

2024-07

Developing Species-Specific Allometric Models to Estimate Aboveground Biomass of Eucalyptus Globulus of Smallholder Plantation in Wogera District, Central Gondar Highlands of Ethiopia

Birhan, Fentaye

<http://ir.bdu.edu.et/handle/123456789/17382>

Downloaded from DSpace Repository, DSpace Institution's institutional repository



BAHIR DAR UNIVERSITY

COLLEGE OF AGRICUTLURE AND ENVIRONMENTAL SCIENCES

DEPARTEMENT NATURAL RESOURCE MANAGEMENT

PROGRAM IN ENVIRONMENT AND CLIMATE CHANGE

**DEVELOPING SPECIES-SPECIFIC ALLOMETRIC MODELLS TO ESTIMATE
ABOVEGROUND BIOMASS OF *EUCALYPTUS GLOBULUS* OF SMALLHOLDER**

**PLANTATION IN WOGERA DISTRICT, CENTRAL GONDAR HIGHLANDS OF
ETHIOPIA**

Msc Thesis

BY;

Fentaye Birhan

**SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE
DEGREE OF MASTER OF SCIENCE (MSc) IN ENVIRONMENT AND CLIMATE
CHANGE PROGRAM**

July, 2024

Bahirdar, Ethiopia



BAHIR DAR UNIVERSITY

COLLEGE OF AGRICULTURE AND ENVIRONMENTAL SCIENCES

DEPARTEMENT NATURAL RESOURCE MANAGEMENT

PROGRAM IN ENVIRONMENT AND CLIMATE CHANGE

**DEVELOPING SPECIES -SPECIFIC ALLOMETRIC MODELLS TO ESTIMATE
ABOVEGROUND BIOMASS OF *EUCALYPTUS GLOBULUS* OF SMALLHOLDER
PLANTATION IN WOGERA DISTRICT, CENTRAL GONDAR HIGHLANDS OF
ETHIOPIA**

MSC THESIS

BY;

FENTAYE BIRHAN

**SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE
DEGREE OF MA`STER OF SCIENCE (MSc) IN ENVIRONMENT AND CLIMATE
CHANGE PROGRAM**

Major Advisor: Beyene Belay (Phd)

Co–advisor: Yohannis Gebremariam (Phd Candidate)

May, 2024

Bahirdar, Ethiopia

THESIS APPROVAL SHEET

As members of the Board of Examiners of the Master of Sciences (M.Sc.)thesis open defense examination, we have read and evaluated this thesis prepared by Fentanyl Birhan entitled **DEVELOPING SPECIES-SPECIFIC ALLOMETRIC MODELLS TO ESTIMATE ABOVEGROUND BIOMASS OF *EUCALYPTUS GLOBULUS* OF SMALLHOLDER PLANTATIONS IN WOGERA DISTRICT, HIGHLANDS OF CENTRAL GONDAR,ETHIOPIA** We here certify that the thesis is accepted for fulfilling the requirements for the award of the degree of Master of Sciences (MSc.) in Environment and Climate Change.

Board of Examiners

Name of the external examiner

Signature

Date

Menale Wondie (PhD)



11 / 07 / 2024

Name of the internal examiner

Signature

Date

Habtamu Assaye (Phd)



12 / 07 / 2024

Name of the chairman

Signature

Date

Melese Geberyesse (Phd)



14 / 07 / 2024

Name of Department head

Signature

Date

Abebe Aschalew (Phd)

DECLARATION

This is to certify that this thesis entitled “**DEVELOPING SPECIES - SPECIFIC ALLOMETRIC MODELS TO ESTIMATE ABOVEGROUND BIOMASS OF *EUCALYPTUS GLOBULUS* OF SMALLHOLDER PLANTATIONS IN WOGERA DISTRICT, HIGHLANDS OF CENTRAL GONDAR, ETHIOPIA**” submitted in partial fulfillment of the requirements for the award of the degree of Master of Science in “**Environment and Climate Change**” to the Graduate Program of College of Agriculture and Environmental Sciences, Bahirdar University by Miss. **Fentayl Birhan (ID.No. BDU1300998)** is an authentic work carried out by her under my guidance. The matter embodied in this project work has not been submitted earlier for the award of any degree or diploma to the best of my knowledge and belief.

Name of the Student

Fentaye Birhan

Signature & Date  28/5/2024

Name of the Supervisors

Beyene Belay (PhD) (Major Advisor)

Signature & Date  28/5/2024

Yohannis Gebremariam (Co Advisor)

Signature & Date  28/ 5 2024

ACKNOWLEDGEMENT

My first gratitude is to the Almighty God. Who gave me health and strength during my studies and was with me everywhere? Next, I would like to extend my great and deepest thanks to my advisor, Dr. Beyene Belay. His advice, valuable comments, suggestions, and corrections were supportive at any time, from the beginning up to the finalization of my thesis. Besides, my deepest gratitude goes to my co-advisor, Yohannis Gebremariam, for his critical comments and kindness in supporting me. Furthermore, I would like to thank my instructor, Asmamaw Alemu (PhD), for his demonstrative appreciation, reinforcement, and comments. I need and greatly acknowledge Bahirdar University for giving me a chance at a BDU Talent Scholarship for preparing this study. I am also happy to acknowledge Gondar University and particularly those in the department of forestry for allowing all research facilities that were used during my study, and my staff's M/r Amare Gebeye and Kirobel Motebayenore for helping during data collection and all fieldwork and giving me comments. Last but not least, this study would have never been what it is now had it not been for the sponsorship of the Restoration of Sacred Forests and Degraded Landscapes for Climate Resilience and Livelihood Improvement project for their financial support. At the end, I acknowledge my colleagues as BSc teachers Alemu and Nega.

DEDICATION

To my sister Alemaz Motbaynore, great inspirers of my heart and mind. She does not live in Ethiopia, but she is always with me. I am so proud of you.

ABBREVIATION/ACCRONOMYS

AGB	Aboveground biomass.....	1
AIC	Akaike Information Criterion	21
CO ₂	Carbon dioxide.....	8
DBH	Diameter at breast height	2
GHGs	Green House gas.....	8
H	Total tree height.....	2
MAPE	mean absolute percentage error	23
REDD ⁺	Reducing Emissions from Deforestation and Forest Degradation	2
RMSE)	Root mean square error	23
RSE	Residual Standard Error	21
V	volume	19

ABSTRACT

In Ethiopia, smallholder farmers commonly grow eucalyptus plantations in their farmland and other communal areas for short-rotation harvests (4–5 years). Eucalyptus trees are rapidly expanding in the central highlands of Ethiopia and in the Amahara region. It gives socioeconomic, environmental, and ecological benefits. The expansion and socioeconomic value of Eucalyptus plantations have been studied in the study area. Hence, this study was conducted to develop a species-specific allometric model to estimate the aboveground biomass of this smallholder plantation using the destructive method. The sample design was applied using both purposive and simple random sampling techniques. A total of 60 trees with diameters at breast height ranging from 2.1 to 12.6 cm were randomly harvested and separated into tree components (stem, branch, leaf, and twigs) weighted in the field and in the laboratory for sample dry and fresh weight analysis. Model development was done using 75% of the total data set, whereas the remaining 25% was used for model validation. Eight different above-ground equations and three height prediction equations were developed and tested. Diameter at the breast height, total height, and woody density were used as predictor's variables, whereas aboveground biomass is a dependent variable. For the height prediction model, the diameter was used as an independent variable. The best aboveground biomass models were selected based on the statically indices the highest coefficient determination $\text{adj}iR^2$, and the lowest residual standard error, Akaike information criteria, correction factor, mean absolute percentage error, and root mean square error. Species-specific models using the three simple predictor variables fitted the data in the form of: $\ln(Y) = -2.875 + 1.243\ln(D) + 1.631\ln(H) + 0.665\ln(p)$ was selected as the best fit model for Wogera areas. This model has coefficient determination ($\text{Adj}i R^2$) (0.94), residual standard error (0.230), Akaike Information Criteria (1.297), a correction factor (1.027), a mean absolute percentage error (15.71%), and a root mean square error (2.88). Comparing the current model (M6) with the four general existing models, the current model approximately predicted the smallholder plantation better than the general existing model, followed by model $\ln Y = -2.187 + 0.916 \ln(D^2 H \rho) / 0.112 (D^2 H \rho)^{0.916}$. The best-fit model for the height prediction model was model (M3) with $\text{adj}iR^2$ (0.84), RSE (0.102), and AIC (-78) in the form $\ln H = 1.400 + 0.5 (\ln D)$. Based on the findings, it is possible to conclude that the developing species-specific models are preferable to accurately estimate aboveground biomass and height prediction allometric models compared to the existing or previously developed general models.

Key words; aboveground biomass, Allometric model, *Eucalyptus globulus* and tree height.

TABLE OF CONTENTS

CONTENTS	Pages
THESIS APPROVAL SHEET	iii
DECLARATION.....	iv
ACKNOWLEDGEMENT	v
DEDICATION	vi
ABBREVIATION/ACCROMOMYS	vii
TABLE OF CONTENTS	ix
CONTENTS	ix
LIST OF TABLES	xii
LIST OF FIGURES	xiii
LIST OF APPENDIX TABLES.....	xiv
LIST OF APPENDIX FIGURES	xv
Chapter 1. INTRODUCTION	1
1.1. Background.....	1
1.2. Statement of the Problem	3
1.3. Objectives	4
1.3.1. General Objective.....	4
1.3.2. Specific Objective	4
1.4. Research Questions.....	4

(Continued)

Chapter 2. LITERATURE REVIEW	5
2.1. Eucalyptus Plantation in Ethiopia.....	5
2.2. Role of Smallholder Plantation.....	6
2.3 Aboveground Biomass Estimation	6
2.4. Aboveground Carbon stock Estimation.....	7
2.5. Allometric Models	9
2.6. Height Prediction Model.....	11
Chapter 3.MATERIALSAND METHODS.....	13
3.1. Description of the Study Area	13
3.1.1. Climate and Soil Type.....	13
3.1.2. Land Use Type of the Study Area.....	14
3.2. Sampling Design and Techniques.....	14
3.2.1. Biomass Measurement	15
3.2.2. Sample tree Selection.....	15\
3.2.3. Aboveground Biomass Estimation.....	15
3.3. Laboratory Measurement.....	16
3.4. Data Analysis	17
3.5. Allometric Equation Development	18
3.5.1. Model Development.....	18

(Continued)

3.5.2. Model Selection and Validation.....	19
3.6. Comparison of the Current Model with the previous General Model	21
3.7. Tree Height Prediction Model Development and Selection	22
Chapter 4. RESULT AND DISCUSSION	24
4.1. Characteristics of the Measured Trees.....	24
4.2. Model development and selection	25
4.3 Model Validation	29
4.4. Comparison of the Current Model with the Previously GeneralModels	31
4.5. Height Prediction Model Development and Selection	33
Chapter 5. CONCLUSION.....	37
Chapter 6. RECOMMENDATION	38
REFERENCE	39
BIOGRAPHY	68

LIST OF TABLES

Table	page
Table 1: Allometric equation types tested for estimating total aboveground biomass For <i>Eucalyptus globulus</i>	18
Table 2:Selected previously published models	22
Table 3: Allometric equation types developed for total height prediction model for <i>Eucalyptus globulus</i>	23
Table 4:Statistical summary for tree parameters used in developing or fitting and validating allometric models for aboveground biomass estimation and height prediction model	24
Table 6: Mean absolute percentage error (MAPE(%)) and relative root mean square error (RSME) for AGB estimation allometric equations developed using a 25% (17) independent set of data.....	28
Table 7: Comparison of the current best selected model with the existing models using the whole measured data (N=60).....	31
Table 8: Developed Allometric model to prediction total height of <i>Eucalyptus globulus</i> smallholder plantation	34

LIST OF FIGURES

Figure	page
Figure 1: Study Area Map	13
Figure 2: Scatter plot of tree aboveground tree biomass (AGB) vs. potential predictor variables (diameter, height, and wood-specific density).	25
Figure 3: Scatter plots of residual values versus predicted value of the three best allometric fit models Predicted value in log scale.....	30
Figure 4: Comparison of the current model with previously general equation used to estimate aboveground biomass of smallholder plantation of <i>Eucalyptus globulus</i> tree.	33
Figure 6: Residual and observed plots against predicted height for the best-fit model for this study	36

LIST OF APPENDIX TABLES

Appendix Table	page
Appendix 1 Table 1 Bottem stem diameter disk sub sample Laboratory Result	56
Appendix 1 Table 2 Mid and top stem diameter disk sub sample Laboratory Result.....	60
Appendix 1 Table 3 Leave and branch biomass sub sample laboratory Result	64

LIST OF APPENDIX FIGURES

Appendix Figure	page
Appendix 4 figure 1: Photo taken during field data collection	66
Appendix 4 figure 2: The photos show laboratory analysis of samples taken in the Laboratory	67

Chapter 1. INTRODUCTION

1.1. Background

Eucalyptus species are well-adapted and familiar tree species in various weather conditions around the world. About 20 million hectares are planted with them, mostly in temperate, tropical, and subtropical climates. These plants are among the globally most farmed forest species (Tsegaye Bekele, 2015; Mekonnen Daba, 2016). It belongs to the family Myrtaceae, an ever-green flowering tree that consists of some 800 species. It is the dominant tree species commonly found in the central highlands of Ethiopia since 1895 (Mesfin Abebe & Wubalem Tadesse, 2003; Haileab Zegeye, 2010).

Smallholder Ethiopian farmers frequently plant eucalyptus tree species on their farmlands. As a result, since the 19th century, eucalyptus plantations in the shape of woodlots have greatly expanded throughout the Amhara region, including the study area. Currently, even smallholder farmers are shifting their crop land to Eucalyptus plantations (Yordanos sete & Getahun Abreham, 2021). Additionally, as Eucalyptus plantations become more popular as a source of charcoal and fuel wood for humans, they reduce pressure on remaining natural forests. These plantation forests not only produce wood products but also contribute significantly to the mitigation of climate change by sequestering and fixing carbon (Hartono & Kusmana, 2020). This can provide economic, environmental, and social benefits in addition to helping to prevent climate change through carbon sequestration.

In tropical areas, cutting carbon emissions from deforestation and degradation is a major opportunity (Canadell & Raupach, 2008). his study focused on aboveground biomass (AGB) because it represents the largest carbon pool of forest vegetation and is directly impacted by deforestation and degradation (Kenzo *et al.*, 2009; Basuki *et al.*, 2022).

The primary use of allometric regression models is as mathematical functions that connect a tree's dry mass to one or more tree dimensions; diameter at breast height (DBH) and total tree height (H) are the two most important single tree metrics that describe the composition and structure of forests (H) and also include woody density (Ebuy *et al.*, 2011; Sturrock *et al.*, 2011; Birhanu Kebede *et al.*, 2018). Most of the allometric models now in use for estimating

tree aboveground biomass in the tropics were created from forest ecosystems (Brown *et al.*, 1989; Brown, 1997; Chave *et al.*, 2005; 2014). However, due to their inherent uncertainty, these models are unable to sufficiently reveal the tree biomass in a given region or limited area in the tropics, including Ethiopia. To attain greater degrees of accuracy and precision, it is crucial to apply site-specific and species-specific allometric equations (Djomo *et al.*, 2010; 2016; Admassu *et al.*, 2022). This is because different tree species have different allometric biomass estimations and also because the wood density of the species, the floristic composition, and the growth performance of the species-environment affect the type of allometric model (Kaonga Martin & Smith Bayliss, 2010).

Therefore, species-specific allometric equations are the most accurate and precise. Developing a reliable way for measuring biomass carbon associated with trees in smallholder plantations is critical for helping smallholder farmers benefit from the emerging carbon market and benefit from carbon offset schemes (Roshetko, 2015; Pravalprukskul, 2018).

A species-specific allometric model that was constructed helps in the understanding of the functions played by smallholder plantations in the Ethiopian carbon cycle, especially climate change. To study the carbon stock, species-specific allometric models are helpful and accurate biomass estimation is essential to measuring changes in both biomass and carbon stocks (Banerjee *et al.*, 2022). Plantations owned by smallholder farmers are not the same as plantations owned by states. These frequently supply smallholder plantations with fuel, charcoal, and poles so that the smallholders may manage the plantations and ensure their sustainable use (Nambiare *et al.*, 2021). On the other side When measuring height in an area where it is time-consuming, unreliable, and more challenging to measure in a dense plantation task than the diameter parameter, the height with the D relation model is one of the most crucial models (Mugasha *et al.*, 2013; 2019). This study also focused on developing an allometric model based on species was used to estimate the aboveground biomass of *Eucalyptus globulus* smallholder plantation trees, taking into account the harvesting method, robustness testing, and height prediction models.

1.2. Statement of the Problem

In the Ethiopian highlands, *Eucalyptus globulus* is among the most exotic species grown widely and has great socioeconomic and environmental significance. Eucalyptus woodlots are mostly established by Ethiopian smallholder farmers and have varying uses for wood charcoal production, construction, and different uses (Abebe Birara *et al.*, 2019). For REDD+ as well as climate adaptation and mitigation, accurate aboveground biomass estimation is essential. In order to increase productivity and store a known quantity of carbon in biomass both above and below ground, including Eucalyptus species, forest plantations are a valuable resource for inventories and biomass assessment (Ostadhashemi *et al.*, 2014).

A generic allometric equation for carbon allocation and aboveground tree biomass estimation in tropical and subtropical has been studied by many researchers for the Eucalyptus species (Williams *et al.*, 2005; Gonzalez *et al.*, 2013; Missanjo *et al.*, 2015; Gonzalez *et al.*, 2021). However, general models show uncertainty, which yields overestimated and underestimated biomass for specific species and areas (Daba and Teshome Soromessa., 2019). Allometric models must be developed based on site and species to get accurate and precise estimates. In most studies, biomass and carbon quantities of trees vary with soil, management, climate, and species. For enhanced biomass estimates at study sites, site-specific biomass models are needed (Mugasha *et al.*, 2012).

The AGB models depend on several variables, including tree height, diameter, and wood density. However, accurate tree height measurement in the field is labor-intensive, costly, time-consuming, prone to measurement errors, and challenging to measure in dense plantations. For this reason, D-height relation models are empirically based on the diameter variable, which is the most readily measured, least time-consuming, and capable of predicting individual tree height (Shamaki *et al.*, 2016). In the study area of Wogera district, most plantations are *Eucalyptus globulus* (white tree) owned and managed by smallholder farmers and provide socioeconomic purposes. Various studies have been carried out in the study area and Ethiopia on smallholder Eucalyptus globulus plantations about their expansion, role, effect, ecological, and socioeconomic aspects, and different problems related to this tree and site are studied (Tegegne Derbe *et al.*, 2018; Abebe Birara. *et al.*, 2019; Yordanos sete &

Getahun Abreham, 2021; Mulugeta Zewdie, 2008; Mulugeta Zewdie *et al.*, 2009; Kebede Gizachew, 2017; Beleyenehe Dessie *et al.*, 2022). However, there is still a research gap in the process of developing aboveground biomass models. No scientific data was gathered and examined concerning species-specific allometric models for estimating aboveground biomass and height prediction models to predict the aboveground biomass of the smallholder plantations in the study area.

1.3. Objectives

1.3.1. General Objective

This study aimed to develop species-specific allometric models for estimating the aboveground biomass of *Eucalyptus globulus* smallholder plantation in wogera district central Gondar High lands of Ethiopia

1.3.2. Specific Objective

- Species-specific allometric models for estimating the aboveground biomass and carbon stock for *Eucalyptus globulus* of smallholder Plantation
- To compare the current species-specific allometric models with other general allometric models
- To develop a height prediction model (Height-Diameter relationship) for *Eucalyptus globulus* smallholder plantation

1.4. Research Questions

- ❖ What is an accurate species-specific allometric model for estimating the aboveground biomass for *Eucalyptus globulus* smallholder plantation in the study area?
- ❖ How do we compare the current species-specific allometric models with other general allometric models in the study area?
- ❖ What is an accurate species-specific height prediction model for *Eucalyptus globulus* smallholder plantation in the study area?

Chapter 2. LITERATURE REVIEW

2.1. Eucalyptus Plantation in Ethiopia

Eucalyptus plantations have expanded considerably among smallholders and small forestry firms in Ethiopia, placing them in second place in Africa in terms of area planted with Eucalyptus (Mesfin Abebe & Wubalem Tadesse, 2003; Biruk Ketsela, 2012). Eucalyptus trees cover 90% of the total planted forest area in Ethiopia. This exotic species was first introduced to Ethiopia around the end of the 19th century (Pohjonen & Pukkala, 1990). Growing Eucalyptus began in Ethiopia around 1890, during the regime of Emperor Menelik II, to reduce the shortage of wood. At the same time, *Eucalyptus globulus* was planted as the main tree species in the central highlands of Ethiopia in the 19th century (Getahun Amare, 2003).

Eucalyptus is frequently planted in woodlots in my study area and is a great asset for planters contributes to rural development and poverty reduction in Ethiopia (Abebe Birara *et al.*, 2019). For this tree, decisions about the species solely based on the perceived negative ecological impacts are not sensible when it is planted on the right sites with good management planning and proper tending operations focusing on its economic, social, and ecological impacts (Jagger & Pender, 2003).

This tree also contributes to the contribution of climate change mitigation at the regional and national levels, and its impact on the local community is highly im0perative and essential for mutual benefits (Alemayehu Asabeneh & Melka Yoseph, 2022). Trees also play a key role in the global carbon cycle. Managing forests through agroforestry, forestry, and plantation systems is seen as an important opportunity for climate change mitigation and adaptation (Meragiaw Misganaw, 2017). According to (Ribeiro *et al.*, 2015), plants, especially those with fast-growing species such as Eucalyptus and its cultivars, represent a short-term and cost-efficient alternative for sequestering carbon, which would then be emitted into the atmosphere. Eucalyptus species can supply wood in good quantities within 4–5 years from relatively small areas, and this woodlot plantation of land in the study area has been successfully established and increased since 1970 (Tegegne Derbeet *al*, 2018).

2.2. Role of Smallholder Plantation

A smallholder plantation is a plantation Managed forest, established for subsistence or fuel wood, timber, fodder, and local sale by planting and seeding in the orchards, forest gardens process of afforestation, with and other even age class and regular spacing (Herbohn andMedrilzam, 2014; Obidzinski & Dermawan, 2010).

People in rural areas have long planted smallholder trees all across the tropics, including Ethiopia (Fauzi & Rohadi,2015). These serve rural communities in a variety of ways, providing fuel wood, fodder, and poles, building materials for daily use and construction, as well as environmental benefits like helping to mitigate global and national climate change and balancing greenhouse gas emissions that promote photosynthesis. (Nawir *et al.*, 2007).In my study area for *Eucalyptus globulus* smallholder tree has been studied by many researchers but not all address, so this study conduct add the reliable estimation of aboveground biomass site specific allometric model and height prediction model for biomass estimation carbon stock and to climate change mitigation role through the correct estimation of biomass.

2.3 Aboveground Biomass Estimation

The biomass of a forest is the total mass of living things there. It is the weight of all living things in the environment, and it can be exactly calculated by weighing every living item. (Condit, 2008).To model bioenergy, food security, environmental assessment, and climate change research, biomass is a crucial element. Nevertheless, estimating biomass remains a difficult undertaking, particularly in regions with complicated forest stand patterns and environmental conditions (Lali *et al.*, 2015). Most of the biomass in a forest is from trees, and the focus of methods for estimating biomass is measuring the above-ground portion of trees because it is directly impacted by deforestation and degradation and represents a large carbon pool(Kanninen, 2005). On the other hand, the part of the tree's biomass that is below the roots is much more difficult to measure. For this reason, nearly all inventories of forest biomass refer only to aboveground weight(Condit, 2008). Biomass is also an indicator of site productivity, both in biological and economic terms, and it is important to maintain the implementation of sustainable forest management and plans(Návar, 2009; Zianis &Mencuccini, 2005).In this study, the fastest-growing and most successful smallholder

plantations have significance for socioeconomic purposes. *Eucalyptus globulus* smallholder tree developed a site-specific allometric model and a height prediction model that were used to estimate the above-ground biomass and carbon stock. Biomass is a function of diameter at breast height (D), total height (H), and wood density in a given location and site. However, the contribution of these variables to the above-ground biomass differs from site to site depending on the succession stage of the forest, disturbance levels, species composition, age, management, etc (Ebuy *et al.*, 2011; Henry *et al.*, 2011).

It is of great significance for determining the most effective way to analyze carbon storage, dynamics, monitoring, and estimating lost or emitted carbon during deforestation, and it gives us an idea of the forest's potential to sequester and store carbon in the forest ecosystem (Vashum KT, 2012). In particular, for dominating and extensively distributed, quickly growing, short-term, and commonly grown smallholder eucalyptus species, the creation of site-specific, dependable allometric models is advised to increase the accuracy of such estimations (Fayolle *et al.*, 2013; Lin *et al.*, 2017; Moussa *et al.*, 2019). This study also attempts to estimate biomass involving parameters such as DBH, diameter at the breast height, total tree height, and woody density with different regression equations.

2.4. Aboveground Carbon stock Estimation

Climate change is agreed as a global threat to the environment and human wellbeing. Green House gas GHGs are produced by deforestation, burning fossil fuels, and industrial CO₂ emissions. As a result, it has been proposed that using forests for agroforestry, plantations, and reforestation is one of the best land management strategies for reducing atmospheric CO₂ levels through photosynthesis. Additionally, over 70% of all Soil organic carbon and over 80% of all terrestrial aboveground carbon C are stored in forest ecosystems (Binyam, 2014). Forest carbon evaluation has received more attention after the Paris Agreement. It is necessary to provide realistic values of the carbon stored in the terrestrial biosphere (Lorenz & Lal, 2010; Calfapietra *et al.*, 2012). With the increasing concentration of carbon dioxide in the Earth's atmosphere as the result of deforestation there is need to estimate biomass and carbon pools in tropical forests (Houghton, 2005). This is, particularly, essential in Africa where reliable biomass data is lacking, Accurate estimates of biomass are important for the assessment of carbon stocks toward understanding carbon

variations in response to world climate changes, monitoring ecological processes such as wood production and nutrient cycling and sustainable forest management (Vieira *et al.*, 2008; Rahman *et al.*, 2021).

These days, forests and woodland ecosystems serve as significant carbon sinks, and protecting them is one of the most viable ways to combat the growing global warming threat (Barbati *et al.*, 2007; Lorenz & Lal, 2010). When the amount of carbon dioxide in the atmosphere and its impact on climate change worldwide keep rising. To offer information on the worldwide carbon budget and to understand the global climate, modeling the aboveground biomass of forest and woodland ecosystems is necessary (Ekoungoulou *et al.*, 2018; Löf *et al.*, 2019; Henry *et al.*, 2020).

Accurate estimates of carbon stocks depend to a greater degree on the availability and adequacy of the allometric equations that are used to estimate tree biomass (Yehualashet Belete *et al.*, 2019). One of the biggest and most productive sources of stored carbon worldwide is smallholder farmers in developing countries. However, in developing nations, determining, monitoring, and quantifying the amount of carbon that trees on smallholder farms are removing from the atmosphere continues to be extremely difficult (Kuyah *et al.*, 2013). REDD+ (Reduced Emissions from Deforestation and Degradation, Plus Sustainable Forest Management, Conservation) is also a significant essential mechanism to address the issues of climate change in developing countries. It needs accurate, standard and reliable information of forest carbon stock and biomass production (Toirambe *et al.*, 2013; Missanjo *et al.*, 2015). In Ethiopia there is rare site specific allometric model for smallholder plantation developing site specific allometric equations is necessary to accurately quantify the biomass and carbon storage of the smallholder plantation tree.

2.5. Allometric Models

The accuracy and applicability of allometric models have a significant impact on the estimation of aboveground biomass (AGB). For the purpose of measuring biomass and carbon storage in the terrestrial forest ecosystem, allometric equations are crucial (Amsalu Abich *et al.*, 2019). Biomass equations are a common and cost-effective method to estimate the biomass of tree species present in plantations (Ostadhashemi *et al.*, 2014). The aboveground tree components are estimated using biomass estimation equations, also referred to as allometric regression models. These equations relate the tree dry mass (obtained by the direct method) to measurable variables and/or tree dimensions, such as diameter at breast height (DBH, at 1.3 m from the ground), total tree height (H), woody density, and other variables (Yehualashet Belete *et al.*, 2019).

For the best-performing stem diameter selection algorithm, a range of 17–95 individuals were needed to achieve biomass predictions with a standard deviation within 5% of the mean. This indicates that allometric models must be based on sufficient data to ensure accurate and precise predictions (Oxburgh *et al.*, 2015). Nevertheless, funding and the goal of the research also influence how many sample trees are chosen. Sometimes factors unrelated to prediction accuracy, like time and cost, determine the sample size (Chave *et al.*, 2005).

Regression equations were developed for the accumulation of biomass with age across all productivity classes for each forest type. Consequently, much of the uncertainty associated with the estimates of total carbon storage and the rates of carbon accumulation in the world's forests can be attributed to uncertainties at the local or regional level (Author *et al.*, 2012). There are two ways to measure aboveground biomass in the field: the direct method of harvesting and the indirect method that uses the allometric equations DBH and total height (Ravindranath & Ostwald, 2008). In this study, the direct measurement of tree aboveground biomass (AGB) involved felling a representative number of trees and measuring their fresh parts (stem, branch, leaf, etc.) used for model development in the field and the oven-dry process in the laboratory. This method is high-cost and time-consuming, but in terms of model accuracy and validation, it is the best method, and when the trees are harvested for short rotation, it is possible to use this method for model development (Blake *et al.*, 2021).

The researchers developed site and species-specific allometric models for aboveground biomass estimation for different trees in different areas, such as in Ethiopia Mana Angetu Forest for (*Olea europaea* L. subsp. *Cuspidata* by (Birhanu kebede & Teshome Soromessa, 2018) studied by (Amsalu Abich *et al.*, 2019; 2021) for, *Combretum-terminalia* woodlands and dry deciduous woodland ecosystems in Amhara, Northwest Ethiopia. In dry lands of Ethiopia for the invasive species *Prosopis juliflora* (Dessie Assefa *et al.*, 2022), and (Mulugeta Zewideet *et al.*, 2009), for *Eucalyptus Globulus* in high lands of Ethiopia etc.

Have used these techniques to develop allometric models with various sampling techniques and allometric model selection criteria, which include the three predictor variables and the two predictor variables height and DBH and also others parameter. They have come to the conclusion that, in order to estimate aboveground biomass more accurately than general models, each species requires an allometric model that is specific to its site and species in the Ethiopian forest. When there is an allometric difference and one model is not appropriate for a particular species or location. The most straightforward technique for estimating above-ground biomass and the carbon stocks stored in the forest ecosystem is the harvest method. The harvesting method is limited to a small area or small tree sample sizes. Nevertheless, it determines the biomass accurately for a particular area; to validate and be accurate, the model was the best method, and the trees had to be harvested and weighted (Jibrin & Abdulkadir, 2015; Kaonga Martin & Smith Bayliss, 2010).

However, until today, no specific study has been reported regarding the development of site-specific allometric models for the estimation of smallholder plantations of *Eucalyptus globulus* trees. Therefore, the aim of this study was to develop a site-specific allometric model using this method to estimate the above-ground biomass of smallholders. Generalized allometry exists for tropical trees, but site- and species-specific models are more accurate and reduce biomass estimation uncertainty at the local level (Litton & Kauffman, 2008 ; Bosques & Secundarios, 2019; Amsalu Abich *et al.*, 2019; 2021).

The primary causes of the variance in biomass amongst woods are environmental differences (Rocha *et al.*, 2020). The factors that affect the regression biomass models are soil properties, climate conditions, etc (DeLucia *et al.*, 2000; Antonio *et al.*, 2007; Urban *et al.*, 2013). Allometric biomass models vary in species and in site (Montagu *et al.*, 2005). Due to this, site-specific allometric relationships are required for the conversion of forest inventory measurements to regional-scale estimates of forest carbon sequestration (Sawadogo *et al.*, 2010).

This study also developed Species -specific allometric models for estimating the aboveground biomass of the smallholder plantation *Eucalyptus globulus*, which is found in the study area and is managed and owned by smallholder farmers. In addition to these, to determine the strength and significance of the best-fitting models, compare the developed models to the existing general allometric models when they are developed in tropical or elsewhere and validate this allometric equation by using different statistical indices that were applied for comparing and evaluating the statically. Carbon exists as carbon dioxide, which is one of the greenhouse gases (GHG) in the atmosphere and has an enormous influence on the impact of climate change. Therefore, a common method to quantify carbon stocks in forests is the use of allometric regression models to convert forest inventory data to estimates of aboveground biomass (Chave *et al.*, 2014; Mohd Zaki *et al.*, 2018).

2.6. Height Prediction Model

One of the key characteristics of forest stands is the correlation between tree height (H) and diameter at breast height (D). Furthermore, H is a necessary variable in models of volume and aboveground biomass. But measuring height takes longer than measuring D. Error factors for height measurements include visual obstructions, rounded crown shapes, bending trees, and sloped terrain (Mugasha *et al.*, 2013, 2019). Allometric models used in above-ground forest biomass estimation depend on tree height, diameter, and wood density as predictive variables (Sullivan *et al.*, 2018). While measurements of stem diameter and wood density can be obtained easily, tree height measurements can be time-consuming and difficult. This often results in the exclusion of tree height as a variable for predicting the aboveground biomass of trees.

Other studies have demonstrated that including tree height can significantly improve aboveground biomass estimates. Applicable height-diameter models that make the estimation of tree height easier are typically constructed in order to guarantee that tree height is included as a predictor variable in the estimation of aboveground biomass(Rutishauser *et al.*, 2013). Because there are large differences in tree height for a given stem diameter, forest type, and location, incorporating tree height can greatly improve aboveground biomass estimations(Feldpausch *et al.*, 2011).

Tree height and diameter correlations In this way, it lowers the costs related to forest inventory by creating models to estimate the heights of the remaining trees in the stand(Paulo *et al.*, 2011). Even within the same forest stand, different tree species have different H and D relationships. The relationship varies even within the same species, with variations in stand densities, tree sizes, species compositions, stand ages, and site conditions. This impact is frequently taken into account when building models with extra variables(Poorter *et al.*, 2006).As a result, it's crucial to develop and validate accurate models for predicting tree height based on D. Additionally, accurate tree height estimations are critical for evaluating biomass above ground and have a significant impact on models of forest growth that are based on ecological and ecophysiological processes and guarantee sustainable management. Assessments of the biomass of forest stands have also typically been taken into account(Zhang *et al.*, 2019).

Chapter 3. MATERIALS AND METHODS

3.1. Description of the Study Area

The study was carried out in the central Gondar Amhara Region's Wogera district, which is located at 12°46'06.5"N and 37°37'26.5"E (Figure 1). The district is about 1821 km² in size. The distances are approximately 32 kilometers from Gondar city and 213 kilometers northwest of Bahir Dar, the Amhara region's capital. The region is located at an average altitude of 2812 meters above sea level. In the district, there are about 250,493 people, of 122,635 are women and 127,858 are men. With a population density of 137 people per km², and 94% live in rural areas (Kassegne Asenake *et al.*, 2021).

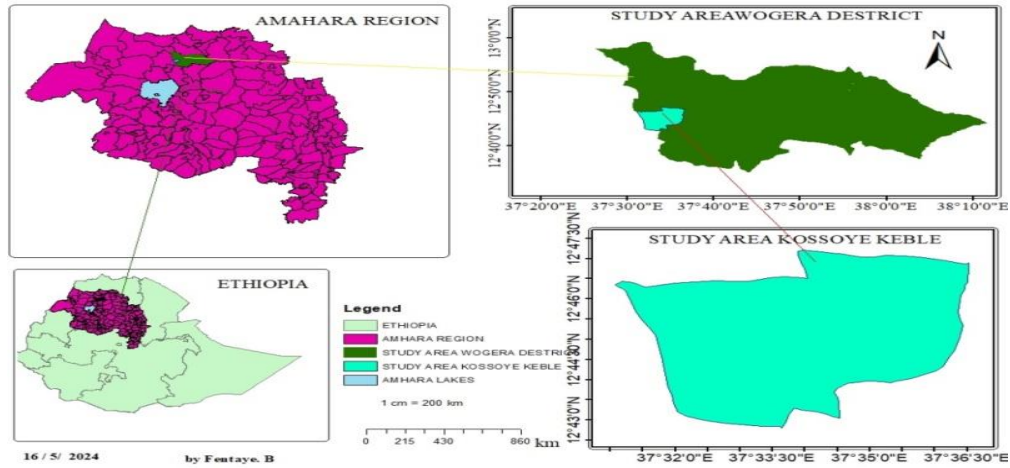


Figure 1: Study Area Map

3.1.1. Climate and Soil Type

The study area is classified as follows by the Ethiopian agro-ecological classification: highlands (56%), lowlands (14%), and 4% frost. The average annual temperature is between 14 °C and 33 °C. The range of the annual average rainfall depends on the geographical type and is between 1000 and 1600 mm. The predominant soil type in the region is combisol, which is recognized as fertile soil.

3.1.2. Land Use Type of the Study Area

The major land uses in the study area include cultivated land, grazing land, and the plantation of exotic species. In the district, the majorities of plantation forests are made of *Eucalyptus globulus* and are commonly owned and managed by smallholder farmers. Almost 70% of the plantations are *Eucalyptus globulus* (Kassegn Asnakew *et al*, 2021). When the plantations were between four and six years old, the local producers harvested the stands. However, five years of age was the most common harvesting age. The main stem was cut down and used to make firewood, charcoal, and construction poles. Smallholder farmers harvest the tree between March and May. The spacing between trees was on average 0.5 m x 0.5 m, which is the traditional planting spacing practiced by most of the local farmers in the study area. Native tree species like *Cordia africana*, *Rhamnus prinoides* and *Olea africana* are found in the landscape of the study area.

3.2. Sampling Design and Techniques

Both purposive and simple random sampling was employed to collect the data in this study. In the first step, Wogera district was selected purposefully due to the availability of wider *Eucalyptus globulus* plantations. In the second step, Kossoye Keble was selected in consultation with district agriculture office experts because of better area coverage of smallholder plantations and road accessibility. In addition, the selected Keble has better plantation cover with different age ranges to get representative sample plots. Farmers in Kossoye Keble were willing to harvest sampled trees. Then, a fundamental sample inventory of smallholder plantations was carried out in this area to collect data on *Eucalyptus globulus* smallholder plantation trees.

3.2.1. Biomass Measurement

3.2.2. Sample tree Selection

For this study, *Eucalyptus globulus* plantation with the ages of 4 and 5 years was considered, as there was not enough plantation to sample ages above 5 years. For each age class, six plots measuring 10 m by 10 m were sampled on six different smallholders' plantation sites to cover the variation in stand growth resulting from management techniques, soil fertility, and other parameters when different smallholder plantation areas were selected. Consultation with Keble Agriculture Office experts deepened the availability of the above reasons. All trees in each sample plot were measured for DBH with the help of diameter tape. In addition, the total height of representative trees was measured using a hypsometer. However, a total of 60 sample trees (30 trees for each age class) were harvested for model development. That means, in the different farmers, as the number of sample plots was six for each age class, five trees were randomly selected on each sample plot. To select five sample trees for harvesting, a random sampling technique was used from the list of trees recorded for DBH measurement on each sample plot. The total tree height of the 60 sample trees was measured using a tape meter after they fell to minimize errors.

3.2.3. Aboveground Biomass Estimation

The selected trees were measured and marked. Then felled trees were measured for total height using a measuring tape. The trees felled for biomass estimation were separated into stems, brunches, leaves, and twigs. The fresh mass of each component was weighted in the field using a 50 kg scale hanging balance with a precision of 0.1 g. Before weighing the fresh weight, the stems were cut into sections to make them suitable for hanging balance measurements. Fresh weights of about 200g for leaves, twigs, and branches were randomly collected and placed in plastic bags. Then samples in the plastic bag were tagged and taken to the laboratory for dry biomass determination. The stem disks, 5 cm thick, were sampled from different sections of each sampled tree (base, middle, and top). In total, 180 stem disks were taken to the laboratory after weighing the fresh weight for corresponding oven-dried biomass estimation. For wood density estimation, many sub-sections 1 m to 2 m long were taken and immediately weighted in the field. In addition, the diameter of each sampled log was measured both at the bottom and top in the field. Generally, the field measurement procedure and the

biomass calculation in this research followed the procedures of the FAO Food Manual for the destructive sampling method (Picard, 2012).

3.3. Laboratory Measurement

All samples collected in the field were taken to the laboratory at the University of Gondar, Agricultural and Environmental Science College, for oven-dried biomass estimation. The leaves were oven-dried at 70°C by monitoring changes until we reached a constant weight. Stem desks and branches were oven-dried at 105°C until all the moisture became zero or constant weight (Picard *et al.*, 2015). The dried weight of each oven-dried sample was recorded after removal from the oven. The total dried weights (TDWc) of each component of the sample trees were calculated based on the total fresh weights of each component (TFWc) measured in the field and the ratios of dried weight to fresh weight (SDWc/SFWc) calculated for each component in the laboratory was calculated using the formula of (Equation 1).

$$TDWc = TFWc \frac{SDWc}{SFWc} \quad \text{Equation 1 (Huynh et al., 2021).}$$

Where: TDWc is the total dry weight of a component (stem, branches and leaves); TFWc is the total fresh weight of this component measured in the field; SDWc and SFWc are the dry sample weight and fresh weight samples for this component. The total aboveground biomass of each sampled tree was calculated as the sum of total dry weight.

$$TDW_{tree} = TDWS + TDWB + TDWL \quad \text{Equation 2}$$

Where; Total Dry Weight of each tree aboveground biomass was TDWS Total dry weight of stem, TDWB Total dry weight of branch and TDWL Total dry weight of leaf.

For wood-specific gravity estimation, for fresh stems and sample discs, diameters of the lower and upper levels of sides were used to calculate the volume (V) using the Smalian's formula (Sillett *et al.*, 2019).

$$V = \frac{\pi \times L}{8} (D1^2 + D2^2) \quad \text{Equation 3}$$

Where; V represents the volume, L the length of the stem and D1 and D2 the diameters at the lower and upper sides of the tree $\pi = 3.14$. Wood basic density (g cm^{-3} each disc (and tree) were determined as the ratio of dry mass to green .

$$\text{Dry Mass } \rho = \frac{DM}{GV} \quad \text{Equation 4}$$

Where ρ = wood basic density (g cm^{-3}), DM = subsample oven-dried mass (g), and GV= subsample fresh volume of each tree (cm^3) calculated from (Equation 3) .The stem, branches and leaves (Xiang *et al.*, 2016) based on (equation2).

3.4. Data Analysis

The data was arranged and organized on the Excel datasheet. The data measured both in the field and laboratory was used to estimate the aboveground biomass components (stem, leaf, and brunch) of the eucalyptus tree and wood density. To create biomass regression models, the summarized data on D, H, wood density, and total aboveground biomass (AGB) were employed. One independent variable, the DBH variable, was employed in the creation of the height prediction model. The software package (CaRet) classification and regression training (Max *et al.*, 2008) Statistical Package R (version 4.2.1) was applied to generate allometric equations and generate all of the resultant graphics.

3.5. Allometric Equation Development

3.5.1. Model Development

The commonly used eight allometric models were developed for estimating the aboveground biomass of *Eucalyptus globulus* tree species. According to (Ulleret *et al.*, 2016) Before starting the model development, the data were split into two sets by random sampling. The first data set contained 75% of the data used for training or fitting model allometric models, while the second set contained the remaining 25% of the data, based on the availability of the biomass data most developed allometric models validated by independent data 20 – 30 % of the data was used for validation of the developed allometric models. Allometric models for aboveground biomass estimation were developed using field-measured predictor variables (D, H and wood density), whereas the aboveground tree biomass (AGB, kg tree⁻¹) was used as a dependent (response) variable.(Table 1).

Table 1: Allometric equation types tested for estimating total aboveground biomass For *Eucalyptus globulus*

Model no.	Predictor	Equation type	Source
M1	D	$Y = a + bD^2$	(Brown <i>et al.</i> , 1989)
M2	D	$Y = a + bD + cD^2$	
M3	D	$\ln(Y) = a + b\ln(D)$	(Brown, 1997)
M4	D,H	$\ln(Y) = a + b\ln(D) + c\ln(H)$	(Djomo <i>et al.</i> , 2010)
M5	D, ρ	$\ln(Y) = a + b\ln(D) + c\ln(\rho)$	
M6	D, H	$\ln(Y) = a + b\ln(D) + c\ln(H) + d\ln(\rho)$	(Nelson <i>et al.</i> , 1999) (Chave <i>et al.</i> , 2005)
M7	D,H, ρ	$\ln(Y) = a + b\ln(D^2 * H)$	
M8	D, H, ρ	$\ln(Y) = a + b\ln(D^2 * H * \rho)$	

Where Y: is the predicted tree biomass value in kg and a, b, c and d are the fitted parameters, ln:natural logarithm H: is total height D:is diameter at the breast height ρ : is Woody Density calculated in this study by using (Equation 4)

3.5.2. Model Selection and Validation

All the models listed above were tested based on different parameters. Models with a prediction power of total aboveground biomass using the number of variables (diameter, height, and wood density) were selected using three parameters. First, we develop equations using only diameter as a predictor. Then we stepwise include height and density and analyze their effects on the predictive quality of the models. The best-fit allometric model was selected based on goodness-of-fit statistics. The model with the lowest Akaike Information Criterion (AIC), residual standard error (RSE), and highest coefficient of determination (Adj R²) values was selected as the best-fit model (Chave *et al.*, 2005; Kuyah, 2012; Mugasha *et al.*, 2013). Diagnostic plots of observed values versus fit and residual trends were also used to assess model performance. For each of the models tested, the following indicators of goodness of fit are reported:

Adjusted R²: corrects the coefficient of determination by accounting for an increasing number of independent variables.

$$\text{Adj}R^2 = 1 - \frac{\frac{RSS}{n-p}}{TSS/(n-1)} \text{Equation 5}$$

Where n = number of samples p= number of observation paramter

RSS =Residual sum of squares, $RSS = \sum_{i=1}^n (y_i - f(x_i))^2$ important to determines how well a regression model represents the data in the model.

y_i = the i th value of the variable to be predicted

$f(x_i)$ = predicted value of y_i

n = upper limit of summation

TSS= total sum of squares = $\sum_i^n ((y_i - \hat{y})^2)$

n refers to the index, or location, of the value in the sample, and it is initialized to 1, the position of the first sample value.

y_i refers to the sample value at the index,

$\hat{y}$ refers to the mean of the sample.

Residual standard error of estimate (RSE): square root of the residual variance around the regression function.

$$RSE = \sqrt{\sum (y - \hat{y})^2 / df} \quad \text{Equation 6}$$

y: The observed value; $\hat{y}$: The predicted value; df: The degrees of freedom, calculated as the total number of observations – total number of model parameters.

Akaike Information Criterion (AIC): the measure of goodness of fit of a regression model. The regression equation with the lowest AIC value is the best estimator

$$AIC = -2 \ln(L) + 2p \quad \text{Equation 7}$$

Where p is the number of parameters in the regression model, L the likelihood of the data under the according regression model ln: natural logarithm

In forest biomass studies, the error variances for the allometric nonlinear equations based on arithmetical units of measurement are not constant over all observations (heteroscedasticity) in most cases. Using log-transformed data for linear regressions when estimating the parameters in nonlinear models is one of the most commonly used methods for eliminating the influence of heteroscedasticity, which measures the linear regression assumption. Due to this, the allometric equations were performed using a natural logarithmic transformation because the transformation corrects the data for heteroscedasticity (Astivia & Zumbo, 2019). The predicted values are on the x-axis. If the scatter plot does not show any pattern, it means the data are free from heteroscedasticity, and vice versa. With this transformation, the variances of the entire data were corresponding to meet the prerequisites of the linear regression. However,

log transformation introduces a systematic bias on the original scale that is generally corrected with a correction factor CF depending on the residual standard error (RSE).

Correction factor: according to the predicted value using log-transformed allometric equation is multiplied by CF to correct underestimation. The larger the RSE, the more uncertain regression models predict biomass values, and the larger the correction factor (Chave *et al.*, 2005).

$$CF = \exp\left(\frac{RSE^2}{2}\right) \quad \text{Equation 8}$$

CF Correction Factor, RSE =residual standard error,exp= exponential function

Validation was carried out after the allometric equations were performed. The equations were validated using independent data from model selection. That means the 25% set of data randomly selected from the total sampled trees (60 trees) was used to validate data. The predictive power of the allometric models or validated using mean absolute percentage error (MAPE) and Root mean square error (RMSE) (Djomo *et al.*, 2016).

$$1. \text{ MAPE (\%)} = \frac{100}{n} \sum_{i=1}^n \left| \frac{y - \hat{y}}{\hat{y}} \right| \quad \text{Equation 9}$$

$$2. \text{ RMSE} = \frac{1}{n} \sum_{i=1}^n (y - \hat{y})^2 \quad \text{Equation 10}$$

where y and y_i are observed AGB of the independent dataset and $\hat{y}$ and $\hat{y}_i$ are the AGB predicted using the allometric model being validated, n is the number of observations. A positive validation has previously been recommended when $-20\% \leq \% Y \leq 20\%$ (Huang *et al.*, 2003).

3.6. Comparison of the Current Model with the previous General Model

For comparison with the current models, four general models were selected. These models are frequently used in tropical forests, and in Ethiopia, the models were selected for comparison. and all models except for the (Brown, 1997)(Table 2). Models have three predictor variables. After selecting the allometric models, we calculated our mean AGB using the models and then predicted the biases. When applied to all 60 of the destructive data points. Besides these, to compare and display in further detail using the graphs of observed aboveground biomass

against the common variable D, which serves as the common variable for all of the chosen existing general models.

Table 2: Selected previously published models

Source	Predictor variable	Models Equation
(Chave <i>et al.</i> , 2005)	D, H, ρ	$\ln Y = -2.187 + 0.916 \ln(D^2 H \rho) / 0.112 (D^2 H \rho)^{0.916}$
(Chave <i>et al.</i> , 2014)	D, H, ρ	$\ln Y = 0.0673 (D^2 H \rho)^{0.976}$
(Brown, 1997)	D	$\ln Y = -2.134 + 2.53 \ln(D)$
(Mahmod <i>et al.</i> , 2019)	D, H, ρ	$\ln(B) = -2.46 + 2.171 \ln(D) + 0.367 \ln(H) + 0.161 \ln(\rho)$

$\ln Y$ = logarithm of total aboveground biomass: H= total Height D=Diameter at the breast

3.7. Tree Height Prediction Model Development and Selection

The total height had been used as the dependent variable in the height-diameter relationship model developed for smallholder plantations, and there was only one independent variable—the DBH variable. For this study, three height prediction models that have been widely applied in the past for different plantations were assessed and developed (Table 3). The developed and validation processes are similar in the AGB prediction model development: model fitting (75%), and for validation (25%), data are used. The best fit model was chosen according to the highest and lowest values of $\text{adj}R^2$, RSE, and AIC, respectively, which are statistical analyses used to assess goodness of fit used for model selections are sufficient when used together (Chave *et al.*, 2005).

Table 3: Allometric equation types developed for total height prediction model for *Eucalyptus globulus*

Mod No.	Predictor	Equation type	Source
M1	DBH	$H = a + bDBH^2$	(Adeyemi and Ukaegbu, 2016; Koirala <i>et al.</i> , 2017)
M2	DBH	H	
M3	DBH	$= a + bDB + c DBH^2$ $\ln(H) = a + b\ln(DBH)$	

Chapter 4. RESULT AND DISCUSSION

4.1. Characteristics of the Measured Trees

The summary of both data sets (model development and model validation) is presented in Table 4. Accordingly, the mean values of DBH, height, wood density, and total dry aboveground biomass in the model fitting data were 6.33 cm, 9.96 m, 0.36 g/cm³, and 6.73 kg, respectively.

Similarly, the mean values of DBH, height, wood density, and total dry aboveground biomass for model validation data were 6.24 cm, 9.71 m, 0.35 g/cm³, and 6.56 kg, respectively (table 4). The summary result showed no significant difference in data arithmetic variables between model development and validation data. This minimized personal errors or bias in validating allometric models developed using the fitting of development data.

Table 4: Statistical summary for tree parameters used in developing or fitting and validating allometric models for aboveground biomass estimation and height prediction model

Tree parameters	Fitting data (n=43)				Validation data (n=17)			
	Mean.	Max.	Min.	Sd.	Mean.	Max.	Min.	Sd.
DBH (cm)	6.33	12	2	2.97	6.24	12	2.1	3.21
Height (m)	9.96	14.2	5.2	2.37	9.71	14.2	5	2.97
Wood density (gcm ⁻³)	0.36	0.71	0.18	0.12	0.35	0.64	0.09	0.13
Dry biomass (kg)	6.73	23.46	0.67	6.41	6.56	23.94	0.68	6.67

The correlation between measured tree parameters (height, diameter, and wood density) and total aboveground biomass is presented (Figure 2). As shown in the graph, the total aboveground biomass had a positive correlation with total tree height and diameter at the breast both graphs are rise in right. However, the wood density didn't show either an increasing or decreasing trend against the aboveground biomass no cluster pattern (Stegenet *al.*, 2009).

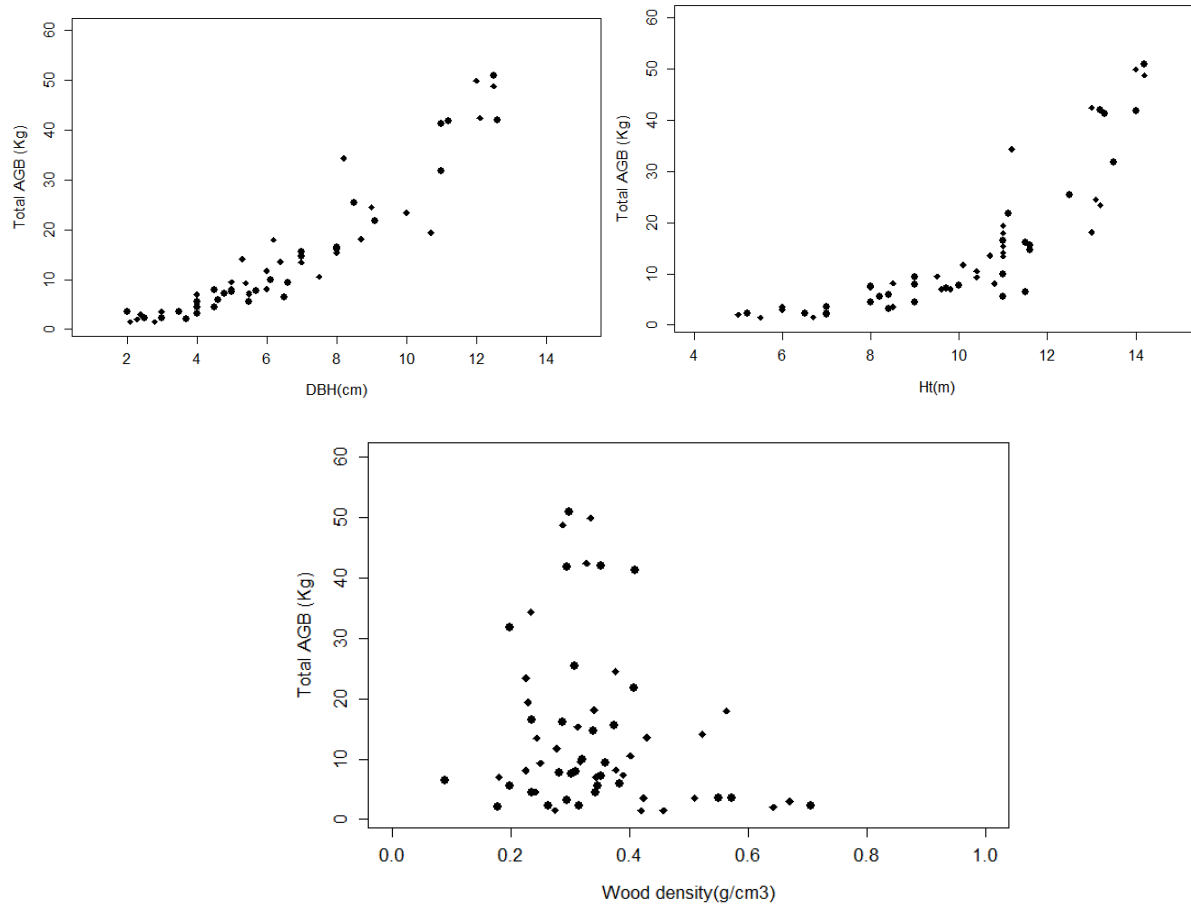


Figure 2: Scatter plot of tree aboveground tree biomass (AGB) vs. potential predictor variables (diameter, height, and wood-specific density).

4.2. Model development and selection

In this study, eight allometric equations were assessed and developed to estimate the total aboveground biomass of *Eucalyptus globulus* plantations (Table 5). Two of the models (M1 and M2) of the eight allometric equations were created using normal data, while the remaining six model equations (M3–M8) were created using log-transformed data. The results showed that coefficient determination ($\text{adj } R^2$) values varied from 0.866 to 0.94, which implies the aboveground biomass could be explained by 94% with the developed model. The residual standard error ranges from 0.230 to 4.98; the Akaike Information Criteria ranges from 1.297 to 264.04; and the correction factor ranges from 1.027 to 1.055 were the statistically well-fitting values. Model M6 had the highest coefficient determination ($\text{adj } R^2$) value among the

developed models, whereas model M1 had the lowest coefficient determination ($\text{adj}R^2$) value. The residual standard error (RSE) value of model one (M1) was greater than that of model six (M6). In terms of Akaike information criteria, AIC, model five (M5) had the smallest value, model one (M1) had the greatest, and in terms of the correction factor (CF), model M6 had the smallest value and model 4 had the largest value from the developed model (Table 5). In this study, coefficient determination ($\text{adj} R^2$) values greater than or equal to 0.86%, which is near 1, indicate that all the created models fit well. It has been reported that as the $\text{adj} R^2$ value is closer to 1, the model is considered the best to explain the aboveground biomass of trees (Chicco et al., 2021) (Table 5).

Table 5: Developed allometric model to estimate total aboveground biomass *Eucalyptus globulus* smallholder plantation in this study

Mod.	Equation Type	A	B	C	D	Adj.R ²	RSE	AIC	CF	Rank
M1	$Y = a + bD^2$	-12.782	4.28			0.866	4.98	264.04	-	8
M2	$Y = aD + bD^2$	14.322	82.361	17.5		0.904	4.214	250.63	-	7
M3	$\ln(Y) = a + b\ln(D)$	-0.965	1.847			0.878	0.328	30.11	1.055	5
M4	$\ln(Y) = a + b\ln(D) + c\ln(H)$	-2.854	1.201	1.327		0.897	0.302	23.88	1.047	6
M5	$\ln(Y) = a + b\ln(D) + c\ln(\rho)$	-0.608	2.013	0.577		0.910	0.282	18.15	1.041	3
M6	$\ln(Y) = a + b\ln(D) + c\ln(H) + d\ln(\rho)$	-2.875	1.243	1.631	0.6	0.940	0.230	1.297	1.027	1
M7	$\ln(Y) = a + b\ln(D^2 * H)$	-2.047	0.747			0.895	0.304	23.60	1.047	4
M8	$\ln(Y) = a + b\ln(D^2 * H * \rho)$	-1.602	0.831			0.931	0.247	5.58	1.031	2

Model M2, which uses only D as a predictor variable, was found to be better with an $\text{adj}R^2$ value than M4 and M7, which use both D and H as predictor variables. That means M2 using only D as a predictor could explain about 90.4% of the variability during aboveground biomass estimation. This result agreed with the regional biomass model (Basuki *et al.*, 2009; Kuyah, 2012) which reported that adding height as a predictor did not improve the aboveground biomass estimation performance of allometric models.

Generally, this study in model M1 developed model showed that tree diameter alone is a strong and important predictor variable, explaining most of the variability in the AGB (86.6%–90.4%). This result is consistent with the previous studies in Ethiopia (Mulugeta

Zewdie *et al.*, 2009 ; Birhanu kebede &Teshome Soromessa, 2018;Amsalu Abich *et al.*, 2019)for plantation and natural ecosystem respectively and also in western Kenya (Kuyah, 2012; Kuyah *et al.*, 2013;) for agroforestry system for *Eucalyptus saligna* species and pan tropical equation (Brown *et al.*, 1989 ; Brown, 1997). All of which suggested that allometric models using D alone are strong predictor models for aboveground biomass estimation. In addition, measuring the tree diameter is very easy, cheap, and accurate compared to other tree parameters.

Of course, using H and D as compound predictor variables improved the overall accuracy of allometric models. For example, unlike M2, M4, and M7, they added H as a predictor variable, which greatly decreased the models' RSE and AIC values. It implies that the accuracy of models in aboveground biomass estimation improved when combining H and D as predictor variables. Similar to what(Gadisa Demie *et al.*,2023)reputed for native perennial plant the agricultural landscape of Central Ethiopia, and (Segura, 2005) reported for the tropical humid forests in Costa Rica¹, the model fit improved by adding H allometric model development and in general model (Chave *et al.*, 2005; 2014) for all types of forest. Conclude that height is a commonly used variable; it can lead to less biased estimates of the aboveground biomass. When model fitting includes height as a predictor variable, as studied by (González *et al.*,2013) which was increase the Accuracy of the model. According to (Feldpausch *et al.*,2011), tree height at various sites with varying allometry is an important independent variable, and this is also the case in the current study.

Adding woody density as the predictor variable in the D-based model, in this study, AGB was improved and a good fit explained 91%, reducing RSE and AIC than adding height (M5). The results agree with the previous study on the tropical biomass equation (Chave *et al.*, 2014 , 2005;Djomo *et al.*, 2010), and regional mixed species (Basuki *et al.*, 2009; Kuyah, 2012; Mukuralinda *et al.*, 2021) and for mixed secondary forests (Ketterings *et al.*, 2001; Xu *et al.*, 2015). Research findings demonstrated that wood density must be taken into consideration when including Species -specific equations in order to improve accuracy and yield a more accurate estimate of biomass. When comparing DBH, height, and wood density, the influence of wood density becomes quite noticeable. Allometric models that included wood density as a predictor variable with diameter greatly reduced the RSE and AIC and increased the R^2

compared to total tree height. This implies adding woody density to the model as the predictor with diameter has improved the predictive performance of the models and aboveground estimation accuracy (M5). However, the findings in this study showed that woody density is a very important predictor variable for aboveground biomass estimation. Allometric models of *Eucalyptus globulus* smallholder plantation forests in the study area than the Adding height as the predictor variable. Fitting the model and increasing the accuracy of the predictive model,

Model M6 and model M8 were able to predict the variation of AGB in about 93%–94% of smallholder plantations (Table 6). This showed that the combination of total height and woody density with tree diameter as predictor variables highly improved the accuracy of allometric models to estimate the AGB of *Eucalyptus globulus* tree planation at smallholder levels. Several previous studied models, like the general pan-tropical equation and regional biomass equation (Nelson *et al.*, 1999; Chave *et al.*, 2005,2014; Djomo *et al.*, 2010) and in Ethiopia species- specific model (Amsalu abich *et al.*, 2021; Dessie Assefaet *et al.*, 2022). also showed similar results that allometric models' performance in estimating aboveground biomass was enhanced in combing three tree parameters (height, diameter and wood density).

Table 5: Mean absolute percentage error (MAPE(%)) and relative root mean square error (RSME) for AGB estimation allometric equations developed using a 25% (17) independent set of data.

Mod.	Equations	MAPE (%)	RMSE (kg)	Rank
M1	$Y = -12.782 + 4.28D^2$	80.64	5.44	8
M2	$Y = 14.322 + 82.361D + 17.5D^2$	26.48	3.57	7
M3	$\ln(Y) = -0.965 + 1.847\ln(D)$	25.32	4.31	5
M4	$\ln(Y) = -2.854 + 1.201\ln(D) + 1.327\ln(H)$	25.71	4.30	6
M5	$\ln(Y) = -0.608 + 2.013\ln(D) + 0.577\ln(\rho)$	18.52	2.94	3
M6	$\ln(Y) = -2.875 + 1.243\ln(D) + 1.631\ln(H) + 0.665\ln(\rho)$	15.71	2.88	1
M7	$\ln(Y) = -2.047 + 0.747\ln(D^2 H)$	25.40	4.21	4
M8	$\ln(Y) = -1.602 + 0.831\ln(D^2 H^2 \rho)$	19.20	3.14	2

Note: Total dry aboveground biomass (Y), Diameter at breast height (D), total tree height (H)

Generally, based on the four model selection criteria, Model 6 ($\ln Y = -2.875 + 1.243 (D) + 1.631 (H) + 0.665 (\rho)$), which combined three predictor variables, was found to be the first-ranked best allometric model. Model six recorded the highest adj R^2 (0.94) and the lowest RSE (0.230) and CF (1.027) values of all tested models. Similarly, Model M8 ($\ln Y = -1.602 + 0.831 \ln(D^2 H \rho)$) was the second-ranked best model next to Model M6 and had the second highest R^2 (0.931) and the lowest RSE (0.247), AIC (5.58) and CF (1.031) next to Model M6.

The finding of this study that the allometric model, which uses three predictor variables (D, H, and ρ), gave the best performance (M6) agreed with the findings of the of the species -specific model for peat swamp forests in *Combretum-Terminalia* woodlands in Ethiopia (Amsalu Abich *et al.*, 2021) Respectively, and for pan-tropical biomass equations (Nelson *et al.*, 1999; Chave *et al.*, 2005). The selected model M6 Showed The majority of the variation in the increase in aboveground tree biomass in the current study can be explained by DBH when combined with wood density and total height.

4.3 Model Validation

To rank the final best model out of the selected models, MAPE and RMSE were calculated using a 25% independent data set of trees (Table 6). The validation result showed that the MAPE% value of selected models ranged from 15.71% to 80.64%. Accordingly, M6, combining diameter, height, and wood density as ($\ln Y = a + b \ln D + c \ln H + d \ln \rho$) showed the lowest MAPE (15.71%). The expected value of MAPE is zero and a percentage different from zero shows the deviation of predicted mean AGB by the given model relative to the observed mean AGB. Hence, M6 is the best model of all the tested models with the lowest prediction error relative to the observed AGB. Similarly, Since the relative value of the residual is squared, RMSE offers a strong tool for both validating equations and determining the final ranking in allometric models (Dijomo *et al.*, 2016). The validation results still showed that M6 was found to be the best model with the lowest RMSE (2.88) errors produced in this models to estimate the *Eucalyptus globulus* smallholder plantations is reduced .

The diagnostic scattered residual plots against the predicted AGB for the three selected models are presented in Figure 5. The diagnostic scattered residual plots against the predicted AGB of the three selected best-fitted AGB models for our study species-specific model indicate an even spread of residuals above and below the zero line with no systematic trend (Figure 3). This suggests that natural log-transformed multiple linear regressions are effective in stabilizing error variance, and this shows model appropriateness for reducing heteroscedasticity (no constant error in the observed data. The best-selected model (M6) errors in the residual plots were uniformly distributed between ± 6 , which implies that the mean difference between observed and predicted could be zero (Packard, 2013)(Figure 3). This indicates that the selected models (M6) had a good fit.

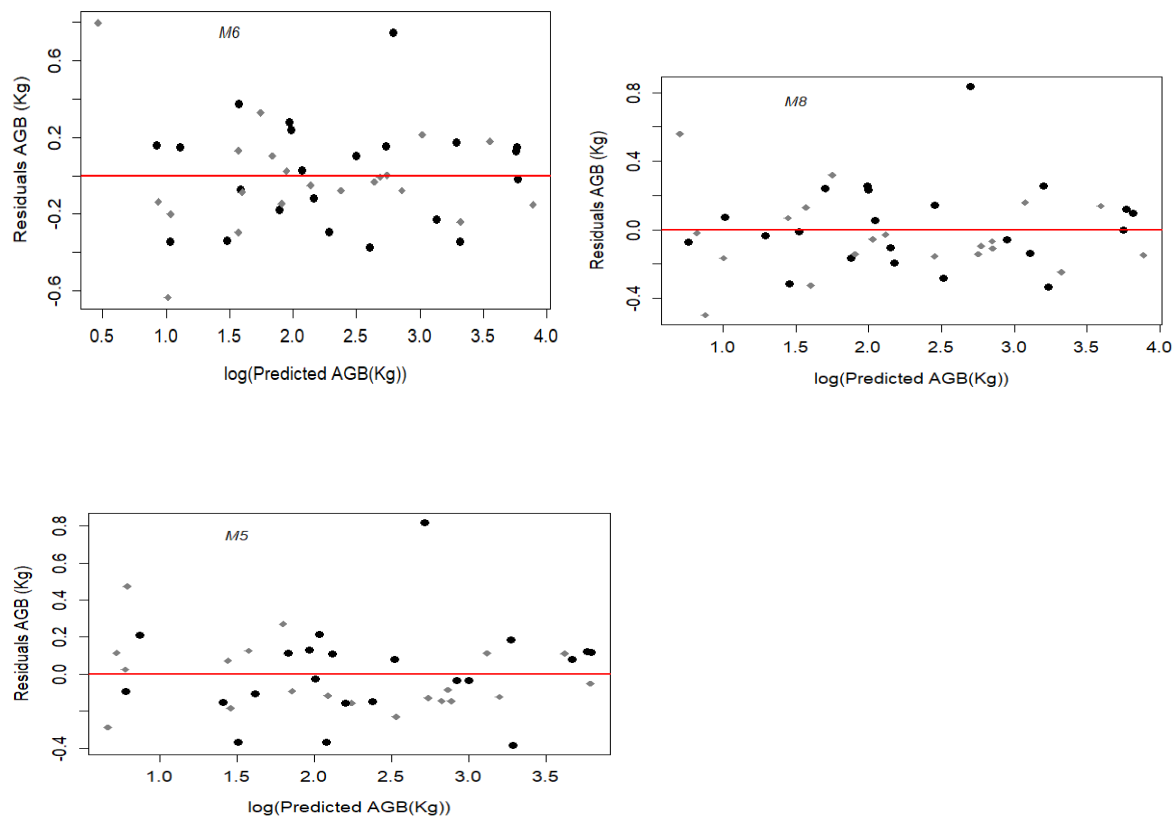


Figure 3: Scatter plots of residual values versus predicted value of the three best allometric fit models Predicted value in log scale

4.4. Comparison of the Current Model with the Previously General Models

The current species-specific allometric aboveground biomass models developed in this study (M6) were compared with the four existing common general allometric models (Table 7).

Table 6: Comparison of the current best selected model with the existing models using the whole measured data (N=60).

Models sources	Mean biomass(kg/Tree)		Bias (%)
	Measured	Predicted	
Current selected model	14.22	13.92	-2.11
(Chave <i>et al.</i> , 2005)		12.53	-11.88
Chave <i>et al.</i> , 2014)		10.56	-25.74
(Brown, 1997)		18.13	27.50
Mahmood <i>et al.</i> , 2019)		12.26	-13.78

The result showed that the predicted AGB, with the current general-compared models, ranged from 10.56 kg to 18.13 kg. Similarly, the relative error of the current study model (M6) and general developed models ranged from -2.11% to 27.5%. Hence, the current study model (M6) recorded the lowest relative bias error (-2.11%) of the other general models. This shows that using general models as AGB estimation models for Eucalyptus plantations in the study area could either highly underestimate or overestimates the AGB. This finding implies that the use of the general model is associated with biased estimates of aboveground biomass (AGB) when they are applied at a particular site and species (Henry *et al.*, 2011; Mugusha *et al.*, 2013). Hence, Species-specific allometric equations are very important to boost the prediction accuracy of models.

According to (Huang *et al.*, 2003). A bias of less than $\pm 10\%$ is considered acceptable, which is recommended as the bias measure of systematic deviation of model prediction from measured data. The average deviation for individual trees of the previously published models is always higher than that of model M6 (Table 7). As presented in Table 7, the allometric equations of (Chave *et al.*, 2005; 2014), and (Mahmood *et al.*, 2019), showed an underestimation of AGB compared to the observed AGB, whereas (Brown, 1997) overestimated the predicted AGB value.

The total AGB versus DBH plot graph (Figure 4) showed that the current model (M6) approximately estimates by -2.11% of the observed data in the previous general model. The purple cross represented the -11.88% underestimation of AGB in the (Chave *et al.*, 2005) model: $\ln Y = -2.187 + 0.916 \ln(D^2 H \rho) / 0.112 (D^2 H \rho)^{0.916}$. A green cross was underestimated by -25.74% using the model (Chave *et al.*, 2014), $\ln Y = 0.0673 (D^2 H \rho)^{0.976}$. In addition to overestimating AGB by (Brown, 1997) 27.50%, the model, $\ln Y = -2.134 + 2.53 \ln(D)$. (Mahmood *et al.*, 2019) model, the red curve represents a -13.78% underestimate of AGB $\ln(Y) = -2.46 + 2.171 \ln(D) + 0.367 \ln(H) + 0.161 \ln(\rho)$. According to this findings (Chave *et al.*, 2005), the model seems to perform better when compared to the other three general models and becomes underestimated. So using the four previously developed general models applied in this study to estimate *Eucalyptus globulus* species became underestimation and overestimation because models should be applied to specific DBH sites and species ranges (Chave *et al.*, 2005; 2014; Henry *et al.*, 2011; Mugusha *et al.*, 2013).

In general, this finding concludes that there were variations in the aboveground biomass using the general equation and the specific equation. When using general allometric models, the equations' estimations varied and the errors increased (Figure 4). Similar to this, a general allometric model is shown for a range of sites that could expand over a wider geographic area, but it excludes different factors that could affect the biomass of trees. However, as the name suggests, the species-specific approach is highly specialized for a specific site in a certain environmental condition in particular, such as stand growth, age, and management. As a result, using the current models is appropriate for estimating the aboveground biomass of smallholder plantations of *Eucalyptus globulus*. In addition, when there is no available height and woody density data using model M2, which uses only diameter as a predictor variable, it is more preferable to estimate the AGB of *Eucalyptus globulus* plantations in the study area.

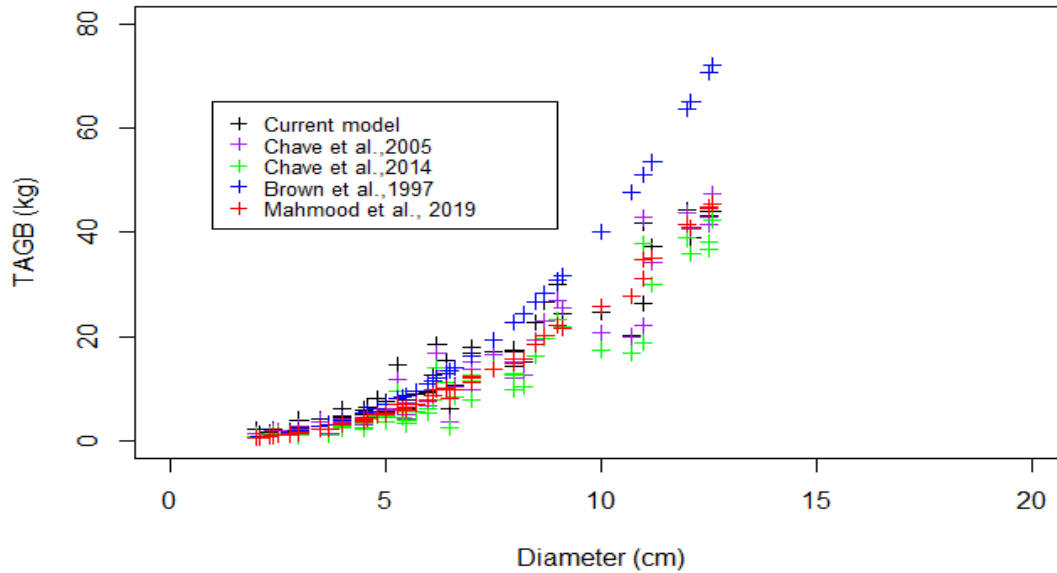


Figure 4: Comparison of the current model with previously general equation used to estimate aboveground biomass of smallholder plantation of *Eucalyptus globulus* tree.

4.5. Height Prediction Model Development and Selection

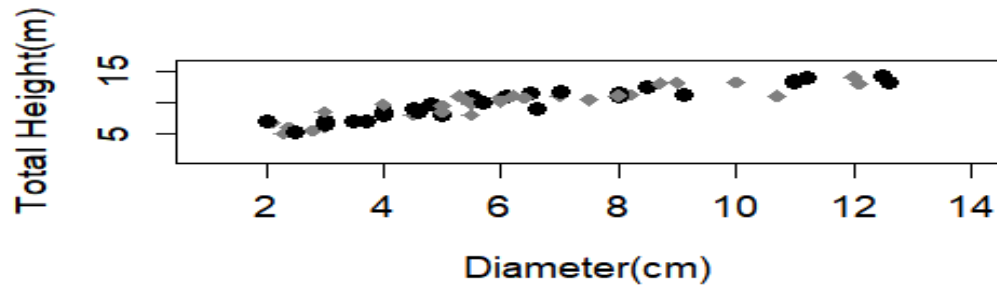


Figure 5: Scatterplots of Total height versus the potential of predictor Diameter

To understand the relationship between diameter and height, we used a scatter plot graph. The correlation between the diameter and the height of the scatter plot showed that the trend increased with the diameter increase (see figure 5). This indicates a strong positive relationship. The coefficient determination ($\text{adj}R^2$) values for models ranged from 0.81 to 0.86 (Table 8). This shows that the developed models were well fitted, and the dependent

variable height of smallholder plantations was predicted by 81% to 86% with the independent variable diameter parameter, which indicates the study area easily by measuring the diameter and can be used to predict the total height. This result also agrees with (Liu *et al.*, 2017), pointed out that the diameter at breast height used as the independent variable in the allometry equation of tree height can more accurately represent the change in tree height.

Table 7: Developed Allometric model to prediction total height of *Eucalyptus globulus* smallholder plantation

Mod.	Equation Type	A	B	C	d	Adj.R ²	RSE	AIC
M1	$H=a+bD^2$	5.29	0.74			0.81	1.02	142.82
M2	$H=a+D+D^2$	10.04	14.73	-3.71		0.86	0.88	128.85
M3	$\ln(H)=a+b\ln(D)$	1.40	0.5			0.84	0.10	-78.6

$\ln H$; natural logarithm of height H ; Height D ; Diameter M modela, b , c and d are the model's fitted parameters; RSE is the residual standard error; Adj R^2 is the coefficient of determination, AIC is the Akaike Information Criterion, CF is Correction factor and $n = 43$.

The RSE ranged from 0.102 to 1.09, and the AIC ranged from -78. to 142.82. The largest RSE was recorded by model M1, while the lowest model, M3, based on the three good fitnesss (Table 8), ranked the best model, M3, log models, which is rankly the first selected model from the three developed models. Followed by model M2, whereas model M1 was the last-ranked model the developed height-diameter models are presented in Table 8.

According to the criteria used for selecting the most suitable prediction model (M3), the logarithmic height-diameter functions performed better than the two models for tree height predictions in the smallholder plantation. This model recorded the highest adjR2 (0.84) and the lowest RSE (0.10) and AIC (-78.6). Although the adjR2 value (0.84) was lower than the values reported by (Adeyemi and Ukaegbu, 2016) between 0.75 and 0.9 for *Gmelina arborea* plantations, (Caetano *et al.*, 2014), ranging from 0.82 to 0.95 for brazil nut trees, and in Ethiopian Geda forest, ranging from 0.88 to 0.89 for *Cupressus lusitanica* (Mengsha Tsega *et al.*, 2018).

This finding suggests that the height was influenced by the type of species the site, and the. Each type of species requires a different height diameter relation model for each plantation species. According to (Vieilledent *et al.*, 2012), a basic height-diameter allometry is required to accurately estimate biomass and carbon stocks from plot inventories when biomass allometric models for a specific species are not present. This study supported these findings and developed the logarithm height model for small plantations found in the study area and similar geographical areas to estimate accurate aboveground biomass. The selected model was validated by using the scattered plot residual and observed plots against predicted height. The best-selected models are presented in Figure 6, model M3.

The figure shows that the mean error (observed minus predicted) was approximately zero, which implies that the model was a good fit. Also, the observed versus predicted scatter plot shows that the points are close to each other, which indicates the model was a good fit and is equally distributed (Koirala *et al.*, 2017).

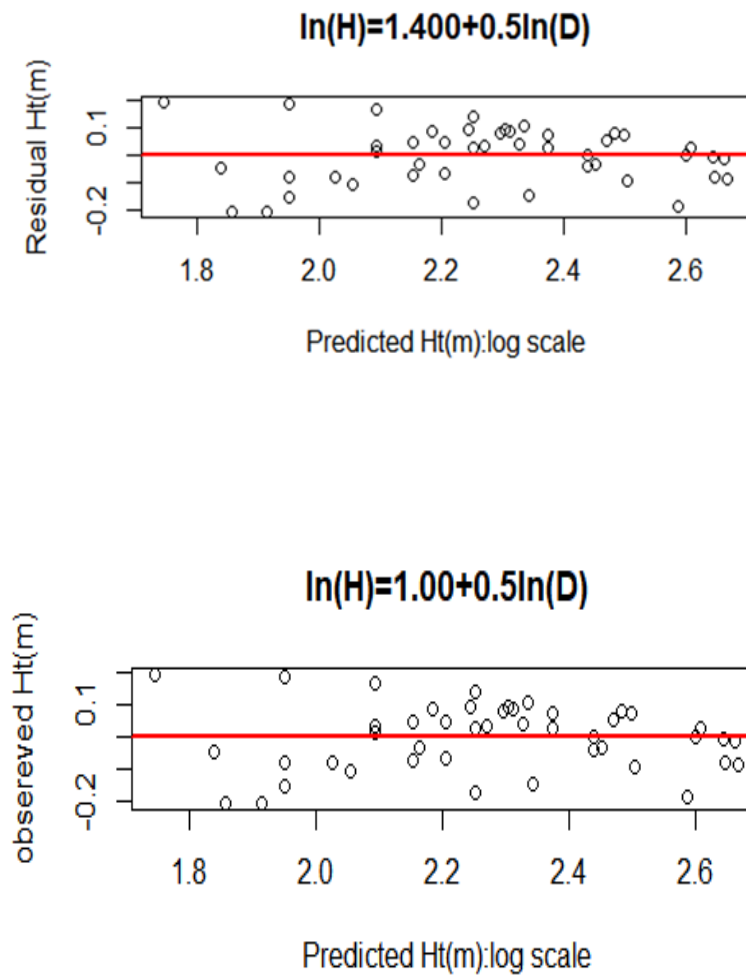


Figure 5: Residual and observed plots against predicted height for the best-fit model for this study

Chapter 5. CONCLUSION

This study developed eight species-specific aboveground biomass estimation allometric models by using 60 destructive sample trees for *Eucalyptus globulus* smallholder plantations. The diameter range is 2.1–12.6 cm. This finding in model M1 showed that using tree diameter as a single predictor variable highly decreased the aboveground prediction efficiency of allometric models. Developed M4 and M5, similarly combining tree diameter and tree height, still resulted in lower accuracy in estimating the AGB of the plantation. However, the selected best-fitted model, M6, combining the three predictor variables (diameter, height, and wood-specific density), allometric models, highly improved the aboveground biomass estimation of the models. According to the developed measuring criteria, the best-fitted model is the one that combines the three predictor variables in the form of $\ln(Y) = -2.875 + 1.243\ln(D) + 1.631\ln(H) + 0.665\ln(\rho)$ used to estimate the aboveground biomass of the Eucalyptus plantation in Wogera district. This developed model still showed better aboveground biomass estimation potential compared with the other four existing general models, which have been used by many researchers in different parts of the world and reduced the errors of estimation. On the other hand, the best-developed height prediction model was: $\ln(H) = 1.400 + 0.5 \ln(D)$, which could help to estimate tree height using measured tree diameter. Because, in reality, measuring tree height, especially in dense plantation forests, is very challenging and time-consuming. Hence, such diameter-height relation allometric models are very important to estimate the height of each tree with its measured diameter at breast height.

Chapter 6. RECOMMENDATION

Based on these findings, it is recommended to estimate the aboveground biomass of such plantations using species-specific allometric models. This can avoid the underestimation or overestimation of biomass production, which could affect both the grower and buyers during the selling and buying of plantations in the study area. In this study, it is recommended to use the three variables (tree diameter, height, and wood density). For estimating the aboveground biomass of *Eucalyptus globulus* smallholder plantation in Wogera

District Of course, it is not always easy to measure and use all the required tree variables. Hence, selecting and using better allometric model equations that use diameter only as a predictor variable is recommended. Model M2 in this study is recommended to use easily measured diameter and estimate the biomass of the *Eucalyptus globulus* smallholder plantations in the study area.

REFERENCE

- AbebeBiraraDessie,MirieAbate Tadie, TayeMeleseMekie. (2019).Eucalyptus :The Popular Exotic Tree Crop in Ethiopia.Acta Scientific Agriculture.3:50–56. <https://doi.org/10.31080/ASAG.2019.03.0607>.
- Adeyemi, A.A. and Ukaegbu, O. C. (2016). Tree height-diameter and yield functions for *Gmelina arborea* (roxb.) stand in edondon gmelina plantation, cross river state, nigeria.Journal of Research in Forestry.8(2): 126–144.
- Admassu, A., Teshome, S., & Tura, B. (2022). Allometric Equation for Aboveground Biomass Estimation for Selected Trees Shrubs in Gesha-Sayilem Moist Afromontane Forest. Journal of Forest Research, 11(4): 1–8. <https://doi.org/10.35248/2168-9776.22.11.323>.
- Alemayehu Asabeneh &, & Melka Yoseph. (2022). Small scale eucalyptus cultivation and its socioeconomic impacts in Ethiopia : A review of practices and conditions. Trees, Forests and People.(8), 100269. <https://doi.org/10.1016/j.tfp.2022.100269>.
- Amsalu Abich, Tadesse Mucheye, Mequanent Tebikew, Yohannis Gebremariam, Asmamaw Alemu. (2019). Species-specific allometric equations for improving aboveground biomass estimates of dry deciduous woodland ecosystems. Journal of Forestry Research, 30(5), 1619–1632.
- Amsalu Abich, Asmamaw Alemu, Yohannis Gebremariam, Tadesse Mucheye, Kassaye Gurebiyaw, Meseret Kassie. (2021). Allometric models for predicting aboveground biomass of *Combretum-Terminalia* woodlands in Amhara, Northwest Ethiopia.Trees, Forests and People. 5: 100122.
- Antonio, N., Tomé, M., Tomé, J., Soares, P., & Fontes, L. (2007). Effect of tree, stand, and site variables on the allometry of *Eucalyptus globulus* tree biomass. Canadian Journal of Forest Research, 37(5), 895–906.
- Astivia, O. L. O., & Zumbo, B. D. (2019). Heteroskedasticity in multiple regression analysis: What it is, how to detect it and how to solve it with applications in R and SPSS. Practical Assessment, Research and Evaluation, 24(1), 1–16.

- Author, V., Vaudry, R., Andriamanohisoa, S. F. D., Rakotonarivo, O. S., Razafindrabe, H. N., Rakotoarivony, C. B., Ebeling, J., Vieilledent, G., Vaudry, R., Andriamanohisoa, S. F. D., Rakotonarivo, O. S., & Randrianasolo, H. Z. (2012). A universal approach to estimate biomass and carbon stock in tropical forests using generic allometric models. *The Ecological Society of America A*, 572=583.
- Banerjee, K., Sahoo, C. K., Bal, G., & Paul, R. (2022). Allometric model based on dendrometrical measurements in mangroves of western Bay of Bengal. *Tropical Ecology*, 63(3), 351–364. <https://doi.org/10.1007/s42965-021-00215-9>
- Barbati, A., Brusselen, J. Van, & Lindner, M. (2007). *The Role of Forests in Carbon Cycles, Sequestration, and Storage: "Climate Change Mitigation, Forest Management and Effects on Biological Diversity*. News letter.5.
- Basuki, T. M., Leksono, B., Baral, H., Andini, S., Wahyuni, N. S., Artati, Y., Choi, E., Shin, S., Kim, R., Yang, A., Samsudin, Y. B., & Windyarini, E. (2022). Allometric Equations for the Biomass Estimation of *Calophyllum inophyllum L.* in Java , Indonesia. 1–15.
- Basuki, T. M., van Laake, P. E., Skidmore, A. K., & Hussin, Y. A. (2009). Allometric equations for estimating the above-ground biomass in tropical lowland Dipterocarp forests. *Forest Ecology and Management*, 257(8): 1684–1694. <https://doi.org/10.1016/j.foreco.2009.01.027>
- Belayneh Dessie, Mintesinot Taye¹, Zablun Adane, Ayana Jember (2022). Analysis of soil carbon and income over *Acacia decurrens* and *Eucalyptus globulus* land uses in the highlands of Ethiopia. *Journal of Environmental Studies and Sciences*, 1-12. <https://doi.org/10.1007/s13412-022-00784-8>.
- Birhanu kebede & Teshome Soromessa. (2018). Allometric equations for aboveground biomass estimation of *Olea europaea L.* subsp. *cuspidata* in Mana Angetu Forest. *Ecosystem Health and Sustainability*, 4(1): 1–12 <https://doi.org/10.1080/20964129.2018.1433951>.

- Biruk Ketsela Hailemichael. (2012). *The Contribution of Eucalyptus Woodlots to the Livelihoods of Small Scale Farmers in Tropical and Subtropical Countries with Special Reference to the Ethiopian Highlands*. Master Thesis. In Swedish University of Agricultural Sciences Faculty of Forest Sciences Department (Issue 89), 1654-1367.
- Blake, S. T., Nusa, E., Sadono, R., Wardhana, W., Yudha, P., Putra, A., & Idris, F. (2021). *Allometric Equations for Estimating Aboveground Biomass of*. *jtfm*. 27:24–31. <https://doi.org/10.7226/jtfm.27.1.24>.
- Bosques, D. E. N., & Secundarios, T. (2019). species-specific biomass equations for small-size tree species in secondary tropical forests. *Tropical and Subtropical Agroecosystems*, 22: 735–754.
- Brown. (1997). *Estimating Biomass and Biomass Change of Tropical Forests*: Food and Agriculture Organization of the United Nations, Rome .
- Brown S, Gillespie AJR, Lugo AE (1989) Biomass estimation methods for tropical forests with applications to forest inventory data. *For Sci* 35(4):881–902.
- Caetano, A. C., Ribeiro, S. C., de Macedo, R. L. G., & Dias, B. A. S. (2014). Height-diameter equations for Brazil nut intercropped with rubber tree in the South of Minas Gerais. *Floresta*, 44(3), 497–504. <https://doi.org/10.5380/rf.v44i3.32514>.
- Calfapietra, C., A. Barbati, L. Perugini, B. Ferrari, G. Guidolotti, A. Quatrini, and P. Corona. 2015. Carbon stocks and potential carbon sequestration of different forest ecosystems under climate change and various management regimes in Italy. *Ecosystem Health and Sustainability* 1(8):25. <http://dx.doi.org/10.1890/EHS15-0023>.
- Canadell, J. G., & Raupach, M. R. (2008). Managing forests for climate change mitigation. *Science*, 320(5882), 1456–1457. <https://doi.org/10.1126/science.1155458>
- Chave J, Andalo C., Brown S, Cairns MA, Chambers JQ., Eamus D, Fořlster H., Fromard F., Higuchi N, Kira T., Lescure JP., Nelson BW, Ogawa H, Puig H, Rieřra B, Yamakura T (2005) Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia* 145:87–99.

- Chave J, Rejou-Mechain M, Buřquez A, Chidumayo E, Colgan MS, Delitti WB, Duque A, Eid T, Fearnside PM, Goodman RC, Henry M, Martınez-Yrızar A, Mugasha WA, Muller-Landau HC, Mencuccini M, Nelson BW, Ngomanda A, Nogueira EM, Ortiz-Malavassi E, Peřlissier R, Ploton P, Ryan CM, Saldarriaga JG, Vieilledent G (2014) Improved allometric models to estimate the aboveground biomass of tropical trees. *Glob Change Biol* 20:3177–3190.
- Chicco, D., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Computer Science*, 7: 1–24. <https://doi.org/10.7717/PEERJ-CS.623>
- Condit, R. (2008). Methods for estimating above - ground biomass of forest and replacement vegetation in the tropics. Center for Tropical Forest Science Research Manual. 73pp.
- Damena Edae Daba and Teshome Soromessa. (2019). The accuracy of species-specific allometric equations for estimating aboveground biomass in tropical moist montane forests: case study of *Albizia grandibracteata* and *Trichilia dregeana*. *Ecosystem Health and Sustainability*. 5(1), 86–97. <https://doi.org/10.1080/20964129.2019.1591169>.
- Dagm Fiker Abate . (2020). *An ecological-economic approach to assess impacts of Eucalyptus Woodlot Expansion in Agroforest Landscapes of Northern Ethiopia*, Master Degree, de Agronomia, Universidade de Lisboa Brigitte, Portugal 49pp.
- DeLucia, E. H., Maherali, H., and Carey, E. V. (2000). Climate-driven changes in biomass allocation in pines. *Global Change Biology*, 6(5):587–593. <https://doi.org/10.1046/j.1365-2486.2000.00338.x>.
- Dessie Assefa., Asnake Mekuriaw , Mathias Tesfaye, Habtamu Sewnet, Beyene Belay. (2022). Mapping of *Prosopis juliflora* rate of expansion and developing species - specific allometric equations to estimate its aboveground biomass in the dry land of Ethiopia. *Modeling Earth Systems and Environment*, 0123456789. <https://doi.org/10.1007/s40808-022-01495-3>

- Djomo, A. N., Ibrahima, A., Saborowski, J., & Gravenhorst, G. (2010). Allometric equations for biomass estimations in Cameroon and pan moist tropical equations including biomass data from Africa. *Forest Ecology and Management*, 260(10): 1873–1885. <https://doi.org/10.1016/j.foreco.2010.08.034>
- Djomo, A. N., Picard, N., Fayolle, A., Henry, M., Ngomanda, A., Ploton, P., McLellan, J., Saborowski, J., Adamou, I., & Lejeune, P.(2016).Tree allometry for estimation of carbonstocksinAfricantropical forests*Forestry*.89(4):446–455. <https://doi.org/10.1093/forestry/cpw025>.
- Ebuy, J., Lokombe, J. P., Ponette, Q., Sonwa, D., & Picard, N. (2011). Allometric equation for predicting aboveground biomass of three tree species. *Journal of Tropical Forest Science*, 125–132.
- Ekoungoulou, R., Nzala, D., Liu, X., & Niu, S. (2018). Tree Biomass Estimation in Central africanforestsusing allometricmodels.209–237. <https://doi.org/10.4236/oje.2018.83014>.
- Fauzi, M. I. D., & Rohadi, D. (2015). Complex regulatory frameworks governing private smallholder tree plantations in Gunungkidul District , Indonesia. *Forest Policy and Economics Journal*. 59(1–6).Www.Elsevier.Com/Locate/Forpol Complex.
- Fayolle, A., Doucet, J., Gillet, J., Bourland, N., & Lejeune, P. (2013). Forest Ecology and Management Tree allometry in Central Africa : Testing the validity of pantropical multi-species allometric equations for estimating biomass and carbon stocks. *forest ecology and management*,305:29–37. <https://doi.org/10.1016/j.foreco.2013.05.036>
- Feldpausch T. R., L. Banin¹,O. L. Phillips¹, T. R. Baker¹, S. L. Lewis¹, C. A. Quesada,K. Affum-Baffoe, E. J. M. M. Arets, N. J. Berry¹, M. Bird, E. S. Brondizio, P. de Camargo, J. Chave, G. Djagbletey, T. F. Domingues,M. Drescher, P. M. Fearnside,M. B. Franc., N. M. Fyllas, G. Lopez-Gonzalez, A. Hladik, N. Higuchi, M. O. Hunte, Y. Iida, K. A. Salim, A. R. Kassim, M. (2011).Biogeosciences, 8: 1081–1106.
- Gadisa Demie, Mesele Negash, Zerihun Asrat, Lojka Bohdan.(2023). Species-specific and multi-species allometric models for estimating aboveground biomass of native perennial

- plant species grown in the agricultural landscape of Central Ethiopia. *AgroforestSyst* **98**, 179–196 (2024). <https://doi.org/10.1007/s10457-023-00898-0>.
- Getahun Amare. (2003). Eucalyptus farming in Ethiopia: the case for eucalyptus woodlots in the Amhara region.
- Gibbs, H. K., Brown, S., Niles, J. O., & Foley, J. A. (2007). Monitoring and estimating tropical forest carbon stocks: making REDD a reality. *Environmental Research Letters*, 2(2007):045023. <https://doi.org/10.1088/1748-9326/2/4/045023>.
- Gonzalez-Benecke, C. A., Fernández, M. P., Albaugh, T. J., Ahumada, R., Bown, H. E., Gayoso, J., Gerding, V., Mardones, O. B., Rodríguez, A. R., & Rubilar, R. (2021). General above-stump volume and biomass functions for *Pinus radiata*, *Eucalyptus globulus* and *Eucalyptus nitens*. *Biomass and Bioenergy*, 155: 106280.
- Gonzalez-garcía, M., Hevia, A., Majada, J., Barrio-anta, M., & Gonza, M. (2013). Above-ground biomass estimation at tree and stand level for short rotation plantations of *Eucalyptus nitens*(*Deane & Maiden*) *Maiden in Northwest*. *Biomass and Bioenergy*.54: 147-157. <https://doi.org/10.1016/j.biombioe.2013.03.019>.
- Haileab Zegeye. (2010). Environmental and Socio-Economic Implications of Eucalyptus in Ethiopia. *Eucalyptus Species Management, History, Status and Trends in Ethiopia*.Proceedings from the Congress Held in Addis Ababa.September 15th-17th, 2010, September 2010, 184–205.
- Hartono, R., & Kusmana, C. (2020). Allometry of Biomass and Carbon Stock of Planted *Eucalyptus grandis* Forest in Toba Highland. *International Conference of Science, Technology, Engineering, Environmental and Ramification Researches*, 1, 129–131. <https://doi.org/10.5220/0010102401290131>
- Henry, M., Picard, N., Trotta, C., Manlay, R., Valentini, R., Bernoux, M., & Saint André, L. (2011). Estimating tree biomass of sub-Saharan African forests: a review of available allometric equations. *Silva Fennica* 45(3B): 477–569.
- HerbohnJohn ,MedrilzamMedrilzam. (2014). A Small-Scale Forestry Perspective on

Constraints to Including REDD in International Carbon Markets.Small-scale Forestry.
<https://doi.org/10.1007/s11842-002-0001-3>

Houghton, R. A. (2005). *Tropical deforestation as a source of greenhouse gas emissions*. ,*Tropical deforestation and climate change* / edited by Paulo Moutinho and Stephan Schwartzman. -- Belém - Pará - Brazil : IPAM - Instituto de PesquisaAmbiental da Amazônia ; Washington DC - USA : ISBN: 8587827-12-X.

Huang, S., Yang, Y., Wang, Y., Amaro, A., Reed, D., & Soares, P. (2003). A critical look at procedures for validating growth and yield models.*Modeling Forest Ecosystem*. 0271: (271–292).

Huynh, T, Lee, D. J., Applegate, G., & Lewis, T. (2021). Field methods for above and belowground biomass estimation in plantation forests. *MethodsX*. 8:101192.
<https://doi.org/10.1016/j.mex.2020.101192>.

Jagger Pamela, Pender John (2003).The role of trees for sustainable management of less-favored lands: the case of eucalyptus in Ethiopia .*Forest Policy and Economics* 5;83 -95.

Jibrin, A., & Abdulkadir, A. (2015). Allometric Models for Biomass Estimation in Savanna Woodland Area, Niger State, Nigeria. *International Journal of Environmental*.9(4): 275–283.

Kanninen, S. &. (2005). Allometric models for tree volume and total aboveground biomass in a tropical humid forest in Costa Rica. *Biotropica*,37(1):2–8.
<https://doi.org/10.1111/j.1744-7429.2005.02027>.

Kaonga Martin &, & Smith Bayliss. (2010). Allometric models for estimation of aboveground carbon stocks in improved fallows in eastern Zambia. *Agroforestry Systems*, 78(3), 217–232. <https://doi.org/10.1007/s10457-009-9253-7>

Kapinga, K., Syampungani, S., Kasubika, R., Yambayamba, A. M., & Shamaoma, H. (2018). Species-specific allometric models for estimation of the above-ground carbon stock in miombo woodlands of Copperbelt Province of Zambia. *Forest Ecology and Management*, 417(February), 184–196. <https://doi.org/10.1016/j.foreco.2018.02.044>

- Kassegn Asnakew Seyoum, Bekalu Melis Alehegn, Asmamaw Alemu Abteu. (2021). Effect of *Eucalyptus Globulus* Woodlot Plantation on Selected Soil Physico-Chemical Properties , Wheat Yield in Wogera District , Amhara Region , Ethiopia. 6(2), 39–49. <https://doi.org/10.11648/j.ajset.20210602.14>
- Kebede Gizachew. (2017). Expansion of eucalypt woodlot and its factors in Cheha District, Southern Ethiopia. World Scientific News, (66): 163-180.
- Kenzo, T., Ichie, T., Hattori, D., Itioka, T., Handa, C., Ohkubo, T., Kendawang, J. J., Nakamura, M., Sakaguchi, M., Okamoto, M., Tanaka-oda, A., Sakurai, K., Ninomiya, I.,(2009). Development of Allometric Relationships for Accurate Estimation of above- and Below- Ground Biomass in Tropical Secondary Forests in Sarawak , Malaysia.Journal of Tropical Ecology.25(4):pp. 371-386 (Jul.,<https://doi.org/10.1017/S0266467409006129>
- Ketterings, Q. M., Coe, R., Noordwijk, M. Van, Ambagau, Y., & Palm, C. A. (2001). Reducing uncertainty in the use of allometric biomass equations for predicting above-ground tree biomass in mixed secondary forests.Forest Ecology and Management. 146, 199–209.
- Koirala, A., Kizha, A. R., & Baral, S. (2017). Modeling Height-Diameter Relationship and Volume of Teak (*Tectona grandis* L. F.) in Central Lowlands of Nepal. Journal of Tropical Forestry and Environment, 7(1), 28–42. <https://doi.org/10.31357/jtfe.v7i1.3020>.
- Kuyah, S. (2012). *Allometric Equations for Estimating Tree Biomass in Agricultural Landscapes in Western Kenya*.PhdThesis, Jomo Kenyatta University of Agriculture Kenya .
- Kuyah, S., Dietz, J., Muthuri, C., Noordwijk, M. Van, & Neufeldt, H. (2013). Allometry and partitioning of above- and below-ground biomass in farmed eucalyptus species dominant in Western Kenyan agricultural landscapes.Biomass and Bioenergy,55, 276–284. <https://doi.org/10.1016/j.biombioe.2013.02.011>.
- LaliKumar t ,PriyakantSinha, Subhashni Taylor, and Abdullah F. Alqurash.(2015). Review of

the use of remote sensing for biomass estimation to support renewable energy generation. .15093SS.

- Lin, K., Lyu, M., & Jiang, M. (2017). Improved allometric equations for estimating biomass of the three *Castanopsis carlesii* H . forest types in subtropical China. *New Forests*, 48(1), 115–135. <https://doi.org/10.1007/s11056-016-9559-z>.
- Litton, C. M., & Kauffman, J. B. (2008). Allometric models for predicting aboveground biomass in two widespread woody plants in Hawaii. *Biotropica*. 40(3): 313–320. <https://doi.org/10.1111/j.1744-7429.2007.00383.x>.
- Löf, M., Madsen, P., Metslaid, M., & Witzell, J. (2019). Restoring forests: Regeneration and ecosystemfunctionforthefuture.*NewForests*,50(2),139–151. <https://doi.org/10.1007/s11056-019-09713-0>.
- Lorenz, K., & Lal, R. (2010). Carbon sequestration in forest ecosystems. In *Carbon Sequestration in Forest Ecosystems*. <https://doi.org/10.1007-978-90-481-3266-9>.
- Mahmood, H., Siddique, M. R. H., Costello, L., Birigazzi, L., Abdullah, S. M. R., Henry, M., Siddiqui, B. N., Aziz, T., Ali, S., & Al Mamun, A. (2019). Allometric models for estimating biomass, carbon and nutrient stock in the Sal zone of Bangladesh. *Forest-Biogeosciences and Forestry*, 12(1), 69.
- Mandal, R. A., Yadav, B. K. V., Yadav, K. K., Dutta, I. C., & Haque, S. M. (2013). Development of Allometric Equation for Biomass Estimation of *Eucalyptus camaldulensis*: A study from Sagarnath Forest, Nepal. *International Journal of Biodiversity and Ecosystems*, 1(1), 1–7.
- Max Kuhn Pfizer Global R&D(2008). Building Predictive Models in R Using the caret Package. *Journal of Statistical Software*,28(5).
- Mekonnen Daba. (2016). The Eucalyptus Dilemma : The Pursuit for Socio-economic Benefit versus Environmental Impacts of Eucalyptus in Ethiopia. *Journal of Natural Sciences Research*, 6(19), 127–137.

- Mengesha Tsega, Awoke Guadie, Zebene Lakew Teffera, Yigez Belayneh & Dongjie Niu (2018) Development and Validation of Height-Diameter Models for *Cupressus lusitanica* in Gergeda Forest, Ethiopia, Forest Science and Technology. 14:3. 138-144, DOI:10.1080/21580103.2018.1482794.
- Meragiaw Misganaw. (2017). Role of Agroforestry and Plantation on Climate Change Mitigation and Carbon Sequestration in Ethiopia. Journal of Tree Sciences, 36(1), 1. <https://doi.org/10.5958/2455-7129.2017.00001.2>.
- Mesfin Abebe & Wubalem Tadesse. (2003). *Eucalyptus in Ethiopia: risk or opportunity* In M. A. & W. Tadesse (Ed.), Ethiopian Institute of Agricultural Research, Ethiopia (Issue November). January, 2014, pp 65.
- Missanjo, E., Kamanga-thole, G., & Bonongwe, D. (2015). Allometric Equations for Estimation of Above Ground Biomass of *Eucalyptus camaldulensis* in Malawi. Journal of Basic and Applied Research International, 2(2) 2395 - 3438.
- Mohd Zaki, N. A., Latif, Z. A., & Suratman, M. N. (2018). Modelling above-ground live trees biomass and carbon stock estimation of tropical lowland Dipterocarp forest: integration of field-based and remotely sensed estimates. International Journal of Remote Sensing, 39(8), 2312–2340. <https://doi.org/10.1080/01431161.2017.1421793>.
- Montagu, K. D., Düttmer, K., Barton, C. V. M., & Cowie, A. L. (2005). Developing general allometric relationships for regional estimates of carbon sequestration - An example using *Eucalyptus pilularis* from seven contrasting sites. Forest Ecology and Management, 204(1), 115–129. <https://doi.org/10.1016/j.foreco.2004.09.003>.
- Moussa, M., Abasse, T., Abdou, I. K., & Larwanou, M. (2019). Applying an indirect method for estimating and modelling the aboveground biomass and carbon for wood energy in the arid ecosystems of Aïr Tenéré of Niger. 11: 115–126. <https://doi.org/10.5897/JENE2019.0795>.
- Mugasha, W.A., Eid, T., Bollandsås, O.M., Malimbwi, R.E., Chamshama, S.A.O., Zahabu, E. 2012 Allometric models for prediction of aboveground biomass of single trees in miombo

- woodlands in Tanzania. In Proceedings of the First Climate Change Impacts, Mitigation and Adaptation Programme Scientific Conference. Climate Change Impacts, Adaptation and Mitigation (CCIAM), Tanzania, pp. 8–18.
- Mugasha, W. A., Bollandås, O. M., & Eid, T. (2013). Relationships between diameter and height of trees in natural tropical forest in Tanzania. *Southern Forests*, 75(4), 221–237. <https://doi.org/10.2989/20702620.2013.824672>.
- Mugasha, W. A., Mauya, E. W., Njana, A. M., Karlsson, K., Malimbwi, R. E., & Ernest, S. (2019). Height-Diameter Allometry for Tree Species in Tanzania Mainland. *International Journal of Forestry Research*, 2019. <https://doi.org/10.1155/2019/4832849>.
- Mukuralinda, A., Kuyah, S., Ruzibiza, M., Ndoli, A., Leon, N., & Muthuri, C. (2021). Allometric equations, wood density and partitioning of aboveground biomass in the arboretum of Ruhunde, Rwanda. *3(2020)*. <https://doi.org/10.1016/j.tfp.2020.100050>.
- Mulugeta Zewdie. (2008). *Temporal Changes of Biomass Production, Soil Properties and Ground Flora in Eucalyptus globulus Plantations in the Central Highlands of Ethiopia*. Doctoral Thesis, Swedish University of Agricultural Sciences Uppsala, 74pp.
- Mulugeta Zewdie, M., Olsson, M., & Verwijst, T. (2009). Above-ground biomass production and allometric relations of *Eucalyptus globulus* Labill. coppice plantations along a chronosequence in the central highlands of Ethiopia. *Biomass and Bioenergy*, 33(3): 421–428. <https://doi.org/10.1016/j.biombioe.2008.08.007>
- Návar, J. (2009). Biomass component equations for Latin American species and groups of species. *Annals of Forest Science*, 66(2), 208–208.
- Nambiar, E. K. S. (2021). Small forest growers in tropical landscapes should be embraced as partners for Green-growth: Increase wood supply, restore land, reduce poverty, and mitigate climate change. *trees Forests and People*. 6: 100154.
- Nawir, Kassa, H., Sandewall, M., Dore, D., Campbell, B., Ohlsson, B., & Bekele, M. (2007). Stimulating smallholder tree planting – lessons from Africa and Asia. *Unasylva*. 58, 53–58.

- Nelson, B. W., Mesquita, R., Pereira, J. L. G., De, S. G. A., Teixeira, G., & Bovino, L. (1999). Allometric regressions for improved estimate of secondary forest biomass in the central Amazon. *Forest Ecology and Management* .117: 149–167.
- Nugroho, N. P. (2014). Developing Site-Specific Allometric Equations for Above-Ground Biomass Estimation in Peat Swamp Forests of Rokan Hilir District, Riau Province Indonesia. *Journal of Forestry Research*, 1(1), 47–65.
<https://doi.org/10.20886/ijfr.2014.1.1.47-65>.
- Obidzinski, A. K., & Dermawan, A. (2010). Smallholder timber plantation development in Indonesia : what is preventing progress ? *International forestry Rev.* 12(4), 339–348.
- Ostadhashemi, R., Shahraji, T. R., Roehle, H., & Limaei, S. M. (2014). Estimation of biomass and carbon storage of tree plantations in northern Iran. *Journal of Forest Science*, 60(9), 363–371. <https://doi.org/10.17221/55/2014-jfs>
- Otukei, J. R., & Emanuel, M. (2015). Estimation and mapping of above ground biomass and carbon of Bwindi impenetrable National Park. *ALOS PALSAR* .4(1), 1–13.
- Packard GC (2013) Is logarithmic transformation necessary in allometry? *Biol J Lin Soc* 109:476–486.
- Paulo, J. A., Tomé, J., & Tomé, M. (2011). Nonlinear fixed and random generalized height-diameter models for Portuguese cork oak stands. *Annals of Forest Science*, 68(2), 295–309. <https://doi.org/10.1007/s13595-011-0041-y>.
- Picard, N., L. Saint-André, and M. Henry. 2012. *Manual for Building Tree Volume and Biomass Allometric Equations: From Field Measurements to Prediction*,. Rome: Food and Agricultural Organization of the United Nations, 213 pp.
- Picard, N., Rutishauser, E., Ploton, P., Ngomanda, A., & Henry, M. (2015). Should tree biomass allometry be restricted to power models? *Forest Ecology and Management*, 353, 156–163.
- Pohjonen, V. and Pukkala, T., 1990. Eucalyptus globulus in Ethiopian forestry. *For. Ecol.*

Manage.,36: 19-31.

- Poorter, L., Bongers, L., & Bongers, F. (2006). Architecture of 54 Moist-Forest Tree Species : Traits , Trade-Offs , and Functional Groups Accessed : 07-06-2016 19 :87(5), 1289–1301.
- Pravalprukskul, P. (2018). *Assessing the contribution of Grevillea robusta trees to farm-scale carbon fluxes in the Central Highlands of Kenya*. Master thesis,University ofCopenhagen,Kneya,74pp
- Rahman, M. S., Donoghue, D. N. M., Bracken, L. J., & Mahmood, H. (2021). Biomass estimation in mangrove forests: A comparison of allometric models incorporating species and structural information. *Environmental Research Letters*, 16(12).
- Ravindranath N. H., Madelene Ostwald.(2008).*Carbon Inventory Methods Handbook for Greenhouse Gas Inventory, Carbon Mitigation and Roundwood Production Projects.ISBN-13: 978-1-4020-6546-0*.
- Ribeiro Sabina Cerruto, Carlos Pedro BoechatSoares, Lutz Fehrmann4 ,LaércioAntônioGonçalvesJacovine Klaus von Gadow (2015). Above and below ground biomass and carbon estimates for Aboveground and belowground biomass and carbon estimates for clonal eucalyptus trees in southeast brazil.39(2): 353-363
- Rocha, S. M. G., Vidaurre, G. B., Pezzopane, J. E. M., Almeida, M. N. F., Carneiro, R. L., Campoe, O. C., Scolforo, H. F., Alvares, C. A., Neves, J. C. L., Xavier, A. C., & Figura, M. A. (2020). Influence of climatic variations on production, biomass and density of wood in eucalyptus clones of different species. *Forest Ecology and Management*, 473(82), 118290.
- Roshetko, James M.Bertomeu, Manuel (2015). Multi-species and multifunctional smallholder tree farming systems in Southeast Asia: timber, NTFPs, plus environmental benefits,Annals of Silvicultural Research,39(02):62-69.
- Rutishauser, E., Noor'an, F., Laumonier, Y., Halperin, J., Rufi'ie, Hergoulach, K., & Verchot, L. (2013). Generic allometric models including height best estimate forest biomass and

- carbon stocks in Indonesia. *Forest Ecology and Management*, 307, 219–225. <https://doi.org/10.1016/j.foreco.2013.07.013>.
- Sawadogo, L., Savadogo, P., Tiveau, D., Dayamba, S. D., Zida, D., Nouvellet, Y., Oden, P. C., & Guinko, S. (2010). Allometric prediction of above-ground biomass of eleven woody tree species in the Sudanian savanna-woodland of West Africa. *Journal of Forestry Research*, 21(4), 475–481. <https://doi.org/10.1007/s11676-010-0101-4>.
- Segura, M. (2005). Allometric Models for Tree Volume and Total Aboveground Biomass in a Tropical Humid Forest in Costa Rica 1. 37(1), 2–8.
- Shamaki, S., Akindele, S., Isah, A., & Mohammed, I. (2016). Height-diameter Relationship Models for Teak (*Tectona grandis*) Plantation in Nimbria Forest Reserve, Nigeria. *Asian Journal of Environment & Ecology*, 1(1):1–7. <https://doi.org/10.9734/ajee/2016/3063>.
- Stegen James C., Nathan G. Swenson , Renato Valencia , Brian J. Enquist , Jill Thompson .(2009).Variation in above-ground forest biomass across broad climatic gradients.*Global Ecol. Biogeogr.*18 : 617–625.
- Sturrock, R. N., Frankel, S. J., Brown, A. V, Hennon, P. E., Kliejunas, J. T., Lewis, K. J., Worrall, J. J., & Woods, A. J. (2011). Climate change and forest diseases. *Plant Pathology*, 60(1):133–149.
- Sullivan, M. J. P., Lewis, S. L., Hubau, W., Qie, L., Baker, T. R., Banin, L. F., Chave, J., Cuni-Sanchez, A., Feldpausch, T. R., & Lopez-Gonzalez, G. (2018). Field methods for sampling tree height for tropical forest biomass estimation. *Methods in Ecology and Evolution*, 9(5):1179–1189.
- Tegegne Derbe, Sisay Yehuala, and Agitew Genanew. (2018). Factors Influencing Smallholder Farmers Adoption of Eucalyptus Woodlot in Wogera District , North Gondar Zone , (IJSRM),06(07): EM-2018-566-574. <https://doi.org/10.18535/ijsrm/v6i7.em07>.
- Toirambe, B., Kearsley, E., Haulleville, T. De, Hufkens, K., Baert, G., Huygens, D., Kebede, Y., Defourny, P., Bogaert, J., & Beeckman, H. (2013). Conventional tree height–diameter relationships significantly overestimate aboveground carbon stocks in the Central Congo

- Basin Elizabeth. *Nature Communications*, 4, 2269. <https://doi.org/10.1038/ncomms326>.
- Tsegaye Bekele. (2015). Integrated Utilization of *Eucalyptus globulus* grown on the Ethiopian Highlands and its Contribution to Rural Livelihood : A Case Study of Oromia , Amhara and Southern Nations Nationalities and People ' s Regional State Ethiopia. *International Journal of Basic and Applied Sciences*, 4(2), 80–87.
- Uller Heitor Felipe, Laio Zimmermann Oliveira, Aline Renata Klitzke, Jackson Roberto Eleotério , Alfredo Celso Fantini, Alexander Christian Vibrans.(2019).Aboveground biomass quantification and tree-level prediction models for the Brazilian subtropical AtlanticForest.SouthernForests.81(3):20702620<https://doi.org/10.2989/00306525.2019.1581498>.
- Urban, J., Holušová, K., Menšík, L., Čermák, J., & Kantor, P. (2013). Tree allometry of Douglas fir and Norway spruce on a nutrient-poor and a nutrient-rich site. *TreesStructure and Function*. 27(1) : 97–110. <https://doi.org/10.1007/s00468-012-0771-y>.
- Vashum KT, J. (2012). Methods to estimate above ground biomass and carbon stock in natural forests a review 2157 7625 . *J Ecosyst Ecogr* ISSN:2157-7625 JEE, an Open Access Journal, 2(4.1000116), 2 of 8. <https://doi.org/10.4172/2157-7625.1000116>
- Vieilledent, G., Vaudry, R., Andriamanohisoa, S. F. D., Rakotonarivo, O. S., Randrianasolo, H. Z., Razafindrabe, H. N., Rakotoarivony, C. B., Ebeling, J., & Rasamoelina, M. (2012). A universal approach to estimate biomass and carbon stock in tropical forests using generic allometric models. *Ecological Applications*, 22(2), 572–583.
- Vieira, S. A., Alves, L. F., Aidar, M., Araújo, L. S., Baker, T., Batista, J. L. F., Campos, M. C., Camargo, P. B., Chave, J., Delitti, W. B. C., Higuchi, N., Honorio, E., Joly, C. A., Keller, M., Martinelli, L. A., De Mattos, E. A., Metzker, T., Phillips, O., Dos Santos, F. A. M. (2008). Estimation of biomass and carbon stocks: The case of the Atlantic Forest. *Biota Neotropica*, 8(2), 21–29. <https://doi.org/10.1590/S1676-06032008000200001>
- Williams. Richard J., Ayalsew Zerihun Kelvin D. Montagu, Madonna Hoffman, Lindsay B. Hutley and Xiaoyong Chen .(2005)Allometry for estimating aboveground tree biomass in tropical and subtropical eucalypt woodlands: towards general predictive

equations..Australian Journal of Botany,53;607-619.

- Xiang, W., Zhou, J., Ouyang, S., & Zhang, S. (2016). Species-specific and general allometric equations for estimating tree biomass components of subtropical forests in southern China. *European Journal of Forest Research*, 135(5), 963–979. <https://doi.org/10.1007/s10342-016-0987-2>.
- Xu, Y., Zhang, J., Franklin, S. B., Liang, J., Ding, P., Luo, Y., Lu, Z., Bao, D., & Jiang, M. (2015). Improving allometry models to estimate the above- and belowground biomass of subtropical forest, China. *Ecosphere*, 6(12), art289. <https://doi.org/10.1890/ES15-00198.1>
- Yehualashet Belete, Abere Fentahun, Birhanu Kebede, Teshome Soromessa.(2019).Nondestructive allometric model to estimate aboveground biomass: an alternative approach to generic pan-tropical models.*Journal of Environmental Studies and Sciences*, hal-02265451. <https://hal.science/hal-02265451>.
- Yordanos sete& Getahun Abreham. (2021). Estimating Land Expectation Value of Smallholder Farmers' Eucalyptus Woodlot Products in Wogera District, Northern Ethiopia. *Reasearch Sqaure*.
- Zhang Yuzhen, Shunlin Liang and Lu Yang (2019).A Review of Regional and Global Gridded Forest Biomass Datasets.*Remote Sens*. 2019, 11, 2744; doi:10.3390/rs11232744.
- Zianis, D., & Mencuccini, M. (2005). Aboveground net primary productivity of a beech (*Fagus moesiaca*) forest: A case study of Naousa forest, northern Greece. *Tree Physiology*, 25(6), 713–722. <https://doi.org/10.1093/treephys/25.6.713>.

APPENDEDIX

University of Gondar
College of Agriculture and Environmental Science
Department of Forestry

የግንባታና የአካባቢ ሳይንስ ኮሌጅ
የፍትሕና የፖለቲካ ሳይንስ
ተግባር: ግንባታ 04/ 8/ 1971/16
Ref.No. AE /02/04/08/ 70/ 24
ተግባር: 11 / 2016 / 9/97
Date: 10 / 07 / 2024

To the Department of Natural Resource Management
Bahirdar University

Subject: Confirming Laboratory Works of Mrs. Fentaye Birhan

As you know your MSc. student, Mrs. Fentaye Birhan, has been doing a thesis entitled as 'Developing Species Specific Allometric Modells to estimate aboveground biomass of *Eucalyptus globulus* smallholder Plantation in Wogera District, Central Gondar Highlands of Ethiopia'. To estimate the aboveground biomass and woody density, she has used oven dry and sensitive balance at the laboratory of the College of Agriculture and Environmental sciences, University of Gondar. Thus, we would like to confirm that she has done afromention laboratory works in our laboratory. Please also refere the 10 pages of laboratory records enclosed with this letter.

With regards,

ሙሉ ሙሉ ወይም
Mekuria Zewdie Ayalew
አብባባይ የፍትሕና የፖለቲካ ሳይንስ
ቤት
Head, Department of
General Forestry

የግንባታና የአካባቢ ሳይንስ ኮሌጅ
UNIVERSITY OF GONDAR
College of Agriculture and Environmental Sciences
Department of General Forestry

Web: www.uog.edu.et Phone: 058-811-9165 P.o.box: 196, Gondar, Ethiopia
Fax: 058-114-1240 Mobile: 09-18-46-4732 E-mail: zmekuria3@gmail.com
አባባይ ሰጻፊ የፍትሕና የፖለቲካ ሳይንስ ይገኛል In replying, please quote our ref.No

Appendix 1 Table 1 Bottem stem diameter disk sub sample Laboratory Result

Laboratory Result

Place: University of Gondar Colleges Agricultural and Environmental Sciences

Date, _____

DBH = Diameter at the breast height
BD = Bottom Diameter
MDD = Mid Diameter Disk
H = tree total height
g = gram
DW = dry weight
FW = Tree
LS = Leaf cm = centimeter
BS = bi n meter

Disk sub Sample Laboratory Result

code	c	No_tree	Tree_age	Plot_No	DBH_cm	Ht_m	T1 = BD_DBH_cm	T1 = BD_FW_g	T1 = BD_DW	T1 = MDD_DBH_cm
		1	4	1	4.5	9	6.5	116	51.5	3.3
code		2	4	1	3	6	T2 = BD_DBH_cm	T2 = BD_FW_g	T2 = BD_DW	T2 = MDD_DBH_cm
							3.9	25.9	10.7	3.1
code		3	4	1	8.5	12.5	T3 = BD_DBH_cm	T3 = BD_FW_g	T3 = BD_DW	T3 = MDD_DBH_cm
							9.9	330	148	6.8
code		4	4	1	2.8	5.5	T4 = BD_DBH_cm	T4 = BD_FW_g	T4 = BD_DW	T4 = MDD_DBH_cm
							3.6	19	8.9	2.5
code		5	4	1	5	8	T5 = BD_DBH_cm	T5 = BD_FW_g	T6 = BD_DW	T5 = MDD_DBH_cm
							6.4	70	28	4.4
code		6	4	2	2.4	6	T6 = BD_DBH_cm	T6 = BD_FW_g	T6 = BD_DW	T6 = MDD_DBH_cm
							3.6	32	14	2.1
code		7	4	2	4	8.2	T7 = BD_DBH_cm	T7 = BD_FW_g	T7 = BD_DW	T7 = MDD_DBH_cm
							5.2	67.5	32.4	3.9
code		8	4	2	5.3	11	T8 = BD_DBH_cm	T8 = BD_FW_g	T8 = BD_DW	T8 = MDD_DBH_cm
							6.4	78.4	33	4.2
code		9	4	2	11	13.5	T9 = BD_DBH_cm	T9 = BD_FW_g	T9 = BD_DW	T9 = MDD_DBH_cm
							12.4	353.4	144.5	9.4
code		10	4	2	6	10.8	T10 = BD_DBH_cm	T10 = BD_FW_g	T10 = BD_DW	T10 = MDD_DBH_cm
							7.4	160.4	56.8	4.9
code		11	4	3	3	7	T11 = BD_DBH_cm	T11 = BD_FW_g	T11 = BD_DW	T11 = MDD_DBH_cm
							3.9	25.9	11.4	2.8
code		12	4	3	5	8.5	T12 = BD_DBH_cm	T12 = BD_FW_g	T12 = BD_DW	T12 = MDD_DBH_cm
							6.5	84.5	40.7	4.2
code		13	4	3	7	11.6	T13 = BD_DBH_cm	T13 = BD_FW_g	T13 = BD_DW	T13 = MDD_DBH_cm
							7.8	153	67.6	5.8
code		14	4	3	5.5	8	T14 = BD_DBH_cm	T14 = BD_FW_g	T14 = BD_DW	T14 = MDD_DBH_cm
							6.5	80	35.2	4.6
code		15	4	3	4.8	9.7	T15 = BD_DBH_cm	T15 = BD_FW_g	T15 = BD_DW	T15 = MDD_DBH_cm
							6	76.8	35.8	3.2



code	16	4	4	2.1	6.7	T16 = BD_DBH_cm T16 = BD_FW_g T16 = BD_DV T16 = MDD_DBH_cm	3.5	30	13.1	2.6
code	17	4	4	6.6	9	T17 = BD_DBH_cm T17 = BD_FW_g T17 = BD_DV T17 = MDD_DBH_cm	8.3	167	76.2	6.2
code	18	4	4	4.5	8	T18 = BD_DBH_cm T18 = BD_FW_g T18 = BD_DV T18 = MDD_DBH_cm	6.2	58.5	21	5.1
code	19	4	4	3.7	7	T19 = BD_DBH_cm T19 = BD_FW_g T19 = BD_DV T19 = MDD_DBH_cm	5	60.4	31	3.3
code	20	4	4	10	13.2	T20 = BD_DBH_cm T20 = BD_FW_g T20 = BD_DV T20 = MDD_DBH_cm	11.5	390	161.2	8.5
code	21	4	5	4	8	T21 = BD_DBH_cm T21 = BD_FW_g T21 = BD_DV T21 = MDD_DBH_cm	5.4	80	51.5	3.2
code	22	4	5	2.8	5.5	T22 = BD_DBH_cm T22 = BD_FW_g T22 = BD_DV T22 = MDD_DBH_cm	3.4	22	8.9	2.4
code	23	4	5	5.5	11	T23 = BD_DBH_cm T23 = BD_FW_g T23 = BD_DV T23 = MDD_DBH_cm	6.2	78.4	34	4.3
code	24	4	5	7.5	10.4	T24 = BD_DBH_cm T24 = BD_FW_g T24 = BD_DV T24 = MDD_DBH_cm	9.3	268	144.5	8.1
code	25	4	5	9.1	11.11	T25 = BD_DBH_cm T25 = BD_FW_g T25 = BD_DV T25 = MDD_DBH_cm	10.3	410	185	6.2
code	26	4	6	12.1	13	T26 = BD_DBH_cm T26 = BD_FW_g T26 = BD_DV T26 = MDD_DBH_cm	13.6	485	129.3	9.5
code	27	4	6	6.1	11	T27 = BD_DBH_cm T27 = BD_FW_g T27 = BD_DV T27 = MDD_DBH_cm	7.2	185	95	4.5
code	28	4	6	8.2	11.2	T28 = BD_DBH_cm T28 = BD_FW_g T28 = BD_DV T28 = MDD_DBH_cm	10.2	540	233	8
code	29	4	6	2	7	T29 = BD_DBH_cm T29 = BD_FW_g T29 = BD_DV T29 = MDD_DBH_cm	4.1	55	23.1	3.2
code	30	4	6	10.7	11	T30 = BD_DBH_cm T30 = BD_FW_g T30 = BD_DV T30 = MDD_DBH_cm	12.4	221	89.5	5



code	31	5	1	11	13.3	T31 = BD_DBH_cm T31 = BD_FW_g T31 = BD_DV T31 = MDD_DBH_cm	12.5	405	215	8
code	32	5	1	6	10.1	T32 = BD_DBH_cm T32 = BD_FW_g T32 = BD_DV T32 = MDD_DBH_cm	7.6	170	75	5
code	33	5	1	3.5	7	T33 = BD_DBH_cm T33 = BD_FW_g T33 = BD_DV T33 = MDD_DBH_cm	4.1	70.5	32.6	3.2
code	34	5	1	9	13.1	T34 = BD_DBH_cm T34 = BD_FW_g T34 = BD_DV T34 = MDD_DBH_cm	10.2	420	193	6.5
code	35	5	1	4	8.4	T35 = BD_DBH_cm T35 = BD_FW_g T35 = BD_DV T35 = MDD_DBH_cm	5.2	219	98.5	3.3
code	36	5	2	5.5	9.8	T36 = BD_DBH_cm T36 = BD_FW_g T36 = BD_DV T36 = MDD_DBH_cm	7	198	57.5	3.6
code	37	5	2	6.5	11.5	T37 = BD_DBH_cm T37 = BD_FW_g T37 = BD_DV T37 = MDD_DBH_cm	8	3667	123.5	5
code	38	5	2	3	8.5	T38 = BD_DBH_cm T38 = BD_FW_g T38 = BD_DV T38 = MDD_DBH_cm	4	195	92	3
code	39	5	2	8	11.5	T39 = BD_DBH_cm T39 = BD_FW_g T39 = BD_DV T39 = MDD_DBH_cm	9.6	300	122.5	7.2
code	40	5	2	12	14	T40 = BD_DBH_cm T40 = BD_FW_g T40 = BD_DV T40 = MDD_DBH_cm	13.6	620	284.6	9.7
code	41	5	3	11.2	14	T41 = BD_DBH_cm T41 = BD_FW_g T41 = BD_DV T41 = MDD_DBH_cm	12.6	465	189.3	9.3
code	42	5	3	6.2	11	T42 = BD_DBH_cm T42 = BD_FW_g T42 = BD_DV T42 = MDD_DBH_cm	7	175	89.6	4.7
code	43	5	3	4.5	9	T43 = BD_DBH_cm T43 = BD_FW_g T43 = BD_DV T43 = MDD_DBH_cm	6.5	165	78	3.3
code	44	5	3	7	11	T44 = BD_DBH_cm T44 = BD_FW_g T44 = BD_DV T44 = MDD_DBH_cm	10.2	540	233	8
code	45	5	3	3	6.5	T45 = BD_DBH_cm T45 = BD_FW_g T45 = BD_DV T45 = MDD_DBH_cm	4.1	260	112	2.9



code	46	5	4	8.7	13	T46 = BD_DBH_cm T46 = BD_FW_g T46 = BD_DV T46 = MDD_DBH_cm
code	47	5	4	4.6	8.4	9.8 350 104 7
code	48	5	4	5	9.5	T47 = BD_DBH_cm T47 = BD_FW_g T47 = BD_DV T47 = MDD_DBH_cm
code	49	5	4	7	11.6	5.6 78.3 34.2 4
code	50	5	4	2.3	5	T48 = BD_DBH_cm T48 = BD_FW_g T48 = BD_DV T48 = MDD_DBH_cm
code	51	5	5	5.7	10	6.5 105.1 49.3 4.3
code	52	5	5	6.4	10.7	T49 = BD_DBH_cm T49 = BD_FW_g T49 = BD_DV T49 = MDD_DBH_cm
code	53	5	5	8	11	7.7 163.2 67.7 5.4
code	54	5	5	12.5	14.2	T50 = BD_DBH_cm T50 = BD_FW_g T50 = BD_DV T50 = MDD_DBH_cm
code	55	5	5	2.5	5.2	3.5 33.9 16.8 2.4
code	56	5	6	5.4	10.4	T51 = BD_DBH_cm T51 = BD_FW_g T51 = BD_DV T51 = MDD_DBH_cm
code	57	5	6	12.6	13.2	7 121 52.4 4.5
code	58	5	6	8	11	T52 = BD_DBH_cm T52 = BD_FW_g T52 = BD_DV T52 = MDD_DBH_cm
code	59	5	6	12.5	14.2	8.2 168 69.3 5.8
code	60	5	6	4	9.6	T53 = BD_DBH_cm T53 = BD_FW_g T53 = BD_DV T53 = MDD_DBH_cm
						10.3 193.9 88.9 8.4
						T54 = BD_DBH_cm T54 = BD_FW_g T54 = BD_DV T54 = MDD_DBH_cm
						14.5 573.9 269.5 10
						T55 = BD_DBH_cm T55 = BD_FW_g T55 = BD_DV T55 = MDD_DBH_cm
						3.2 30 12.3 2.0
						T56 = BD_DBH_cm T56 = BD_FW_g T56 = BD_DV T56 = MDD_DBH_cm
						7.5 280 123 5.0
						T57 = BD_DBH_cm T57 = BD_FW_g T57 = BD_DV T57 = MDD_DBH_cm
						13 465 192 9.0
						T58 = BD_DBH_cm T58 = BD_FW_g T58 = BD_DV T58 = MDD_DBH_cm
						10 420 166.5 7.0
						T59 = BD_DBH_cm T59 = BD_FW_g T59 = BD_DV T59 = MDD_DBH_cm
						14 560 276.5 1.0
						T60 = BD_DBH_cm T60 = BD_FW_g T60 = BD_DV T60 = MDD_DBH_cm
						6.3 110 49.5 4.0



Appendix 1 Table 2 Mid and top stem diameter disk sub sample Laboratory Result

Appendix 1 Table 2 Mid and top stem diameter disk sub sample Laboratory Result

T1 = MD_FW_g	T1 = MD_DW_g	T1 = TD_DBH_cm	T1 = TD_FW_g	T1 = TD_DW_g
29	13.3	2.5	15.6	7
T2 = MD_FW_g	T2 = MD_DW_g	T2 = TD_DBH_cm	T2 = TD_FW_g	T2 = TD_DW_g
23	11.4	2.3	15	6.4
T3 = MD_FW_g	T3 = MD_DW_g	T3 = TD_DBH_cm	T3 = TD_FW_g	T3 = TD_DW_g
177.5	64.5	3.8	28	12.5
T4 = MD_FW_g	T4 = MD_DW_g	T4 = TD_DBH_cm	T4 = TD_FW_g	T4 = TD_DW_g
16	9	1.9	18	7.5
T5 = MD_FW_g	T5 = MD_DW_g	T5 = TD_DBH_cm	T5 = TD_FW_g	T5 = TD_DW_g
37	16.4	2.9	21	10
T6 = MD_FW_g	T6 = MD_DW_g	T6 = TD_DBH_cm	T6 = TD_FW_g	T6 = TD_DW_g
28	12.3	1.6	16	7
T7 = MD_FW_g	T7 = MD_DW_g	T7 = TD_DBH_cm	T7 = TD_FW_g	T7 = TD_DW_g
20	9.3	2.7	19	8
T8 = MD_FW_g	T8 = MD_DW_g	T8 = TD_DBH_cm	T8 = TD_FW_g	T8 = TD_DW_g
54	23	2.4	24	11
T9 = MD_FW_g	T9 = MD_DW_g	T9 = TD_DBH_cm	T9 = TD_FW_g	T9 = TD_DW_g
193.9	95.5	6.5	98.5	45.1
T10 = MD_FW_g	T10 = MD_DW_g	T10 = TD_DBH_cm	T10 = TD_FW_g	T10 = TD_DW_g
54.5	25.8	3.3	29.2	13.1
T11 = MD_FW_g	T11 = MD_DW_g	T11 = TD_DBH_cm	T11 = TD_FW_g	T11 = TD_DW_g
21.8	10.2	2.3	10.4	5
T12 = MD_FW_g	T12 = MD_DW_g	T12 = TD_DBH_cm	T12 = TD_FW_g	T12 = TD_DW_g
55.8	30	3.1	15.2	8.4
T13 = MD_FW_g	T13 = MD_DW_g	T13 = TD_DBH_cm	T13 = TD_FW_g	T13 = TD_DW_g
76.8	35.5	3.8	33.9	16.8
T14 = MD_FW_g	T14 = MD_DW_g	T14 = TD_DBH_cm	T14 = TD_FW_g	T14 = TD_DW_g
42	18.6	3.1	33	14.5
T15 = MD_FW_g	T15 = MD_DW_g	T15 = TD_DBH_cm	T15 = TD_FW_g	T15 = TD_DW_g
25.2	10.2	2.3	15.5	7



T16 = MD_FW_g	T16 = MD_DW_g	T16 = TD_DBH_cm	T16 = TD_FW_g	T16 = TD_DW_g
16.2	6.8	1.8	8.5	4
T17 = MD_FW_g	T17 = MD_DW_g	T17 = TD_DBH_cm	T17 = TD_FW_g	T17 = TD_DW_g
90.3	42.5	4.2	55.5	30
T18 = MD_FW_g	T18 = MD_DW_g	T18 = TD_DBH_cm	T18 = TD_FW_g	T18 = TD_DW_g
30.5	12	3.4	15.5	8
T19 = MD_FW_g	T19 = MD_DW_g	T19 = TD_DBH_cm	T19 = TD_FW_g	T19 = TD_DW_g
23	11	2.4	16.2	7
T20 = MD_FW_g	T20 = MD_DW_g	T20 = TD_DBH_cm	T20 = TD_FW_g	T20 = TD_DW_g
180	62.1	3.5	50	23.9
T21 = MD_FW_g	T21 = MD_DW_g	T21 = TD_DBH_cm	T21 = TD_FW_g	T21 = TD_DW_g
32	13.3	2.4	18	7
T22 = MD_FW_g	T22 = MD_DW_g	T22 = TD_DBH_cm	T22 = TD_FW_g	T22 = TD_DW_g
16	9	1.9	20	7.5
T23 = MD_FW_g	T23 = MD_DW_g	T23 = TD_DBH_cm	T23 = TD_FW_g	T23 = TD_DW_g
58	25.5	2.4	26	11
T24 = MD_FW_g	T24 = MD_DW_g	T24 = TD_DBH_cm	T24 = TD_FW_g	T24 = TD_DW_g
195	95.5	3.5	45	22
T25 = MD_FW_g	T25 = MD_DW_g	T25 = TD_DBH_cm	T25 = TD_FW_g	T25 = TD_DW_g
220	99.5	2.8	68	31
T26 = MD_FW_g	T26 = MD_DW_g	T26 = TD_DBH_cm	T26 = TD_FW_g	T26 = TD_DW_g
300	148.7	5.5	150	88
T27 = MD_FW_g	T27 = MD_DW_g	T27 = TD_DBH_cm	T27 = TD_FW_g	T27 = TD_DW_g
88	36.3	2.5	22	9.3
T28 = MD_FW_g	T28 = MD_DW_g	T28 = TD_DBH_cm	T28 = TD_FW_g	T28 = TD_DW_g
320	158	2.7	210	97
T29 = MD_FW_g	T29 = MD_DW_g	T29 = TD_DBH_cm	T29 = TD_FW_g	T29 = TD_DW_g
27	12	1.6	12.5	7
T30 = MD_FW_g	T30 = MD_DW_g	T30 = TD_DBH_cm	T30 = TD_FW_g	T30 = TD_DW_g
55.5	23.3	3	25	11



T31 = MD_FW_g	T31 = MD_DW_g	T31 = TD_DBH_cm	T31 = TD_FW_g	T31 = TD_DW_g
250	116	3.5	70	27.3
T32 = MD_FW_g	T32 = MD_DW_g	T32 = TD_DBH_cm	T32 = TD_FW_g	T32 = TD_DW_g
85.5	23.3	3.3	30	13.2
T33 = MD_FW_g	T33 = MD_DW_g	T33 = TD_DBH_cm	T33 = TD_FW_g	T33 = TD_DW_g
27	12.1	1.6	12.6	5.1
T34 = MD_FW_g	T34 = MD_DW_g	T34 = TD_DBH_cm	T34 = TD_FW_g	T34 = TD_DW_g
210	97	2.6	48	21.3
T35 = MD_FW_g	T35 = MD_DW_g	T35 = TD_DBH_cm	T35 = TD_FW_g	T35 = TD_DW_g
25	11.3	2.5	141	62.5
T36 = MD_FW_g	T36 = MD_DW_g	T36 = TD_DBH_cm	T36 = TD_FW_g	T36 = TD_DW_g
23.7	13.2	2.5	17	7.3
T37 = MD_FW_g	T37 = MD_DW_g	T37 = TD_DBH_cm	T37 = TD_FW_g	T37 = TD_DW_g
254	106.6	3.5	170	76.4
T38 = MD_FW_g	T38 = MD_DW_g	T38 = TD_DBH_cm	T38 = TD_FW_g	T38 = TD_DW_g
123	58	1.5	23	10.5
T39 = MD_FW_g	T39 = MD_DW_g	T39 = TD_DBH_cm	T39 = TD_FW_g	T39 = TD_DW_g
260	112	3.2	67.5	30
T40 = MD_FW_g	T40 = MD_DW_g	T40 = TD_DBH_cm	T40 = TD_FW_g	T40 = TD_DW_g
340	145.6	3.5	220	100
T41 = MD_FW_g	T41 = MD_DW_g	T41 = TD_DBH_cm	T41 = TD_FW_g	T41 = TD_DW_g
300	148.7	6.5	180	88
T42 = MD_FW_g	T42 = MD_DW_g	T42 = TD_DBH_cm	T42 = TD_FW_g	T42 = TD_DW_g
78	35.1	2.4	18	8.2
T43 = MD_FW_g	T43 = MD_DW_g	T43 = TD_DBH_cm	T43 = TD_FW_g	T43 = TD_DW_g
96	43.3	2.4	62	29.7
T44 = MD_FW_g	T44 = MD_DW_g	T44 = TD_DBH_cm	T44 = TD_FW_g	T44 = TD_DW_g
320	158	2.7	210	97
T45 = MD_FW_g	T45 = MD_DW_g	T45 = TD_DBH_cm	T45 = TD_FW_g	T45 = TD_DW_g
20	9.7	1.8	19	8.5



T46 = MD_FW_g	T46 = MD_DW_g	T46 = TD_DBH_cm	T46 = TD_FW_g	T46 = TD_DW_g
200	92.3	4.4	98.5	63.5
T47 = MD_FW_g	T47 = MD_DW_g	T47 = TD_DBH_cm	T47 = TD_FW_g	T47 = TD_DW_g
22.5	39.5	2.4	18.5	15.5
T48 = MD_FW_g	T48 = MD_DW_g	T48 = TD_DBH_cm	T48 = TD_FW_g	T48 = TD_DW_g
45.5	22.1	3.1	31	14.2
T49 = MD_FW_g	T49 = MD_DW_g	T49 = TD_DBH_cm	T49 = TD_FW_g	T49 = TD_DW_g
80.4	35.8	3.8	41.2	16.8
T50 = MD_FW_g	T50 = MD_DW_g	T50 = TD_DBH_cm	T50 = TD_FW_g	T50 = TD_DW_g
18.5	7.5	1.8	13.2	5.6
T51 = MD_FW_g	T51 = MD_DW_g	T51 = TD_DBH_cm	T51 = TD_FW_g	T51 = TD_DW_g
50.5	23.3	2.8	21.5	10.4
T52 = MD_FW_g	T52 = MD_DW_g	T52 = TD_DBH_cm	T52 = TD_FW_g	T52 = TD_DW_g
86.8	35.5	3	22	10.7
T53 = MD_FW_g	T53 = MD_DW_g	T53 = TD_DBH_cm	T53 = TD_FW_g	T53 = TD_DW_g
144	64.4	4.3	55.8	30
T54 = MD_FW_g	T54 = MD_DW_g	T54 = TD_DBH_cm	T54 = TD_FW_g	T54 = TD_DW_g
213.9	98.5	4.5	86.8	38.2
T55 = MD_FW_g	T55 = MD_DW_g	T55 = TD_DBH_cm	T55 = TD_FW_g	T55 = TD_DW_g
16	7.3	1.6	13	5.2
T56 = MD_FW_g	T56 = MD_DW_g	T56 = TD_DBH_cm	T56 = TD_FW_g	T56 = TD_DW_g
240	106.6	3.5	160	76.4
T57 = MD_FW_g	T57 = MD_DW_g	T57 = TD_DBH_cm	T57 = TD_FW_g	T57 = TD_DW_g
310	148.7	4.5	185	88
T58 = MD_FW_g	T58 = MD_DW_g	T58 = TD_DBH_cm	T58 = TD_FW_g	T58 = TD_DW_g
256	156	2.7	110	97
T59 = MD_FW_g	T59 = MD_DW_g	T59 = TD_DBH_cm	T59 = TD_FW_g	T59 = TD_DW_g
222	103	4.5	120	50.5
T60 = MD_FW_g	T60 = MD_DW_g	T60 = TD_DBH_cm	T60 = TD_FW_g	T60 = TD_DW_g
50	23	3.3	35	14.2



Appendix 1 Table 3 Leave and branch biomass sub sample laboratory result

Leave and branch biomass sub sample laboratory result

Leave sub sample laboratory Result										Branch sub samp RESULT		
No_tree	Tree_age	PLOT_N	DBH_cm	Ht_m	CODE	LS-FW_g	CODE	LS_DW_g	CODE	BS-FW_g	CODE	BS_DW_g
1	4	1	4.5	9	T1 =	200	T1 =	87	T1 =	200	T1 =	98
2	4	1	3	6	T2 =	200	T2 =	93	T2 =	200	T2 =	99
3	4	1	8.5	12.5	T3 =	200	T3 =	90.5	T3 =	200	T3 =	92
4	4	1	2.8	5.5	T4 =	200	T4 =	93	T4 =	200	T4 =	101
5	4	1	5	8	T5 =	200	T5 =	93	T5 =	200	T5 =	97
6	4	2	2.4	6	T6 =	200	T6 =	86	T6 =	200	T6 =	89.8
7	4	2	4	8.2	T7 =	200	T7 =	97.15	T7 =	200	T7 =	99
8	4	2	5.3	11	T8 =	200	T8 =	88	T8 =	200	T8 =	99
9	4	2	11	13.5	T9 =	200	T9 =	78	T9 =	200	T9 =	85
10	4	2	6	10.8	T10 =	200	T10 =	78	T10 =	200	T10 =	82
11	4	3	3	7	T11 =	200	T11 =	87.6	T11 =	200	T11 =	90
12	4	3	5	8.5	T12 =	200	T12 =	81	T12 =	200	T12 =	78
13	4	3	7	11.6	T13 =	200	T13 =	87	T13 =	200	T13 =	98
14	4	3	5.5	8	T14 =	200	T14 =	93	T14 =	200	T14 =	92
15	4	3	4.8	9.7	T15 =	200	T15 =	91	T15 =	200	T15 =	96.5
16	4	4	2.1	6.7	T16 =	200	T16 =	88	T16 =	200	T16 =	93.1
17	4	4	6.6	9	T17 =	200	T17 =	86	T17 =	200	T17 =	94
18	4	4	4.5	8	T18 =	200	T18 =	90	T18 =	200	T18 =	92.1
19	4	4	3.7	7	T19 =	200	T19 =	96	T19 =	200	T19 =	95
20	4	4	10	13.2	T20 =	200	T21 =	87	T21 =	200	T21 =	89
21	4	5	4	8	T21 =	200	T22 =	89	T22 =	200	T22 =	98
22	4	5	2.8	5.5	T22 =	200	T23 =	93	T23 =	200	T23 =	101
23	4	5	5.5	11	T23 =	200	T24 =	88	T24 =	200	T24 =	94
24	4	5	7.5	10.4	T24 =	200	T25 =	78	T25 =	200	T25 =	85
25	4	5	9.1	11.11	T25 =	200	T26 =	96	T26 =	200	T26 =	101
26	4	6	12.1	13	T26 =	200	T27 =	92	T27 =	200	T27 =	89
27	4	6	6.1	11	T27 =	200	T28 =	95.4	T28 =	200	T28 =	88.8
28	4	6	8.2	11.2	T28 =	200	T29 =	85.7	T29 =	200	T29 =	97
29	4	6	2	7	T29 =	200	T30 =	86.3	T30 =	200	T30 =	92
30	4	6	10.7	11	T30 =	200	T32 =	93	T32 =	200	T32 =	97

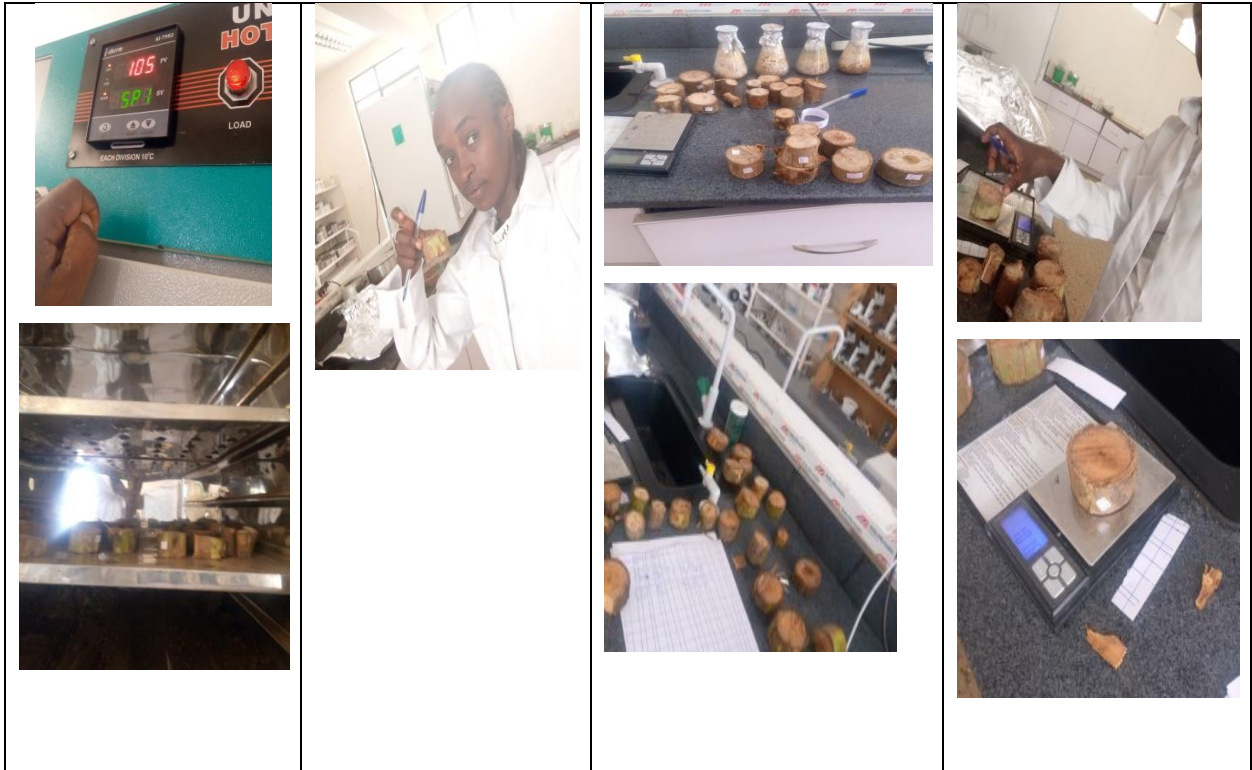


31	5	1	11	13.3 T33=	200 T33=	90.5 T33=	200 T33=	98.2
32	5	1	6	10.1 T34=	200 T34=	92 T34=	200 T34=	94
33	5	1	3.5	7 T35=	200 T35=	86.3 T35=	200 T35=	92
34	5	1	9	13.1 T36=	200 T36=	89 T36=	200 T36=	96.2
35	5	1	4	8.4 T37=	200 T37=	89 T37=	200 T37=	98.2
36	5	2	5.5	9.8 T38=	200 T38=	99.5 T38=	200 T38=	95
37	5	2	6.5	11.5 T39=	200 T39=	96 T39=	200 T39=	106
38	5	2	3	8.5 T40=	200 T40=	83 T40=	200 T40=	88
39	5	2	8	11.5 T41=	200 T41=	84 T41=	200 T41=	95.3
40	5	2	12	14 T42=	200 T42=	92 T42=	200 T42=	98.5
41	5	3	11.2	14 T43	200 T43	97 T43	200 T43	102
42	5	3	6.2	11 T44=	200 T44=	95.4 T44=	200 T44=	88.8
43	5	3	4.5	9 T44=	200 T44=	97 T44=	200 T44=	90.3
44	5	3	7	11 T45=	200 T45=	85.7 T45=	200 T45=	97
45	5	3	3	6.5 T46=	200 T46=	88 T46=	200 T46=	98
46	5	4	8.7	13 T47=	200 T47=	86.3 T47=	200 T47=	94.6
47	5	4	4.6	8.4 T46=	200 T46=	89.2 T46=	200 T46=	96
48	5	4	5	9.5 T49=	200 T49=	89 T49=	200 T49=	98
49	5	4	7	11.6 T50=	200 T50=	89 T50=	200 T50=	98
50	5	4	2.3	5 T51=	200 T51=	89 T51=	200 T51=	87
51	5	5	5.7	10 T52=	200 T52=	88 T52=	200 T52=	98
52	5	5	6.4	10.7 T53=	200 T53=	90 T53=	200 T53=	95
53	5	5	8	11 T53=	200 T53=	82.3 T53=	200 T53=	88
54	5	5	12.5	14.2 T54=	200 T54=	90.3 T54=	200 T54=	93.2
55	5	5	2.5	5.2 T56=	200 T56=	86.3 T56=	200 T56=	102
56	5	6	5.4	10.4 T55=	200 T55=	96 T55=	200 T55=	106
57	5	6	12.6	13.2 T56	200 T56	97 T56	200 T56	102
58	5	6	8	11 T57	200 T57	93 T57	200 T57	97
59	5	6	12.5	14.2 T59	200 T59	96 T59	200 T59	101
60	5	6	4	9.6 T60	200 T60	98 T60	200 T60	102





Appendix 4 figure 1: Photo taken during field data collection



Appendix 4 figure 2: The photos show laboratory analysis of samples taken in the Laboratory

BIOGRAPHY

The author was born in central Gondar, Gondar zone, at the specific place of college, *Kebele* 18, on November 16, 1998. She attends her elementary class at Keble 16 (Leuale Alemayhu) elementary school, and then her higher class attends Shenta secondary school. After the completion of her high school, she joined her BSc degree program at Ambo University College of Agriculture and Veterinary Science in the Department of Forestry. She is a gold model from the female students of the College of Agriculture and Veterinary with CGPA of 3.93. After graduating, she joined Bahirdar University in 2019 to pursue her MSc in regular post graduated program in environment and climate change through the Bahirdar University Talent Scholarship and she is accomplished M.Sc. with CGPA 3.85 in 2021. Now she is working in the Gondar University Colleges of Agriculture and Environmental Science Forestry Department.