees with diameters of less than 10 cm were integrated in the study so as to achieve an even spread in diameter classes; however, this was only possible for *E. gomphocephala*. An indication that the desired representative distribution in the data was not fully attained as the height was not significant in most of the models as indicated in Section 4.3. This means the spread of height might have been not large enough, showing the need to extend the data for larger and smaller trees in the future.

5.1.1. Diameter height Model

Height prediction models were formulated in order to assist in future biomass assessment. During future biomass inventories, diameters will be the principle variable to be measured and used to predict other parameters such as height, hence saving time and reducing on costs during forest biomass assessment (Philip, 1994; Champion *et al.*, 2005; Brandeis *et al.*, 2006).

From the two parameterised models for predicting height, Model 4.2 was the best fitting model ($R^2 = 0.72$). Literature shows that similar models are used in growth and yield studies to predict heights of trees. However, in most growth and yield studies, age is included as a predictor variable (van Laar & Akça, 2007). For instance van Wyk *et al.* (2001) reported a model in form of $h = -22.45 + 1215.419(age) - 9.013(age^2)$ for height prediction on *Eucalyptus* growing on the dry west coast of South Africa. In this study, age was not included since sampling was done on two species (*E. cladocalyx and E. grandis x camaldulensis*) having almost the same age and only *E. gomphocephala* had a third age class.

5.1.2. Volume Models

Volume was multiplied with basic density to determine biomass of the stem wood and bark. However, the upscaling procedure in this study employed volumes of one meter stem sections, which were summed to make a total stem biomass. In studies where average density is used to calculate the entire stem biomass; this model can be used to determine the total stem volume. Moreover, it was for this reason that models directly predicting stem volume were considered equally important as recommended in van Laar and Akça (2007). The formulated models in Table 4.2 showed that Model 4.4 was the best fitting model. The predicted values and residuals plots for this model did not show a clear pattern denoting that the model had achieved the assumption of homoscedasticity when dbh and h were transformed and used as predictor variables as suggested by Parresol (1999) and Ackerman *et al*. (2012). Furthermore, Lowore and Warren (1997) explained that dbh was a better predictor variable for volume as compared to h, which did not fit well in their study on the Miombo woodlands in Zimbabwe. In most cases volume models are formulated based on transformed dbh, d^2h and ba while h is included to improve the model fit.

5.2. UPSCALING MODELS

The upscaling procedure involved two stages; Upscaling 1 and Upscaling 2. In Upscaling 1, the samples were reconstructed to the tree level while in Upscaling 2 the tree components were scaled up to the stand level. During this exercise, different models were constructed for the three species and a pooled model (general model for all the species) was also fitted. While the species specific models have to be considered very preliminary due to a lack of samples, the pooled model stabilised better. However, the data pooling came at the cost of species specificity.

5. 2.1. Pooled crown model

Separate models were selected for predicting branch wood and foliage biomass for the pooled data. Model 4.8 in Table 4.3 was selected as the best model for predicting pooled foliage biomass. This model explained 70% of biomass variation and all its parameters were significant ($p < 0.05$). Furthermore, Model 4.8 satisfied the assumptions of normality and homoscedasticity, which were tested based on the residuals and the predicted values. The good fit of the model can be attributed to the basal area used as a predictor variable in

parameterising the model. Salmaca (2007) reported that models formulated based on basal area had a good fit as compared to models based on diameters.

Model 4.13 [ln (B_{bm}) = 2.05 + 1.96ln (d)] was selected as the best fitting model for the pooled branch biomass. This model explained 78% of the biomass variation and was significant with a smaller p-value ($p < 0.05$). The plots for the predicted value against residuals showed clearly that a noticeable pattern did not exist hence the assumption of homoscedasticity being satisfied. In addition to homoscedasticity, a Shapiro-Wilk test for normality indicated that the normality assumption was satisfied.

5. 2.2. Eucalypts species crown biomass model

The models chosen to predict separate foliage biomass for the three eucalypt species were all significant and had high R^2 values between 0.65 and 0.77. The R^2 values indicate that the models explained more than 65% of the variation on biomass. The model of *E. cladocalyx* explained the highest percentage of 77% on foliage biomass while the models of *E. grandis x camaldulensis* had the lowest percentage explaining biomass variation. These variations on foliage biomass model for the species can be attributed to the number of branches involved in each model. In this case the *E. cladocalyx* model had the largest number of branches in the sample which correlated well with the diameters hence having a better fit. Furthermore, in order to confirm the validity of the model, Seifert and Seifert (2013) recommended plotting predicted values against residuals. There was no clear pattern on all the foliage model plots hence the validity of the models, and homoscedasticity of the residuals being satisfied.

The selected branch wood models for the three eucalypt species were all significant ($p < 0.05$). The selected models explained 71 to 81% of the variation on branch biomass by using ba and d as predictor variables. Homoscedasticity was achieved by ln-transformation. Seifert and Seifert (2013) and Ackerman *et al.* (2012) explained that when ln-transformation is performed on the model, the chances of achieving uniformity on the variance increase. The normality assumption for the models was tested using a Shapiro-Wilk test, which showed that the residuals were normally distributed ($p > 0.05$). Besides normality, homoscedasticity was tested by plotting the predicted values against the residuals, which did not indicate any clear noticeable pattern.

5.3. DENSITY DETERMINATION

Density determination was important for this study because it is part of the definition of biomass of the stem (Seifert & Seifert, 2013). As stated earlier in Section 4.2.5, two methods were used to determine density; (1) water displacement, and (2) CT-scanning method. The two methods revealed that the densities found from CT-scanning method were substantially higher than those from the displacement method. The mean density according to the displacement method was 620.65 kg/m^3 while that for the CT-scanning was 810.24 kg/m^3. The results from displacement method are in line with Botman (2010) who reported mean densities for *E. camaldulensis* and *E. cladocalyx* as 588 kg/m^3 and 650 kg/m^3 respectively. However, McMahon *et al.* (2010) reported higher density values of 800 kg/m^3 and 700 kg/m^3 for *E. gomphocephala* and *E. cladocalyx* respectively, which are in the same range with the densities obtained from CT-scanning. So it was decided that the CT-based densities were used, since CT-scanning has previously been shown to provide reliable results for density measurements (du Plessis & Seifert, 2012; du Plessis, Meincken & Seifert, 2013). The differences were attributed to wrong application of the water displacement measurement, which occurs if the sample touches the ground of the water basin. This was for sure a problem since, while soaked, several samples were sinking and not in the equilibrium, which is necessary for a correct application of the water displacement measurement (Seifert, personal communication).

The comparison of the wood density across the three tree species indicated that the densities were not statistically different among the three species. However, in most studies it has been revealed that *E. cladocalyx* has high density, followed by *E. gomphocephala* while *E. grandis x camaldulensis* has the lowest density as compared to the other two species (Botman, 2010). In view of the arid growing conditions in which these trees are growing, the mean densities for these eucalypt species are expected to be higher as compared to the trees growing in the high rainfall area (Poynton, 1979; Botman, 2010; McMahon *et al*., 2010).

5.4. BIOMASS MODELS

5.4.1. Pooled biomass Model

The pooled model predicting stem biomass was better as compared to the other component (stem, foliage, bark and branches) models with regards to its explained variance. The stem

model explained 98% of the variation on the biomass when dbh and h were used as predictor variables. The goodness of fit can be attributed to the logarithm transformation and accurate CT-scanning method used in the determination of stem density (Kalender, 2011; du Plessis & Seifert, 2012). The foliage model did not show a similarly high explanation value as shown by the larger MSE and lower value of R^2 (0.64). Saint-André *et al*. (2004) reported that foliage biomass is expected to have a lower fit because of the variation on the amount of leaves on the branches, which depends to some extent on the season, diseases and defoliating events. Branch biomass model explained 88% of the variation while the bark biomass explained 91% of the variation on biomass. Saint-André *et al*. (2004) reported a similar range of 0.77 to 0.98 on R^2 on the biomass study in Democratic Republic of Congo (DRC) on eucalypts hybrids.

The total biomass model had a higher MSE and a lower R^2 as compared to the stem model for the pooled data, the latter model having the best fit on the system of equations. The total pooled model explained 96% of the variation of the total biomass by using dbh and h as predictor variables. The relative goodness of fit for the total biomass model can be explained by taking into account the variation and errors in all the four biomass components models. This is because the total biomass model incorporated all the four component biomass data (Saint-André *et al*., 2004) and is therefore also a compound function of the single model accuracies.

5.4.2. Individual eucalypt species biomass models

Foliage biomass models for the three eucalypt species were the least fitting model on all the systems of equations as indicated by 60 to 79% explanation of the variation in the foliage biomass. Stem biomass models were the best fitting model with lower MSE and RMSE as compared to the other components models. Thus stem biomass model explained above 95% of the variation on stem biomass. Bark biomass and branch biomass models also fitted well, explaining above 60% of the biomass variation. All the components models clearly satisfied the assumptions of normality and homoscedasticity as shown in Section 4.3 of Chapter 4. Saint-André *et al*. (2004) parameterised biomass models for eucalypt in which stem biomass model had the highest R^2 of 0.97 while the foliage and dead branches had the lowest R^2 of 0.51, which is similar with the results in the present study.

The total biomass models for the three eucalypt models explained over 98% of the variation on the total biomass. These models had the lowest MSE and RMSE as compared to the component models on all the systems of equation confirming the good fit. The results were similar to the models formulated in Israel in which the total models had the best fit. For instance, a model of the form ln(y) = -0.990+0.830ln (d^2h) was parameterised for predicting total eucalypt biomass, which explained 97% of the variation on total biomass (Zahar & Karschon, 1984). The best parameterised biomass models are summarised according to species in Equation 18 to 37.

i. Pooled biomass Models

Stem: ln (Stem) = -5.59+2.16 ln (dbh) + 1.45 ln (h) (18)

Foliage: ln (Foliage) = -2.36 + 1.58 ln (dbh) (19)

Bark: ln (Bark) = -3.49 +0.73ln (d^2h) (20)

Branches: ln (Branch) = -3.62 + 1.47ln (d^2h) -2.07ln (h) (21)

Total: ln (Total) = -3.35 +2.16ln (dbh) + 0.80ln (h) (22)

ii. *E.cladocalyx* biomass models

Stem: ln (Stem) = -4.73 +1.802ln (dbh) + 1.57ln (h) (23)

Bark: ln (Bark) = 2.81 + 0.23ln (d^2h) - 0.59ln (h) (24)

Foliage: ln (Foliage) = -8.58 + 3.45 ln (dbh) (25)

Branches: ln (Branches) = -14.96 +2.07 ln (d^2h) (26)

Total: ln (Total) = -4.014 + 2.33ln (dbh) + 0.82ln (h) (27)

iii. *E.gomphocephala* biomass models

Stem: ln (Stem) = -0.91 + 1.902ln (dbh) (28)

Bark: ln (Bark) = -1.21 + 1.99ln (d^2h) (29)

Foliage: ln (Foliage) = -0.68 + 1.44ln (dbh) (30)

Branches: ln (Branches) = -4.40 + 5.85ln (dbh) (31)

Total: ln (Total) = -1.156 + 1.89ln (dbh) + 0.75ln (h) (32)

iv. *E.grandis x camaldulensis* biomass models

Stem: ln (Stem) = -3.86 +1.73ln (dbh) (33)

Bark: ln (Bark) = -3.41 + 0.72 ln (d^2h) + 1.33ln (h) (34)

Foliage: ln (Foliage) = -0.68 + 1.44 ln (dbh) (35)

Branches: ln (Branch) = -8.94 + 1.45ln (d^2h) (36)

Total: ln (Total) = -3.49 +2.22ln (dbh) +0.79ln (h) (37)

5.5. PROPAGATED ERROR

Samalca (2007) reviewed different biomass models and reported that regression errors contribute significantly to the overall precision of the mean aboveground biomass. About 65% of the total variation in the review was attributed to the regression error. Such variation indicates that ignoring such errors can yield flawed biomass quantities. Propagated error in the present study was 2.63% per tree, which is substantially lower than the variation reported on tropical forest biomass in Chave *et al.* (2004) of 10%. The difference between the reported propagated error in the present study and in Chave *et al.* (2004) can be attributed to method in which the data was collected and the higher homogeneity of the trees in a plantation. On the other hand, Chave *et al.* (2004) report about models derived from pooled data on multiple species in the tropics, which had higher variability hence having a bigger value of error propagated.

Other contributing sources of error such as measurement errors increase the total propagated error hence resulting in incorrect biomass quantities. Böhringer (1999) and Samalca (2007) explained that the need for a precise quantification procedure of errors by taking into account all possible sources is important in biomass studies and relevant to the objectives of UNFCCC and Kyoto Protocol. Unfortunately, measurement errors were not included in the study because of the complexity in their quantification. Furthermore, Chave *et al.* (2004) reported that using a small number of trees in the biomass studies contributes to the magnitude of the error, and recommended to use 50 trees in order to have an error of less than 10%. Therefore, more work should be dedicated to improving the predictive accuracy of the biomass model by having a larger sample numbers.

5.6. DRYING SERIES

5.6.1. Discs

The average weight change on the discs when the samples were dried from 60 to 105 ºC was 6%. Forrest (1968) reported a lower weight loss of 3% when drying from 65 to 103 ºC. However, the latter study was based on *Picea mariana* and *Pinus radiata*. For the eucalypt species in the present study, weight changed drastically between 65 ºC and 80 ºC as shown in Figure 4.28. The drastic weight change can be attributed to the large amount of moisture lost during this temperature range and sample density. *E. grandis x camaldulensis* had the highest change of 7% while *E. cladocalyx* and *E. gomphocephala* reduced by 5.5% on average. The high weight change in *E. grandis x camaldulensis* can be attributed to its lower density which allows high moisture loss as compared to the other two species. Botman (2010) reported that density for *E. cladocalyx* and *E. gomphocephala* was higher than that of both *E. grandis* and *E. camaldulensis*.

It was evident from the correlation between drying temperature and weight change that a linear relationship exists. Table 4.4 shows Model 4.58 which explained 89% of the variation in the biomass percentage using drying temperature as a predictor variable. This model was parameterised with temperature between 60 to 105 ºC hence it can only be used efficiently with temperatures between this same range otherwise extrapolation[9] can yield incorrect predictions.

5.6.2. Bark

The outcomes on the bark sub samples showed the amount of weight change when drying from 60 to 105 ºC. On average bark weight dropped by 4% for all the *Eucalyptus* species. *E. gomphocephala* had the highest change in weight of 5% which can be largely attributed to the thickness and high density of its bark as compared to *E. cladocalyx* and *E. grandis x camaldulensis*. The larger bark thickness is directly related to the moisture content that a bark can hold hence losing a larger amount of water during the drying process

[9] Extrapolation is the process of estimating, beyond the original observation interval, the value of a variable on the basis of its relationship with another variable.

(Saint-André *et al*., 2004). The drastic bark weight change of 3% occurred between 65 ºC and 80 ºC showing that when the bark is dried to 80 ºC, a small variation exist as compared to drying at standard temperature of 105 ºC.

5.6.3. Branches

Branch weight reduced to 97.8% for all the species. Van Laar and Akça (2007) reported a similar weight change for the *Pinus radiata* when temperature was increased from 70 to 103 ºC. Although van Laar and Akça (2007) reported total weight change, branch biomass can be within the same range as they are considered to have similar amounts of moisture content as compared to the stem wood while having high moisture content as compared to the leaves (Saint-André *et al*., 2004). *E. grandis x camaldulensis* had the highest weight change of 3.5% while *E. cladocalyx* had the lowest weight change of 1%. The variation in the amount of branches weight change can be associated with a number of physical factors such as density and initial moisture content of the branches (Forrest, 1968).

5.6.4. Foliage

Seifert and Müller-Starck (2009) reported weight variation on the study of biomass of cones on *Picea abies* (Norway spruce). By drying at 38 ºC, the weight of the total cones including winged seeds was reduced to 84%; at drying temperature of 60 ºC the dry weight reduced to 80% and a reduction to 78% was attained when temperature was dried at the standard drying temperature of 105 ºC. It is evident from the study on spruce that weight only reduced by 2.5% when dried from 60 to 105 ºC. Foliage biomass for the eucalypt species had similar results with weight reduced by less than 2.5%. The low decrease in foliage biomass can be attributed to the rate at which foliage dry and the amount of moisture content in the foliage.

The results obtained within this drying study demonstrate clearly the importance of a reporting of drying temperatures in biomass studies. With further drying series on further tree species, a better picture on the feasibility of transfer functions as the ones developed in this study could be gained in the future. Transfer function could be used to make results of different authors that worked on different drying temperatures comparable. This is an identified lack of knowledge (Seifert & Seifert, 2013) and should be receiving more attention in the future.

Chapter 6 : CONCLUSION AND RECOMMENDATIONS

6.1. CONCLUSION

The intent of this study was to develop a set of biomass models that could be used in determining total aboveground biomass for the three eucalypt species in typically arid conditions. It was shown that *E. cladocalyx*, *E. gomphocephala* and *E. grandis x camaldulensis* have been grown in South African plantations for a number of years, however, limited models exists for predicting biomass especially under arid growing condition. Most of the models, which exist on these species were developed based on small sample sizes, and samples dried at temperatures less than the standard drying temperature of 105 ºC leading to a proportional over-estimation of biomass. Besides biomass models, the present study determined the changes in weight when the samples are dried at different temperatures. Thus, correction on estimation of biomass in cases when biomass samples are dried at temperatures other than the standard drying temperature can be accomplished using transfer functions similar to those developed here.

Four sets of additive logarithms transformed models were parameterised for the biomass components (stem wood, bark, branches and foliage) using simultaneous equations developed in "`systemsfit`" R statistical package based on each species and pooled data. There was a strong positive relationship between biomass and dbh while biomass and h were weakly correlated because of the limited spread in height which was as a result of a small sample size used in the study (33 trees). Above average values of R^2 were obtained on the formulated biomass model, which were all significant, providing a first biomass model for drought tolerant eucalypts in South African west coast.

Changes were noted for all the components when biomass samples were dried under different temperatures. Stem wood had the highest weight percentage reduction bark weight reduced followed by branches and the bark. Furthermore, foliage weight had the lowest weight change as compared to the other components. The three eucalypt tree species did not show any difference in their drying pattern. Nonetheless, these changes are affected by different physical properties such as density, moistures content and bark thickness. Consequently, biomass variation between species is expected. In order to obtain more uniform results close

to the standard biomass drying temperature, biomass samples except for stem wood must be dried at least at 80 ºC to save energy.

The total propagated error as a result of sampling and regression procedure was small. Upscaling 1 (Sampling) contributed large percentage of the error as compared to Upscaling 2 (regression). Therefore, these errors can either underestimate or overestimate the biomass by the magnitude of the error.

These pooled biomass models developed in this study will offer a realistic option for carrying out an extensive inventory of total stand aboveground biomass for the selected eucalypt species growing under arid condition in the area of sampling. The species-specific models are certainly limited in their application to the stands where the sampling took place but provide a first orientation on species-specific differences.

Furthermore, the models will act as the baseline for harvesting, growth and yield, and in further biomass studies. Generally, these models could be used as tools for monitoring and long term management planning but should be parameterised with at least 30 to 50 trees per species from a wider variety of sites to grant a higher accuracy.

6.2. RECOMMENDATIONS

The model established in this study will serve as a baseline for further biomass studies as motioned in Section 6.1. Practically, these models will be useful in the biomass monitoring for eucalypt species growing on the dry west coast of South Africa and other regions experiencing similar climatic conditions. The following recommendations have been proposed for effective utilisation of these models, and further research.

Recommendation 1: Limited sampled trees

The study was carried out with a limited number of trees in which certain parameters such as height did not fit well because of uneven representation. In future research, additional sample trees we be needed to increase the precision and range of biomass estimation. Therefore, sampling should be carried out carefully so that clustering of the data is avoided. Smaller and bigger trees have to be well represented in the data in order for the parameters to have a good fit.

Recommendation 2: Extrapolation and prediction

The formulated models in this study can be applied on the three selected eucalypt species within the diameter range (7.2 to 37.1 cm) for the sampled trees. Extrapolation beyond the limits of diameters range is not recommended because inaccurate biomass quantities can be obtained. Thus, the predictions should be made within the specific diameter range. In addition, model validation should be done prior to using these models in order to ascertain the prediction precision. The pooled model for all three species is an improvement on the single species models developed, considering the limited tree numbers. Despite losing specificity; it has a more stable fit through pooling all sample trees.

Recommendation 3: Drying temperatures

This study clearly indicated that biomass should be reported on samples dried at 105 ºC in order to avoid overestimation of biomass, especially for stem wood. In cases where lower biomass sample drying temperatures are required, correction of biomass overestimation should be carried out using additional samples dried at the standard temperature and developing transfer functions similar to those developed in this study.

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APPENDIX I

FIELD DATA COLLECTION SHEETS

GENERAL INFORMATION

Name of recorder:…….. …..Site:…….....

Date:…….Species:……..

Sample tree number:…….....Size:…….....

TREE SAMPLING MEASUREMENTS

DBH[cm]:	Total Height [m]:	Height Crown Base [m]:
Stump height [cm]:	Stump diameter[cm]:	

Diameter for discs collection

Height [m]	**d_1 [cm]**	**d_2 [cm]**
1 (dbh).		
2 (0.25).		
3 (0.6).		
4 (3 cm o.b.)		

Heights for the tip

Ø [cm]	**Height [m]**
5cm	
3cm	

Sampled branches

No	**Height [m]**	**Ø [cm]**
1		
2		
3		
4		
5		
6		
7		
8		
9		

Stem diameters

h [m]	d_1 [cm]	d_2 [cm]
0.3		
1		
1.3		
2		
3		
4		
5		
6		
7		
8		
9		
10		
11		
12		
……..		
……..		
3cm(Ø)		

All Branches

No	h [m]	Ø [cm]
1		
2		
3		
4		
5		
6		
7		
8		
9		
10		
11		
12		
13		

APPENDIX II

BIOMASS DATA SET

TREE _NO.	SPECIES	DBH(cm)	H(m)	D^2H	STEM VOLUME(m^3)	STEM(kg)	BARK(kg)	BRANCHES(kg)	FOLIAGE(kg)	TOTAL(kg)
1	*E.gxc*	30.20	14.80	13498.19	0.46	287.83	37.59	155.22	23.55	504.19
2	*E.gxc*	34.40	17.70	20945.47	0.76	433.09	36.83	182.20	25.17	677.28
3	*E.gxc*	25.40	15.70	10129.01	0.38	255.04	24.20	73.68	14.51	367.43
4	*E.gxc*	16.10	12.30	3188.28	0.13	75.26	9.30	13.79	5.50	103.85
5	*E.gxc*	25.10	15.00	9450.15	0.34	211.19	21.43	68.11	12.01	312.74
6	*E.gomphocephala*	25.90	13.90	9324.26	0.31	181.07	26.19	64.18	13.49	284.94
8	*E.gomphocephala*	21.40	12.60	5770.30	0.20	127.39	15.44	17.74	6.59	167.16
9	*E.gomphocephala*	24.40	11.50	6846.64	0.22	110.19	17.41	50.41	8.69	186.70
10	*E.cladocalyx*	32.60	13.00	13815.88	0.33	165.93	24.47	220.80	33.10	444.36
11	*E.cladocalyx*	25.10	13.85	8725.64	0.32	197.55	20.22	36.88	8.69	263.35
12	*E.cladocalyx*	25.00	14.30	8937.50	0.27	192.49	23.60	59.51	7.71	283.31
13	*E.cladocalyx*	33.50	13.00	14589.25	0.46	253.57	35.33	241.25	42.73	572.88

TREE _NO.	SPECIES	DBH(cm)	H(m)	D^2H	STEM VOLUME(m^3)	STEM(kg)	BARK(kg)	BRANCHES(kg)	FOLIAGE(kg)	TOTAL(kg)
14	*E.cladocalyx*	29.50	17.60	15316.40	0.59	372.04	36.21	151.80	28.37	588.42
15	*E.cladocalyx*	21.50	16.15	7465.34	0.30	187.05	25.13	23.33	10.84	246.35
16	*E.cladocalyx*	29.60	18.05	15814.69	0.52	183.61	34.83	95.32	21.10	334.86
17	*E.cladocalyx*	30.40	15.75	14555.52	0.57	407.25	49.71	94.08	19.89	570.94
18	*E.cladocalyx*	37.10	16.00	22022.56	0.69	413.96	44.90	234.57	39.21	732.64
19	*E.gomphocephala*	31.70	12.74	12802.30	0.57	421.23	37.06	123.83	20.64	602.76
20	*E.gomphocephala*	27.60	19.40	14778.14	0.50	416.89	29.34	95.60	24.87	566.70
21	*E.gomphocephala*	32.60	18.00	19129.68	0.61	403.20	49.76	146.88	22.16	622.00
22	*E.gomphocephala*	20.40	16.00	6658.56	0.22	124.36	17.74	17.24	3.45	162.79
23	*E.gomphocephala*	25.50	16.20	10534.05	0.38	207.72	30.59	50.53	6.62	295.46
24	*E.gxc*	36.50	17.50	23314.38	0.73	562.47	51.36	296.09	52.04	961.96
25	*E.gxc*	24.10	14.10	8189.42	0.30	166.39	25.09	82.14	6.47	280.08
26	*E.gxc*	21.60	14.00	6531.84	0.23	162.54	18.91	53.85	13.62	248.91
27	*E.gxc*	26.80	16.98	12195.72	0.40	244.64	23.53	117.24	18.28	403.69

TREE _NO.	SPECIES	DBH(cm)	H(m)	D^2H	STEM VOLUME(m^3)	STEM(kg)	BARK(kg)	BRANCHES(kg)	FOLIAGE(kg)	TOTAL(kg)
29	*E.gomphocephala*	15.25	10.20	2372.14	0.06	37.90	9.58	28.23	17.89	93.60
30	*E.gomphocephala*	8.00	7.90	505.60	0.01	6.58	2.30	3.94	3.60	16.42
31	*E.gomphocephala*	10.70	8.70	996.06	0.02	13.95	4.71	6.81	5.38	30.85
32	*E.gomphocephala*	7.20	7.80	404.35	0.05	4.70	2.71	5.16	2.00	14.57
33	*E.gomphocephala*	11.90	9.55	1352.38	0.04	16.82	4.11	14.80	8.91	44.64