UPSCALING THE ASSESSMENT OF BIOPHYSICAL FOREST PARAMETERS FROM HIGH TO MEDIUM RESOLUTION SATELLITE IMAGERY IN KAZIMZUMBWI FOREST RESERVE, COASTAL REGION, TANZANIA

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by

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Thesis submitted to the International Institute for Geo-information Science and Earth Observation in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation, Specialisation: Forestry for Sustainable Development

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I dedicate this Thesis to my lovely family

Abstract

Forests actively contribute to the world's environmental stability and are used as economic resources to produce subsistence and industrial forest products. Remote sensing has been considered a low cost approach suited to broad scale forest inventory. Estimation of forest stand parameters such as biomass, stocking density, average crown diameter and species by group in a large area using remotely sensed data has considerable contribution to sustainable management and utility of natural resources. Biophysical forest properties have most commonly been estimated from remotely sensed data through use of vegetation indices. The objective of the study was to find the possibility of upscaling high to medium resolution imagery using Quickbird and ASTER images respectively. Ground field inventory revealed above ground biomass of 15.8 tonnes.ha^{-1}, 4135 stems.ha^{-1}, and basal area of 6.49m^2.ha^{-1}. Afzelia quanzensis was found to dominate the forest with 1186 stems.ha^{-1}(28.7%). Crown diameter from multi resolution segmentation performed in high resolution imagery found relationships between dbh and biomass measured in the field for all trees in general, *Albizia petersiana*, *Afzelia quanzensis* and *Brachystegia boehmii*. It was not possible to perform upscaling from high to medium resolution imagery using spectral characteristics. Results from the relationships between Normalized Difference Vegetation Index (NDVI) from Quickbird image to Aster image were poor; R^2 =0.1. Enhanced Vegetation Index (EVI) extracted from both images was also poor; R^2 = 0.14. Differences in cell size between high resolution imagery (Quickbird) and medium resolution imagery (ASTER) contributed to failure. The Quickbird cell size does not present full object while the ASTER present full object(s).

Key words: upscaling, multi-resolution segmentation, crown diameter, biophysical forest parameters, medium resolution imagery, miombo woodlands

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1. INTRODUCTION

1.1. Background

1.1.1. Forest roles on environment

Forest is defined as "Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use."(FAO, 2005; FAO, 2006) (See also http://www.fao.org/forestry/53459/en/.).

Forests actively contribute to the world's environmental stability and are used as economic resources to produce subsistence and industrial forest products. In addition, they have cultural and recreational value. They perform multiple roles, such as preventing soil degradation and erosion, protecting watersheds or stabilizing mountainous areas. They limit the greenhouse effect contributing to global warming; by absorbing CO_2 (the main greenhouse gas), inversely, forest degradation increase CO_2 emissions (Patenaude *et al.*, 2004)

Forests serve as natural habitats to almost two thirds of all Earth's species, therefore acting as a strong hold to safeguard biodiversity. On an economic level, forests may be used as direct source of energy or raw materials. Finally, forests play a cultural role in almost all societies, as mythical sceneries or historical backgrounds and as living habitats for about 60 million people worldwide; indigenous and non-indigenous (FAO, 2005).

Currently, there is a growing interest in biomass studies due to increasing recognition on the contribution of forests in the global carbon cycle. Forests play an important role in carbon cycle as they dominate the terrestrial vegetation which exchange CO_2 and O_2 with the atmosphere through photosynthesis and respiration. Carbon absorbed by plants is transformed into carbohydrates that are then stored in plant tissues during growth forming a component of plant biomass (Patenaude *et al.*, 2004; Samalca *et al.*, 2007).World's greatest concern on CO_2 is an understanding of global carbon cycle been one of the fundamental steps in addressing green house gases (GHG) (Fig 1-1). Understanding how forest ecosystems perform this important function, requires better and frequent quantification of its structure. In addition, estimation of forest structural attributes, such as aboveground biomass, is an important step in identifying the size of terrestrial carbon pools (IPCC, 2001; Drake *et al.*, 2002).

Carbon dioxide (CO_2) is the most important anthropogenic Green House Gases (GHG). Its annual emissions have grown between 1970 and 2004 by about 80% from 21 to 38 Gigatonnes (Gt), and representing about 77% of total anthropogenic GHG emissions in 2004. The rate of growth of CO_2-eq emissions was much higher during the recent 10-year period of 1995-2004 (0.92 $GtCO_2$-eq per year) than during the previous period of 1970-1994 (0.43 $GtCO_2$-eq per year) (IPCC, 2007). According to

FAO (2005) forest is estimated at 3952 million hectares which is approximately 30% of the total land, decreasing by 6 million each year due to selective logging, deforestation and other human related activities. Forests are the most widely distributed ecosystem on the earth, affecting the lives of most humans daily, either as an economic good or an environmental regulator.

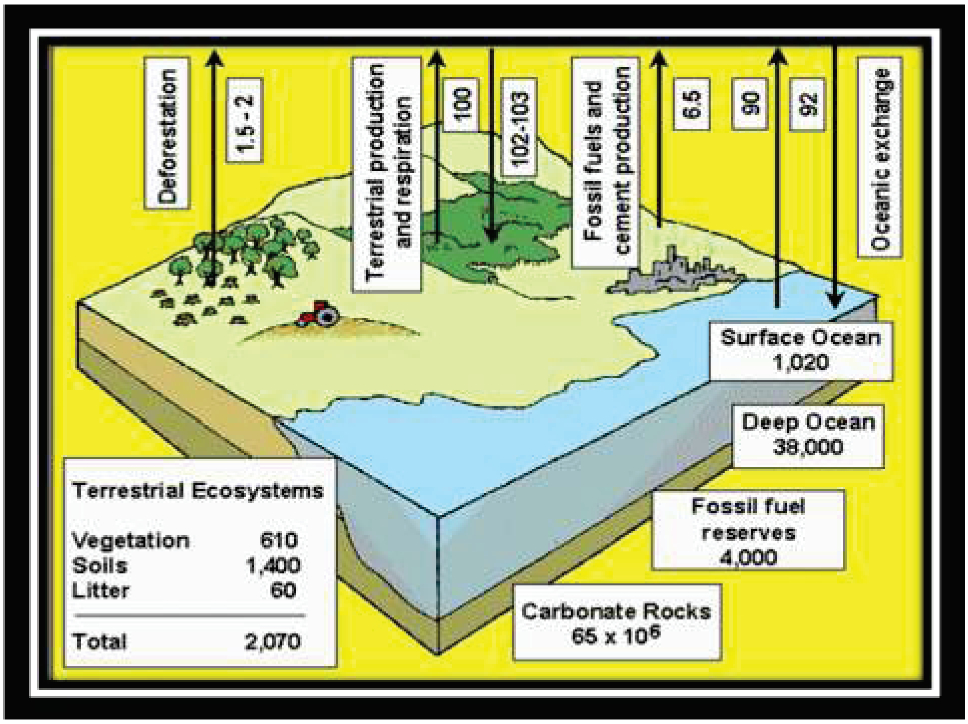

Figure 1-1: Carbon pools and CO_2fluxes between the earth and the atmosphere
Source: Edinburgh Centre for Carbon Management (http://www.eccm.uk.com/climate.htm)

Remarkable point of concern which has negative effects on forests is rapid population growth leading to increased demand for land and forest resources. Human demand for fuel wood, charcoal production and construction materials from miombo woodlands makes it amenable to rapid changes (Aguma *et al.*, 2002; Mutanga *et al.*, 2004; Backeus *et al.*, 2006). In Tanzania, declining of miombo woodland is mainly contributed by charcoal production, declining fallow periods in shifting cultivation, keeping animals above carrying capacity and casual burning (Isango, 2007). This leads to reduction in forest cover and hence its biomass production. Other main reasons affecting forests are selective harvesting of valuable timber, clear cutting for cultivation, selective harvesting of wood fuel, building material, medicines by local communities, seasonal fire, grazing and browsing and industrial scale of fuel wood for curing of tobacco (Pearce and Gumbo, 1993)

Forestry has long been and will likely always be a worldwide societal concern with issues that require appropriate attention by government policy makers to ensure conservation, meeting the demand for forest resources and preservation for future generations.

1.1.2. Remote sensing as a tool to monitor forest

Remote sensing is defined as "Detection, recognition or evaluation of objects by means of distant sensing or recording devices" (Franklin, 2001; Kerle *et al.*, 2004). Knowledge of remote sensing facilitates data collection and analysis method to forest management practices when integrated with spatial and non spatial data forming the basis for decision making (Franklin, 2001). Good management of forest resources need reliable and on time information of their status (Kayitakire *et al.*, 2006). Remote-sensing instruments allow for the collection of digital data through a range of scales in a synoptic and timely manner.

The use of remotely sensed images allows for the mapping of large areas efficiently and in digital manners that ease accuracy assessment and integration with geographic information systems. Availability and accuracy of the information obtained from the images depend entirely on the resolution which is a quality of any remote sensing image and can be referred to as the ability on the sensor of any system to acquire image data with specific characteristics (Franklin, 2001).

Resolutions can be grouped as spectral, spatial, temporal and radiometric resolutions. Franklin (2001) and Aplin (2006) defined spatial resolution as the projection of the detector element through which the sensor optics within the sensor instantaneous field of view, the higher the spatial resolution; the higher the ability to detect smaller objects. Generally it was explained as the spatial details of remotely sensed imagery (Aplin and Atkinson, 2001; Aplin, 2006). High spatial resolution imagery is the one with ground pixel size of less than 5m. Examples of images with high spatial resolution are IKONOS EROS A EROS B QuickBird SPOT-5 (Kayitakire, 2006). High resolution satellite images provide an opportunity to access information about individual trees in the tropical forest (Garzelli and Nencini, 2006; Lu, 2006; Gomes and Ferreira, 2007). Imagery at high spatial resolution provides greater spatial details which allow delineation of small features than courser spatial resolution imagery. The reason behind is that in high resolution case, earth surface varies at lower spatial frequency than image sampling and features can be resolved while for the low resolution, variability of earth's surface is at higher spatial frequency than imagery sampling (Aplin, 2006; Wulder *et al.*, 2008).

Estimation of forest stand parameters in large area using remotely sensed data has proved to be efficient in providing important data for sustainable management of natural resources. Using high resolution satellite imagery such as IKONOS or QUICKBIRD, it is possible to extract biophysical properties of individual trees e.g. stocking density, average crown diameter and species by group (Dial *et al.*, 2003; Lu *et al.*, 2004). The ability to extract such parameters quickly diminishes with lower-resolution imagery when pixel spacing is increasing (Woodcock *et al.*, 1988; Pouliot *et al.*, 2002).
High resolution reported used to quantify assessment of boundaries of automated forest stand delineation (Woodcock, 2006; Radoux and Defourny, 2007), delineation of tree crowns using high spatial resolution remotely sensed imagery where minimal and maxima were used as primary feature for the delineation process (Culvenor, 2002) and detecting single tree (Hirschmugl *et al.*, 2007). Wulder (2002) reported possibility of extracting tree location and basal areas within a minimum distance of 1.5m crown diameter been identified as reliable for tree location using high resolution imagery. High resolution imagery have been used in the extraction of spatial pattern of forest stands when utilizing local variance of stimulated high spatial resolution (Coops and Culvenor, 2000). When using multi-scale filtering and non-parametric classification, high resolution imagery has enabled extraction of urban trees with high accuracy (Ouma and Tateishi, 2008). However, high resolution imagery has a drawback of oversampling leading to variation within features which results into error in feature identification (Aplin and Atkinson, 2001; Aplin, 2006). Application of high spatial

resolution is bottlenecked by having high variation and shadows caused by canopy and topographic which may create difficulty in developing model for above ground biomass (AGB) estimation, lack of shortwave infra red image which is often important to AGB estimation, further more it needs more time to implement data analysis than medium spatial resolution but also is expensive in terms of image purchase (Lu, 2006).

Combinations of spectral and spatial information extraction techniques are promising for increasing the accuracy of estimates of forest inventory and biophysical parameters. (Wulder, 1998). Accordingly, a variety of image-processing techniques have been developed for the estimation of forest inventory and biophysical parameters from remotely sensed images for example, Landsat, ASTER, QUICKBIRD, IKONOS, SPOT (Aplin and Atkinson, 2001; Xu *et al*., 2003; Muukkonen and Heiskanen, 2007; LeMay *et al*., 2008).

Medium spatial resolution on the other hand, ranges from 10 to 100 m (Lu, 2006). At local and regional scale Landsat data have been frequently used to estimate biomass (Foody *et al*., 2003; Lu *et al*., 2004; Lu, 2006). Problems facing estimation of biomass using medium spatial resolution reported as saturation of canopy reflectance when above ground biomass(AGB) reaching 15kg.m^{-2} (Lu *et al*., 2004) and complex forests impacts shadows caused by canopy and topography (Steininger, 2000; Lu *et al*., 2004). As forests are a complex and widely distributed ecosystem, remote sensing provides a valuable means of monitoring them but remote sensing still requires field data for verification.

1.1.3. Object oriented image analysis

Forests with complex structure vary with dimension and reflectance characteristics, have also shadows between tree crowns a problem which delineation needs special attention (Bunting and Lucas, 2006). Object oriented image analysis can be used to support this extraction by splitting the image into zoned partial series of different characteristics known as image objects which can be classified according to the criteria set (Baatz *et al*., 2000; Leckie *et al*., 2003; Gitas e*t al*., 2004; Gamanya *et al*., 2007; Kellenberger and Bühler, 2007; Lamonaca *et al*., 2008). Information contained in relationship between adjacent pixels including texture and shape information allows identification of individual object as opposed to single pixels (Thomas *et al.*, 2003). Segmentation of individual crowns as objects leads to better classification when object oriented classification is used (Baatz *et al*., 2000; Atzberger, 2004; Benz *et al*., 2004; Wang *et al*., 2004; Kimani, 2005).

1.1.4. Relationship between biophysical forest parameters with spectral characteristics

A wide range of vegetation indices have been used in remote sensing for the estimation of biomass of tropical secondary forests resulting in significant relationship between middle infrared and stand age, height, volume and biomass (Steininger, 2000; Foody et al., 2003; Mutanga et al., 2004). The measured and predicted biomass from vegetation indices differ markedly from one site to another hence not transferable. (Foody *et al*., 2003). NDVI; the mostly used vegetation indices related to aboveground biomass across spatial, temporal and ecological scales for relatively long time scales (Dong *et al*., 2003). Other exploratory and analytical methods like regression models can be used to predict structural parameters for tropical forest for example above ground biomass and carbon stocks for a given value of spectral characteristics (Chidumayo, 1988; Chidumayo, 1990; Gougeon, 1995; Dong *et al*., 2003; Couteron *et al*., 2005). Spectral characteristics have the disadvantages when estimating forest parameter. Lu (2004) reported vegetation indices sensitive to internal factors such as canopy geometry, terrain factors and species composition that greatly affect reflectance. External factors affecting vegetation indices are sun elevation, zenith angle and atmospheric conditions (Lu *et al*., 2004)

1.1.5. Research problem and justification

Tanzania has a total area of about 94.5 million ha out of which about 88.6 million ha is covered by landmass and the rest (5.9 million ha) is for inland water (FAO, 2005). Out of total land area, forests and woodlands cover about 38% (≈33.5 million ha) while about 3% arable land, 40% is under permanent crop land and the rest (19%) is left for other land uses (FAO, 2001). About 13 million ha out of the forested land has been set aside as permanent forest reserves under the central government managed for either productive or protective purpose (URT, 1998; Malimbwi *et al*., 2005).

Protective forests for catchment and biodiversity functions occupy about 1.6 million ha, a relatively small area compared to total forestland area (Malimbwi *et al.*, 2005). In spite of their relatively smaller area, catchment forest reserves are undoubtedly valuable in Tanzania. Forest policy stipulates that forest reserves are supposed to be managed for production and/or protection purposes based on approved management plans (URT, 1998). According to the national land covers and land use reconnaissance carried out, miombo woodlands cover 374 356 km^2 equivalent to 93.2% of total forest area of Tanzania (Mnangwone, 1999; Isango, 2007).

Miombo woodland of Tanzania is facing management problems which make it amenable to rapid changes. Those management problems are related to policies and practices, lack of resource data bearing in the fact that data collected from indigenous forest take more part on industrial wood, lack of experts particularly on forest inventory and the problem of forest fires (Pearce and Gumbo, 1993).
Furthermore, accurate information on the management of miombo forests is of important. FAO (2005) reported that Tanzania as among ten countries with largest forest net loss per year between the year 2000 to 2005. Other countries are Brazil, Indonesia, Sudan, Myanmar, Zambia, Nigeria, Democratic Republic of the Congo, Zimbabwe; Venezuela (Bolivarian Republic of) had a combined net forest loss of 8.2 million hectares .$year^{-1}$.

Estimation of forest stand parameters such as biomass, stocking density, average crown diameter and species by group in a large area using remotely sensed data has considerable contribution to sustainable management and utility of natural resources (Lu *et al*., 2004; Mabowe *et al*., 2006). This is because; sustainable management of natural forests depends on information available on the growing stock. Acquisition of forest growth information is a prerequisite for any forest management system and sustainable land use (Chamshama *et al*., 2004). For that purpose, a ground forest inventory was traditionally carried out to establish the status of the forest with regard to stand structure, species composition and regeneration (Lu, 2006). However, the traditional forest inventory is high demanding not only in terms of field work, manpower, cost and time but also limited to a small area (de Gier, 1989; Kasischke *et al*., 1997; de Gier, 2003; Couteron *et al*., 2005; FAO, 2006; DeFries *et al*., 2007).
Application of remote sensing has been used when large area is to be covered. Usually high to medium resolution imageries have been used to detect different forest categories and combined with ground trusting data for the estimation of forest parameters such as biomass and volume (Foody *et al.*, 2006; LeMay *et al.*, 2008).

Predicting stand parameters for tropical forests from remotely sensed data has numerous important applications, such as estimating above-ground biomass and carbon stocks and providing spatial information for forest mapping and management planning, as well as detecting potential ecological determinants of plant species distributions (Defries *et al*., 2000; Drake *et al*., 2002; Couteron *et al*., 2005; Samalca *et al*., 2007). FAO (2005) defined above ground biomass as “All living parts above the soil including stem, stump, branches, bark, seeds, and foliage”. Application of remote sensing and geographical information system will support analysis and assessment for better management of our forests.

Lu (2006) argued that biomass estimation remains a challenging task, especially in those study areas with complex forest stand structures and environmental conditions. The use of optical sensor data or radar data is more suitable for forest sites with relatively simple forest stand structure than sites with complex biophysical environments. However, a combination of spectral responses and image textures improves biomass estimation performance.

Object-oriented processing techniques are becoming more popular compared to traditional pixel-based image analysis (Gamanya *et al.*, 2007; Su *et al.*, 2008) and by delineating crowns which in mixed forest by the use of image segmentation techniques for high resolution imagery (Atzberger, 2004; Bunting and Lucas, 2006; Definiens, 2006; Wuest and Zhang, 2009). The pressing need is to improve precision, accuracy, timeliness, completeness and cost effectiveness of forest information. Budgetary constraints force to opt for more innovative methods by analyzing information from high resolution images in order to produce individual tree based tree forest inventories.

In Tanzania, few biomass studies using ground work inventory have been done for the Eastern Arc Mountain forests (Munishi and Shear, 2004) and for the miombo woodlands around Kitulangalo area (Malimbwi *et al*., 1994). Upscaling of these studies has been limited due to lack of resources and man power. Otherwise, application of remote sensing techniques, with an advantage of high spatial coverage has not yet been fully explored in miombo woodland of Tanzania.
This study tested the correlation between high and medium resolution satellite imagery spectral characteristics for the possibility of upscaling the later for biomass and number of stems estimations in the region and country as a whole. This is expected to be a cost effective approach since the application of high resolution imageries to cover a large area is at present very expensive and not often available.

1.2. Objectives

1.2.1. Main objective

The overall objective of this study was to test the possibility to upscale assessment of biophysical forest parameters from high to medium resolution satellite imagery in miombo woodlands of Tanzania.

1.2.2. Specific objectives

1. To assess how accurate crown diameter and stem count can be derived from high resolution imagery in miombo woodland of Tanzania.

2. To assess how accurate crown diameter and stem count derived from high resolution imagery can estimate biophysical forest parameters.
3. To assess the accuracy with which these forest stand parameters derived from high resolution satellite imagery can be correlated with spectral information in lower resolution imagery.

1.2.3. Research Questions

1. How accurate can crown diameter and stem count be derived from high resolution imagery in the miombo woodlands of Tanzania?
2. How accurate can biomass be estimated with crown diameter and stem count extracted from high resolution imagery?
3. How strong is the correlation between forest stand parameters derived from high resolution satellite imagery and spectral information in medium resolution imagery?

1.3. Research approach

During the entire research, the following research flow pathway was followed (fig. 1-2)

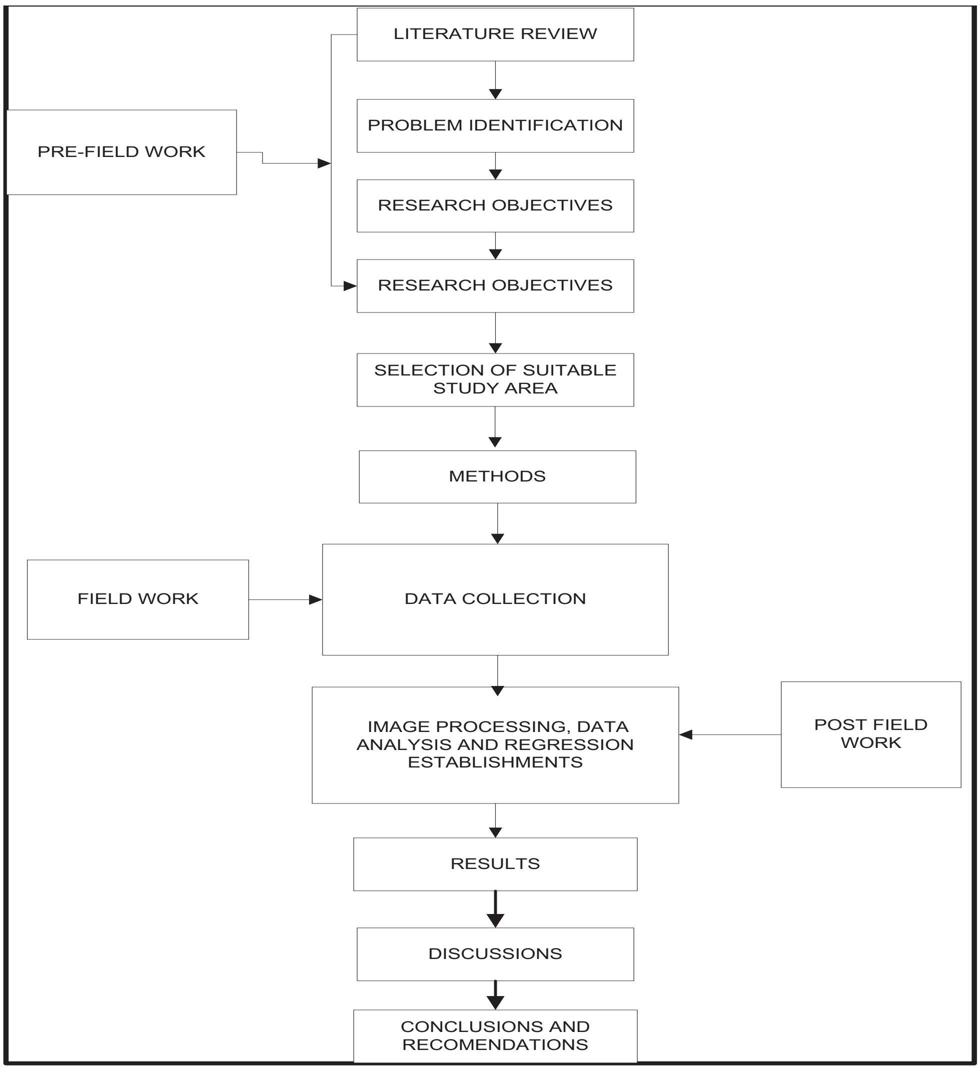

Figure 1-2: Research flow pathway

1.4. Method flow Pathway

The following (Fig 1-3) method flow pathway was followed in order to answer research questions and meet study objectives

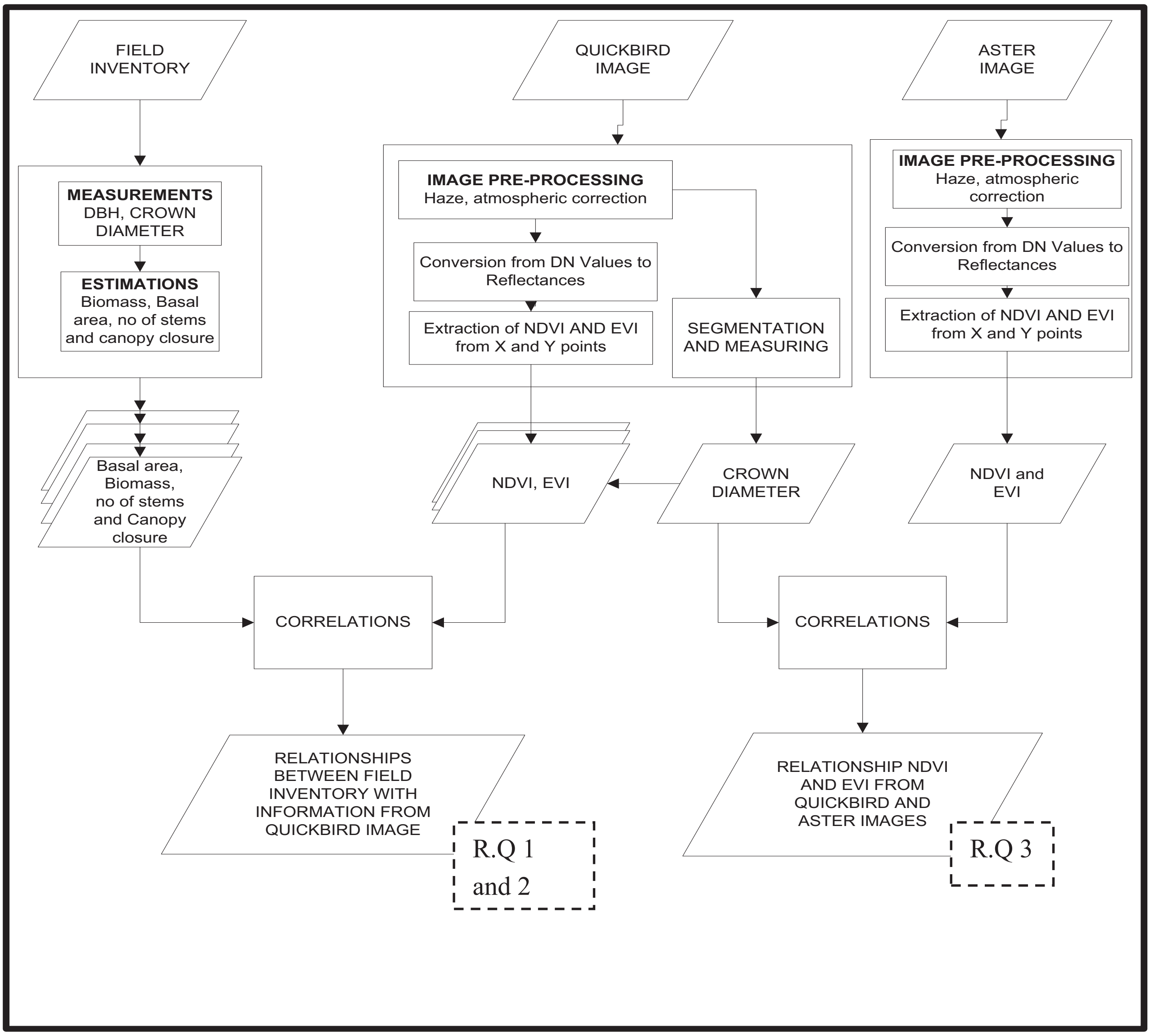

Figure 1-3: Research flow path

R.Q = Research Question

2. METHODS AND MATERIALS

2.1. Description of the study area

2.1.1. Selection of the study area

Kazimzumbwi Forest Reserve with a total area of 4,862.5 ha was selected for the study. The forest reserve was selected for two reasons: Firstly, it composed of miombo woodlands (488 ha) which is the main type of woodland in Tanzania (URT, 1998); the rest is occupied by closed forests composed of trees with multi-story canopy strata. Secondly, availability of Quickbird images of good quality to extract spectral characteristics. Unsupervised classified image of Kazimzumbwi Forest Reserve clearly distinguished the forest reserve in two strata based on vegetation types. These are closed forests composed of trees with multi-storey canopy strata and open woodland with scattered trees. The study concentrated on the woodland stratum (488 ha) with open canopy where the biophysical properties of single tress could be easily measured. According to the inventory report (Malimbwi *et al*., 2005) it was revealed also that the area is moderately flat.

2.1.2. Role of the miombo woodlands in climate change problem

Kazimzumbwi Forest Reserve being one of the miombo woodlands, can provide important information which if upscaled to vast area of miombo in the country can help the management of natural forests which in turn can help mitigate the emissions impacts to the climate.
Forests have four major roles in climate change: they currently contribute about one-sixth of global carbon emissions when cleared, overused or degraded; they react sensitively to a changing climate; when managed sustainably, they produce wood fuels as a benign alternative to fossil fuels; and finally, they have the potential to absorb about one-tenth of global carbon emissions projected for the first half of this century into their biomass, soils and products and store them - in principle in perpetuity (FAO, 2009).

In the event that substantial areas of miombo are cleared for cereal crop agriculture, 6 to 10 Pg of C could be released. On the other hand, if the woodlands are managed to maximise carbon storage, a similar amount could be taken up. In both cases, about half of the change in carbon stocks occurs in the soil, and the rest in the biomass. Net primary production in miombo woodlands is 900-1600 g m^{-2} yr^{-1} (Chidumayo *et al*., 1996; Frost, 1996). Composition of miombo woodlands appears to be relatively uniform over large regions suggesting a broad similarity in key environmental conditions. (Frost, 1996).

The annual increment of the woody-plant biomass is no more than 3-4% in mature stands. These rates, which define the upper limit of the sink strength, could increase slightly under an atmosphere high in carbon dioxide, but given the pervasive nutrient limitations, an increase in net primary production of greater than 15% is unlikely. Well-managed tropical pastures in comparable environments in South America can have a high carbon density, especially if the roots are deep (Fisher *et al*., 1994; Frost, 1997). (http://www.geog.psu.edu/geclab/miombo/igbp41.htm)

2.1.3. Ownership and Surrounding Communities

Forest in Tanzania can be distinguished into four groups based on the ownership: Private, Village, Local Authority and Central Government Forest Reserves (URT, 2002). Kazimzumbwi forest reserve were the study was conducted is owned by Central Government. The forest is surrounded by six villages namely: Buyuni, Chanika, Kisarawe, Kazimzumbwi, Maguruwe and Kisanga. These villages are found in Msongolo and Masaki wards, Sungwi and Msongola Divisions, Kisarawe/Ilala districts. The forest occupies and area of about 4,862. ha (Stubblefield, 1994; Malimbwi et al., 2005). Kazimzumbwi among the four forest reserves in the district. Other forest reserves are Pugu (2410 ha), Masaganya (2,899 ha) and Ruvu South Forest Reserve (25,000 ha).The district has village forest reserves of Chakenge and Kisanga with 316 ha and 101 ha respectively. Another forest type present in the district is forest in General land of Gwata Kidunda (1,911), Gwata Mzenga (75,200) Kihare Marui(60,000 ha) and Vikumburu (57,000ha)(Malimbwi *et al*., 2005)

Kazimzumbwi FR and the neighbouring Pugu FR include part of what was once a much larger forest extending to within 10km from Dar es Salaam. According to the original gazetted map, Pugu and Kazimzumbwi forests were contiguous in 1956, but were separated in 1968. The close proximity of Kazimzumbwi FR to Dar-es-Salaam and its outlying populations mean that the forest reserve is under significant resource use pressure from local communities that are dependent on it. In recent years high intensity resource use has led to conflict between forestry officials and local communities (Hall *et al*., 2004).

2.1.4. Mapping Information

Kazimzumbwi forest reserve is shown on a border map of scale1: 25,000 of the year 1962 and also on a topographic map of a scale 1:50,000, sheet name 186/3 Kisarawe of the year 1987. Kazimzumbwi forest Reserve was gazetted in 1954 by R.L. Hopper during the colonial period. In the beginning, it was primarily a productive forest reserve and the intention was to support the growing Dar es Salaam with timber, building poles and firewood. Later in the 1980’s the Ministry of Natural Resources and Tourism (MNRT) stopped the harvesting licences in the forest (Malimbwi *et al*., 2005).

2.1.5. Location and Topography

The forest is located between Lat/Long: $6^o55'$ – 7^o00 S, $39^o01'$ – $39^o05'$ E. Altitude ranges from 110 to 214 meters above sea level on a relatively flat terrain. Kazimzumbwi Forest Reserve located 2 km away from Kisarawe Township and can easily be accessed by roads and pathways. Kazimzumbwi Forest Reserve is about 20 km South West of Dar-es Salaam which is the capital city of Tanzania. (Fig 2-1)

2.1.6. Physical features

The area has red to brown sandy-clay soils overlaying kaolinitic sandstone; with a pH range 5-6 predominant. One permanent stream drains from the forest reserve and provides a water supply to some of the local people. In the past (when forest was more extensive on the Pugu Hills) streams draining from the area used to supply water to Dar es Salaam.

2.1.7. Rainfall

Kazimzumbwi FR is influenced by tropical East African oceanic temperatures that are slightly modified by altitude. Data from nearby weather station at Kisarawe shows that, the average annual rainfall for the area is 1,236 mm. The rain season is usually from November to March after a long dry season from April to October (Stubblefield, 1994).

2.1.8. Vegetation

The Forest Reserve encompasses a diverse assemblage of vegetation communities and rich floral and faunal species diversity. The reserve comprises a mosaic of closed dry forest, Brachystegia forest, scrub, woodland, wooded grassland and riverine/swamp forest. Miombo woodland tree species important for timber including *Afzelia quanzensis*, *Manilkara sasbarensis* and *Brachystegia boehmii* dominate the area (Malimbwi *et al*., 2005).

White (1983) reported that out of 190 recognized forest tree species in the coast region, 91 are endemic to the area. The relatively low number of forest dependent species, and subsequently high number of ecological generalists, is thus to be expected (Stubblefield, 1994; Clarke and Dickinson, 1995).

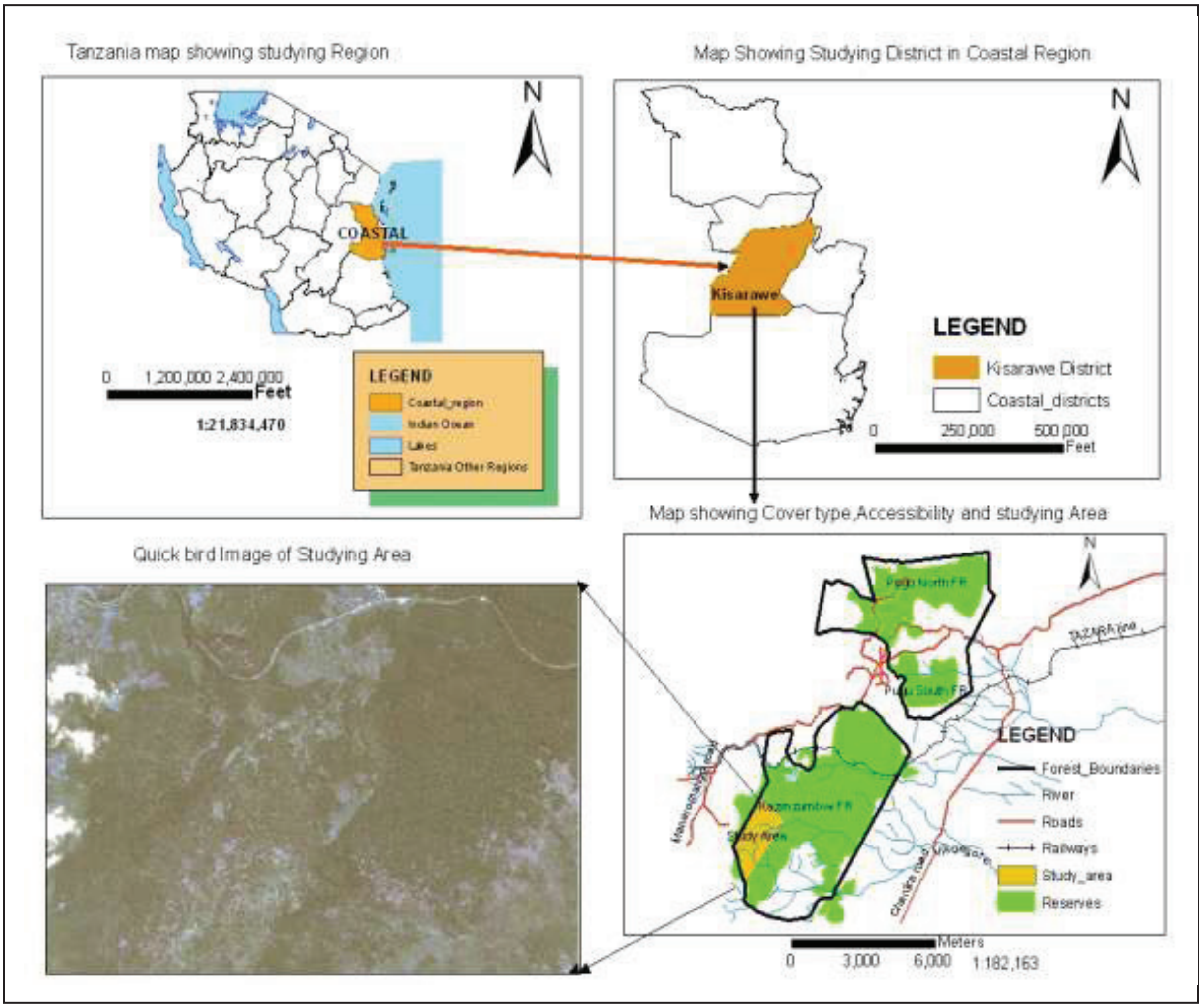

Figure 2-1: Location of study area within Kazimzumbwi Forest Reserve in Coastal

2.2. Method

2.2.1. Data collection

2.2.1.1. Secondary data collection

Secondary data were collected from institutions, individual and government offices.

- The data collected from Mensuration Department, Sokoine University of Agriculture Morogoro was used to prepare 3rd order polynomial equation.The equation was not biased estimated biomass hence used to estimate biomass in the study area. (Appendix 1).
- Forest description and boundaries data was obtained from the office of District Natural Resources Officer Kisarawe District, Manager of Kazimzumbwi Pugu and also from the consultants who prepared the report inventory of Coastal Region 2005
- Forest topographic map was obtained from International Institute for Geo-Information Science and Earth Observation (ITC). The Topographic map was used to digitize study area with other vector data e.g. roads, rivers, railway line, forest reserve boundary and description of the study area. It was also used in the field to locate forest boundaries and other features during data collection activity
- List of trees in vernacular names and Botanical names was obtained from District Natural Resources Officer Kisarawe, Manager Tanzania Tree Seed Agency and the consultants who prepared the report inventory of Coastal Region 2005. This list enabled the changing of all vernacular names given by local tree identifiers to known Botanical names (Appendix 2)
- Equation for calculating crown diameter of the trees was obtained from the website http://www.murderousmaths.co.uk/books/BKMM7xea.htm retrieved on 24 October 2008. Crown diameters of the individual trees were calculated assuming they have an ellipsoidal area.
- ASTER image downloaded from ASTER website (http://glcf.umiacs.umd.edu/data/aster/), while Quickbird image was supplied by "Kyoto Project; Think Global Act Local."

2.2.1.2. Primary data collection

Ground measurements were important in 'calibrating' the products for high resolution imagery which were then aggregated to Aster resolution. Field data was necessary for conventional biomass estimation within the forest (FAO, 2001).

2.2.2. Sample plot measurements

The composition of miombo woodlands appears to be relatively uniform over large regions suggesting a broad similarity in key environmental conditions (Frost, 1996). Composition of miombo can be looked up in terms of stand structure composition and richness. Forest stand structure can be described as the distribution of species and tree sizes in a forest area (Husch *et al*., 1982). Structure has been also defined as the distribution of trees by diameter classes. Composition is the assemblage of plant species that characterize the vegetation (Martinez Morales *et al*., 2008). The most common measure of composition is richness (the number of different species) and abundance (the number of individuals per species found in specified area). Sample plot measurements are a prerequisite to determine the sampling level within a study area.

The idea of the random points was generated to quickbird image by using arc tools in Arc Map. Randomization was made in such a way that it was possible to cover all variation in the entire study area. Garmin Global Positioning System (GPS) receiver which was set in Universal Transverse Mercator Projection system was used to locate the plot centres generated in the field (Fig 2-2).

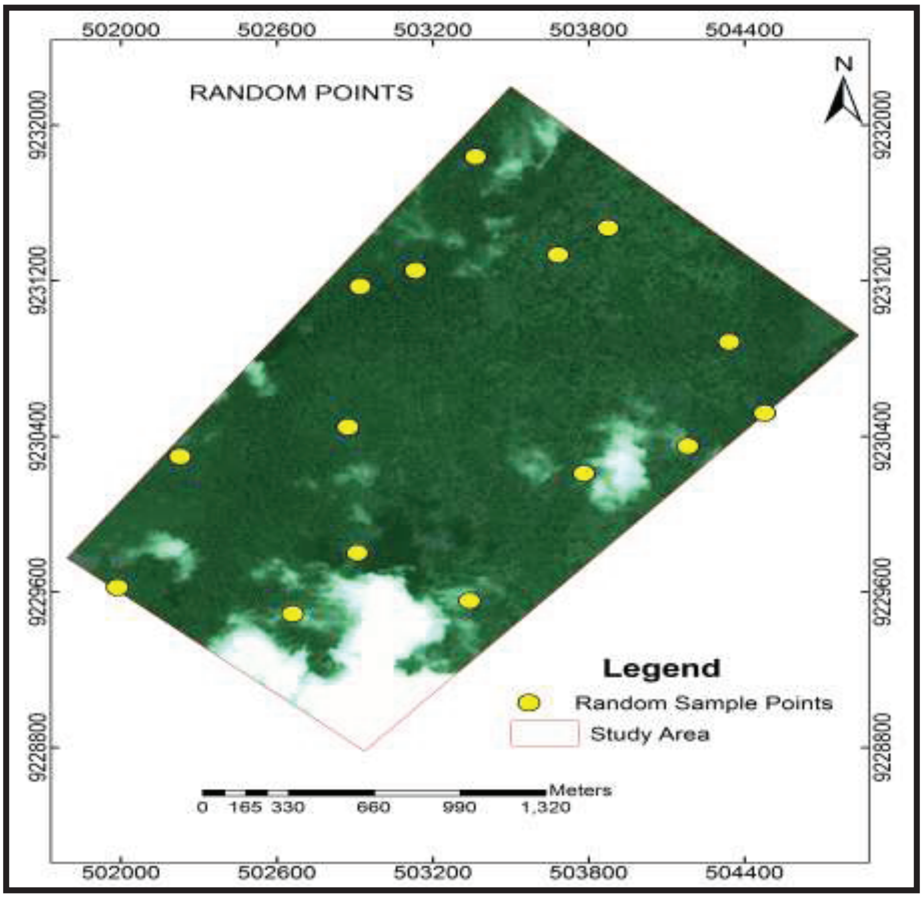

Figure 2-2: Distribution of Random points for the sample plots

Circular concentric plots with varying radii were laid in the forest reserve, the following data were collected:

- within 2 m radius: all trees 1 < dbh < 5 cm was measured,
- within 5 m radius: all trees 5.1 < dbh < 10 cm was measured,
- within 10 m radius: all trees 10.1 < dbh < 15 cm was measured,
- within 15 m radius: all trees >15.1 cm dbh was measured.

The same shape and size of plots was used in the National Inventory in Tanzania (Haule and Munyuku, 1994) and other inventories done in other parts of the country within same type of woodland. (Nduwamungu, 1996; Malimbwi and Mugasha, 2000). Circular plots were chosen in respect to other types of plots due to the fact that are easy, quick to lay in the field and determination of trees inside the plot is less problematic (de Gier, 1989; de Gier, 2003). Also a single dimension which is radius can be used to define the perimeter and circular plots has no predetermined orientation (Husch et al., 2003). Error due to not observing plot boundary reported to be a major drawback of using circular plot (Husch et al., 1982; Husch et al., 2003). Other plots types which are not common to miombo woodland are square, rectangular plots and triangular plots.

2.2.3. Sampling units

In forest inventory, probability and non probability sampling designs have been applied which aim at making clear observation on population and giving estimates that are representative of a population. Systematic sampling was applied in this study because reported to be cheaper, provide reliable estimates of a population, travel between units is easy and faster (Husch *et al*., 2003).

For the actual inventory work the plots with similar shape and size as those used pilot survey was laid out systematically all over the selected area (Fig 2-3). In addition to dbh measurements crown diameters and of small, medium and large trees in terms of dbh were measured. Number of stems encountered in a plot was determined from dbh tally.

Then the number of sampling units (n) required to attain a desired precision at sampling allowable error (E) of 10% was given by:

$$n = \frac{CV^2 t^2}{E^2}$$

Where: CV = Coefficient of variation (standard deviation/mean)

t = this is a value of t obtained from n-1 degree of freedom of the pilot study at 10% probability level (Philip, 1983; Husch *et al*., 2003). From the above formula 28 sampling plots (n) were obtained for field measurement. Selection of number of plots were of sampling which probability of selecting a tree base on its basal area (Husch *et al*., 2003) (Table 1)

Table 1: Derivation of 28 sampling plot for field ground inventory

Plot no	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Basal area(m2/ha)	6.5	9.6	10.7	8.3	9.3	8.9	9.3	4.9	7.3	6.4	9.6	3.4	4.8	6.7	4.8
Mean	7.40														
Standard deviation	2.20														
C.V	0.30														
C.V2	0.09														
t2	3.09														
E2	0.01														
n	28.														

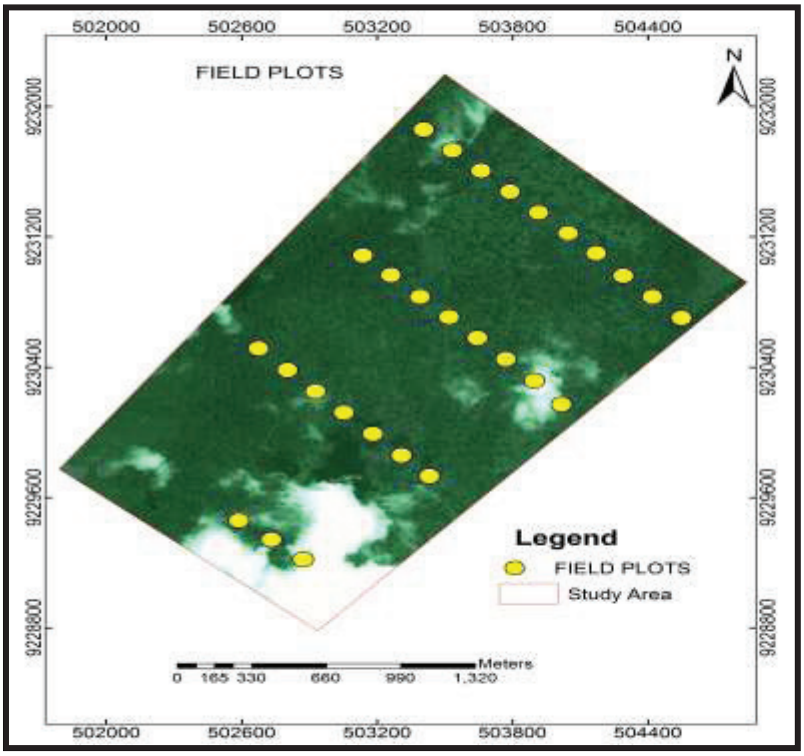

Figure 2-3: Distribution of sampling points on the study area

2.2.4. Number of transects

To find number of transects, one line across the longest distance on the study area was established. Four transects were laid across the longest distance as shown (fig 2-3). Distance from one transect to another was 750m. The first transect was laid half the distance between transects i.e. 375m from the north border of the study area as a precaution that trees near border reported to be somewhat different from those which are inside the interior forest (Husch *et al*., 2003).

2.2.5. Field measurements

Diameter at breast height (dbh) is the parameter related to most characteristics of the tree namely biomass, crown diameter leaf area index and volume (Gering, 1995; Bartelink, 1996; de Gier, 1999; de Gier, 2003; Lu *et al*., 2004; Pokharel, 2008). Dbh is one of the directly measurable dimension from which tree cross sectional area, surface area and volume can easily be computed (Husch *et al*., 2003). Dbh is applied to measurement from all types of trees including deciduous and coniferous trees (Getzin *et al*., 2008). All trees in the 28 plots, their dbh measured and recorded stipulated in sect 2.2.3. It applied also to the trees found solitary within and outside of the study area. Sources of error during measurements can be due to how measurements were taken, modelling and application of the entire equation (Cunia, 1986). To minimise errors in measurements, great care was taken to make sure that calliper oriented toward plot centre and second one perpendicular (de Gier, 1999). All diameter measurements taken were over bark and done by using tree diameter calliper.

Crown diameters play a key role mostly in determining important variables for wildlife habitat suitability, and index models. Ability to predict crown diameter from dbh provides a good estimate for crown diameter (Gering, 1995). Advantage of crown diameters is that it can be used to estimate dbh and tree volume which will help to know tree and forest health management (Husch *et al*., 2003).

Crown diameters for small, medium and large trees in the plot and individual trees found in solitary were measured for the crown diameters. Measurements were taken basing on the longest branch on both ends at right angle-recorded (k_1); another measurement perpendicular to it (k_2). By the use of measuring tape both were recorded in meters. To make sure that the end of the branches was taken appropriately, suunto hypsometer was used to check for the 900.

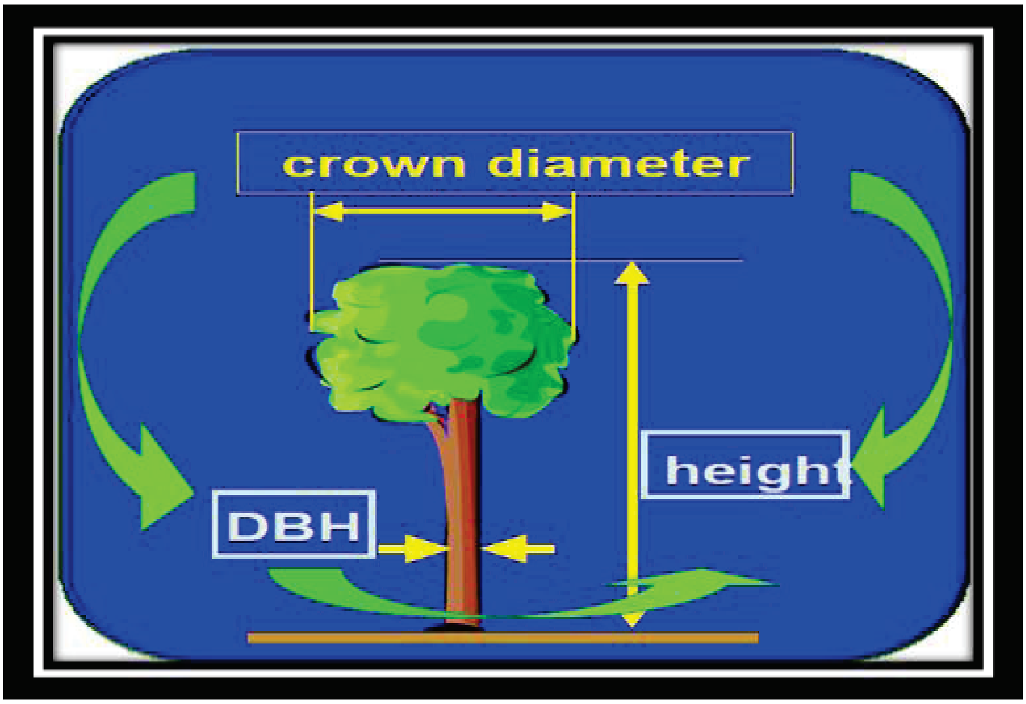

Figure 2-4: Measurements of crown diameter and dbh
Source: Adapted from (Hirata, 2008)

Coordinates for each plot centres for the sample plots, sampling units and individual tree coordinates was taken by the use of Garmin Global Positioning System (GPS) receiver set in Universal Transverse Mercator (UTM) 1984, Arc 1960 Country Zone 37 South of the Equator. To make better accurate measurements, after the GPS set on, sufficient time was allowed to acquired enough satellites and accuracy reading five or below.

Local names of all measured trees were recorded later translated to scientific names using available checklist compiled from previous studies at the area (Appendix 2). All readings was recorded in field form (Appendices 3 and 4) which were later transferred to an excel sheet in the computer. GPS coordinates of measured trees for crown and for plot centre was taken for later identification on the Quickbird and ASTER images.

Slope within the plots were measured in cases where it was suspected to exceed five percent. This was done through cross verification by taking measurements up and down the said slope by two enumerators standing at a distance of 30m through plot centre along the slope. For all slopes measured no slope which exceeded 5%, so less a need to use conversion tables for the plot areas. Slopes above five percent have an adverse effect on the plot size (de Gier, 1999).

3. DATA ANALYSIS

3.1. Introduction

The information obtained from the field was analyzed using regression model. Regression model is an empirical model which involves modelling and analyzing numerical (quantitative) data consisting of values of dependent and one or more independent variables. Regression models are also used to predict stand parameters such as percentage green vegetation cover, crown diameter and stand age (Gougeon, 1995; Cohen *et al*., 2001). A good model is determined by a number of factors such as index of fit, root mean square coefficient of determination and simplicity (Schroeder et al., 1997). Regression models have been used in miombo woodlands to estimate standing wood of miombo woodlands, yield re-growth and volume of fuel production and wood biomass (Chidumayo, 1988; Chidumayo, 1990; Malimbwi et al., 1994; Gering, 1995; Cohen et al., 2001; Chamshama *et al*., 2004; Couteron *et al*., 2005; Muukkonen and Heiskanen, 2005; Samalca *et al*., 2007; Heurich, 2008)

3.2. Estimation of Biomass using ground inventory

In order to estimate biomass for the established plots in the field, a mixed species equation was developed using weighted curvilinear regression technique aided by POLYREG program. Biomass estimation equation used in this study established from the data collected and oven dry from miombo woodland at Kitulangalo Forest Reserve in Morogoro Region Tanzania (Chamshama *et al*., 2004).

Third degree polynomial equation using dbh as an independent variable in most cases considered significant and unbiased (de Gier, 1999). Polynomial equation appear in the form $y= b_o +b_1x +b_2 x_2+ b_3x_3$; where y = dependent variable (estimated biomass in kg/tree), x= independent variable (dbh in cm) with regression coefficients b_1, b_2 and b_3 respectively. Before weighing, residual showed that they were not constant by forming a funnel like shape which variances were increasing as one moves along Y axis, so a need of weighing became of important. Equation was weighted because big trees do deviate more from the regression equation (de Gier, 1999; Parresol, 1999). During weighting 1^{st}, 2^{nd} and 3^{rd} order polynomial with backward elimination was used, x_1 variable was removed because of being non-significant (at 5% confidence level)

Biomass equation was established to enable estimation of the biomass kg/tree) of the sampling plots using individual trees measurement. Estimated biomass was used to correlate with spectral characteristics from high resolution imagery and medium resolution imagery.

3.3. Crown closure estimation from the ground inventory

Individual tree crown areas measured in the plot was summed up to get crown closure, which was the area covered by tree crowns. Total crown area was again divided by plot area in order to convert it to per hectare basis. The equation was used to determine the crown area of tree which was not measured.
Crown area was calculated by the formula
CA = $(\pi * k_1 * k_2)/4$; where: CA= crown area (m^2), π= constant (3.412) and k_1, k_2 = perpendicular lengths measured for crown respectively (m)
Crown closure = summation of crown area of individual trees in the plot/plot area

3.4. Number of stems estimation from the ground inventory

Number of stems was obtained from diameter tallies by using number of stems counted in each plot divided by plot size
Number of stems.ha-1= Total number of trees in each diameter class in a plot / Total area of sampled plot

3.5. Basal area (G)

Basal area (G) is the cross section area of the stem or stems of a plant or of all plants in a stand, generally expressed as square units per unit area. Stand Basal Area is a useful parameter in forest measurement because is relatively easily collected and can be related to many other parameters of interest for example, site density and stand volume. Tree basal is used to determine percent stocking (Nix, 1997). Mean stand basal area (G) is determined by totalling the basal area of each tree in the plot, and dividing by the area of the plot (Brack, 1997).
Basal area of trees within the plot was by summing the basal areas of individual trees calculated the formula
$G = \pi * D2 / 4*10,000$; where, G = Basal area (m^2/ha), π = constant (3.142), D = Diameter at breast height (cm).10000 corrects for the units from m^2 to hectare basis (1 ha = 10,000 m^2)

3.6. Crown diameter estimation using high resolution imagery

The QuickBird satellite collects both multi-spectral and panchromatic imagery concurrently and Pan-sharpened composite products in natural or infrared colours are offered. Strips of length up to 250 km in length can be collected in a single pass (Gomes and Ferreira, 2007).
The sensor records the reflected radiation from the Earth’s surface in the blue, green, red and near-infrared portions of the electromagnetic spectrum with a spatial resolution of 2.44 m (Table 2). In addition to these multispectral bands; has a panchromatic band with 0.61m spatial resolution. The pan-sharpened Quickbird data with 0.61m resolution offered by Digital Globe was used in this research, as the 2.44m resolution of multispectral bands alone was considered too coarse to detect the edges of individual tree crowns and shadows. Pan-sharpening is a fusion technique used to increase the spatial resolution of a multispectral image by combining it with a fine spatial resolution panchromatic (black/white) image, while preserving the spectral information in the multispectral image (Vrabel, 1996)

Table 2: Technical details of Quickbird Sensor.

Launch	1999		
Orbit	450 km altitude;93 minutes orbit time;10.30 an equator crossing time (descending)an inclination of 97.2 sun-synchronous		
Nominal Swath Width	16.5 km at Nadir		
On board storage	128 Gbit (approximately 57 scenes)		
Dynamic range	11 bits per pixel		
RESOLUTION	PANCHROMATIC	MULTISPECTRAL	
Basic	0.61m at Nadir,0.72m at 250 off- Nadir nadir	2.44m at Nadir; 2.88m 250 off-nadir	
Standard and ortho rectified	Resample at 0.6/0.7m GSD	Resample at 2.4/2.8m GSD	
Spectral	450-900nm	Blue	450-520nm
		Green	520-600nm
		Red	630-690nm
		Infrared	760-900nm

The Image acquired with information in Table 3 was geo-referenced, radiometrically calibrated, corrected for sensor and platform induced distortions and mapped to a cartographic projection. Atmospheric correction performed to the image to link spatially and geometrically raw data to the real world for extraction of spectral properties.

Table 3: Information of the Quickbird image used in the study

Projection Type	Universe Transverse Mercator(UTM) 1984
Spheroid	Clarke 1880
Datum	Arc 1960(Tanzania)
UTM Zone	37 South of the Equator
ACQUISITION DATE	May 8th, 2008
DOWNLOADED DATE	Nov 13th,2008;14:53
RESOLUTION	0.6m

Most of the areas within study area had cloud cover. Haze correction was done to the image by using Erdas Imagine (Atmospheric Correction Work Station 2 (ATCOR, 2004). The following specifications were applied during haze corrections: Solar zenith140, solar azimuth of 39, altitude -6.9

longitude 39.0; correction was run for the thick corrections.

3.6.1. Image segmentation

Segmentation of the crowns was done in software Definiens Developer 7 which is powerful to delineate crowns of the individual trees. One of the basic classification procedures was multi-resolution segmentation. Purpose of segmentation is to extract information from an image in such a way that the output image contain much less information than the original one, but the little information contain much more relevant to other models of an automatic vision system than the discarded information. Individual tree crown segmentation is frequently required in forest inventory, biomass measurement, change detection and tree species recognition (Valérie and Marie-Pierre, 2006).

Segmentation extracts the outlines of different regions into which are made up of pixels which have something in common (Definiens, 2006). Similar brightness or colour which may indicate they belong to the same object or facet of an object. By this means of segmentation, a hierarchical network of image objects is constructed in which small objects are made sub-objects of larger ones. Multi-resolution segmentation yield image object of similar size, while different structures in an image and is embedded in different scaled of resolution (Baatz *et al*., 2000; Definiens, 2006). Definiens developer has the advantage of exporting result for further process in other software.

Total of 184 individual trees were measured for dbh and crown diameter in the field. Out of those 42 points found completely cloud area in Quickbird image hence not possible to find their areas during multi-resolution segmentation. Those points were deleted from the total trees for consideration in the study. Multiresolution segmentation performed in this study regarded scale parameter of 50, shape 0.1, smoothness and compactness of 0.5 as the appropriate segmentation to obtain image objects of good size. Parameters for the segmentation was based on previous literatures that suggest ways to obtain best parameters (Baatz *et al*., 2000; Navendu, 2006). During segmentation a total of 76,795 objects were obtained from the subsetted study area.

In order to obtain required crown areas during segmentation, the following parameters were considered: scale parameter, shape, compactness and image layers were set. Shape heterogeneity has been described as a value that describes the change of the objects shape with respect to smoothness and compactness (Benz *et al*., 2004). Scale parameter in the segmentation process set a threshold for the maximum increase in heterogeneity of two merging segments. The larger the scale parameter the larger the segment objects grows (Baatz et al., 2000; Benz *et al*., 2004). On increasing crown shape parameter, diameter at breast height relate more to crown diameter (Paulo *et al*., 2002). Different scale parameters were tested to enable selecting suitable and appropriate parameters for the segmentation of the quickbird image to attain reliable polygons resembling object. Scale parameters tested for suitable parameter were 10,30,50,70 and 90. Shape factor of 0.1, scale parameter of 50, compactness value of 0.5 and smoothness value 0.5 with band combination of 4, 2, 1 (RGB) gave better segmentation hence used (Fig 3-1) .

Figure 3-1: Segmentation results showing tree crown polygons

$$f = w \cdot h_{color} + (1 - w) \cdot h_{shape}$$ ……………………1

Where, f is the threshold fusion value for merging segments, h_{color} is the heterogeneity criterion for color and h_{shape} is the heterogeneity criterion for shape (Benz et al., 2004).

$$h_{shape} = w_{cmpct} \cdot h_{cmpct} + \left(1 - w_{cmpct}\right) \cdot h_{smooth}$$ …..2

Where hcmpct and hsmooth are heterogeneity for compactness and smoothness respectively

The heterogeneity criteria for shape (h_{shape})describe the improvement of shape with respect to two components smoothness and compactness:
Heterogeneity for smoothness and compactness can further be elaborated under the following equation

$$h_{smooth} = n_{Merge} \cdot \frac{l_{Merge}}{b_{Merge}} - \left(n_{Obj1} \cdot \frac{l_{Obj1}}{b_{Obj1}} + n_{Obj2} \cdot \frac{l_{Obj2}}{b_{Obj2}} \right)$$ …………..3

$$h_{cmpct} = n_{Merge} \cdot \frac{l_{Merge}}{\sqrt{n_{Merge}}} - \left(n_{Obj1} \cdot \frac{l_{Obj1}}{\sqrt{n_{Obj1}}} + n_{Obj2} \cdot \frac{l_{Obj2}}{\sqrt{n_{Obj2}}} \right)$$ ………………..4

Where, n is the object size, l is the object perimeter and b is the perimeter of a bounding rectangle.

3.6.2. Export of tree crown polygons

After the segmentation, crown polygon as shape files exported to Arc map where an area of each polygon (crown) was determined. Polygon areas were joined to the attribute table of individual tree attributes so as to match with trees having such crown areas measured in the field. Area of each of the crown point of the tree was recorded and calculated for its crown diameter (CD). With the high resolution images to be used, the crown dimensions in terms of diameter and area was obtained to give the total area of canopy closure.

3.7. Extraction of NDVI from Aster and Quickbird images

Normalized Difference Vegetation Index (NDVI) was extracted from ASTER (Medium resolution imagery and Quickbird (High resolution imagery) The NDVI is successful as a vegetation measure in that it is sufficiently stable to permit meaningful comparisons of seasonal and inter-annual changes in vegetation growth and activity. The strength of the NDVI is in its rationing concept, which reduces many forms of multiplicative noise (illumination differences, cloud shadows, atmospheric attenuation, and certain topographic variations) present in multiple bands (Huete et al., 2002; Bagan *et al*., 2005). NDVI use the highest absorption and reflectance regions of the chlorophyll hence make it preferable as the good index to use. One of the disadvantage of the using NDVI as a vegetation index is the issue of saturation.
Normalized Difference Vegetation Index from Quickbird image was done in Erdas imagine, using Band 3 (Red and Band 4 (Near Infra Red) combination.

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}$$

…………………………….. Equation 5

Where PNIR and = PRED are reflectances from Near Infra Red and Red bands respectively (Rouse et al., 1974; Huete et al., 2002). Quickbird image band four (760-900nm) and Band three (630-690nm) reflectance was used. NDVI values exported to arc map for the values extraction to the 28 field points NDVI was regressed to NDVI from the ASTER image to find the correlation between the two relating to the biophysical forest parameters measured on fields. These biophysical forest parameters measured was number of stems, crown diameter, crown canopy closure and biomass.

3.8. Measurements of individual tree crowns from the quickbird image

Points taken by the aid of GPS for individual tree diameter measurements were overlaid on the quickbird image; crown diameters were measured the same way as in the field. Crown diameters were computed and related to the one obtained from the field inventory.

3.9. Relationship between crown diameter and (dbh)

A regression equation was performed in SPSS to find a relationship between crown diameters from segmentation and measured from the quickbird image (High resolution imagery). Crown diameter was used as dependent variable in regression equation while dbh was an independent variable. Coefficient of determination and standard error of estimation was determined between these two variables.

3.10. Relationship between crown diameter with biomass

As in sections 3.8, relationships between crown diameter with biomass was found using SPSS software (Moore and McCabe, 2003).

3.11. Medium resolution imagery (ASTER)

Several studies were conducted to correlate above-ground biomass of tropical forest to different vegetation indices and band ratios (Foody et al., 2003; Lu et al., 2004). Complex band ratios investigated by Foody et al. (2003) also showed high correlation with above-ground biomass. The vegetation indices and band ratios which were investigated in this study are those that were previously found to have high correlation with tropical forest above-ground biomass (Foody et al., 2003)

ASTER (Advanced Spaceborne, Thermal Emission and Reflection Radiometer) is an imaging instrument that is flying on NASA's Terra Satellite launched in December 1999. It consists of three distinct telescope subsystems which measure radiation in visible near-infrared (VNIR), shortwave-infrared (SWIR) and thermal infrared (TIR) regions of spectrum. Aster has 14 bands in total but, there are only 3 bands with 15m resolution in VNIR which are used to obtain a detailed map. In visible near infra-red, there are two telescopes, one which faces backwards along the track and the other that faces at the nadir. It operates in three visible light and near-infrared bands with 15m and swath width of 60km. (http://www.aster.org.uk).
Additionally, a backward looking near infra red has the capability of providing stereo coverage.

For the purpose of this study concern is only for the bands VNIR which has the resolution of 15m.The image was acquired in form of hierarchical data format (hdf extension), imported to Erdas imagine, Very Near Infra-Red (VNIR) and Short wave Infra Red (SWIR) extracted, geometric corrections performed according to the study area specifications(Table 4).

Table 4: Information of the ASTER image used in the study

Projection Type	Universe Transverse Mercator(UTM) 1984
Spheroid	Clarke 1880
Datum	Arc 1960(Tanzania)
UTM Zone	37 South of the Equator
ACQUISITION DATE	Dec 8th,2006
RESOLUTION	15m
Path rows	166-65

The image which has the information in table 5 had 42.2 % haze and the remaining percentage been a clear land pixels in the study area. Haze correction was performed to the image by using Erdas Imagine Atmospheric Correction Workstation 2 (ATCOR, 2004; Ustin, 2004). The following specifications were used during haze corrections: solar zenith 26.5 and solar azimuth of 26.6. Atmospheric correction have the importance of yielding good and reliable results by using of the ground reflectance data retrieved from the satellite can be compared to ground measurements.

Vegetation indices selected for this study was Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) among others (Appendix 5) Model for making NDVI values built in Erdas imagine was used producing NDVI image which was then exported to Arc map; focal statistics was carried out to calculate statistics on a raster over a specified neighbourhood (3x3) which eventually made size of the pixel to be 45mx45m. Focal statistics again would make on average the pixel cells within each neighbourhood cell. This was performed because the plot size was 15m radius while the pixel resolution of Aster is 15m x15m for Very Near Infra Red (VNIR) bands.

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}}$$

Where P_{NIR} and = P_{RED} are reflectances from Near Infra Red (0.76-0.86) and Red (0.63-0.69) reflectances respectively (Rouse *et al*., 1974; Huete *et al*., 1997; Schowengerdt, 1997; Huete *et al*., 2002).

Values for each point of the plot was extracted and exported to excel. Vegetation index obtained was correlated with NDVI index in high resolution imagery (quickbird image). NDVI was regressed with crown closure calculated from the field data plots to find how it can explain canopy covers on the ground.

3.12. Calculation of EVI from aster and quickbird images

The enhanced vegetation index (EVI) was developed to optimize the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through a de-coupling of the canopy background signal and a reduction in atmosphere influences (Figure 3-2).

Proposed formular of EVI derivation (Huete *et al*., 1997; Huete *et al*., 2002) and applied by (Gao et al., 2000; Wang *et al*., 2005) was not used because it required blue band which is not available in ASTER image.

$$EVI = G * \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + C_1 * \rho_{Red} - C_2 * \rho_{Blue} + L}$$

……………………Equation 6

Where ρNIR= NIR reflectance,ρ Red= red reflectance, ρBlue= Blue reflectance, C1= Atmospheric Resistance Red correction coefficient, C2= Atmospheric Resistance Blue correction coefficient, L=Canopy Background Brightness correction factor and G =Gain factor The coefficients in the EVI algorithm are, L=1, C1 = 6, C2 = 7.5, and G = 2.5 (Huete et al., 1997)

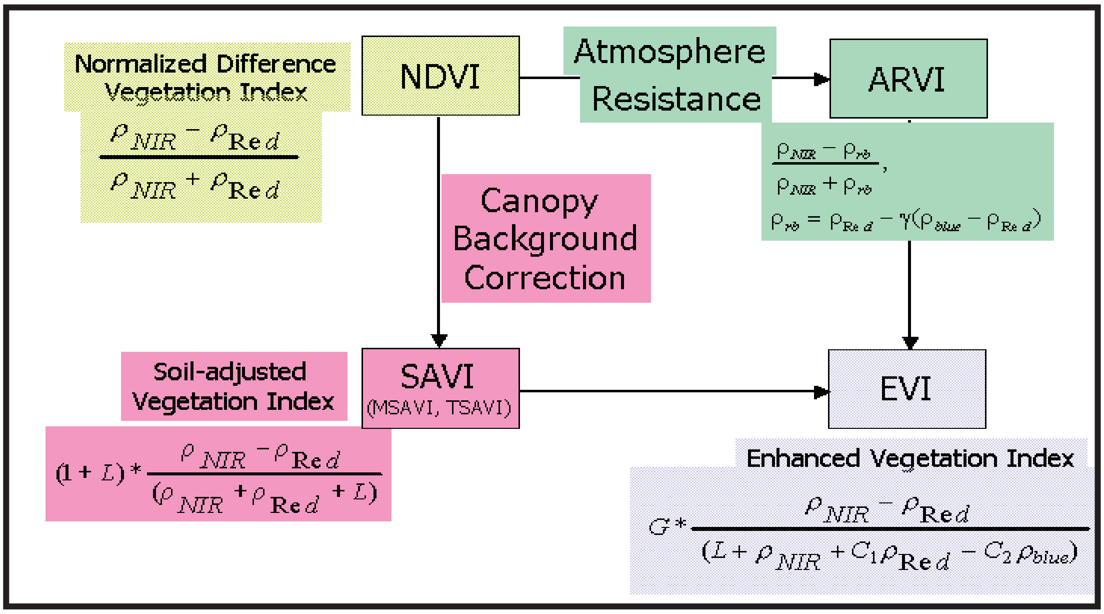

Figure 3-2: Combined soil -and atmosphere-resistance vegetation indices
Source: Adapted from the website (http://tbrs.arizona.edu/forest/projects/evi.htm)

Instead, two bands version of EVI (EVI2) formular proposed by (Jiang et al., 2008; Miura et al., 2008) was applied to calculate EVI for both images.

EVI= G [(ρNIR- ρ Red)/ (ρNIR +C1* ρ Red * L)]* ....Equation 7

Where, ρNIR= NIR reflectance, ρRed= red reflectance, C1= Atmospheric Resistance Red correction coefficient (2.4), L= Canopy Background Brightness correction factor (1) and G =Gain factor (2.5).

All formulae have in common gain factor and canopy background brightness correction factor though have differences (Table 6).

Table 5: Differences between two formulae for EVI calculation

	EVI (Huete *et al.*, 1997)	EVI (Jiang *et al.*, 2008; Miura *et al.*, 2008)
Presence/Absence of Blue Band	Present	Absent
Constants	C1=6, C2= 7.5	C1= 2.4, C2 Absent
Number of Bands	Three bands: Blue Red, and NIR	Two bands: Red and NIR

4. RESULTS

4.1. Biomass equation

Developed biomass equation was used to estimate biomass in Kazimzumbwi forest reserve. During development of the suitable equation for biomass estimation, different weights was tried to come up with reduced variance of the residual which with the weight of 2.1. Coefficient of determination was increased from 0.92 to 0.94 indicating that weighting improves regression and provides a good fit. Otherwise Furnival index was increased from 14.9 to 15.1 (Fig 4-1 and Fig 4-2). Unweighted residuals and graphs for the developed equation to estimate biomass are presented in appendices 6 and 7. Equation used for biomass estimation was: $Y = B_O + B_1 * X_1 + B_2 * X_2$

Where; Y=Biomass (kg/tree), B_O=2.7D-02, B_1=8.67D-02, X_1=dbh^2, B_2=1.199D-02, X_2=dbh^3, and dbh = diameter at breast height (cm), D = Exponent

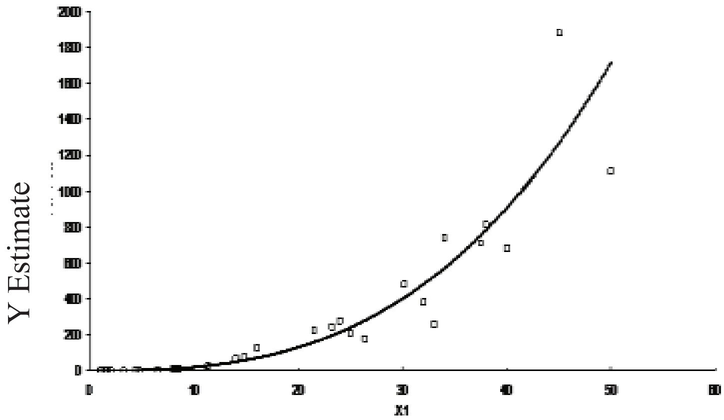

Figure 4-1: Regression data and line

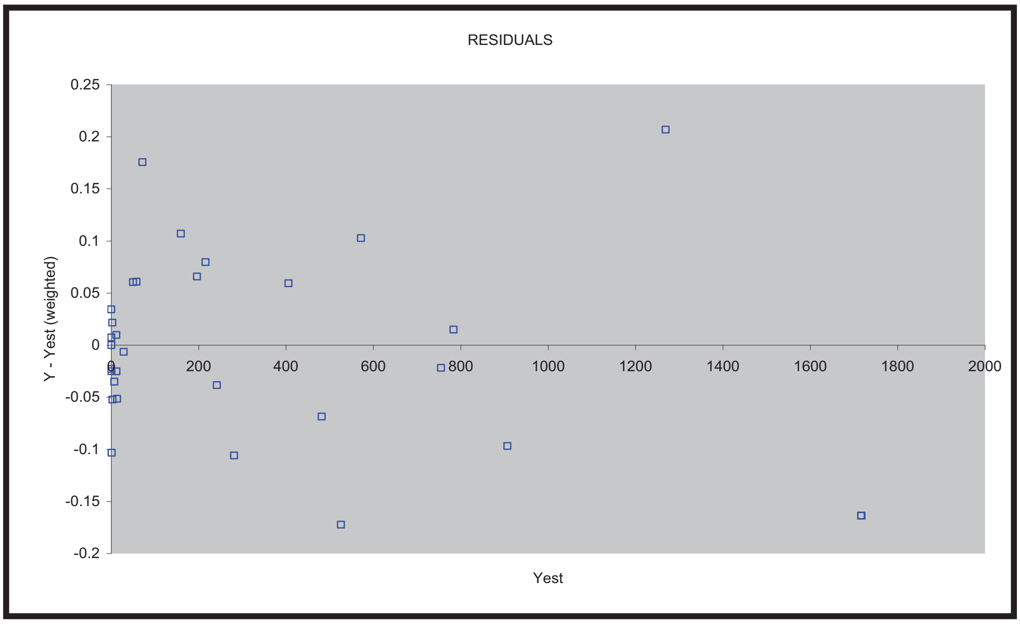

Figure 4-2: Weighted residual plots

4.2. Field inventory results

According to the ground inventory sampling intensity was 0.01 with a total sampling area of 2 ha.The calculaled plot size was 0.071 ha. Unit of measure of all parameters were calculated per hectare basis: biomass (tonnes per ha), stems (number of stems per hectare) and basal area ($m^2.ha^{-1}$).

4.2.1. Number of stems per ha and dominant tree species

Stem density per ha was found to be 4135 , of which *Afzelia quanzensis* had the highest representation, of 1186 number $stems.ha^{-1}$ as shown in Fig. 4-3 and appendix 8.

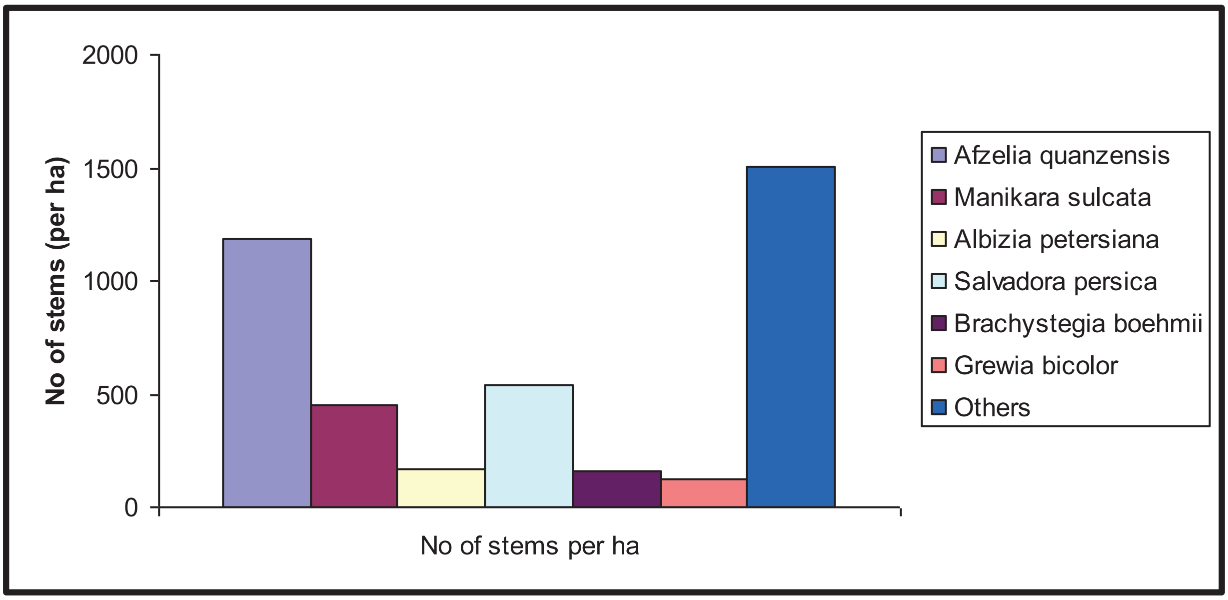

Figure 4-3: Dominant tree species

As seen from Fig 4-3, Afzelia quanzesis found to have high number of stems (28.68%) when compared to *Salvadora persica* (13%) and *Manilkara sulcata* (11.9%). *Grewia bicolour* (3%), *Brachystegia boehmii* (4%)

4.2.2. Distribution of diameter classes

Distribution of diameter classes showed that class of 1 to 10 had high number of stems compared to the other classes o 11 to 20 (60), 21 to30 (7), 31 to 40 (1) and 51 to 50 (1)(Table 6 and Appendix 9).

Table 6: Diameter class distribution

Diameter classes	no of stems
1 to 10	4067
11 to 20	60
21 to 30	7
31 to 40	1
41 to 50	1

4.2.3. Basal area (G)

Data collected from the study area revealed a Mean Basal area of 6.49$m^2.ha^{-1}$; showing low values compared basal areas from other forest reserves. Maximum and minimum basal areas were 9.88 and 3.88 $m^2.ha^{-1}$ respectively (Fig 4-4 and Appendix 10).

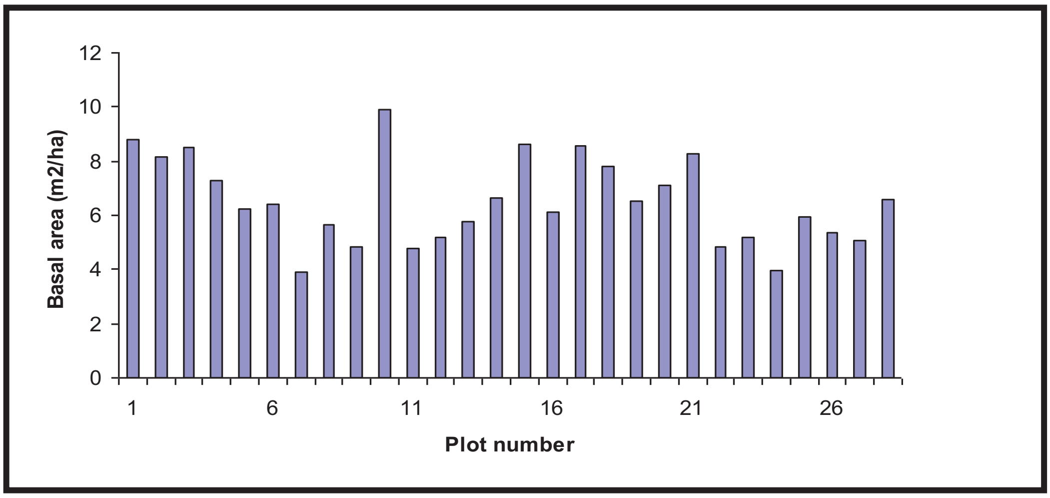

Figure 4-4: Distribution of basal areas (m2.ha-1) in field plots

4.2.4. Biomass computation from the ground inventory

Using the equation established, the estimated biomass was 15.8tonnes.ha-1. Regarding the woodland coverage in Kazimzumbwi FR (488.4 ha) estimated biomass was about 7Gt of above ground biomass.

4.2.5. Relationships between crown diameters with dbh and biomass from inventory

Measurements of relationship between dbh with crown diameter in the field trees for general trend, tree species with trees more than ten trees as a group measured in the field. (*Albizia petersiana, Afzelia quanzensis and Brachystegia boehmii).*

4.2.5.1. General trend

The study found a significant relationship between dbh with crown diameter as a general trend for all measured trees in the field. Regression between the dbh and crown diameter revealed that 74% of relationship is explained by the regression line. (Fig 4-5)

Regression performed showed a significant positive relationship between dbh and crown diameter from field measurements of all trees in general (Regression, b_1=0.26, SE= 0.013, t =20, df = 142 and $p < 0.001$) where; b_1=slope, SE= standard error and df = degree of freedom.

Regression of crown diameter versus biomass as a general trend for measured trees showed that crown diameter explain about 0.9 of the biomass at 95% probability level (Fig 4-6).

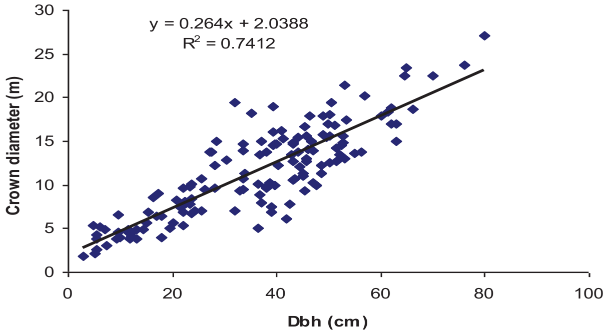

Figure 4-5: Dbh versus Crown diameter, General trend (Field measurements)

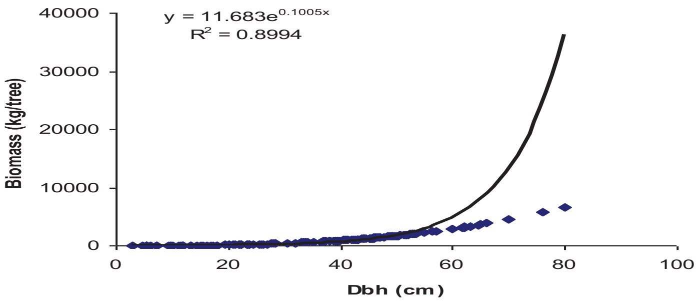

Figure 4-6: Dbh versus biomass, General trend (Field measurements)

4.2.5.2. Albizia petersiana

Dbh versus crown diameter of measured Albizia petesiana tree species in the field, showed significant positive relationship. The regression line explained 75% of relationship between crown diameter (response variable) with dbh (explanatory variable). (Regression, b1=0.248, SE= 0.045, t =5.5, df = 10 and $p < 0.001$). (Fig 4-7)

Relationship between crown diameter with biomass in *Albizia petersiana* was exponential. Regression of crown diameter versus biomass of, *Albizia petersiana* explained about 0.97 of the Biomass at 95% confidence level (Fig 4-8).

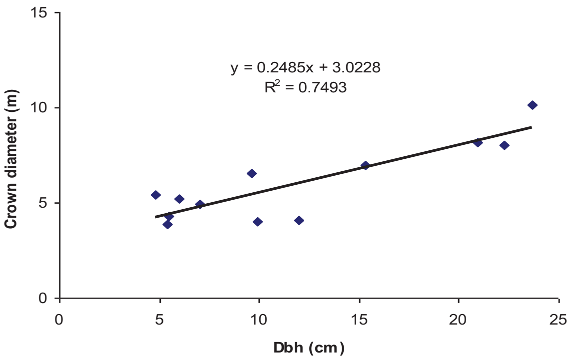

Figure 4-7: Dbh versus Crown diameter, *Albizia petersiana* (Field measurements)

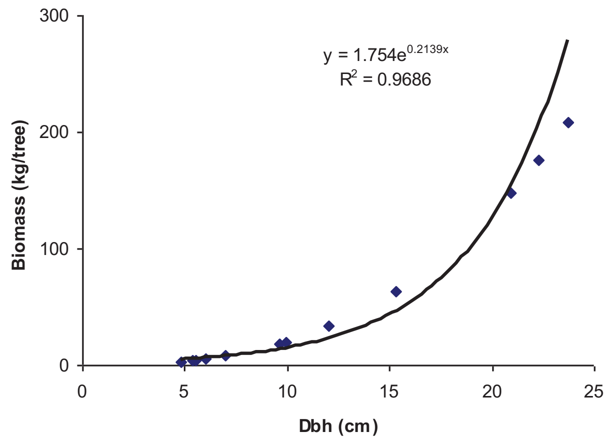

Figure 4-8: Dbh versus biomass, *Albizia petersiana* (Field measurements)

4.2.5.3. Afzelia quanzensis

Afzelia quanzensis showed positive relationship between dbh diameter.The regression line explained 64% of the relationship between dbh and crown diameter at a confidence level of 95% (Regression, b1 = 0.21, SE= 0.042, t=5, df= 10 and $p < 0.001$) (Fig. 4-9).

Relationship between crown diameter and biomass in Afzelia quanzensis was exponential. Regression of crown diameter and biomass of, Afzelia quanzensis explained about 0.92 of the biomass at 95% confidence level (Fig 4-10).

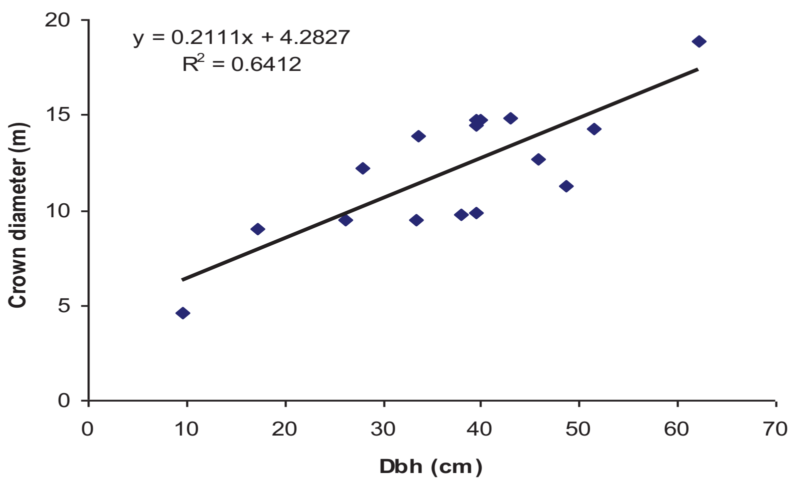

Figure 4-9: Dbh versus Crown diameter, *Afzelia quanzensis* (Field measurements)

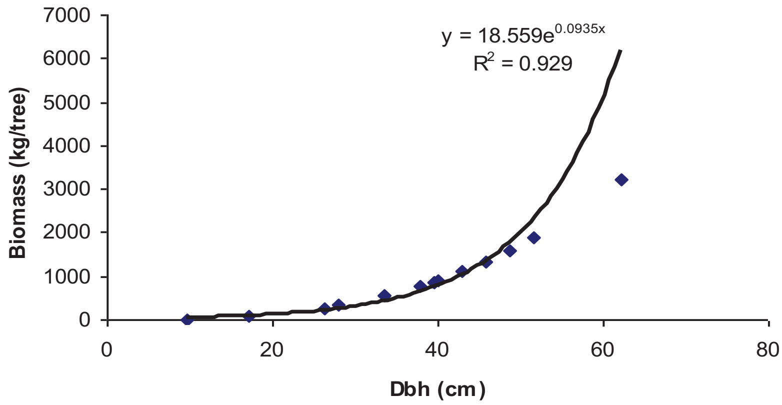

Figure 4-10: Dbh versus biomass, *Afzelia quanzensis* (Field measurements)

4.2.5.4. Brachystegia boehmii

Brachystegia boehmii showed positive relationship between dbh versus crown diameter. The regression line explained 75% of the relationship between dbh and crown diameter at a probability level of 95% (Regression, b1 = 0.27, SE= 0.20, t=13.4, df= 62 and $p<0.001$) (Fig 4-11)
Relationship between crown diameter and biomass of *Brachystegia boehmii* was exponential. The regression of crown diameter and biomass of, *Brachystegia boehmii* explained about 0.92 of the biomass at 95% confidence level Fig (4-12)

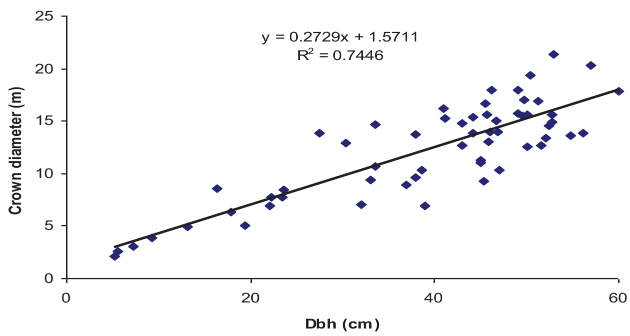

Figure 4-11: Dbh versus Crown diameter, *Brachystegia boehmii* (Field measurements)

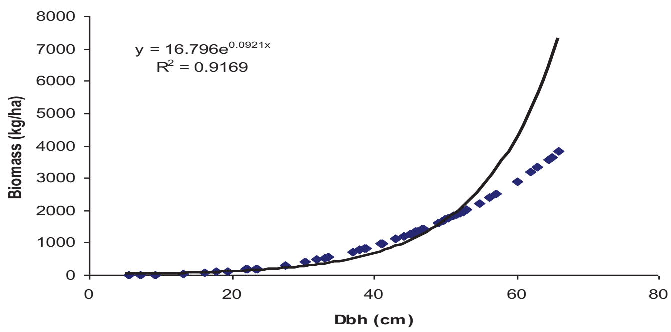

Figure 4-12: Dbh versus biomass, *Brachystegia boehmii* (Field measurements)

4.3. High resolution imagery results

4.3.1. Relationships between crown diameter with dbh and biomass from segmentation

4.3.1.1. General trend

Regression performed reveal there was a significant positive relationship between dbh and crown diameter from multiresolution segmentation with R2 = 0.66. (Regression, b_1=11.27, SE= 0.012, t =16.58, df = 141 and p<0.001) (Fig 4-13).

Relationship between crown diameter with biomass was exponential, giving an impression that crown diameter increase exponentially with the biomass

Regression of crown diameter versus biomass of individual tree, dbh explain about 61% of the crown diameter at 95% probability level. (Regression, b_1=198, SE = 15, df = 140 and p < 0.001) Fig. (4-14).

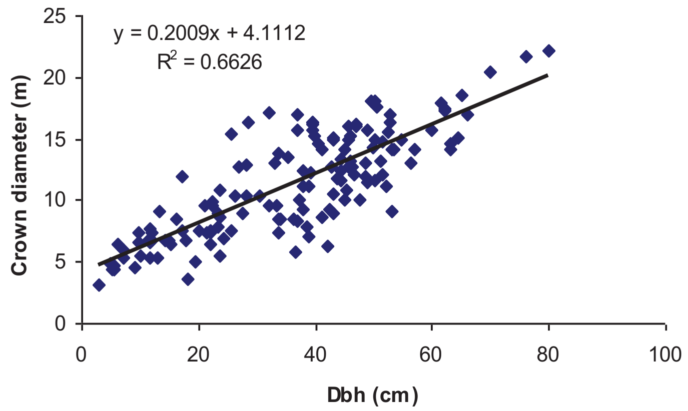

Figure 4-13: Dbh versus crown diameter (General trend)

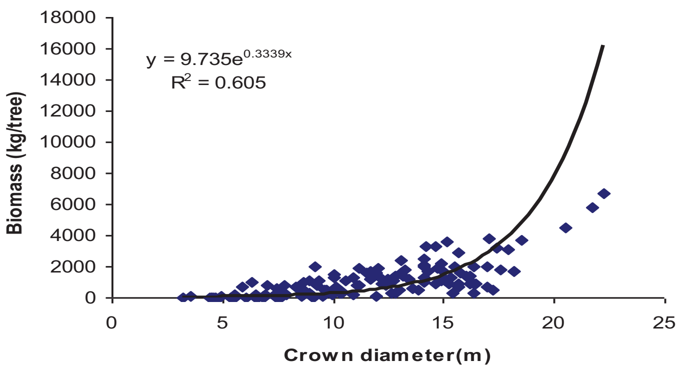

Figure 4-14: Dbh versus biomass (General trend)

4.3.1.2. Albizia petersiana

Relationship between dbh versus crown diameter from multiresolution segmentation by scatter plot showed strong positive relationship (Regression, b_1=0.285, SE= 0.036, T= 7.9, df = 10 and $p < 0.001$) Regression line explain 86% of relationship between crown diameter (response variable) with dbh (explanatory variable).

Regression performed showed that there was a significant positive relationship between dbh and crown diameter from multiresolution segmentation (Regression, b_1=0.285, SE= 0.036, t =7.9, df = 10 and $p < 0.001$) (Fig 4-15).

Regression of crown diameter versus biomass of individual tree, dbh explain about 82% of the crown diameter at 95% probability level. From the statistics performed, we concluded that there is a positive relationship betwen crown diameter and biomass (Regression, b_1=32, SE = 4.128, t= 7.8 df = 10 and $p < 0.001$) (Fig 4-16)

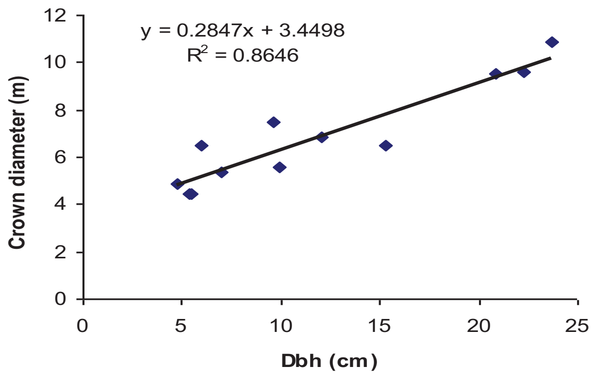

Figure 4-15: Dbh versus crown diameter (*Albizia petersiana*)

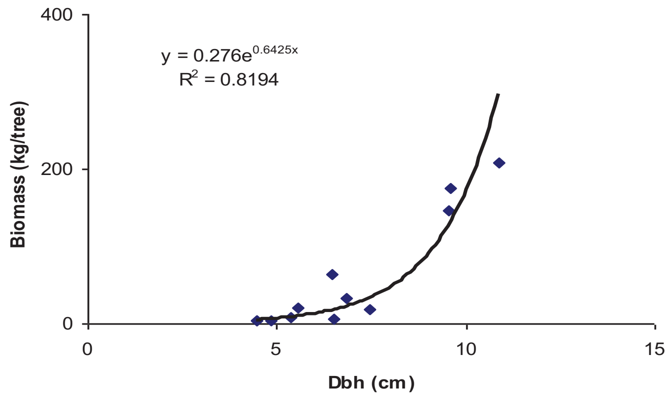

Figure 4-16: Dbh versus biomass (*Albizia petersiana*)

4.3.1.3. Afzelia quanzensis

Results revealed that there was a significant positive relationship between dbh and crown diameter from multiresolution segmentation R2=0.54 (Regression, b_1=0.165, SE= 0.041, t =4.051, df = 14 and p<0.001 (Fig 4-17).

Regression of crown diameter versus biomass of individual tree, dbh explain about 57 % of the crown diameter at 95% probability level. From the statistics performed, we concluded that there is a positive relationship betwen crown diameter and biomass (Regression, b_1= 168, SE = 57.4, df = 14 and p < 0.005) (Fig 4-18).

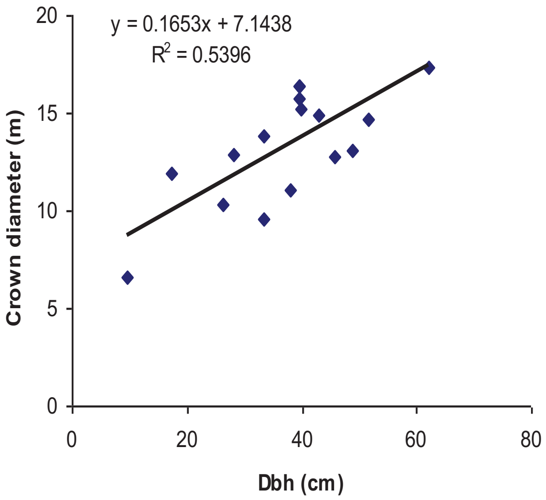

Figure 4-17: Dbh versus crown diameter (*Afzelia quanzensis*)

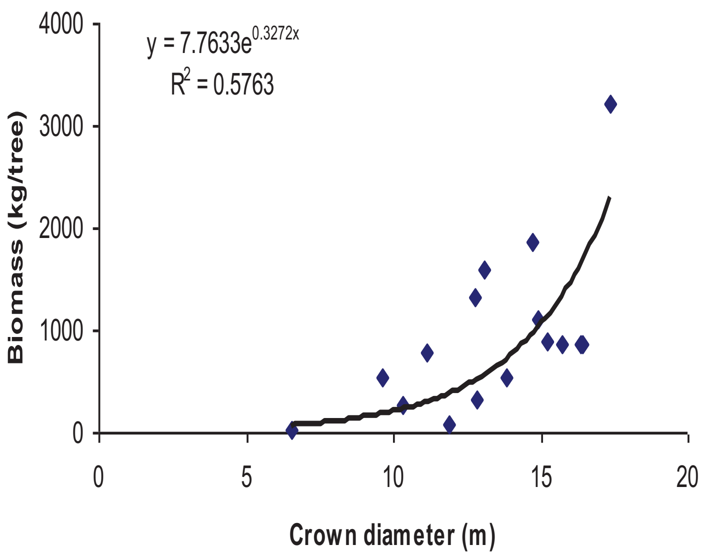

Figure 4-18: Dbh versus biomass (*Afzelia quanzensis*)

4.3.1.4. Brachystegia boehmii

Relationship between dbh versus crown diameter from multiresolution segmentation by scatter plot showed good relationship, R^2=0.7 (Regression, b_1=0.2, SE=0.016, t= 12.43, df = 62 and p <0.001). (at 95%confidence level) (Fig 4-19).Crown diameter with biomass resulted in positive relationship; regression line explaining 65% of the relationship (Fig 4-20)

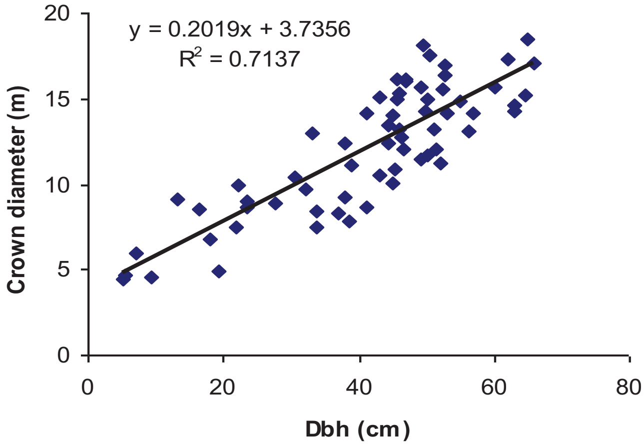

Figure 4-19: Dbh versus crown diameter (*Brachystegia boehmii*)

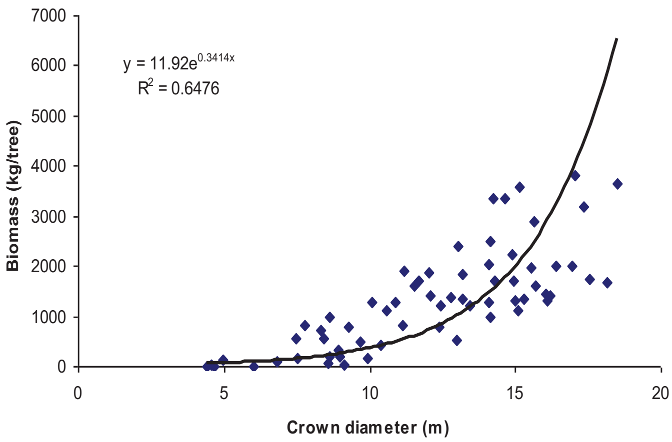

Figure 4-20: Dbh versus biomass (*Brachystegia boehmii*)

4.3.2. Relationships between crown diameter with dbh and biomass by manual measurements

It was possible to estimate tree crown diameters from the quickbird image using the arc map tools. Tree crowns was identified and measured as explained in the analysis (sections 3.6).

4.3.2.1. General trend

Measuments of the crown diameters from the Quickbird image using arc map tool, for all trees measured in the field showed good relationship between dbh versus crown diameter. Regression line was able to explain 63% of the relationships (b_1 =0.21, S.E =0.013, t = 15.6 and $p < 0.001$) (Fig 4-21)

Crown diameter versus biomass resulted in 0.9 of the relation explained by the regression line at 95% probability level (Fig 4-22).

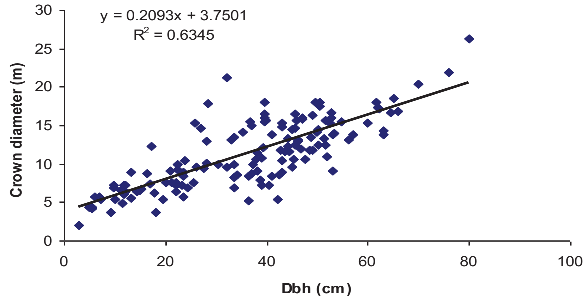

Figure 4-21: Dbh versus Crown diameter, General trend (Quickbird image measurements)

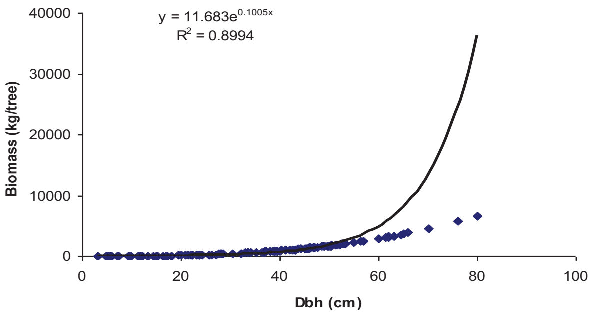

Figure 4-22: Crown diameter versus Biomass, General trend (Quickbird image measurements)

4.3.2.2. Albizia petersiana

Measuments of the crown diameters from the Quickbird image using arc map tool for Albizia petersiana tree species measured in the field showed good relationship (95% probability level) between dbh versus crown diameter. Regression line was able to explain 91% of the relationships (b_1 = 0.29, S.E = 0.03, t = 10 $p < 0.001$) (Fig 4-23)

Biomass relatioship with crown diameter 0.97 was explained by the exponential regression equation (Fig 4-24)

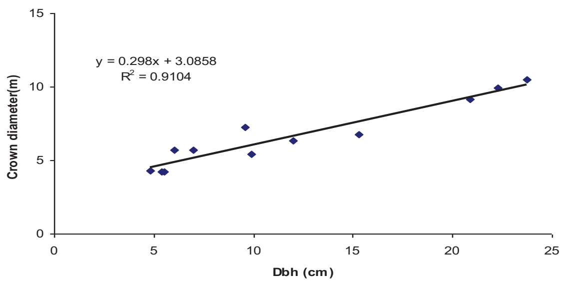

Figure 4-23: Dbh versus Crown diameter, *Albizia petersiana* (Quickbird image measurements)

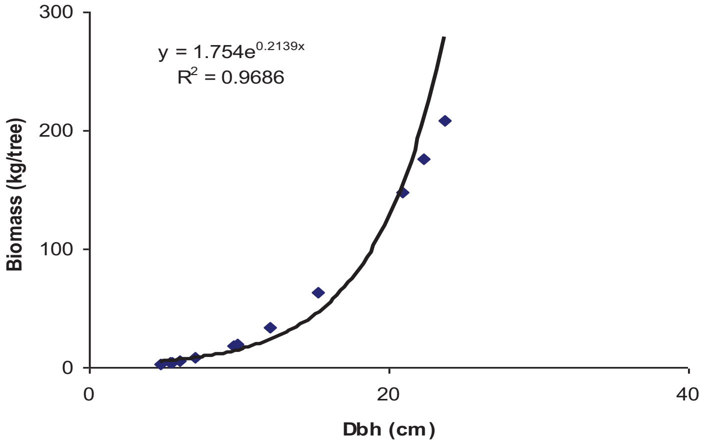

Figure 4-24: Crown diameter versus Biomass, *Albizia petersiana* (Quickbird image measurements)

4.3.2.3. Afzelia quanzensis

Measuments of the crown diameters from the Quickbird image using arc map tool, for Afzelia quanzensis measured in the field we found good relationship between dbh versus crown diameter. Regression line was able to explain 0.59 of the relationships (at 95% confidence level) (b_1 =0.17, S.E = 0.042, t = 4 and p = 0 001) (Fig 4-25). Biomass versus dbh relationship of *Afzelia quanzensis* showed $R^{2=}$ 0.93 (Fig 4-26)

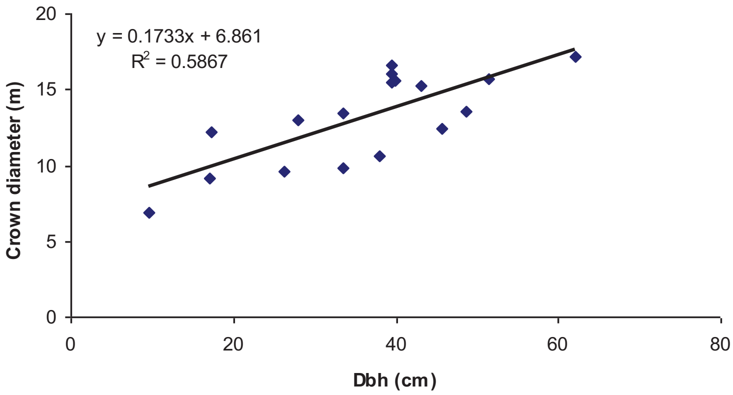

Figure 4-25: Dbh versus Crown diameter, *Afzelia quanzensis* (Quickbird image measurements)

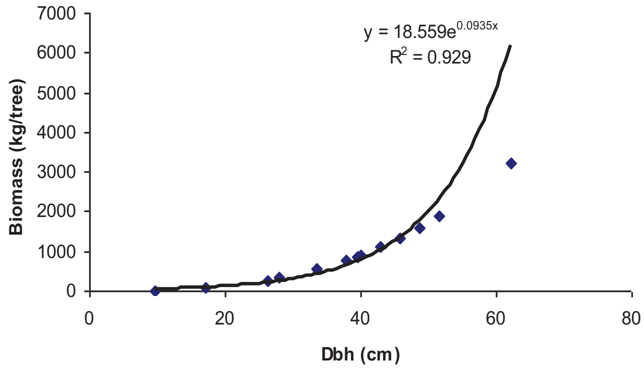

Figure 4-26: Crown diameter versus Biomass, *Afzelia quanzensis* (Quickbird image measurements)

4.3.2.4. Brachystegia boehmii

Measuments of the crown diameters from the Quickbird image using arc map tool, Brachystegia boehmii measured in the field we found good relationship between dbh versus crown diameter. Regression line was able to explain 0.72 of the relationships at 95 % confidence level. ($b_1 = 0.21$, S.E = 0.016, $t = 12.8$ and $p < 0.001$) (Fig: 4-27). Biomass resulted into 0.92 of the relationship explained by the regression line (4-28).

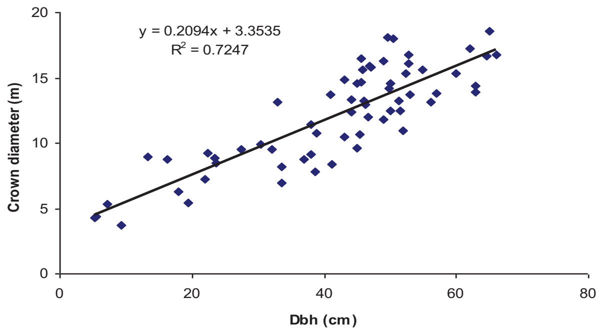

Figure 4-27: Dbh versus Crown diameter, *Brachystegia boehmii* (Quickbird image measurements)

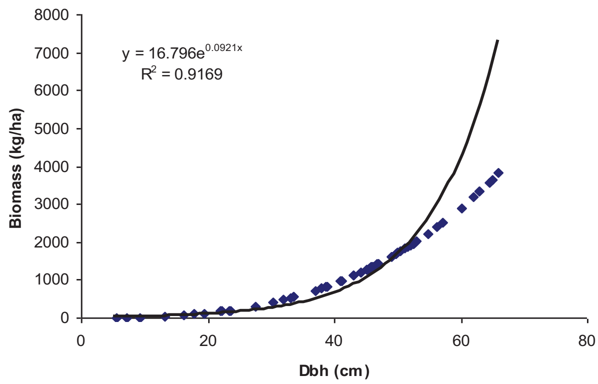

Figure 4-28: Crown diameter versus biomass, *Brachystegia boehmii* (Quickbird image measurements)

4.4. Spectral relationships between high and medium resolution imagery

4.4.1. Normalized Difference Vegetation index (NDVI)

Out of 28 plot centres from which NDVI was extracted; 13 points were cloud free from both images. Presence of cloud cover data availability in those regions on the ground is a problem (de Gier and Hussin, 1996). NDVI values from quickbird image were ranging from 0.33 to 0.58 while in ASTER image the range was from 0.64 to 0.77. Results revealed there is a significant differece between NDVI extracted from the Quickbird to Aster image; R^2=0.1 (Regression, b_1=0.15, SE=0.13, t= 1.2, df=12 and p = 0.27) (Fig 4-29 and Appendix 11).

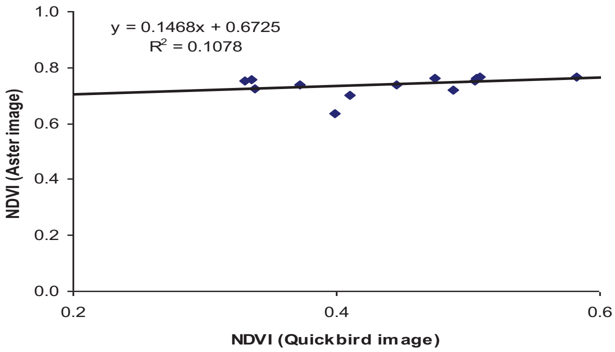

Figure 4-29: Relationship between NDVI from Aster and Quickbird images

NDVI maps for the two images indicated really difference in the distibution of greenness between two images of the study area (Fig 4-30).

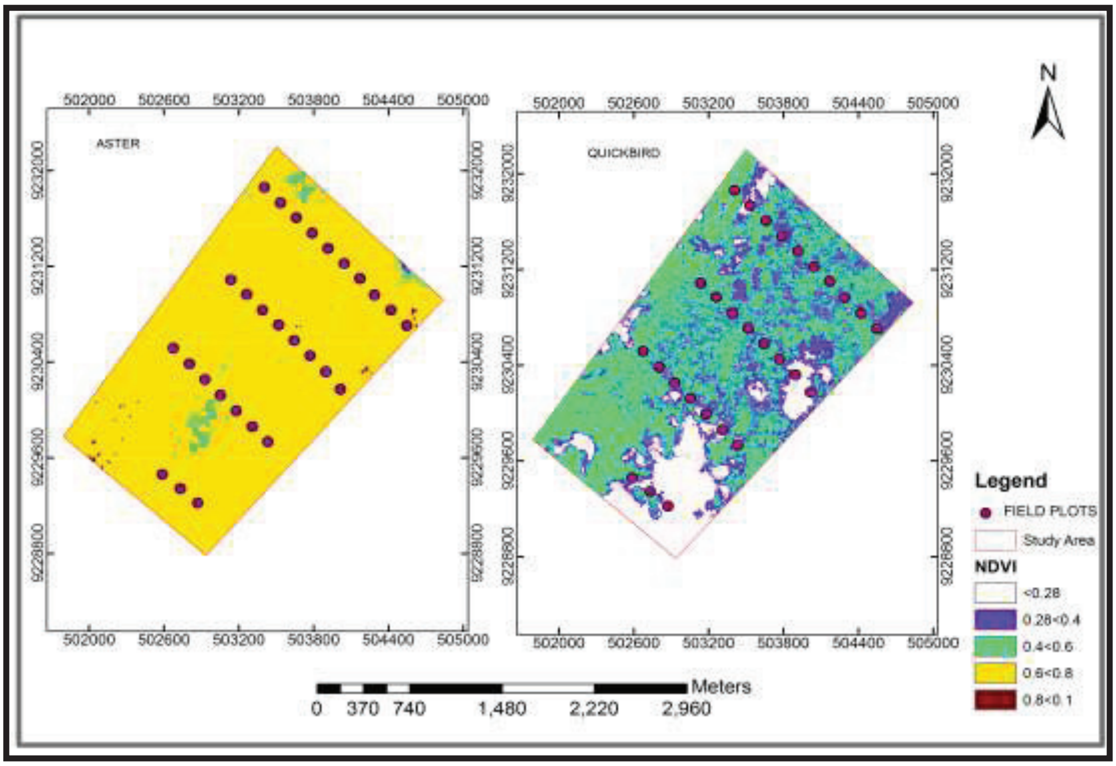

Figure 4-30: Left; NDVI image (Aster image), right; NDVI image (Quickbird image)

4.4.2. Enhanced Vegetation Index (EVI)

Values extracted from Aster image ranged from 1.24 to 1.69 where as in Quickbird image was ranging from 0.33 to 2.38. Results shows that there was a significant difference between EVI derived from regressions of both images (Quickbird and Aster) R^2= 0.14, (Regression, b_1 = 0.14, S.E = 0.1, t = 1.37 and p = 0.2). (Fig 4-31 and appendix 12)

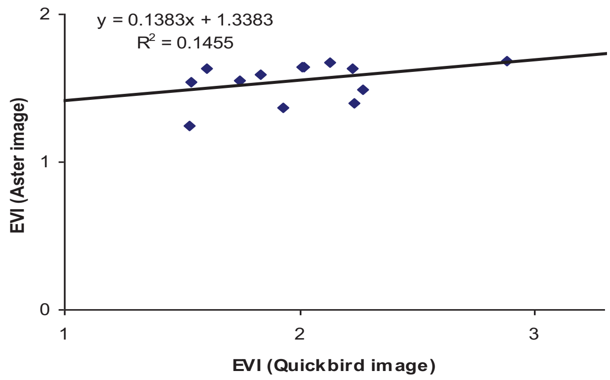

Figure 4-31: Relationship between NDVI from Aster and Quickbird images

EVI maps for indicated differences in the distibution of greeness between two images of the study area (Fig. 4-32).

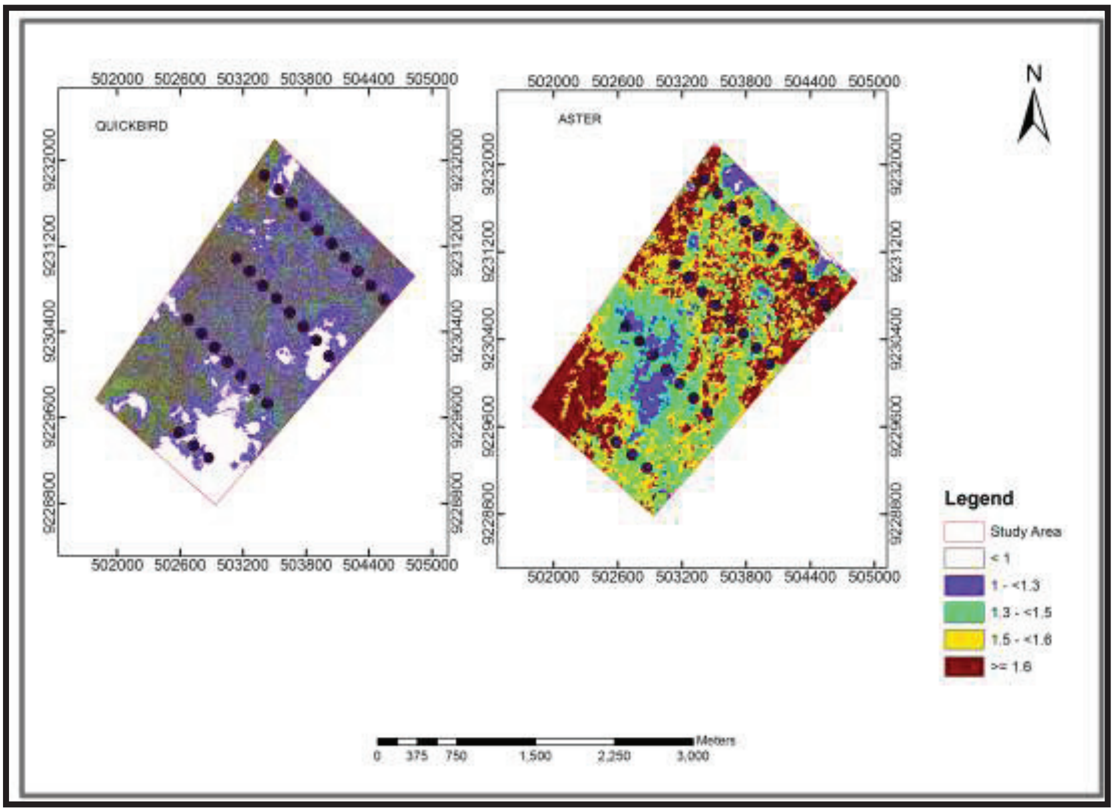

Figure 4-32: Left; EVI image (Quickbird image), right; EVI image (ASTER image)

4.5. Upscaling high to medium resolution imagery

Upscaling medium resolution imagery from high resolution imagery was based on the relationship shown by forest stand parameters with spectral characteristics form high resolution and medium resolution imageries

4.5.1. Relationship between Biomass with NDVI from ASTER and Quickbird images

Relationship between biomass (tonnes.ha-1) from the regression equation on both images was poor and not reliable at all. Results showed that only 0.1 from ASTER (b_1=11.3. S.E 29, t = 0.38 p > 0.05) (Fig 4-33) and 0.15 from Quickbird image (b_1= 17.3, S.E= 12.5, t = 1.4 and p > 0.05) of the relationship was explained by the regression line as illustrated by Fig 4-34. Result shows that there was no significant relationship between biomass extracted from ASTER and Quickbird images.

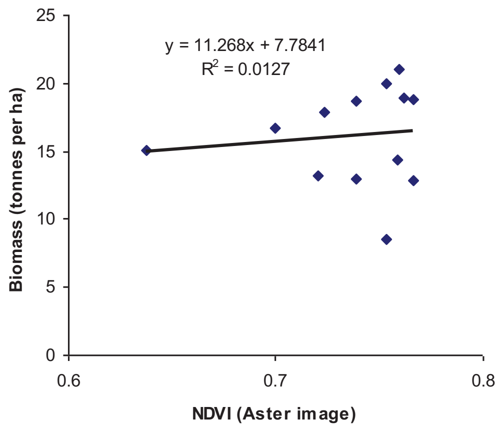

Figure 4-33: Relationship between biomass with NDVI from ASTER image

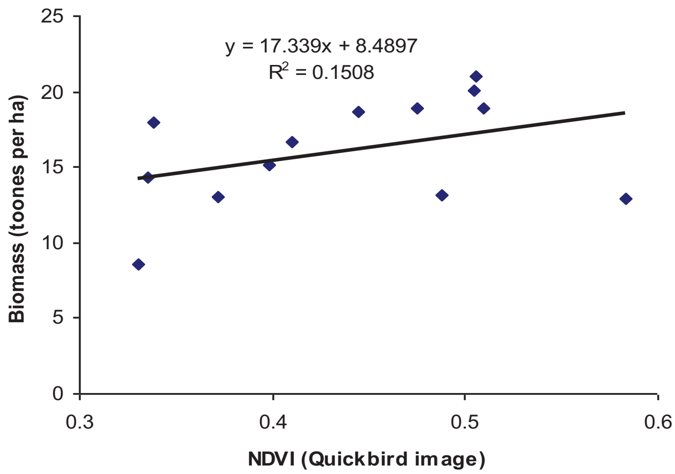

Figure 4-34: Relationship between biomass with NDVI from Quickbird image

4.5.2. Relationship between no of stems with NDVI from ASTER and Quickbird images

Results from the regression performed showed that there is no significant relationship between umber of stems with NDVI from Quickbird image (b_1 = -31.9, S.E = 150, t = -0.2, p = 0.8) while the same results obtained from the relationship between NDVI from ASTER image with number of stems (b_1 =-356, S.E =320, t = -1.1, p = 0.29). Figures4-35 and 4-36 illustrates these results.

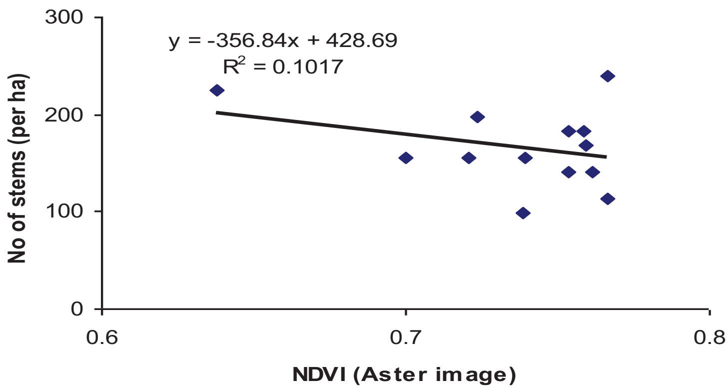

Figure 4-35: Relationship between no of stems with NDVI from ASTER image

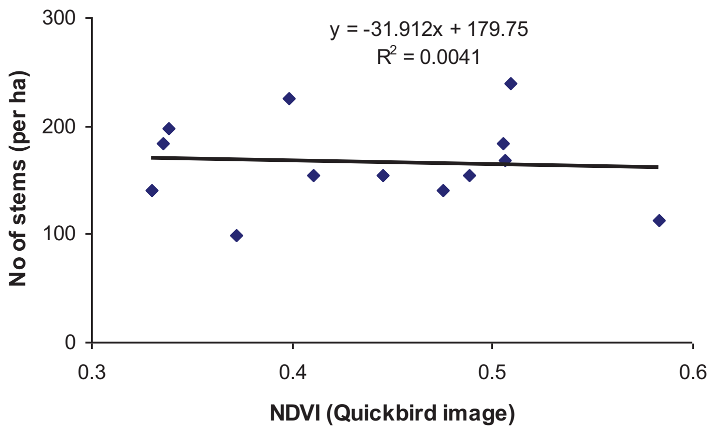

Figure 4-36: Relationship between no of stems with NDVI from Quickbird image

4.5.3. Relationship between basal area with NDVI from ASTER and Quickbird image

Results between basal area with NDVI extracted from ASTER (b_1= -13.4, S.E = 14.2, t = -0.94, p=0.367) and Quickbird (b_1 = 0.77, S.E = 6.6, t = 0.12 and p=0.12) showed no significant relationship with basal area Fig 4-37 and 4-38 represent this results.

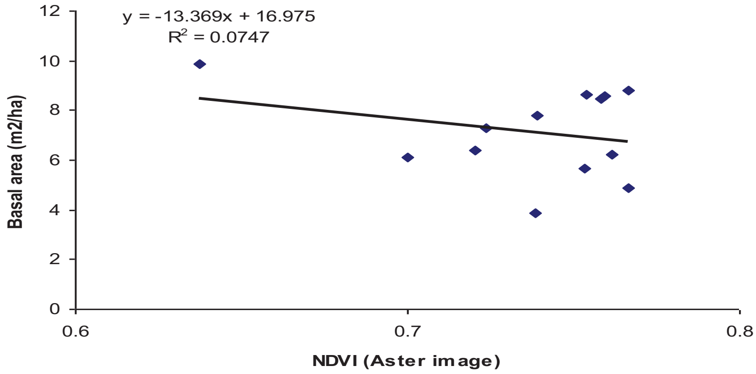

Figure 4-37: Relationship between basal area with NDVI from ASTER image

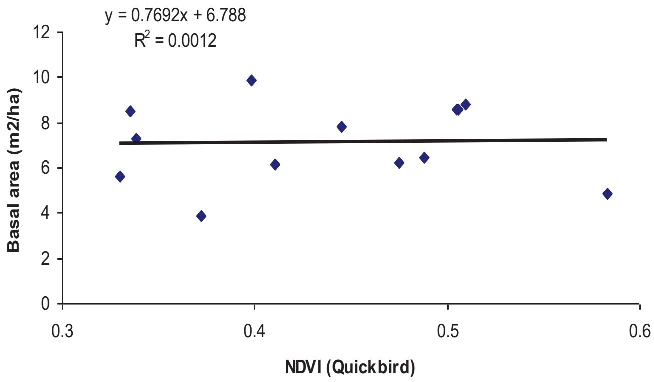

Figure 4-38: Relationship between basal area with NDVI from Quickbird image

4.5.4. Relationship between canopy closure with NDVI from ASTER and Quickbird image

There was a positive relationship between canopy closures with NDVI extracted from ASTER image (Fig 39). Coefficient of determination from regression (R^2) was 0.62 (b_1 =0.29, S.E = 0.07, t = 4.3 and $p < 0.05$) (Fig 4-39).while Quickbird image NDVI resulted into weak relationship (R^2=0.47) with significant positive correlation with crown closure (b_1 =0.11, S.E = 0.04, t = 3.12 and $p < 0.05$). (Fig.4-40)

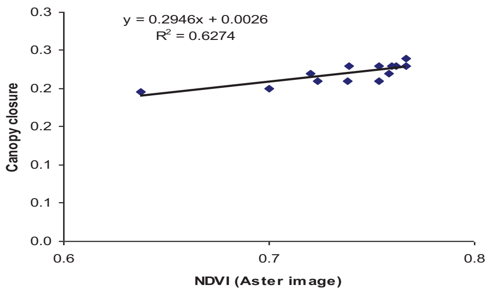

Figure 4-39: Relationship between NDVI from Aster image with canopy closure

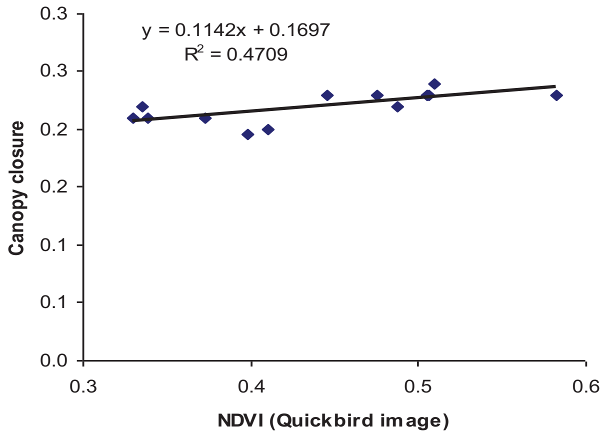

Figure 4-40: Relationship between NDVI from Quickbird image with canopy closure

5. DISCUSSIONS

5.1. Field inventory

5.1.1. Diameter class, Biomass and basal area distribution

Number of trees distribution according to diameter classes show a trend which indicates that it has more trees in the dbh class of 1 to 10 cm (99%). Consequently there is a decreasing number of stems per ha as diameter classes increase. This is a typical nature of natural forests, exihibiting a reversed J-shape (Malimbwi *et al*., 1994; Chamshama *et al*., 2004; Isango, 2007). Miombo species regenerate largely through coppice re-growth and root suckers rather than seeds (Robertson 1984). Stumps of almost all miombo woodland trees have the ability to produce sucker shoots (Chidumayo, 1988).
Although seeds of majority of miombo trees and shrubs generally germinate immediately after dispersal when there is enough moisture, tree density in re-growth miombo woodland decreases with time due to moisture and heat stress. The majority of seedlings of miombo trees experience a prolonged period of successive shoot die-back during their development phases in order to cater for these stresses. Shoot die-back is caused by water stress and/or fire during the dry season. Also with the case of suckers and coppice fire can either slow or accelerate growth. If a destructive fire occurs before dominant shoots attain a safe height to escape mortality, the process of sucker shoot domination reverts to the initial stage and stumps respond by producing an equal or larger number of replacement shoots (Chidumayo, 1988).

Higher number of trees in the diameter classes of 1 to 10 cm is much higher in Kazimzumbwi Forest Reserve is contributed by:

- natural dying of bigger trees or being extracted for timber and poles for building purposes Fig 5-1) It was estimated Mung'ng'o *et al*.,(1996) that around 50% of the available poles had been taken in accessible areas with around 20% in the forest interior.
- Frequent annual fires due to casual burning, wild animal hunting and encroachment of some portion of the forest. Species which dominated the study area are mostly fire tender species; which decline under regular burning and increase if there is a total protection. Mature trees die during dry season burning by the rate of 2.5% per year. (Frost, 1996).
- Timber and charcoal business is much contributed by rapid population growth in villages around the forest reserve.Villages around the forest currently experiencing rapid growth due to natural growth of the population but also due to in-migrants (de Gier and Hussin, 1996; Malimbwi *et al*., 2005). Population increase to the surrounding villages tend to increase dependency on forest as the source of income generating to support their daily life (de Gier and Hussin, 1996). It was reported by Sayer (2005) that about 300 million people rely on forest at different degrees for fuel wood, medicinal plants and forest foods. About 60 million indiginous people around the world almost wholly depend on the forest and forest products. Trees with big diameters are removed (Fig 5-3) leaving trees of small diameters. Although timber extraction in this forest is supposed to be done on exotic species by licenced people, the activity has remained uncontrolled. (Mung'ong'o *et al*., 1996). Due to conservation efforts including regular patrols, involving local communities in conservation currently undertaken by Forest and Beekeeping division, trees are now increasing in diameters.

Figure 5-1: Felled trees Afzelia spp (left) and Albizia spp (right) ready for lumbering

Source: Field photographs by Seleboni John

The study found that *Afzelia quanzensis* have high number of stems per ha (28.68% when compared to other tree species; *Salvadora persica* (13%), *Manilkara sulcata* (11.9). *Jubernadia, Brachystegia* and / or *Isoberlinia* are known to be among the dominant tree species in miombo woodland (White, 1983; Chidumayo, 1987)

Apparently all of these dominant tree species are the most preferred tree species for charcoal making and timber for commercial and local consumptions. Other tree species found in the study area with lesser abundances were; *Acacia robusta, Hymmenaea verrucosa, Commiphora spp, Manilkara sasbarensis, Dalbegia melanoxylon, Cassia abbreviate, Bridelia micrantha, Pteleopsis myrtifolia, Ehretia amoena, Tamarindus indica, Sclerocarya birrea, Commiphora spp, Cassia abbreviate, Euclea divinorum, Pteleopsis myrtifolia, Baphia kirkii, Ozoroa obovata, Strychnos spinosa, Margaritaria discoidea* and *Trema orientalis* (Appendix 13)

Malimbwi (2005) reported timber potential for Kazimzumbwi Forest Reserve was lost described by the effect of illegal pitsawing and intensive charcoal burning. *Afzelia quanzensis, Pseudolachnostylis maprouneifolia*, *Manilkara sasbarensis* and *Brachystegia boehmii* of dbh ranging between 6cm and 60 cm of reported to be cut from the forest (Malimbwi *et al*., 2005). The same problems within miombo woodlands of Tanzania was reported from Mpanda District for Inyonga, Msanginia, Mpanda North East Forest Reserve, Mulele Hills where encroachment, illegal timber harvesting and intensive charcoal burning contributed to reducing number of stems (Chamshama *et al*., 2004; Malimbwi *et al*., 2005) and miombo woodlands of Malawi (Abbot and Homewood, 1999). Such a removal of stems it will lead to reducing growing stock and hence transform forest into modified natural forest which in future no any progress towards sustainable and balance ecosystem (FAO, 2005)

In previous studies conducted in miombo woodland, basal area was found to range from 8 to16 $m^2.ha^{-1}$ (Backeus *et al*., 2006; Isango, 2007). This study reported a basal area of 6.49$m^2.ha^{-1}$ which is low compared to other reported figures (Table 8). Main reason contributed to low basal area being less number of trees with big diameters per unit area.

Table 7: Inventory Report of Mpanda District Forest Reserve, 2005

S/no.	Name of the forest reserve	Basal area(m2.ha-1)
1	Msaginia	6.98 ± 1.31
2	Mulele Hills	9.9 ± 0.5
3	Mpanda North East	10.23 ± 0.8
4	Rungwa	8.34 ± 0.75
5	Tongwe	10.54 ± 0.71
6	Nkamba	7.88 ± 0.89

Source: Inventory Report of Mpanda District Forest Reserve, 2005 (Malimbwi et al., 2005)

5.1.2. Relationships between crown diameter with Dbh and biomass (Field inventory)

Relationship between crown diameters with dbh from the field inventory revealed that increase of one meter of the crown diameter had the proportional increase of 0.26 cm dbh for general trend, 0.24 cm Albizia petersiana, and 0.21cm for Afzelia quanzensis and 0.27 cm for Brachystegia boehmii. From this trend it indicates that there are some variations of increase of crown diameter against dbh between species in miombo woodlands of Tanzania. The highest increment was shown by Brachystegia boehmii as compared to general trend, Albizia petersiana, or Afzelia quanzensis. Increment of trees primarily depend on the size of the assimilation apparatus of the crown and its efficiency to produce organic matter (Turski *et al*., 2008).

Increment of single unit of biomass (kg/tree) for all measured trees in general was by 11.63 m, 1.75 m for *Albizia petersiana*, 18.56 for *Afzelia quanzensis* and 16.8 m for *Brachystegia boehmii*.
Difference found between crown diameter and biomass with crown diameter caused due to crown architecture which control leaf area and its display for effective sunligh capture and photosynthesis for that case then acuumulation of the biomass is related to crown structure which differ between tress species (Chmura *et al*., 2007; Ozdemir, 2008).
Conclusion: Relationships between crown diameters with dbh and biomass in miombo woodlands of Tanzania found to be different between species.

5.2. Relationships between crown diameter with Dbh and biomass (Quickbird)

Two types of approaches for identifying and extracting objects of interest from remote sensing images are recognized till recent years, namely: manual and task specific automated approach. The former approach involves the use of trained image analysts to manually identify features of interest (individual trees in this context). The later approach involves techniques which facilitate segmentation of crowns from individual trees. These techniques are “valley” following; where there is shade between trees (Gougeon, 1995), edge finding (Pinz 1999), morphology (Barbezat and Jacot, 1999) and semi-variogram and slope breaks (Wulder *et al*., 2000).

Various studies have been made to find the relationship between crown diameters and dbh based on individual tree measurements (Gering, 1995; Stellingwerf and Hussin, 1997; Popescu *et al*., 2003; Hemerya *et al*., 2005; Kubo *et al*., 2007; Larsen, 2007; Pokharel, 2008). Hemerya *et al* (2005) indicated that all species have higher crown diameter/dbh ratios when they are young, but the ratio reduces as stem diameter increases, beginning to stabilize around 30cm dbh walnut (Juglans regia).The study (Hemerya *et al.*, 2005) revealed that crown diameter varies with tree species, tree height, site and stand density. Ozdemir (2008)used shade of individual tree on estimating volume and biomass after segmentation by visual aid delineation and computer aided automatic classification resulting into classification between stem volume with shade area and crown area.

Some of the crown areas have been seen to be underestimated which might be due to pixels assigned to vallies, optimization to improve separation, overbroken, difficulties for trees that are alligned at 900 to the sun illumination and have little or no shade at all which become not easy to identify.
Relationships between dbh versus crown diameters by multiresolution segmentation for general trends for all measured trees had R^2 of 0.66. This general trend performance was due to major contribution by individual trees as group of species or individual tree species. General trend showed that increase in one meter crown diameter leads into increase in by dbh 0.2 cm, 0.28 cm for *Albizia petersiana*, 0.16 for *Afzelia quanzensis* and 0.2 for *Brachystegia boehmii*.

The other 34% of the relationship not explained by the regression line might be contributed by image segmentation problems including appropriate scale (Strahler et al., 1986), some small diameter trees (1cm to 10cm) which at a time they can be overestimated and big diameter tree (>70 cm) being under estimated during multiresolution segmentation. This might also be due to differences in crown nature between trees within species and between tree species. Within tree species differences in crown diameters are due to age while between different species,every tree have its nature of the crown and branch orientations and shaded areas within the canopy , major branches or the ground (Blackburn and Milton, 1995; Warner *et al*., 2000; Ustin, 2004)

Relationship between crown diameter with biomass was exponential, giving an impression that crown diameter increase exponentially with the biomass; it increases to certain diameter when crown is able to support and photosynthesize food for the entire tree maintaining the crown diameter or rather increasing at a very small marginal units. In this study we found that for general trend for all trees, increment of one unit of biomass (kg/tree) corresponded to 9.7m, 0.27 m *Albizia petersiana*, 7.7 m *Afzelia quanzensis* and 11.92m *Brachystegia boehmii*.
Segmentation process was successful because most individual trees measured was away from other trees, this enabled brightest part of the crown known (Gougeon, 1995; St-Onge *et al.*, 2008). Deep shadows between trees facilitated separation of the brightest parts of the tree crowns (Gougeon, 1995)
Measuments of the crown diameters from the Quickbird image using arc map tool, for all trees measured in the field revealed good relationship between dbh and crown diameter. The regression line was able to explain 63% of the relationships.

Generally, we found that Albizia petersiana had good correlation between crown diameter versus diameter at breast height and biomass (86% and 82% respectively). Afzelia quanzensis found having low correlation compared to Albizia petersiana with coefficients of determination (R^2) of 0.53 and 0.57 repectively.

Although many authors have generally concluded that object based methods were more effective than spectral methods,there are still problems in the transition zone between contrasting objects in highly heterogenous areas (Carleer and Wolff, 2004; Martinez Morales *et al*., 2008). Woodland ecosystems in tropics constitute a greater variety of tree species and more heterogenous canopy background due to large number of shrubs and tree species. Recommended to develop classification approach to differentiate transitional areas to make more accurate and reliable forest resources inventories (Martinez Morales *et al*., 2008).

This can be explained from the fact that polygons segmented from the Definiens developer do not define individual tree crowns properly. All areas with different spectral characteristics are identified as different polygons.Secondly, some GPS points taken range from an error of one up to five meters. For that case such a radius of five meters is already the polygon of another tree.There is a problem of shadow casted the other side of the tree during image aquiring. Those shade areas are also considered different polygons and hence mislead the areas of true polygons.

5.3. NDVI relationship between high versus medium resolution imagery

NDVI values from the ASTER image which was aquired in the month of Dec 8th 2006 was high; ranging from 0.64 to 0.77 indicating that high greeness in the field area as compared to of high resolution with NDVI ranging from 0.33 to 0.58. This probably might be contributed by:

- Pixel from the quickbird image does not present full object as what ASTER image does (pixel size of 15 and after focal statistics reaching up to 45m). Quickbird image have the pixel size of 0.6m (Fig 5-2). High resolution imagery provides more spatial details and for that case fewer mixed pixels. However then, increasing spatial resolution may lead to over sampling resulting in variation within individual trees which again introduced erros and mismatch between NDVI between the two images (Aplin, 2006)

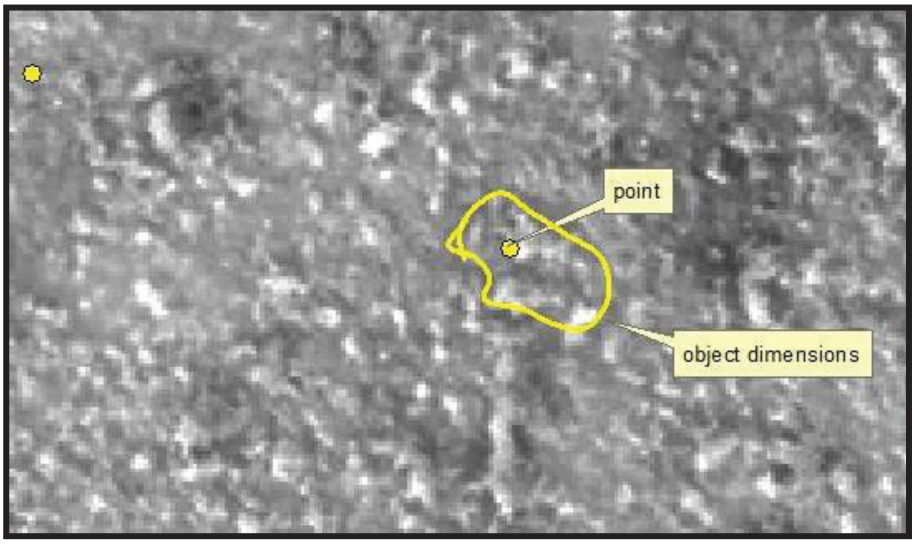

Figure 5-2: Size of the full tree object compared to point taken for NDVI in quickbird image

- Characteristics of trees in miombo woodland of shedding leaves during periods of the year.
- Miombo woodlands long dry season starts April to October while most rains start from March to November. During early periods of dry periods all trees shade their leaves (except miombo woodlands which are evergreen). Tree leaves starts again sprouting the period just before the rain starts.
- Removal of trees for lumbering and charcoal burning (Fig 5-3). There is good accessibility to the forest by the surrounding neighbourhood villages and hence no natural barrier in all boundaries of the forest. Miombo woodlands are mostly prefered due to the diversity in the use of its wood Trees with big diameters when are extracted from the plots reflectances decreases because no photosynthetic material detected within the same plot area in the quickbird image of the year 2008.

Figure 5-3: Tree cut and charcoal kiln(left), charcoal ready to be taken out of forest reserve (right)

Source : Photos taken during field work by Seleboni John

- Another factor which might have contributed to differences in NDVI for the two images is the seasonal differences between acquiring the two images. Aster image was acquired on December the time which most of the trees has not yet shed the leaves while Quickbird image was acquired when trees has shed most of their leaves. Difference in seasonality has positive impact on the spectral reflectances focusing on the vegetation aspect of the forest. NDVI is sensitive to phenological changes in season related to canopy pigmentation (Lu *et al*., 2004).

- Fire is another factor which might have contributed to differences in NDVI variations between two years. Fire reduces the regeneration power of the trees by resprouting of the big cut trees. Fire in the study area is dominant due to fire set by the surrounded villages during farm preparations (Figure 5-4)
-

Figure 5-4: Fire in miombo woodlands

Source: (Frost, 1996)

5.4. Upscaling high to medium resolution satelite imagery imagery

5.4.1. Crown closure

Crown closure is the percentage canopy projected to a horizontal plane over a unit ground area (Xu et al., 2003; Kim *et al.*, 2006). Crown closure can be used to depict stand density also have directly related to NDVI (Kim *et al*., 2006). Statistical correlation analysis performed between crown closure and spectral properties proved depend on accuracy of ground measured and remote sensing data (Cihlar, 2000). Some errors have been reported when calculating crown closure.

Relationship between canopy (crown) closure with spectral characteristics both high resolution (Quickbird) and medium resolution imagery (ASTER) showed good relationship with NDVI (R^2 =0.62) though high in ASTER image than in Quickbird image (R^2 =0.47). ASTER image is able to accomodate more of the objects compared to quickbird image due to differences in pixel size (Sections 5.5.4: Fig 4-39 and Fig. 4-40). Errors which bring the relationship low may be error associated with common closure modelling method, error associated with crown closure calculation of the plots and error associated with variability of crown closure within the plot (Gill *et al*., 2000). An attempt had been made to find the relationship between Crown closure with NDVI and EVI (Xu *et al*., 2003), showing good relationship (R^2 =0.7 Near Infra Red (NIR, Red and Blue in Landsat TM was able to adequately model crown closure with R^2= 0.8% (Xu *et al*., 2003). As other studies suggested, errors may also due be to total reflectance of the forest canopy is a combination of illuminated and shaded components of the tree crowns as well as background (Canisius and Chen, 2007).

5.4.2. Biomass, Basal area and number of stems

Results from this study revealed very poor relationship between biomass with NDVI and EVI from both Quickbird and ASTER images. Previous studies have the same findings stating that vegetation indices are sensitive to canopy, geometry terrain factors, species composition (internal factors) while sun elevation angle, zenith view angle and atmospheric condition as external factors which affect adversely vegetation reflectances (Lu *et al.*, 2004). Within miombo woodlands some trees shade leaves on different seasons of the year while others are evergreen which make different spectral characteristics at different times which does not at all relate to biomas. It was reported Blackburn and Milton (1995) that spectral reflectances of deciduos forest changes markedly throughout the year as the season changes and nature of individual trees and phenology of the canopy. Fire, which is the common phenomenon in miombo woodland had an effect on reflectances as it tend to increase Short Wave Infra Red (SWIR) giving high NDVI than really depicted on the vegetation (Silva *et al*., 2004).
Vegetation has high NIR reflectances due to scattering of mesophyll cells and red reflectance due to absorption by chlorophyll. Areas with clouds results into negative values because of high reflectances in Red than in NIR. Values near to zero are either on soils or bare meaning the same reflectances in both Red and NIR reflectances.

Saturation which is the relationship between biomass and NDVI is a known issue in forests (Mutanga et al., 2004). It works under the sense that when canopy cover increases amount of red light can be absorbed by the leaves reach a peak while NIR still increasing due to multiple scattering with leaves.
The reflectance spectum of green vegetation in visible spectrum is controlled by contribution from the chlorophyll. Different tree species have different reflectance spectum which is mainly caused by water content and chlorophyll. Reflectance bias occurs among the NIR reflectance data from satelite products potentially caused by absolute callibration errors in cloud shadow contaminations.
So because of the poor relationship between biomass with NDVI it was not possible to continue with upscaling biomass from high to medium resolution imagery. Higher relationships between biomass and NDVI could have permitted production of woody biomass map of the area (de Gier and Sakouhi, 1995). Studies reported poor relationship betwen biomass and NDVI due to inconsistence and unsatisfactory influences of the background reflectance and canopy structure on the overall pixel reflectance (Peddle *et al*,1999).

5.5. Limitations of the study

- Both images were mostly covered by clouds which were beyond level which can be removed by the available softwares within the plot areas established in the field. 15 plot centres were completely within total cloud area and no any spectral information was possible.
- . Each image was taken on different season which lead to different readings of the spectral characteristics between two images. Time of acquiring both images were not compatible in terms of season and years
- Availability of very limited number of the images within the study area due to most of them being with much cloud.

6. CONCLUSION

6.1. Research outcomes

The objective of this study was to find the possibility of upscaling biophysical forest parameters from high to medium resolution imagery in miombo woodlands of Tanzania.

The study concluded the following that crown diameter can be derived from high resolution imagery (Quickbird) accurately. Relationships with general trend for all trees and for group of species were high enough to conclude the possibility of deriving crown diameter from high resolution imagery. However it was not possible to derive number of stems accurately from high resolution imagery.

Biomass related strongly with crown diameter derived from high resolution imagery as well as ground inventory data. This is an indication that there is a positive correlation between crown diameters with biomass in miombo woodlands of Tanzania. Otherwise, this study proved poor correlation between numbers of stems extracted from the high resolution imagery with the biomass.
Relationship between biomass with NDVI and EVI derived from Quickbird image was poor. Poor relationship between NDVI and EVI from ASTER and Quickbird images with biomass was not enough to predict biomass therefore upscaling above ground biomass was not possible. The same applied to basal area and number of stems.

Generally; the study concluded that spectral data can not be upscaled from high resolution imagery using quick bird image to medium resolution imagery using Aster image.This is because ASTER image with 15m spatial resolution often contains many mixed pixels which may contain one or more than one objects (trees) in a single pixel compared to quickbird image with a pixel size of 0.6m which does not present full object (tree) Remote sensors in this aspect capture canopy information rather than individual tree information.

6.2. Recommendations

- The biomass equation developed and used to estimate biomass in this study can be used in miombo woodlands of Tanzania because considered unbiased.
- Plot centres should be well marked accurately otherwise errors due to GPS reading and geometry correction of the image will lead to a very serious transfering the from intended. The consequence of this, features in the field differ from the spectral characteristics extracted from the image hence be source of running into negative answers.
- Use of alternative imaging technology like for example CASI (Compact Airborne Spectragraphic Imagery) which can utilize other properties apart from spectral relationship can be researched further.
- Use of subsampling method in biomass estimation for miombo woodlands could give good results hence provide reliable and unbiased equation for estimating biomass.Sub sampling is not biased, robust and less destructive.

- Identifying and distinguishing by classification should be further researched utilizing different tree species in miombo woodland of Tanzania.
- Taking GPS points to the individual trees and/ or group of trees need care also. Recording erros shift completely position of the crown and hence mislead all other calculation. At least individual trees should be away from 5m.
- Accurate assessment of biomass using remote sensing still need further advanced techniques.
- Images which are to be compared recommended be free of clouds and of the same season due to difference in leaf characteristics on different periods of the year.

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APPENDICES

Appendix 1: Attributes of sample trees taken for development of tree component biomass polynomial equation for Kazimzumbwi forest Reserve, Coastal Region, Tanzania.

Tree No	Botanical Name	StD (cm)	Dbh (cm)	Ht (m)	Tree biomass (kg tree-1)			Tree V (m3 tree-1)		
					Stem	Brch	Total	Stem	Brch	Total
1	*Brachystegia boehmii*	19.4	14.0	10.8	53.32	12.07	65.39	0.095	0.014	0.109
2	*Sclerocarya birrea subsp.caffra*	34.0	33.0	11.9	163.53	96.01	259.54	0.458	0.111	0.569
3	*Combretum adonogonium*	21.9	14.8	8.4	46.26	29.14	75.40	0.070	0.022	0.092
4	*Combretum molle*	28.5	23.2	10.3	157.23	87.79	245.02	0.218	0.078	0.296
5	*Acacia gerrardii*	38.9	34.0	15.0	570.36	170.58	740.94	0.831	0.059	0.890
6	*Acacia polyacantha subsp. campylacantha*	40.0	32.0	16.4	335.58	47.15	382.73	0.643	0.031	0.674
7	*Combretum molle*	2.7	2.0	2.7	0.38	0.09	0.47	0.001		0.001
8	*Brachystegia boehmii*	6.5	4.4	3.5	2.73	0.48	3.21	0.005		0.005
9	*Dombeya rotundifolia*	2.5	1.7	2.7	0.26		0.26	0.001		0.001
10	*Julbernardia globiflora*	1.8	1.0	1.7	0.11	0.05	0.16			
11	*Julbernardia globiflora*	26.2	25.0	10.6	134.48	74.07	208.55	0.230	0.037	0.267
12	*Terminalia mollis*	11.6	11.3	7.0	19.98	7.39	27.37	0.048		0.048
13	*Sclerocarya birrea subsp.caffra*	57.0	50.0	15.0	926.58	184.93	1111.51	1.898	0.069	1.967
14	*Julbernardia globiflora*	19.7	16.0	10.5	90.86	39.85	130.71	0.111	0.015	0.126
15	*Zahna africana*	25.0	21.5	9.6	146.12	80.45	226.57	0.186	0.040	0.226
16	*Diplorhynchus condylocarpon*	32.0	26.4	10.2	99.53	79.26	178.79	0.312	0.034	0.346
17	*Brachystegia microphylla*	25.5	24.0	14.6	206.36	72.57	278.93	0.243	0.017	0.260
18	*Xeroderris stuhrmannii*	41.5	40.0	15.0	537.54	145.20	682.74	0.910	0.094	1.004
19	*Brachystegia boehmii*	38.5	38.0	16.0	652.86	161.83	814.69	1.207	0.096	1.303
20	*Lonchocarpus bussei*	8.8	8.0	5.7	10.12	2.36	12.48	0.003	0.001	0.004
21	*Boscia salicifolia*	9.0	8.5	4.7	8.40	0.65	9.05	0.003		0.003
22	*Pseudolachnostylis maprouneifolia*	4.8	4.7	2.4	1.78	0.06	1.84	0.003		0.003
23	*Dichrostays cinerea*	9.0	8.1	4.1	10.05	0.01	10.06	0.006	0.005	0.011
24	*Bauhinia petersiana*	2.1	1.5	2.9	0.22	0.06	0.28			
25	*Bridelia cathartica*	7.1	6.5	4.4	4.01	1.19	5.20	0.008		0.008
26	*Pterocarpus angolensis*	2.5	1.1	2.1	0.12		0.12			
27	*Crossopteryx ferbrifuga*	3.8	3.2	2.2	0.07	0.05	0.12	0.001		0.001
28	*Xeroderris stuhrmannii*	50.0	45.0	18.4	1594.55	287.26	1881.81	2.292	0.116	2.408
29	*Brachystegia boehmii*	32.5	30.1	12.5	349.82	131.56	481.38	0.493	0.083	0.576
30	*Brachystegia boehmii*	38.8	37.5	11.3	584.73	126.04	710.77	0.947	0.060	1.007
					78%	22%	100%	92%	8%	100%

Where: StD = Stump diameter; dbh = Diameter at Breast Height; Ht = Tree total Height (m); V = Volume and Brch = Branch.

Only diameter at breast height (dbh) was used to develop biomass estimation equation in this study

Appendix 2: Tree species found in the study area.

S.no	**Vernacular name of tree species**	**Botanical name of tree species**
1	mtete	*Savadora persica*
2	mtunda	*Manilkara sasbarensis*
3	mchedi	*Manilkara sulcata*
4	mkongo	*Afzelia quanzesis*
5	mkenge	*Albizia gummifera*
6	mtonga	*Strychnos spinosa*
7	msani	*Brachystegia microphylla*
8	mpiwipwi	*Lannea schweifnfurthii*
9	mkwaju	*Tamarindus indica*
10	mgomba kilangu	*Ozoroa obovata*
11	mzikoziko	*Ehretia amoena*
12	mkenge kigozi	*Albizia petersiana*
13	mkundekunde	*Cassia abbreviata*
14	msani	*Brachystegia bussei*
15	mgovu	*Pteleopsis myrtifolia*
16	mng'ongo	*Sclerocarya birrea spp caffra*
17	mkuruti	*Baphia kirkii*
18	mnangu	*Hymaenea verucosa*
19	mkole	*Grewia bicolor*
20	mkongowe	*Acacia robusta*
21	myombo	*Brachystegia boehmii*
22	mkonze	*manilkara mochisia*
23	msinzila	*Bridelia cathartica*
24	mpehe	*Trema orientalis*
25	mburuzu	*?*
26	mdaa	*Euclea divinorum*
27	msiga	*Dobera loanthifolia*
28	mlama	*combretum spp*
29	mkengemaji	*Albizia spp*
30	mpingo	*Dalbegia melanoxylon*
31	mjenga ua	*Commiphora spp*
32	mtondoro	*Jubernadia spp*
33	mpiwipwi	*Lannea schweifnfurthii*

Appendix 3: Plot data recording form

Plot data Recording Form

Date …………… Name of Recorder: ……………… ……

Transect number ……… Plot number ………………………

Coordinates: X: ……………………………. Y: ………………………………..

Slope: ………………………………………

Number of Stems: ……………………………

S.no	Vernacular name of the tree species	Dbh(cm)	Crown diameter(m)		Remarks
			K_1	K_2	

Note that:

K_1=East to west measurements of the crown diameter of the tree

K_2= North to South measurements of the crown diameter of the tree

Appendix 4: Individual tree measurement recording form

Individual tree measurements recording form

Date: ………………………..

Form number: …… Name of a Recorder ……………………… Date: ………………

S.no	**Coordinates**		**Vernacular name of the tree species**	**Dbh (cm)**	**Crown diameter**	
	X coordinate	**Y coordinate**			**K_1**	**K_2**

Note that:

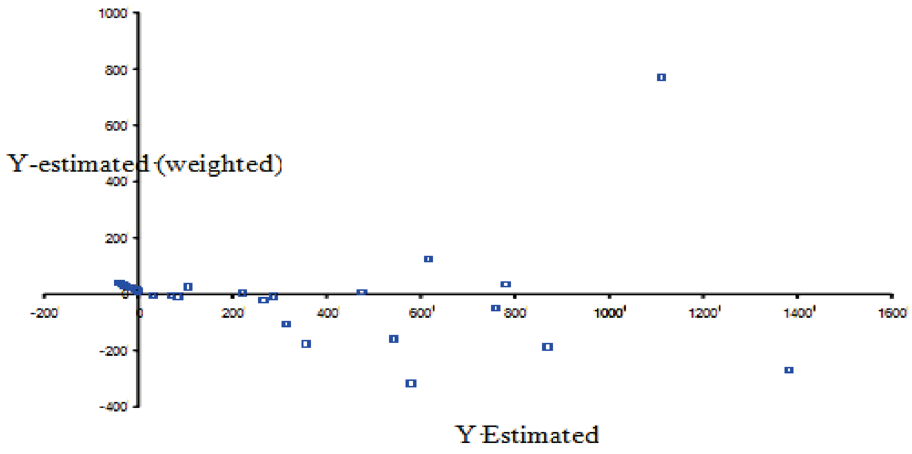
K_1=East to west measurements of the crown diameter of the tree

K2= North to South measurements of the crown diameter of the tree

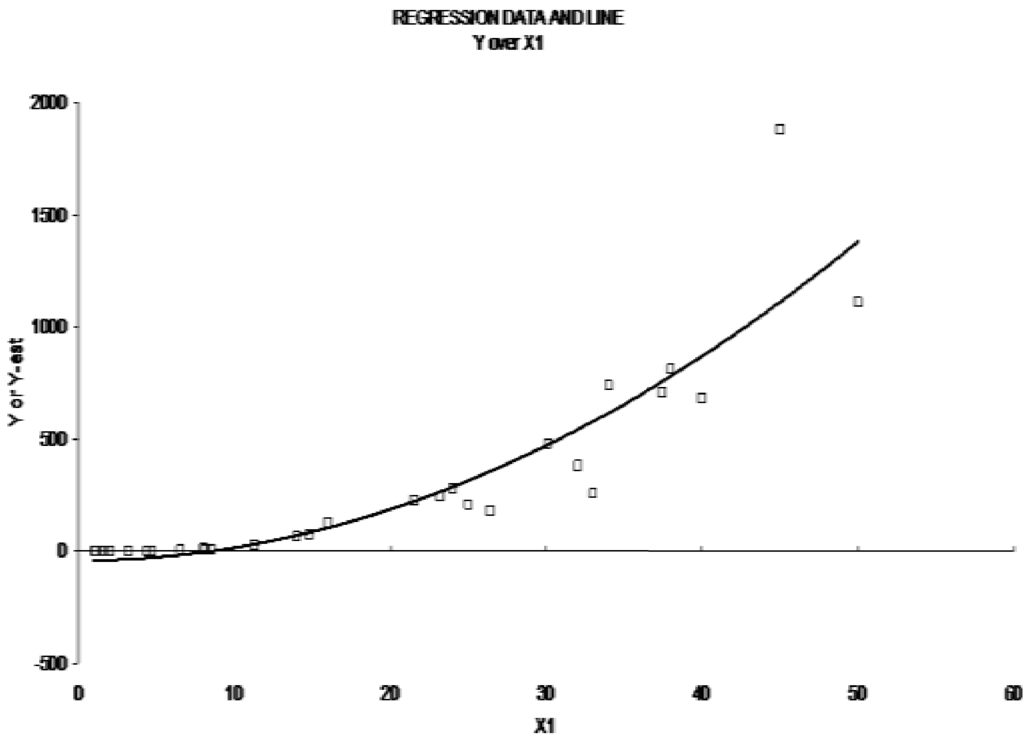
Appendix 5: Vegetation Indices

Name	**Equation**	**Reference**
Simple ratio (SR)	$\frac{\rho_{TM4}}{\rho_{TM3}}$	(Pearson and Miller, 1971)
Normalised difference vegetation index (NDVI)	$\frac{\rho_{TM4}-\rho_{TM3}}{\rho_{TM4}+\rho_{TM3}}$	(Rouse *et al*., 1974)
Perpendicular vegetation index (PVI)	$\frac{\rho_{TM4}-a\rho_{TM3}-b}{\sqrt{1+a^2}}$, a = 0.9, b = 0.1	(Richardson and Wiegand, 1977)
Transformed soil-adjusted vegetation index (TSAVI)	$\frac{a(\rho_{TM4}-a\rho_{TM3}-b)}{a\rho_{TM4}+\rho_{TM3}-ab}$, a = 0.9, b = 0.1	(Baret *et al*., 1989)
Mid-infrared vegetation index (MVI)	$\frac{\rho_{TM4}}{\rho_{TM5}}$	(Fassnacht *et al*., 1997)
Greenness vegetation index (GVI)	$-0.2848\rho_{TM1}-0.2435\rho_{TM2}$ $-0.5436\rho_{TM3}+0.7243\rho_{TM4}$ $+0.0840\rho_{TM5}-0.1800\rho_{TM7}$	(Christ and Cicone, 1984)
EVI	$EVI = G*\frac{\rho_{NIR}-\rho_{Red}}{\rho_{NIR}+C_1{}^*\rho_{Red}-C_2{}^*\rho_{Blue}+L}$ G= 2.5, C_1=6, C_2=7.5 and L=1	(Huete *et al*., 1997)
EVI	EVI= G* [(ρNIR- ρ Red)/ (ρNIR +C_1* ρ Red * L)] G = 2.5, C_1=2.4, and L=1	(Jiang *et al*., 2008; Miura *et al*., 2008)

Appendix 6: Graph showing Residual plots for un-weighted 3rd polynomial equation



Appendix 7: Graph showing regression data and line for un-weighted 3rd polynomial equation



Appendix 8: Distribution of number of stems (stems.ha-1) of different tree species with their diameter classes.

S.no	Vernacular name	Botanical Name	DBH CLASSES (cm)					Grand Total
			1-10	11-20	21-30	31-40	41-50	
1	mtete	*Savadora persica*	539	5	1			544
2	mtunda	*Manilkara sasbarensis*	117	2	1			120
3	mchedi	*Manilkara sulcata*	316	6				322
4	mkongo	*Afzelia quanzesis*	1167	17	2			1186
5	mkenge	*Albizia gummifera*	9	3	1	1	1	14
6	mtonga	*Strychnos spinosa*	199					199
7	msani	*Brachystegia microphylla*	85					85
8	mpiwipwi	*Lannea schweifnfurthii*			1			1
9	mkwaju	*Tamarindus indica*	41					41
10	mgomba kilangu	*Ozoroa obovata*	204					204
11	mzikoziko	*Ehretia amoena*	18	3				22
12	mkenge kigozi	*Albizia petersiana*		1				1
13	mkundekunde	*Cassia abbreviata*	5					5
14	msani	*Brachystegia bussei*	66	6	1	1		73
15	mgovu	*Pteleopsis myrtifolia*	256					256
16	mng'ongo	*Sclerocarya birrea spp caffra*		1				1
17	mkuruti	*Baphia kirkii*	171					171
18	mnangu	*Hymaenea verucosa*	5					5
19	mkole	*Grewia bicolor*	117	5				122
20	mkongowe	*Acacia robusta*	61	1				63
21	myombo	*Brachystegia boehmii*	5					5
22	mkonze	*manilkara mochisia*	9					9
23	msinzila	*Bridelia cathartica*	42					42
24	mpehe	*Trema orientalis*	184	1				185
25	mburuzu	*?*	14					14
26	mdaa	*Euclea divinorum*	57					57
27	msiga	*Dobera loanthifolia*			2			2
28	mlama	*combretum spp*	47	1				48
29	mkengemaji	*Albizia spp*	156	1				157
30	mpingo	*Dalbegia melanoxylon*	42	1				43
31	mjenga ua	*Commiphora spp*	38	1				39
32	mtondoro	*Jubernadia spp*	71	2				73
33	mpiwipwi	*Lannea schweifnfurthii*	28	1				30
		Grand Total	4067	60	7	1	1	4135

Appendix 9: Table showing Biomass distribution of Biomass (tonnes.ha-1) to different tree species to dbh classes

S.no	Vernacular name	Botanical Name	DBH CLASSES					Grand Total
			1-10	11-20	21-30	31-40	41-50	
1	mtete	*Savadora persica*	1.04	0.26	0.07			1.37
2	mtunda	*Manilkara sasbarensis*	0.52	0.18	0.09			0.80
3	mchedi	*Manilkara sulcata*	0.73	0.59				1.32
4	mkongo	*Afzelia quanzesis*	1.96	1.04	0.38			3.38
5	mkenge	*Albizia gummifera*	0.13	0.21	0.09	0.38	0.39	1.21
6	mtonga	*Strychnos spinosa*	0.36					0.36
7	msani	*Brachystegia microphylla*	0.19					0.19
8	mpiwipwi	*Lannea schweifnfurthii*			0.16			0.16
9	mkwaju	*Tamarindus indica*	0.40					0.40
10	mgomba kilangu	*Ozoroa obovata*	0.39					0.39
11	mzikoziko	*Ehretia amoena*	0.41	0.15				0.55
12	mkenge kigozi	*Albizia petersiana*		0.05				0.05
13	mkundekunde	*Cassia abbreviata*	0.04					0.04
14	msani	*Brachystegia bussei*	0.22	0.33	0.08	0.22		0.85
15	mgovu	*Pteleopsis myrtifolia*	0.50					0.50
16	mng'ongo	*Sclerocarya birrea spp caffra*		0.04				0.04
17	mkuruti	*Baphia kirkii*	0.41					0.41
18	mnangu	*Hymaenea verucosa*	0.06					0.06
19	mkole	*Grewia bicolor*	0.64	0.17				0.81
20	mkongowe	*Acacia robusta*	0.17	0.07				0.24
21	myombo	*Brachystegia boehmii*	0.08					0.08
22	mkonze	*manilkara mochisia*	0.12					0.12
23	msinzila	*Bridelia cathartica*	0.14					0.14
24	mpehe	*Trema orientalis*	0.34	0.04				0.38
25	mburuzu	*?*	0.10					0.10
26	mdaa	*Euclea divinorum*	0.12					0.12
27	msiga	*Dobera loanthifolia*			0.35			0.35
28	mlama	*combretum spp*	0.27	0.03				0.30
29	mkengemaji	*Albizia spp*	0.40	0.04				0.44
30	mpingo	*Dalbegia melanoxylon*	0.10	0.06				0.16
31	mjenga ua	*Commiphora spp*	0.07	0.03				0.10
32	mtondoro	*Jubernadia spp*	0.17	0.10				0.27
33	mpiwipwi	*Lannea schweifnfurthii*	0.01	0.06				0.08
Grand Total			10.09	3.46	1.22	0.59	0.39	15.75

Appendix 10: Table showing estimated stand parameters

PLOT No	Canopy closure (ha-1)	Basal area(m3.ha.-1)	Number of stems(ha-1)	Biomass (tonnes.ha-1)
1	0.24	8.80	239	18.86
2	0.04	8.13	127	14.44
3	0.22	8.49	183	17.91
4	0.21	7.29	197	18.94
5	0.23	6.22	141	13.17
6	0.22	6.42	155	12.98
7	0.21	3.88	99	8.55
8	0.21	5.64	141	12.89
9	0.23	4.86	113	15.08
10	0.20	9.88	225	20.55
11	0.13	4.76	113	10.99
12	0.73	5.19	127	16.34
13	0.64	5.74	141	16.47
14	0.31	6.63	197	18.44
15	0.23	8.61	183	20.03
16	0.20	6.14	155	16.69
17	0.23	8.59	169	21.01
18	0.23	7.80	155	18.67
19	0.24	6.50	155	18.07
20	0.15	7.12	211	15.60
21	0.50	8.27	127	36.17
22	0.38	4.86	113	15.08
23	0.08	5.17	127	10.43
24	0.07	3.97	113	8.05
25	0.05	5.92	113	11.08
26	0.13	5.35	141	11.62
27	0.11	5.09	127	10.97
28	0.15	6.60	141	13.62

Appendix 11: NDVI values from quickbird and Aster images

PLOT number	EASTINGS	NORTHINGS	NDVI from Quickbird image	NDVI from Aster image
1	503407	9231859	0.51	0.77
2*	503534	9231731	0.14	0.71
3	503661	9231606	0.34	0.76
4	503789	9231477	0.34	0.72
5	503916	9231349	0.48	0.76
6	504046	9231222	0.49	0.72
7	504171	9231098	0.37	0.74
8	504291	9230961	0.33	0.75
9	504420	9230832	0.58	0.77
10	504549	9230703	0.40	0.64
11*	504017	9230172	0.19	0.77
12*	503897	9230317	0.14	0.68
13*	503772	9230450	0.68	0.74
14*	503644	9230579	0.37	0.77
15	503519	9230708	0.50	0.75
16	503390	9230832	0.41	0.70
17	503262	9230965	0.51	0.76
18	503137	9231085	0.45	0.74
19*	502676	9230515	0.36	0.65
20*	502804	9230382	0.37	0.66
21*	502929	9230252	0.39	0.65
22*	503053	9230121	0.42	0.63
23*	503181	9229990	0.15	0.72
24*	503309	9229859	0.18	0.67
25*	503433	9229732	0.26	0.76
26*	502872	9229221	0.04	0.72
27*	502732	9229342	0.36	0.73
28*	502588	9229459	0.39	0.71

Plot numbers with asterisk mark (*) were not considered for value extraction due to presence of clouds

Appendix 12: EVI values from quickbird and Aster images

	COORDINATES		IMAGES	
PLOT_NO	X	Y	ASTER	QUICKBIRD
1	503407	9231859	1.66	1.72
2*	503534	9231731	1.35	0.58
3	503661	9231606	1.54	1.12
4	503789	9231477	1.06	1.44
5	503916	9231349	1.65	1.57
6	504046	9231222	1.50	1.57
7	504171	9231098	1.62	1.21
8	504291	9230961	1.61	1.04
9	504420	9230832	1.59	2.42
10	504549	9230703	1.26	1.30
11*	504017	9230172	1.39	0.70
12*	503897	9230317	1.57	0.57
13*	503772	9230450	1.72	1.71
14*	503644	9230579	1.37	1.20
15	503519	9230708	1.60	1.63
16	503390	9230832	1.41	1.45
17	503262	9230965	1.63	1.52
18	503137	9231085	1.71	1.34
19*	502676	9230515	1.41	1.14
20*	502804	9230382	1.37	1.18
21*	502929	9230252	1.28	1.19
22*	503053	9230121	1.30	1.37
23*	503181	9229990	1.18	0.98
24*	503309	9229859	1.24	1.10
25*	503433	9229732	1.32	1.22
26*	502872	9229221	1.18	0.34
27*	502732	9229342	1.59	1.15
28*	502588	9229459	1.55	1.31

Plot numbers with asterisk mark (*) were not considered for value extraction due to presence of clouds.

Appendix 13: Samples of some tree species found in the study area.

Brachystegia boehmii matured tree with seeds (left), young tree (Right)

Acacia robusta matured tree (left) young tree (right)