Allometric Equations for Estimating Tree Biomass in Agricultural Landscapes in Western Kenya

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DECLARATION

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

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DEDICATION

This work is dedicated to my late Grandmother, Roselany Muyela Kuyah and to all those who have supported my academic life. This is for you!

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The Grace of God Makes the Difference (I Cor. 15:10).

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ABBREVIATIONS

AIC	Akaike information criterion
AGB	Aboveground biomass
ANOVA	Analysis of variance
BGB	Belowground biomass
BM	Biomass
C	Carbon
CF	Correction factor
CO_2	Carbon dioxide
CV	Coefficient of variation
DBH	Diameter at breast height
EPA	Environmental protection agency
FAO	Food and agriculture organization of the United Nations
FBA	Fractal branch analysis
GHG	Greenhouse gas
GLA	Gap light analyzer
GLM	Generalized linear model
GPS	Global positioning system
ha	Hectare
IPCC	Intergovernmental panel on climate change
ICRAF	World Agroforestry Centre

JKUAT	Jomo Kenyatta University of Agriculture and Technology
LAI	Leaf area index
LAI*e*	Effective leaf area index
P	Probability value
RCD	Root collar diameter
RS	Root-to-shoot ratio
RMSE	Root mean square error
RSE	Residual standard error
$\mathbf{R^2}$	Coefficient of determination
$\mathbf{R^2_{adj}}$	Adjusted coefficient of determination
MRV	Measurement, reporting and verification
REDD	Reducing emissions from deforestation and forest degradation
REALU	Reducing emissions from all land uses
SD	Standard deviation
SE	Standard error
SEE	Standard error of the estimate
TTB	Total tree biomass
p	Scaling factor
q	Allocation factor

ABSTRACT

Much of the quantification of carbon (C) in trees usually relies on allometric equations, which relate different measureable properties of organisms to each other. Because biomass inventories are generally conducted to survey standing trees and since standing trees cannot be weighed to gauge their mass, allometric equations provide one of the only ways for estimating C stocks in standing trees. Assessment of tree biomass in agricultural landscapes has remained a great challenge because accurate, reliable and cost effective methods for monitoring C storage in trees were lacking. The high heterogeneity and diverse management effects on trees in agricultural landscapes limit the use of standard allometric equations developed for forests. This study aimed to develop allometric equations to establish a valid basis of up-scaling of landscape biomass C in agricultural landscapes. Ninety seven trees (diameter at breast height, DBH: 3-102 cm) randomly selected across three 100 km^2 benchmark sites in Western Kenya were destructively sampled to determine aboveground (AGB) and belowground (BGB) biomass. Allometric equations were developed using standard destructive sampling methods and functional branch analysis (FBA). Crown cover and effective leaf area index (LAI*e*) were estimated from hemispherical photographs. The equations developed fit the data well with over 95% of the observed variation in biomass explained by DBH. Diameter alone provided reliable estimation of biomass with about 90% accuracy. Published equations that could otherwise be considered appropriate for

Western Kenya misjudged AGB and BGB by between 11-22% and 21-35%, respectively. FBA-derived allometry for trees with comparable branching form produced results similar to estimates from an allometry built through standard destructive sampling techniques. Agricultural mosaics of Western Kenya were estimated to hold about 22 t C ha^{-1} in standing trees; with 17 (standard error, SE 0.02) t C ha^{-1} in AGB of which leaves, branches and stem constitute 4, 39 and 57%, respectively; while the root system stock about 5 (SE 0.01) t C ha^{-1}. The mean canopy cover (and standard deviation, SD) for the three sites evaluated was 45.3% (SD 18.8), 55.1% (SD 23.6) and 40.8% (SD 18.6) while mean LAI*e* was 0.65 (SD 0.83), 1.00 (SD 0.83), and 0.59 (SD 0.53) for Lower, Middle and Upper Yala, respectively. The study confirms that DBH serves as a more straightforward and robust proxy for estimating tree biomass in complex agricultural landscape mosaics. Advanced FBA techniques have great potential as a non-destructive approach for generating species-specific allometric equations for estimating tree C stocks and thus reducing measurement effort and impact. Equations developed will find greater application for programs interested in measurement, monitoring, management and up-scaling of tree C stocks to a landscape level.

Keywords: Agricultural landscapes, Allometric equations, Carbon stocks, Functional branch analysis, Hemispherical photography

CHAPTER ONE

1.0 GENERAL INTRODUCTION

1.1 Background of the study

Climate change has emerged as a major hazard to progress in developing countries, largely threatening food security, regional stability and ecosystem integrity. Climatic changes are attributed to variations in atmospheric levels of greenhouse gases (GHGs). The primary agent of climate change is Carbon (iv) dioxide (CO_2), which constitutes the lion share, 60% of the GHG emissions, (IPCC, 2006). Other GHGs linked to climate change include methane, nitrous oxide and reactive gases such as sulphur dioxide, nitrogen oxide, carbon monoxide and hydro-carbons. While most of the increase in atmospheric levels of CO_2 is attributed to a rise in burning fossil fuel, land use and land use change represent leading anthropogenic processes that release CO_2 to the atmosphere (IPCC, 2003).

Agricultural ecosystems represent an important component in C sequestration, defined in this study as the capture and storage of C that would otherwise be emitted to and remain in the atmosphere as CO_2 (Henry et al., 2010). Trees in agro-ecosystems store C through fixation of atmospheric CO_2 into biomass, some of which is indirectly sequestered as soil organic C during putrefaction (Nair et al., 2009). In addition, trees on farms alleviate the pressure on natural forests by supplying timber and fuelwood, which would otherwise be sourced from forests (Albrecht and Kandji, 2003). Although woody vegetation play the important role of a C sink, their disturbance by natural or human activities lead to release of C into the atmosphere (IPCC, 2003). Hence, initiatives such as forest protection, afforestation and reforestation are actively being undertaken to reduce CO_2 emissions into the atmosphere and absorb atmospheric CO_2 into long-lived vegetation (Verbist et al., 2011). In addition, trees are widely being included in farmland to expand existing C sinks, conserve available C pools and substitute fossil fuel with green energy (Velarde et al., 2010).

Strategies for lowering atmospheric CO_2 have evolved from reducing emissions from deforestation (RED), to include reduced forest deforestation and degradation (REDD) and finally enhancement of forest stocks, REDD+ (Verbist et al., 2011). Currently, a whole landscape approach (REDD++), also known as reducing emissions from all land uses (REALU) is favored. REALU includes activities that help to conserve biomass as well as enhance, fix and store C in various land uses, in addition to forests (Velarde et al., 2010). These mitigation mechanisms have the potential for greater emission reduction and projects involved could benefit greatly from C sequestered. Therefore, it is essential to devise ways of accurately measuring tree C stocks in agricultural landscapes, which is a prerequisite to establishing payment schemes for C sequestration (Nair et al., 2009) and also a precondition for the United Nations framework convention on climate change member states to develop, publish and periodically update national GHG inventories of emissions by sources and removals by sinks (IPCC, 2006).

1.2 Trees on farms

Kenyan smallholder farmers have a strong tradition of actively managing a variety of multipurpose trees on farms (Kuyah, 2008). In Western Kenya, tree planting is mainly farm-based with a mix of exotic and indigenous trees dominating the landscape. Although trees were previously planted separate from crops, most trees are currently planted on farms, along boundaries or simultaneously with crops, depending on land size and/or the utility of the species (Kituyi et al., 2001). Boundary planting is adopted to minimize competition with crops while competitive trees such as *Eucalyptus* spp are often planted in woodlots for households with large land sizes (Kuyah, 2008). When integrating trees with crops, farmers select trees that can grow with crops without reducing yields, yet still providing social, economic and environmental services, which would otherwise require heavy financial investment (Jamnadass et al., 2011).

In Kenya, the majority of timber and non-timber wood products are obtained from farm estates, presenting an opportunity for farmers to have access to additional income from their land (FAO, 2011). This trend is further spurred by the increasing need for woody biomass as feed stocks for bio-energy (Kiplagat et al., 2011). Therefore, many smallholder farmers plant multipurpose trees that complement other enterprise on the farm. Despite the effort to increase tree cover in Kenyan farms, the demand for wood and non-wood tree products in the country outstrips their supply, largely due to a rapidly increasing human population and depletion of their natural sources (Kiplagat et al., 2011). In Western Kenya, low agricultural yields and high human population have caused degradation of natural forests and conversion of marginal lands into agriculture (Shepherd and Soule, 1998). To meet the high demand for tree products and services, the region is increasingly focusing on conserving and also increasing trees in the landscape. Considerable success has been achieved through introduction of fast growing tree species (Kuyah, 2008) and adoption of agroforestry technologies (Jamnadass et al., 2011). Enhanced integration of trees in farmlands has also been promoted by the opportunity to receive payments from C sequestration (Nair et al., 2009).

1.3 Biomass production and partitioning

Climatic factors such as solar radiation, temperature and water availability affect plant growth. These factors, together with nutrient availability, genetics and tree age influence biomass production and partitioning in trees (Keith et al., 2000). In the semi-arid tropics, water availability is a major factor that limits plant growth and that determines the natural distribution and productivity of trees (Kuyah, 2008). Plants respond to water shortage by reducing growth of shoot and investing more in root production (Gower et al., 1992). Conversely, biomass production generally increases in response to increase in rainfall and temperature unless other limiting factors exist.

Trees require nutrients for growth and development. Most tropical soils contain limited supplies of nutrients due to degradation and intense agricultural use (Shepherd and Soule, 1998). Hence, biomass production and partitioning is affected differently by nutrient elements, depending on the relative limitation of the element and its function

(Keith et al., 2000). Nutrient deficiency retards growth and affects the proportion of biomass in various components through shifting partitioning between foliage and fine roots (Gower et al., 1992). High nutrient availability results in increased growth rate, increased canopy components and high shoot-to-root ratio (Keith et al., 2000).

Genetic factors influence the yield potential and the growth form of trees, while tree age determines total biomass as well as allocation and distribution of biomass across different components for individual trees and stands of the same species. Total above- and below-ground biomass accumulates throughout the development of individual trees and stands; however, partitioning among components changes with age (Gower et al., 1992). As trees age, they allocate proportionally less biomass to leaves and branches and more to the stem (Zewdie et al., 2009). When estimating biomass using allometric equations, the relationship developed will thus vary in response to these and many other factors (Chave et al., 2004).

1.4 Biomass estimation

1.4.1 Importance of biomass estimation

The dramatic decline in forest cover and new opportunities for C credits has raised interest in measuring and monitoring C pools and fluxes in various land use types. These measurements aim to predict future changes in C concentration and to develop C management strategies (Eamus et al., 2000). While farmers in developing countries are one of the world's largest and most efficient producers of sequestered C, at present there is no reliable way to calculate or verify how much C their activities remove from the atmosphere. Developing a quick and reliable method to predict and account for the amount of C stored in the landscape is therefore essential if individuals or communities are to benefit from C markets by growing trees on their farms.

Approximately 87% of agriculturally dominated landscapes in sub-Saharan Africa have tree cover >10% (Zomer et al., 2009). In Western Kenya, trees represent the most important aboveground C pool of perennial plants growing on-farm (Henry et al., 2009). Assessing biomass in such landscape mosaics is crucial for sustainable management of woody vegetation. When trees are managed as a source of renewable energy, one needs to know how much biomass is available at a given time to be able to determine how much fuel wood is available for use.

Assessing biomass in agricultural landscapes has gained more attention because of the role of trees in the global C cycle (Albrecht and Kandji, 2003). Periodic measurement of biomass accumulation can be used to establish the potential of agroforestry systems to sequester C. One can further determine the production potential and/or suitability of a particular species for a given purpose, such as sustainable charcoal production (Okello et al., 2001). Measurement approaches designed to predict harvest yield help to assess biomass loss or accumulation over time. This makes biomass estimation an essential component of monitoring C sequestration (Eamus et al., 2000). By establishing the rate of biomass production, one can determine C sequestration potential of a particular species, allowing the valuation of the capacity of trees in agricultural landscapes to offset anthropogenic C emissions.

1.4.2 Approaches to biomass estimation

The contribution of trees in mitigating climate change has led to increased efforts in refining methods for estimating AGB and BGB. Accurate and reliable estimation of biomass in agro-ecosystems is desired to meet measuring, reporting and verifying (MRV) requirements for C accounting for any broader based approaches including also anthropogenically modified landscapes. Tree biomass can be estimated using direct or indirect approaches. Direct method involves cutting and weighing trees in the field and represents the most accurate way to quantify biomass (Brown, 1997). However, harvesting a sufficient number of trees to represent the size and species distribution in an ecosystem is time consuming, destructive, labour intensive, expensive and difficult to implement in remote areas (Brown, 2002). Also, the number of trees that would have to be sampled is large, leading to loss of tree diversity and its associated benefits. Destructive harvesting of trees in long-term studies and reforestation projects is therefore not sustainable, restricting the approach to small areas and small sample sizes. To circumvent destructive sampling and its attendant challenges, indirect approaches have been devised. Indirect methods include use of allometric relationships (Brown, 1997), functional branch analysis (van Noordwijk and Mulia, 2002), photographic techniques (Jonckheere et al., 2004) and remote sensing (Gibbs et al., 2007). Although indirect methods have many advantages over direct methods, field measurements are still indispensable, providing ground data for validating estimates from indirect approaches.

1.4.3 Allometric equations as a tool for biomass estimation

Much of the assessment of aboveground C stocks in trees usually relies on allometric equations through conversion of easy-to-measure parameters, such as diameter at breast height (DBH) to biomass. Measureable parameters such as DBH and/or tree height are regressed against harvested dry weight to yield allometric equations. Equations developed are then used to convert simple physical parameters to biomass. The sum of all trees within a plot is obtained to estimate plot-level biomass. Provided statistical representativeness, such plot-level biomass can then be up-scaled to landscape estimates. Carbon in measured trees is obtained by multiplying biomass estimate by the C fraction of biomass. The default C fraction value for AGB in tropical species recommended by IPCC (2006) is 0.47. As slight variability of C fractions exist between species or tree compartments, projects may use the IPCC default value or may choose to determine the actual C concentration in their samples by element analysis.

Allometric equations describing natural relationships are not always linear. Different models are fitted to the data until the model that best describes a particular species or environmental condition is obtained. This may require logarithmic transformations of the data in order to homogenize the variance over the entire range of the sample data. However, the logarithmic transformation can lead to a bias towards underestimating biomass (Sprugel, 1983). The bias is accounted for by multiplying the estimate by a correction factor, CF (Chave et al., 2005).

Allometric power function equations are commonly used in biomass estimation, although some studies have reported the use of polynomial equations (Henry et al., 2011). For this study, the power function model was resorted to, based on tree geometry and function, and the fact that the power function equations remain reasonable for small extrapolations outside the calibration range, thus providing a more natural scaling than the polynomial equations. Furthermore, the polynomial equations tend to have 3 or 4 parameters, which have no direct biological interpretation, while those of the power law have (Ketterings et al., 2001). Studies have reported power function relationships that relate tree biomass with structural parameters like DBH or DBH in combination with height and/or wood density (Brown, 1997; Chave et al., 2005).

1.4.4 Limitations of existing allometric equations

The quality of the allometric equation depends on the empirical data used. A major limitation to allometry development for agricultural landscapes is the non-representativeness of the data from which the equations are constructed (Brown, 1997). When allometric equations are constructed from a small sample, they are unlikely to be truly representative of the landscape population in terms of size and species distribution. In most cases, larger diameter trees are often underrepresented and only few species of interest are captured (Eamus et al., 2000). Given that farmers manage trees through selective harvesting of stems, lopping of branches or maintaining a variety of species on farms, the form and size of these trees is likely to be different from that in a forest or single-species stand. Hence most equations are likely to misjudge biomass if applied to agricultural landscapes without empirical validation.

Published equations used for tropical species are purely constructed for estimating AGB e.g. Brown (1997) or BGB e.g. Mokany et al. (2006). Total tree biomass (TTB) is then obtained by adding up estimates from AGB and BGB equations. A common problem with this approach is that allometric equations show different relationships for different parts of a tree, and each equation estimates biomass with some uncertainty. Aggregating estimates from different equations to obtain TTB may therefore yield poor estimates due to associated errors. In addition, estimates derived from such equations may not be accurate because of the "species specific" or "generalized" nature of the equations used (Nair et al., 2009). This calls for empirically validated equations for estimating TTB without the need to determine ABG or BGB. Because of several limitations with allometry development in Eastern Africa, and due to the changing nature of allometric relationship with location, land cover type and management practices, there is need to develop allometries for trees with differing age, planting arrangements, management strategies and from a wider geographic area.

1.5 Statement of the problem

While allometric relations have been developed in conventional areas such as forests, estimation of biomass in agricultural landscapes had remained a great challenge due to lack of accurate, reliable and cost effective methods for monitoring their C storage in trees. The high spatial and temporal heterogeneity of agricultural landscapes, particularly, the heterogeneity of trees arising from natural differences in species composition and alteration of their structural form by management practices, limit the application of standard allometries developed for forests, such as those cited by the IPCC (2006). Therefore, those marginal landscapes have long been neglected both in their emissions and also their C stocks and sequestration potentials.

There exist few allometric equations in East Africa developed for particular, rather homogenous systems such as forests, and are mainly species specific (Henry et al., 2011). Most of these equations were derived from a limited number of tree sizes, smaller study sites and/or are restricted to one species in a given region and therefore have limited application in multi-species landscapes with variable characteristics such as those found in complex agricultural mosaics of Western Kenya. There are also global equations commonly used in the absence of species specific equations (Brown, 1997; Chave et al., 2005). However, both the local equations developed for East Africa and broadly derived global equations have not been validated for the region and their compatibility with agricultural mosaics is limited as trees in these landscapes are often managed and rarely mono-specific.

1.6 Justification of the study

The international debate on REDD++ has called for strict carbon MRV methods. All subsequent mechanisms aiming at conserving C stocks in various land use types have included agricultural landscapes, which have led to increased interest in assessing C under such land use (Verbist et al., 2011). REDD++ has emerged as an important broad-based approach to climate change mitigation with targets of greater emission reductions, reduction of leakage and increased benefits for local people (Velarde et al., 2010). The success of this approach hinges upon robust, reliable and efficient procedures being available for evaluating C stocks across the whole landscape. Since smallholder farmers in most developing countries integrate trees in their farms, they are likely to benefit economically if the C sequestered by trees in their farms is sold in C markets (Nair et al., 2009). However, lack of efficient methods for monitoring C storage in agricultural landscapes might constrain the success of such C offset programs.

Allometric equations developed in this study will improve the reliability of future biomass estimates in Western Kenya and serve as a vital tool for MRV of forest and agroforestry C pool sizes in systems where destructive sampling is not recommended. These new allometric equations are a valuable addition to the AgroforesTree Database maintained by ICRAF to enable future C offset project managers to measure the biomass and C in common agroforestry trees. Guidelines established in this study will allow for better and more efficient assessment of landscape C and a robust way of assessing C on the ground for validating spatial up-scaling methods such as remote sensing.

1.7 Objectives

The overall objective of the study was to develop allometric equations to establish a valid basis for up-scaling landscape scale tree biomass in agricultural landscapes in Western Kenya. The specific objectives of the study were to:

1. Develop robust allometric equations for estimating aboveground biomass using diameter at breast height as the primary predictor variable;
2. Develop reliable allometric equations for estimating aboveground biomass using crown area as the primary predictor variable;
3. Develop improved allometric equations and root-shoot ratios for estimating belowground biomass;
4. Develop allometric equations for estimating the biomass of *Eucalyptus* spp found in agricultural landscapes in Kakamega, Western Kenya;
5. Derive scaling rules for tree biomass estimation using fractal branch analysis;
6. Determine canopy cover and leaf area index for agricultural landscapes in Western Kenya using canopy hemispherical photographs.

1.8 Research questions

The study addressed the following research questions:

1. How accurate is diameter at breast height as a predictor of aboveground biomass of trees in agricultural landscapes?
2. How suitable is crown area as a predictor of aboveground biomass of trees in agricultural landscapes?

iii. How accurate are allometric relationships for belowground biomass over root-to-shoot ratios?
iv. How variable are biomass estimates derived from species-specific and mixed species equations?
v. Why do allometric biomass equations differ between tree species?
vi. Can hemispherical photography be used as a ground-based tool for estimating canopy cover and leaf area index in agricultural landscapes?

1.9 Hypotheses

The study hypothesized that:

i. Diameter at breast height is the most suitable parameter for the prediction of above- and below-ground biomass of trees in agricultural landscapes;
ii. Fractal branch analysis provides a transparent non-destructive tool for derivation of allometric coefficients for biomass estimation;
iii. Hemispherical photography is an effective non-destructive tool for estimating canopy cover and leaf area index in agricultural landscapes.

CHAPTER TWO

2.0 MATERIALS AND METHODS

2.1 Introduction

This chapter introduces the study site, describes the sampling approach, provides a detailed account of measurements taken and explains how individual measurements were performed. The relevance of the sampling approach and the significance of each measurement to the objective of the study are also explained. Measurement of diameters, tree height, crown area and the approaches used to estimate wood density and C content are described in section 2.4. Destructive sampling to determine above- and below-ground fresh weights and subsequent sub-sampling to determine dry weights is explained in section 2.5. Model development and evaluation is explained in section 2.6 while description of published models evaluated is provided in section 2.7.

2.2 Site description

The study was conducted between January and August 2010 in three 100 km^2 sentinel sites (Lower, Middle and Upper Yala) along the Yala River basin in Western Kenya (Figure 2.1). The sites were previously used in the Western Kenya integrated ecosystem management project, aimed at improving productivity and sustainability of land use systems in the Yala River basin (Boye et al., 2008). The Yala River basin covers an area of 3351 km^2 and drains into the Winam Gulf in Lake Victoria (Boye et al., 2008). The basin covers an altitudinal gradient of 1200-2200 m above sea level and receives a mean daily maximum temperature of 27.4 °C and mean daily minimum of 12 °C.

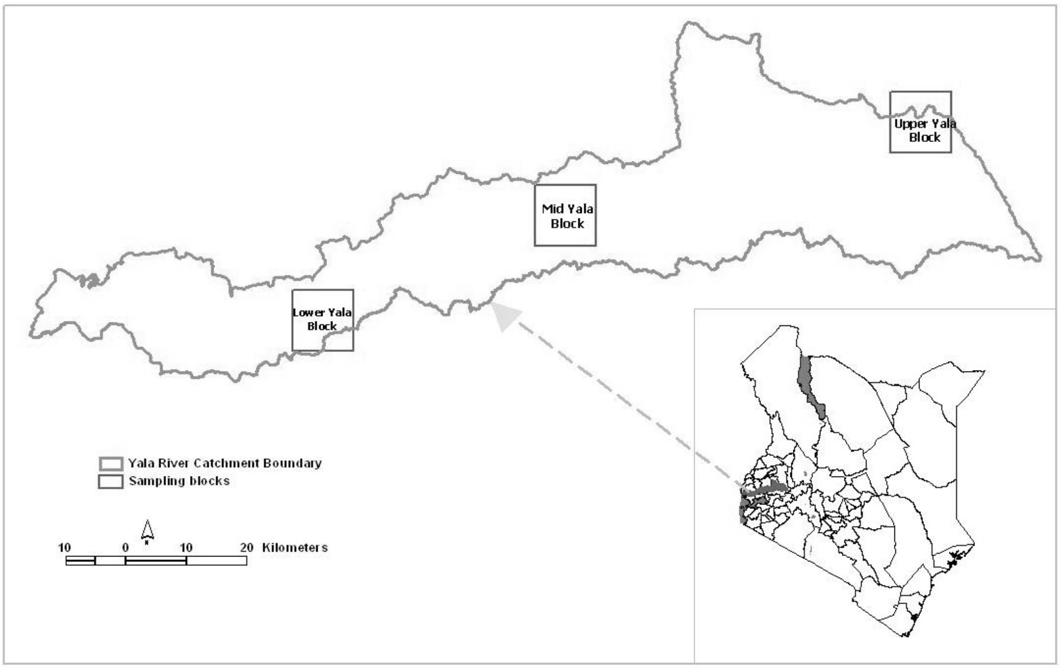

Figure 2.1 The location of the three 10 x 10 km study sites (Lower, Middle and Upper Yala) investigated in the Yala River basin of Western Kenya.

The basin receives annual rainfall of about 1400-1800 mm, decreasing westwards and following a bimodal distribution (i.e. long rains from March to July and short rains from August to November), which allows two cropping seasons per year. Dominant soil types in Western Kenya include Acrisols, Ferralsols and Nitisols (Jaetzold and Schmidt, 1982). The soils are characterized by a good physical structure but low nutrient reserves due to prolonged weathering and intense agricultural use (Shepherd and Soule, 1998). Generally, the landscape is gently undulating in the East and fairly flat in the West, with a few scattered groups of hills (Jaetzold and Schmidt, 1982). Site specific information on biophysical and climatic conditions of each site is summarized in Table 2.1.

Table 2.1 Biophysical and climatic conditions of the Lower, Middle and Upper Yala. Soil properties captured to a depth of 15 cm (Boye et al., 2008).

Attribute	Lower Yala	Middle Yala	Upper Yala
Longitude	34°28'19.62"E	34°49'13.01"E	35°20'14.60"E
Latitude	0°1'12.33"S	0°7'51.57"N	0°17'27.14"N
Altitude, range (m)	1200 - 1450	1430-1720	2100-2400
Rainfall, mean annual (mm)	1479	1950	1028
Temperature, mean annual (°C)	21.9	20.5	16.7
Slope, average (%)	7.6	12.8	2.3
Soil texture (%)			
Clay	8	46	24.6
Clay loam	45	15	-
Sandy loam	7	-	0.5
Silty loam	-	6	0.5
Silty clay	7	32	74.3

Diverse land use systems exist in Western Kenya, ranging from subsistence smallholder farms in Lower and Middle Yala to more cash-crop oriented farms in Upper Yala. Due to high population and sub-division of farms according to traditional heritage systems, average farms in Western Kenya are small, ranging from 0.2 ha in

Middle Yala to 0.8 ha in Lower Yala; however, large parcels of land exist in Upper Yala (Boye et al., 2008). Woody vegetation form part of a composite agricultural landscape varying from individual free standing trees to pockets of stands that consist of indigenous and exotic forms managed in different ways (Glenday, 2006). Trees and shrubs are grown around the homestead, in woodlots, cropland and also along farm boundaries (Henry et al., 2009). Woodlots occur mainly as small, mono-specific clusters of cultivated trees in Middle Yala (usually *Eucalyptus* spp) and Upper Yala (mainly *Acacia mearnsii*). Considerable areas in Lower Yala have bushes on farms with indigenous shrubs and naturalized exotic species.

The three sites chosen represent the natural gradient of the Yala River basin in terms of elevation, slope, rainfall regimes and land use. The Lower Yala is located in Siaya and Kisumu Counties. The site is characterized by undulating hills, medium to steep slopes, plateaus and valley floors draining directly into the Yala River (Boye et al., 2008). Larger portions of woody grassland in Lower Yala have been converted to agriculture with little thicket and woody cover remaining. The major crop grown is maize and in some areas maize in combination with sweet potatoes and cassava. The Middle Yala site is located in Vihiga and partly in Kakamega County. The site hosts the Kaimosi forest and a part of the Kakamega forest reserve. The landscape consists of mountainous highlands with numerous small streams and clusters of wetlands (Boye et al., 2008). Tea is the major cash crop in this area while maize, beans, banana and sweet potatoes are grown for subsistence. The area has relatively ample tree cover with eucalyptus species dominating the landscape. The Upper Yala is located in Uasin

Gishu County, towards the source of the Yala River. It is characterized by medium gradient hills, shallow depressions, wetlands and flood plains with small permanent streams (Boye et al., 2008). The area is mainly under maize production with smaller portions of wheat and few shrubs and trees in the landscape.

2.3 Sampling design and nomenclature

The sentinel sites chosen consist of 10 x 10 km benchmark sites, each divided into 16 sub-clusters of 2.5 x 2.5 km with 10 plots in each cluster. For this study, three plots of 30 x 30 m (0.09 ha) each were randomly selected in each cluster for biomass sampling. A randomized selection of the plots ensured coverage of the entire catchment and also the representative mix of tree species in the area. Sampling biomass across the three sites ensured that a wider range of species and trees of identical species along an altitudinal gradient were captured.

Sixty percent of the measurements were collected in the Middle Yala while the Lower and Upper Yala contributed 20% of the harvested trees each; an approach adopted based on relative abundance of trees per block. Trees were stratified by size into 6 diameter classes of 2.5-10, 10.1-20, 20.1-30, 30.1- 40, 40.1- 60 and >60 cm to achieve an adequate spread of diameter classes in the sample. In each diameter class, 12 individual trees were randomly selected for harvesting resulting in a total of 72 trees. Due to the few number of larger trees (DBH >60 cm) in selected plots, additional trees of the same diameter were semi-randomly sourced from remaining plots within the blocks. An additional 25 trees were randomly harvested in the Middle Yala for adding to *Eucalyptus* trees among the 72 harvested to develop equations specific to dominant *Eucalyptus* spp in the area. All trees with DBH >2.5 cm within each plot sampled were identified and measured. A total of 825 trees were non-destructively measured across all the three sites for estimating representative biomass C.

Plots were geo-referenced and the farmers' administrative location, sub-location, village and contact adequately described to facilitate follow-up activities. The global positioning system (GPS) coordinates of the plot center were located using GPSMAP 60CSx (Garmin International Inc., USA) and recorded according to the nomenclature L1C1P1, MC1P1 and UC1P1 for Lower Yala cluster 1 plot 1, Middle Yala cluster 1 plot 1 and Upper Yala cluster 1 plot 1, respectively. From the center identified by the GPS device, a 30 x 30 m plot was established and marked with a placard. Target trees were numbered following the plot nomenclature with a numerated initial T ($T_1 \ldots T_n$). The species name was recorded and where scientific names could not be attributed in the field, a sample labeled with a local name was retained for later identification. The influence of management through pruning and coppicing was recorded.

2.4 Measurements procedures

2.4.1 Diameter

Diameter at breast height is commonly used for biomass estimation because it can easily be measured with high accuracy, repetitively, and generally follows commonly acknowledged forestry conventions (West, 2009). Diameter at breast height was measured with diameter tapes. Prior to measurements, tree trunks were cleared of dirt and other alien phyto-material such as lichens or moss. Measurements were taken at 1.3 m above the ground level with the tape held tightly and horizontally to the tree axis (Plate 2.1). Conventional methods of DBH estimation were used on trees with anomalies. Root collar diameter (RCD), also known as basal diameter was measured just above the onset of roots, approximately 15 cm above the soil level using a caliper or diameter tape as appropriate.

Plate 2.1 Measurement of (a) diameter at breast height, (b) root collar diameter, and (c) a stump with indentation. Measurements taken along the depressions overestimated tree size.

2.4.2 Height

Tree height can serve as an additional predictor variable in support of DBH. Total tree height i.e. the vertical distance from the base of the tree to the uppermost point was determined in-situ by a hypsometer (Vertex III and Transponder T3, Haglöf, Sweden) according the user manual prior to felling each tree. The measurement was then repeated for all target trees. The average height of multiple-stem trees was calculated as a simple arithmetic mean of the heights of all stems. After cutting the tree, tree height was confirmed with a 50 m tape measure.

2.4.3 Crown area

Crown area can be detected and quantified automatically from high resolution satellite imagery, making it a suitable parameter for linking ground based measurements to large scale remotely sensed information. To determine the crown area of an individual tree projected onto the ground below it, the largest extension of the crown was identified visually and a clinometer (Suunto Clinometer, PM-1520) with percent scale used to locate the position vertically below the crown edge for all crowns. Crown diameter was measured crosswise with measuring tape, the largest diameter (*l*) and the diameter perpendicular to it (*w*). Crown area (ca) was calculated assuming an elliptical crown shape, $ca = \pi\{(l/2)\times(w/2)\}$.

2.4.4 Wood density and carbon content

Wood density has been reported to be a valuable supporting parameter for biomass estimation particularly where high species diversity with a large range of wood densities exist (Basuki et al., 2009). Three methods (coring, water displacement and measured disc dimensions) were used to estimate wood density of sampled trees. Using the coring method, samples were collected by coring a depth approximately the radius of the stem at DBH, radius of the main branches and radius of the main roots using a carpenter’s awl and a 2.5 cm bit. Larger stems, branches and roots were cored to the length of the bit, 20 cm. Wood chips were collected from the hole with a spatula and their fresh weight determined using a top pan electronic scale 300±0.1 g (TSA series, Avery Berkel Ltd.). Wood density was then determined as the ratio of dry weight of the cored material to volume of the core; where volume (*v*) was calculated from the radius (r) and depth (h) of the core: $v = \pi \times r^2 \times h$.

A disc, about 2 cm thick was cut from the main branches and roots for each tree sampled for determination of its volume by immersion and measurement of disc dimensions. A calibrated container capable of holding the sample was filled with water to a noted mark and the sample carefully sunk into the water with a needle without touching sides or bottom. The volume of the displaced water equals the sample's volume. The thickness (*l*) and diameter (*d*) of the same disc were measured crosswise with a caliper. The sample volume (*v*) was calculated as $v = \pi \times (d^2 / 4) \times l$, assuming a regular cylindrical shape. Oven-dry weight of the same samples was determined after drying it to a constant weight in a well-ventilated oven at 105 °C for 24 hours.

The C concentration of biomass for individual harvested trees was determined by element analysis of subsamples cored at breast height. Subsamples were ground to fine powder, sieved using a 0.5 mm sieve and stored in zip lock bags. Approximately 2 mg of each sample were placed in tin capsules (Analytical Technologies Inc., Valencia, CA, USA) then analyzed for C using a CN-analyzer (Thermo-Quest Flash EA1112) according to manufacturer's protocol.

2.5 Biomass sampling

2.5.1 Aboveground biomass

The direction of felling trees was determined by examining the inclination of the target tree and the surrounding field. Target trees were cut at the lowest point possible using a chain saw (Husqvarna AB, Sweden) for larger trees, DBH >10 cm and a machete for smaller trees. A strong rope was used to guide trees to the correct falling direction; a tractor was used to pull large trees in order to minimize possible damage of private property. Felled trees were separated into stem (main trunk of the tree from the base to the top), branches (lateral wood arising from the stem together with twigs) and foliage (leaves). A flat and solid surface was prepared to provide a level ground for the scale in order to ensure accurate measurements. The stem and larger branches were sectioned into weighable pieces, <300 kg and weighed on an electronic bench scale (AWD120 Avery weight-tronix Ltd., USA) in the field (±0.1 kg). The weight of the portion converted to wood scrapings and saw dust during partitioning of the stem was calculated from volume of the chain saw gap multiplied by the wood density calculated from the cored material as described in section 2.4.4. Small branches were bundled together and leaves collected in large tared bags for weighing in the field.

2.5.2 Belowground biomass

The whole root system within a radius of 2 m from the edge of the stump and a depth of up to 2 m was unearthed to remove the stump and all coarse roots (>2 cm diameter).

For two trees where permission was not granted to uproot the whole system due to the presence of other valuable trees within 2 m, a quarter section of the root system within the same radius and depth was excavated. The proximal and distal diameters of all coarse roots excavated were measured using calipers for later estimation of biomass of unexcavated roots. In some cases it was not possible to capture the whole root at the 2 m length; where roots intersected or intertwined, they were cut to allow for excavation. In this case, the diameters of the section removed from the stump were measured. Soil embedded in the stump joints and on root surfaces was removed. Stumps from larger trees were sectioned into practically weighable pieces, <300 kg. Small root pieces and retrievable sizeable wood chips from the chopping with machete were placed in tared sacks and weighed.

The biomass of unexcavated roots was determined by allometric equations relating the dry weights of excavated root segments to their proximal and distal diameters, assuming that root biomass follows a power law for allometric scaling (van Noordwijk and Mulia, 2002). Equations were then fitted with *a* and *b* parameter that best matched calculated root biomass (BM_{root}), assuming it represents $BM_{root} = a \times \{(d_1)^b - (d_2)^b\}$, where d_1 is the initial diameter while d_2 is the diameter at the cut end, about 2 m away from the stem base. The log version was fitted with ordinary least squares to allow for increasing variance with diameters: $\log(BM_{root}) = \log(a) + \log\{(d_1)^b - (d_2)^b\} + error$. The missing root biomass was calculated as, $BM_{root} = a \times (d_2)^b$. The sum of the missing root biomass over all roots was determined and expressed as fraction of the calculated biomass to estimate the proportion of root biomass that remained unmeasured. The procedure was repeated to determine species specific bias estimates. The estimated missing biomass for each root was added to the respective tree.

2.5.3 Subsampling and drying

Representative portions (subsamples) were taken from the stems, branches, leaves and roots for fresh weight determination using a 3000 g scale (±0.1 g) in the field. One to two discs of a freshly felled tree, 2 cm thick, were taken around (i.e. just above and below) breast height. Three discs, 2 cm thick, were taken along the lower, middle and upper end of the branch to account for variation in wood density along the branch. About 100-150 g of leaves was collected in tared sample bags.

Subsamples were stored in labeled sample bags and transported to the laboratory for dry weight determination. Larger subsamples were broken into sizes to fit the oven and labeled individually. Subsamples were oven dried at 105 °C for 24 hours as no further weight loss occurred beyond that point. However, larger subsamples that showed a slight decrease in weight were returned into the oven for a further 12 hours. Component biomass was calculated by multiplying subsample dry-to-green weight ratio with component fresh weight. Total AGB was obtained by adding up the biomass of leaves, branches and stems while TTB was obtained by adding up AGB and BGB.

2.6 Data management, modelling and statistical analysis

Field data were recorded on data sheets prepared before field activities and adapted during field work to capture tree size and biomass measurements. Field and laboratory data were transferred to excel workbook and the raw data screened for outliers in scatter plots. The scatter plots also assisted in visually assessing the relationships between dependent and independent variables. Data analysis was carried out in Genstat 12th Edition (VSN International Ltd.) while graphs were produced in SigmaPlot version 11 (Systat Software Inc.).

2.6.1 Development and evaluation of allometric equations

Raw data were transformed to stabilize the variance and generally make the data normally distributed for analysis and modeling. Transformation of data introduces error which was commonly corrected by multiplying the estimate by a CF depending on the residual standard error (RSE) of the regression procedure (Sprugel, 1983). The CF was determined as $CF = \exp(\frac{SEE^2}{2})$ where SEE is the standard error (SE) of the estimate of the regression (Sprugel, 1983). A generalized linear model (GLM) with gamma distribution and log link function was used (in chapters three, five and six) to avoid the problem of back transformation. GLM was adopted after determining that the relationship of standard deviation (SD) and mean is one in which SD is proportional to mean, or the variance is proportional to the square of the mean.

Allometric power function equations, $Y = aX^b$ and their linear equivalents, $\ln(Y) = a + b \times \ln(X)$ were used to predict biomass (*Y*) from independent variables (*X*).

In cases where the data did not meet the preconditions for using GLM (chapter four), data were transformed using the natural logarithm to normalize and linearize them. Logarithmic equations were developed as $\ln(Y) = a + b\ln(X)$ then back-transformed to a power function form, $Y = aX^b$ for estimation of biomass. The anti-log of the intercept of the equations was multiplied by a CF in order to account for bias introduced by log transformation of the data.

The optimal operational sample size was determined by assessing the model fit of equations developed with samples of 66, 60, 54 and 48 trees; with 6, 12, 18 and 24 trees held out of the regression sample for validation. Table 2.2 shows allometric coefficients, R^2, RSE and model bias used in selecting the best sample size for equation. A sample size (of 66 trees) with high $R^2 = 0.98$; smaller RSE, 0.12 and small bias, 1.62% was selected for equation development (appendix 3.1). The high R^2 value of equations with a sample size of 60, 54 and 48 trees is attributed to holdout of trees with a weak DBH-biomass relationship. Bias for various holdouts ranged between -34.9 and 29.7%; thus averaging the 12 validation results greatly reduced variability.

Table 2.2 Allometric relationship between DBH and AGB for selecting of suitable sample size.

Sample size	Equation	R^2	P-value	RSE	Bias %
72	$AGB = 0.088 \times (dbh)^{2.470}$	0.983	<0.001	0.119	-
66	$AGB = 0.091 \times (dbh)^{2.461}$	0.984	<0.001	0.124	2.1
60	$AGB = 0.089 \times (dbh)^{2.472}$	0.986	<0.001	0.131	5.1
54	$AGB = 0.089 \times (dbh)^{2.472}$	0.985	<0.001	0.138	6.4
48	$AGB = 0.094 \times (dbh)^{2.457}$	0.985	<0.001	0.146	5.2

All equations were fitted by including *ln*(DBH), *ln*(H), *ln*(ρ) and *ln*(ca) as separate predictors, so that they each were attributed an own scaling parameter. This was due to the identical scaling rule inhibiting a detailed assessment of the effect of additional explanatory variables for equations fitted with compound derivatives of DBH, height, wood density and crown area; such as $\ln(AGB) = a + b \times \ln(dbh^2 \times H)$ or $\ln(AGB) = a + b \times \ln(dbh^2 \times H \times \rho)$. Equations were developed using a sample size of 66 trees (training set) and an additional 6 trees for validation. One tree was randomly selected from each diameter class for the validation set, while the remaining 66 trees were used to develop the equation. The process was repeated 12 times with different random selections such that each tree in the sample was used once for validation. This approach was adopted because the holdout sample of six trees was considered too small a number for validation to adequately reveal errors. In particular, having one tree per diameter class to validate the models would not have allowed a class-wise assessment of bias and prediction error.

The fit of the models was assessed in terms of bias and error. Bias is an important statistic for landscape-level application as the bias would not cancel out when making predictions for many trees in a landscape. For models that consistently over- or underestimate biomass within a diameter class, the expected value of the relative error is not zero; however, if on average across all trees in a diameter class the model does not over- or underestimate biomass, then there is no bias. The quality of the estimate was determined by assessing the difference between the predicted and measured biomass and the relative error expressed as, $Bias\,\% = (\frac{predicted\ BM - measured\ BM}{measured\ BM}) \times 100$ (Chave et al., 2005). When considering predictions for individual trees, the typical size of error is more important than the bias. This typical error of a single prediction was measured by root mean square error (RMSE), determined as $RMSE = \sqrt{\frac{\sum(bias\%)^2}{n}}$. Root mean square error helped to describe the variability of bias, as zero bias might result from under- or over-estimates canceling out during the prediction of many trees, while the prediction for an individual tree may be inaccurate.

The coefficient of determination, defined for non-linear models as $R^2 = 1 - \frac{residual\,variance}{total\,variance}$ from the GLM fit, and Akaike’s Information Criterion, AIC (Akaike, 1981) were used as measures of goodness of fit. However, bias and RMSE were given much weight and used to compare and select the most suitable equation. The use of R^2 was limited to equations with a single explanatory variable while adjusted R^2 (R^2_{adj}) was used for models with two or more variables to reflect both the number of independent variables in the equation and the sample size.

2.6.2 Evaluation of selected published allometric equations

The suitability of using published equations to estimate biomass in agricultural landscapes was assessed based on the accuracy of estimates obtained, mathematical simplicity and the practicability of use. The equation of Henry et al. (2009) constructed from data collected in Western Kenya; Chave et al. (2005) for global dry, moist and wet forests; Chave et al. (2001) for pantropical moist forests; Brown et al. (1989) for pantropical forests; Brown (1997) for global dry, moist and wet forests and Djomo et al. (2010) for pantropical moist forest were evaluated (Table 2.3). The equations of Cairns et al. (1997) and Mokany et al. (2006) for estimating BGB and the IPCC default root-to-shoot ratio, RS (IPCC, 2006) were also assessed.

The global equations by Chave et al. (2005) and Brown (1997) are generic, stratified by climatic zones i.e. wet for high rainfall area with >3500 mm year^{-1} (standardized to sea level conditions) and no seasonality, moist for areas with 1500-3500 mm year^{-1} and a short dry season, and dry for areas with rainfall <1500 mm year^{-1} and a dry season of several months.

Table 2.3 Selected published allometric equations for estimating aboveground and belowground biomass of tropical vegetation.

Equation	Eco-climatic zone	Author
$AGB = 0.136 \times (dbh)^{2.320}$	global dry forest	Brown, 1997
$AGB = 0.118 \times (dbh)^{2.530}$	global moist forest	Brown, 1997
$AGB = 21.297 - 6.530 \times dbh + 0.740 \times dbh^2$	global wet forest	Brown, 1997
$AGB = 0.044 \times (dbh \times H \times \rho)^{0.972}$	pantropical	Brown et al., 1989
$AGB = 0.112 \times (dbh^2 \times H \times \rho)^{0.916}$	global dry forest	Chave et al., 2005
$AGB = 0.051 \times (dbh^2 \times H \times \rho)$	global moist forest	Chave et al., 2005
$AGB = 0.078 \times (dbh^2 \times H \times \rho)^{0.940}$	global wet forest	Chave et al., 2005
$AGB = 0.135 \times (dbh)^{2.420}$	neotropical	Chave et al., 2001
$AGB = 0.125 \times (dbh)^{2.562}$	pantropical moist	Djomo et al., 2010
$AGB = 0.051 \times (dbh^2 \times H)^{0.930}$	western Kenya	Henry et al., 2009
$BGB = 0.347 \times AGB^{0.884}$	tropical forests	Cairns et al., 1997
$BGB = 0.489 \times AGB^{0.890}$	tropical forests	Mokany et al., 2006

Equations by Chave et al. (2005) were built with data from natural forests growing in tropical climates, excluding plantations or managed forests. Chave et al. (2001) was developed from datasets spanning moist to wet tropical forests while equations by Brown (1997) were developed for broadleaf forests from a database that included trees with DBH 5-148 cm.

The diameters of all non-harvested trees measured in each 0.09 ha plot were converted to biomass using equations developed in this study. The biomass of individual trees was summed up to yield plot level biomass. Plot level biomass estimates were up-scaled to estimate the representative landscape biomass stock per hectare. Biomass estimates in tonnes per hectare (t ha^{-1}) were converted to C stock (t C ha^{-1}) by multiplying the estimate by the C concentration determined by element analysis of C content in samples. The SE of the landscape level C per hectare was estimated from the plot-to-plot variation in estimated biomass.

CHAPTER THREE

3.0 ABOVEGROUND BIOMASS ESTIMATION USING DIAMETER

3.1 Introduction

A variety of allometric equations have been developed for estimating AGB in tropical species. Some are broadly derived, covering a wider geographic range such as Chave et al. (2005) and Brown (1997) while others are specific for a certain location, such as Ketterings et al. (2001) and Basuki et al. (2009). Species specific equations also exist, e.g. Okello et al. (2001) in Kenya, Cole and Ewel (2006) in Costa Rica and Navar (2009) in Mexico. For general purposes, FAO recommends global equations stratified by ecological zones, particularly where site or species specific equation are not available (Brown, 1997).

Diameter at breast height has been widely used and recommended as an adequate growth parameter for estimating AGB because it can easily be measured with higher accuracy and provides better estimates (Eamus et al., 2000). However, a single allometric relationship based on DBH alone may not accurately estimate biomass across different ecosystems (Keith et al., 2000). This is because the relationships between tree biomass and stem allometric properties vary depending on tree age, management practices and biophysical characteristics of the site (Henry et al., 2011). Allometric equations may therefore be refined by including wood density, height or crown area. A combination of DBH, height and/or wood density has been used to estimate AGB by various authors (Brown, 1997; Chave et al., 2005; Henry et al., 2009). Conversely, few studies have reported relationships of biomass with crown metrics (Sah et al., 2004; Sampaio and Silva, 2005), and at present, no study provides validated equations for estimating AGB using crown area as a supporting variable.

This study evaluated diameter-based allometric equations as a non-destructive tool for estimating AGB in agricultural landscapes. The specific objectives of this investigation were to:

i. Develop diameter-based equations for estimating AGB through empirical, destructive measurements;
ii. Determine the influence of height, wood density and crown area as supporting proxies for estimating AGB in agricultural landscapes;
iii. Test the suitability of published global and local equations for estimating AGB in agricultural landscapes of Western Kenya;
iv. Determine the potential role of agricultural landscapes in C sequestration through estimation of representative AGB C stocks.

3.2 Method

Measurement procedures for DBH, height, wood density and crown area and biomass sampling are provided in chapters 2.4 and 2.5. Aboveground biomass and the biomass of leaves, branches and stem were regressed on DBH alone and DBH in combination with height, wood density and/or crown area to obtain allometric coefficients for estimating biomass. Allometric power function equations, $Y = aX^b$ and their linear equivalents, $\ln(Y) = a + b \times \ln(X)$ where Y is the dependent variable, X is the independent variable, a is the intercept and b is the scaling exponent, were used to predict biomass from independent variables. Equations for estimating AGB and the biomass of stem, branches and leaves using DBH alone as predictor variable were built as follows.

$\ln(AGB) = a + b \times \ln(dbh)$ ....Equation 3.1

$\ln(BM_{stem}) = a + b \times \ln(dbh)$ ....Equation 3.2

$\ln(BM_{branch}) = a + b \times \ln(dbh)$ ....Equation 3.3

$\ln(BM_{leaves}) = a + b \times \ln(dbh)$ ....Equation 3.4

Height (H), wood density (ρ) and crown area (ca) were also evaluated as supporting parameters for estimation of AGB as follows.

$\ln(AGB) = a + b \times \ln(dbh) + c \times \ln(H)$ ....Equation 3.5

$\ln(AGB) = a + b \times \ln(dbh) + c \times \ln(\rho)$ ....Equation 3.6

$\ln(AGB) = a + b \times \ln(dbh) + c \times \ln(ca)$ ....Equation 3.7

$\ln(AGB) = a + b \times \ln(dbh) + c \times \ln(\rho) + d \times \ln(ca)$ ....Equation 3.8

$\ln(AGB) = a + b \times \ln(dbh) + c \times \ln(H) + d \times \ln(\rho)$ ....Equation 3.9

$\ln(AGB) = a + b \times \ln(dbh) + c \times \ln(H) + d \times \ln(ca)$ ....Equation 3.10

$\ln(AGB) = a + b \times \ln(dbh) + c \times \ln(H) + d \times \ln(\rho) \times e \times \ln(ca)$ ....Equation 3.11

3.3 Results

3.3.1 Species distribution and dendrometric relationships

A total of 922 trees representing 39 species were measured; destructively (72 trees) and non-destructively (850 trees) along the Yala River basin. The sampling strategy represented well species abundance and distribution across the landscape (Figure 3.1). Tree species that were dominant in the harvested sample also occurred as the most frequent species among the non-harvested trees measured across the three sites. More than 80% of the trees encountered are not native to East Africa.

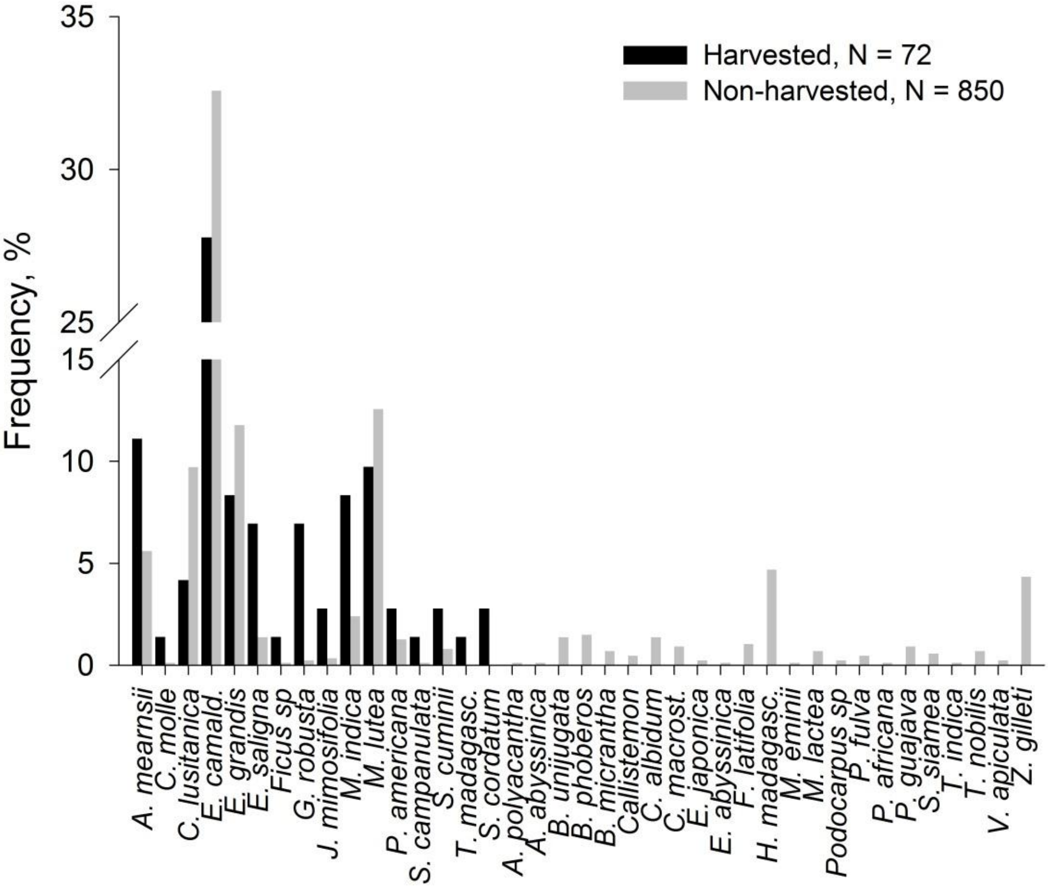

Figure 3.1 Distribution of harvested and non-harvested tree species measured along the River Yala basin. The 25 eucalyptus trees harvested in Middle Yala are included as non-harvested trees.

The most common species encountered were *Markhamia lutea* (58.3%) in Lower, *Eucalyptus camaldulensis* (44.5%) in Middle and *A. mearnsii* (59.4%) in Upper Yala. Other species commonly found along the basin include *Mangifera indica*

(14.3%) in Lower, *Eucalyptus grandis* (13.7%) and *Cupressus lusitanica* (10.6%) in Middle and *Eucalyptus grandis* (16.7%) in Upper Yala.

The total AGB for the 72 harvested trees (basal area: 4 m^2 ha^{-1}) was 34.3 t ha^{-1} with leaves, branches and stems contributing 3.5, 39.1 and 57.4%, respectively. While most of the tree biomass is held in the stem (44.5%), branches and leaves represent 30.2 and 2.7% of the TTB. About 1.1% of the total AGB was lost through cutting trees (felling) and sectioning stems and branches into practically weighable pieces (<300 kg). Losses due to sectioning trees were proportional to tree size and branching pattern (Figure 3.2).

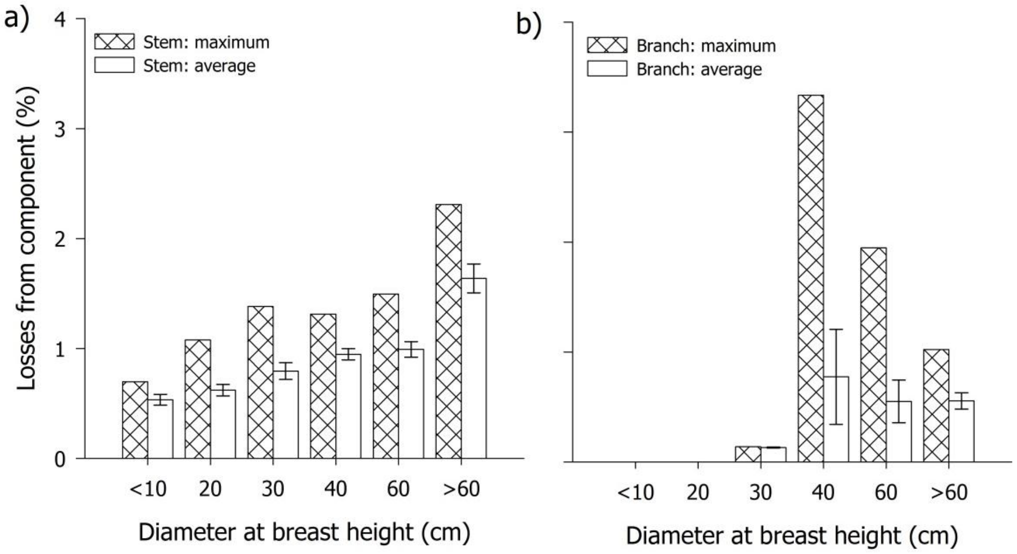

Figure 3.2 Portions converted to wood scrapings and saw dust during felling of trees and partitioning of (a) stem and (b) branches into practically weighable pieces for trees of various sizes.

Losses directly related to sectioning the stem and branches were 1.4% and 0.7% of the respective total component biomass. Greater losses, more than 1% of stem biomass were observed in larger trees, with losses as high as 2% recorded in most large trees, DBH >60 cm, with prolific branching.

Harvested trees were stratified into six diameter classes, resulting in even distribution of DBH. The distribution for DBH, height and crown area for non-harvested trees was positively skewed; indicating that the landscape is dominated by small diameters, short trees and small crowns (Figure 3.3b).

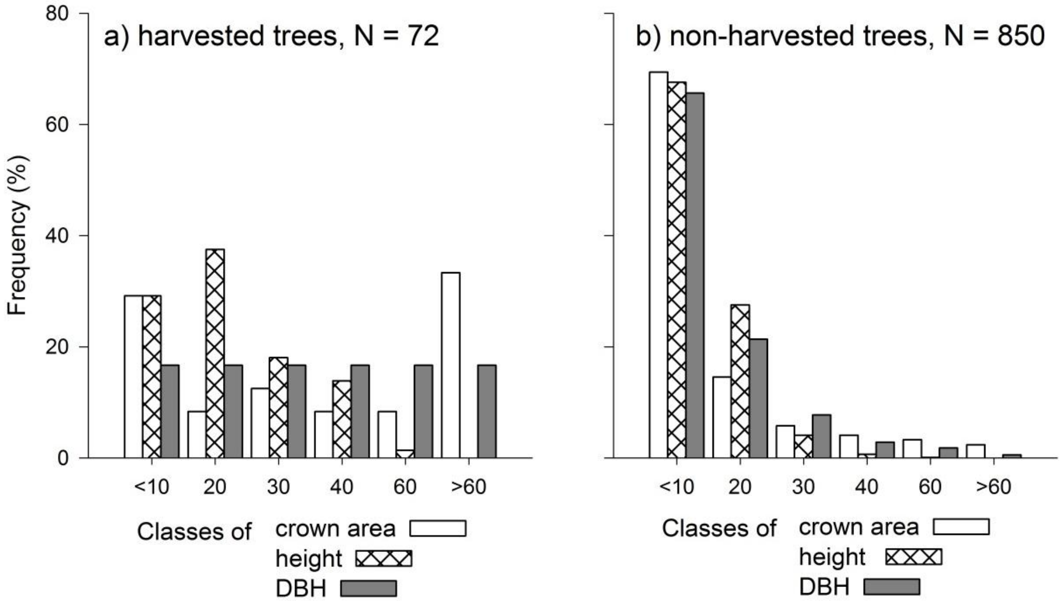

Figure 3.3 Distribution of crown area, height and diameter at breast height (DBH) for (a) harvested trees, and (b) non-harvested trees measured along the Yala River basin.

Diameter at breast height, crown area and height for the harvested trees ranged from 3.2-102 cm, 0.4-286.5 m^2 and 4.2-36.6 m, respectively. The corresponding range for non-harvested trees was 2.5-89.5 cm, 0.2-272.5 m^2 and 2.4-38.6 m for DBH, crown area and height. The correlation between DBH and height was moderate for trees from the three sites evaluated (Figure 3.4); both for harvested (R^2 = 0.55) and non-harvested trees (R^2 = 0.58). However, a strong correlation was observed between DBH and height for trees from individual sites: Middle, R^2 = 0.73, Upper, R^2 = 0.84; except the Lower Yala, R^2 = 0.50, possibly due to the lower spread of diameters in this block.

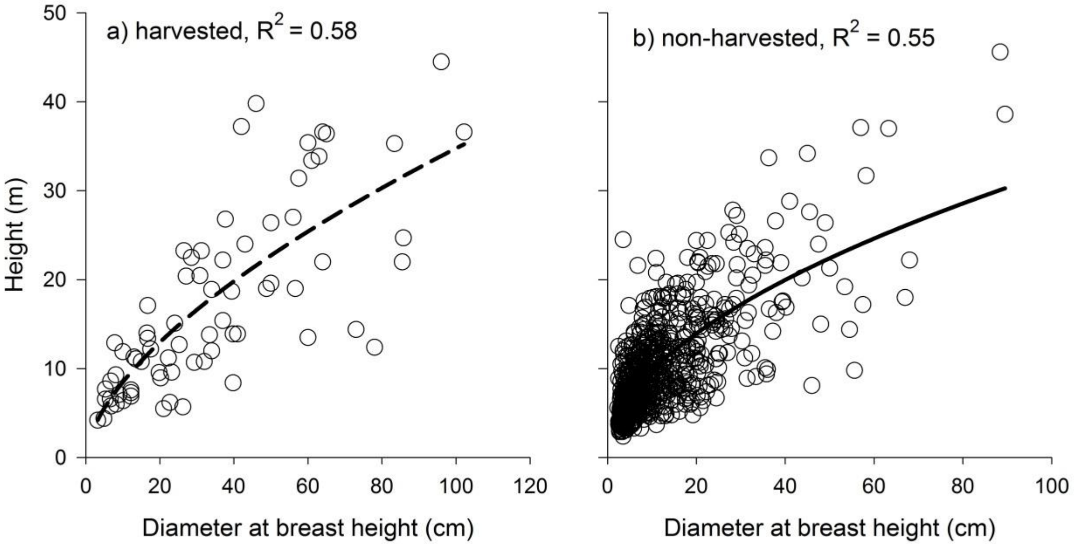

Figure 3.4 Relationship between diameter at breast height and height for (a) harvested trees, and (b) non-harvested trees measured across the three sites evaluated.

The variability in the DBH-height relationship was greater in smaller trees, DBH <20 cm (R^2 = 0.38 for Lower, R^2 = 0.42 for Middle and R^2 = 0.04 for Upper Yala) compared to trees with DBH >20 cm (R^2 = 0.61 in Upper and R^2 = 0.62 in Middle Yala); again, except for Lower Yala (R^2 = 0.11). Trees in Lower Yala were generally short compared to those in Middle and Upper Yala.

Diameter at breast height had a strong and significant relationship with AGB (R^2 = 0.98; $P<0.001$) and the biomass of stem (R^2 = 0.96; $P<0.001$), which is evident of biomass increment with increasing DBH (Figure 3.5). The correlation between DBH and the biomass of branches (R^2 = 0.88) and leaves (R^2 = 0.81) was moderate.

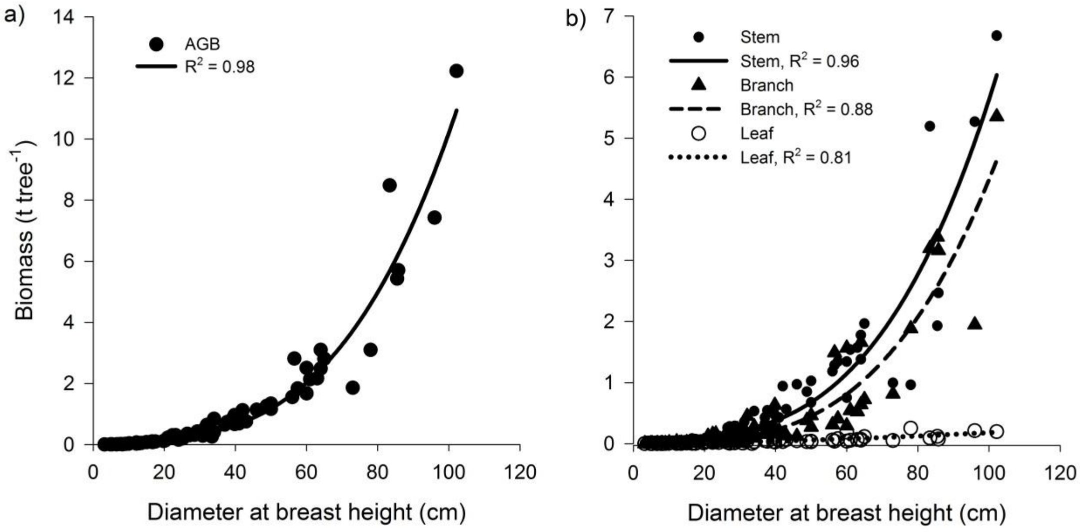

Figure 3.5 Relationship between diameter at breast height and (a) aboveground biomass, and (b) the biomass of stem, branches and leaves.

3.3.2 Wood density and carbon content

Wood density for aboveground woody parts (stem and branches) ranged from 0.28 g cm^{-3} in *Spathodea campanulata* to 0.78 g cm^{-3} in *Syzygium cordatum*. The overall mean±SE (and median) wood density for the sampled trees was 0.52±0.02 g cm^{-3}. Whereas the mean wood densities between the three sites were not significantly different (Lower = 0.53±0.03 g cm^{-3}, Middle = 0.50±0.02 g cm^{-3} and Upper Yala = 0.58±0.03 g cm^{-3}), statistically significant differences ($P<0.001$) were observed among trees of different sizes and species. Species dominant at altitude >2200 m (e.g. *A. mearnsii*) had high mean values (0.66±0.03 g cm^{-3})

compared to *M. lutea* (0.41±0.03 g cm^{-3}), a species dominant at 1200 m above sea level. A mean of 0.39±0.03 g cm^{-3} was recorded for smaller trees, DBH <10 cm while for larger trees, DBH >60 cm had a higher mean (0.61±0.03 g cm^{-3}).

Wood density values determined by water displacement method for branches and roots compared well to corresponding values determined by measurement of disc dimensions (Figure 3.6a). The correlation coefficient between the two methods was high for the branches (R^2 = 0.88) but moderate for the roots (R^2 = 0.64). The measured dimensions approach yielded lower estimates than water displacement, although the mean wood density for branches determined by water displacement (0.54 g cm^{-3}) was not statistically significantly different from that determined by measured dimensions (0.53 g cm^{-3}). In contrast, mean wood density for roots determined by water displacement (0.48 g cm^{-3}) was significantly different from 0.45 g cm^{-3} estimated by disc dimension ($P<0.05$). The range of wood density determined by water displacement for branches and roots, 0.30-0.73 g cm^{-3} and 0.32-0.64 g cm^{-3} was comparable to 0.29-0.69 g cm^{-3} and 0.29-0.66 g cm^{-3} established by measured dimensions. There was as strong correlation between stem and branch wood density determined by coring, R^2 = 0.74 (Figure 3.6b). The mean wood density for stem 0.54 g cm^{-3} and branches (0.55 g cm^{-3}) determined by coring compared well with estimates for branches determined by displacement and measured dimensions.

The mean (±SE) carbon content for the 72 trees used in this study was 47.6±0.09% with values ranging from 46.4 % in *P. americana* to 49.6 % in *G. robusta*. ANOVA showed that C content in the stems (47.6±0.16%), branches (47.4±0.15%) and roots (47.7±0.14%) were not significantly different. Biomass weighted means for the stems, branches and roots were 47.8, 47.5 and 48.0%.

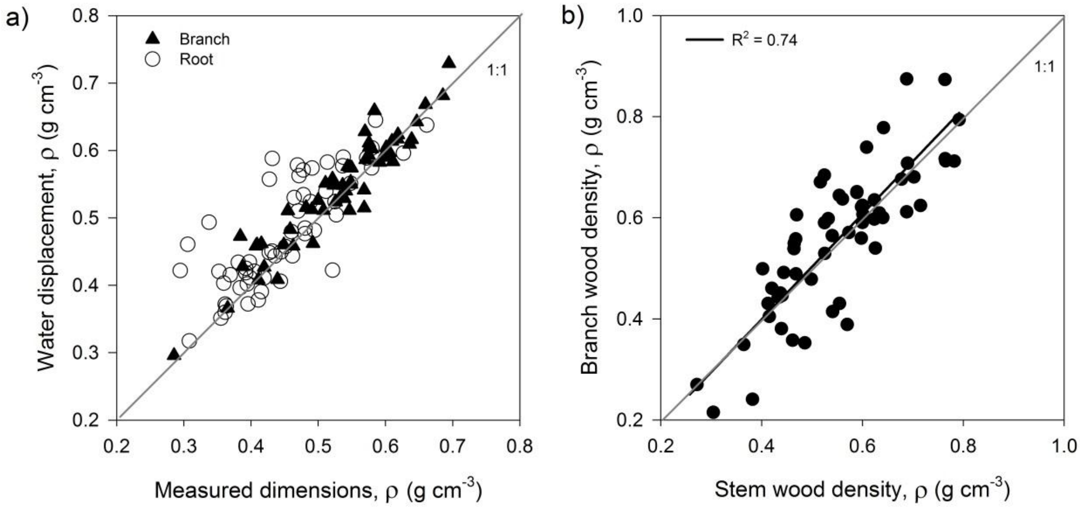

Figure 3.6 Comparison of (a) wood density determined using water displacement method to measured disc dimensions, and (b) wood densities for branches and stem determined by coring method.

3.3.3 Performance of allometric models developed

Equation 3.1 predicted AGB and the biomass of stems and branches of harvested trees with high accuracy, but overestimated leaf biomass (Table 3.1). Wood density data did improve model fit, crown area data marginally improved model fit while height data did not (Table 3.2). Equation 3.1 is presented as the most suitable and simple equation for estimating AGB in the investigated agricultural landscapes. However, where trees differ substantially in form and wood density, equation 3.6 is considered as an appropriate alternative when additional explanatory variables such as height, wood density and crown area are available for use; mainly because equation 3.6 has a lower AIC value, improved model fit and requires only two parameters (DBH and wood density).

Table 3.1 Allometric coefficients for estimating AGB (equation 3.1), stem biomass (equation 3.2), branch biomass (equation 3.3) and leaf biomass (equation 3.4).

Component	a(SEE)	b(SEE)	R^2	Bias %
Equation 3.1	0.091(0.131)	2.472(0.039)	0.984	-4.63
Equation 3.2	0.059(0.174)	2.442(0.052)	0.970	-4.06
Equation 3.3	0.010(0.351)	2.772(0.104)	0.910	-1.55
Equation 3.4	0.084 (0.282)	1.702(0.084)	0.856	8.64

Table 3.2 Allometric coefficients for estimating aboveground biomass using DBH in combination with height (equation 3.5), wood density (equation 3.6), crown area (equation 3.7), and DBH in combination with height, wood density and/or crown area (equation 8 to 11).

Equation	a	b	c	d	e	R^2_{adj}	AIC	Bias %
Equation 3.5	0.092	2.488	-0.028			0.977	99	-4.77
SEE	0.149	0.065	0.089					
Equation 3.6	0.225	2.341	0.730			0.984	72	-5.26
SEE	0.209	0.041	0.140					
Equation 3.7	0.107	2.318	0.101			0.979	95	-4.57
SEE	0.161	0.098	0.059					
Equation 3.8	0.253	2.213	0.705	0.086		0.985	71	-5.06
SEE	0.220	0.085	0.140	0.050				
Equation 3.9	0.221	2.301	0.062	0.755		0.984	73	-5.04
SEE	0.211	0.064	0.076	0.143				
Equation 3.10	0.106	2.281	0.039	0.110		0.979	96	-4.46
SEE	0.169	0.129	0.093	0.063				
Equation 3.11	0.319	2.097	0.119	0.743	0.112	0.985	70	20.34
SEE	0.218	0.111	0.079	0.140	0.059			

3.3.4 Performance of existing allometric equations

Figure 3.7 shows the biomass estimation by equation 3.1 developed in this study compared to existing local and global equations recommended for tropical species (parameters of published equation are described in section 2.6.2). A scatter of the measured AGB values and the corresponding trend-line is plotted for comparison. The equations of Chave et al. (2005) for dry forests over-predicted biomass while the equations of Brown (1997) for wet forests and Henry et al. (2009) for Western Kenya under estimated biomass.

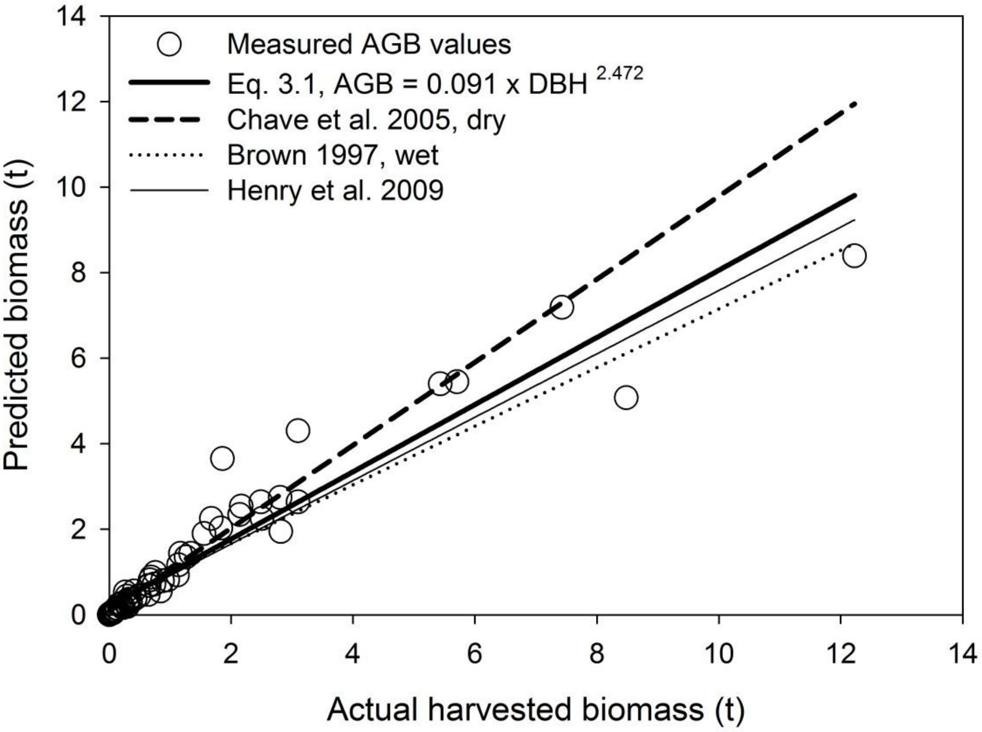

Figure 3.7 Comparison of actual biomass harvested and biomass predictions by equation 3.1 and selected published equations.

All equations showed patterns in prediction error across trees of different sizes. Equation 3.1 was the most optimal, comparing well with the equation of Chave et al. (2005) for dry forests (Figure 3.8).

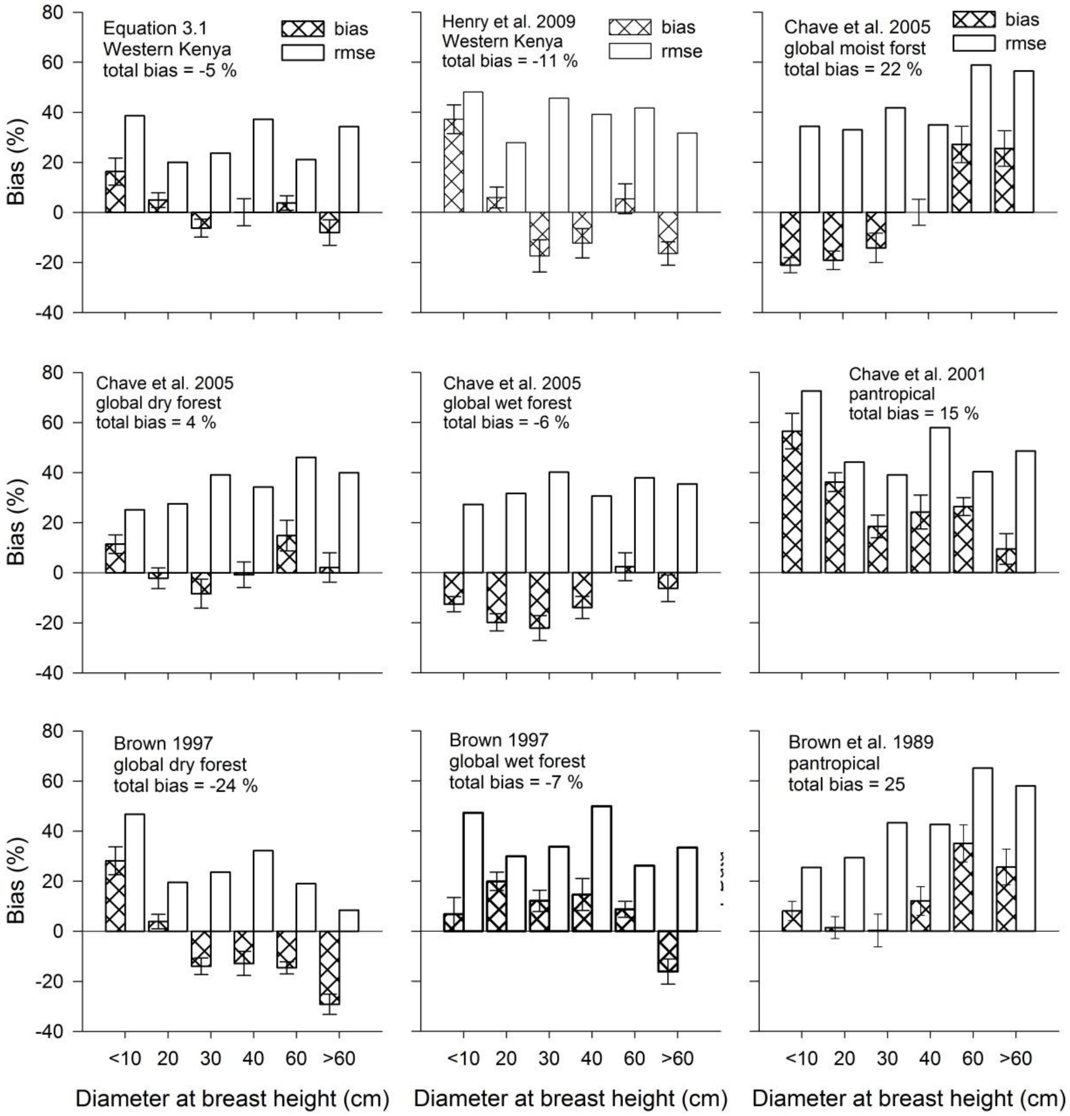

Figure 3.8 Disaggregation of bias for different equations across trees of various sizes.

However, like most published models, equation 3.1 overestimated biomass for smaller trees, <20 cm but had relatively consistent bias (<5%) across diameter classes. Chave et al. (2005) equation for dry forest had a good spread of error across the diameter classes except for smaller (DBH <10 cm) and trees with DBH ≥60 cm; which showed relatively high errors, 11% and 14% respectively. The equation of

Brown (1997) for wet forests overestimated the biomass of smaller trees (DBH <60 cm) by an average of 12%; with greater errors encountered between DBH size 20-40 cm, while it underestimated the biomass for trees with DBH >60 cm by 16%. The pan-tropical equation by Chave et al. (2001) overestimated biomass by 15% while the equation of Henry et al. (2009) underestimated biomass by 11%.

Additional globally renowned equations by Chave et al. (2005) for moist forests and Brown et al. (1989) pantropical equations overestimated biomass by about 25%. Other equations tested such as Djomo et al. (2010), moist forest equations by Brown (1997), Brown et al. (1989) and Chave et al. (2005) overestimated biomass by more than 50%. Root mean square error shows that the trend in prediction of single trees varied across size class for different equations. For example, the equations of Brown et al. (1989) for pantropical forests gave poor estimates for larger trees while Brown (1997) for dry forests gave better estimates for larger trees. The equations developed in this study maintained a similar level of bias across diameter classes which make it more robust than other tested equations.

3.3.5 Representative aboveground tree biomass carbon

Small trees, DBH <10 cm dominated the landscape (65.6%) though they accounted for only 4.8 % of the estimated biomass (Figure 3.9). In contrast, larger trees (DBH >40 cm) were very few (2.5%) but held most of the biomass (47.6%). Also, more than 75% of the crowns were <15 m^2, 80% of the DBH were <15 cm and 66% of the heights were <10 m. Tree biomass for the 3 blocks differed significantly ($P<0.001$)

with higher biomass estimated in Middle (63%) compared to Upper (21%) and Lower (16%) sites. Representative AGB in agricultural landscape mosaics of Western Kenya was estimated to be 36.2±0.03 t ha^{-1} using equation 3.1. Using a C concentration of 48% determined from elemental analysis of carbon content in samples, agricultural landscapes evaluated were estimated to hold 17.5±0.01 t C ha^{-1} in standing trees.

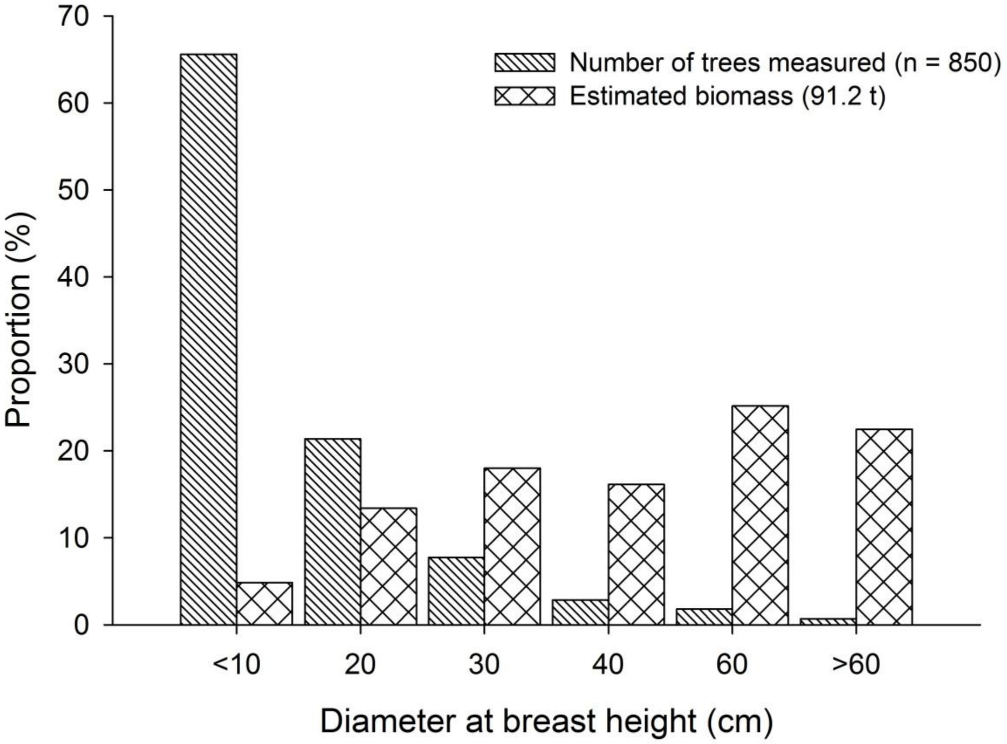

Figure 3.9 Distribution of non-harvested trees measured per diameter class and their share of estimated biomass for the River Yala basin.

3.4 Discussion

3.4.1 Dendrometric relationships

The diameter-height relationships varied across the three sites evaluated. This is attributed to species-specific differences in biomass partitioning patterns and their responses to different environmental conditions; different tree species dominated different sites. The weak relationship between height and biomass are likely to have contributed to a high variability in height of trees encountered because different trees species dominated different sites. Management is likely to have also influenced the relationship between height and biomass given that 20% of the trees sampled were pruned. Height increased almost linearly with diameter, but seemed to reach only a species specific maximum height. This is in line with the observation that trees of a particular species in a given location have a maximum height.

The minimum DBH of 2.5 cm was adopted to take care of the slow growing species of the semi-arid environments in Lower Yala. Unlike in Lower Yala, trees in Middle and Upper Yala attained greater heights, indicating a benign environment that allows rapid growth for effective light interception. In the semi-arid environment of Lower Yala light competition is less important compared to belowground competition for water and nutrients resulting in plants with shorter heights.

3.4.2 Wood density and carbon content

The results show that wood density was affected by tree size. Smaller trees, DBH <10 cm had a low mean of 0.39 g cm^{-3} while a high mean of 0.61 g cm^{-3} was observed in larger trees, DBH >60 cm. This observation contrasts a report by Basuki et al. (2009), that increasing DBH is not followed by an increase in wood density. Similarly, wood density significantly varied between species but not location. This suggests that wood density from a database could be useful for improving the precision of allometric equations rather than taking measurements for each location. Both mean and median (0.52 g cm^{-3}) wood density of tree species sampled varied considerably but was well within the range of tropical African forests, 0.3-0.9 g cm^{-3} (Brown, 1997).

A direct comparison of wood densities from measurement of disc dimensions and water displacement carried out on branch and root samples from 60 trees showed that values derived from the separate methods on the same individual samples were comparable. Thus, either of the methods can accurately provide wood density estimates. The water displacement method was considered most suitable because of ease of use and applicability to trees that might be hard to core. Since branch wood density had a relatively high correlation with stem wood density (R^2 = 0.74) and since the mean wood densities determined by the coring method for the two sections were comparable (0.55 g cm^{-3} and 0.54 g cm^{-3}), wood density could be estimated for trees in agricultural mosaics using branch sections without having to core or cut the main stem of the tree.

Carbon budgets are often based on the assumption that plant biomass comprises of 50% C, which was considered fairly high compared to 47.6±0.09% determined and used for this study to convert biomass into C. This value is close to the IPCC default, 47% (IPCC, 2006) but higher than 43% reported by (Ren et al., 2009) for Mangrove plantations in Southern China.

3.4.3 Performance of allometric models developed

Equation 3.1, $AGB = 0.091 \times (dbh)^{2.472}$ with DBH as the only explanatory variable provided a satisfactory estimation of biomass since the total variation explained by the relationship is high (98%) and the associated bias was small (5%). The results indicate that DBH is a strong indicator of aboveground biomass, which implies that the variability of biomass of trees in agricultural landscapes is largely explained by its relationship to DBH. The importance of the results comes from assessment of how large the actual errors are, whether there is bias and how these depend on diameter, for the quality of landscape level measures will depend on this. Likewise it is also noteworthy that the overall R^2 is as much a function of the diameter distribution of the sampled trees as of the fit of the model. The apparently small differences in the equations for small trees could add up to a large amount of C when looking at a landscape; this is an example of the bias problem. The results agree with previous reports (Basuki et al., 2009; Brown et al., 1989) that DBH alone is a good predictor of biomass especially in terms of the multiple tradeoffs between accuracy, cost and practicability of measurements.

The relatively low R^2 value for the generic diameter-leaf biomass relationship and the inability to predict leaf biomass with high accuracy may be due to the variable leaf phenology between species. Leaves are also highly susceptible to weather and interplant competition and it is likely that crown geometry was influenced by such factors in addition to management impacts (e.g. pruning) leading to the heterogeneity as observed for leaf biomass between trees (Cole and Ewel, 2006; Navar, 2009).

Including total tree height data did not substantially improve biomass predictions in this study when compared to using DBH alone. These findings contrast results from Panama (Bastien-Henri et al., 2010), the humid lowlands of Costa Rica (Cole and Ewel, 2006) and Sumatra, Indonesia (Ketterings et al., 2001), all reporting that height substantially improves model fit. However, conclusions similar to those found in this study were drawn by Basuki et al. (2009) for Kalimantan, Indonesia, and by Nelson et al. (1999) for a mixed species equation in the Brazilian Amazon. The error associated with the equations of Chave et al. (2005) for global wet forests supports this study’s contention that height does not improve biomass estimation in Western Kenya.

The results concur with previous reports that wood density data increases accuracy (Basuki et al. 2009; Chave et al. 2005). The effect of wood density becomes particularly conspicuous when comparing DBH, height, wood density and the biomass of larger trees: *S. cordatum* with DBH 83.4 cm, height 35.3 m and wood density 0.8 g cm^{-3} had AGB of 8.5 t (measured biomass) compared to 7.4 t of *E. camaldulensis* with DBH 96 cm, height 44.5 m and wood density 0.6 g cm^{-3}. Thus, the dry weight of *S. cordatum*, despite shorter and thinner smaller, exceeds the dry weight of *E. camaldulensis* by 14.2%.

Crown area as an input variable marginally improved model fit. The significant correlation between DBH and crown area (R^2 = 0.83) corresponds to the relationship between crown area and AGB, R^2 = 0.85 (Figure 4.2). Since the correlation between DBH and AGB is high, the addition of crown area is expected to only increase R^2 slightly. Difficulties or certain degrees of subjectivity associated with measuring crown area are frequently the reason for not including it as a parameter in biomass equations. However, crown geometry in agricultural landscapes and its heterogeneity reflects specific interplant competition and management; hence incorporation of crown area would improve the accuracy of equations for trees in such landscapes.

3.4.4 Suitability of existing equations

Existing equations that initially appeared suitable for estimating AGB in Western Kenya generally misjudged biomass. However, bias and biomass prediction of equation 3.1 compare well with the performance of widely recognized global equations of Chave et al. (2005) for dry forests. This indicates that most biomass equations are not necessarily site specific and may be applicable across broader conditions. However, using exclusively climatic criteria to describe the region of applicability for global equations proved to be problematic. The mean annual rainfall and temperature for the study sites do not match the criteria defining the forest type associated with the equation performing best, i.e. dry forests by Chave et al. (2005) and wet forests by Brown (1997). The average catchment rainfall across River Yala basin would suggest the equation for moist forests to be adequate. However, the use of the tropical moist forest equations of Chave et al. (2005) and Brown (1997) lead to a substantial overestimation of biomass compared to dry and wet forests equations by the same authors. Nevertheless, Chave et al. (2004) reported the choice of allometric equation to be the most important source of error in biomass estimation, which underlines the importance of empirical validation considering that a global tropical forest type classification does not seem to be intuitive. The equations of Djomo et al. (2010), Brown (1997) for moist forest and Chave et al. (2005) for moist forest applied to inventory data from Western Kenya indicate the magnitude (22-92%) by which an equation can misjudge biomass when developed in one area and applied in another area without prior validation or calibration.

Using the published equations to predict landscape biomass for non-harvested trees, the equation by Henry et al. (2009) and Brown (1997) for wet forests gave generous estimates of 36.1 t ha^{-1} and 39.1 t ha^{-1} respectively. These amounts are exaggerated although the two equations were found to underestimate biomass by 11% and 7%. This discrepancy is explained by the disaggregation of error by DBH class. For instance Henry et al. (2009) overestimated the biomass of smaller trees by 37% and larger trees by 5% while the equation of Brown (1997) overestimated biomass of trees with DBH <60 cm by 7 to 20% and underestimated the biomass of few larger trees by 16%. Hence, the use of equations to measure landscape biomass should consider disaggregation of error by size class as well as the predictability of single trees that varies for different equations.

3.4.5 Representative landscape biomass carbon

Agricultural practices such as nitrogen fertilization, paddy cultivation, animal production and pasture maintenance by burning favour GHG emissions. However, judicious integration of trees in agricultural landscapes improves farm productivity while providing opportunities to create C sinks. AGB estimates determined in this study from Western Kenya (17.4±3.9 t C ha^{-1}) were higher than 9-11 t C ha^{-1} reported by Henry et al. (2009), in the same region, but within C storage range of 4-22 t C ha^{-1} reported by Albrecht and Kandji (2003) for Western Kenya. Whereas the present study focused only on AGB in live trees, Albrecht and Kandji (2003) determined AGB in live trees, litter, deadwood, understory, and crops in some improved fallows, while Henry et al. (2009) determined C stocks in aboveground perennial biomass considering a mixture of agroforestry and cropping systems.

Underrepresentation of larger diameter trees is a common problem in the development of allometric equations (Brown, 1997), which can be overcome by sampling a consistent number of trees per DBH class. However, the landscape studied is dominated by small trees indicating a renewed effort in tree planting. The few larger trees account for most of the C stocks in the area, underlining the need to accurately estimate biomass for large trees. The high biomass harvested and estimated for the Middle and Upper Yala was accounted for by the presence of tall, larger DBH trees compared to the Lower Yala. This variation is attributed to the differences in area climatic conditions and edaphic factors. Sufficient rainfall and the relatively fertile soils of the Middle Yala (1950 mm) favor rapid growth of trees. In contrast, degraded soils and low rainfall (1479 mm) of Lower Yala can explain a lower tree density and limited tree growth in the area.

3.4 Conclusion

The simpler power function model using DBH alone gave good fit ($R^2 = 0.98$) and performed best, with about 95% accuracy. Diameter at breast height was thus confirmed to be a reliable predictor of AGB in complex agricultural landscapes in Western Kenya. The accuracy of diameter predictions can be improved by wood density and crown area, particularly in trees that differ significantly in architecture. The equations developed are robust, derived from diverse species growing in a wider geographic range and influenced by management impacts, and will be useful for programs assessing C stocks and storage potential by trees in agriculturally dominated landscapes.

CHAPTER FOUR

4.0 ABOVEGROUND BIOMASS ESTIMATION USING CROWN AREA

4.1 Introduction

Conventional allometries determine biomass from measurements of DBH or volume. It is currently not possible to derive either of these measurements directly from non-destructive measurements such as remote sensing. As a result, DBH is commonly used in allometric relations to estimate biomass. Diameter is preferred as predictor variable because it can be measured with ease and high accuracy, and explains over 95 % of the variability observed in AGB (Brown, 1997). As biomass estimates at larger scales require remotely sensed data, new allometric relations are required using crown area and/or tree height as predictors of biomass, both of which can be derived from remote sensing. Studies have shown that crown area can be used as primary predictor variable, especially in low-growing multi-stemmed trees (Sah et al., 2004). Determination of biomass as a function of crown area can therefore be carried out traditionally using field-based inventory plots or from aerial imagery. However, challenges with using crown area as a predictor variable abound, ranging from inability to measure crown area accurately to lack of consistent allometric equations (Gibbs et al., 2007).

Remote-sensing techniques have emerged as a promising alternative to destructive sampling. Collection of high resolution imagery that allows individual tree-level measurements such as height and crown dimensions makes it possible to measure and monitor biomass in large areas at potentially low cost and less time (Drake et al., 2003). Information derived from overhead imagery can then be used to obtain relationships between remotely determined crown metrics and field measured parameters. Previous studies such as, Drake et al. (2003) and Massada et al. (2006) have already established significant relationships between remotely sensed crown metrics e.g. crown projection area and tree structural characteristics such as DBH, and even AGB although studies that relate biomass directly to crown area are scarce. Remotely determined crown area measurements for particular plant types can therefore be used to derive estimates of AGB using allometric equations. This requires a new generation allometry using crown area as a predictor of AGB to provide a basis for calibration and validation of remote sensing estimates.

The objective of this study was to develop reliable crown area-based equations for estimating AGB for trees in multi-species agricultural landscapes of Western Kenya. The specific objectives of the study were to:

i. Develop allometric equations based on crown area for AGB estimation,
ii. Evaluate the influence of height and wood density on crown area predictions.

4.2 Method

The 72 trees used to develop diameter equations (chapter three) were used to develop equations for estimating AGB using crown area. Twenty of the 25 trees harvested in Middle Yala were used to evaluate the performance of crown area equations developed in the area. Scatter diagrams of raw data were plotted to identify outliers and visually assess the relationships between crown area and DBH, height or biomass. Log transformed data for AGB as well as the biomass of stems, branches and leaves were used to derive prediction equations using crown area (ca) alone and ca in combination with height (H) and/or wood density (ρ). The following equations were tested:

$\ln(AGB) = a + b \times \ln(ca)$ ……………………………………………………Equation 4.1

$\ln(AGB) = a + b \times \ln(ca) + c \times \ln(\rho)$ ……………………………………………..Equation 4.2

$\ln(AGB) = a + b \times \ln(ca) + c \times \ln(H)$ ……………………………………………Equation 4.3

$\ln(AGB) = a + b \times \ln(ca) + c \times \ln(H) + d \times \ln(\rho)$ …………………………….....Equation 4.4

A similar approach was used to derive equations for estimating biomass of stem, branches and leaves with crown area alone as predictor.

$\ln(BM_{stem}) = a + b \times \ln(ca)$ ……………………………………………..Equation 4.5

$\ln(BM_{branches}) = a + b \times \ln(ca)$ …………………………………………………Equation 4.6

$\ln(BM_{leaves}) = a + b \times \ln(ca)$ ……………………………………………..Equation 4.7

Allometric equations for estimating AGB were also developed using trees with crown area < 20 m^2 and > 20 m^2.

$\ln(AGB) = a + b \times \ln(ca < 20m^2)$ ……………………………………………Equation 4.8

$\ln(AGB) = a + b \times \ln(ca > 20m^2)$ ……………………………………………Equation 4.9

All equations were developed using a training set of 66 trees with an additional 6 trees for validation using multiple sample hold out.

4.3 Results

4.3.1 Biometric relationships

Crown area was significantly correlated with DBH ($R^2 = 0.86$; $p<0.001$) but not with height ($R^2 = 0.41$) for harvested trees (Figure 4.1). Similarly, the relationship between crown area and DBH for non-harvested trees measured across the three sites evaluated was strong ($R^2 = 0.89$). Even if investigated separately, trees taken from the same site also showed a strong correlation between crown area and DBH: Middle ($R^2 = 0.77$), Upper ($R^2 = 0.84$) and Lower Yala ($R^2 = 0.86$). A fairly weak relationship was observed between crown area and height for non-harvested trees ($R^2 = 0.38$).

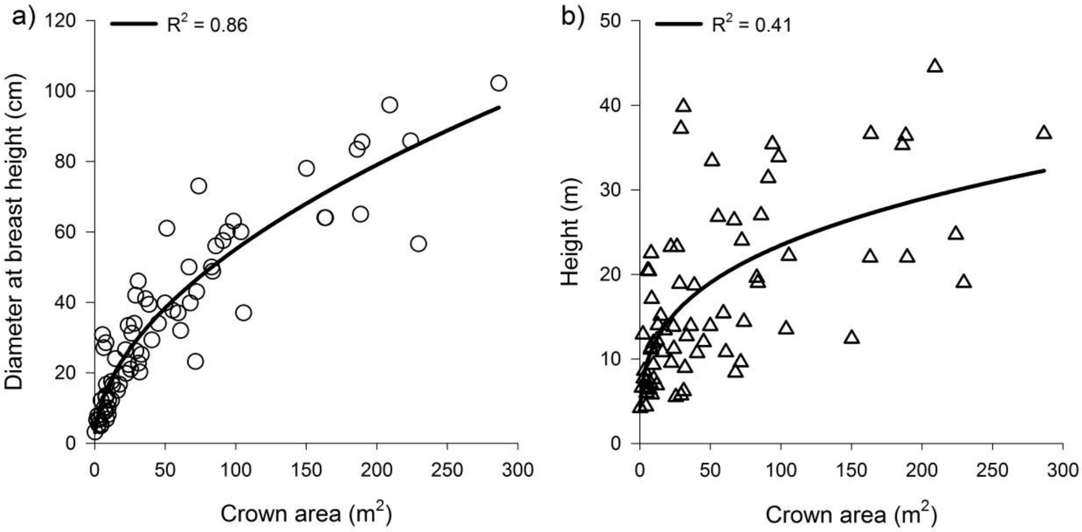

Figure 4.1 Scatter plots showing the relationship between (a) crown area and DBH, and (b) crown area and tree height for harvested trees

Crown area explained 85% of the variability observed in AGB for harvested trees (Figure 4.2); however, crown area explained only a small fraction of variability observed in AGB for trees with smaller crowns, 20 m^2 ($R^2 = 0.39$) compared to trees with larger crowns, >20 m^2 ($R^2 = 0.74$). The correlation between crown area and the biomass of stems ($R^2 = 0.73$) and branches (R^2 0.82) was strong and significant ($P<0.001$), while the relationship between crown area and foliage biomass was moderate ($R^2 = 0.60$).

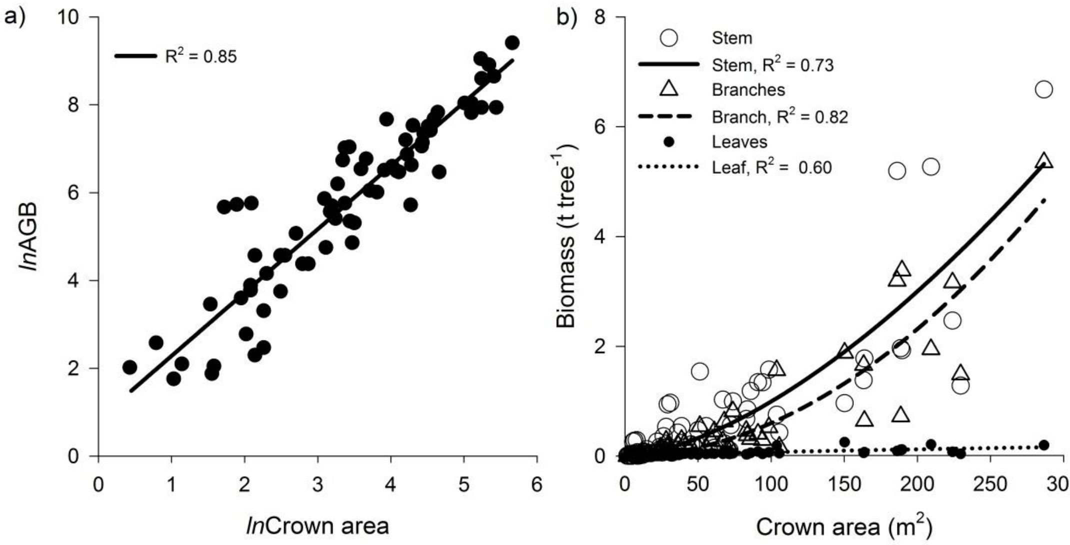

Figure 4.2 Regressions of biomass as a function of crown area for (a) aboveground biomass (AGB), and (b) the biomass of stems, branches and leaves.

4.3.2 Performance crown area equations

Equation 4.1, $AGB = 2.568 \times ca^{1.418}$ based on crown area alone predicted AGB for harvested trees with a bias of 18.8%, about twice the error associated with the equation 3.1 based on DBH (Table 4.1). Evaluation of the performance of equation 4.1 using 20 trees harvested in Middle Yala showed that equation 4.1 overestimated AGB by 30.2%; a similar test on equation 3.1 revealed a bias of 13.1%. Addition of height (equation 4.2) and wood density data (equation 4.3) improved the R^2 by 6 and 1.9%, respectively, while a combination of both height and wood density data (equation 4.4) improved R^2 by 7.8%. Similarly, height and wood density data reduced the bias associated with equation 4.1 by 7.2 and 1.8%. Wood density data improved the performance of the model for the trees harvested from Middle Yala by reducing the bias from 30.2 to 9.9% while height data did not.

Table 4.1 Allometric coefficients for estimating AGB using crown area alone (equation 4.1) or crown area in combination with height (equation 4.2), wood density (equation 4.3) and both height and wood density (equation 4.4).

Equation	a	b	c	d	R^2_{adj}	P-value	RSE	Bias %
Equation 4.1	2.568	1.418			0.846	<.001	0.120	18.8
SEE	0.263	0.073						
Equation 4.2	0.398	1.123	1.062		0.906	<.001	0.121	11.6
SEE	0.348	0.072	0.160					
Equation 4.3	11.336	1.258	1.401		0.865	0.002	0.120	16.9
SEE	0.522	0.084	0.434					
Equation 4.4	1.738	0.965	1.058	1.384	0.925	<.001	0.121	8.1
SEE	0.463	0.074	0.142	0.323				
Equation 3.1	0.091	2.472			0.982	<.001		8.2
SEE	0.131	0.039						

Equations for stem (equation 4.5), branches (equation 4.6) and leaves (equation 4.7) greatly overestimated their respective biomass by about the same relative error, both for trees from all three sites evaluated and trees from Middle Yala (Table 4.2).

Table 4.2 Allometric equations for estimating the biomass of stem, branches and leaves.

Equation	a	b	R^2	P value	RSE	Bias 1
Equation 4.5	1.898	1.345	0.771	<.001	0.120	31.5
SEE	0.318	0.088				
Equation 4.6	0.245	1.707	0.895	<.001	0.120	22.1
SEE	0.254	0.070				
Equation 4.7	0.628	1.026	0.827	<.001	0.120	14.5
SEE	0.204	0.056				
Equation 4.8	3.732	1.181	30.5	0.003	0.201	-18.4
SEE	0.712	0.348				
Equation 4.9	4.397	1.302	74.4	<.001	0.151	39.3
SEE	0.487	0.115				

Equation 4.8 and 4.9 developed from trees with crown area less than 20 m^2 and crown area greater than 20 m^2, respectively, showed different degrees of accuracy. Equation 4.8 underestimated AGB of trees from all three sites evaluated by 18.4% and trees from Middle Yala by 1.9%, while equation 4.9 overestimated biomass in both cases by 39.3 and 61.2%, respectively. The equation by Sampaio and Silva (2005) that

use crown area as AGB predictor, $AGB = 1.710 \times ca^{1.118}$ for Brazilian dry forests underestimated the AGB by 68.8% and for trees from Middle Yala by 62.1%.

Figure 4.3 shows the disaggregation of the relative error across trees in different size classes. Equation 4.1 overestimated the biomass of smaller trees (DBH ≤10 cm) by 106.2% but underestimated the biomass of larger trees (DBH >40 cm) by about 10%. Height data effectively lowered the bias associated with equation 4.1 for trees with DBH <40 cm, but resulted in overestimation of the biomass of trees with DBH >60 cm. Conversely, wood density greatly reduced the bias of crown area based equation leading to underestimation in trees with DBH >40 cm. A combination of height and wood density data effectively reduced bias to <5% for trees with DBH >20 cm and to 50.4 from 106.2% for trees with DBH ≤10 cm. Equation 4.8 showed decreasing overestimation, from 194.7% for small trees (<10 cm) to 11.3 % for trees with DBH 30 cm to underestimation by 14.2% for larger trees (DBH >40 cm). In contrast, equation 4.9 underestimated the biomass of trees with DBH <20 cm, but increasingly overestimated biomass with increasing tree size.

Equation 4.1 estimated representative aboveground landscape biomass to be 44.6±0.03 t ha^{-1}, which is 22.5% more than 36.4±0.03 t ha^{-1} estimated by equation 3.1 in chapter 3. Equation 4.4 with crown area, height and wood density estimated representative biomass to be 43.3 t ha^{-1} while the equation 4.8 derived from trees with smaller crowns, <20 m^2 underestimated biomass (11±0.02 t ha^{-1}), and equation 4.9 from trees with crown area >20 m^2 estimated representative biomass rather generously

(49.8±0.03 t ha^{-1}). Equation 4.4 is considered to be the most adequate since it had the lowest relative error of 8.1% from cross validation and 4.2% for trees from Middle Yala. Crown area estimated aboveground C stocks in agricultural landscape mosaics of Western Kenya to be 20.8 t C ha^{-1}. Conversion of biomass (43.3 t ha^{-1}) to C was achieved by multiplying biomass estimates with the actual C concentration in tree samples (48%) determined by element analysis.

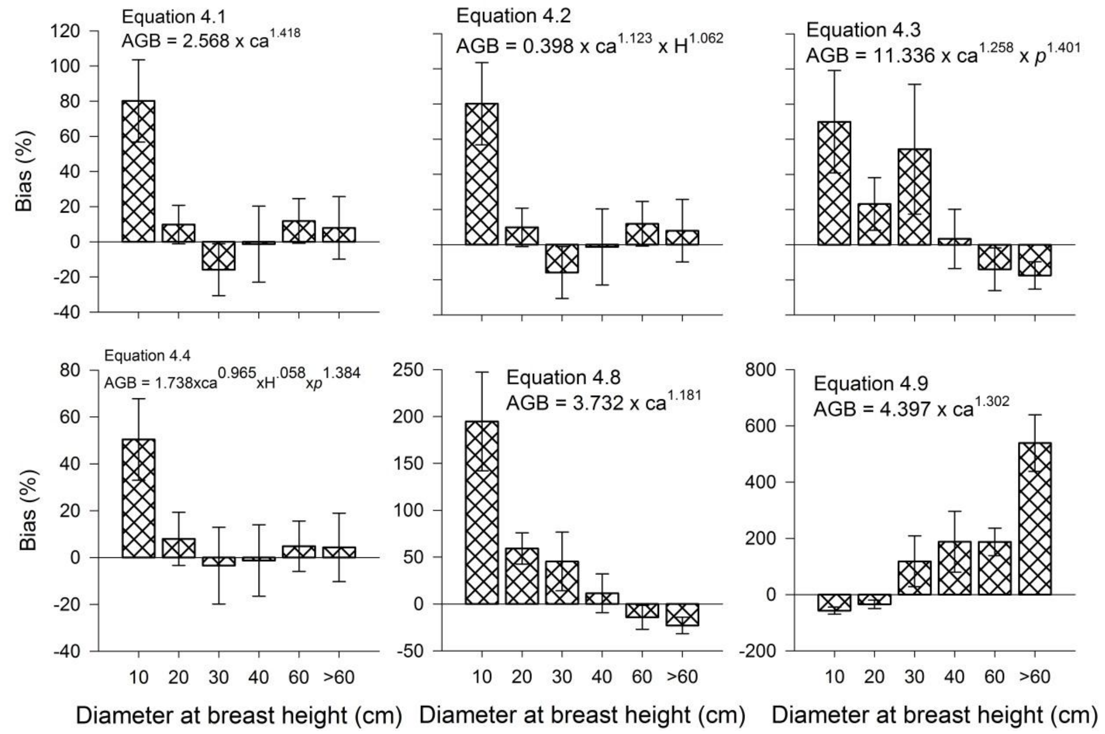

Figure 4.3 Variation of the predictive accuracy across tree sizes for equation with crown area alone (equation 4.1), crown area and height (equation 4.2), crown area and wood density (equation 4.3), crown area, height and wood density (equation 4.4) and the equations developed from trees with crown area <20 m^2 (equation 4.8) and crown area >20 m^2 (equation 4.9).

4.4 Discussion

4.4.1 Biometric relationships

Allometric equations based on crown area had a good fit with 85% of the variation in AGB explained by crown area. Similarly, crown area explained a large fraction of the variability in each biomass component, with the greatest variability observed explained in branches. The correlation between crown area and AGB determined in this study compares well with R^2 determined by Sampaio and Silva (2005) for Brazilian semi-arid Caatinga plants ($R^2 = 0.74$). The strength of crown area-AGB relationship was dependent on the size category; being weak for trees with smaller crowns. Trees of different sizes have variable crown geometry due to interplant competition and particularly in agricultural landscapes due to management impacts, e.g. pruning, with higher relative impact on smaller trees. This underlines that the precision of crown area models would be of significance if constructed from trees selected by crown area and not by DBH, as it was done in this study. The high R^2 value for crown area-branch biomass relationship endorses crown area dynamics being more closely related to crown biomass than to trunk dynamics. However, exceptions clearly exist particularly in agricultural landscapes, where trees are commonly pruned and in some cases tree crowns intersect with each other. The strong relationship between crown area and DBH indicate that stem diameter is an important indicator of crown size.

The lower accuracy in predicting leaf biomass is likely to be caused by highly variable leaf phenology and the smaller amount of leaf biomass, 2.9% of the TTB. The high relative error also corresponds to the observation that crown area accounts for only 60% of the variability in leaf biomass ($R^2 = 0.60$). The presence and absence of crowns that intersect and the influence of management through pruning can easily lead to an uneven relationship between crown area and stem biomass. Management influence on crown area can also be brought about through certain planting patterns. For example, trees growing under competition have small irregular crowns compared to those growing in open spaces with the tendency of developing regular widespread crowns, which in turn has implications on foliage biomass. Predictions of biomass from small crowns turned out slightly poorer because of the high variability in these small-crown trees. Smaller trees can be reached more easily and are more prone to interventions through management compared to larger trees. The impacts of human interventions on crowns in the study area i.e. lopping the branches for certain large-DBH trees increased the variability of crown areas in larger trees, particularly for trees with crown area greater 60 m^2. Thus, a model based on crown area can attain similar biomass predictions as a DBH model only under the conditions that the target trees follow a rather uniform distribution of crowns and diameters. This is the case of the non-harvested trees for which the crown area model produced a relatively small bias.

4.4.2 Performance of crown area equations

Equation 3.1 overestimating AGB by 22.5% might be explained by less variability in AGB explained by crown area ($R^2 = 0.86$) relative to the variability in AGB explained by DBH ($R^2 = 0.98$). The relationship between crown area and biomass is likely to have been affected by the greater heterogeneity in terms of species diversity and silvicultural interventions. A total of 16 different species were destructively sampled while 20% of all trees evaluated were pruned. The misjudgment of biomass by our equation confirms previous suggestions that species-specific crown area allometries could provide more accurate estimates of biomass than mixed-species equations (Sah et al., 2004). Prediction of AGB using crown area can be improved by adding height and wood density as additional explanatory variables. Adding height to the equations improved model fit and reduced model bias by about 6 and 7 %, indicating that crown area alone majorly explains variation associated with lateral branching while height, although currently only estimated by experimental and costly means of remote sensing, e.g. lidar, provides explanation to variation associated with extension growth (Halpern et al., 1996). This is consistent with findings by Sah et al. (2004) that crown area in combination with height could be used to estimate AGB. Similar trends have been observed in DBH based equations, indicating that height and also wood density improves model accuracy (Chave et al., 2005). The suitability of mixed species equation by Sah et al. (2004), $BM = 0.446 \times ca^{0.121} \times H^{3.222}$ for AGB estimation using crown area (ca) and height (H) was not tested because it was designed for shrub-like trees and had lower allometric coefficients.

Uncertainties in using crown area based models may be related to the variability in the relationship between crown area and biomass. The relationship between crown area and biomass is dynamic due to the competition between neighbouring trees and silvicultural interventions. Silvicultural treatments such as irrigation, fertilizing, thinning and initial spacing can influence crown structure leading to temporal and spatial variations in AGB. Modifications of tree canopies by silvicultural interventions and variations in climatic and edaphic factors result in changes in AGB, which in turn lower the consistency of crown area allometries (Drake et al., 2003). This uncertainty can be minimized by using equations that adequately capture the variability of populations being studied, either by using species-specific equations or mixed species equations from an appropriate group (Sah et al., 2004). While most studies recommend models with fewer variables because of practicality of use, equations with multiple variables such as the one developed in this study maybe less sensitive to variations in plant form associated with site and age.

4.5 Conclusion

Crown area-based allometries established in this study provide unique information that is highly relevant and very scarce for agricultural mosaics. Although obtaining remote sensing information on height is still a technical challenge and information on wood density is not possible to obtain from remote sensing, these parameters improve the accuracy of crown area based equations and should be included when available. The equations developed in this study should be applied with caution, especially when extrapolating beyond the range of the regression data or when applying them in environments greatly different from those found in Western Kenya.

CHAPTER FIVE

5.0 BELOWGROUND AND TOTAL TREE BIOMASS ESTIMATION

5.1 Introduction

Trees in agricultural landscapes play an important role in the global carbon cycle as sinks for C. Their roots hold significant amounts of biomass, mostly sequestered in coarse roots, while C in fine roots is rather dynamic due to their high turnover. Upon decomposition these roots directly transfer C into the soil, where it may be stored in the medium term. Despite the huge potential of the BGB fraction for C storage, data on its distribution is generally very limited and methods for BGB estimation are poorly established and not standardized for different land-use systems (Mokany et al., 2006). BGB is commonly estimated using direct approaches such as cores or pits for fine roots and excavation for coarse roots or indirect approaches using allometric equations or RSs. The choice of the method used depends on the vegetation type, site condition, desired accuracy and available resources. The excavation method is the most robust approach for tree vegetation (Niiyama et al., 2010). Nevertheless, it is limited with regard to the extent to which roots can be unearthed. Extraction of roots with increasing distance from the stem in farmlands can lead to disproportionate destruction of farmers' crops or adjacent trees. In this case, the whole root is not excavated; missing segments are estimated through extrapolation.

Various methods are available for estimating biomass of roots not captured by excavation. Spek and van Noordwijk (1994) proposed estimation of total root size using proximal root diameters. This approach requires details on branching patterns of roots (van Noordwijk and Mulia, 2002) and has been successfully used to estimate root length (Ong et al., 1999; Smith, 2001) and biomass (Ozier-lafontaine et al., 1999). Allometric equations could also be used to estimate missing root biomass by relating the diameter of the point cut at the end of the root to its biomass (Niiyama et al., 2010). While destructive sampling provides the most accurate method for estimating BGB, the method is expensive, labour intensive and time consuming, hence BGB is often reported as a proportion of AGB using allometric relations or RS (Mokany et al., 2006). The reliability of RS as predictor of BGB has long been questioned since RSs are affected by edaphic factors (Keith et al., 2000), differ among vegetation types (Luo et al., 2005), vary between plants of different ages (Laclau et al., 2000) and are affected by silvicultural interventions (Eamus et al., 2000).

Default IPCC values (IPCC, 2006) are widely used to estimate BGB in places without regionally valid or species specific RSs. The application of broadly derived forest-based RSs to agricultural landscapes is constrained by factors influencing biomass allocation in trees, which abound in these landscapes and tend to vary from site to site. For example, trees in farms are managed through pruning and coppicing, and periodically benefit from silvicultural practices such as fertilization or irrigation that is intended to improve crop production. In Sub-Saharan Africa and particularly in Eastern Africa, only a few studies have been conducted on BGB (Henry et al., 2011).

Previous work (Ong et al., 1999; Smith, 2001) tackled even aged, small diameter trees grown on single sites. At present, no study has been undertaken digging up entire roots at landscape scale in Eastern Africa and particularly at this scale in a highly heterogeneous agricultural context. A certain risk may thus be associated with vouching for the validity of available allometries for use in East African agricultural landscapes, since they were developed from data derived from non-agricultural vegetation and are therefore likely to misjudge biomass in agricultural landscapes if used without prior validation.

This study was undertaken to develop local generic equations and improved RSs for estimating BGB in agricultural landscapes in Western Kenya. The specific objectives of the study were to:

i. Develop allometric equations for estimating BGB in agricultural landscapes;
ii. Develop allometric equations for estimating TTB in agricultural landscapes;
iii. Derive improved root-to-shoot ratios for trees in agricultural landscapes;
iv. Determine the suitability of published allometric equations and root-to-shoot ratios recommended for tropical tree species,

5.2 Method

Allometric equations for estimating BGB were built using DBH, AGB and RCD as primary predictor variables and height or wood density as supporting variables to DBH. Measurement procedures for DBH, height, RCD and wood density are described in section 2.4. Biomass sampling to determine above- and below-ground dry weights is outlined in section 2.5. The following equations were built using GLM, and transformed to allometric power function equations, $Y = aX^{b}$,where Y is the dependent variable, X is the independent variable, a is the intercept and b is the slope.

$\ln(BGB) = a + b \times \ln(AGB)$ ....Equation 5.1

$\ln(BGB) = a + b \times \ln(DBH)$ ....Equation 5.2

$\ln(BGB) = a + b \times \ln(RCD)$ ....Equation 5.3

$\ln(BGB) = a + b \times \ln(DBH) + c \times \ln(H)$ ....Equation 5.4

$\ln(BGB) = a + b \times \ln(DBH) + c \times \ln(\rho)$ ....Equation 5.5

$\ln(BGB) = a + b \times \ln(DBH) + c \times \ln(ca)$ ....Equation 5.6

Allometric equations were also built using BGB data not corrected for unexcavated roots.

$\ln(BGB_{not\,corrected}) = a + b \times \ln(AGB)$ ....Equation 5.7

$\ln(BGB_{not\,corrected}) = a + b \times \ln(DBH)$ ....Equation 5.8

$\ln(BGB_{not\,corrected}) = a + b \times \ln(DBH)$ ....Equation 5.9

A similar approach was used to derive equations for estimating TTB using DBH and RCD as main predictors and height and wood density as variables supporting DBH.

$\ln(TTB) = a + b \times \ln(DBH)$ ....Equation 5.10

$\ln(TTB) = a + b \times \ln(RCD)$ ....Equation 5.11

$\ln(TTB) = a + b \times \ln(DBH) + c \times \ln(H)$ ....Equation 5.12

$\ln(TTB) = a + b \times \ln(DBH) + c \times \ln(\rho)$ ....Equation 5.13

$\ln(TTB) = a + b \times \ln(DBH) + c \times \ln(ca)$ ....Equation 5.14

All equations were developed using a sample size of 66 trees (training set) and an additional 6 trees for validation.

5.3 Results

5.3.1 Biometric relationships

Belowground biomass of the harvested trees was 8.8 t ha^{-1}, accounting for 20.4% of the TTB and equivalent to 25.5% of harvested AGB. The fraction of *coarse root* biomass not captured by excavation was estimated to be 38.9%. This bias varied greatly per species, ranging from below 30% in *Eucalyptus* spp*, G. robusta and Ficus* spp to over 60% in *A. mearnsii*, *Bridellia micrantha*, *Jacaranda mimosifolia*, *M. indica* and *Persia americana* (Appendix). The unexcavated root biomass was estimated to be 2.7 t which is about 12.5% of the total BGB. Thus, a volume of 2 m radius and 2 m deep around a tree only represents about 87.5% of total BGB, particularly for larger trees whose roots spread widely and deeply.

Diameter at breast height and AGB showed a strong correlation with BGB and explained over 95% of the variability observed in BGB (Figure 5.1). Although the relationship between DBH and root biomass was not linear for the entire dataset, a linear relationship (R^2 = 0.90) best described the correlation for larger trees (DBH >40 cm) compared to a power function relationship (R^2 = 0.86). Root collar diameter and DBH had a strong correlation with TTB, explaining 93% and 96% of the variability observed in TTB (Figure 5.2). Although both DBH and RCD were significant predictors of TTB (P<0.001), greater variability was observed in the RCD-BGB relationship compared to the DBH-BGB relationship.

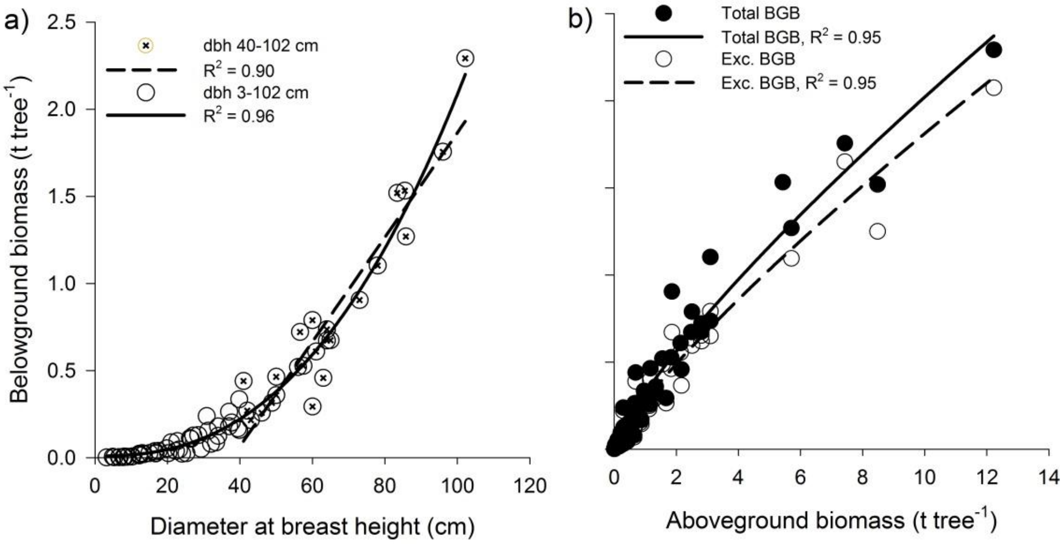

Figure 5.1 Regressions of belowground biomass (BGB) as a function of (a) diameter at breast height, and (b) aboveground biomass. Exc. BGB indicates total tree biomass corrected for roots not extracted

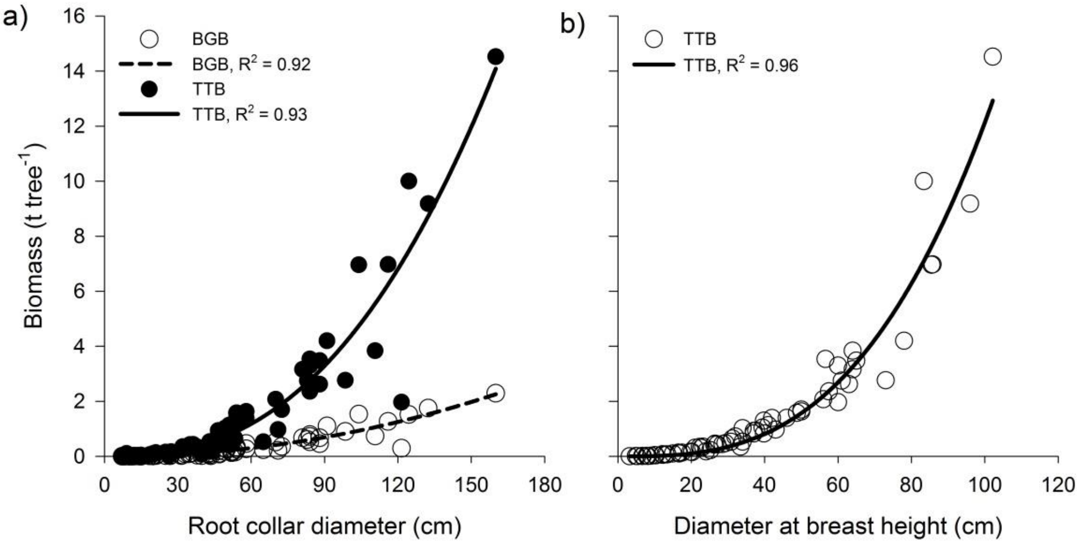

Figure 5.2 Regression of total tree biomass (TTB) and belowground biomass (BGB) as a function of (a) root collar diameter, and (b) diameter at breast height

Root wood density values ranged from 0.28 to 0.76 g cm^{-3} with a mean±SE of 0.51±0.01 and median of 0.50 g cm^{-3}. Wood density data was normally distributed but tended to aggregate between 0.5 and 0.6 g cm^{-3}. There was a general increase in wood density with increasing DBH (Figure 5.3a). A direct comparison of wood density of roots to wood density of aboveground parts of the same tree showed moderate correlation (Figure 5.3b), both for stem (R^2 = 0.62) and branches (R^2 = 0.49). Analysis of variance showed significant differences between root wood density and wood density of stem and branches (P<0.05).

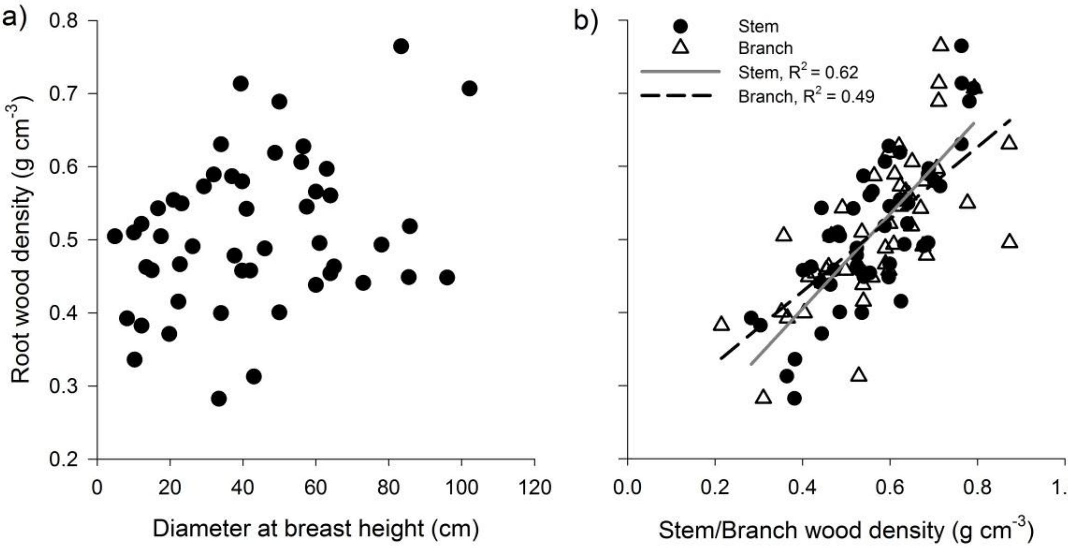

Figure 5.3 Scatter plots showing (a) the variation of wood density across trees of different sizes, and (b) a direct comparison of wood density of root with that of aboveground parts, stem and branch

5.3.2 Root-to-shoot ratios

Root-to-shoot ratios for all the 72 trees harvested ranged from 0.12 to 1.11 with a mean±SE of 0.32±0.02, coefficient of variation (CV) of 51% and a median of 0.28.

The RS values tended to aggregate between 0.20 and 0.40. Variability of RS showed significant differences (P<0.001) among the 3 sites examined. The Lower Yala had higher RS values with respect to the mean (0.45±0.05), median (0.39±0.05) compared to the Middle (mean = 0.31±0.02, median = 0.27±0.02) and Upper Yala (mean = 0.23±0.02, median = 0.19±0.02). The corresponding mean values derived from data not corrected for unexcavated root biomass were 0.39±0.05, 0.27±0.02 and 0.19±0.02 for Lower, Middle and Upper Yala, respectively. This trend is concomitant with mean RS values for dominant species in each site i.e. *M. lutea*, (RS = 0.53±0.11) in Lower, *E. camaldulensis* (RS = 0.34±0.03) in Middle and *A. mearnsii* (RS = 0.17±0.01) in Upper Yala. RSs decreased with increasing DBH and AGB (Figure 5.4). Variability was greater in trees with smaller DBH, <40 cm than trees with larger DBH. Most heavily pruned trees or coppices had consistently high RS values (>0.5).

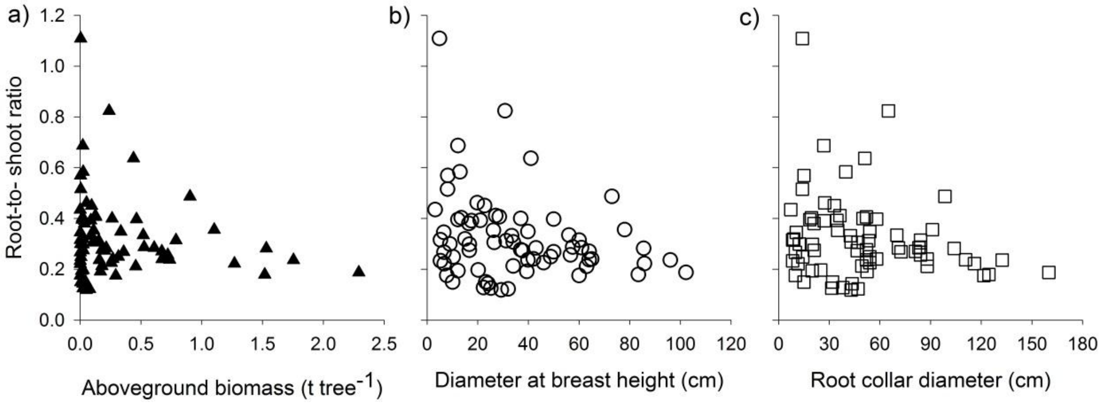

Figure 5.4 Variability of root-to-shoot ratios across (a) aboveground biomass, (b) diameter at breast height, and (c) root collar diameter.

5.3.3 Allometric equations for belowground biomass

Equation 5.1 and 5.2 overestimated the biomass of harvested trees by 13.9 and 10.2% respectively, while equation 5.3 over-predicted biomass by 35.4% (Table 5.1). Height was not a significant predictor variable in the equation while wood density was ($P<0.05$). The use of height data as additional explanatory variables did not improve model fit while wood density data improved model fit by 3.9%. Height and wood density data did not provide significant reduction of the bias associated with the diameter only equation. Equations derived from data not corrected for missing biomass for the three primary predictor variables, DBH (equation 5.7), AGB (equation 5.8) and RCD (equation 5.9) underestimated biomass by 11.3, 48.4 and 49.6%, respectively.

RS mean developed in this study overestimated biomass by 15.3% while the RS median underestimated BGB by less than -1%. The equation of Cairns et al. (1997) and Mokany et al. (2006) underestimated root biomass by 34.7 and 20.9%, each. Assessment of the relationship between actual measured biomass and the biomass predicted by various functions showed that equation 5.1 produced results close to those obtained from the IPCC default RS, and that the RS median overestimated biomass, while the equations by Mokany et al. (2006) and Cains et al. (1997) underestimated biomass (Figure 5.5).

Table 5.1 Allometric coefficients for estimating BGB using AGB (equation 5.1), DBH (equation 5.2), RCD (equation 5.3), DBH and height (equation 5.4), DBH and wood density (equation 5.5) and DBH, height and wood density (equation 5.6)

Equation	a	b	c	d	R^2/R^2_{adj}	P-value	RE %
Equation 5.1	0.490	0.923			0.954	<.001	13.9
SEE	0.153	0.026					
Equation 5.2	0.048	2.303			0.960	<.001	10.2
SEE	0.199	0.059					
Equation 5.3	0.024	2.283			0.921	<.001	35.4
SEE	0.354	0.095					
Equation 5.4	0.055	2.416	-0.191		0.959	0.123	9.4
SEE	0.223	0.097	0.134				
Equation 5.5	0.087	2.257	0.611		0.961	0.027	10.1
SEE	0.347	0.063	0.273				
Equation 5.6	0.095	2.357	-0.165	0.575	0.961		9.5
SEE	0.353	0.100	0.131	0.273			
Equation 5.7	0.413	0.926			0.948	<.001	-11.3
SEE	0.160	0.027					
Equation 5.8	0.040	2.311			0.952	<.001	-48.4
SEE	0.212	0.063					
Equation 5.9	0.019	2.294			0.919	<.001	-49.6
SEE	0.355	0.095					

Equations 5.7, 5.8 and 5.9 uses AGB, DBH and RCD as predictor variables but are derived from data not corrected for missing root biomass

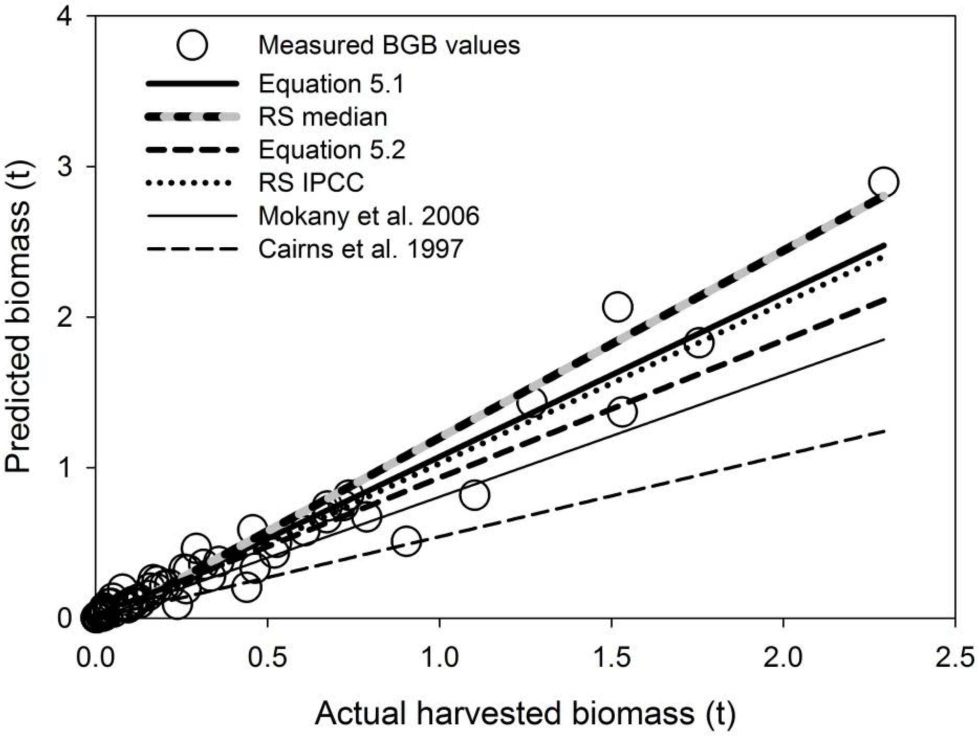

Figure 5.5 Comparison between the actual biomass and the biomass predicted by allometries developed in this study (equation 5.1, 5.1 and RS median) and published allometries recommended for tropical species.

Allometric equations and RSs developed in this study overestimated BGB of small trees, DBH <10 cm by >35% (Figure 5.6). Equation 5.1 overestimated BGB across all size classes except for DBH 40-60 cm. Equation 5.2 consistently overestimated biomass slightly while equation 5.3 grossly overestimated BGB of small trees by 96% (DBH 2.5-10 cm), 32% (DBH 10-20 cm) and 41% (DBH 20-30 cm). The performance of the RS mean was highly variable across diameter classes, while the RS median predicted BGB with minor error, <10% across all the diameter classes. All published equations underestimated BGB for all tree size categories except the equation of Mokany et al. (2006), which overestimated BGB for small trees, DBH <10 cm.

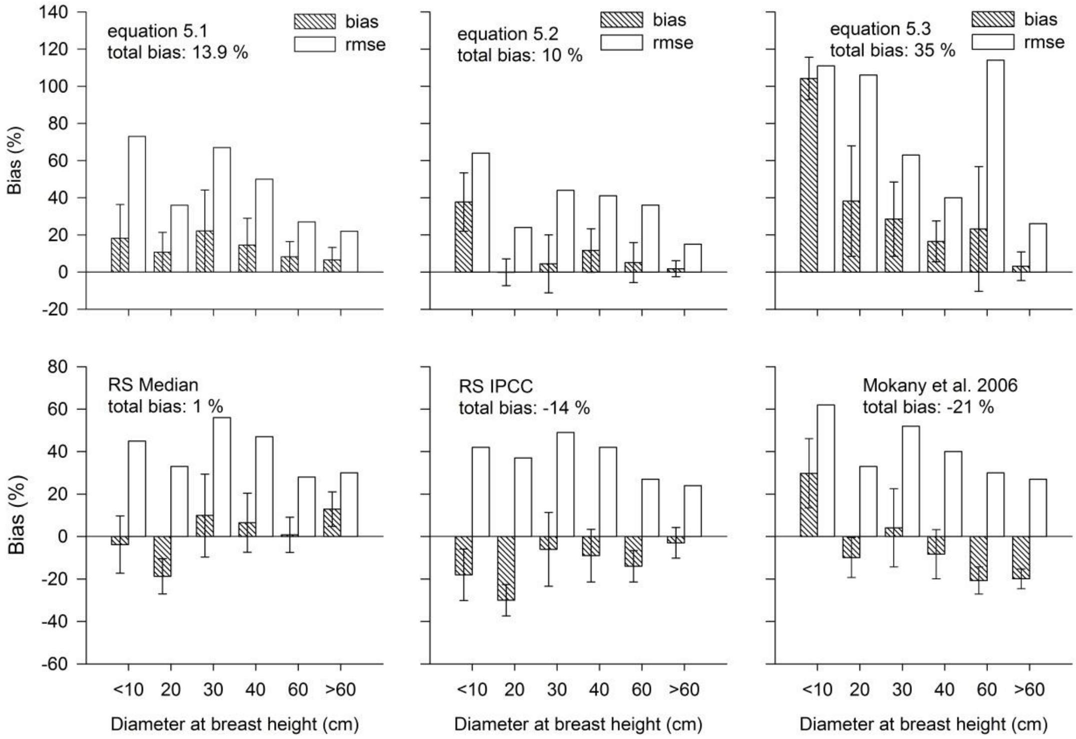

Figure 5.6 Performance of biomass functions developed in this study and published biomass functions (IPCC default RS and Mokany et al. 2006) recommended for tropical species.

The error discrepancy between biomass predicted by published equations and the actual field-measured biomass increased with tree size. The accuracy of the equations tested varied across the three sites evaluated, with moderate errors for Middle, high negative errors in Lower and high positive errors in Upper Yala (Figure 5.7). Equation 5.2 is considered the most suitable equation as it estimated BGB with relatively low error across the three sites; and specifically across trees of different sizes and each site of the three sites.

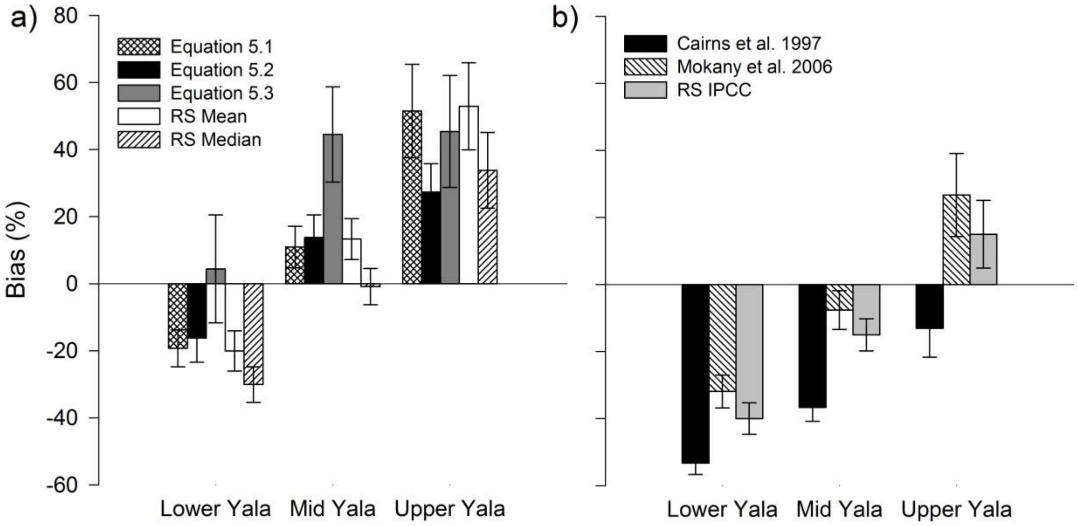

Figure 5.7 Accuracy of biomass functions across the three sites evaluated: (a) allometric equations and RSs developed in this study and (b) published allometries recommended for tropical species.

5.3.4 Allometric equations for total tree biomass

Equation 5.10, $TTB = 0.124 \times (dbh)^{2.458}$ predicted TTB with a bias of 6.1% while equation 5.11, $TTB = 0.077 \times (rcd)^{2.367}$ underestimated TTB of harvested trees by 39% (Table 5.2). Although height was a significant predictor variable in the equation compared to wood density ($P<0.05$), the inclusion of height and wood density as additional explanatory variables to equation 5.10 did not improve model fit. The predictive accuracy of equation 5.10 and 5.11 show variation across the different size classes (Figure 5.8).

Equation 5.10 was consistent and conservative in estimating TTB across the size classes except for DBH <10 cm, where biomass was overestimated by 14.3%.

Table 5.2 Allometric coefficients for estimating total tree biomass using DBH (equation 5.10), RCD (equation 5.11), and DBH in combination with height (equation 5.12), wood density (equation 5.13) and both height and wood density (equation 5.14).

Equation	a	b	c	d	R^2/R^2_{adj}	AIC	P-value	RE %
Equation 5.10	0.1237	2.4583			0.99		<.001	6.1
SEE	0.1240	0.0369						
Equation 5.11	0.0771	2.3668			0.93		<.001	39
SEE	0.3387	0.0909						
Equation 5.12	0.1324	2.5151	-0.0954		0.98	94	0.194	6
SEE	0.1399	0.0610	0.0839					
Equation 5.13	0.2811	2.3481	0.6734		0.96	68	<.001	4.2
SEE	0.1868	0.0373	0.1249					
Equation 5.14	0.2861	2.3719	-0.0383	0.6640	0.98	70	<.001	14.2
SEE	0.1912	0.0579	0.0714	0.1267				

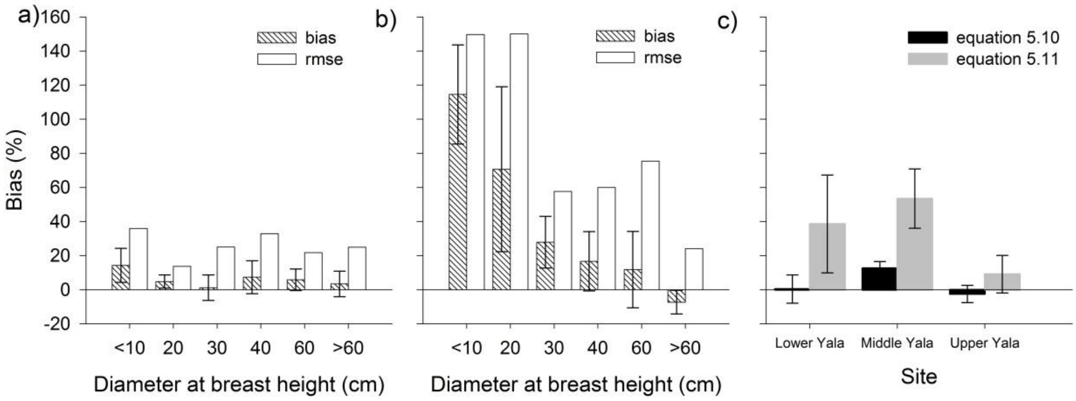

Figure 5.8 Performance of (a) equation 5.10, and (b) equation 5.11 across trees of different diameters, and (c) the comparative performance the two equations across the three sites.

Conversely, equation 5.11 overestimated the biomass of smaller trees by 114.5% (DBH <10 cm), 70.7% (DBH <20 cm) and 27.9% (DBH <30 cm); but underestimated the biomass of larger trees (DBH >60 cm) by 7.3%. Equation 5.10 stably estimated biomass across all three sites with conservative estimates observed in the Lower (RE <1%) and Upper Yala (RE = -2.5%) and moderate overestimates in the Middle Yala (12.6%). Contrary, RCD overestimated biomass by 38.6, 53.4 and 9.1% for Lower, Middle and Upper Yala.

5.3.5 Representative landscape biomass: implication of tree dimensions

Equation 5.1 and 5.2 estimated representative landscape BGB to be 10.9±0.01 and 11.5±0.01 t ha^{-1}, respectively while the mean RS estimated representative landscape BGB to be 10.5±0.06 t ha^{-1}. The equations by Cairns et al. (1997) and Mokany et al. (2006) estimated representative BGB to be 6.1±0.03 and 8.9±0.05 t ha^{-1} whereas the IPCC default RS yielded an estimate of 8.7±0.05 t ha^{-1}. Representative BGB estimated by various equations is consistent with the validation tests done on harvested trees, indicating that existing allometric equations recommended for tropical species would generally underestimate BGB in Western Kenya. Using the 0.48% actual C content determined by element analysis for harvested trees, representative landscape belowground tree C was estimated at 5.0±0.01 t C ha^{-1}.

Biomass is held in the few large trees found in the landscape (Figure 5.9). Small trees, DBH <10 cm constituted 65.6% of all trees encountered in the landscape but held only 6.4% of the estimated BGB. Conversely, larger trees (DBH ≥40 cm) represented 2.4% of the trees surveyed in the landscape but held un-proportionally high amounts (43.1%).

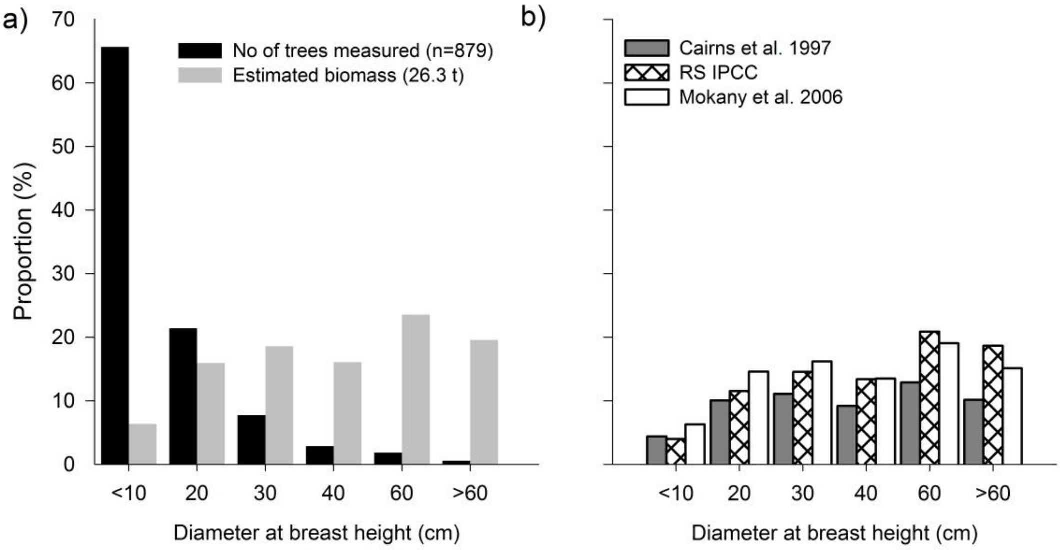

Figure 5.9 The distribution of (a) non-harvested trees measured according to diameter class and their share of estimated belowground biomass, and (b) belowground biomass estimated by published equations for trees of various size categories

The analysis of bias in small and large trees underscored the influence of tree size, particularly of large individuals. The 14% RE for the small trees (DBH <10 cm) by equation 5.10 leads to overestimation of TTB by about half a ton of C (0.4 t C) whereas a similar error (-14%) on larger trees (DBH >60 cm) by equation 5.11 results in underestimation of C stocks by 1.8 t C. Equation 5.10 estimated representative landscape TTB to be 47.1 t ha^{-1}, thus, agricultural mosaics of Western Kenya hold 22.6 t C ha^{-1} in standing trees.

5.4 Discussion

5.4.1 Belowground biomass captured by excavation

The proportion of BGB after correcting for missing root biomass relative to AGB of 26% in this study is closer to the average of 24% proposed by Cairns et al. (1997) for tropical forests. Management practices and availability of nutrients and water in agricultural landscapes greatly influence the growth form of trees, and therefore these factors may have significantly affected the proportion of BGB relative to AGB. Resh et al. (2003) captured 75% of the coarse roots within 1 m^2 area centred on the tree stump (maximum DBH, 25 cm) in eucalypt plantations in Tasmania, Australia. The high biomass encountered in the study could also be attributed to the sampling approach taken, which captured most of the roots and minimized the need for extrapolation in many cases.

This study acknowledges that the 2 m radius (from the edge of the tree stump) and 2 m depth excavated is below the extent and maximum rooting depth of larger trees. However, given that root biomass reduces sharply with increasing distance from the tree stump (Green et al., 2007) and that whole stumps were unearthed, the chosen area captured the majority of the root biomass. Vertically, procedures employed captured most roots along the soil profile between 0.4-2 m depth. This is consistent with observations by Schenk and Jackson (2002) that globally 50% of all roots are within the upper 0.3 m while 95% of all roots are within the upper 2 m of the soil profile. The remaining unexcavated root biomass was estimated by an allometric relationship between biomass of captured roots and their respective distal diameters, thus whole root biomass was estimated. The proportion of coarse root biomass not captured by excavation determined in this study (38.9%) accounted for 12.5% of the total BGB and was less than 23% given by Niiyama et al. (2010) as the amount by which total BGB will be underestimated if correction for missing roots is not done.

5.4.2 Variability of root-to-shoot ratios

The median RS of 0.28 obtained in this study is similar to the mean RS recommended by IPCC for subtropical dry forests with shoot biomass >20 t ha^{-1} (IPCC, 2006) but lower than RS of 0.56 for the same vegetation type with shoot biomass <20 t ha^{-1}. The mean (0.32) and median RS (0.28) obtained in this study is lower than the average RS reported for conifers in Great Britain, RS = 0.36 (Levy et al., 2004) and mangroves, RS = 0.60 (Komiyama et al., 2008). Conifers in the temperate and mangroves in the intertidal zone require a bottom-heavy shape for survival. The high RS obtained in this study is attributed to management influence, particularly pruning (20% of the trees sampled were managed through pruning) and coppicing commonly practiced in agricultural landscapes. For example, farmers often cut branches to reduce the size of the crown to minimize tree-crop competition for light; an intervention which reduces the amount of AGB relative to BGB. Studies have attributed lower RS values to sampling methods, where root biomass is underestimated with most research extracting roots to a depth of 1 m within the radius of 1 m from the tree center (Ren et al., 2009; Green et al., 2007).

Variation of RS across the 1000-2000 mm rainfall gradient confirms that RSs depend on ecological zonation and suggest a shift from the 4:1 shoot-to-root ratio used as IPCC (2006) default value for humid tropics towards 3:1 for semi-arid tropics. Differences in site conditions, particularly soil type and precipitation may account for the variation in RS among the three sites. This is in agreement with the general trend of decreased C allocation to belowground with increased nutrient and water availability (Keith et al., 2000). More favorable soil conditions and higher annual precipitation in Middle and Upper Yala are expected to have enhanced shoot biomass at the expense of root biomass. A similar trend was observed by Mokany et al. (2006) and Luo et al. (2005) supporting the hypothesis that RS decreases with increase in soil moisture content (Gower et al., 1992). The high RS in Lower Yala can also be related to less water and nutrient availability associated with coarse soils in the area compared to finer soils of Middle and Upper Yala (Mokany et al., 2006). The higher CV for Middle and Upper Yala reflects greater heterogeneity in terms of species composition and management influence. Variation in RS across the sites is also indicative of decreasing root biomass with increasing altitude, a trend that was also observed by Luo et al. (2005). Species distribution is another possible influence on the lower RS in Upper (dominant species: *A mearnsii*; RS = 0.17) and the high RS in Lower Yala (dominant species: *M. lutea*; RS = 0.53). RS decreased (to a rather low but stable level) as shoot biomass (and also DBH) increased, a trend also observed by Mokany et al. (2006) and Cairns et al. (1997) and linked to buildup of biomass in AGB components as the tree grows (Laclau et al., 2000).

5.4.3 Performance of developed and existing biomass functions

Aboveground biomass explained 95% of the variation in BGB, a value comparable to $R^2 = 0.93$ given by Mokany et al. (2006) for forests and woodlands but higher than $R^2 = 0.83$ reported by Cairns et al. (1997). The strong correlation between AGB and BGB has often been explained by the root biomass basically being the extension of the stem underneath and its divergence into large roots (Resh et al., 2003). In this study the stem held more than 50% of the total AGB. The regression of BGB as a function of DBH yielded a high R^2 (0.96), indicating that diameter accounted for most of the variation observed in BGB. The R^2 of 0.93 obtained in this study for the RCD-TTB relationship is higher than 0.73 reported by Bastien-Henri et al. (2010) for tropical species grown under differing regional climates across the Isthmus of Panama.

The results show that BGB could be estimated from aboveground tree parameters such as DBH and AGB, while AGB itself also being a derived parameter. Equation 5.1 based on AGB of harvested trees predicted BGB with about 85% accuracy while equation 5.2 based on DBH predicted BGB with about 90% accuracy. This study considers equation 5.2 to address most directly and adequately the principle of conservativeness than equation 5.1, which requires C projects to strictly curb overestimation. Equation 5.3 misjudged BGB of harvested trees by 35.4% and greatly overestimated the biomass of small trees, thus would likely overestimate representative biomass when used in a landscape dominated by small trees such as those in Western Kenya. While RCD may be a useful parameter to estimate BGB in areas dominated by coppices or when trees are already cut down and only stump dimensions are available, the high bias associated with equation 5.3 shows that the parameter may greatly misjudge biomass in agricultural landscapes. Equation 5.2 and 5.3 had almost identical power coefficients but more than a factor 2 difference in intercept, suggesting a strong taper between RCD and DBH especially for larger trees and also for coppices. However, the strong taper may have been occasioned by the greater uncertainty in measuring RCD in larger trees compared to DBH measurements.

Including height as an additional predictor variable did not improve R^2, similar to findings by Brassard et al. (2011) for a range of species from the boreal forests of Ontario, Canada. Instead, wood density data improved model fit by 3.9 % but did not improve the predictive accuracy of the diameter-only equation. Disaggregation of error along different tree sizes greatly influenced the accuracy of allometric equations as biomass was disproportionately held in larger trees. Given that most of the biomass (e.g. 47%) is held in few larger trees (2%), it is imperative to get estimates of larger trees correctly (Brown, 1997). While the equations developed in this study considered trees of varying ages, age-specific allometric equations have been recommended in stands that are heavily dominated by small trees (Fatemi et al., 2011).

The study found that using IPCC recommended equations by Cairns et al. (1997) and Mokany et al. (2006) would underestimate biomass in agro-ecosystems by 34.7 and 20.9% respectively. Thus the representative C stocks estimated for the landscape by the two equations (2.9±0.01 and 4.3±0.01 t C ha^{-1}) are far below the value determined by equation 4.2 (5±0.01 t C ha^{-1}) and the conservative value determined by the median RS (4.9±0.01 t C ha^{-1}). The differences between estimates from published and developed equations are likely caused by site conditions influencing the biomass partitioning between above- and below-ground or the differences in sampling methodologies (Brassard et al., 2011). The differences in the performance of the equation of Mokany et al. (2006), Cairns et al. (1997) and the ones developed in this study are indicative of the different ecosystems that the respective studies covered. A similar case was also encountered for estimation of AGB using the equation of Brown (1997) and Chave et al. (2005) where the description of the climatic preconditions was misleading with regard to the area studied (chapter 3).

5.4.4 Equations for estimating total tree biomass

The lower RMSE values of equation 5.10, for estimating TTB using DBH show that it is superior to equation 5.11 that uses RCD, although the relative errors across DBH classes are similar. Although equations 5.10 estimated TTB with high precision across all tree size classes and across all three sites, it remains challenging to precisely estimate the biomass of small trees due to the inherent variability of biomass in these trees. Small (young) trees would commonly not have a well-developed root system yet, which renders them much more vulnerable to (or at least dependent on) edaphic factors such as nutrient and water supply. A problem that would even out quite a bit once they establish properly, grow in size and overcome these existential limitations. The variability of mature trees is caused by management practices like selective harvesting of stems, e.g. for poles, lopping of branches to provide fuelwood and pollarding to reduce light competition with crops. Such interventions can alter biomass without directly affecting DBH. Differences in biomass estimation by equation 5.7 and equation 5.8 were more substantial for larger trees, DBH >50 cm. Equation 5.8 had large deviations from the actual biomass showing that RCD is less suited for estimating TTB in agricultural landscapes compared to DBH. The differences were pronounced in Lower Yala and in smaller trees which are more subject to management practices and more susceptible to edaphic limitations compared to larger trees

Although equations 5.7 predicted TTB with high precision across tree size classes and in all three sites evaluated, it is difficult to predict the biomass of small trees with high precision because of the variability of biomass in these trees. This variability is brought about by management practices like selective harvesting of stems e.g. for poles, looping of branches to provide wood for fuel and pollarding to reduce competition with crops, which can change biomass without changing DBH. Differences in biomass estimation by equation 5.7 and equation 5.8 (derived from data not corrected for missing root biomass) were magnified in larger trees, DBH >50 cm. Equations 5.8 had large deviations from the actual biomass showing that RCD is less suited for estimating TTB in agricultural landscapes compared to DBH. The differences were pronounced in Lower Yala and in smaller trees which are subject more to management practices compared to larger trees.

Although increased accuracy is expected from introducing more variables particularly to generic allometric models, adding tree height and wood density data did not improve model fit or accuracy in this case. A possible explanation was natural differences in canopy architecture among species and modifications of tree canopy by management (Segura et al., 2006).This contrasts several reports that height improves model fit (Bastien-Henri et al., 2010; Chave et al., 2005); although many reports concur that height adds little to the proportion of variance explained, since height and diameter are in themselves closely correlated (Ketterings et al., 2001). The models were validated per site to assess whether the models had to be applied across the Yala basin only or could also be used for small projects at singular specific sites. The equation developed for estimating TTB gives better estimates for individual sites and is also sufficient for biomass estimation across the whole basin. Representative landscape TTB predicted by equation 5.7 (22.6 t C ha^{-1}) corresponds to the sum of AGB (5.27 t C ha^{-1}) and BGB (17.36 t C ha^{-1}) predicted by separate equations constructed for above- and below-ground biomass C from the same data; hence equation 5.7 can be used to obtain accurate estimates of TTB without first estimating AGB, then using AGB to estimate BGB and finally summing up the two estimates to approximate TTB.

5.5 Conclusion

Regionally valid generic equations for BGB and TTB were constructed from a representative sample of trees randomly selected and stratified by size class from agriculturally dominated landscapes without considering health, damage or dominance of the trees. Allometric equations with DBH as predictor variable and the median RS provided a more accurate means for estimating BGB and are recommended for use in Western Kenya due to their conservative way of estimating biomass. The equations presented in this study for BGB will allow for estimation of BGB in agricultural landscapes without the high cost of excavating the root system. Furthermore, the equation developed for TTB will significantly improve the accuracy of estimating biomass C in agricultural landscapes without the intermediate steps of determining above- and below-ground biomass fractions.

CHAPTER SIX

6.0 BIOMASS DYNAMICS FOR DOMINANT *EUCALYPTUS*

6.1 Introduction

Fast growing species such as eucalyptus have been introduced in many tropical countries to mitigate the dwindling supply of wood, especially for timber and biomass fuel (FAO, 2011). In East Africa, eucalyptus species are common in farmed landscapes and the preferred species in managed plantations (Kituyi et al., 2001). Eucalyptus is popular because of its fast-growing nature, multiple uses and importance as a 'cash crop'(FAO, 2011). The higher proportion of eucalyptus in agricultural landscapes is largely due to greater attention given to trees on farms, mainly because of their ability to couple economic with social services and environmental benefits. Despite the acknowledged importance of eucalyptus trees, there is little knowledge about the amount of C that will be emitted to the atmosphere when areas dominated by these species are converted to other land use.

In Kenya, the majority of timber and non-timber wood products are obtained from farm estates, presenting an opportunity for farmers to have access to additional income from their land (Kiplagat et al., 2011). To meet the high demand for tree products and services, considerable efforts have been focused on conserving and also increasing trees in the landscape. Two kinds of eucalyptus trees exist on Kenyan farms: (1) naturalized eucalyptus introduced from Australia in the colonial era and (2) eucalyptus hybrids introduced from South Africa. Eucalyptus plantations provide raw material for industries, such as sawmilling, pulp and charcoal while eucalyptus in agricultural landscapes supply timber, poles, building material and fuelwood, both for domestic and commercial purposes. Despite considerable efforts made in increasing trees on farms, quantities of major biofuel trees continue decreasing in Kenya (Kituyi et al., 2001). This decline is attributed to high demand for timber, food crop cultivation, human settlement and harvesting trees for fuelwood (FAO, 2011).

The IPCC (2003) provides methodologies for estimating tree C stocks. The IPCC default values are normally used where further data is not available, choosing a Tier 1 approach. This practice uses equations provided at a global scale, stratified by eco-climatic zones such as those cited in (IPCC 2006). Chapter 3 and 5 of this study showed that application of broadly derived forest-based equations to trees in agricultural landscapes yields biased estimates. Such bias can be minimized by applying Tier 2 or Tier 3 approaches, where country specific models determined for local conditions are used. In this case, equations that adequately address unique project circumstances are either developed or chosen from literature. Since tree species differ in architecture and wood gravity (Chave et al., 2004), species specific equations are necessary to produce reliable biomass estimates (Henry et al., 2011). However, insufficient species specific equations exist, particularly in sub-Saharan Africa where less than 1% of the tree species have country-specific equations (Henry et al., 2011). Since it is not practical to fell trees to develop equations for each species, and because destructive sampling is generally not acceptable for rare species or in areas where the eventual objective is to conserve trees, biomass equations that cover trees with comparable architecture could be developed. This study aimed to create biomass equations for eucalyptus species in Western Kenyan agricultural landscapes. The specific objectives of the study were to:

i. Develop allometric equations for estimating biomass in *Eucalyptus* species;
ii. Determine biomass distribution in the above- and below-ground compartments.

6.2 Method

Data from 48 destructively sampled trees consisting of *E. camaldulensis (*29), *E. grandis* (11) and *E. saligna* (8) were pooled to develop biomass equations for eucalyptus species encountered in the Middle Yala site. Two assumptions were made: (1) trees in the same genus exhibit similarities in growth form and that the allometry of woody biomass for trees growing under similar conditions does not differ significantly within the same genus (Fatemi et al., 2011; Senelwa and Sims, 1998). Allometric equations for estimating biomass of different components were built using DBH and RCD as the main predictors, and height, wood density and crown area as supporting variables to DBH. Measurement procedures for DBH, height, RCD, wood density and crown area are described in section 2.4. Biomass sampling to determine above- and below-ground dry weights is outlined in section 2.5.

Allometric equations were developed using 42 trees, validated using six trees from each of the eight holdouts as explained in section 2.6.1. All equations were built using

GLM and transformed to allometric power function equations, $Y = aX^b$ where Y is the dependent variable, X is the independent variable, a is the intercept and b is the scaling exponent. The following equations were developed using DBH as the predictor variable:

$\ln(AGB) = a + b \times \ln(DBH)$ ……..……………………………………………Equation 6.1

$\ln(BGB) = a + b \times \ln(DBH)$ ……..……………………………………………Equation 6.2

$\ln(TTB) = a + b \times \ln(DBH)$ ……..……………………………………………Equation 6.3

$\ln(BM_{stem}) = a + b \times \ln(DBH)$ ……..…………………………………………Equation 6.4

$\ln(BM_{branches}) = a + b \times \ln(DBH)$ ……..………………………………………Equation 6.5

$\ln(BM_{leaves}) = a + b \times \ln(DBH)$ ……..……………………………………....Equation 6.6

A similar approach was used to develop equations with RCD as the predictor variable.

$\ln(AGB) = a + b \times \ln(RCD)$ ……..…………………………………...……Equation 6.7

$\ln(BGB) = a + b \times \ln(RCD)$ ……..…………………………………………..Equation 6.8

$\ln(TTB) = a + b \times \ln(RCD)$ ……..…………………………………...……Equation 6.9

$\ln(BM_{stem}) = a + b \times \ln(RCD)$ ……..………………………………………Equation 6.10

$\ln(BM_{branches}) = a + b \times \ln(RCD)$ ……..……………………………………Equation 6.11

$\ln(BM_{leaves}) = a + b \times \ln(RCD)$ ……..……………………………………..Equation 6.12

The effect of height, wood density and crown area as supporting parameters to DBH was tested as follows:

$\ln(AGB) = a + b \times \ln(DBH) + c \times \ln(H)$ ……………………….……..………...Equation 6.13

$\ln(AGB) = a + b \times \ln(DBH) + c \times \ln(\rho)$ ……………………………………..Equation 6.14

$\ln(AGB) = a + b \times \ln(DBH) + c \times \ln(ca)$ …………………………….…………Equation 6.15

$$\ln(MB_{stem}) = a + b \times \ln(DBH) + c \times \ln(H) \quad \text{Equation 6.16}$$

$$\ln(BM_{stem}) = a + b \times \ln(DBH) + c \times \ln(\rho) \quad \text{Equation 6.17}$$

$$\ln(BM_{stem}) = a + b \times \ln(DBH) + c \times \ln(ca) \quad \text{Equation 6.18}$$

$$\ln(BM_{branch}) = a + b \times \ln(DBH) + c \times \ln(H) \quad \text{Equation 6.19}$$

$$\ln(BM_{branch}) = a + b \times \ln(DBH) + c \times \ln(\rho) \quad \text{Equation 6.20}$$

$$\ln(BM_{branch}) = a + b \times \ln(DBH) + c \times \ln(ca) \quad \text{Equation 6.21}$$

6.3 Results

6.3.1 Biomass equations

Figure 6.1 shows the regression of biomass as a function of (a) DBH and (b) RCD for estimating biomass of different fractions. Diameter at breast height was strongly and significantly correlated with above- and below-ground biomass, accounting for 98 and 96% of the variation in above-and below-ground biomass fractions, respectively (Figure 6.1a). Likewise, the regression of stem and branch biomass as a function of DBH was significant ($P<0.001$) with high R^2 values of 0.97 and 0.95. Foliage, however, had a moderate correlation, indicating that DBH accounted only for about 85% of the variation in leaf biomass. RCD was more closely related to BGB ($R^2 = 0.91$) than to AGB ($R^2 = 0.88$) and explained 87, 86 and 82% of the variations observed in stem, branch and leaf biomass, respectively (Figure 6.1b).

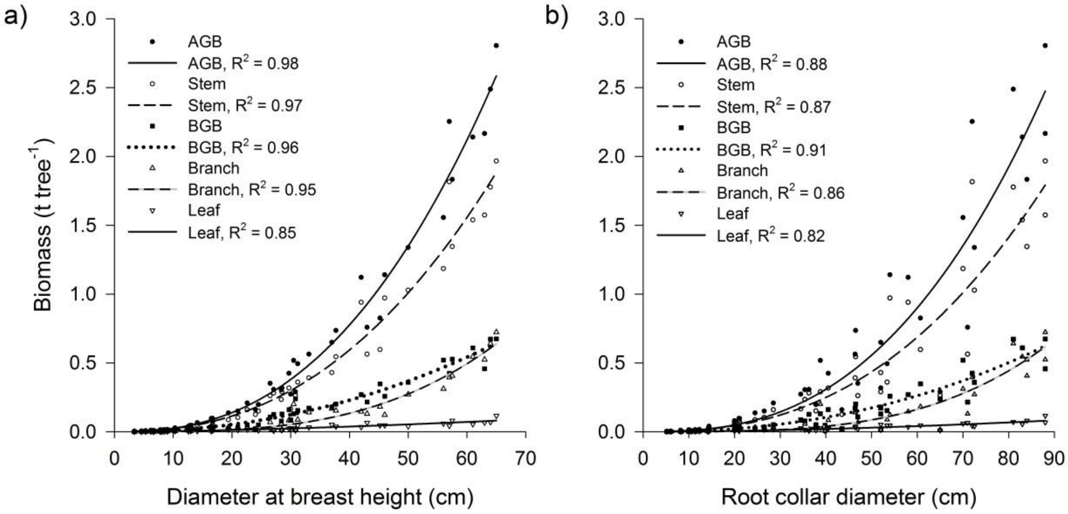

Figure 6.1 Regression of biomass as a function of (a) diameter at breast height, and (b) root collar diameter for aboveground biomass (AGB), stem biomass, belowground biomass (BGB), branch biomass and leaf biomass.

Tree height showed a strong positive correlation with DBH, a near normal distribution and greater variance for harvested trees of larger diameter, DBH >30 cm (Figure 6.2). The height distribution for non-harvested trees was negatively skewed, with more than 58 and 35% of the trees measured having height values between 10 and 20 m, respectively. A moderate correlation was observed between DBH and height of harvested (R^2 = 86%) and non-harvested trees (R^2 = 69), respectively.

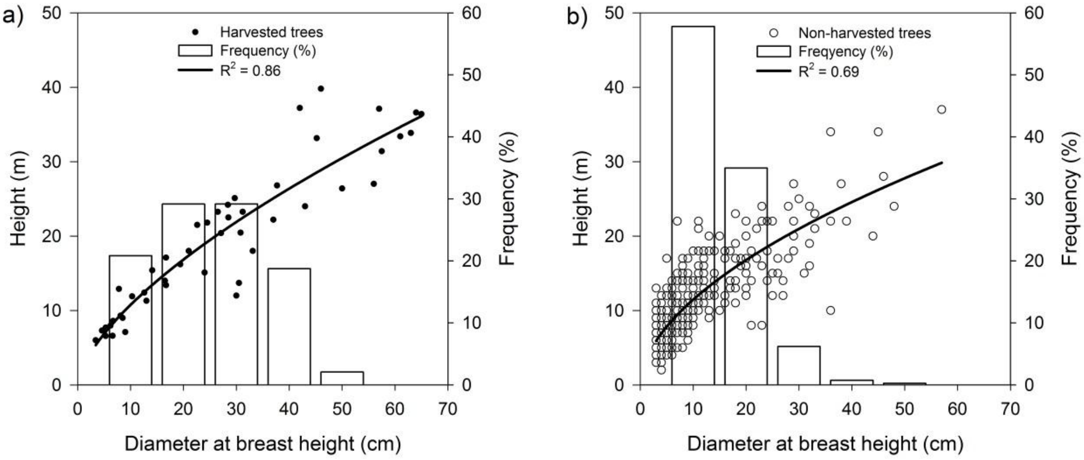

Figure 6.2 Relationship between height and diameter at breast height for (a) harvested trees and (b) non-harvested trees sampled in Middle Yala, Western Kenya. The vertical bars represent height distribution across diameter classes based on stratification of DBH into <10, 20, 30, 40 and >50 cm.

Empirical allometric coefficients for estimating biomass of different components based on DBH and RCD are presented in Table 6.1. DBH was a significant predictor variable for all compartments (P<0.001) and estimated stem and AGB with a small bias (2.5%). However, DBH overestimated belowground and branch biomass by 30% and foliage biomass by 16%. RCD was a significant predictor variable for all biomass component (P<0.001) but overestimated most component biomass by about 30%, except foliage biomass which was estimated with a small bias of 3.5%.

Table 6.1 Allometric coefficients for estimating aboveground biomass (equation 5.1, 6.7), belowground biomass (equation 6.2, 6.8), total tree biomass (equation 6.3, 6.9), stem (equation 6.4, 6.10), branches (equation 6.5, 6.11) and leaves (equation 6.6, 6.12) using (a) DBH, and (b) RCD.

	Equation	a	b	SEE(a)	SEE(b)	P-value	R^2	Bias %
a)	Equation 6.1	0.085	2.471	0.090	0.029	<.001	0.994	2.5
	Equation 6.2	0.029	2.432	0.205	0.065	<.001	0.962	29.9
	Equation 6.3	0.114	2.463	0.093	0.029	<.001	0.993	6.0
	Equation 6.4	0.058	2.496	0.109	0.035	<.001	0.991	3.6
	Equation 6.5	0.009	2.652	0.272	0.087	<.001	0.947	30.0
	Equation 6.6	0.042	1.847	0.217	0.069	<.001	0.938	16.1
b)	Equation 6.7	0.040	2.458	0.274	0.079	<.001	0.941	29.2
	Equation 6.8	0.011	2.469	0.233	0.067	<.001	0.971	30.7
	Equation 6.9	0.051	2.461	0.247	0.071	<.001	0.962	24.2
	Equation 6.10	0.027	2.483	0.276	0.079	<.001	0.943	28.5
	Equation 6.11	0.004	2.631	0.435	0.125	<.001	0.872	94.4
	Equation 6.12	0.024	1.830	0.298	0.085	<.001	0.899	3.5

Local generic equations developed in chapters 3 and 4 for estimating above- and below ground biomass in agricultural landscapes overestimated biomass by 10 and 47.8%, respectively. Whereas both equations from chapter 3 and 4 and the equations developed for *Eucalyptus* generally overestimated biomass (Figure 6.3), the equations for *Eucalyptus* still yielded estimates about twice more accurate than those from the generic equations.

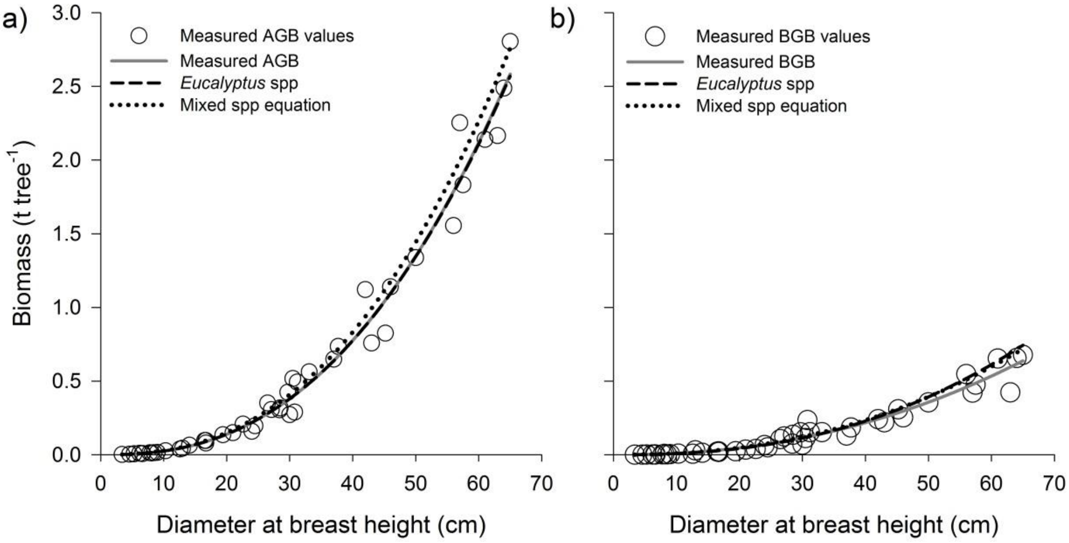

Figure 6.3 Comparisons of biomass predictions by equations developed for *Eucalyptus* and the mixed species equation developed in chapter 3 and 4 for estimating (a) aboveground biomass (AGB), and (b) belowground biomass (BGB).

The diameter-based equation for stem and AGB showed low bias, <5% across the diameter classes above 10 cm DBH (Figure 6.4). However, DBH showed variation in error disaggregation across the size classes for belowground biomass, overestimating the biomass of trees with DBH <20 cm by over 30%. Diameter based equations for estimating branch and leaf biomass showed high and variable bias across tree size. Allometric equations based on RCD overestimated all components by over 20% for most diameter classes except for trees with DBH >50 cm, where biomass was estimated with bias of about 10%.

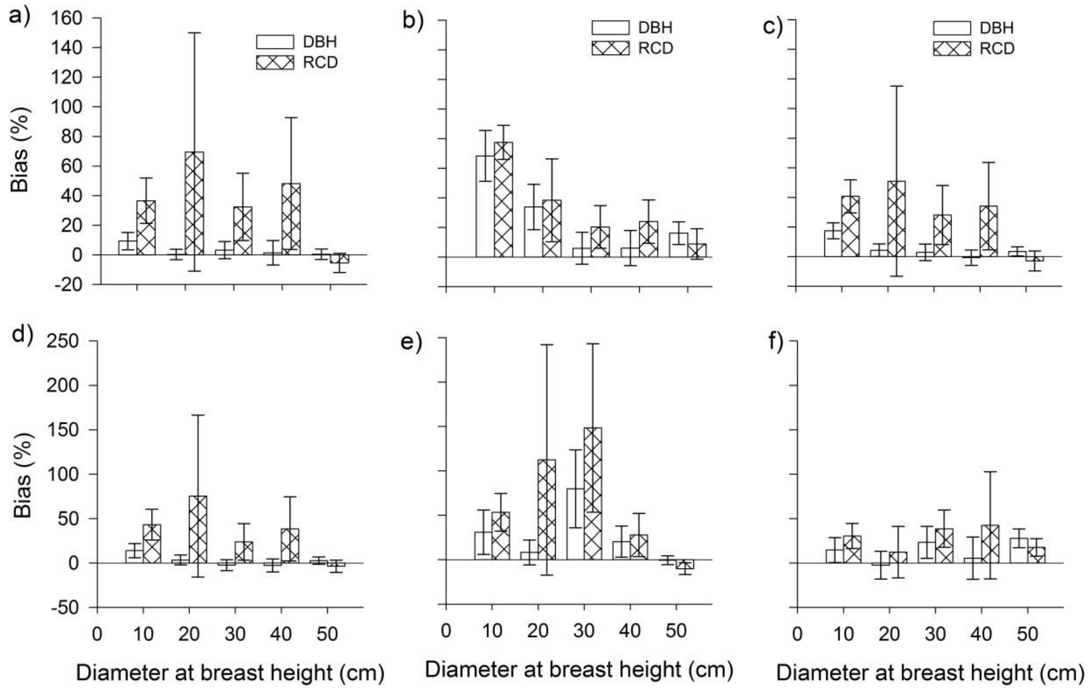

Figure 6.4 Disaggregation of relative error associated with equations for estimating (a) AGB, (b) BGB, (c) TTB, (d) stem biomass, (e) branch biomass and (f) leaf biomass using DBH and RCD.

Height was a significant predictor variable only for aboveground, stem and branch biomass (Table 6.2; $P<0.05$). Crown area was a significant predictor variable for only branch biomass while wood density was not a significant predictor variable for any of the components. Height, crown area and wood density did not improve R^2, which was already high ($R^2 = 0.99$). AIC showed that height was a more suitable proxy for the estimation of AGB of *Eucalyptus* (AIC = 46) than wood density (AIC = 61) and crown area (AIC = 62).

Table 6.2 Allometric equations for estimating (a) aboveground biomass (b) stem biomass (c) branch biomass using DBH and height (equation 6.13, 6.16, 6.19), DBH and wood density (equation 6.14, 6.17, 6.20) and DBH and crown area (equation 6.15, 6.18, 6.21), respectively.

	Equation	a	b	c	P-value	R^2_{adj}	AIC	RE %
a)	Equation 6.13	0.067	2.307	0.260				
	SEE	0.143	0.083	0.123	0.041	0.994	46	2.3
	Equation 6.14	0.095	2.464	0.120				
	SEE	0.161	0.032	0.106	0.268	0.991	61	-9.0
	Equation 6.15	0.079	2.476	0.016				
	SEE	0.114	0.062	0.038	0.680	0.991	62	-13.1
b)	Equation 6.16	0.032	2.089	0.646				
	SEE	0.141	0.082	0.122	<.001	0.994	43	-79.4
	Equation 6.17	0.072	2.477	0.184				
	SEE	0.201	0.040	0.133	0.175	0.989	74	-8.0
	Equation 6.18	0.044	2.663	-0.085				
	SEE	0.131	0.071	0.044	0.059	0.988	80	3.3
c)	Equation 6.19	0.018	3.164	-0.803				
	SEE	0.428	0.249	0.370	0.036	0.948	43	27.6
	Equation 6.20	0.008	2.662	0.028				
	SEE	0.505	0.102	0.334	0.934	0.933	53	13.6
	Equation 6.21	0.015	2.138	0.347				
		0.310	0.167	0.103	0.002	0.933	53	-0.5

6.3.2 Biomass apportionment

The contribution of different components to the total tree biomass varied considerably. AGB accounted for 78.9% of the total tree biomass, with the stem, branches and leaves contributing 73.7, 22.3 and 4.0% to AGB, respectively. Much of the tree biomass was held in the stem, which constituted up to 58.2% of the total tree biomass, while branches and leaves contributed 17.6 and 3.2% of the total tree biomass. While the proportion of stem biomass was almost constant for all sizes classes, the proportion of branch biomass showed, on average, an increase with tree size; although the trend was not continuous. Changes in biomass allocated to leaves complemented those observed in the stem and branches inversely. The proportion of foliage declined from 14.3% in small trees (DBH <10 cm) to 3.3% in high biomass trees (DBH >50 cm). At any diameter, the variation in the proportion of AGB in the stem was large and constant.

The BGB of the harvested trees accounted for 21.1% of the total tree biomass, yielding an overall RS of 0.27, which varied across the diameter classes. The biomass of coarse roots not captured by excavation was estimated to be 0.85 Mg, which is 9.2% of the total BGB for harvested trees. RS ranged between 0.14-1.07 with a mean±SE of 0.31±0.02 and median of 0.28. RS for individual trees showed a slight decrease with increase in tree size (Figure 6.5). High RS values, >0.5 were mainly associated with coppiced trees as indicated in Figure 6.5a plotted against DBH, which is less sensitive to the effects of silvicultural intervention than RCD.

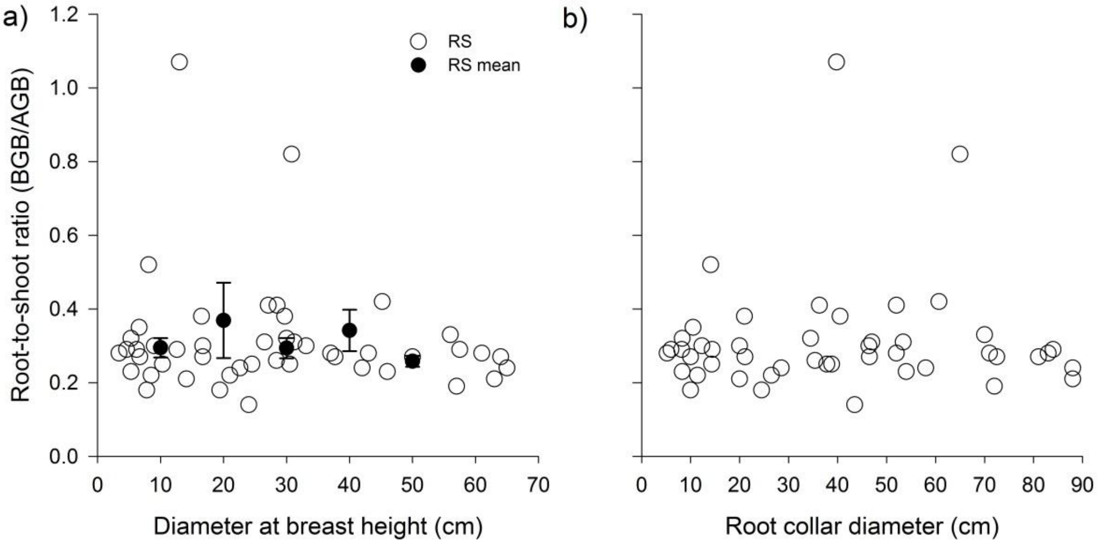

Figure 6.5 Variability of root-to-shoot ratio (RS) for individual trees across (a) diameter at breast height, and (b) root collar diameter. The vertical bars in (a) indicate the mean RS for each of the diameter classes.

The equations with DBH alone, $AGB = 0.085 \times (dbh)^{2.471}$ and $BGB = 0.029 \times (dbh)^{2.432}$ estimated biomass held in *Eucalyptus* to be 18.7±0.2, and 5.6±0.1 t ha^{-1} for above and below-ground fractions, respectively. The stems, branches and leaves were each estimated to hold 13.8±0.02, 2.7±0.004 and 1.3±0.001 t ha^{-1}. This trend is consistent with the respective proportions outlined for above- and below-ground segments of harvested trees. Biomass estimates obtained from DBH-only equations for different components were converted to C stocks using the 47.5% C fraction determined for the *Eucalyptus* by element analysis. *Eucalyptus* in agricultural landscapes of Western Kenya were then estimated to stock about 9.0±0.01 t C ha^{-1} in AGB, most of which was held in the stem, 6.6±0.01 t C ha^{-1}; while belowground systems contribute about

2.7±0.003 t C ha^{-1}. In total, *Eucalyptus* dominated agricultural landscapes in Western Kenya stock 11.7±0.01 t C ha^{-1} in live tree biomass.

6.4 Discussion

6.4.1 Biomass equations

Diameter at breast height and RCD had a strong positive relationship with all biomass components evaluated (R^2 = >0.90). Such high R^2 have been reported by Zewdie et al. (2009) for branches (0.79), stems (0.94) and AGB (0.86) in *E. globulus* plantations from central Ethiopia. The relationship between leaf biomass and DBH was weaker than the comparable stem-biomass relationship, possibly due to leaves (and also branches) being ephemeral tissues that are affected more by changes that alter allometric relationships (Rubilar et al., 2010). For example removal of large branches to provide wood, improve form and reduce competition with other trees and crops is a common practice in agricultural landscapes. Such silvicultural operations, together with interplant competition and other factors modify the canopy size of individual trees and may affect the allometric relationships between diameter and component biomass.

The DBH alone was the best independent variable for describing the different biomass components, estimating stem, aboveground and total tree biomass with about 95% accuracy. BGB was overestimated by both RCD and DBH based equations, confirming previous reports that BGB is a major component of uncertainty in measuring total tree biomass (Keith et al., 2000). While RCD is a useful parameter for estimating BGB, especially when trees are already cut down and only stump dimensions are available, the bias associated with RCD as proxy for biomass in this study was high and showed greater variability across tree size than DBH. This high and inconsistent bias could be attributed partly to uncertainties in measuring RCD where stems tend to exhibit a much more fluted cross section. This is even more pronounced with increasing tree size. The biomass of branches and leaves could not be accurately estimated using DBH possibly due to the ephemeral nature of these components (Rubilar et al., 2010).

The biomass of small trees was generally overestimated, though the tendency to overestimate biomass dropped with increasing tree size. A similar observation was made by Pérez-Cruzado and Rodríguez-Soalleiro (2011) on *Eucalyptus nitens* plantations in northwestern Spain. This indicates that error in biomass estimation depends on the average tree size. Other authors have reported the importance of tree size in both formulation of allometric equations and the range to which the equations are applied (Chave et al., 2004; Pérez-Cruzado and Rodríguez-Soalleiro, 2011). The biomass values of the smallest trees strongly affect the values of the model parameters in the allometric relation (Chave et al., 2001), while at the same time it is difficult to accurately estimate the biomass trees with DBH >20cm, which form more than 80% of the trees encountered in agricultural landscapes of Western Kenya (chapter 3). Local generic equations developed in chapters 3 and 5 overestimated AGB by 10% and BGB by over 45%. This underscores the need for genera- or species- specific equations and indicates that genetic differences in tree architecture may have a significant influence on metric scaling relationships.

Height, wood density and crown area data did not improve the relationship between DBH and any of the tree biomass components. Whereas including height as an additional predictor variable to DBH has been reported to increase R^2 for *E. globulus* coppice plantations (Zewdie et al., 2009) and other mixed species equations (Ketterings et al., 2001), findings from this study showed that addition of height data neither improved R^2 nor significantly reduced RE in diameter based equations. This observation is in line with several conclusions that height, as an additional predictor, only adds marginal value to the predictive ability of diameter-based equations (Basuki et al., 2009; Nelson et al., 1999).

Height was a significant predictor of stem biomass, and has been found to improve stem biomass estimates elsewhere (Pérez-Cruzado and Rodríguez-Soalleiro, 2011). However, height did not improve accuracy of predicting AGB due to the compensatory relationship between stem and canopy mass (Montagu et al., 2005). This compensatory relationship results in similar AGB for trees of the same diameter, but different partitioning in leaves, branches and stems. Compensatory relationships have been observed in *E. nitens* plantations in northwestern Spain (Pérez-Cruzado and Rodríguez-Soalleiro, 2011) and *Eucalyptus pilularis* from seven contrasting sites in Australia (Montagu et al., 2005).

Wood density marginally improved model fit for AGB and stem biomass but did not improve the predictive power of the diameter based equations, contrary to findings in chapter 3 and previous reports (Basuki et al., 2009; Chave et al., 2005). This could be due to much lower variation in wood density relative to tree size between trees sampled; hence stem wood density did not appear to affect the allometric relationship between DBH and biomass of aboveground parts (Montagu et al., 2005). Height and/or wood density allows for the influence of site factors and differences between tree species. The influence of these parameters was not obvious in trees evaluated, possibly because they belong to the same genus with one species, *E. camaldulensis* dominating the dataset, and were sampled from a site with near similar climatic and soil conditions.

6.3.2 Biomass apportionment

Eucalyptus species have the potential to contribute a significant amount of C sequestered in Western Kenya’s agricultural landscapes since they represent 59.4% of all trees encountered in the Kakamega area (chapter 3). This dominance has been observed for decades (Senelwa and Sims, 1998). The stem biomass accounted for the largest proportion of individual tree AGB across all size classes, followed by branches and leaves. This division agrees with results from the studies on growth of *E. globulus* in central Ethiopian plantations (Zewdie et al., 2009) and *E. nitens* plantations on the coast of Arauco, Chile (Muñoz et al., 2008); both studies reported the stem biomass proportion greater than 75% of AGB. The proportion of leaf biomass (4%) determined in this study compares well with 3% given by (Muñoz et al., 2008).

The proportion of stem biomass increased slightly with tree size, consistent with the biomechanical requirements of the stem; as tree biomass increases, the stem increases in diameter in order to provide greater mechanical strength in support of the increasing weight. Whereas the biomass of stems, branches and BGB generally increased proportionally with tree size, the biomass of leaves tended to decrease. Previous studies have also demonstrated that trees allocate proportionally less biomass to leaves and more to stem as they age, resulting in a decrease in leaf biomass with tree size (Zewdie et al., 2009).

Belowground biomass is an important C pool for many vegetation types and land-use systems identified by the IPCC (2006). The proportion of BGB relative to TTB determined in this study (21%) is slightly lower than 26% given by Cairns et al. (1997). The RS median value determined in this study (0.28) is identical to the RS median determined for mixed species in chapter 5 but higher than the IPCC default value of 0.24±0.14 for tropical hardwood species (Cairns et al., 1997). The median RS was preferred to the RS mean (0.31±0.02) to reduce the influence of large outliers in the dataset arising from coppices or pruning. However, both the RS mean and RS median are lower than 0.38 given by Eamus et al. (2002) for an open *Eucalyptus* forest in a savanna in north Australia. Trees are more likely to have invested less in BGB as water and nutrients are not considered limiting in the area. The low RS compared to other studies may indicate that a high biomass proportion was allocated to stems, branches and leaves as a possible mechanism to confer a competitive advantage, allowing trees to out-compete neighbors by growing in height and expanding crown area to shade out competitors.

6.5 Conclusion

Diameter based equations predicted biomass of most compartments with 95% accuracy, and with about the same relative error across trees of different sizes. Given that DBH is easy to measure with high accuracy, the equations provide a basic tool for estimating biomass and C stocks of eucalyptus for purposes such as bio-energy and C sequestration. These equations can be applied to *Eucalyptus* in agricultural landscapes in similar agro-ecological zones, provided that tree growth parameters fall within similar ranges of the sampled population.

CHAPTER SEVEN

7.0 FRACTAL BRANCH ANALYSIS

7.1 Introduction

Forest inventories are generally conducted to survey standing trees. Because standing trees cannot be weighed to gauge their mass, biomass equations provide one of the only ways for estimating C stocks in standing trees (West, 2009). However, the main method for developing biomass equations is to engage in destructive sampling, where trees are felled, measured and weighed and then an equation is fit to the resulting data. The main limitation of the standard allometric approach is cutting trees to make an equation. Further, the trees used to fit an equation may not be representative of other trees to which the resulting equation will be applied. Most improvements to biomass equations focus on the second problem (Brown, 1997), but the most direct way to solve this problem would be to cut down many more trees across a broader area to assure representativeness. Unfortunately, the latter would worsen the first problem and is generally unacceptable in areas where the ultimate goal is to conserve trees.

Functional branch analysis (FBA) is a model-based method that combines measurements of tree branches with other data to characterize the fractal geometry of tree form and derive allometric scaling coefficients of equations that relate DBH to biomass (van Noordwijk and Mulia, 2002). A major advantage of FBA over the traditional approach is that the coefficients of a biomass equation can be derived from measurements of standing trees, without the need to cut them (Santos-Martin et al., 2010). FBA model derives a proxy of tree mass from proxy estimates of whole tree volume (which are derived from tree stem and branch measurements) that are combined with inputs describing the density of tree volume components (e.g., stems and twigs). It is not expected that the FBA method could produce better estimates of biomass equation coefficients than those derived from destructive sampling, but it may be able to produce very similar equations without the need to fell trees, and thus could be broadly applied to develop localized biomass equations, especially in situations where destructive sampling is impossible or undesirable.

In this study, standard biomass equations derived from destructive sampling of trees in Western Kenya were directly compared to equations derived from FBA for the same trees to see how substitutable the FBA method is for the standard destructive sampling approach for estimating the coefficients of biomass equations. The specific objectives were to:

i. Derive allometric scaling rules for estimating AGB on suitable tree species from agricultural landscapes of Western Kenya;
ii. Determine the similarity or difference of estimations from FBA equations to estimations from equations built using standard sampling techniques.

7.2 Methods

Measurements for FBA were collected on destructively sampled trees following procedures suggested by van Noordwijk and Mulia (2002). The tree is conceptually divided into “links” which occur between branching junctures, except the first link, which is between the ground and the first fork. Starting with the first link, the lower (proximal) diameter ($D_{proximal}$), the diameter in the middle of the link (D_{middle}), the diameter at the distal end of the link (D_{distal}) and length of each link were measured with calipers and tape measure respectively. The diameters of each link were measured once and again in a perpendicular direction and averaged to account for non-circular branch shapes. At the first branch point, the continuing main stem was defined and then the largest ‘branch’ (usually the second largest link at a forking point) was selected and followed to a terminal (usually leaf-bearing) shoot at the end of a path through the tree’s branching network, repeating the measurements on each successive link in the path. Then, returning to the main stem link, it was measured and followed to the next branching point; this process was repeated, moving up the tree, following and measuring links to different terminal shoots. The successive, non-repetitive link number and its parent link number were noted and recorded. Link measurements were repeated to the tip of the tree (or in some cases for a minimum of about 100 measurements per tree) ending at the ultimate leaf bearing twigs.

The diameters and lengths of links at each ramification that were not followed to a terminal twig were also measured to allow for calculation of the scaling factor (p) for the change in total cross-sectional area at branching points: $p = D_B^2 / \sum_{i=1}^{n} D_A^2$, where D_B and D_A are the stem diameters above and below a branching point and n is the number of branches at that point; and an ‘allocation’ parameter (q) describing the relative size of the largest link at a branching point: $q = Max\left(D_A^2\right) / \sum_{i=1}^{n} D_A^2$, where Max($D_A$) is the diameter of the largest stem after a branch point (Spek and van Noordwijk, 1994; van Noordwijk and Mulia, 2002).

FBA is written in Visual Basic language and has been packaged into an Excel®-based software package called WanFBA (Santos-Martin et al., 2010), which can be used to take the prerequisite data and convert it into the necessary biomass equation. FBA takes the input data (Santos-Martin et al., 2010) and generates a proxy mass through FBA rules (van Noordwijk and Mulia, 2002) using some stochastic modeling, so that FBA does not generate the same results with each run. The woody part of the tree was classified into “twigs”- defined as links with diameter less than 2 cm; “branch-links” between 2 and 8 cm; and “wood-links” above 8 cm. FBA ver. 1.4 allows for these subcategories to be defined to allow for differences in scaling relationships for different-sized branches.

7.3 Results

7.3.1 Inputs for the FBA model

Input variables from measurements of the felled trees are shown in Table 7.1. In addition to mean values for these parameters, FBA requires probability distributions for p and q, and that both p and q are independent of link diameter to allow for the use of fractal branching rules to derive allometric scaling coefficients. The correclation coefficients between p and link diameter and q and link diameter (Figure 7.1) were very low indicating the general independence of p and q and link diameters. This lack of correlation between p and q parameters and link diameter has also been reported in earlier studies (Salas et al., 2004 Smith, 2001).

Table 7.1 Tree attributes and input variable values used to parameterize the FBA model. Other than the number of sample trees (n), table values are means {SD}, [range].

Parameter	*A. mearnsii*	*E. camald.*	*E. grandis*	*M. indica*
n	8	15	7	8
DBH (cm)	25.3{10.36}	43.5{16.63}	15.8{8.18}	37.9{22.98}
Number of Branches	2.09 {0.31}	2.10 {0.48}	2.13 {0.38}	2.5 {0.73}
p	1.03 {0.25}	1.20 {0.42}	1.23 {0.48}	1.0 {0.31}
q	0.77 {0.15}	0.79 {0.42}	0.81 {0.14}	0.6 {0.16}
Minimum diameter (cm)	0.37 [0.47]	0.31 [0.40]	0.30 [0.39]	0.37 [0.37]
Twig length (cm)	22.5{16.3}	32.5{27.6}	29.7{26.5}	18.7{15.2}
Branch length (cm)	49.9{31.9}	92.3{81.1}	65.6{70.3}	38.5{29.7}
Wood length (cm)	82.5{63.8}	159.0{243.8}	80.4{112.3}	62.7{57.7}
Wood density (g cm^{-3})	0.63{0.09}	0.53{0.08}	0.42{0.02}	0.56{0.05}

The distribution of p values revealed a wide range of values, but with modal values tightly centered around p = 1, which is the theoretical value based on da Vinci's rule, indicating a conservation of cross-sectional area across branching points, especially for larger links which approached a fairly constant p value. However, the distributions were distinctly skewed toward higher p values (> 1.25, Figure 7.1), particualrly for twigs and smaller branches. This much greater cross-sectional area below a fork relative to the sum of the cross-sectional areas of ramifications above a fork could be generally attributed to dieback of terminal twigs or epicormal branching in cases where larger links have higher values for p (e.g., *E. camaldulensis*).

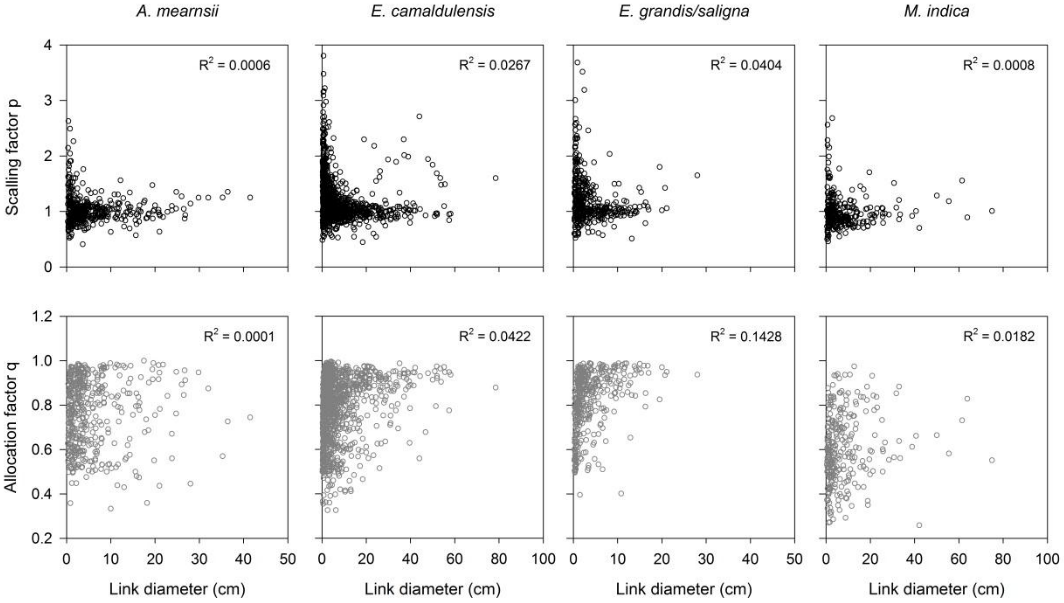

Figure 7.1 Dispersion of the scaling factor p (above) and allocation parameter q (below) as a function of link diameter for *A. mearnsii, E. camaldulensis, E. grandis/saligna* and *M. indica.*

The distribution of q values, which are bounded between 0 and 1, was fairly wide with most values of q > 0.5, which indicates a perfect fork; q < 0.5 indicates that there were more than two branches at the branching point and q > 0.5 indicates that one branch was larger than the others. For *A. mearnsii* and *M. indica* the distribution of q values was generally even, while both *E. grandis* and *E. camaldulensis* showed a skewness toward higher q values, particualarly for larger links. The latter generally indicates a stronger apical dominace for the *Eucalyptus spp*. than the other two species.

The remaining parameters required fitting linear regression models to determine the intercept and slope of length-diameter relationships for twig, branch, and wood components (Table 7.2). The coefficients for branch and wood components ‘a’ and ‘b’ were not used in the FBA model, but were substituted with an intercept ‘a’, determined as the average of the measured link lengths and a default value zero for the slope ‘b’.

7.3.2 Biomass equations

Species-specific equations for *A. mearnsii*, *M. indica,* and *E. camalduslensis* derived from the FBA model overestimated biomass of harvested trees while the equation for *E. grandis/saligna* underestimated biomass (Table 7.3). Although FBA provides allometric coefficients for estimating biomass of branches and foliage biomass, it was not possible to validate the accuracy of equations for these components since field data did not take into account the size categories of branches, and twigs and leaves; hence these components are not described in this study.

Table 7.2 Coefficients of linear regression (a, intercept and b, slope) for length-diameter (D-L) relationships and the range length used to parameterize the FBA model for twig, branch and wood components.

Link	Parameter	*A. Mearnsii*	*E. camald.*	*E. grandis*	*M. indica*
Twigs	a	6.263	31.305	28.813	6.207
	b	16.610	1.426	1.063	12.656
	Range length	0.447	0.627	0.654	0.506
	R^2	0.247	0.001	0.001	0.158
Branches	a	49.945	92.340	65.642	38.491
	Range length	0.458	0.696	0.875	0.569
	R^2	0.088	0.053	0.016	0.056
Wood	a	82.460	159.758	80.439	62.719
	Range length	0.617	0.768	0.949	0.699
	R^2	0.110	0.119	0.025	0.067
Single D-L relationship	a	28.84	39.319	31.848	22.87
	b	2.86	7.442	4.7387	2.145
	Range length	0.525	0.696	0.757	0.613
	R^2	0.298	0.214	0.073	0.212

Table 7.3 The accuracy of allometric biomass equations derived from FBA model and standard method for estimating AGB.

Species	Method	Biomass equation	bias (%)
A. mearnsii	FBA	$AGB = 0.110 \times DBH^{2.530}$	+9.3
A. mearnsii	Standard	$AGB = 0.163 \times DBH^{2.379}$	+0.7
E. camaldulesnis	FBA	$AGB = 0.121 \times DBH^{2.456}$	+33.2
E. camaldulesnis	Standard	$AGB = 0.096 \times DBH^{2.444}$	+0.7
E. grandis/saligna	FBA	$AGB = 0.084 \times DBH^{2.336}$	-19.4
E. grandis/saligna	Standard	$AGB = 0.052 \times DBH^{2.649}$	+0.6
M. indica	FBA	$AGB = 0.089 \times DBH^{2.559}$	+20.6
M. indica	Standard	$AGB = 156 \times DBH^{2.326}$	-8.4
Eucalyptus spp	FBA	$AGB = 0.095 \times DBH^{2.453}$	+5.2
Eucalyptus spp	Standard	$AGB = 0.075 \times DBH^{2.514}$	+2.7
A. mearnsii/M. indica	FBA	$AGB = 0.096 \times DBH^{2.590}$	+28.3
A. mearnsii/M. indica	Standard	$AGB = 0.021 \times DBH^{2.280}$	+1.7
Mixed species	FBA	$AGB = 0.104 \times DBH^{2.464}$	+9.7
Mixed species	Standard	$AGB = 0.101 \times DBH^{2.454}$	+2.5

A direct comparison of predicted and actual harvested biomass on a 1:1 line shows that the FBA derived equation for individual species predicted AGB of smaller trees with greater accuracy compared to larger trees which exhibited high variance between the actual and predicted biomass (Figure 7.2). The largest discrepancies were found in *A.*

mearnsii and *E. camaldulensis* while *M. indica* and *E. grandis/saligna* showed a general good equivalence between the predicted and the measured biomass.

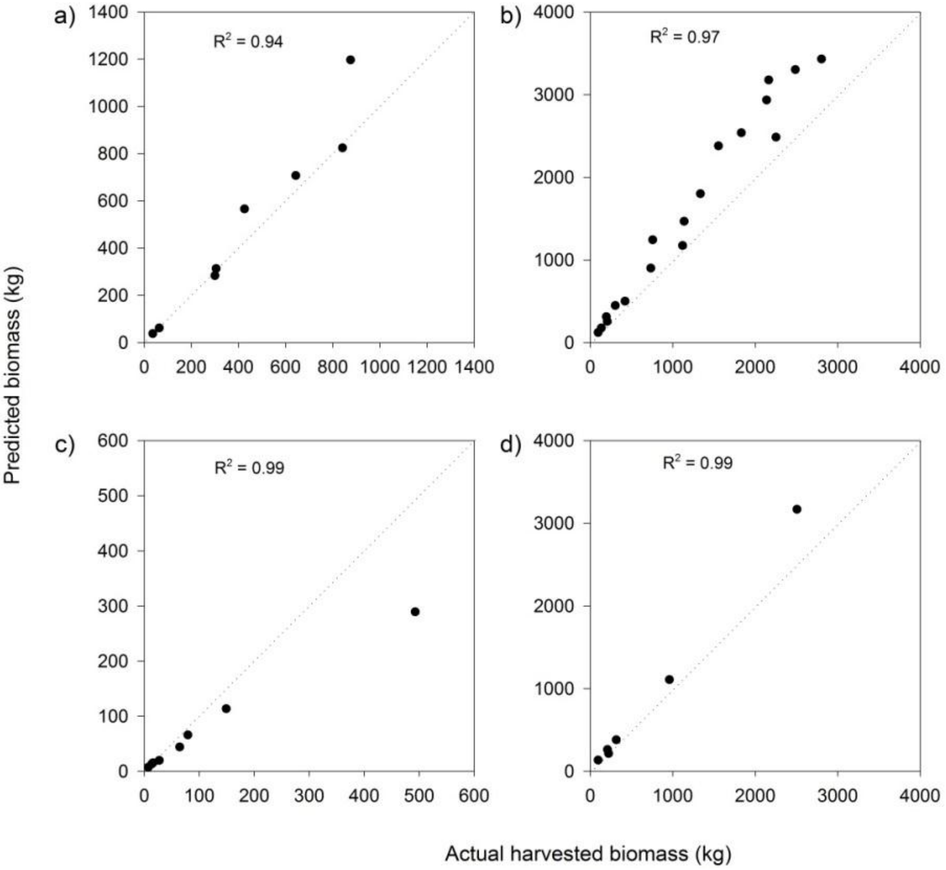

Figure 7.2 Direct comparisons of actual biomass harvested and biomass predicted by equations derived from FBA for (a) *A. mearnsii*, (b) *E. camaldulensis*, (c) *E. grandis/saligna* and (d) *M. indica*.

The mixed-species equation calibrated with the FBA model was generally precise, but overestimated biomass on average, with a bias of about 9.7% (Figure 7.3). Most of the error came from overestimation of the proxy mass of some larger trees by the equation. As expected, the standard empirical biomass equation which predicted actual mass from DBH performed considerably better than the FBA-derived equation.

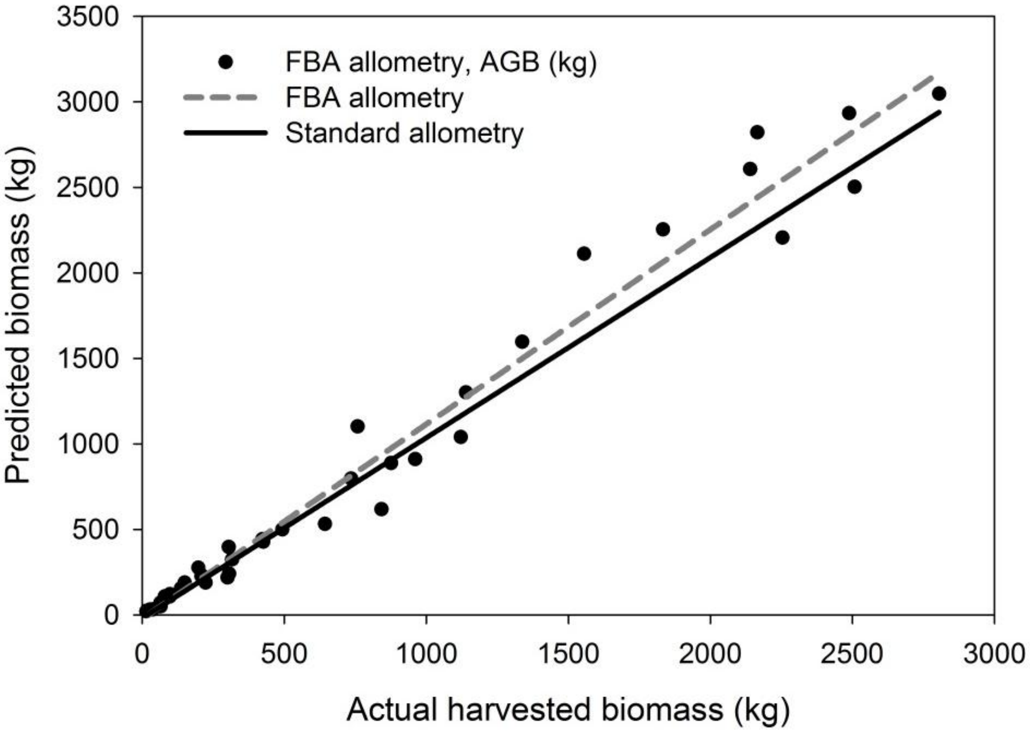

Figure 7.3 Correlation between actual harvested biomass and the biomass predicted by the mixed-species models derived by FBA model and standard destructive sampling method

Additionally, comparable trends were observed; both equations overestimated the biomass of smaller trees (DBH <20 cm: 15.4 and 8.7%) but estimated biomass of larger trees (DBH >20) with high accuracy, bias = 7.8 and 0.4%, respectively. However, variations existed in the bias for individual species tested. The FBA derived equation underestimated the biomass *E. saligna* by 19.4%, each, but overestimated the biomass of *A. mearnsii, E. camaldulensis* and *M. indica* by 9.3, 33.2 and 20.6%, each.

Conversely, the standard allometry estimated biomass with a smaller bias, <10% in all species.

The FBA allometry and standard allometry for trees with considered having similar form showed contrasting results for the two categories (Figure 7.4). The FBA allometry for *A. mearnsii* and *M. indica* produced very different results from the standard allometry for the same trees, with the FBA-derived equation over-predicting biomass for trees of all sizes.

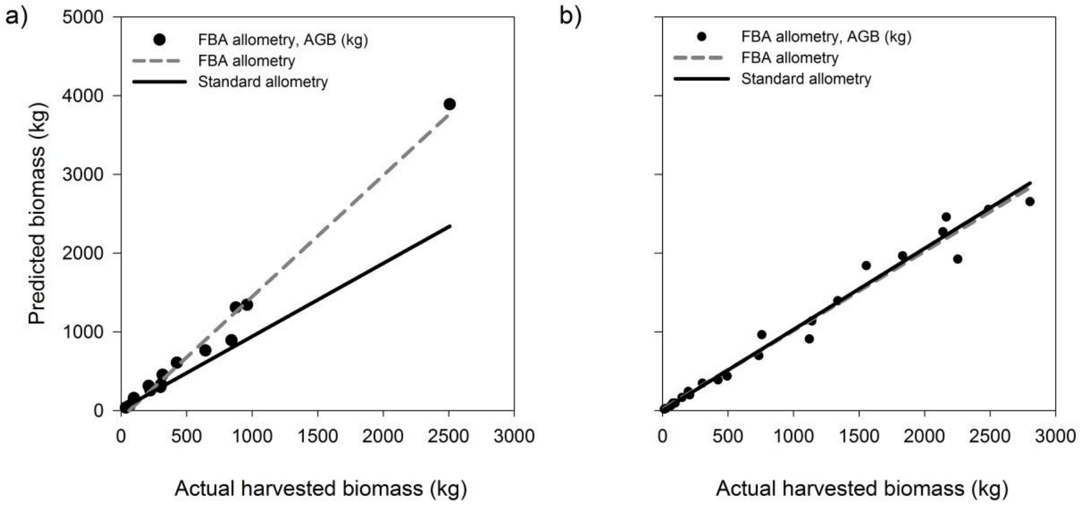

Figure 7.4 Correlation between actual harvested biomass and the biomass predicted by the FBA derived allometry and standard allometric approach for trees considered to have comparable branching patterns: (a) *A. mearnsii* and *M. indica*, (b) Eucalyptus spp (*E. camaldulensis* and *E. grandis*)

The standard allometry (bias = 1.7%) was about sixteen times better than the FBA allometry (bias = 28.3%). The FBA allometry for *Eucalyptus* spp produced results close to those of the standard allometry. However, the standard allometry (bias= 2.7 %) was almost twice more accurate than the FBA-based allometry (bias= 5.2%).

7.4 Discussion

The results of this study suggest that the FBA method of estimating the allometric scaling coefficients of tree biomass equations can produce reasonably accurate, mixed-species equations that are similar to, but less accurate than standard allometric equations, and without the need to fell and weigh trees. However, the method worked better for trees with simpler branching structures (i.e., *Eucalyptus spp*.) than for species with more complex branching (i.e., *M. indica* and *A. mearnsii*). The difference between the mixed-species and species-specific FBA allometries indicates that genetic differences in branching architecture has a significant influence on allometric scaling relationships. Equations derived for trees considered to have similar branching characteristics: (i) *A. mearnsii*, *M. indica*, and (ii) *E. camaldulensis, E. grandis, and E. saligna* clearly shows that trees which have a more complex branching architecture have a more complex allometry and so the biomass equations derived from the FBA method are more error prone. Another possibility is that *A. mearnsii* and *M. indica* might not be a good grouping, if they have very different branching architecture. The study did not have enough trees to subdivide the analysis further.

The scaling coefficient “b” of the resultant biomass equations showed variation among tree species evaluated, ranging between 2.4-2.6; thus lower than the proposed universal value of 2.66 (West et al., 1999) in *A. mearnsii* and *Eucalyptus* spp; while *M. indica* had an equivalence scaling coefficient of 2.6. The branching patterns of tress influence coefficients of the biomass equations, yielding variations in the scaling rule for individual tree species around the universal 8/3 rule. The variability of scaling coefficient “b” among the species evaluated affected the precision of biomass estimates by respective models. The coefficient “b” for mixed species (2.464) was also lower than the proposed universal 2.66 (West et al., 1999) but close to 2.454 for the equation determined by standard sampling methods. A previous study by Santos-Martin et al. (2010) also found that FBA-dervied predictions can come close to observed biomass across trees for some species, but the latter study did not compare FBA-derived predictions to estimates from the standard approach. Thus, FBA appears to provide a viable non-destructive approach for generating species-specific equations for quantification of AGB in trees for some species. However, a better understanding of how the inputs affect the outputs in Wan FBA is certainly needed to improve the accuracy of the model, particularly for tree species with more complex crown architectures.

It should be recognized that the measurements of link lengths and branch diameters are necessary for parameterizing the FBA model. In this study, such measurements were easily obtained because the trees had been felled. Getting the necessary measurements on standing trees requires either a professional tree climber to climb and measure the various links in the path, or the use of some kind of optical dendrometers. In the former case, this could be quite challenging, especially on larger trees and for smaller, upper branches where safety could become a major issue. New tools have recently become available which are capable of measuring these branch parameters, such as the ®Mantax (laser) caliper with 'gator eyes', for measuring stem and branch (link) diameters out of reach, and the ®True Pulse 360° laser rangefinder, for measuring link lengths.

Another issue is the necessity to input wood density estimates. For this study, wood density was known for the population because wood samples were lab-analyzed for this property from samples taken from the felled trees. In a 'non-destructive' application, either cores would need to be extracted from a sample of trees to obtain wood density estimates for the population or published values would have to be introduced into FBA. A sensitivity analysis of FBA revealed that a 10% difference in wood density input in the model generates an approximately 10% difference in the scaling coefficient 'a' and the resultant biomass estimates, holding all other factors constant. This latter result is what would be expected, given that the rest of the parameters essentially help generate a proxy volume for the tree, which at a given density has a given mass. So, if the actual wood density in the population of interest differs by about 10% from a published value for wood density used as an input in FBA, the resulting allometric equation will be biased by 10% in the resulting biomass estimates. This argues that a small amount of destructive sampling (i.e., wood coring) might be necessary to calibrate the biomass equation using FBA, even if the model otherwise produces good estimates from link measurements of standing trees.

Another issue regarding practical application of the FBA method is how many links need to be measured within trees and how many trees need to be measured to capture FBA parameters sufficiently to represent the tree branching architecture for a species or species group. The data from this study show that there is a high degree of variability both within and between trees for many of the input parameters. As there can be an enormous number of branches in a tree, it is not practical to measure every branch in every tree to calibrate the FBA method. Van Noordwijk and Mulia (2002) suggest at least 50 measurements, but this depends on the acceptable uncertainty level that will be associated with the estimates of the coefficients of the allometric equation. If the crown architecture of trees of a species or group of species is similar (i.e., between tree variation is low), then these measurements can be spread about several trees of the same species within a stand or forest to get a species- or species group-average for that area. This choice of how many branches to measure within a tree or within a stand or forest, depends largely on how the allometric equations are to be developed, e.g., species-specific, and how much variation within and between trees is expected or observed.

7.5 Conclusion

Fractal branch analysis appears to provide a viable non-destructive approach for generating species specific equations for quantification of aboveground C in trees. However, further adjustments to the approach are needed to improve accuracy. Variation in accuracy of the equations developed indicates the need to verify FBA derived models, especially when derived from tree species which differ considerably. Efficient, non-destructive sub-sampling methods for obtaining the necessary tree measurements of standing trees are therefore needed to calibrate the FBA algorithm. If the fractal tree is a good approximate of the form and volume of the average tree to which it is applied and the average wood density is a good approximation of the density of the average tree, then the FBA method should give very similar results to the standard allometric approach.

CHAPTER EIGHT

8.0 CANOPY COVER AND LEAF AREA INDEX

8.1 Introduction

Attributes of canopy structure such as canopy cover and leaf area index (LAI) are useful input parameters for climate, meteorological or hydrological models. Whereas canopy cover is mainly valued using indirect methods (Jennings et al., 1999), estimation of LAI on tree or farm scale can be achieved practically by direct methods, which requires stripping and measuring of plant foliage (Jonckheere et al., 2004). Indirect methods are destructive, laborious, time consuming and expensive, especially if the study area is very large (Bréda, 2003). Hence at stand and landscape scale, LAI could be estimated effectively using non-destructive systems e.g., fisheye photography (Frazer et al., 1999).

Hemispherical photography, also known as fisheye photography is a technique for assessing canopy structure and light environment beneath plant canopies (Jonckheere et al., 2004). The technique entails photograph acquisition in the field, and registration, classification and calculation, done using software (Frazer et al., 1999). Photographs are taken from below a canopy looking upward using a camera fitted with a special wide-angle lens (180°). Consistently orienting the camera north allows for subsequent analysis of light regimes, which requires modeling the daily sun trajectory. Photographs taken under uniform sky conditions provide optimal contrast between the leaves and the sky (Frazer et al., 1999). These conditions usually occur when the sky is uniformly overcast, at dawn or at dusk. High resolution digital cameras are commonly used; they capture images directly in digital form, eliminating the expense, time and errors associated with photographic films and film development (Frazer et al., 2001; Jonckheere et al., 2004). A variety of commercial and free software e.g., HemiView (Delta-T Device, Cambridge, UK), WinSCANOPY (Regent Instruments, Canada), Gap light analyzer, GLA (Frazer et al., 1999) have been developed for processing hemispherical imagery.

This study was designed to estimate canopy attributes for trees in agricultural landscapes in Western Kenya using hemispherical photography. The specific objectives of the study were to estimate:

i. Tree canopy cover;
ii. Effective leaf area index.

8.2 Methods

8.2.1 Setting up of photographic equipment

Canopy cover, defined as the fraction of pixels that do not lie in between crown gaps and equivalent to (Jennings et al., 1999) 'canopy closure', and the effective leaf area index (LAI*e*) of the plots sampled were estimated from images taken by a high-resolution Nikon CoolPix P5000 (Nikon Corporation, Tokyo, Japan) digital camera with an FC-E8 fisheye lens. LAI, defined as half the total area of leaves per unit ground horizontal surface area (Jonckheere et al., 2004) was calculated as effective

LAI (LAI*e*) since it does not account for the non-random distribution of foliage and includes the sky obstruction by branches and stems (Bréda, 2003).

Two diagonal transects, each 42.2 m long and intersecting at the centre of the plot were set up within all 30 x 30 m plots sampled for biomass (Plate 8.1). Photo-stations were positioned every 10.6 m from the start to the end of transects, creating a total of 9 photo points which translated to 9 images per plot. This systematic spread of sampling points ensured a representative cover of the plot. The lens was fixed to the camera and the camera mounted on a leveling tripod pointing directly upwards (Plate 8.1).

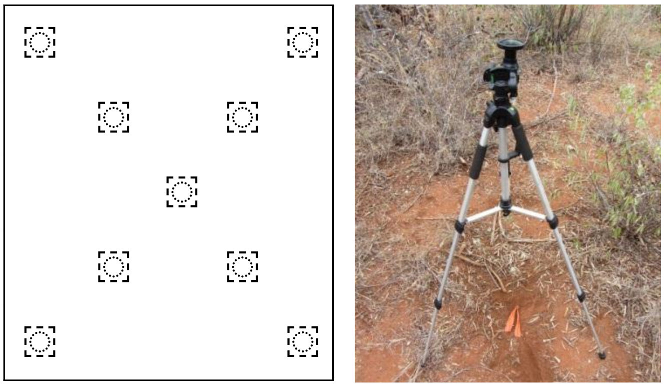

Plate 8.1 Indicative sampling positions, 10.6 m apart in a 30 x 30 m plot (left) and a camera with fisheye lens mounted on a tripod stand (right) for taking fisheye photographs.

The camera was aligned with the magnetic north by adjusting the tripod corner pins and its body leveled by adjusting the bubble levels. Photographs were taken with the camera set to automatic mode, highest resolution (3648 x 2736 pixels), automatic metering with flash disabled, 100ISO sensitivity, underexposed by 1.0 F-stop and images saved in lossless JPEG. Photographs were taken under uniform sky conditions to reduce errors due to the interference of direct sunlight where circumstances permitted.

8.2.2 Image analysis

Photographs were analyzed for canopy openness and LAI*e* using GLA version 2.0 (Frazer et al., 1999). GLA is a Windows-based image processing software designed to import, display and analyze digital hemispherical photos (Frazer et al., 1999). Images were opened and registered to determine the orientation and circular extent of the exposure. Configuration settings of some images were edited to reflect the atmospheric conditions. Images were thresholded manually to accurately classify each pixel as either sky (white) or non-sky (black) pixel and the calculations run to compute the canopy structure (Frazer et al., 1999). Plate 8.2 shows a photograph before and after setting the threshold.

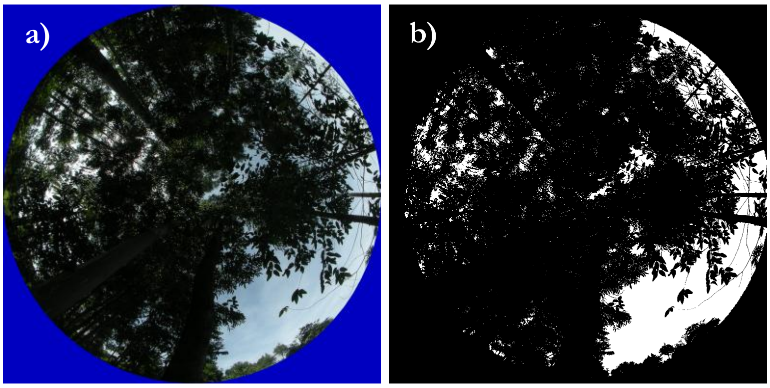

Plate 8.2 Plot level hemispherical photographs (a) before setting the threshold, and (b) after manually setting the threshold value to classify pixels into sky and non-sky regions. The ratio of the canopy-to-sky is used to approximate effective leaf area index.

Because the threshold process is a subjective one, the entire procedure was repeated twice more and the mean canopy openness and LAI*e* computed. Descriptive statistics were run to obtain plot means, SE and SD for estimates of canopy cover and LAI*e*.

8.3 Results

A total of 223 photographs from 28 plots were selected for analysis after discarding 29 photos due to glare and image defects. The mean percent canopy cover of the 28 plots ranged from 10.9-90.1 and varied spatially among the sites evaluated (Figure 8.1). Plots in Middle Yala had the highest mean canopy cover with values between 12.6-83.1% followed by those in Lower Yala while Upper Yala plots had the least means with values in range from 10.9-90.1% (Table 8.1). Within and between site comparisons of the data revealed statistically significant differences in mean canopy cover estimates ($P<.001$). Also, SE was markedly larger for mean canopy cover data from Upper (2.9) compared to Middle (2.2) and Lower Yala (2.3).

Plots with higher stocking or greater canopy cover also had the highest LAI*e* values. The overall mean LAI*e* determined for the three sites was 0.81 with values in the range from 0.01-4.31. LAI*e* values determined for the Lower, Middle and Upper Yala were in the range from 0.01-4.31, 0.01-2.55 and 0.02-3.04, respectively. Higher mean LAI*e* were estimated for the Middle and Lower than Upper Yala site (Table 8.1). An ANOVA demonstrated that site influences on variance of the sites canopy cover were slightly different for measures of LAI*e* ($P<0.05$).

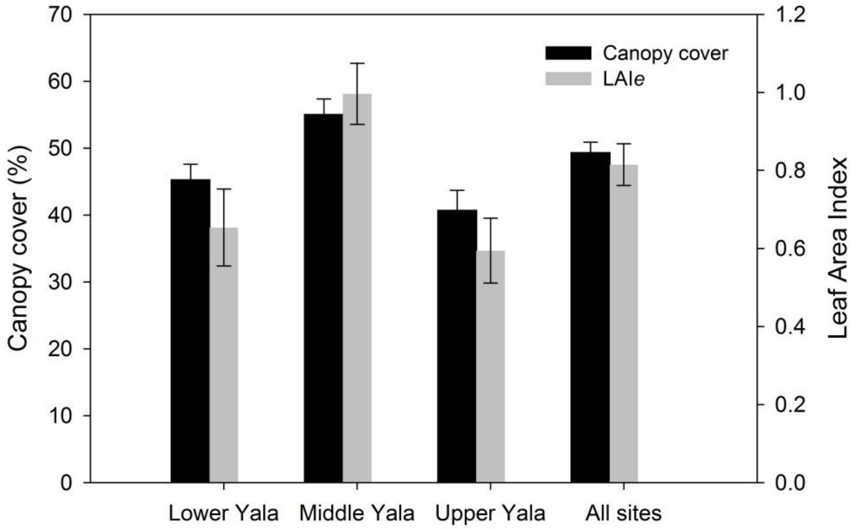

Figure 8.1 Mean canopy cover and effective leaf area index extracted from photos taken in 30 x 30 m plots in the Lower, Middle and Upper Yala sites in Western Kenya.

Table 8.1 Canopy cover and leaf area index determined for the Lower, Middle and Upper Yala sites in Western Kenya. Other than the number of sample photographs (n), and the standard deviation (SD), table values are means [range].

Site	n	Canopy cover		Leaf area index	
		Mean	SD	Mean	SD
Lower Yala	70	45.3[75.7]	18.8	0.7[4.3]	0.8
Middle Yala	112	55.1[77.5]	23.6	1.0[3.0]	0.8
Upper Yala	41	40.8[72.2]	18.6	0.6[2.5]	0.5
All sites	223	49.4[79.2]	22.1	0.8[4.3]	0.8

8.4 Discussion

8.4.1 Canopy cover and effective leaf area index estimates

Canopy cover and LAI*e* estimated for agricultural landscapes in Western Kenya varied across the three sites evaluated. The low canopy cover and LAI*e* values in the Upper Yala are attributed to scant woody vegetation in what is mainly considered cropland, while successive low values in Lower Yala reflect intermittent vegetation patterns consisting of dense semi-natural bushes on farms, sparsely distributed indigenous shrubs and few exotic tree species in the landscape. The relatively high canopy cover and LAI values for the Middle Yala area is attributed to the abundance of mono-specific clusters of eucalyptus woodlots and high tree density on farms in the area. The mean canopy cover determined for Lower (45.3%), Middle (55.1%) and Upper Yala (40.8%) is higher than the 30% given by Hufkens et al. (2008) for semi-arid woodland of the Heihe River basin in arid northwest China.

Plots with high canopy cover also had high leaf area indices. This concurs with previous reports that canopy cover and stand density have a strong linear relationship (Asner et al., 2003). The mean LAI*e* estimated for Lower (0.65), Middle (1.00) and Upper Yala (0.59) is well within the range 1.3(SD 0.9) for semiarid landscapes to 8.7(SD 4.3) for tree plantations (Asner et al. 2003). However, the values are higher than 0.22 determined equally by LAI-2000 Plant Canopy Analyzer and Ceptometer for arid ecosystems (White et al., 2000). The mean estimates established in this study are lower than the global average for tropical deciduous broadleaf forests, 3.9(SD 2.5) as well as tropical evergreen broadleaf forest, 4.8(SD 1.7) given by Asner et al. (2003). The LAI*e* (0.59) estimated for the semi-arid Lower Yala area is in line with (0.58) estimated by Hufkens et al. (2008) for semi-arid woodland of the Heihe River basin in arid northwest China.

The large SD for each of the sites indicates great variation in LAI*e* values (Lower = 0.53, Middle = 0.83 and Upper Yala = 0.83) and all the three sites (0.80). These variations suggest a highly heterogeneous canopy structure in the landscape. Variability of LAI*e* within the plots and across the three sites was possibly influenced by the spatial variation of the canopy, growth form of trees and the management practices. The presence of non-tree elements such as crops in the Upper Yala might have added to the spatial heterogeneity of the canopy. Although canopy cover and LAI*e* values calculated in this study are close to those found in the literature (Asner et al., 2003; Hufkens et al., 2008; White et al., 2000); these comparisons must still be seen in the context of anthropogenic intervention that has a permanently large impact on the spatial distribution of biomass, beyond naturally variable parameters such as stand age, species and climatic effects.

8.4.2 Uncertainties in estimating canopy cover and leaf area index

Uncertainties in the canopy cover and LAI*e* measurements determined in this study arose from image classification, influence of the slope, sun glares and scattered clouds, and the fact that indirect methods generally underestimate LAI. The optimum threshold value for differentiating between vegetation and sky patches was set manually. Manual image classification is subjective (Jonckheere et al., 2004) and therefore an average of three rounds of analysis was used to minimize the bias arising from pixel classification.

LAI*e* estimates determined in this study can be used as an estimate of true LAI in agricultural landscapes of Western Kenya. LAI*e* is converted to true LAI by correcting for light obstruction from non-leafy canopy material and the effects of foliage clumping (Bréda, 2003). However, studies have shown that LAI*e* estimates from indirect approaches could well approximate LAI in broadleaf forests (Asner et al., 2003). This is because foliage clumping is unlikely to be a significant source of error in indirect estimates of LAI in stands of broadleaf species (Chen, 1996; Macfarlane et al., 2000). Eriksson et al. (2005) also showed that there is minor benefit from making full correction for leaf aggregation and woody contribution in deciduous stands.

8.5 Conclusions

Hemispherical photography is a potentially promising tool offering an alternative means for indirect measurement of canopy attributes also in agricultural landscapes. Canopy cover and LAI*e* varied spatially among the sites evaluated, with high values in Middle Yala and lower values in the Lower and Upper Yala, correspondingly. These variations suggest a highly heterogeneous canopy structure in the landscape. Plots with higher stocking or greater canopy cover also had the highest LAI*e* values. Given that indirect methods are significantly easier to implement and that they can be applied repetitively to many studies over very large geographical areas, hemispherical photography could be used as a ground-based method essential for quantifying canopy cover and LAI*e* for calibrating spectral indices. The results are useful and could be used later to determine relative changes in canopy cover and LAI within the landscape, also describing the impact of land use change trajectories.

CHAPTER NINE

9.0 GENERAL CONCLUSIONS AND RECOMMENDATIONS

9.1 General conclusions

Developing allometric equations that are applicable to agricultural landscapes is critical for accurate accounting of C stock for REDD++ and for national GHG inventories for agriculturally dominated countries. The local generic equations developed for estimating AGB (chapter 3) and BGB (chapter 5) are robust and can be used to obtain reliable biomass estimates in most agricultural landscapes, both at small and large scale. The equations were developed from a sample that was truly representative of the population of trees in agricultural landscapes of Western Kenya in terms of size and form. The sample included diverse tree species, a wide diameter range incorporating larger trees, varied silvicultural practices and a fairly wide altitudinal and rainfall gradient. The equations resulted to be practical, requiring DBH as the only variable, and were consistently accurate across different locations and trees of different sizes. These equations have an advantage over ones requiring height or wood density as additional predictor variables of maintaining a sufficient level of accuracy, while waiving otherwise tedious additional measurements, hence minimizing the inventory cost for estimating tree biomass.

Although the equations presented in chapter 3 and 5 are generic, three species (*E. camaldulensis, M. lutea* and *A. mearnsii*) dominated the landscape, rendering the equations region or pseudo-species specific. Applying these equations to vegetation types with major differences in abiotic conditions may therefore increase the error compared to the levels in this study. The study also established that management significantly affects biomass and contributes to the heterogeneity of the landscape; hence RSs should be used with care considering soil and management conditions.

Published equations that could otherwise be considered appropriate for Western Kenya misjudged above- and below-ground biomass by between 11-22% and 21-35%, respectively. This underscores the need for empirical validation of equations developed in different geographical, ecological and management contexts. Factors such as the mix of species, the fact that trees in agricultural landscapes are often grown in stands that are not closed and may include isolated trees, and that crowns may be cut during growth affect the validity of applying equations to agricultural landscapes that have been created in other contexts. Studies may also underestimate BGB by up to 12.5%, particularly for larger trees, if root biomass is only captured within a 2 m radius and 2 m depth. Biomass estimates in agricultural landscapes can also be underestimated if branches and foliage, which constitute about 33% of the TTB, are excluded from the accounting protocol. Similar underestimation could also occur if forest based equations, developed from merchantable stem and that omit branches and foliage biomass are used to estimate biomass in agricultural landscapes without adequate expansion factors. Elsewhere, Chave et al. (2004) discussed the importance of estimating biomass of small trees, lianas and bamboo, which may represent 10% of the total AGB stock. This underlines the importance of including all components of live biomass in C accounting.

Chapter 6 demonstrated that species specific equations are more accurate in estimating biomass of particular tree species than local generic or global equations. It confirms the observation that allometric equations are greatly influenced by tree architecture and wood density, which tend to vary among species (Chave et al., 2004). This is consistent with results in chapter 7 where differences between the mixed-species and species-specific equations derived from FBA are attributed to differences in branching architecture.

Chapters 3 to 6 reveal that accuracy of biomass estimation varies across tree size with large errors among small trees (DBH <20 cm) although the largest difference in estimated biomass was observed in high biomass trees. Large trees hold most of the biomass, which emphasizes the need to assess their biomass correctly. Since larger trees in these landscapes are scarce, both cultural and practical restrictions inhibit sampling them destructively. This leads to an underrepresentation of larger trees, whose inclusion in biomass equations would improve the consistency of the allometries for landscapes with bigger trees (Brown, 1997)

Wood density was found to be the most important additional explanatory variable for AGB estimation for the generic equations but not for species specific equation. Height and crown area data did not improve model fit substantially. Wood density data from inventories should therefore be used where available to improve the accuracy of biomass estimations, particularly for mixed species or trees from sites with contrasting climatic, edaphic or management conditions.

Chapter 4 demonstrates that crown area can be an effective predictor of AGB, especially when supported by height and/or wood density data. Studies have shown that crown area and/or height could be used as primary predictor variables, especially in low-growing multi-stemmed trees (Halpern et al., 1996; Sah et al., 2004). However, challenges of using crown area in biomass estimation abound, ranging from issues of measuring crown area accurately to the lack of consistent allometric equations based on crown area (Gibbs et al., 2007). The new allometric relations using crown area provide valuable information rarely available in agricultural mosaics and may form a basis for new generation allometries using crown area as a predictor of AGB. Further refinement of equations based on crown area will allow for calibration and validation of remote sensing estimates directly where to date crown area was used to first estimate e.g. DBH which was then entered into further allometries to yield biomass.

The study showed that hemispherical photography can be reliably used to derive ground-based measurements of canopy cover and LAI*e*. Canopy cover estimates from hemispherical photography could be used to validate cover estimates from aerial photographs or satellite images or as a variable in models to predict stand volume from aerial photographs.

9.2 Recommendations for future work

While the study achieved the objective of developing allometric equations for estimating landscape scale tree biomass in complex agricultural mosaics, the following recommendations emerged to improve biomass estimation in agricultural landscapes:

- Equations presented in this study need to be tested in other areas to determine their applicability across a wider range of agricultural landscapes in Eastern Africa.
- A study to relate allometric scaling and tree form and the relationship between tree form and remote sensing based allometric scaling is recommended. This could be done to determine the suitability of using crown area equations, and canopy cover and leaf area index estimates from hemispherical photography to validate estimates from remote sensing.
- This study only evaluated the performance of the equations developed in terms of bias in landscape level prediction and prediction of single trees. An analysis of error propagation effects that may occur during the scaling process, including sampling, measurement errors and errors in the estimates of model parameters is recommended.
- Variability can be high within complex agroforestry systems and productivity depends on several factors such as climate, soil properties, stand age, species composition and the way the system is managed. A study to determine how

these factors affect biomass C in agricultural landscapes could help in identifying causal relationships.

- Further adjustments to the FBA approach is required to improve accuracy through the use of efficient, non-destructive subsampling methods for obtaining the necessary measurements on standing trees needed to calibrate the FBA algorithm.

REFERENCES

Akaike, H., 1981. Journal of Econometrics. Journal of Econometrics. 16, 3–14.

Albrecht, A., Kandji, S.T., 2003. Carbon sequestration in tropical agroforestry systems. Agriculture, Ecosystems and Environment. 99, 15–27.

Asner, G.P., Scurlock, J.M.O., Hicke, J.A., 2003. Global synthesis of leaf area index observations: implications for ecological and remote sensing studies. Global Ecology and Biogeography. 12, 191–205.

Awal, M., Ishak, W.I.W., Bockari-Gevao, S., 2010. Determination of Leaf Area Index for Oil Palm Plantation Using Hemispherical Photography Technique. Pertanika J. Sci. & Technol. 18, 23–32.

Bastien-Henri, S., Park, A., Ashton, M., Messier, C., 2010. Biomass distribution among tropical tree species grown under differing regional climates. Forest Ecology and Management. 260, 403–410.

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, 1684–1694.

Boye, A., Verchot, L., Zomer, R.J., 2008. Baseline Report, Yala and Nzoia River Basins. Western Kenya Intergrated Ecosystem Management Project. Findings from the Baseline Surveys. World Agroforestry Centre, Nairobi, Kenya.

Brassard, B.W., Chen, H.Y.H., Bergeron, Y., Paré, D., 2011. Coarse root biomass allometric equations for *Abies balsamea*, *Picea mariana*, *Pinus banksiana*, and

Populus tremuloides in the boreal forest of Ontario, Canada. Biomass and Bioenergy. 35, 4189–4196.

Brown, S., 1997. Estimating Biomass and Biomass Change of Tropical Forests: a Primer. FAO Forestry Paper - 134. FAO, Rome, Italy.

Brown, S., 2002. Measuring carbon in forests: current status and future challenges. Environmental Pollution. 116, 363–72.

Brown, S., Gillespe, A.J.R., Lugo, A., 1989. Biomass estimation methods for tropical forests with application to forest inventory data. Forest Science. 35, 881–902.

Bréda, N.J.J., 2003. Ground-based measurements of leaf area index: a review of methods, instruments and current controversies. Journal of Experimental Botany. 54, 2403–2417.

Cairns, M.A., Helmer, E.H., Baumgardner, G.A., 1997. Root biomass allocation in the world’ s upland forests. Oecologia. 111, 1–11.

Chave, J., Andalo, C., Brown, S., Cairns, M., Chambers, J., Eamus, D., Fölster, H., Fromard, F., Higuchi, N., Kira, T., Lescure, J., Nelson, B.W., Ogawa, H., Puig, H., Riéra, B., Yamakura, T., 2005. Tree Allometry and Improved Estimation of Carbon Stocks and Balance in Tropical Forests. Oecologia. 145, 87–99.

Chave, J., Condit, R., Aguilar, S., Hernandez, A., Lao, S., Perez, R., 2004. Error propagation and scaling for tropical forest biomass estimates. Philosophical transactions of the Royal Society of London. B. 359, 409–20.

Chave, M.E., Rie, B., Ge, E., 2001. Estimation of biomass in a neotropical forest of French Guiana: spatial and temporal variability. Journal of Tropical Ecology. 17, 79–96.

Chen, J.M., 1996. Optically-based methods for measuring seasonal variation of leaf area index in boreal conifer stands. Agricultural and Forest Meteorology. 80, 135–163.

Cole, T., Ewel, J., 2006. Allometric equations for four valuable tropical tree species. Forest Ecology and Management. 229, 351–360.

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, 1873–1885.

Drake, J.B., Knox, R.G., Dubayah, R.O., Clark, D.B., Condit, R., Blair, J.B., Hofton, M., 2003. Above-ground biomass estimation in closed canopy Neotropical forests using lidar remote sensing: factors affecting the generality of relationships. Global Ecology and Biogeography. 12, 147–159.

Eamus, D., Chen, X., Kelly, G., Hutley, L., 2002. Root biomass and root fractal analyses of an open Eucalyptus forest in a savana of north Australia. Aust. J. Bot. 50, 31–41.

Eamus, D., McGuinness, K., Burrows, W., 2000. Review of Allometric Woody Biomass for Queensland, the Northern Territory and Western Australia.

National carbon accounting system technical report No . 5A. Office. Australia for the Australian Greenhouse Office, Canberra, Australia.

Eriksson, H., Eklundh, L., Hall, K., Lindroth, A., 2005. Estimating LAI in deciduous forest stands. Agricultural and Forest Meteorology. 129, 27–37.

FAO, 2011. Eucalyptus in East Africa. Socio-economic and environmental issues. Gessesse, D., Erkossa, T. (Eds.). FAO, Rome, Italy.

Fatemi, F.R., Yanai, R.D., Hamburg, S.P., Vadeboncoeur, M.A., Arthur, M.A., Briggs, R.D., Levine, C.R., 2011. Allometric equations for young northern hardwoods: the importance of age-specific equations for estimating aboveground biomass. Canadian Journal of Forest Research. 891, 881–891.

Frazer, G.W., Canham, C.D., Lertzman, K.P., 1999. Gap Light Analyzer (GLA) Version 2.0: Imaging software to extract canopy structure and gap light transmission indices from true-colour fisheye photographs, user’s manual and program documentation. Program. Simon Fraser University, Burnaby, British Columbia, and the Institute of Ecosystem Studies, Millbrook, New York.

Frazer, G.W., Fournier, R. a., Trofymow, J. a., Hall, R.J., 2001. A comparison of digital and film fisheye photography for analysis of forest canopy structure and gap light transmission. Agricultural and Forest Meteorology. 109, 249–263.

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.

Glenday, J., 2006. Carbon storage and emissions offset potential in an East African tropical rainforest. Forest Ecology and Management. 235, 72–83.

Gower, S.T., Vogt, K.A., Grier, C.C., 1992. Carbon dynamics of Rocky Mountain Douglas-Fir: Influence of Water and Nutrient Availability. Ecological Monographs. 62, 43–65.

Green, C., Tobin, B., O'Shea, M., Farrell, E.P., Byrne, K.A., 2007. Above- and belowground biomass measurements in an unthinned stand of Sitka spruce (*Picea sitchensis* (Bong) Carr.). European Journal of Forest Research. 126, 179–188.

Halpern, C.B., Miller, E.A., Geyer, M.A., 1996. Equations for predicting aboveground biomass of plant species in early successional forests of the Western Cascade Oregon. Northwest Science. 70, 306–320.

Henry, M., Besnard, A., Asante, W.A., Eshun, J., Adu-bredu, S., Valentini, R., Bernoux, M., Saint-andré, L., 2010. Wood density, phytomass variations within and among trees, and allometric equations in a tropical rainforest of Africa. Forest Ecology and Management. 260, 1375–1388.

Henry, M., Picard, N., Trotta, C., Manlay, R.J., 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, 477–569.

Henry, M., Tittonell, P., Manlay, R.J., Bernoux, M., Albrecht, A., Vanlauwe, B., 2009. Biodiversity, carbon stocks and sequestration potential in aboveground biomass in smallholder farming systems of western Kenya. Agriculture , Ecosystems and Environment. 129, 238–252.

Hufkens, K., Bogaert, J., Dong, Q., Lu, L., Huang, C., Ma, M., Che, T., Li, X., Veroustraete, F., Ceulemans, R., 2008. Impacts and uncertainties of upscaling of remote-sensing data validation for a semi-arid woodland. Journal of Arid Environments. 72, 1490–1505.

IPCC, 2003. Good practice guidance for land use, land-use change and forestry, in: Penman, J., Gytarsky, M., Hiraishi, T., Krug, T., Kruger, D., Pipatti, R., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. (Eds.), IPCC National Greenhouse Gas Inventories Programme. Institute for Global Environmental Strategies (IGES) for the Intergovernmental Panel on Climate Change (IPCC), Hayama, Japan.

IPCC, 2006. Agriculture, forestry and other land use, in: Eggleston, H., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. (Eds.), IPCC Guidelines for National Greenhouse Gas Inventories. Intergovernmental Panel on Climate Change, IPCC/IGES, Hayama, Japan.

Jaetzold, R., Schmidt, H., 1982. Farm management handbook of Kenya. Volume II: Natural conditions and farm management information. Ministry of Agriculture, Nairobi, Kenya.

Jamnadass, R., Gebrekirstos, A., Neufeldt, H., Muthuri, C., Dawson, I., Kindt, R., Nyberg, Y., Dietz, J., Bayala, J., Kuyah, S., Ong, C., Montes, C.S., Weber, J., Hairiah, K., van Noordwijk, M., 2011. Trees as providers of environmental services in multifunctional landscapes are vulnerable to climate change, in: How trees and people can co-adapt to climate change: reducing vulnerability through multifunctional agroforestry landscapes. World Agroforestry Centre (ICRAF), Nairobi, Kenya, pp. 63–77.

Jennings, S.B., Brown, N.D., Sheil, D., 1999. Assessing forest canopies and understorey illumination: canopy closure, canopy cover and other measures. Forestry. 72, 59–73.

Jonckheere, I., Fleck, S., Nackaerts, K., Muys, B., Coppin, P., Weiss, M., Baret, F., 2004. Review of methods for in situ leaf area index determination Part I. Theories, sensors and hemispherical photography. Agricultural and Forest Meteorology. 121, 19–35.

Keith, H., Barrett, D., Keenan, R., 2000. Review of Allometric Relationships for Estimating Woody Biomass for New South Wales, the Australian Capital Territory, Victoria, Tasmania and South Australia. National Carbon Accounting System Technical Report No. 5B. Carbon. Australia for the Australian Greenhouse Office, Canberra, Australia.

Ketterings, Q., Coe, R., van Noordwijk, M., Ambagau, Y., Palm, C., 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.

Kiplagat, J.K., Wang, R.Z., Li, T.X., 2011. Renewable energy in Kenya: Resource potential and status of exploitation. Renewable and Sustainable Energy Reviews. 15, 2960–2973.

Kituyi, E., Marufu, L., Wandiga, S.O., Jumba, I.O., Andreae, M.O., Helas, G., 2001. Biofuel availability and domestic use patterns in Kenya. Biomass and Bioenergy. 20, 71–82.

Komiyama, A., Ong, J.E., Poungparn, S., 2008. Allometry, biomass, and productivity of mangrove forests: A review. Aquatic Botany. 89, 128–137.

Kuyah, S., 2008. Comparative study of performance and water use of *Eucalyptus grandis*, Eucalyptus hybrids, *Grevillea robusta* and *Cordia africana* in Thika, Kenya. Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya.

Laclau, J., Bouillet, J., Ranger, J., 2000. Dynamics of biomass and nutrient accumulation in a clonal plantation of Eucalyptus in Congo. Forest Ecology and Management. 128, 181–196.

Levy, P., Hale, S., Nicoll, B., 2004. Biomass expansion factors and root:shoot ratios for coniferous tree species in Great Britain. Forestry. 77, 421–430.

Luo, T., Brown, S., Pan, Y., Shi, P., Ouyang, H., Yu, Z., Zhu, H., 2005. Root biomass along subtropical to alpine gradients: global implication from Tibetan transect studies. Forest Ecology and Management. 206, 349–363.

Macfarlane, C., Coote, M., White, D. A., Adams, M. A., 2000. Photographic exposure affects indirect estimation of leaf area in plantations of *Eucalyptus globulus* Labill. Agricultural and Forest Meteorology. 100, 155–168.

Massada, A.B., Carmel, Y., Tzur, G.E., Grünzweig, J.M., Yakir, D., 2006. Assessment of temporal changes in aboveground forest tree biomass using aerial photographs and allometric equations. Canadian Journal of Forest Research. 36, 2585–2594.

Mokany, K., Raison, J., Prokushkin, A., 2006. Critical analysis of root: shoot ratios in terrestrial biomes. Global Change Biology. 12, 84–96.

Montagu, K., Duttmer, K., Barton, C.V., Cowie, A., 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, 113–127.

Muñoz, F., Rubilar, R.A., Espinosa, M., Cancino, J., Toro, J., Herrera, M., 2008. The effect of pruning and thinning on above ground aerial biomass of *Eucalyptus nitens* (Deane & Maiden) Maiden. Forest Ecology and Management. 255, 365–373.

Nair, P.K., Kumar, M.B., Nair, V.D., 2009. Agroforestry as a strategy for carbon sequestration. Journal of Plant Nutrition and Soil Science. 172, 10–23.

Navar, J., 2009. Allometric equations for tree species and carbon stocks for forests of northwestern Mexico. Forest Ecology and Management. 257, 427–434.

Nelson, B.W., Mesquita, R., Pereira, L.G., de Souza, S.G., Batista, T., Couto, B., 1999. Allometric regressions for improved estimate of secondary forest biomass in the central Amazon. Forest Ecology and Management. 117, 149–167.

Niiyama, K., Kajimoto, T., Matsuura, Y., Yamashita, T., Matsuo, N., Yashiro, Y., Ripin, A., Kassim, A. Rahman, nur Supardi, N., 2010. Estimation of root biomass based on excavation of individual root systems in a primary dipterocarp forest in Pasoh Forest Reserve, Peninsular Malaysia. Journal of tropical ecology. Cambridge University Press. 26, 271–284.

Okello, B.D., Connor, T.G.O., Young, T.P., 2001. Growth, biomass estimates, and charcoal production of *Acacia drepanolobium* in Laikipia, Kenya. Forest Ecology and Management. 142, 143–153.

Ong, C.K., Deans, J.D., Wilson, J., Mutua, J., Khan, A.A.H., 1999. Exploring below ground complementarity in agroforestry using sap flow and root fractal techniques. Agroforestry Systems. 44, 87–103.

Ozier-lafontaine, H., Lecompte, F., Sillon, J.F., 1999. Fractal analysis of the root architecture of *Gliricidia sepium* for the spatial prediction of root branching, size and mass: model development and evaluation in agroforestry. Plant and Soil. 209, 167–180.

Pérez-Cruzado, C., Rodríguez-Soalleiro, R., 2011. Improvement in accuracy of aboveground biomass estimation in *Eucalyptus nitens* plantations: Effect of bole sampling intensity and explanatory variables. Forest Ecology and Management. 261, 2016–2028.

Ren, H., Chen, H., Li, Z., Han, W., 2009. Biomass accumulation and carbon storage of four different aged *Sonneratia apetala* plantations in Southern China. Plant and Soil. 327, 279–291.

Resh, S.C., Battaglia, M., Worledge, D., Ladiges, S., 2003. Coarse root biomass for eucalypt plantations in Tasmania, Australia: sources of variation and methods for assessment. Trees - Structure and Function. 17, 389–399.

Rubilar, R.A., Allen, H.L., Alvarez, J.S., Albaugh, T.J., Fox, T.R., Stape, J.L., 2010. Silvicultural manipulation and site effect on above and belowground biomass equations for young *Pinus radiata*. Biomass and Bioenergy. 34, 1825–1837.

Sah, J.P., Ross, M.S., Koptur, S., Snyder, J.R., 2004. Estimating aboveground biomass of broadleaved woody plants in the understory of Florida Keys pine forests. Forest Ecology and Management. 203, 319–329.

Salas, E., Ozier-lafontaine, H., Nygren, P., 2004. A fractal root model applied for estimating the root biomass and architecture in two tropical legume tree species. Annals of Forest Science. 61, 337–345.

Sampaio, E.V.S.B., Silva, G.C., 2005. Biomass equations for Brazilian semiarid caatinga plants. Acta Botanica Brasilica. 19, 935–943.

Santos-Martin, F., Navarro-cerrillo, R., Mulia, R., van Noordwijk, M., 2010. Allometric equations based on a fractal branching model for estimating aboveground biomass of four native tree species in the Philippines. Agroforestry Systems. 78, 193–202.

Schenk, H.J., Jackson, R.B., 2002. The Global Biogeography of Roots. Ecological Monographs. 72, 311–328.

Segura, M., Kanninen, M., Suárez, D., 2006. Allometric models for estimating aboveground biomass of shade trees and coffee bushes grown together. Agroforestry Systems. 68, 143–150.

Senelwa, K., Sims, R.E.H., 1998. Tree biomass equations for short rotation eucalyptus grown in New Zealand. Biomass and Bioenergy. 13, 133–140.

Shepherd, K.D., Soule, M.J., 1998. Soil fertility management in west Kenya: dynamic simulation of productivity, profitability and sustainability at different resource endowment levels. Agriculture, Ecosystems and Environmentand Environment. 71, 131–145.

Smith, D.M., 2001. Estimation of tree root lengths using fractal branching rules: a comparison with soil coring for Grevillea robusta. Plant and Soil. 229, 295–304.

Spek, L.Y., van Noordwijk, M., 1994. Proximal root diameter as a predictor of root size for fractal branch models II. Numerical models. Plant and Soil. 164, 119–127.

Sprugel, D., 1983. Correcting for bias in log-transformed allometric equations. Ecology. 64, 209–210.

Velarde, S.J., Ugarte-guerra, J., Capella, J., Sandoval, M., Hyman, G., Castro, A., Marín, J., Barona, E., 2010. Reducing emissions from all land uses in Peru. Final National Report. ASB Partnership for the Tropical Forest Margins, Nairobi, Kenya.

Verbist, B., Vangoidsenhoven, M., Dewulf, R., Muys, B., 2011. Reducing emissions from deforestation and degradation (REDD). KLIMOS, Leuven, Belgium, pp. 1–43.

West, G.B., Brown, J.H., Enquist, B.J., 1999. A general model for the structure and allometry of plant vascular systems. Nature. 400, 664–667.

West, P., 2009. Tree and Forest measurement, Second edi. Springer, London.

White, M.A., Asner, G.P., Nemani, R.R., Privette, J.L., Running, S.W., 2000. Measuring Fractional Cover and Leaf Area Index in Arid Ecosystems: Digital Camera, Radiation Transmittance, and Laser Altimetry Methods. Remote Sensing of Environment. 74, 45–57.

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, 421–428.

Zomer, R.J., Trabucco, A., Coe, R., Place, F., 2009. Trees on Farm: Analysis of Global Extent and Geographical Patterns of Agroforestry. ICRAF Working Paper no. 89. World Agroforestry Centre, Nairobi, Kenya.

van Noordwijk, M., Mulia, R., 2002. Functional branch analysis as tool for fractal scaling above- and belowground trees for their additive and non-additive properties. Ecological Modelling. 149, 41 – 51.

APPENDICE

Appendix 2.1 Schematic representation of field events: (a) cutting a standing tree using a chain saw, (b) sectioning the stem, (c) weighing a sectioned stem piece, (d) striped leaves from branches, (e) weighing branches, (f) weighing leaves, (g) excavating the root system, (h) unearthed stump (i) splitting a large stump (j) weighing a sectioned stump (k), weighing a large root (l) weighing small root pieces.

Appendix 3.1 Cross validation for equation 3.1. The average of the parameters from the twelve holdouts yields equation 3.1, $AGB = 0.091 \times dbh^{2.472}$. Values of model coefficients (a, b), standard error of the estimate (se), coefficient of determination (R^2) and model bias % are presented.

Holdout	a	b	SEE(a)	SEE(b)	R^2	Bias %
1	0.081	2.497	0.129	0.038	0.985	-26.9
2	0.090	2.470	0.137	0.041	0.982	-4.1
3	0.089	2.478	0.134	0.040	0.983	-4.1
4	0.090	2.474	0.135	0.040	0.983	3.1
5	0.091	2.472	0.133	0.040	0.983	11.6
6	0.097	2.448	0.127	0.038	0.984	-34.9
7	0.095	2.458	0.135	0.040	0.983	-11.7
8	0.090	2.471	0.133	0.040	0.984	-13.5
9	0.096	2.455	0.123	0.037	0.986	-3.8
10	0.087	2.488	0.120	0.036	0.987	29.7
11	0.091	2.471	0.134	0.040	0.983	9.9
12	0.089	2.478	0.131	0.039	0.984	26.1

Appendix 5.1 Estimation of the fraction of root biomass not captured by excavation. Fitted allometric coefficients were used to estimate the missing root biomass from the distal root diameters, and expressed as a fraction of the calculated biomass (BM %). N describes the number of root pieces per species.

Species	N	Log(a)	SEE(log(a))	b	SEE(b)	R^2	BM %
Acacia mearnsii	51	-3.328	0.750	2.200	0.330	0.665	62
Bridelia micrantha	19	-0.6	1.350	1.197	0.560	0.530	61
Combretum molle	15	-3.601	0.550	2.334	0.230	0.789	37
Cupressus lusitanica	22	-3.953	0.570	2.017	0.300	0.610	47
Eucalyptus camaldulensis	234	-3.423	0.210	2.070	0.080	0.767	31
Eucalyptus grandis	9	-3.708	0.730	1.756	0.400	0.938	29
Eucalyptus saligna	47	-3.574	0.660	1.975	0.300	0.590	27
Ficus sp.	6	-7.425	1.300	3.263	0.430	0.811	28
Grevillea robusta	64	-3.125	0.550	2.090	0.190	0.809	28
Jacaranda mimosifolia	9	-0.817	1.980	1.104	0.630	0.754	62
Mangifera indica	51	-3.611	0.690	2.286	0.290	0.721	65
Markhamia lutea	65	-3.425	0.380	1.880	0.160	0.809	38
Perseia americana	11	-4.913	0.590	2.625	0.250	0.753	61
Syzygium cordatum	33	-3.559	1.010	2.312	0.310	0.614	58
Syzygium cuminii	11	-3.575	1.000	1.914	0.380	0.881	44
Trilepisium madagasc.	11	-2.338	2.330	1.648	0.770	0.678	38

Appendix 5.2 Cross validation for equation 5.1. The average of the parameters from the twelve holdouts yields equation 5.1, $BGB = 0.490 \times AGB^{0.923}$. The intercept (a), scaling exponent (b), standard error of estimates (se) and coefficient of determination (R^2) are provided

Holdout	a	b	SEE(a)	SEE(b)	R^2
holdout 1	0.420	0.948	0.147	0.025	0.958
holdout 2	0.504	0.916	0.157	0.026	0.952
holdout 3	0.518	0.918	0.151	0.025	0.954
holdout 4	0.488	0.924	0.153	0.026	0.956
holdout 5	0.511	0.915	0.154	0.026	0.954
holdout 6	0.505	0.915	0.155	0.026	0.953
holdout 7	0.486	0.918	0.144	0.024	0.959
holdout 8	0.515	0.913	0.154	0.026	0.953
holdout 9	0.488	0.924	0.155	0.026	0.954
holdout 10	0.459	0.933	0.152	0.025	0.957
holdout 11	0.491	0.924	0.157	0.026	0.952
holdout 12	0.491	0.924	0.157	0.026	0.952
Average	0.490	0.923	0.153	0.026	0.954

Appendix 5.3 Cross validation for equation 5.2. The average of the parameters from the twelve holdouts yields equation 5.2, $BGB = 0.048 \times dbh^{2.303}$. The intercept (a), scaling exponent (b), standard error of estimates (se) and coefficient of determination (R^2) are provided

Holdout	a	b	SEE(a)	SEE(b)	R^2
holdout 1	0.050	2.291	0.198	0.059	0.959
holdout 2	0.039	2.360	0.192	0.057	0.962
holdout 3	0.048	2.299	0.203	0.060	0.958
holdout 4	0.048	2.303	0.201	0.060	0.960
holdout 5	0.050	2.290	0.202	0.060	0.958
holdout 6	0.049	2.293	0.202	0.060	0.959
holdout 7	0.048	2.301	0.204	0.061	0.958
holdout 8	0.051	2.276	0.198	0.059	0.959
holdout 9	0.042	2.332	0.192	0.057	0.964
holdout 10	0.048	2.302	0.194	0.058	0.963
holdout 11	0.049	2.294	0.203	0.061	0.958
holdout 12	0.049	2.294	0.203	0.061	0.958
Average	0.048	2.303	0.199	0.059	0.960

Appendix 5.4 Cross validation for equation 5.3. The average of the parameters from the twelve holdouts yields equation 5.3, $BGB = 0.024 \times rcd^{2.283}$. The intercept (a), scaling exponent (b), standard error of estimates (se) and coefficient of determination (R^2) are provided.

Holdout	a	b	SEE(a)	SEE(b)	R^2
holdout 1	0.026	2.260	0.354	0.095	0.924
holdout 2	0.026	2.255	0.356	0.096	0.922
holdout 3	0.026	2.258	0.366	0.098	0.916
holdout 4	0.026	2.252	0.364	0.098	0.917
holdout 5	0.026	2.263	0.362	0.098	0.917
holdout 6	0.026	2.258	0.367	0.098	0.915
holdout 7	0.025	2.268	0.369	0.099	0.915
holdout 8	0.009	2.521	0.277	0.074	0.940
holdout 9	0.025	2.265	0.360	0.097	0.921
holdout 10	0.025	2.268	0.357	0.096	0.927
holdout 11	0.026	2.260	0.342	0.092	0.929
holdout 12	0.025	2.268	0.369	0.099	0.915
Average	0.024	2.283	0.354	0.095	0.921