THE PERFORMANCE OF LOCAL GENERIC ALLOMETRIES IN ESTIMATING BIOMASS CARBON OF TREES IN AGRICULTURALLY DOMINATED LANDSCAPES OF NYANDO BASIN, KENYA

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A Thesis Submitted in Partial Fulfilment for the Degree of Master of Environmental Studies (Climate Change and Sustainability) In the School of Environmental Studies of Kenyatta University

MAY 2014
DECLARATION

This thesis is my original work and has not been presented for a degree in any other University or any other award.

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Signature:............................ Date:16/05/2014

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World Agroforestry Centre (ICRAF), Nairobi
DEDICATION

This thesis is dedicated to:

My dad Mr. Apollo Liech Okore and mum Mrs. Ruth Akinyi Okore for your belief in the importance of education and knowledge. You have always sacrificed your comfort and given my siblings and I your invaluable support in our knowledge-seeking endeavours since my childhood. I am proud of you mum and dad.
ACKNOWLEDGEMENTS

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I extend immense appreciation to Dr. Moses Kirega for encouraging me to undertake this research, Prof John Gathenya, Dr. Jane Gathenya for their mentorship and Dr. John Muriuki, the immediate former Chairman of Environmental Education Department, Kenyatta University for facilitating the collaboration between Kenyatta University and ICRAF.

I owe much thanks to Unilever Tea Kenya for making available their plantation for sampling, besides offering logistical support during the fieldwork. My heartfelt gratitude is extended to Hellen Ochieng’ and Ruth Mutinda (ICRAF Training Officers) for their support and facilitation on administrative matters at ICRAF, Tom Ochinga, Donald Agwa, Peter Okoth and Luka Anjeho of ICRAF Kisumu Site, for their technical assistance during fieldwork.
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<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
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<tbody>
<tr>
<td>AfSIS</td>
<td>Africa Soil Information System</td>
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<tr>
<td>AGB</td>
<td>Aboveground Biomass</td>
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<td>BGB</td>
<td>Belowground Biomass</td>
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<tr>
<td>CD</td>
<td>Crown Diameter</td>
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<tr>
<td>CF</td>
<td>Correction Factor</td>
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<tr>
<td>COP</td>
<td>Conference of Parties to the UNFCCC</td>
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<td>DBH</td>
<td>Diameter at Breast Height</td>
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<tr>
<td>FAO</td>
<td>Food and Agricultural Organization</td>
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<tr>
<td>GDP</td>
<td>Gross Domestic Product</td>
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<tr>
<td>GHG</td>
<td>Greenhouse Gas</td>
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<tr>
<td>GPS</td>
<td>Global Positioning System</td>
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<td>ICRAF</td>
<td>World Agroforestry Centre</td>
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<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
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<td>IPC</td>
<td>International Finance Corporation</td>
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<tr>
<td>KP</td>
<td>Kyoto Protocol</td>
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<tr>
<td>LDSF</td>
<td>Land Degradation Surveillance Framework</td>
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<tr>
<td>RE</td>
<td>Relative Error</td>
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<tr>
<td>Acronym</td>
<td>Description</td>
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<tr>
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<tr>
<td>REALU</td>
<td>Reducing Emissions from All Land Uses</td>
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<tr>
<td>REAP</td>
<td>Reduced Emissions Agricultural Policy</td>
</tr>
<tr>
<td>RED</td>
<td>Reducing Emissions from Deforestation</td>
</tr>
<tr>
<td>REDD</td>
<td>Reducing Emissions from Deforestation and forest Degradation in developing countries</td>
</tr>
<tr>
<td>REDD+</td>
<td>REDD plus conservation, sustainable management of forests and enhancement of forest carbon stocks</td>
</tr>
<tr>
<td>RSE</td>
<td>Residual Standard Error</td>
</tr>
<tr>
<td>SD</td>
<td>Stump Diameter</td>
</tr>
<tr>
<td>SEE</td>
<td>Standard Error of Estimation</td>
</tr>
<tr>
<td>TAGB</td>
<td>Total Above-ground Biomass</td>
</tr>
<tr>
<td>UNFCCC</td>
<td>United Nations Framework Convention on Climate Change</td>
</tr>
<tr>
<td>UTK</td>
<td>Unilever Tea Kenya</td>
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<tr>
<td>WKIEMP</td>
<td>Western Kenya Integrated Ecosystem Management Programme</td>
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ABSTRACT

Climate change is a real phenomenon whose effects ought to be mitigated, based on assessments that are informed by scientific evidence. Trees in agricultural landscapes play a significant role in mitigating climate change hence a robust inventory of tree biomass in these landscapes is essential for the accurate estimation of their potential in sequestering carbon. Therefore, applicable allometric equations that yield accurate biomass estimates of trees in agricultural landscapes are essential. This study sought to develop and test the performance of local generic allometries (multi-species equations) for estimating biomass carbon. The study was undertaken in the Nyando Basin and it involved obtaining non-destructive measurements of trees (e.g., DBH, tree height, crown diameter) and destructive measurements (trunk, branch, leaf and root biomass). Regression analysis was then run on various predictive parameters (e.g., DBH, height and crown diameter) to derive allometric equations and to test their accuracy. The obtained biomass was used to determine the biomass carbon by an adequate conversion factor of 0.47. The performance of local generic allometries and globally recommended equations for tropical trees was tested on 33 destructively sampled trees from two sites in the Nyando Basin whose diameters at breast height ranged from 7.1 cm to 70.6 cm. Eighteen trees of several species were sampled on the site in the lower block of the basin. The site sampled in the upper block of the basin was a plantation with pure stand of *Eucalyptus grandis*. Local equations estimated aboveground biomass (AGB) with lower error compared to published global equations for tropical ecosystems, which overly estimated or underestimated AGB. The local equation by Kuyah et al. (2012a) conservatively estimated AGB with a relative error (RE) of -2.7% while the site-generated equation had a RE of 5.5%. The local equations also underestimate biomass for the smaller trees while overestimating the biomass of the larger trees but within an acceptable range of error. Both the local and global equations performed with varying accuracies in estimating belowground biomass (BGB) and their resultant RE were quite high. The RE of Kuyah 2 equation and the site-generated equation (Equation 3) were 53.0% and 8.9% respectively while the RE for the global equations by Mokany et al. (2006) and Cairns et al. (1997) were 64.9% and 13.0% respectively. The study concludes that local generic allometries developed in a specific agricultural landscape perform better than global ones in estimating biomass in the sampled agricultural landscapes. The study therefore recommends the use of local allometries in biomass carbon assessment for agricultural landscapes.
CHAPTER ONE: INTRODUCTION

1.1. Background of the study

Climate change has emerged in recent times to be a major thematic subject of discussion at both national and international discourses due to the impacts it has had on the environment, economies and even security. The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) presents more comprehensive and enhanced climate models that now permit attribution of human contribution to detected changes in more climate systems (Alexander et al., 2013). It is therefore practically possible to trace the human-induced drivers of climate change and mitigate them. Mitigating climate change, which entails reducing the sources of greenhouse gases (GHGs) and/or enhancing carbon sinks (McMullen & Jabbuor, 2009), has consequently been underscored in the Kyoto Protocol (UNFCCC Secretariat, 1998).

Mitigating the emission of these gases involves utilization of renewable energy (e.g., hydro-generated, geothermal, wind, tidal, and solar power), enhancing energy use efficiency (e.g., use of fuel efficient end-use industrial equipment and motor vehicles, adoption of natural day lighting in buildings and use of non-motorized transport and change in lifestyle) (Bernstein et al., 2007). The major GHG sinks that could be enhanced to sequester carbon include oceans, biomass, freshwater systems, sediments and the soil (McMullen & Jabbuor, 2009). Out of
these sinks, biomass, especially in tree-based ecosystems, provide a great opportunity for climate change mitigation (Eamus et al., 2000).

Conscious of the significance of forest-based mitigation, the COP 11 in Montreal, Canada in 2005 considered the concept of REDD (Reducing Emissions from Deforestation and forest Degradation) (Velarde et al., 2010). REDD was later adopted in the Bali Action Plan (Negra & Wollenberg, 2011). The conceptualization of reducing emissions from forests has enjoyed significant dynamism. Reference to this concept has evolved from RED (Reducing Emissions from Deforestation) to REDD (Reducing Emissions from Deforestation and forest Degradation) to REDD+, which includes conservation, sustainable management of forests and enhancement of forest carbon stocks (Hyvarinen & Gaafar, 2010; Probert et al., 2011; Velarde et al., 2010). To guarantee the promise of REDD+, the Cancun Agreements made provisions that obligated REDD+ participating countries to develop information systems on REDD+ safeguards (UN-REDD Programme Secretariat, 2012).

However, REDD+ does not incorporate peat lands that comprise already eliminated forest cover, but are still emitting carbon dioxide and account for 3-5% of global carbon dioxide emissions (van Noordwijk et al., 2009). Besides, REDD+ stands a high risk of being hampered by high opportunity costs if REDD+ is preferred to high-value agriculture, hence a disincentive for potentially viable landscapes (Swallow et al., 2007). Consequently, an all-encompassing
approach of Reducing Emissions from All Land Uses (REALU) has been put forth; and it incorporates the REDD+ mechanisms and all alterations in land cover that have an effect on carbon storage such as; peat lands, trees outside forest, agro-forests, plantations or natural forest (van Noordwijk et al., 2009). Under the REALU approach, also known as REDD++, attention has been given to agriculture, including the dimension of trees in agricultural landscapes and how it can reduce emissions (van Noordwijk & Minang, 2011; Velarde et al., 2010).

Furthermore, tree-based ecosystems have been identified to have the potential of aiding the global efforts to mitigate climate change by way of sequestering carbon such as agroforestry (Achard et al., 2008; Mckechnie et al., 2011). Therefore, effective and efficient estimation of biomass in forest and agriculture-based landscapes is imperative for accurate carbon inventory. Allometries in this case can improve the estimation of biomass in woody ecosystems and consequently carbon sequestration potential of these ecosystems (Chave et al., 2005).

Farmlands in Western Kenya have a great potential of sequestering carbon. This is particularly underscored by the increasing uptake of agroforestry in the region by farmers. Besides, the government’s target of encouraging farmers to have at least 10% of their farms covered with trees is likely to positively impact tree cover in the Nyando Basin. Agroforestry has been identified as a practice that can alleviate extreme rural poverty in Nyando Basin, while bolstering the conservation of natural resources and promoting sustainable development (WKIEMP, 2006).
1.2. **Statement of the problem**

The adverse effects of climate change on human life, livelihoods and the ecosystem have made it necessary to have appropriate climate change mitigation strategies. The Kyoto protocol identifies enhancing of GHG sinks as one of the broad climate change mitigation approaches (McMullen & Jabbuor, 2009; UNFCCC Secretariat, 1998). Biomass in agriculturally dominated landscapes provides a great potential for enhancement of these sinks, as a strategy for climate change mitigation. Estimation of biomass in agricultural landscapes is essential for, evaluation of emission reduction across all landscapes, ensuring that every tree-based landscape is captured (Ekadinata et al., 2010).

Use of appropriate allometries is one of the robust ways of estimating tree biomass with least destruction to trees and the environment. However, most allometries that have been developed previously were based on forest ecosystems. Hence, estimation of biomass carbon in agriculturally dominated landscapes has been considered a great challenge due to the heterogeneity and diverse management outputs that characterize these landscapes (Dietz & Kuyah, 2011). However, equations that have been developed for agricultural landscapes in East Africa have not been validated for wider applicability. On the other hand, the global equations derived from data from non-agricultural ecosystems have been found to poorly predict biomass in agriculturally dominated landscapes (Kuyah et al., 2012a).
Actual cutting down and weighing of trees essentially provides the most accurate and direct way of obtaining tree biomass. However, besides the fact that the sampled biomass is lost, it is expensive, labour intensive, and practically limited to a small area (Basuki et al., 2009). Therefore, non-destructive approaches such as the use of allometries have been devised to ease the challenges associated with the destructive approach of tree logging. Allometries estimate biomass as a function of measureable parameters such as diameter at breast height (DBH) or DBH in combination with height and/or wood density. Tree biomass can then be up-scaled to landscape level with other methods such as remote sensing. In order to determine the carbon sequestration potential of agriculturally dominated landscapes, accurate biomass estimates are required (Eamus et al., 2000).

The lack of accounting and verification procedures for biomass carbon resources has prevented governments from up-scaling and integrating tree-based carbon projects in their development plans (VCS, 2012). Kenya, for instance is yet to develop an elaborate protocol for integrating trees in agricultural landscapes. On-farm trees in Nyando basin hold considerable potential in sequestering carbon, while generating benefits to farmers. It is therefore imperative to have allometries that can facilitate the accurate determination of biomass carbon in these agriculturally dominated landscapes of Nyando basin.

Allometric equations need validation before being applied in estimating biomass in agriculturally dominated landscapes, prompted by the high heterogeneity of
agricultural landscapes due to their species diversity and the diverse management practices. Existing equations developed using data from agricultural landscapes were from the Yala Basin, which bears almost similar agro-climatic characteristics. While global equations recommended for tropical ecosystems were developed using trees from forest ecosystems. Therefore, this study was undertaken with an aim of validating the allometric equations developed for agricultural landscapes in the Yala Basin by comparing the performance of these equations with other global equations and the site-generated allometric equations developed using data from the Nyando Basin.

1.3. Research questions

i) Are the local generic allometries developed in the Yala Basin appropriate for estimating carbon in trees found in the agriculturally dominated landscapes of Nyando Basin?

ii) How is the performance of the equations recommended for tropical tree species in estimating the biomass carbon of trees in the agricultural landscapes of Nyando Basin?

iii) What is the best-fitting model from the developed site-specific generic allometric equations in estimating biomass carbon in trees found in the agriculturally dominated landscapes of Nyando Basin?
1.4. Research Hypotheses

i) The estimated biomass obtained by local generic allometric equations are not significantly different from the actual biomass of trees when applied in the Nyando River Basin;

ii) Global equations recommended for tropical tree species yield significantly different biomass estimates from actual biomass in the Nyando Basin’s agriculturally dominated landscapes

1.5. Objectives

The overall objective of this study was to develop and test the performance of local generic allometries for application in estimating biomass carbon in trees in the agriculturally dominated landscapes of Nyando Basin.

The specific objectives of the study were to:

i) Test the performance of local generic allometries developed in Yala Basin in estimating carbon in trees found in the agriculturally dominated landscapes of Nyando Basin;

ii) Test the suitability of equations recommended for tropical tree species in estimating the biomass carbon of trees in the Nyando Basin; and

iii) Develop site-specific generic allometries for the agriculturally dominated landscapes of two distinct locations of the Nyando Basin.
1.6. **Significance of the study**

Trees in agricultural landscapes play a significant role in sequestering carbon and are therefore essential for mitigating climate change (McKechnie et al., 2011). Agricultural landscapes in Western Kenya have a great potential sequestering carbon; hence, there is need for feasible mechanisms of inventorying the tree biomass sinks in these areas, as well as the entire East Africa. This study undertook to validate and develop allometries that could aid the estimation of biomass carbon in these agriculturally dominated landscapes. Therefore, the findings of this study embodied developed and validated allometries of great significance in aiding carbon stock inventory in Kenya and quantifying accruable benefits to farmers from planting and retaining trees on their farms.

1.7. **Definition of operational terms**

**Adaptation:** Adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities (UNFCCC, n.d).

**Allometry:** The quantitative relationship between relative dimensions of parts of an organism and its overall size (Gayon, 2000). In the case of trees, the relative dimensions are normally easily measurable parameters such as DBH.
Biomass Carbon: The carbon contained in mass of live or dead organic matter, usually calculated as a fraction of the biomass in consideration.

Bio-sequestration: The process of increasing the carbon content of a reservoir in the biosphere often obtained from the atmosphere.

Climate change: A change of climate that is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and that is in addition to natural climate variability observed over comparable time periods (UNFCCC, n.d).

Destructive sampling: A procedure involving the cutting down of a tree as a sample and measuring its various components, which cannot otherwise be obtained when the tree is whole and intact. These parameters include the weight of its trunk, branches, leaves and roots.

Holdout: A selection of sampled trees with an exception of six trees, eliminated from all the DBH classes. A holdout contains 27 trees that were used to generate allometric models, whose average parameters were fitted in the site-specific equations.
<table>
<thead>
<tr>
<th><strong>Mitigation:</strong></th>
<th>A human intervention to reduce the sources or enhance the sinks of greenhouse gases (McMullen &amp; Jabbuor, 2009).</th>
</tr>
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<tbody>
<tr>
<td><strong>Mixed species:</strong></td>
<td>A site with different tree species growing within its boundaries</td>
</tr>
<tr>
<td><strong>Sinks:</strong></td>
<td>Reservoirs that absorb carbon that has been released from another part of the carbon cycle. These sinks include the atmosphere, terrestrial biosphere (usually including freshwater systems), oceans, and sediments (McMullen &amp; Jabbuor, 2009).</td>
</tr>
<tr>
<td><strong>Tree:</strong></td>
<td>A woody perennial plant with a single main stem, or in the case of a coppice, several stems and has more or less definite crown (Gschwantner, et al., 2009), often with a height of 4.5 meters and above.</td>
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CHAPTER TWO: LITERATURE REVIEW

2.1. Introduction

This chapter reviews existing literature on the broad theme of climate change and the human contribution to the phenomenon of climate change. It goes on to identify various climate change mitigation strategies before narrowing down to bio-sequestration as a mitigation intervention. Agricultural landscapes are then vouched for in the chapter as important carbon sinks, whose climate change mitigation potential ought to be accurately assessed and established. Hence, the use of allometric equations in biomass estimation is then reviewed and presented. The chapter concludes by identifying the literature gaps in the development and application of allometric equations.

2.2. Climate change

Global climate change is a phenomenon that has received overwhelming scientific evidence-based support. Alexander et al. (2013) assert that it is highly probable that humans have induced most of the dominant causes of climate change since the mid-20th century. There is consensus in the scientific community that the actual and probable scenarios of climate change at the global level may have serious ramifications on humanity (Seacrest et al., 2000). The nature of slow turnaround of climate change effects has made it difficult to effectively communicate the phenomenon in a clear and easily perceivable way (Moser,
Besides, climate change should not just be viewed as an environmental issue since it affects every aspect of development (IFC, 2012). In fact, according to UNEP (2014), if Kenya invests 2% of its GDP annually in green economy interventions, GDP would exceed the business as usual scenario by 12% ($45 billion) by 2030.

Sustained emission of GHGs at or beyond the present proportion would lead to further warming and stimulate numerous changes in the global climate system in the 21st century that would certainly be above the levels observed in the 20th century, predicted to rise by between 1.8°C and 4°C by the end of the 21st century (IPCC, 2007a). For instance, Bernstein et al. (2007) reveal that the global GHG emissions induced by human activities have increased since pre-industrial times, with an increase of 70% between 1970 and 2004. This sustained emission of GHGs into the atmosphere could reduce the global GDP by 5-20 percent each year (Stern, 2007).

Although Africa accounts for a very small fraction of global carbon emissions, it remains to be the most vulnerable continent to climate change, aggravated by the multiple stresses and low adaptive capacity of the continent (IPCC, 2007b). The high number of households that are essentially dependent on agriculture further compound situation, which continues to be adversely affected by climate change (Verchot et al., 2007). In Kenya, for instance, agriculture contributes 26% of
GDP and 98% of the crop output is rain-fed. This means that the economy is immensely vulnerable to the vagaries of climate change (Parry et al., 2012).

In as much as the agriculture and agroforestry-based sectors are often impacted by climate change, they themselves are emitters of GHGs, accounting for approximately a third of global emissions (Seeberg-Elverfeldt & Tapio-Bistrom, 2010). Rudel (2009) proposes a reduced emissions agricultural policy (REAP) as an effective, efficient and equitable policy option that governments can take. Therefore, mitigation could help avert the plausible damages climate change poses to human systems, thereby boosting sustainable development pathways that lessen vulnerability to climate change and significantly cut GHG emissions (Rogner et al., 2007). Mitigation, encompassing human interventions aimed at both reducing the sources and/or enhancing the sinks of GHGs (McMullen & Jabbuor, 2009) has been at the core of international climate change discourses. Article 3.3 of the Kyoto Protocol (KP) provides for the adoption of schemes for estimating the net changes in greenhouse gas removals by sinks resulting from direct human-induced land-use change and forestry activities (UNFCCC Secretariat, 1998).

On its part, the government of Kenya has set an ambitious climate finance and carbon trading policy goal. This goal aims to develop a strong carbon market which will harness benefits for people at all levels, minimize the country’s overreliance on foreign aid, and guarantee resource mobilization for recapitalizing
investments in the country (Government of Kenya, 2011). The Kenya National Climate Change Action Plan (NCCAP) envisages a low-carbon development pathway for the country. This means that emphasis will be on sustainable development and accrual of adaptation-mitigation synergies in achieving the middle-income status by the year 2030 (Government of Kenya, 2013). Bio-sequestration is one of the modalities that portend immense promise for enhancing carbon sinks in Kenya while generating income for the poor and vulnerable communities.

2.3. **Bio-sequestration**

Biological sequestration (bio-sequestration) has in the recent years taken root in the global climate talks. Bio-sequestration encompasses the direct removal of CO\(_2\) from the atmosphere through land-use change, afforestation, reforestation, carbon storage in landfills, and practices that boost soil carbon in agriculture (IPCC, 2007a). Under the UNFCCC, parties are required to regularly report the status of their forest resources and on emerging sequestration mechanisms, such as REDD (UNFCCC, 2008). This kind of global partnership needs to be based on dedication by developing countries to embark on low-carbon, climate resilient development on one hand, and provision of predictable and considerable funding, on the other hand, by developed countries as an incentive for reduced forest-based carbon emissions (UN-REDD Programme Secretariat, 2010).
Trees in agricultural landscapes normally act as buffers of extreme climate variability and help in regulating crop production for farmers (Pramova et al., 2012; Verchot, et al., 2007). With 80% of Nyando basin’s 750,000 residents being dependent on agriculture (Verchot et al., 2008), the attainment of substantive carbon sequestration as enshrined in the REDD++ mechanism, could be achieved through adoption of land management practices such as agroforestry, green fallow, conservation tillage, rotational cropping and return of crop residues (FAO, 2004; Farage et al., 2007; Velarde et al., 2010).

Nonetheless, methodologies for assessing carbon in tree-based systems is not very well established in developing countries (Jenkins et al., 2013), where agroforestry holds immense promise to farmers. Olsson and Jerneck (2010) further maintain that agroforestry might have the greatest potential among these land management practices since it harbours benefits associated with livelihood enhancement and prevention of soil degradation, besides having climate change mitigation value. Agroforestry has the potential of mitigating climate change, while improving food security and livelihoods (Bernard et al., 2010) and exemplifies a set of novel practices that are intended to augment productivity in a way that often contributes to climate change mitigation through improved carbon sequestration (Verchot, 2008).
2.4. Biomass estimation

Besides the well-intended global initiatives to enhance carbon sinks, inventory of biomass-based carbon stocks is yet to pick up in the developing countries. Verchot (2008) submits that a robust and methodical analysis of the carbon stocks in Africa is essential in the provision of information to project managers and investors about the carbon sequestration potential of projects. The determination of the amount of biomass and growth of vegetation is an important facet in carbon sequestration estimation (Eamus et al., 2000). Stocktaking of biomass carbon remains a vital component of national and international carbon inventory that ought to be backed by appropriate quantities.

The accurate and precise measurement of carbon stocks over time, by means of consistent approaches would provide the much-needed information in the determination of changes in carbon stocks (Brown, 2002). Knowledge of the amount of biomass in an ecosystem is often the starting point in biomass carbon estimation. As asserted by Brown and Lugo (1992), most researchers have relied on tree biomass inventory as a reliable way of estimating forest biomass because it accounts for the largest fraction of biomass in that ecosystem. Estimation of tree biomass could be undertaken through the direct destructive method, or non-destructive methods. The direct destructive method yields more precise biomass estimates. However, due to its shortcomings of it being costly, labour-intensive, and spatially limited (Basuki et al., 2009), non-destructive approaches have been developed.
The non-destructive methods include deductions derived from remote sensing, use of biomass conversion and estimation factors, and estimation by use of allometric equations (Bombelli et al., 2009). However, unreliable biomass coefficients often impede accurate extrapolation of biomass when default conversion factors are used. While remote sensing is a plausible technique for large scale biomass estimation (Dobson et al., 1995), it still requires ground based techniques to validate its accuracy (Eamus et al., 2000).

2.5. Allometric equations

Allometry (dimensional analysis) techniques have been traditionally used to measure biomass such that an easily measured parameter (e.g., DBH, DBH combined with plant height) is regressed against harvested plant component weights (Eamus et al., 2000). Moreover, estimation of biomass through allometric equations is normally more accurate compared to estimations obtained by way of regional or global conversion and expansion factors (Bombelli et al., 2009). However, some allometric equations tend to bear inaccuracies in biomass estimates if they are applied in land covers that differ from those from which the equations were developed (Bombelli et al., 2009). There is therefore need to develop regional and national generic allometric equations that could be applicable in estimating tree biomass for a broader geographic expanse (Case & Hall, 2008; Lambert et al., 2005).
Generic equations that are normally stratified according to ecological zones or species are usually based on a substantial number of trees (Brown & Schroeder, 1999), and they cover a wider array of diameters; this increases the accuracy and precision of the equations. Additionally, tropical ecosystems are often highly heterogeneous, thereby making it quite precarious to extrapolate local data for wider application without assessing the representativeness of these data (Chave et al., 2005; Chave et al., 2004).

MacDicken (1997) confers that methods for testing and designing a sampling scheme, as well as approximating the quantity, size, and distribution of established plots for a particular level of preferred accuracy are already well established. However, in as much as generating local allometric regression equations that reflect a profound precision, especially for multi-species equation, requires an adequate number of trees to embody their sizes and distribution, it is normally quite a time consuming and costly exercise (Brown, 2002).

The determination of AGB has reasonably been well established; however the measuring of BGB remains a challenge since it is time consuming and the methods involved are not standardized (Pearson et al., 2007; Bolte et al., 2004; Cairns et al., 1997). The difficulties associated with BGB estimation comprise substantial disparities in the root samples, the need to employ destructive methods, high cost of labour and limited capacity to illustrate the spatial distribution of roots (Bengough et al., 2000). Therefore, more efficiency and
reliability could be achieved by employing a regression model in estimating BGB as a function of AGB (Pearson et al., 2007). Nonetheless, effective estimation of biomass requires accurate and reliable allometries to be deployed in the appropriate ecosystem.

2.6. Literature gaps

Several equations have been developed for tropical ecosystems; however, equations applicable to trees in agricultural landscapes are few. Besides, these equations have not been well established since they have not been validated for wider applicability across different agro-vegetative tropical zones. Allometric equations should not be used beyond their range of validity (Chave et al., 2005), thereby necessitating the need to develop and apply regression models that yield reliable biomass estimates. This study sought to develop and validate existing allometric models (both local and global) in estimation of biomass carbon of trees the agriculturally dominated landscapes of Nyando basin in Western Kenya.
CHAPTER THREE: MATERIALS AND METHODS

3.1. Introduction

This chapter discusses the material and methods deployed to enable the study. It presents the study area, which covers aspects such as the location, climate, geology and soils, and vegetation. It goes on to elucidate the experimental design of the study. This covered the sampling design, how the dendrometric parameters of the trees were measured and the allometric testing approaches.

3.2. Study site

3.2.1. Location

The study was undertaken in the Nyando Basin (Figure 3.1). The basin is situated in Western Kenya covering an area of 3517 km$^2$ and is located between latitude 0°25′S and 0°10′N and longitude 34°50′E and 35°50′E. The river basin drains into the Winam Gulf in Lake Victoria. The Nyando Basin consists of three blocks, which are the Upper, Middle and Lower blocks. The study, however, focused only on the Lower and Upper Blocks.
3.2.2. Climate

The climate of Nyando basin varies from humid to sub-humid, with the lower basin predominantly being sub-humid and the upper basin humid. The mean annual rainfall is about 1450 mm for the lower basin and 1850 mm for the upper basin. The basin normally experiences bimodal rainfall regimes with the long rains occurring between April and June, while the short rains occur between September and December.
3.2.3. Geology and Soils

The soil texture of the Lower Nyando basin ranges from loamy to clayey, while the soil texture of the Upper Nyando basin is largely clay to clay loam (Verchot et al., 2008). The lower basin is dominated by Luvisols, Planosols, Vertisols, Cambisols and Solonet (Andriesse & Van-der-Pouw, 1985) which have impeded drainage and sodic subsoil with less stable aggregates (WKIEMP, 2006). The upper basin is predominantly Ferrasols, Cambisols, Nitisols and Acrisols (Andriesse & Van-der-Pouw, 1985), which are deep to very deep and have shallow humic top soil and stable soil aggregates (WKIEMP, 2006).

3.2.4. Vegetation

Acacia, Balanites, and Combretum species (Njuguna et al., 2004) previously dominated the vegetation in Lower basin. However, the basin has been converted over the years to croplands with spots of planted Eucalyptus and Euphorbia species evident in the farmlands. The main crops grown in the area include maize, sorghum, rice, millet and vegetables (WKIEMP, 2006). The upper basin hosts a portion of the Mau Forest Complex and the remaining patches of Tinderet, Londiani, Timboroa and Nandi South Forests. These forests are habitats of several indigenous tree species, birds and wild fauna. Nonetheless, some exotic trees have been planted within their precincts, such as Pinus patula, Pinus radiata, Eucalyptus spp and Cupressus species (WKIEMP, 2006). Tea plantations dominate the central part of Kericho County, mostly owned by multinationals such as Unilever and Finlays.
3.3. **Experimental design**

3.3.1. **Sampling design**

Two sites, one in Lower and another in Upper Nyando, were each the basic sampling units. The blocks represented the basin in terms of elevation, slope, rainfall regimes and land use (Verchot et al., 2008). The study was conducted in two 100 km$^2$ benchmark sites (Lower and Upper Nyando) along the Nyando River Basin in Western Kenya. The focus areas in the lower block were in a site that had been established, based on the Land Degradation Surveillance Framework (LDSF), developed within the Africa Soil Information System (AfSIS) and used by the Western Kenya Integrated Ecosystem Management Project (WKIEMP). Sampling in the upper block, however, was undertaken within the Unilever Tea Kenya (UTK), where a pure stand of *Eucalyptus grandis* species was sampled.

The sampled trees in Lower Nyando were obtained from an earlier inventory of plots in the AfSIS sentinel sites. These sentinel sites comprised 10 x 10 km blocks, each divided into 16 sub-blocks (clusters) of 2.5 x 2.5 km with 10 plots (30 x 30 m) in each cluster. Vagen et al. (2010) provide more information on the sentinel site approach and the sampling design. The trees were subsequently stratified into DBH classes then random sampling was undertaken per class. The trees were stratified by size into five diameter classes of 2.5-10; 10.1-20; 20.1-30; 30.1-40 and above 40 cm to realize a considerable distribution of diameter classes in the sample. Three trees were randomly selected for harvesting using
random tables from each diameter class, except the class of >40cm, in which six trees were sampled, giving a total of eighteen trees for the Lower Basin. Whereas tree species were not considered in the selection process, random sampling resulted in the abundant species being captured more frequently compared to the rare species (Dietz & Kuyah, 2011).

In Upper Nyando, trees were sampled from within the UTK Estates. Selection of the field was based on the rotational harvesting of trees by UTK, such that the field with ten-year old trees was targeted. Once the field had been identified, it was divided into ten 10 strips using strip transect method such that the entire field was covered. Plots of 30x30m were randomly created in each strip such that there were ten plots. The trees were further stratified into five diameter classes and three trees randomly selected from each class following the same procedure as that of the Lower Basin, resulting in 15 trees for the upper basin and a total of 33 trees for both sites.

3.3.2. Measurement of parameters

The study involved obtaining non-destructive measurements of trees, such as the DBH, tree height and crown diameter. A DBH tape was used in measuring the DBH of the trees, the tree heights were measured using a clinometer, while the crown diameter was measured using a tape measure. Subsequently, the identified trees were destructively sampled for various parameters by felling at 10 cm above the ground using a chainsaw for trees with >10 cm DBH and a machete (panga)
for those with DBH < 10cm. The weight of the tree trunk, branches, and leaves were taken for aboveground biomass. A weighing scale with an error of 100g was used to weigh sub-samples of between 3kg and 300kg, while a weighing scale with an error of 0.05g used to weigh subsamples of less than 3kg. Data on the plot and tree measurements were collected from observation, measurement and weighing then entered into data sheets. Sub-samples of the trunk, branches and leaves were also obtained from the trees for onward drying in the oven to facilitate extrapolation of the total dry mass of the trees.

After felling, the stump diameter of the tree was measured and the coordinates of the tree recorded using a GPS gadget at the centre of the stump. The roots and stump were excavated within a radius of 1 m and to a depth of 0.45 to 1.5 m. Even though trees in the *E. grandis* plantation were spaced at 2 m apart, excavation up to a 1 m radius was possible but with the risk of destroying the roots of adjacent trees. The excavated stump and coarse roots were then weighed for belowground biomass.

### 3.3.3. Allometric model testing and biomass functions

The data were transferred from the field and laboratory data sheets to excel spreadsheets. The data were then cleaned and subsequently subjected to exploratory analysis by plotting on scatter diagrams for purposes of identifying possible outliers. The relationships of the dependent variables (e.g., total AGB, BGB, biomass of trunk, branches, and leaves) and DBH, including its compound
derivatives (DBH\(^2\)H, DBH\(^2\)G, and DBH\(^2\)CD) were assessed from scatter diagrams. SD was also explored as a predictor variable for BGB. Where DBH is diameter at breast height, H is tree height, G is wood-specific gravity, SD is stump diameter and CD is crown diameter (obtained from the average of the crown length and crown width).

Regression analysis was run on the various predictive parameters to derive allometric equations for above and belowground biomass and their accuracy tested. The power function model of regression, which is commonly used to depict growth relationships in biomass studies, was used (Pilli et al., 2006; Zianis & Mencuccini, 2004). The equivalent linear model was also used to depict the corresponding linear relationships between the predictor and respondent variables. To minimize the error in BGB sampling, the coarse roots were excavated to substantial depths and breadths while the unexcavated ones were extrapolated. The extrapolation was done by relating the biomass of the excavated root parts to the biomass of the unexcavated parts. The calculation adhered to the power function relationship of allometric scaling (van Noordwijk & Mulia, 2002; van Noordwijk et al., 1994). The proximal and distal diameters of the excavated roots were measured and used to estimate the biomass of the unexcavated roots as shown in the equation below:

\[
\text{Biomass} = a \times \left( (D_{\text{prox}})^p - (D_{\text{dist}})^p \right)
\]

Where \(D_{\text{prox}}\) is the proximal diameter and \(D_{\text{dist}}\) is the distal diameter.
The validity of local and global allometric equations recommended for tropical ecosystems was tested. This was done by comparing the biomass estimates of the equations and the measured biomass obtained from destructive sampling. The tested equations included:

- Kuyah 1 (Kuyah et al., 2012a): Equation for estimating AGB, developed using DBH and AGB
  \[ AGB = 0.091 \times DBH^{2.472} \]

- Kuyah 2 (Kuyah et al., 2012b): Equation for estimating BGB, developed using DBH and uncorrected BGB
  \[ BGB = 0.0397 \times DBH^{2.314} \]

- Kuyah 3 (Kuyah et al., 2012b): Equation for estimating BGB, developed using SD and uncorrected BGB
  \[ BGB = 0.0193 \times SD^{2.2943} \]

- Kuyah 4 (Kuyah et al., 2012b): Equation for estimating BGB, developed using AGB and uncorrected BGB
  \[ BGB = 0.4131 \times AGB^{0.9259} \]

- Kuyah 5 (Kuyah et al., 2012b): Equation for estimating BGB, developed using DBH and corrected BGB
  \[ BGB = 0.048 \times DBH^{2.303} \]

- Chave 1 (Chave et al., 2005): For dry forest ecosystem
  \[ AGB = \rho \times \exp \left\{ -0.667 + (1.784 \ln DBH) + (0.207 \ln DBH)^2 - (0.028 \ln DBH)^3 \right\} \]

- Chave 2 (Chave et al., 2005): For moist forest ecosystem
\[ AGB = \rho \times \exp \left\{ -1.499 + (2.148 \ln DBH) + \left(0.207[\ln DBH]^3\right) - \left(0.0281[\ln DBH]^5\right) \right\} \]

- Brown 1 (Brown, 1997): For dry forest ecosystem
  \[ AGB = 0.1359 \times DBH^{3.32} \]

- Brown 2 (Brown, 1997): For moist forest ecosystem
  \[ AGB = 42.69 - (12.8DBH) + \left(1.242[DBH]^2\right) \]

- Mokany et al. (2006)  
  \[ BGB = 0.489 \times AGB^{0.89} \]

- Cairns et al. (1997)  
  \[ BGB = 0.3469 \times AGB^{0.8836} \]

The predictive accuracy of the equations was determined by calculating the percentage error between the estimated and actual biomass for each tree (Chave et al., 2005), as shown in the equation below.

\[ \text{% error} = \left( \frac{\text{predicted biomass} - \text{actual biomass}}{\text{actual biomass}} \right) \times 100 \]

To generate the site-based equations, the predictor and dependent parameters were transformed using natural logarithm to generate a linear equivalent relationship of the power function as illustrated below.

- Power function model: \[ Y = \exp^a \times X^b \]
- Linear equivalent model: \[ \ln Y = a + b \times \ln X \]
Where: $Y =$ dependent variable, $X =$ independent variable, $a =$ $y$-intercept coefficient, $b =$ slope coefficient, $\ln =$ natural logarithm, and $\exp =$ exponential.

For purposes of cross-validation (Refaeilzadeh et al., 2009) one tree from each of the five DBH classes was randomly selected and eliminated from the training data set used in the model fitting and the five trees used in predicting the performance of the model. This process was repeated six times with each run having different trees used in developing and validating the models generated. The bias introduced during the back-transformation of the $y$-intercept ($a$) was then corrected by multiplying the back-transformed value with a correction factor derived using the Chave et al. (2005) equation:

$$ CF = \exp \left( \frac{RSE^2}{2} \right). $$

Biomass carbon in the trees was calculated and the results for each equation or combination of equations compared. The biomass carbon was obtained by multiplying the estimates of total tree biomass by a conversion factor. In this study, the default IPCC value of 0.47 recommended for tropical ecosystems was applied (IPCC, 2006). Hence, biomass carbon was estimated as:

$$ BC = TTB \times 0.47 $$

Where $BC =$ biomass carbon and $TTB =$ Total tree biomass.
CHAPTER FOUR: RESULTS AND DISCUSSIONS

4.1. Introduction

Several equations have been developed for estimating biomass in the tropics. However, there exist just a handful of globally recommended and locally developed equations that can be applied in the tropical ecosystems, and specifically in agricultural landscapes. This chapter discusses the performance of various allometric equations in estimating both AGB and BGB in the Nyando Basin using the ratio data obtained from the field. These equations include the mixed species equations for agricultural landscapes by Kuyah et al. (2012a, 2012b), global equations recommended for tropical ecosystems (Chave et al., 2005; Brown, 1997; Cairns et al., 1997; Mokany et al., 2006; IPCC, 2006) and site-based equations developed in the Nyando Basin. The implications of using these allometries for biomass carbon estimation are equally assessed.

4.2. Aboveground biomass

4.2.1. Performance of local generic allometries

As shown in Table 4.1, Kuyah 1 equation estimated AGB in the Nyando Basin with relative error (RE) of -2.7 ± 4.3%. The equation underestimated all measured trees with DBH<30 cm except two: *Balanites aegyptica* (DBH = 28.4 cm) and *E. grandis* (DBH = 30 cm), which were overestimated by 56.1% and 50% respectively.
Table 4.1: Comparison of measured AGB and estimated AGB using Kuyah 1 equation in Nyando Basin, indicating the relative error (RE) of estimation

<table>
<thead>
<tr>
<th>Species</th>
<th>DBH (cm)</th>
<th>Measured AGB (kg)</th>
<th>Estimated AGB (kg)</th>
<th>RE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Albizia coriaria</em></td>
<td>7.1</td>
<td>16.0</td>
<td>11.6</td>
<td>-27.8</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>7.3</td>
<td>14.7</td>
<td>12.4</td>
<td>-15.5</td>
</tr>
<tr>
<td><em>Albizia coriaria</em></td>
<td>8.5</td>
<td>22.4</td>
<td>18.1</td>
<td>-19.3</td>
</tr>
<tr>
<td><em>Acacia polyacantha</em></td>
<td>8.5</td>
<td>14.4</td>
<td>18.1</td>
<td>25.4</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>8.6</td>
<td>20.2</td>
<td>18.6</td>
<td>-8.0</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>9.8</td>
<td>26.9</td>
<td>25.7</td>
<td>-4.7</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>&lt;10</td>
<td>114.6</td>
<td>104.3</td>
<td>-9.0</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>14.2</td>
<td>81.2</td>
<td>64.2</td>
<td>-21.0</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>14.3</td>
<td>70.7</td>
<td>65.3</td>
<td>-7.6</td>
</tr>
<tr>
<td><em>Grewia trichocarpa</em></td>
<td>14.4</td>
<td>70.9</td>
<td>66.5</td>
<td>-6.3</td>
</tr>
<tr>
<td><em>Terminalia brownii</em></td>
<td>16.9</td>
<td>177.9</td>
<td>98.7</td>
<td>-44.5</td>
</tr>
<tr>
<td><em>Acacia gerrardii</em></td>
<td>17.5</td>
<td>213.6</td>
<td>107.6</td>
<td>-49.6</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>17.8</td>
<td>124.4</td>
<td>112.2</td>
<td>-9.8</td>
</tr>
<tr>
<td>10.1 – 20</td>
<td></td>
<td>738.67</td>
<td>514.5</td>
<td>-30.4</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>23.8</td>
<td>235.6</td>
<td>230.1</td>
<td>-2.3</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>24.7</td>
<td>274.5</td>
<td>252.2</td>
<td>-8.1</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>25.8</td>
<td>392.7</td>
<td>280.9</td>
<td>-28.5</td>
</tr>
<tr>
<td><em>Acacia polyacantha</em></td>
<td>28.1</td>
<td>397.6</td>
<td>346.9</td>
<td>-12.7</td>
</tr>
<tr>
<td><em>Balanites aegyptica</em></td>
<td>28.4</td>
<td>228.2</td>
<td>356.2</td>
<td>56.1</td>
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<tr>
<td><em>Eucalyptus grandis</em></td>
<td>30.0</td>
<td>271.9</td>
<td>407.8</td>
<td>50.0</td>
</tr>
<tr>
<td>20.1 – 30</td>
<td></td>
<td>1800.4</td>
<td>1874.2</td>
<td>4.1</td>
</tr>
<tr>
<td><em>Eucalyptus citriodora</em></td>
<td>30.5</td>
<td>517.6</td>
<td>424.9</td>
<td>-17.9</td>
</tr>
<tr>
<td><em>Eucalyptus globulus</em></td>
<td>33.1</td>
<td>562.4</td>
<td>520.1</td>
<td>-7.5</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>33.3</td>
<td>572.5</td>
<td>527.9</td>
<td>-7.8</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>34.2</td>
<td>499.1</td>
<td>563.8</td>
<td>13.0</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>36.4</td>
<td>661.2</td>
<td>657.8</td>
<td>-0.5</td>
</tr>
<tr>
<td><em>Acacia polyacantha</em></td>
<td>37.3</td>
<td>684.9</td>
<td>698.7</td>
<td>2.0</td>
</tr>
<tr>
<td>30.1 – 40</td>
<td></td>
<td>3497.8</td>
<td>3393.1</td>
<td>-3.0</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>41.9</td>
<td>675.6</td>
<td>931.4</td>
<td>37.9</td>
</tr>
<tr>
<td><em>Ficus sur</em></td>
<td>44.2</td>
<td>824.0</td>
<td>1063.0</td>
<td>28.9</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>45.2</td>
<td>824.8</td>
<td>1123.4</td>
<td>36.2</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td>45.6</td>
<td>1102.4</td>
<td>1148.2</td>
<td>4.2</td>
</tr>
<tr>
<td><em>Acacia lahai</em></td>
<td>53.5</td>
<td>2218.7</td>
<td>1704.2</td>
<td>-23.2</td>
</tr>
<tr>
<td><em>Terminalia brownii</em></td>
<td>53.8</td>
<td>2070.3</td>
<td>1728.0</td>
<td>-16.5</td>
</tr>
<tr>
<td><em>Acacia lahai</em></td>
<td>60.2</td>
<td>2141.4</td>
<td>2281.4</td>
<td>6.5</td>
</tr>
<tr>
<td><em>Terminalia brownii</em></td>
<td>63.7</td>
<td>2430.8</td>
<td>2623.5</td>
<td>7.9</td>
</tr>
<tr>
<td><em>Acacia lahai</em></td>
<td>70.6</td>
<td>4105.6</td>
<td>3382.9</td>
<td>-17.6</td>
</tr>
<tr>
<td>&gt;40</td>
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<td>16394.6</td>
<td>15986.0</td>
<td>-2.5</td>
</tr>
<tr>
<td><em>Eucalyptus grandis</em></td>
<td></td>
<td>5576.6</td>
<td>6014.1</td>
<td>-1.5</td>
</tr>
<tr>
<td>Mixed species site</td>
<td></td>
<td>16969.5</td>
<td>15858.0</td>
<td>-3.7</td>
</tr>
<tr>
<td>All measured trees</td>
<td></td>
<td>22546.0</td>
<td>21872.1</td>
<td>-3.0</td>
</tr>
</tbody>
</table>
The overestimation was attributed to the tree’s small crown area and relative shortness (reduced height) compared to other trees in the landscape with almost the same DBH. Nowak and Daniel (2000) maintain that in as much as open-grown trees may often be shorter, they have larger and branchy crowns than plantation or forest grown trees, which boost their biomass. The uniqueness of the characteristics displayed by the *B. aegyptica* influenced the performance of the equation in estimating its AGB. The other tree, *E. grandis*, was overestimated by 49.9% and the error in estimation was because of termite invasion on the tree’s heartwood (xylem tissues) at the basal shoot and roots, indicated by a hollow trunk. This considerably reduced its biomass hence overestimation of its AGB by the equation.

When disaggregated into DBH classes, the DBH class of 10.1 – 20 cm was the most underestimated (RE = -30.4%). While the biomass of trees with DBH>30 cm were underestimated, the RE of estimation was lesser compared to the smaller trees (Figure 4.1). The measured AGB in the mixed species site was higher than that of the *E. grandis* site since more trees were sampled in the site. Besides, most of the large trees were sampled from the mixed species site (Table 4.1). In the mixed species site, the equation estimated AGB with a RE of -3.7 ± 6.8%, and varying accuracy observed across trees of different diameter classes. In this site, the equation generally estimated the biomass of large trees, DBH>30 cm, with greater accuracy than the smaller ones, DBH< 30 cm (Figure 4.1).
Figure 4.1: Disaggregation of error in AGB estimation per DBH class for the mixed species site, E. grandis site and the two sites combined for Kuyah 1 equation and Site equation 1

In the E. grandis plantation site, the equation estimated the AGB of the trees with a RE of $-1.5 \pm 4.8\%$. Trees in the DBH classes of $< 30$ cm were both individually and collectively underestimated, while trees with diameters $>30$ cm were overestimated (Figure 4.1). When the equation was tested on a combination of edge trees from the E. grandis plantation and all trees from the mixed species site, it even performed better, with a RE of $-0.7 \pm 5.9\%$. Tested on all the Eucalyptus spp sampled in both sites, the RE reduced further to $0.1 \pm 5.0\%$. However, when all the Eucalyptus spp were eliminated and the other species tested, the equation’s RE in estimation increased to $-6.1 \pm 7.3\%$. 
4.2.2. Site-specific allometries for aboveground biomass estimation

There was a strong relationship between DBH, including the combination of DBH and other proxies (DBH^2H, DBH^2G, and DBH^2CD), with the AGB of the sampled trees in Nyando Basin. The inclusion of the wood-specific gravity (G) in the compound derivatives of DBH did not amount to much variation in the coefficient of correlation of the various dependent biomass parameters. Since different species on the same site may have varying allometric relationships due to variations in their heights, densities and architectures (Chave et al., 2003), the inclusion of crown diameter (CD) and height (H) in the regression weakened the relationship between the predictor variable and the AGB in the trees of Nyando Basin. However, the inclusion of height in the compound derivative of DBH resulted in the highest value of the coefficient of determination (R^2 = 0.992) in the upper block (Table 4.2).

Due to its close relationship with DBH (site specifically), the inclusion of height in an equation may depict just a small variance in a model for a specific site (Ketterings et al., 2001), hence height has been omitted in several general allometric models (Brown, 1997; Ketterings et al., 2001; Ter-Mikaelian & Korzukhin, 1997). Trunk biomass portrayed the strongest correlation when regressed against a combination of DBH and height (R^2 = 0.96), while for the branch biomass the coefficient of correlation was highest (R^2 = 0.92) when regressed against a combination of DBH and CD (Table 4.2).
Table 4.2: Correlation between DBH, including its proxy combinations and AGB components (trunk, branches, leaves and total AGB)

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Predictor variable</th>
<th>E. grandis site</th>
<th>Mixed species site</th>
<th>Combination of both sites</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>a</td>
<td>b</td>
<td>R²</td>
</tr>
<tr>
<td>Trunk</td>
<td>DBH</td>
<td>0.192</td>
<td>2.197</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>(DBH)²H</td>
<td>0.030</td>
<td>0.903</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>(DBH)²G</td>
<td>0.296</td>
<td>1.098</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>(DBH)²CD</td>
<td>0.462</td>
<td>0.773</td>
<td>0.96</td>
</tr>
<tr>
<td>Branches</td>
<td>DBH</td>
<td>3.94E-04</td>
<td>3.324</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>(DBH)²H</td>
<td>3.090E-05</td>
<td>1.341</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td>(DBH)²G</td>
<td>0.001</td>
<td>1.662</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>(DBH)²CD</td>
<td>0.001</td>
<td>1.183</td>
<td>0.93</td>
</tr>
<tr>
<td>Leaves</td>
<td>DBH</td>
<td>0.001</td>
<td>2.670</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>(DBH)²H</td>
<td>2.06E-04</td>
<td>1.081</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>(DBH)²G</td>
<td>0.002</td>
<td>1.335</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>(DBH)²CD</td>
<td>0.004</td>
<td>0.943</td>
<td>0.93</td>
</tr>
<tr>
<td>AGB</td>
<td>DBH</td>
<td>0.155</td>
<td>2.308</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>(DBH)²H</td>
<td>0.023</td>
<td>0.945</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>(DBH)²G</td>
<td>0.244</td>
<td>1.154</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>(DBH)²CD</td>
<td>0.386</td>
<td>0.813</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Key: G – wood-specific gravity, H – tree height, CD – crown diameter, DBH – diameter at breast height

Regression analysis that was run on the DBH and DBH derivatives confirmed that DBH can singly and accurately be used in estimating the AGB of trees in the
Nyando Basin ($R^2 = 0.98$). Inasmuch as the inclusion of other determinant variables such as height, crown area and density of trees could help improve the predictive accuracy of a model (Deitz & Kuyah, 2011; (Wirth et al., 2004)), DBH is arguably the single-most accurate predictor of AGB (Brown, 1997; Chave et al., 2005; Dietz & Kuyah, 2011). Chave et al. (2005), for instance, attribute the avoidance of using tree height in biomass functions to the difficulty associated with measuring and obtaining tree height. Therefore, the generated site-specific equation solely factored DBH as the predictor variable for AGB. The results of the regression of the six holdouts are outlined in Table 4.3.

Table 4.3: Cross-validation for Equation 1, generated from the averages of the fitted parameters; $\ln(a)$, $\bar{a}$, $\text{se}(\bar{a})$, CF, $a$, $b$, $R^2$.

<table>
<thead>
<tr>
<th>Holdouts</th>
<th>$\ln(a)$</th>
<th>$\bar{a}$</th>
<th>$\text{Se}(\bar{a})$</th>
<th>CF</th>
<th>$a$</th>
<th>$b$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Holdout 1</td>
<td>-1.983</td>
<td>0.138</td>
<td>0.242</td>
<td>1.030</td>
<td>0.142</td>
<td>2.355</td>
<td>0.98</td>
</tr>
<tr>
<td>Holdout 2</td>
<td>-1.936</td>
<td>0.144</td>
<td>0.247</td>
<td>1.031</td>
<td>0.149</td>
<td>2.343</td>
<td>0.97</td>
</tr>
<tr>
<td>Holdout 3</td>
<td>-1.966</td>
<td>0.140</td>
<td>0.188</td>
<td>1.018</td>
<td>0.142</td>
<td>2.363</td>
<td>0.99</td>
</tr>
<tr>
<td>Holdout 4</td>
<td>-2.024</td>
<td>0.132</td>
<td>0.246</td>
<td>1.031</td>
<td>0.136</td>
<td>2.370</td>
<td>0.97</td>
</tr>
<tr>
<td>Holdout 5</td>
<td>-1.991</td>
<td>0.137</td>
<td>0.223</td>
<td>1.025</td>
<td>0.140</td>
<td>2.371</td>
<td>0.98</td>
</tr>
<tr>
<td>Holdout 6</td>
<td>-1.985</td>
<td>0.137</td>
<td>0.208</td>
<td>1.022</td>
<td>0.140</td>
<td>2.351</td>
<td>0.98</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.142</td>
<td>2.359</td>
<td>0.98</td>
</tr>
</tbody>
</table>

Key: $\ln(a)$ – Natural logarithm of intercept, $(\bar{a})$ – uncorrected values of back-transformed intercept, $\text{se}(\bar{a})$ – standard error of estimates, CF – correction factor, $a$ – Intercept, $b$ – scaling exponent and $R^2$ – coefficient of determination.
The best fitting model for estimating biomass in the Nyando Basin with DBH as the single predictor therefore was:

\[ AGB = 0.142 \times DBH^{2.359} \]

When the developed equation was applied in estimating the data from the Nyando Basin, it estimated AGB with an average RE of 5.5 \pm 4.4\%. An individual of *B. aegyptica* (DBH = 28.4cm) was overestimated by 66.9\%, representing the highest overestimation, while at -43.1 \% RE, *Acacia gerardii* (DBH = 17.5cm) was the most underestimated by the equation. This overestimation was attributed to the physiological characteristics of these trees contemplated in paragraph 2, sub-section 4.2.1 of this chapter. Additionally there was no significant difference between the biomass estimates of the local equations applied and the measured biomass. In each case, P > 0.5; therefore, we cannot reject the hypothesis that biomass estimates of the local generic allometric equations are not significantly different from the actual biomass of trees when applied in the Nyando River Basin.

When disaggregated into DBH classes, the equation overestimated AGB of all the classes except the DBH class of 10 - 20 cm (RE = -12.3\%). In the mixed species site, the RE was 3.4 \pm 7.4\%, while in the *E. grandis* site it was 8.0 \pm 4.2\%. When tested on all the sampled non-*Eucalyptus* species, the RE reduced to 1.1 \pm 7.9\% while for all the sampled *Eucalyptus* species, the RE increased to 9.1 \pm 4.7\%. It is
evident that Equation 1 performed better in estimating the AGB of mixed species, compared to how it did on *Eucalyptus spp.* This is attributable to the heterogeneity of the trees used in developing the equation, a finding consistent with the assertion of Dietz and Kuyah (2011) that trees in agricultural landscapes are characterized by high heterogeneity.

### 4.2.3. Global equations recommended for tropical ecosystems

Chave 1 and Brown 1 equations estimated AGB of all measured trees in Nyando Basin with a RE of $35.0 \pm 7.0\%$ and $-10.9 \pm 3.7\%$, respectively. Disaggregation per DBH class showed that while the Chave 1 equation overestimated AGB for all the diameter classes, the Brown 1 equation underestimated AGB in all the diameter classes (Figure 4.2). Chave 1 estimated AGB in the mixed species and *E. grandis* sites with a RE of $32.5 \pm 12.2\%$ and $38.1 \pm 4.9\%$ respectively, while Brown 1 had a RE of $-13.0 \pm 6.3$ and $-8.4 \pm 3.4\%$ for the mixed species and *E. grandis* sites respectively.
Figure 4.2: Disaggregation of RE per DBH class of global equations by Chave et al. (2005) and Brown (1997) for all measured trees.

The equations recommended for moist tropical forests, Chave 2 and Brown 2 both extremely overestimated AGB by $89.5 \pm 10.2\%$ and $52.9 \pm 7.0\%$ respectively. In addition, they overestimated the AGB of all the disaggregated DBH classes (Figure 4.2) and in both the mixed species site and *E. grandis* sites separately.

Brown (1997) and Chave et al. (2005) categorized their equations according to the climatic zones, with a distinction between dry and moist forests, depending on the amount of rainfall they receive annually.
In as much as the study area bore characteristics similar to the moist forests, based on the average annual rainfall it receives, the dry forest equations tended to perform better than the moist forest allometries. In addition, the global equations were developed mainly using data from forest ecosystems and as observed by Kuyah et al. (2012a), they were prone to misjudge biomass in agricultural landscapes. This confirms the hypothesis that global equations yield biomass estimates that are significantly different from the actual biomass (for all the global equations $P < 0.5$).

These equations therefore need to be validated before being authoritatively used in these landscapes; besides, vegetation-specific allometries bear greater accuracy in estimating the biomass of one-species plantations compared to generic ones (Mokany, 2006). The *Eucalyptus spp*., which accounted for most of the sampled trees, were exotic to Kenya hence were growing outside their ecological zone. However, the local equation by Kuyah et al. (2012a) performed better than these global equations in estimating AGB, since it was developed from an almost similar agro-ecological zone and it equally was developed using some *Eucalyptus spp*.
4.3. Belowground biomass

4.3.1. Local generic allometries for agriculturally dominated landscapes

The two equations with DBH as the sole predictor of BGB of Kuyah et al. (2012b) (Kuyah 2 and 5) overestimated BGB by 53.0 ± 10.6% and 80.1 ± 12.6% respectively. Since the root biomass was not corrected for the unexcavated biomass, the equation for corrected biomass (Kuyah 5) was expected to overestimate BGB. Even so, the equation for uncorrected biomass (Kuyah 2) still overestimated biomass (Figure 4.3). The resulting large bias in estimation using the equation for uncorrected biomass could be attributed to varying methodological approaches rather than the functionality of the equation. The excavation of coarse roots was done within a radius of 1m from the edge of the tree stump and a depth of 0.4-1.5m, while in Kuyah et al. (2012b), the coarse roots were excavated within a radius of 2m and a depth of 0.4-2m.

Site-specifically, Kuyah 2 estimated BGB of trees from the mixed species site with greater accuracy (RE = 10.34 ± 9.7%) compared to BGB for the E. grandis site (RE = 104.1 ± 9.8%). In the mixed species site, the equation underestimated BGB of the smaller trees (DBH < 20 cm) by -12.4 ± 15.8% and overestimated BGB of the larger trees (DBH > 40 cm) by 26.2 ± 19.6%. The Kuyah 2 equation was a generic one, developed from several tree species across different agro-ecological zones. Its performance in estimating biomass especially in the E. grandis site resulted in
overestimation (Figure 4.3), given that tree species vary in their rooting depth and coarse root biomass (Jackson et al., 1996; Santantonio et al., 1977).

Figure 4.3: Error disaggregation per DBH class in the E. grandis and mixed species sites for Kuyah 2, Kuyah 3, Kuyah 4, Kuyah 5, Mokany et al. (2006) and Cairns et al. (1997) equations.
It is worth noting that the *E. grandis* site was a plantation, exposed to unique silvicultural conditions and as Resh et al. (2003) noted; variability in coarse root biomass and DBH relationships may vary due to species or site differences, and varying silvicultural practices, such as spacing, pruning and fertilization.

The other equations developed by Kuyah et al. (2012b) (Kuyah 3 and 4) were applied on the excavated BGB and the equation which factored SD as the predictor variable estimated BGB with the least RE (31.1 ± 8.4%) (Figure 4.3). All the four tested equations overestimated the BGB of trees in all diameter classes of the *E. grandis*, while the trees from the mixed species site were estimated with lesser bias but with varying accuracy per diameter class (Figure 4.3). BGB in the mixed species site was estimated by Kuyah 2, 3, 4 and 5 with biases of 10.34± 9.7%, -0.5± 5.2%, 23.8± 11.4% and 29.7 ± 11.3%, respectively. The predictive accuracy of SD in this study is greater than DBH and therefore at variance with the findings of Kuyah et al. (2012b) that DBH is a more accurate predictor of BGB compared to SD.

### 4.3.2. Performance of global equations for tropical ecosystems

The equations by Mokany et al. (2006) and Cairns et al. (1997) overestimated BGB in the two sites by 64.9 ± 12.5% and 13.0± 8.7%, respectively (Figure 4.3). When the equation of Mokany et al. (2006) was applied site-specifically, the RE reduced to 18.1 ± 10.2% in the mixed species site while it increased to 121.1 ±15.0% in the pure stand of *E. grandis*. The equation of Cairns et al. (1997)
underestimated BGB (RE = -19.37± 6.9%) in the mixed species site while it overestimated BGB (RE = 51.9 ± 10.5%) in the *E. grandis* site.

Kuyah et al. (2012b) observe that equations developed in non-agricultural landscapes such as those of Mokany et al. (2006) and Cairns et al. (1997) may wrongly predict biomass in agricultural landscapes, hence need to be validated before being used in these landscapes. The unique silvicultural practices in agricultural landscapes such as conservation tillage, crop rotation, pruning and green fallows often significantly impact biomass prevalence in these landscapes (Farage, et al., 2007; Velarde, et al., 2010). Besides, vegetation-specific allometries bear greater accuracy in estimating the BGB of one-species plantations compared to generic ones (Mokany, 2006).

The results of the study in the mixed species site contrasts the findings of Kuyah et al. (2012b) that the Mokany et al. (2006) equation underestimated biomass but consistent with the findings that the Cairns et al. (1997) equation underestimated biomass. Figure 4.4 illustrates the performance of the equations by Kuyah et al. (2012b) and other global equations in biomass estimation vis-à-vis the excavated root biomass, which is also plotted. Disaggregation per DBH class showed that the equation of Mokany et al. (2006) overestimated BGB of trees in all the diameter classes for both sites. However, while the equation by Cairns et al. (1997) underestimated BGB in all the diameter classes of the mixed
species site, it overestimated BGB for trees in the *E. grandis* site with DBH < 40 cm while larger trees (DBH > 40) were slightly underestimated (Figure 4.3).

**Figure 4.4**: Scatter plots of BGB predicted by Kuyah 2, Kuyah 3, Kuyah 4, Kuyah 5, Mokany et al. (2006) and Cairns et al. (1997) equations.

### 4.3.3. Site-generated allometries for belowground biomass estimation

SD, DBH, AGB and (DBH)^2G all explained > 90% of BGB variability, with SD having the strongest correlation with BGB ($R^2 = 0.96$). The inclusion of height in the compound derivative of BGB weakened the relationship ($R^2 = 0.71$) and increased the standard error of estimation (SEE) of the regression (Table 4.4). The observed effect of the inclusion of height in the regression was attributable to
substantial variation in tree heights; the heights of trees in the mixed species site ranged from 4.5 to 18 m while in the *E. grandis* site the range was 15.7 to 38 m.

**Table 4. 4: Relationship between AGB, DBH, SD, [DBH]²H, and [DBH]²G and BGB**

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Mixed species site</th>
<th>E. grandis site</th>
<th>Combination of both sites</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R²</td>
<td>SEE</td>
<td>R²</td>
</tr>
<tr>
<td>AGB</td>
<td>0.98</td>
<td>0.207</td>
<td>0.96</td>
</tr>
<tr>
<td>DBH</td>
<td>0.98</td>
<td>0.194</td>
<td>0.95</td>
</tr>
<tr>
<td>SD</td>
<td>0.99</td>
<td>0.190</td>
<td>0.98</td>
</tr>
<tr>
<td>(DBH)²H</td>
<td>0.97</td>
<td>0.261</td>
<td>0.95</td>
</tr>
<tr>
<td>(DBH)²G</td>
<td>0.98</td>
<td>0.194</td>
<td>0.94</td>
</tr>
</tbody>
</table>


Mean root: shoot ratio (RS) of the sampled trees was 0.19 ± standard error of 0.02 and the median RS was 0.16. The mixed species site had higher mean and median RS compared to the *E. grandis* site. The mixed species site had a higher RS range (0.09 to 0.43) compared to the *E. grandis* one (0.10 to 0.20), attributable to heterogeneity in the former. Additionally, trees with the maximum and minimum RS values were both from the mixed species site and were the smallest (*Albizia coriaria*) and largest (*Acacia lahai*) in diameter sizes respectively. The coarse roots of the *Acacia lahai* were sampled to a depth of 1 metre. Inadequate root
sampling to a considerable depth and breadth occasioned the low RS of the
*A. lahai*, a pitfall in BGB sampling identified by Mokany et al. (2006).

Though the spacing of trees (2 m) in the *E. grandis* plantation did not allow for a
comprehensive excavation of the roots, differences in altitude between the mixed
species site and the *E. grandis* site, higher precipitation levels and moisture
availability in the *E. grandis* site, reduced the RS in the latter, similar to the
findings of Luo et al. (2005) and Gowerv et al. (1992). Mokany et al. (2006) adds
that plantations may have enhanced shoot biomass at the expense of their BGB
since they tend to be established in fertile and moist soils.

The site-generated equations for BGB were:

- Equation 2: \[ BGB = 0.035 \times DBH^{2.278} \]
- Equation 3: \[ BGB = 0.006 \times SD^{2.581} \]
- Equation 4: \[ BGB = 0.233 \times AGB^{0.959} \]

Equations 2, 3 and 4 overestimated the excavated coarse root biomass by 21.2±
8.7%, 8.9± 6.0%, and 14.5± 8.4% respectively. SD, which was measured at 10 cm
above the ground and marked the beginning of BGB, was the most reliable
predictor of BGB. In as much as there was no coppice in the sampled trees, SD
could be the most reliable predictor of BGB in agricultural landscapes, given that
coppices normally exist in agricultural landscapes. Tables 4.5, 4.6 and 4.7 show
how the equations were generated by cross-validation.
Table 4.5: Cross-validation for Equation 2, generated from the averages of the fitted parameters; \( \text{Ln}(a) \), \( \bar{a} \), se(\( \bar{a} \)), CF, a, b, \( R^2 \).

<table>
<thead>
<tr>
<th>Holdout</th>
<th>Ln(a)</th>
<th>( \bar{a} )</th>
<th>se(( \bar{a} ))</th>
<th>CF</th>
<th>a</th>
<th>b</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Holdout 1</td>
<td>-3.798</td>
<td>0.022</td>
<td>0.415</td>
<td>1.090</td>
<td>0.024</td>
<td>2.391</td>
<td>0.93</td>
</tr>
<tr>
<td>Holdout 2</td>
<td>-3.417</td>
<td>0.033</td>
<td>0.434</td>
<td>1.099</td>
<td>0.036</td>
<td>2.255</td>
<td>0.92</td>
</tr>
<tr>
<td>Holdout 3</td>
<td>-3.538</td>
<td>0.029</td>
<td>0.429</td>
<td>1.096</td>
<td>0.032</td>
<td>2.296</td>
<td>0.92</td>
</tr>
<tr>
<td>Holdout 4</td>
<td>-3.471</td>
<td>0.031</td>
<td>0.417</td>
<td>1.091</td>
<td>0.034</td>
<td>2.275</td>
<td>0.93</td>
</tr>
<tr>
<td>Holdout 5</td>
<td>-3.239</td>
<td>0.039</td>
<td>0.436</td>
<td>1.099</td>
<td>0.043</td>
<td>2.221</td>
<td>0.92</td>
</tr>
<tr>
<td>Holdout 6</td>
<td>-3.290</td>
<td>0.037</td>
<td>0.423</td>
<td>1.094</td>
<td>0.041</td>
<td>2.231</td>
<td>0.92</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>0.035</td>
<td>2.278</td>
<td>0.92</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Key: \( \text{Ln}(a) \) – Natural logarithm of intercept, (\( \bar{a} \)) – uncorrected values of back-transformed intercept, se(\( \bar{a} \)) – standard error of estimates, CF – correction factor, a – Intercept, b – scaling exponent and \( R^2 \) – coefficient of determination.

Table 4.6: Cross-validation for Equation 3, generated from the averages of the fitted parameters; \( \text{Ln}(a) \), \( \bar{a} \), se(\( \bar{a} \)), CF, a, b, \( R^2 \).

<table>
<thead>
<tr>
<th>Holdout</th>
<th>Ln(a)</th>
<th>( \bar{a} )</th>
<th>se(( \bar{a} ))</th>
<th>CF</th>
<th>a</th>
<th>b</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Holdout 1</td>
<td>-5.293</td>
<td>0.005</td>
<td>0.375</td>
<td>1.073</td>
<td>0.005</td>
<td>2.627</td>
<td>0.96</td>
</tr>
<tr>
<td>Holdout 2</td>
<td>-5.141</td>
<td>0.006</td>
<td>0.394</td>
<td>1.081</td>
<td>0.006</td>
<td>2.575</td>
<td>0.95</td>
</tr>
<tr>
<td>Holdout 3</td>
<td>-5.313</td>
<td>0.005</td>
<td>0.373</td>
<td>1.072</td>
<td>0.005</td>
<td>2.623</td>
<td>0.96</td>
</tr>
<tr>
<td>Holdout 4</td>
<td>-5.119</td>
<td>0.006</td>
<td>0.296</td>
<td>1.045</td>
<td>0.006</td>
<td>2.558</td>
<td>0.97</td>
</tr>
<tr>
<td>Holdout 5</td>
<td>-4.948</td>
<td>0.007</td>
<td>0.353</td>
<td>1.064</td>
<td>0.008</td>
<td>2.529</td>
<td>0.96</td>
</tr>
<tr>
<td>Holdout 6</td>
<td>-5.141</td>
<td>0.006</td>
<td>0.381</td>
<td>1.075</td>
<td>0.006</td>
<td>2.576</td>
<td>0.96</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td>0.006</td>
<td>2.581</td>
<td>0.96</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Key: \( \text{Ln}(a) \) – Natural logarithm of intercept, (\( \bar{a} \)) – uncorrected values of back-transformed intercept, se(\( \bar{a} \)) – standard error of estimates, CF – correction factor, a – Intercept, b – scaling exponent and \( R^2 \) – coefficient of determination.
Table 4. 7: Cross-validation for Equation 4, generated from the averages of the fitted parameters; Ln(a), ā, se(ā), CF, a, b, R².

<table>
<thead>
<tr>
<th>Holdouts</th>
<th>Ln(a)</th>
<th>ā</th>
<th>se(ā)</th>
<th>CF</th>
<th>a</th>
<th>b</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Holdout 1</td>
<td>-1.740</td>
<td>0.176</td>
<td>0.287</td>
<td>1.042</td>
<td>0.183</td>
<td>1.007</td>
<td>0.94</td>
</tr>
<tr>
<td>Holdout 2</td>
<td>-1.501</td>
<td>0.223</td>
<td>0.311</td>
<td>1.050</td>
<td>0.234</td>
<td>0.952</td>
<td>0.92</td>
</tr>
<tr>
<td>Holdout 3</td>
<td>-1.599</td>
<td>0.202</td>
<td>0.312</td>
<td>1.050</td>
<td>0.212</td>
<td>0.966</td>
<td>0.93</td>
</tr>
<tr>
<td>Holdout 4</td>
<td>-1.485</td>
<td>0.227</td>
<td>0.289</td>
<td>1.042</td>
<td>0.236</td>
<td>0.952</td>
<td>0.93</td>
</tr>
<tr>
<td>Holdout 5</td>
<td>-1.355</td>
<td>0.258</td>
<td>0.298</td>
<td>1.045</td>
<td>0.270</td>
<td>0.933</td>
<td>0.93</td>
</tr>
<tr>
<td>Holdout 6</td>
<td>-1.387</td>
<td>0.250</td>
<td>0.293</td>
<td>1.044</td>
<td>0.261</td>
<td>0.945</td>
<td>0.93</td>
</tr>
<tr>
<td>Average</td>
<td>0.233</td>
<td>0.959</td>
<td>0.93</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Key: Ln(a) – Natural logarithm of intercept, (ā) – uncorrected values of back-transformed intercept, se(ā) – standard error of estimates, CF – correction factor, a – Intercept, b – scaling exponent and R² – coefficient of determination.

The three developed equations consistently overestimated biomass in the *E. grandis* site across all the diameter classes with the RE for the site being 62.5±9.8%, 34.7 ± 11.2% and 49.4± 13.4% for equations 2, 3 and 4 respectively. The trend in the mixed species site showed underestimation by the three equations for most of the diameter classes, the exceptions being DBH class of 20 to 30 cm for Equation 1 and DBH class > 40 cm for Equations 2 and 3, which were overestimated (Figure 4.5). The RE for the three equations in the mixed species site were 13.2 ± 7.4% (Equation 2), 12.5± 5.1% (Equation 3) and 14.5± 8.5% (Equation 4).
The larger trees in this site were more accurately predicted than the smaller ones with SD predicting their BGB by the least RE of 1.2 ± 12.2% (Figure 4.5). The study also found out that SD was generally a more reliable predictor of BGB for both the site generated equations and the equations of Kuyah et al. (2012b), consistent with the findings of Razakamanarivo et al. (2011) who vouched for the use of SD in estimating BGB. In order to undertake robust estimation of BGB using SD as a biomass predictor, accurate SD values are needed, yet these values are often cumbersome to obtain. Nonetheless, Kuyah et al. (2012b) maintain that there is higher uncertainty in measuring SD compared to DBH, especially for large trees.
4.4. Implications for carbon estimation

Agricultural landscapes comprise substantial amounts of carbon stocks that are essential for carbon inventory envisaged under the REDD++ mechanism (Velarde, et al., 2010) which calls for robust accounting. IPCC (2006) recommends that for any criteria used in biomass carbon inventory to be reliable, it should harbour conservative biases in biomass estimates. In this study, estimation of AGB using allometric equations revealed greater accuracy compared to BGB, a finding consistent with the findings of Cairns et al. (1997) and Pearson et al. (2007). The actual total aboveground biomass (TAGB) for the harvested trees was 22.6 Mg, which when converted by the IPCC recommended conversion factor (0.47), represents 10.6 Mg of carbon. Of the tested equations, Kuyah 1 TAGB estimate was 21.9 Mg, Chave 1 was 24.8 Mg, Chave 2 was 43.4 Mg, Brown 1 was 18.2 Mg, Brown 2 was 35.6 Mg, while Equation 1 (developed in the site) was 22.1 Mg. Equation 1 and Kuyah 1 had the most conservative TAGB estimates at 98% and 97% of the actual TAGB.

The excavated total belowground biomass (TBGB) was 4.03 Mg and of the tested equations for BGB, which were not developed on-site, the one for Cairns et al. (1997) was the most conservative (104% of the excavated TBGB). However, the TBGB estimate of Kuyah 2, which was developed using uncorrected root biomass data, was also reliable (93% of the excavated TBGB). The other three equations by Kuyah et al. (2012b) (Kuyah 3, 4 and 5) may not reliably estimate TBGB in this study, given that they factored the corrected root biomass yet the root biomass
in this study was not corrected for the unexcavated roots. The site-developed equations however were all precise in their estimates; 3.99 Mg, 3.91 Mg and 3.94 Mg for the equations developed with DBH, AGB and SD respectively, as predictors of BGB.
CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

The local generic allometries developed by Kuyah et al. (2012a) in the Yala Basin accurately predicted AGB of the sampled trees (RE = -2.7 ± 4.3%) and were therefore applicable in the Nyando Basin. These results also confirmed that DBH was a reliable predictor of AGB. On the other hand, the equations developed by Kuyah et al. (2012b) did not perform well in estimating BGB when the two sites (mixed species and E. grandis sites) were combined. However, when they were applied on the mixed species site, the equations performed well. The BGB equations by Kuyah et al. (2012b) could therefore be applicable on mixed species.

Site-generated equation (with DBH as the sole-predictor of AGB) equally performed well in estimating AGB (RE = 5.5 ± 4.4%) but was not as accurate as that of Kuyah et al. (2012a). Compared to DBH, SD was found to be a more accurate predictor of BGB for both the equations of Kuyah et al. (2012b) and the site-generated equation. Although the study revealed that SD was a more accurate predictor of BGB than DBH, it might not be very reliable since there are many uncertainties in the measurement of SD in comparison to DBH.

The global equations recommended for tropical ecosystems did not perform well in estimating both AGB and BGB, evidenced by the large RE observed. All the
global equations tested either underestimated or overestimated trees unacceptably. Since agricultural landscapes are unique in vegetation composition and silvicultural management practices, it was expected that these global equations (developed outside agricultural landscapes) would result in inaccurate biomass estimates.

Application of local allometric equations in estimating AGB generally produce conservative results in comparison to the less conservative estimates of BGB yielded by local equations. Varying excavation depths, diverse root characteristics and tree spacing were some of the sources of uncertainties in BGB estimation; confirming the findings of previous studies, that AGB estimation is far more established than the estimation of BGB.

The local equations presented in this study reliably estimate biomass in agricultural landscapes, since they were generated from these very landscapes. Hence, the local equations yielded more conservative biomass estimates than the global equations.

5.2. **Recommendations**

The study focused on assessing the performance of local allometries vis-à-vis other global published equations in estimating biomass carbon. To actualize these findings, this study recommends that:
For assessing tree biomass in agricultural landscapes, allometric equations with DBH as the sole predictor should be used in estimating AGB. The high variation in dendrometric characteristics of trees (interspecific or owing to management) in these ecosystems introduces uncertainties when other variables such as height, crown diameter and wood-specific gravity are incorporated in the equations;

Equations with SD as a predictor of BGB should be preferred to equations with DBH as a predictor when estimating BGB, based on the greater accuracy observed in this study when SD was used in estimating BGB in both sites; and

The local equations presented in this study are reliable instruments of biomass inventory that should be entrenched as nationally accepted equations for estimating biomass in agricultural landscapes of Western Kenya. This is in line with the IPCC’s Tier 3 methodology that requires national carbon stock assessment to be as agro-climatically representative as possible.
5.3. **Suggestion for further study**

- The local generic allometric equations espoused in this study should be tested further in other agro-ecological zones of East Africa so as to validate them for wider application in East Africa as robust tools for biomass carbon inventory.
REFERENCES


group III to the fourth assessment report of the Intergovernmental Panel on Climate Change (pp. 497-540). Cambridge; New York, United Kingdom; USA: Cambridge University Press.


### Appendix I: Budget

<table>
<thead>
<tr>
<th>Item</th>
<th>Unit cost (Ksh)</th>
<th>Unit</th>
<th>Days</th>
<th>Amount (Ksh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Chain saw hire</td>
<td>2,000.00</td>
<td>1 saw</td>
<td>30</td>
<td>60,000.00</td>
</tr>
<tr>
<td>2. Chainsaw oil/fuel</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>5,000.00</td>
</tr>
<tr>
<td>3. Accommodation</td>
<td>1,500.00</td>
<td>3 persons</td>
<td>20</td>
<td>90,000.00</td>
</tr>
<tr>
<td>4. Per diem</td>
<td>1,560.00</td>
<td>2 persons</td>
<td>20</td>
<td>62,400.00</td>
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<tr>
<td>5. Motor vehicle fuel</td>
<td>2,600.00</td>
<td>1 vehicle</td>
<td>45</td>
<td>117,000.00</td>
</tr>
<tr>
<td>6. Sensitization</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>2,000.00</td>
</tr>
<tr>
<td>7. Labour</td>
<td>400.00</td>
<td>7 persons</td>
<td>45</td>
<td>126,000.00</td>
</tr>
<tr>
<td>8. Snacks</td>
<td>600.00</td>
<td>-</td>
<td>25</td>
<td>15,000.00</td>
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<tr>
<td>9. Oven Attendant</td>
<td>10,000.00</td>
<td>1 person</td>
<td>3 months</td>
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<td>10. Purchase of tree seedlings</td>
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<td>50 seedlings</td>
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<td>750.00</td>
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<tr>
<td>11. Tree compensation</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>11,000.00</td>
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<tr>
<td>12. Stationary/ materials</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>2,000.00</td>
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<tr>
<td>13. Binding of thesis</td>
<td>800.00</td>
<td>6 copies</td>
<td>-</td>
<td>4,800.00</td>
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<tr>
<td>14. Miscellaneous</td>
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**Total** 549,150.00
Appendix II: Data sheet for non-destructively sampled biomass parameters

<table>
<thead>
<tr>
<th>Block</th>
<th>Cluster</th>
<th>Plot</th>
<th>Farmer’s Name</th>
<th>Location</th>
<th>GPS ID</th>
<th>Elevation (m.a.s.l.)</th>
<th>Slope</th>
</tr>
</thead>
</table>

Key: R = restricted, NR = not restricted, P = pruned, NP = not pruned, BL = broad leaf, NL = narrow leaf (tick either)

<table>
<thead>
<tr>
<th>Tree No.</th>
<th>Species</th>
<th>DBH (cm)</th>
<th>Height (m)</th>
<th>Crown Diam. (m)</th>
<th>Crown Condition</th>
<th>Tree Type</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>L</td>
<td>W</td>
<td>R</td>
</tr>
</tbody>
</table>

Notes:

________________________________________________________________________________________

Data collected by:
Appendix III: Data sheet for destructively sampled biomass parameters

Date:

<table>
<thead>
<tr>
<th>Tree ID</th>
<th>Species</th>
<th>Height (m)</th>
<th>DBH</th>
<th>Comp. (KSh)</th>
</tr>
</thead>
</table>

**Subsample fresh weight (Kg)**

<table>
<thead>
<tr>
<th></th>
<th>Trunk</th>
<th>Small BR</th>
<th>Large BR</th>
<th>Leaves</th>
<th>Root</th>
</tr>
</thead>
</table>

**Component weights (Kg)**

<table>
<thead>
<tr>
<th>Trunk</th>
<th>Wt (Kg)</th>
<th>D-1 (cm)</th>
<th>D-2 (cm)</th>
<th>Small BR</th>
<th>Large BR</th>
<th>Leaves</th>
<th>Roots</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Leaves for scanning</th>
<th>Stump &amp; tap root (Kg)</th>
</tr>
</thead>
</table>

**Main roots’ length & diameter (cm)**

<table>
<thead>
<tr>
<th>Root</th>
<th>Prox. Diameter</th>
<th>Mid. Diameter</th>
<th>Dist. Diameter</th>
<th>Length</th>
<th>SD (cm)</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Excavated portion (whole, 1/2, 1/4)</th>
</tr>
</thead>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Excavated depth</th>
</tr>
</thead>
</table>

Notes:

Data collected by: