Aboveground woody biomass assessment in Serowe woodlands, Botswana

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by

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Quantitative assessment of aboveground woody biomass in terms of volume, fresh and or dry weight per unit area is a useful way to provide estimates of various tree components that can be harvested. This is more relevant to Botswana forests and woodlands since 53% of the population depends on wood resources for energy purposes in the form of fuelwood. However, the approaches used to quantify the resource can be laborious and time consuming hence costly. It is because of this reason that data on aboveground woody biomass in Botswana is unreliable and scanty. Nonetheless, the technique of remote sensing has become common in forest investigation providing the only realistic and cost effective way of acquiring data over larger areas. The field data is used for validating the remote sensing data. However, one major problem is with the field part which is addressed prominently in this thesis. Two biomass estimation methods; model stem method (Adhikari, 2005; Montes et al., 2000) and the sub-sampling method (de Gier, 1989) were compared in terms of time use efficiency and reliability. It was found that model stem method was very efficient in terms of time usage but not reliable. The sub-sampling method was also efficient in terms of time usage in the field, but was also found to be reliable and a better method in many ways compared to model stem method.

Sub-sampling method provides in-the-field estimates of volume and fresh weight. Dry weight can be calculated after drying the same wood samples (disks) used to calculate the fresh woody biomass. A few light weight pieces of equipment are required for the application of this method and field work can be carried out by only two people. Tree species sampled were *Terminalia sericea*, *Dichrostachys cinerea*, *Ochna pulchra*, *Burkea africana*, *Lonchocarpus nelsii*, *Boscia albitrunca* and *Acacia fleckii*. During the development of biomass equations, it was found that there was no rationale for the development of species-specific equations. Hence mixed-species equation was developed using weighted curvilinear regression technique. This was facilitated by the use of POLYREG and REGDAT programs, resulting in a polynomial biomass equation based on the diameter at ankle height (*dah*). The equation was used to estimate aboveground woody biomass per plot (kg/m²), using the inventory data collected in the field for 169 plots. Next, the potential of satellite based remote sensing techniques combined with biomass estimation method for quantitative assessment of aboveground woody biomass in the study area (Serowe woodlands of Botswana) was investigated. An IKONOS image of February, 2002 was used to derive spectral vegetation indices namely; the Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI) and Perpendicular Vegetation Index (PVI). Vegetation maps were overlaid with the plot shapefile and the mean vegetation indices values were extracted and correlated with aboveground biomass (kg/m²) per plot. However, the relationship between estimated aboveground woody biomass and vegetation indices derived from the IKONOS image showed poor correlation coefficients (R) of NDVI = 0.024, EVI = 0.083, SAVI = 0.077, and PVI = 0.060. Therefore, estimating woody biomass using spectral data proved to be difficult. Hence the biomass map of the study area could not be produced. Though the potential of ground based biomass estimation combined with satellite based remote sensing proved difficult, the practical use of this thesis work can be found in providing adequate and reliable information regarding the woody biomass resource particularly fuelwood.
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1. Introduction

1.1. Fuelwood issue

Traditionally, forests have been used for many products including but not restricted to timber, fodder and fuel (Brown, 1997). Therefore, determining the biomass of forests is a useful way of providing estimates of the quantity of these forest components. Forest studies have been focusing mainly on commercial timber production ignoring other useful components such as fuelwood. Fuelwood in this study is considered synonymous with aboveground woody biomass or just biomass, and the latter is defined as woody material including stem, branches and twigs with diameter 2.5 cm or higher. This is because the focus of the study is on wood resources, therefore diameters of stems and branches more than 2.5 cm were considered to be fuelwood. This was based on the observation by de Gier (1989) that fuelwood dimensions are not erratic; the length of a single piece is often an arms length and the diameter about an arm thickness. Therefore 2.5 cm was taken as a threshold. For that reason, every tree with the diameter of 2.5 cm or higher at the base is included in the study.

An evaluation of literature on the use of biomass in the form of fuelwood shows an ever-increasing recognition of its importance as a source of energy especially for the developing world. It accounts for 60-95 % of the total energy use in the poorest developing countries, 25-60% in the middle income countries (Howe and Gulick, 1980; Kgathi and Mlotshwa, 1997; Leach and Mearns, 1988), 5 % for the European countries (Dessus, 1999) and less than 5 % in the rest of the industrialized world (Leach and Mearns, 1988). It is also the primary cooking fuel for 80 % of the populations in rural Africa (Kgathi and Mlotshwa, 1997). Already consumed in quantities that exceed annual replenishment, the demand for fuelwood is still on the increase, and this is also fuelled by Africa’s rapid population growth accelerated by conversion to charcoal (Kgathi and Mlotshwa, 1997). The obvious results of this dependence on fuelwood are varied. They range from dwindling of the resource because of deforestation to costs of obtaining wood fuels whether in cash or time for harvesting the resource (Kgathi and Mlotshwa, 1997; van Heist and Kooiman, 1992). Fuelwood disappearance increases the distance between the points of consumption and supply. Hence, people spend more time and effort travelling longer distances to collect fuelwood, which time and effort could have been used for more productive activities like food production or education. This in turn contributes enormously to the ongoing poverty vicious circle common to most African countries.

Unfortunately for Africa, statistics on the production of aboveground woody biomass are unreliable because of secondary sources of data used, insufficient methodological detail and unrepresentative data from limited sampling (Northup et al., 2005) and this is equally true for its importance with regard to its economic value. Sekhwela (1997) states that the artificial economic ‘invisibility’ of other wood consuming activities such as fuelwood has resulted in a narrow approach to the woody biomass energy crisis. This, he notes has delayed data collection in other areas of wood use and deforestation by decades, preventing the compilation of comprehensive biomass statistics.
Botswana as one of the developing countries is not an exception. The majority of the population in the country depend on wood resources for fuelwood. Wood resources in Botswana are declining especially near settlements. This has been found to be caused by fuelwood harvesting (Kgathi and Mlotshwa, 1997; van Heist and Kooiman, 1992) particularly for trading purposes. The Government of Botswana statistics (2001) indicates that fuelwood is the leading source of energy for the population of Botswana with 53%. This has caused concern in the relevant organisations and government institutions particularly the Energy Affairs Division (EAD). However, the problem is further compounded by lack of information on the woody biomass resource in the country. Information regarding the quantity of the resource available in our woodlands; the rate of growth of the resource; the rate at which the resource is being harvested; the locations where the resource is abundant; is non existent or unreliable. Lack of information came about because of the expensive nature of forest data collection.

The traditional way of collecting forest data is through manual, field based observation. This approach has the benefit of generating highly accurate measurements, but due to its labour intensive nature, high cost associated with the length of time spent in the field, and often constrained by lack of access (Couteron et al., 2001; de Gier, 1989; de Gier, 1995; Hansen et al., 2002; Harrell et al., 1997; Kasischke et al., 1997), this approach is generally not practical for anything other than local scale studies (Aplin, 2003). Hence, many organisations in Botswana are finding it difficult to invest financial resources and time on this activity, hence non existence or unreliability of data on the resource in Botswana.

Therefore, these problems make energy planning endeavours very difficult. However, attempts have been made to assess and estimate the amount of aboveground woody biomass available in Botswana forests and woodland savannas, using different biomass estimation techniques (Kgathi and Mlotshwa, 1997; Ringrose et al., 1990; Tietema, 1993). The results of these studies were generally too fragmented and conflicting because they were based on different biomass estimation methods. Therefore, they can not be synergised to be used for energy planning purposes since they are not comparable (Tietema, 1993).

For example in 1999, The Government of Botswana commissioned a study on ‘Fuelwood Flow Paths in the city of Francistown’. The aim of the study was to assess the demand and supply of aboveground woody biomass resources in and around the city. The study concluded that the rate of harvesting of the resource is sustainable based on the demand and that the sustainability will continue for a foreseeable future. This was a localised finding based on the data collected in Francistown and not necessarily representative of Botswana in general. Other researchers (Kgathi and Mlotshwa, 1997; Ringrose et al., 1990; Tietema, 1993) revealed that harvesting of aboveground woody biomass resource in Botswana is not met sustainably. This is supported by the increased distance from fuelwood collection points and the sudden mushrooming of fuelwood traders in the country. These contrasting conclusions could be attributed to different aims of carrying out the study and/or to unreliable and fragmented techniques of biomass estimation used.

The central Statistics Office (CSO) in Botswana collects data on biomass products particularly wood products by way of dispatching questionnaires to all operating establishments. This is usually
followed by frequent follow-ups to non-respondents until the response rate is deemed satisfactory, which would be at least 50% (FRA, 2000). Due to the financial and human resource limitations, the Biomass Unit of EAD also collects woody biomass consumption quantities from households and institutions using the same approach. This approach is prone to errors as most institutions would not reveal the actual quantities of woody biomass resources consumed.

One method of Fuelwood Inventory and Monitoring Programme (FIMP) for fuelwood/woody biomass assessment was developed by NRP (PTY) Ltd (2003) commissioned by EAD. The main objective was to provide a benchmark assessment of aboveground woody biomass in Botswana, against which future changes in the resource can be compared, hence enabling and enhancing the sustainable management of fuelwood resource in Botswana. It is led by two main factors; one, is the available information upon the relationship between measurable variables in the field, gathered from extensive literature review, and two, the need to be rapid and repeatable, amongst different observers and in different areas (NRP (PTY) Ltd, 2003). This method applies the regression equations developed by Tietema (1993).

Even though the studies described above, had one thing in common, being forest biomass, the differing research aims, the methods of data collection used and the techniques used to develop biomass equations, makes it difficult for meaningful comparison to be made. Subsequently, data on the biomass resource in Botswana is still fragmented and scanty. Hence this study intends to bridge the data information gap by recommending a technique that has the lowest cost possible and minimum ground work with high rate of reliability.

On the global scale, forest biomass estimation has received more attention in recent years because the change of biomass regionally is associated with vital components of climate change. Forests are terrestrial sink of atmospheric carbon dioxide and play a central role in regulating the exchange of this important greenhouse gas (GHG) between the atmosphere and the biosphere (Harrell et al., 1997). Forests, however, can also be a source of carbon dioxide during the process of respiration and when exposed to fire. Forest biomass also determines the potential carbon emission that could be released to the atmosphere due to deforestation or conversion to non-forest land use (Kasischke et al., 1997; Lu et al., 2002). Therefore, understanding the rates at which different forest ecosystems change, grow, and add new biomass is important in developing more accurate estimates of factors contributing to changes in the atmospheric concentration of carbon dioxide and other greenhouse gases (Houghton, 1996) cited by Kasischke (1997) and also necessary for better understanding the deforestation impacts on global warming and environmental degradation.

The drafting of the Kyoto protocol of the United Nations Framework Convention on Climate Change (UNFCCC) represents an international effort in mitigating global warming by reducing the continued release of greenhouse gases into the atmosphere to 95% of 1990 levels by 2012. The UNFCC stipulates mechanisms whereby storage of carbon in terrestrial sinks may be allowable for inclusion in national greenhouse gas inventories. However, the knowledge on the amount of biomass available in the earth’s terrestrial biomes is limited by the difficulty in obtaining sufficient high quality observations that are representing a region or eco-system type (Kasischke et al., 1997)
1.2. **Biomass estimation methods**

A variety of approaches have been developed to estimate aboveground biomass of forests and woodlands. These methods differ in procedure, complexity and time requirement depending on the specific aim of estimation operation. The approaches can be divided into two main categories: being non-destructive and destructive methods.

1.2.1. **Non-destructive methods of estimating biomass**

Non-destructive method is when biomass of a tree is estimated without felling the tree itself (Montes et al., 2000). This method is mainly applied when the species of interest are rare or protected and can not be destructively sampled to determine allometric relationship (Brown, 1997; Montes et al., 2000; Stewart et al., 1992; Vann et al., 1998). Literature shows that a number of methods of estimating aboveground biomass without necessarily destroying the tree are available under this category.

One such method is whereby a tree is climbed, and successive measurements on stems and branches are taken along with limited sampling of branches which are then weighed (Vann et al., 1998). Stem weight estimates are derived from wood density measurements from cores and sections from dead stems (Vann et al., 1998). The advantage with this method is that the tree is not entirely destroyed but an element of destruction is there. Two major disadvantages with this method are that; firstly, the reliability of the method is not easy to validate since felling is not applied. Secondly, the method can be time consuming and labour intensive as well as cumbersome.

The second and last method considered in this study under this category is the model stem method proposed by Adhikari (2005) adopted and improved from the non-destructive method developed by Montes et al., (2000). The original method (Montes et al., 2000) was developed for *Juniperus thurifera*, a protected tree species, to estimate its volume based on the dimensions of the tree photograph. The method uses grid cells which are superimposed on a photograph rather than weighing the tree itself. Since it is not possible to measure the weight of a tree in the photograph, different components can be estimated from the photograph using approximations of geometric solids and corresponding diameter measurements. Using this method, biomass can be estimated from the volume by using the density of the tree component which is sampled from the tree. Adhikari (2005) concluded that the model stem method is reliable based on the tests done on it. The method does not require heavy machinery, it only requires a camera. However, like the first method, this method also has an element of destructiveness, it becomes destructive the moment a factor of density is included for calculating biomass because that factor was developed using a destructive method.

1.2.2. **Destructive methods of estimating biomass**

Destructive method is when biomass is measured directly by felling the trees (Stewart et al). It is also destructive when biomass is obtained indirectly through sub-sample. A number of methods are available through destructive means. One such method is complete harvesting method. It involves total harvesting of randomly selected plots or individual trees within the plot (Stewart et al., 1992; Vann et al., 1998). This method involves cutting and weighing or cutting, drying and weighing of the whole tree or its components. The method is straight forward and it estimates fresh biomass on the field. It can estimate dry biomass but the procedure is not practical as the whole tree has to be oven dried. Stewart et al., (1992) identified two major limitations regarding this method. Firstly, the
process is destructive hence the chance of observing growth over a longer period is lost. Secondly, the method is prohibitively time consuming hence costly.

The second method is the tree sub-sampling method. This method does not require cutting and weighing or cutting drying and weighing of the whole tree. It estimates aboveground woody biomass from a small, randomly selected sample collected from the tree and weighing or drying and weighing the sample to obtain an unbiased estimate of volume, fresh and dry weight biomass. It works equally well for trees and shrubs. It requires in-the-field data processing. Through past studies (de Gier, 1989; de Gier, 1995; de Gier, 1999; de Gier, 2003) concluded that this method is competent in terms of time and cost as compared to complete tree harvest method for example, a twice executed sub-sampling procedure per tree requires between 10 minutes and two hours, with and average of 30 minutes (depending on the tree size) for a crew of two. It does not require heavy instruments; in fact all instruments can be carried by hand. The disadvantage with the method is that the procedure itself is somewhat complicated. However, de Gier (1989) minimized this problem by writing a program for use with a hand held computer. The sub-sampling method estimates are then used to construct biomass equations.

**Use of biomass equations**

Most researchers (Brown, 1997; Lott et al., 2000; Sah et al., 2004; Stewart et al., 1992; Tietema, 1993; Vann et al., 1998) perceive this method as non-destructive. The method is destructive as far as constructing those equations is concerned. Moreover, when biomass equations are used, it is always necessary that they are validated (Chave et al., 2004). Hence validation entails tree felling of a sufficient number (>25) of representative trees (de Gier, 1999) while Chave et al., (2004) suggests at least 50 trees. Biomass equations are ideal for estimating biomass once they are available (Brown, 1997). But developing these equations for different forests and vegetation types require destructive sampling. Usually a sample of trees are felled and used to develop regression functions from which biomass can be predicted using easily and non-destructively measurable variables such as the tree height and stem diameter (Stewart et al., 1992). The problem associated with allometric equations is the error propagation for biomass estimation. For example, measurement errors in stem diameter, tree height or crown diameters all result in error in estimating aboveground biomass through propagation (Chave et al., 2004). For the construction of the allometric equations, the form of the linear and non-linear models has been built (Fox, J, 1997; Stewart et al., 1992; Vann et al., 1998; Zianis and Mencuccini, 2004) but the most commonly used mathematical model in biomass studies is using a regression on the logarithmic transformed variables (Chave et al., 2004; Zianis and Mencuccini, 2004). For example, Tietema (1993) developed regression curves of 14 tree species in Botswana using power functions after logarithmic transformation. The tree species involved were *Acacia erioloba, Acacia erubescens, Acacia karroo, Acacia luederitzii, Acacia mallefera, Acacia tortilis, Boscia albitruncia, Colophospermum mopane, Combretum apiculatum, Combretum molle, Croton gratissimus, Dycrostachys cinerea, Terminalia sericea,* and *Ziziphus mucronata.* Similarly, Brown (1997) developed biomass equations for both dry and wet regions based on the same logarithmic transformation approach.

Harrel et al., (1997) found that the use of logarithmic transformation mask the true levels of ambiguity. Chave et al., (2004) contends that the residuals represent the departure from a perfect
allometry, and are normally distributed. In addition, the standard deviation of these residuals represents the uncertainty in the biomass estimation due to the allometry itself. Sah et al., (2004) also concluded that logarithmic models generally give under predictions and as such a correction factor has to be applied in the back transformation of the data. Sprugel (1983) cited by Cleemput et al., (2004) found that equations developed with transformed data have the potential for bias. De Gier (1999) found that third degree polynomials with backward elimination, combined with weighing to obtain constant (homoscedastic) residual variance are much better and not biased as compared to power functions. For this reason, logarithmic transformations and power functions will not be used in the development of biomass equations in this study.

Method selection for Botswana
After an intensive literature review about woody biomass estimation methods, a number of approaches described above were found, but it was difficult to outrightly select a method to be applied in this study. Therefore, a criterion was designed for the selection of the method to be used in this study. The method must satisfy the following requirements:

- It must be competent in terms of time and cost associated with data collection.
- It must require less manpower (maximum of three people) without necessarily compromising the reliability of the field data collected.
- It must not require heavy instruments as this may have implications on the financial resources.
- It must be applicable in Botswana for example, it should work equally well for trees and shrubs in the savanna type of ecosystem.

After critically assessing the methods through the set criterion, the model stem method proposed by Adhikari (2005) originally developed by Montes et al., (2000) and the sub-sampling method by de Gier (1989) were both selected as they met all the requirements. The methods would be compared in terms of reliability of the estimated biomass and time requirements in the field and the best method selected and used further in this study. Complete harvesting methods would be used to validate the two methods.

1.3. Relating biomass to image data (Remote sensing)
As already alluded, the traditional way of collecting forest data is through manual, field based observation. This approach has the benefit of generating highly accurate measurements, but due to its labour intensive nature, high cost associated with the length of time spent in the field, and often constrained by lack of access (Couteron et al., 2001; de Gier, 1989; de Gier, 1995; Hansen et al., 2002; Harrell et al., 1997; Kasischke et al., 1997), this approach is generally not practical for anything other than local scale studies (Aplin, 2003). However, the implications of forest analysis extend well beyond the local scale, and there is considerable need for forest investigation at wider spatial scales. As a result, the technique of remote sensing has become common in forest investigation providing the only realistic and cost effective way of acquiring data over larger areas (Aplin, 2003; Couteron et al., 2001; Gemmell and McDonald, 2000). The technique has gained considerable importance in vegetation mapping and monitoring over the last two decades (SADC and ETC-Foundation, 1987). It has also been used directly in ecological studies to; investigate landscape patterns, to exploit correlations among physical, chemical and biotic parameters and to extrapolate known relationships over wider geographic areas or longer time periods (Kasischke et al., 1997). However, a robust
method for extracting forest characteristics from remotely sensed data has yet to be fully developed (Gemmell and McDonald, 2000).

Remotely sensed data is a readily available and accessible (though in some cases it can be costly) global resource that provides wider variety and greater quantity of information relative to traditional mapping data (Repaka et al., 2002). Preferably, woody biomass resource assessment needs to be undertaken using remotely sensed data combined with ground data (SADC and ETC-Foundation, 1987). The ground data would be used for validating the remote sensing data. Highly accurate maps can be derived from satellite image data when combined with ground data (ITC, 2004). One major reason of using remote sensing imagery to estimate woody biomass is that it complements part of the field work which is practically more expensive, by less expensive image analysis (de Gier, 1989). This will of course depend among other things on the cost of acquiring the satellite imagery. Remote sensing provides ancillary benefits such as information about adjacent areas, whereas ground based methods generally only provide information about the specific area of interest. Furthermore, remote sensing provides data at a synoptic scale from a single data-take for resource assessment over large areas (ITC, 2004; SADC and ETC-Foundation, 1987). Moreover, repeat imagery for any scene can be acquired and there is consistency across larger areas, making it suitable for national and international monitoring.

Whilst remote sensing has become a key technique in forest investigation, there are limitations with regard to the spatial detail of these data. Narayan (1999), reports that remote sensing by satellite became a reality in 1972 with the launching of the first earth resources technology satellite (ERTS) by the US. The ground resolution of Landsat 1 then was 80 m. As time went by, better quality and better quantity of satellite remotely sensed data particularly in terms of spatial and temporal resolutions started arriving (Narayan, 1999). Today, Landsat ETM operates in three spatial resolutions; 15 m (Panchromatic), 30 m (bands 1-5,7) and 60 m (band 6) (ITC, 2004).

Recently, more fine spatial resolution satellite sensors have emerged providing imagery with a level of detail that may be sufficient for meaningful and accurate ecological investigation (de Leeuw et al., 2002). Satellite imagery with spatial resolution of 1 m (panchromatic) and 4 m (multi-spectral) is available from satellites such as ‘IKONOS’ and ‘QuickBird’ systems (ITC, 2004). Appendix 8-2 provides a summary of recently launched satellites sensors and their finer spatial resolutions as taken from Aplin (2003).

Fine spatial resolution satellite sensor imagery have been used for a range of ecological applications particularly forest analysis and some of the earliest published examples of IKONOS data exploitation relate to biomass (Aplin, 2003). IKONOS operates in the following spectral bands; 0.45-0.52 µm (1), 0.52-0.60 µm (2), 0.63-0.69 µm (3), 0.76-0.90 µm (4) and 0.45-0.90 µm - Panchromatic (Hansen et al., 2002; ITC, 2004). Its capabilities include capturing a 3.2 m multi-spectral, and 0.82 m panchromatic resolution at nadir with off nadir capabilities of 1 m (panchromatic) and 4 m (bands 1-4) (Satellite Imaging Corporation, 2005). Its applications include both urban and rural mapping of natural resources and of natural disasters, agriculture and forestry analysis, mining, engineering, construction, and change detection.
The advantage of IKONOS as a fine spatial resolution satellite over Landsat ETM with its spatial resolution of 30 m (coarse) is that as spatial resolution increases, the accuracy with which objects are identified, assessed and characterised also increases (Aplin, 2003). Hence, with IKONOS imagery, improved quality and content is higher than in most satellites available today (Satellite Imaging Corporation, 2005). It is able to discriminate and map forest resource features. IKONOS imagery provides valuable source of detailed information for environmental monitoring and development planning (Satellite Imaging Corporation, 2005). However, one major disadvantage of IKONOS imagery is that these data quickly become uneconomic for large area studies. This uneconomic characteristic has led researchers like Morisette et al., (2003), to exploit the possibility of using IKONOS imagery for Moderate Resolution Imaging Spectroradiometer (MODIS) validation elsewhere in Africa including Botswana. The other shortcoming of IKONOS satellite system is that it operates in the visible and near-infra red (NIR) regions of the electromagnetic spectrum, yet visible – IR data do not directly sense any tree or forest stand characteristics that can be directly correlated with changes in biomass (Harrell et al., 1997).

Remote sensing systems operate in several regions of the electromagnetic (EM) spectrum (appendix 8-3). The optical part of the EM spectrum refers to the part in which optical phenomena of reflection and refraction can be used to focus the radiation (ITC, 2004). It extends from X-rays to far infra-red. The longer wavelengths used for remote sensing are in the thermal infra-red and microwave regions (ITC, 2004). The visible region of the EM spectrum is the only portion with the concept of colour. Blue green and red are known as the primary colours or wavelengths of the visible spectrum.

The earth’s surface is made up of different materials both natural and man made. For each material, specific reflectance curves can be established. The curves show the fraction of incident radiation that is reflected as a function of wavelength (ITC, 2004). For vegetation (appendix 8-4), the reflectance characteristics depend on the properties of the leafs such as orientation and structure of the leafs i.e. leaf pigmentation, leaf thickness and composition (cell structure), and on the amount of water in the leaf tissue (ITC, 2004). For example, in the visible bands of the spectrum, the reflection from the blue and red light is relatively low since in this portions light is absorbed by the plants (mainly chlorophyll) for photosynthesis and vegetation reflects somewhat more green light, whereas in the NIR bands reflectance is highest (ITC, 2004). But the amount depends on leaf growth and cell structure.

Spectral Vegetation Indices (VI’s)

As already alluded to, forest investigation using only ground data collection is labour intensive and time consuming. Remote sensing technique can be used to complement ground data collection exercise with carefully selected sampling sites. Recently, there has been considerable interest in using remote sensing to relate biophysical parameters to different spectral vegetation indices (VI’s) derived from satellite imagery. VI’s have been very widely applied to multi-spectral data (Gemmell and McDonald, 2000). They are computed as a carefully chosen combination of reflection coefficients in various wavelengths (Casanova et al., 1998) of the electromagnetic spectrum. The most popular ones using the red and near infrared wavelengths emphasize the difference between the strong absorption of red electromagnetic radiation and the strong scatter of near infrared radiation (Lu et al., 2004). The Normalized Difference Vegetation Index (NDVI) is one of the most commonly used vegetation
indices in many applications relevant to the analysis of the biophysical parameters. NVDI is calculated as the normalized ratio between channel 3 (red) and channel 4 (near-infrared) data sensed by IKONOS. The main advantages of using NDVI for monitoring vegetation are: (i) the simplicity of the calculation; (ii) and the high degree of correlation between NDVI and a variety of vegetation parameters (de Gier, 1995; Hess et al., 1995).

The main advantage of vegetation indices over individual wavebands is that they can be designed to minimize the effects of disturbing factors including soil brightness (Gemmell and McDonald, 2000) on the relationship between reflectance and vegetation characteristics of interest such as canopy cover (Casanova et al., 1998). Undesirable factors are differences in soil background or atmospheric conditions (Casanova et al 1998). For example, Botswana as a semi arid country is characterized by various types of savanna vegetation. The sand covered area (where the study area is located) supports green vegetation consisting of shrub savanna, scattered tree savannah, semi-arid shrub savanna and grass savanna (Ringrose et al., 1999; Selaolo, 1998). Based on this background, the spectral reflectance is expected to be greatly influenced by soil patches on the ground. Thenkabail (2004) found that NDVI calculated from IKONOS imagery is relatively sensitive to soil background effects due to the small pixel size of IKONOS compared with Landsat ETM+ NDVI. Hence NDVI may not give accurate results. To find an index that is independent of soil influence, Wiegand and Richardson (1987) as cited by Casanova (1998), introduced the Perpendicular Vegetation Index (PVI) for which soil reflectance has to be known.

The other vegetation index which could take care of soil background effect is the Soil Adjusted Vegetation Index (SAVI). It is a transformation technique that minimises soil brightness influences from spectral vegetation indices involving red and near-infrared wavelengths. Enhanced Vegetation Index (EVI) is also going to be exploited in this study. Like the SAVI, EVI minimises the soil background effect and enhances the capability of the vegetation index to respond to vegetation abundance. However, difficulties may arise in that, by minimizing the sensitivity of an index to one extraneous factor, the index may then become insensitive to the factor of interest, or sensitive to other extraneous factors (Gemmell and McDonald, 2000).
Conceptual Framework (simplified model)

Figure 1-1  The relationship between ground data and remote sensing

Anticipated problems
Kasischke (1997) noted that studies have demonstrated that approaches using optical remotely sensed data are not appropriate for most terrestrial ecosystems because there is saturation effect at very low levels of biomass. Saturation is when a dependent variable (e.g. biomass) levels off and ceases to increase with increase in the independent variable (e.g. vegetation index). However, in Botswana not much has been done with respect to the relation between VI’s and woody biomass. It is therefore assumed that those problems cited by other researchers will not be experienced since the study area is different from theirs.

1.4. Research problem
Quantitative assessment of aboveground biomass in terms of volume, fresh and or dry weight per unit area is a useful way of providing estimates of various components that can be harvested. Though it is time consuming and labour intensive (Couteron et al., 2001; de Gier, 1989; de Gier, 1995; Hansen et al., 2002; Harrell et al., 1997; Kasischke et al., 1997; Sah et al., 2004) hence costly. Assessment of aboveground biomass in terms of volume and or weight is more relevant for forests and woodlands in Botswana. This is because the major product derived from these forests and woodlands is related to the use of wood. Wood resources in Botswana are declining especially near settlements because of fuelwood harvesting (van Heist and Kooiman, 1992). The Government of Botswana statistics (2001) indicates that fuelwood is the leading source of energy with 53%. Therefore, there is need for interventions to reverse this trend. But due to limited financial and manpower resources, implementation of forestry programmes are seriously affected (Kgathi, 1997; Tietema, 1993; van Heist and Kooiman, 1992). Consequently, informed decision making which is necessary for the effective use of the limited available resources is not done. This decision making process requires information on the magnitude to which the standing woody biomass can meet local demands.
Unfortunately for Botswana, up to date information on aboveground woody biomass resources is lacking. Most of the studies conducted are socio-economic in nature hence concentrating on the demand rather than the supply of woody biomass resources. Therefore, information on supply and demand of fuelwood resource at national level is insufficient, unreliable and also fragmented (Government of Botswana, 2001; Ringrose et al., 1988; Tietema, 1993). To address the woody biomass estimation problem in Botswana in a way that will lead to the alleviation of biomass scarcity and its related problems of irreversible environmental degradation, through informed decision making, there is need for sufficient and accurate data on the various aspects of this resource to be collected.

In this study, two approaches of woody biomass estimation were evaluated. They are: the non-destructive method developed by Montes (2000), modified by Adhikari (2005) and called his modification ‘model stem method’, and the sub-sampling method developed by Valentine (1984) and later adopted and improved by de Gier (1989). The first method was chosen because it can be used to estimate the aboveground woody biomass of each tree without felling the tree. It is based on derivation of aboveground woody biomass calculated from the volume estimated using an ordinary photograph of a tree. Therefore collecting field data using this method would be rapid hence tremendously reducing the overall costs associated with fieldwork. Furthermore, the method is suitable for estimation of volume and biomass of tree stands in open woodlands (Montes et al., 2000) typical of Botswana situation. It was then decided to test this method for this study.

The second method (sub-sampling) was selected because it has been found in past studies by de Gier (1989; 1995; 1999; 2003) to be very reliable and efficient in time usage. Sub-sampling method provides on-the-spot estimates of both volume and fresh weight from a small sample collected randomly from the tree (de Gier, 1989; de Gier, 1999). Tree dry weight can be obtained after oven drying the tree samples collected from the field. Since a rapid and reliable method was required for this study, sub-sampling was found to be suitable. Furthermore, the method met all the requirements for selection.

The methods will be compared in terms of the reliability of their estimates validated through complete harvesting of trees method. Time will also be used as a comparison factor for the two methods. Time factor was added in this study to reduce the high costs normally associated with field data collection. This has been a hindrance to aboveground woody biomass estimation in Botswana since most of the organisations in the country were not willing to fund such expensive activity. Once the best approach for estimating aboveground woody biomass is determined, regression equations will be developed. These equations will be used in future by the relevant authorities for estimating the current standing stock of the resource and in determining whether the standing woody biomass can meet local demands. As a result, adequate and reliable information regarding biomass resource will be available. Such information will be used to guide the decision making process hence making profound basis for the development of sound policies geared towards the protection and conservation of our fragile natural woodlands.

Moreover, this study aims at assessing the link between satellite based remote sensing techniques through use of different spectral vegetation indices and aboveground woody biomass obtained through ground based approaches. Vegetation indices like NDVI, SAVI, PVI and EVI have been found to
correlate with biomass elsewhere and as such they could be exploited for biomass estimation in Botswana.

1.5. **Research objectives**

The main objective of this study is to investigate the potential of ground based biomass estimation method combined with satellite based remote sensing techniques for the quantitative assessment of aboveground woody biomass in the Serowe woodlands of Botswana. The two methods (model stem and sub-sampling) will be compared in terms of time requirement and reliability while complete harvesting will be used for validation.

**Specific objectives**

- To determine which method is most reliable for estimating above ground woody biomass in Serowe woodlands (Botswana) in a timeous manner.
- To develop above ground woody biomass equations of the study area. These equations will be developed after the best approach has been determined. The equations will also be compared with the existing equations.
- To establish a relationship between above ground woody biomass and different vegetation indices being the Normalised Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Perpendicular Vegetation Index (PVI) and Enhanced Vegetation Index (EVI). Consequently, to use the vegetation index which gives the highest correlation with aboveground woody biomass to estimate above ground woody biomass (standing stock) of the entire study area.
- To produce a biomass map of the study area. This map can be used for informed decision making process by the local authorities.

1.6. **Research questions**

- With respect to the aboveground woody biomass estimation methods, which is the most effective in terms of time cost and reliability among the two methods? Even though the method is timeous and reliable, is it practical in terms of applicability on the field?
- What is the relationship between easily measurable tree dimension and estimated aboveground woody biomass?
- How strong is the relationship between vegetation indices (NDVI, SAVI, PVI, and EVI) derived from satellite imagery and estimated aboveground woody biomass? Which of the above mentioned vegetation indices gives a higher correlation with estimated aboveground woody biomass compared to the others?
1.7. Research approach

![Diagram showing the research approach for aboveground woody biomass assessment in Serowe woodlands, Botswana. The diagram includes the following steps:

1. **Field data**
2. **Study area**
   - **Plot selection** (systematic sampling)
   - **Biomass estimation**
   - **Plot identification (GPS)**
   - **Inventory (169 plots)**
   - **Remote sensing data**
     - **IKONOS image study area**
     - **Conversion of DA values to radiance**
     - **Conversion of radiance to reflectance**
     - **Atmospheric correction**
     - **Calculation of vegetation indices maps**
       - NDV
       - SAV
       - EVI
       - PVI

3. **Tree selection & measurement (d.b.h. THC IC)**
4. **Sub-sampling method**
5. **Four stand selection**
6. **Importance sampling**
7. **Disk removal**
8. **Actual measurement using spring balance**
9. **Estimated fresh weight (kg/seq)**
10. **Estimated fresh weight g/seq & volume (m³/seq)**
11. **Estimated fresh weight g/seq & volume (m³/seq)**
12. **Conversion to biomass using density**
13. **Model stem method**
14. **Tree photograph**
15. **Fresh wood volume (m³/seq)**
16. **Conversion to biomass using density**
17. **Actual fresh weight (kg/seq)**
18. **Validation**
19. **Comparison of time, cost and reliability**

**KEY**
- d.b.h. = diameter at breast height (cm)
- TH = total tree height (m)
- IC = crown diameter (m)
- GPS = Global Positioning System
- DN = digital number values
- PolyReg = Polynomial regression program
- RegDal = Regression data program
- NDV = Normalized difference vegetation index
- SAV = Soil adjusted vegetation index
- EVI = Enhanced vegetation index
- PVI = Perpendicular vegetation index

**Calculation of near vegetation index plot**

**Plot biomass**

**Biomass map study area**

**Biomass equation**

**Plot biomass g/m²**

**Relationship sought**

**Biomass map study area**

Boiki R. Mabowe
2. Methods and Materials

![Figure 2-1](image) The study area boundary as delineated by the 10 by 10 km IKONOS image

2.1. Study area selection

For a particular study area to be considered, the following criteria had to be met:

- Cutting of trees for research purposes must be permissible.
- The area should be accessible by foot or by vehicle to afar plots.
- Satellite imagery and maps must be available.
- Support staff should be available.
- The area should be representative of typical Botswana vegetation.

The study was undertaken in the Central district of Botswana where the above mentioned criteria were met. Satellite imagery for the study area was available. The study area was relatively open and accessing afar sample plots by car was possible and this was an advantage on our side given the limited duration of field data collection. Moreover, the study area is located within the Kalahari Research project which is a collaboration effort between ITC and the department of Geological Survey of Botswana (DGS). Therefore the relevant data was available and logistics in terms of transportation, camping facilities and support staff were arranged without difficulty. The study area is representative of typical Botswana vegetation. These are the reasons why the study area was preferred for this research.

The study area is near Serowe village. The village is about 275 km NNE of the capital city, Gaborone. The village can be strictly defined as semi-urban because of the relatively high population for a village and the socio-economic activities found in the village. The Botswana national census for 2001 put the population of Serowe at 42,444 from 30,264 in 1991 with an annual population growth rate of 3.4% (Government of Botswana, 2005). The major land use is agriculture involving rearing of livestock and planting of crops. Livestock is freely roaming the forest in search for good pastures. Kraals for the livestock are constructed from poles and/or bushes cut from the woodland.
The main source of fuel for the village is fuelwood. Therefore, the rate of population growth threatens the availability of tree biomass resource around the village as it is the main source of fuel and also provides building materials like rafters, fencing poles and bush fencing for the village.

**Figure 2-2** Serowe and the study area

**Location**

The study area is within the Kalahari Research Project, which lies between UTM coordinates 400000E to 497000E and 7545000N to 7501000N, covering an area of approximately 2444km² (Obakeng, 2000). An escarpment, running NNE and SSW direction, divides the Kalahari Research Project area into two: the Kalahari Sandveld; comprising sediments of the Kalahari group to the west and Hardveld; comprising an undulating plain with upstanding hill massifs developed on ancient precambrian rocks to the East (Moyo et al., 1993). The IKONOS image which defines the boundary of the study area lies entirely on the Kalahari Sandveld (figure 2-3).

**Figure 2-3** The study area delineated by the IKONOS image within the main Kalahari research project study area
Climate
The Atlas of Botswana (2001) and Obakeng (2000) describe Botswana climate in general and around the study area respectively as continental semi-arid. Botswana is located in the subtropical high pressure belt of southern hemisphere in the interior of Southern Africa far from the oceanic influences. The mean annual rainfall is 400 mm with high diurnal temperature ranges (Selaolo, 1998; Silitshena and McLeod, 1990)

Vegetation and soils
About two thirds of Botswana is covered by Kalahari sands which are infertile (Selaolo, 1998; Silitshena and McLeod, 1990). Various types of savanna vegetation cover much of the country. The sand covered area which includes the study area, supports green vegetation consisting of shrub savanna, scattered tree savanna, semi-arid shrub savanna, grass savanna, and dry deciduous forest woodland (Ringrose et al., 1999; Selaolo, 1998) and the high infiltration and retention capacity of the soils (Selaolo, 1998).

Rains in Botswana extend from late September to March and the different vegetation species are fully green by January and February (Ringrose et al., 1990). However, severe rainfall deficiencies may occur from time to time and large parts of the country may become drought–stricken even for cattle ranching (Government of Botswana, 1999). The common tree species in the study area are *Terminalia sericea*, *Dichrostachys cinerea*, *Ochna pulchra*, *Burkea africana*, *Lonchocarpus nelsii*, *Boscia albitrunca* and *Acacia fleckii*. The materials used in this study can be seen in appendix 8-6.

2.2. Research methods
The approach of forest data collection is through manual and field based observations. This approach is labour intensive (Couteron et al., 2001; de Gier, 1989; de Gier, 1995; Hansen et al., 2002; Harrell et al., 1997; Kasischke et al., 1997) in nature hence costly in terms of the length of time spent in the field. A number of approaches have been developed to estimate aboveground biomass of forests and woodlands. These methods differ in procedure, complexity and time requirement depending on the specific aim of estimation operation. Therefore two methods were selected because they satisfied the set criteria for selection (discussed in chapter 1.2.2). The two methods are; the model stem method proposed by Adhikari (2005) originally developed by Montes et al., (2000) and the sub-sampling method by de Gier (1989).

This study is interested in only one tree component, specifically the aboveground fresh biomass with a minimum diameter of 2.5 cm. The smaller branches falling below this diameter and foliage are not considered. Hence the study does not make a distinction between stems and branches.

2.2.1. Model stem method
Montes et al., (2000) developed a non destructive method in their paper named ‘A non destructive method for estimating aboveground forest biomass in threatened woodlands’. This method is later referred to as Montes method. Adhikari (2005) tested and proposed some improvements in the method. The idea, suggested by his supervisor, prof. A. de Gier, was to test whether the ambiguities present in coding the tree and its branches differently, and the cumbersome process of measuring the diameter of the branch and the trunk in two different directions based on the tilt angle of the branch,
can be reduced and the method simplified. The reasoning behind this is that both the stem and the branches are composed of wood and the interest is in the volume of wood irrespective of whether it is in the branch or the stem, and also irrespective of the tilt angle. Adhikari (2005) therefore tested whether a single coding scheme could be applied for both the branch and the stem by setting up an experiment using a hypothetical tree of known dimensions. Then Adhikari (2005) concluded that the volume represented by the model stem method (figure 2-4), which can be calculated easily, is equivalent to the volume represented by a complex object such as a tree with many branches tilted in many different directions. The model stem method eliminates the problem of counting the number of grids in two different directions to determine the diameter which was necessary in the original Montes method. It also eliminates the need for coding the stem and branches separately. This process reduces a lot of work and the risk of errors that may occur when coding the joints where branches meet the stem. With the original Montes method, a decision has to be taken at these joints as to where exactly does a trunk end and the branch start (Adhikari, 2005). It is against this background that this study used the model stem approach as described by both Adhikari (2005) and Montes et al., (2000).

Figure 2-4   Model stem method proposed by Adhikari, (2005).
The method uses Microsoft Excel for windows for data entry (coding), processing (calculations) and for storage of the results. It estimates volume and biomass of an individual tree. The method is based on measurements and calculations made on an ordinary photograph of the tree. It was applied to estimate the volume and biomass of a Thuriferous Juniper tree species (*Juniperus thurifera*) in Morocco by Montes et al., (2000) and also in Ghana by Adhikari (2005). The method as explained in (Montes et al., 2000) involves 6 major steps as follows:
1. Sampling: Two photographs of each tree from orthogonal views, physical samples of different components of tree (branches and foliage) and tree variable measurements.
2. Calculation of the scale of the photograph.
3. Determination of the volume of the different components of the tree (trunk, branches and foliage).
4. Determination of ‘bulk density’ of these different components.
5. Calculation of biomass for the different components.
6. Validation.

**Step 1: Sampling (photographing trees)**
The tree in the Montes method is photographed from two orthogonal directions of the axial asymmetry of *Juniperus thurifera*, the tree in which the method was applied on. The cross section of this tree is often elliptic. The equation of ellipse area is \( \pi ab \), where \( a \) and \( b \) are the half-axes. The equation of crown surface will be \( \pi a^2 \) under its narrow profile and \( \pi b^2 \) under its wide profile, for a given height. The surface area of the ellipse is thus the geometric mean of the two surfaces \( M = \sqrt{\pi a^2 \times \pi b^2} = \pi ab \), the ellipse area. The tree volume is therefore the geographic mean of the volumes obtained from the two photographs. However, for this study only one photograph per tree was necessary due to the axial symmetry of the tree species in the study area. Hence narrow and wide profile calculation was not necessary.

**Step 2: Calculation of scale**
In the Montes method, the photographs are scanned and the scale calculated. The scale depends upon the size of the grid cells used for data entry, and the resolution used to scan the photograph (in case of an analogue photograph). The scale is obtained from the following equation:

\[
S = \left( \frac{D}{R/100} \times y \right) \times C
\]

Where, \( S \) = the scale; \( D \) = real distance in meters e.g. tree height; \( R \) = Scan resolution (in dpi); \( y \) = tree height on the photograph (mm); and \( C \) = the grid cell size (in mm).

A digital camera was used in this study to take tree photographs, therefore, using the formula described in step 2, was not necessary. Hence, scale was calculated as the simple ratio between the size of the tree in the photograph and the real size of the tree. Since the tree was felled in the field to estimate its biomass using sub-sampling method, the height of the felled tree was measured as accurately as possible using a measuring tape so that it can later be used to calculate the scale of the photograph. For example the scale was calculated as the ration of the true size of the object to the number of grid cells which represent that size.

**Step 3: Volume Calculation**
Each photograph of the tree is imported into EXCEL workbook as background image. A grid of known size is then superimposed on the photograph. Each square of the grid is represented by a ‘pixel’, to which it is attributed a code for different components of the tree. Four kinds of pixels are defined in Montes method with following alphanumeric codes:

- Trunks and vertical or sub-vertical branches = Pixel B (for Branches)
- Trunks and horizontal or sub-horizontal branches = Pixel H (for Horizontal)
- Foliage = Pixel F (for Foliage)
Internal Crown = Pixel M (for Middle of the crown includes inner foliage which can not be seen from outside).

The pixel code corresponding to the observed zone of the tree is placed in each cell of the file e.g., if it was a foliage zone, F was recorded in the cell. Pixel M is not coded directly; its volume is deduced from pixel F.

Volume of the trunk (pixel B)

In the EXCEL worksheet, this pixel corresponds to woody components (stems, branches) in a vertical or sub-vertical position. First, the pixel cells are given the value 1. Then every uninterrupted succession of pixels in a row which corresponds to the diameter (d) of a branch or a stem are summed up. This sector is treated as circular section and is applied to the formula of cylinder volume as follows:

\[ V = 0.25\pi \times d^2 \times h \]

Where, \( h = 1 \) (the height of the grid cell)

Then all circular sections are added for the same row (figure 2-5). The branches and trunk volume to a height \( h \) (\( v_h \)) is then given by the formula:

\[ v_h = \sum_{n=1}^{n} (0.25\pi \times d_n^2) \]

Where \( n \) = number of circular sections for the row under consideration. Therefore, the total volume corresponds to the sum of volumes per row as follows:

\[ V_{total} = \sum_{n=1}^{n} v_h \]

Volume of the horizontal branches (pixel H)

Pixel H corresponds to the wood components (stems, branches) in horizontal or sub horizontal positions. The calculation method is same as that for pixel B, but the calculations are carried out down the columns, rather than across the rows.

Figure 2-5  The three main steps in the computerization of tree volume (Montes et al., 2000)

For the calculation of volumes of the stem (pixel B) and horizontal branches (pixel H), Adhikari (2005) tested and reduced the ambiguities present in coding the stem and its branches differently. Therefore in the model stem method, there is no distinction between stem and branches in a vertical or horizontal position (figure 2-4). Hence the model stem method does not make a distinction between stem and branches. Adhikari (2005) contends that the interest is in the volume of wood, and this wood is found in both the stem and branches irrespective of the tilt angle. Therefore during the calculation of volumes for both the stems and the branches, a single code was assigned to both stems and branches treating them as the same entity.
Volume of pixel F (foliage) and M (middle of crown)
Since this study is concerned only with aboveground woody biomass of dimensions more than 2.5 cm. Volume of foliage which includes both ‘outside crown’ foliage and middle of crown foliage were not calculated.

Step 5&6: Calculation of biomass of each component
The biomass of both components (stem and branches) was determined from the volume and density. Density is defined by Husch et al., (2003) as mass per unit volume expressed in kg/m$^3$ (appendix 8-1). To estimate biomass (kg/tree), the volume calculated in step 3 is multiplied with the density as follows: $B = V \times d$. Where B = the biomass; V= the volume estimated by the pixels for each tissue; and d = the estimated density for each tissue.

2.2.2. The tree sub-sampling method
Valentine et al (1984) proposed a sub-sampling method that produces unbiased estimates of volume, fresh weight and dry weight of trees. The method was subsequently adapted and improved by de Gier (1989) and applied to trees and shrubs of irregular form, growing in natural woodlands. The method was found to be very cost effective and overcame many of the identified constraints in biomass determination (de Gier, 1989; de Gier, 1995; de Gier, 1999; de Gier, 2003). In principle, the method consists of two steps; the first step consists of randomised branch sampling and the second step uses importance sampling. The following is the description of the two steps as described by Valentine (1984) and de Gier (1989).

Step 1: Randomised branch sampling (path selection)
In this step a ‘path’ is selected through a felled tree, starting from the butt and ending at a terminal bud. A path is a series of connected branch segments. The branch is the entire stem system that develops from a single bud (lateral or terminal). This method does not distinguish between a stem and a branch. A segment is defined as part of the branch between two consecutive nodes. At every point of branching, a decision has to be made about the continuation of the path. To determine a path, a selection probability is assigned to each branch emanating from the second node and one is chosen at random. The choice of this branch fixes the second segment of the path. The selection probability of the second segment of the path is denoted as $q_2$ (the first segment of the path has selection probability $q_1=1$). The second segment of the path to a node is followed and a branch is selected by randomized branch sampling with probability $q_3$. The randomized branch sampling is repeated at successive nodes until a terminal shoot is selected with probability $q_n$.

Selection probabilities
The selection probabilities assigned to various branches emanating from each node must add up to one. This continuation is selected with the probability proportional to size, (PPS). ‘Size’ here is equivalent to a proportional measure of the biomass in each one of the possible path continuations and can be approximated by $d^2 l$, where $d$ = diameter at the base of the branch and $l$ is the length of the branch. However, de Gier (1989) found that in the field, the most burdensome activity was the measurement of length of branches of the felled tree for path selection. This is because sometimes when a tree falls, the branches are broken. Therefore the same source made an important alteration in
the computer program designed, whereby for path selection, an estimate of biomass was no longer based on \(d^2l\), but on a power of \(d\) where \(d^2l = a.d^b\). The following (figure 2-6) is a worked example illustrating how the selection probability is executed.

Suppose a tree with a single stem (x) is used for path selection. At the first node above the ground a branch (y) originates from the main stem. This makes two possible paths continuation, each of which will be called a branch. Assuming that each of these branches’ (x and y) base diameters are \(d=7\) cm and \(d=5\) cm respectively, and a random number is drawn, say 0.678 then applying the formula \(a*\sqrt{d}^b\) where \(a\) is the random number and \(b\) is a constant found by de Gier (1989) to be 2.6689,

![Figure 2-6 Path selection](image)

then \(x\) and \(y\) become 122.09 and 49.74 respectively. Based on the PPS then branch \(x\) which happens to be main stem is selected. The path continues to the next node where the procedure is repeated. Path selection terminates when a terminal bud is reached, in this study, when a minimum diameter of 2.5 cm is reached.

The selection probability assigned to a branch is the conditional probability of selecting that branch given that the path has reached the node at which the branch arises. The unconditional probability of selection for the \(k\)th segment included in the path is:

\[
Q_k = \prod_{r=1}^{k} q_r
\]

The biomass of all the above ground components of a tree can be estimated from a single path. However, at least two paths are needed to estimate within tree standard errors. Therefore, estimated fresh weight of a tree can be calculated as follows

\[
\hat{b} = \frac{\sum_{k=1}^{n} b_k}{Q_k}
\]

Where \(Q_k\) is the unconditional selection probability for the \(k\)th segment of the path and \(b_k\) is the weight of the \(k\)th segment.

Step 2: Importance sampling
In this step, the method uses importance sampling, leading to the removal of only one randomly located disk. Importance sampling is a continuous analogue sampling with probability proportional to size. This means that the path of the tree is considered to consist of an infinite number of infinitely thin disks of which one is to be selected with a probability proportional to its diameter squared.

Estimating tree woody biomass volume
In the path, points are located where a change of taper occurs (notably at the butt and just before and after nodes). The diameter is measured at each of these points and the distance to the butt is recorded. From the latter, the distance between any two successive points can be calculated. For each point of
measurement, the diameter squared is divided by its unconditional probability assigned to the segment in which the point is located. This quantity is defined as “inflated area”. For every two subsequent points, two such inflated areas are calculated. Since the distance between two successive points is known, the inflated volume of the corresponding woody section can be calculated. Adding these volumes together, results in an estimate of the total tree woody volume.

*Locating the points for disk removal*

For the weight estimate, a segment or a disk has to be removed at a random point along the path. This point is determined by multiplying a random number by the estimated total tree woody volume. The segment of the path in which this volume is reached is first identified.

*Estimating tree woody fresh weight*

A disk of approximately 10 cm is removed (appendix 8-7). The disk can be split into any number of wedges if it is large, normally up to 4 wedges. The wedges are then weighed individually and one wedge is selected with a probability proportional to wedge fresh weight. The weight of the selected wedge (kg) per unit thickness (m) is determined and divided by its unconditional probability value assigned to the segment from which it is removed resulting in the estimate of the disk fresh weight, from which tree fresh weight can be estimated. The estimate of the tree woody fresh weight is calculated by multiplying this value with the estimated tree woody volume ($m^3$), and by dividing it by the square of the disk diameter ($m^2$).

*Estimating tree woody dry weight*

The dry weight of this disk can be determined after oven drying. This allows for the calculation of estimated dry weight of the tree, in the same manner as fresh weight was estimated. Thus unbiased estimates of the tree woody volume, tree woody fresh weight and tree woody dry weight are obtained.

Though this method appears complicated, (de Gier, 2000) simplified it by designing a program which is installed into an iPac (a portable hand-held computer) and guides the user through all the steps until fresh biomass and wood volume are estimated in the field. The user has to understand the concept but does not need to do the calculations; hence the method is user friendly.

2.2.3. Complete tree harvesting method

This method involves complete harvesting of randomly selected plots or individual trees within plots. In this method the woody biomass of a tree is measured after completely felling the tree, dividing it into its manageable component parts (wood of different sizes) weighing their fresh biomass, then oven drying samples of each component to determine moisture content from which dry weight can be calculated (Stewart et al., 1992). Logically, it is too time consuming to measure a whole tree in this way. This method was used in this study to validate model stem and sub-sampling methods under the assumption that biomass obtained through complete harvesting method is flawless.

Next, a comparison was made between measured aboveground biomass (kg/tree) obtained through complete harvesting method and estimated biomass (kg/tree) obtained through an equation developed in this study. This comparison was also extended to estimated biomass (kg/tree) obtained using
Tietema’s mixed-species equation developed in Botswana (Tietema, 1993) and estimated biomass (kg/tree) obtained using Brown’s mixed-species equation for tropical regions (Brown, 1997).

**Tietema’s biomass equation**

Tietema (1993) developed biomass regression equations for 14 tree species in Botswana, covering mostly the hardveld on the eastern margin of the country. The description of the method as described by Tietema (1993) is as follows. Trees were cut and their total fresh weight (including all the tree components such as stem, branches and foliage) were taken with a spring balance mounted on a crane fitted on the truck. The height and the diameter of the trees were measured before cutting. The crown was measured twice along two perpendicular axes and the average of these two measurements was considered as the crown diameter. The crown basal area was calculated from this crown diameter. The stem diameter was measured at ankle height (dah = 10 cm aboveground) and this measurement was used for calculating the stem basal area (see chapter 2.5). Regressions were calculated as linear regressions after logarithmic transformation. A power curve of the form: 

\[ B = 0.1936 \times BA^{1.1654} \]

was obtained for mixed-species where \( B \) = aboveground fresh biomass (kg/tree) and \( BA \) = basal area calculated from the \( dah \).

**Brown’s tropical region equation**

Brown’s biomass equation was developed for dry zones with rainfall less than 900 mm/year (Brown, 1997). The equation was revised by (Brown, 1997) from Martinez-Yrizar et al., 1992 for dry forest in Mexico. A total of 371 trees of many species with \( dbh \) ranging from 5 to 148 cm obtained from ten different sources and from all the tropical regions were used (Brown, 1997) to develop the following biomass equation for mixed-species:

\[ Y = 10^{[-0.535+\log_{10}(BA)]}; \]

where \( Y \) = the aboveground biomass (kg/tree) and \( BA \) = basal area calculated from \( dbh \).

### 2.3. Spectral vegetation indices (VI’s)

**Processing of IKONOS image**

Using the inventory data collected in the field, the mixed-species equation developed in this study was used to calculate biomass per plot (kg/m²). Relationships between biomass per plot and mean VI’s per plot were sought. The mean VI’s were obtained after processing of IKONOS image (appendix 8-9) of 10×10 km which was acquired in February 2002. Image processing was done so that the VI’s maps can be produced. The radiometric correction was done whereby the digital number values of the IKONOS image were converted to radiance which was then converted to reflectance. The \( L_\lambda \) which is the radiance for spectral band \( \lambda \) at the sensor’s aperture (W/m²/µm/sr) can be obtained in the correct units from IKONOS image product by converting from digital values (\( DN_\lambda \)) using the following equation from Space Imaging (2005):

\[
L_\lambda = \frac{10^4 \times DN_\lambda}{CalCoef_\lambda \times Bandwidth_\lambda}
\]

Where \( CalCoef_\lambda \) = radiometric calibration coefficient [DN/(mW/cm²-sr)] and \( Bandwidth_\lambda \) = bandwidth of spectral band \( \lambda \) (nm). The tables for \( CalCoef_\lambda \), \( Bandwidth_\lambda \) and \( E_{SUN} \) can be seen in appendix 8-9.
Conversion of radiance to reflectance (Space Imaging, 2005):
\[
\rho_p = \left( \frac{\pi L_\lambda d^2}{E_{SUN\lambda} \cos \theta_s} \right)
\]

Where \( \rho_p \) = the at-satellite exo-atmospheric reflectance (or unitless planetary reflectance), \( L_\lambda \) = the radiance for spectral band \( \lambda \) at the sensor’s aperture, \( d \) = the earth to sun distance in astronomical units at the acquisition date, \( E_{SUN\lambda} \) = Mean solar exo-atmospheric irradiances (W/m\(^2\)/\( \mu \)m) and \( \theta_s \) = Solar zenith angle.

The IKONOS mean solar exo-atmospheric irradiance \( (E_{SUN\lambda}) \) is calculated for each of the IKONOS bands by integrating the relative spectral response \( (RSR_\lambda) \) of each band and the solar irradiance over wavelength, (Space Imaging, 2005);
\[
E_{SUN\lambda} = \frac{\int (RSR_\lambda \cdot SolarIrradiance)d\lambda}{\int RSR_\lambda d\lambda}
\]

Next, atmospheric correction was done. The atmosphere is changing all the time and all remote sensing instruments capture information through it. The atmosphere both attenuates light passing through it and scatters light from suspended aerosols (Ray, 1994). The atmosphere can vary strongly across a single scene, especially in areas with high relief. This alters the light seen by the instrument and can cause variations in the calculated values of vegetation indices (Ray, 1994). This is particularly a problem for comparing vegetation index values. Therefore normalization is required to account for variations in sensor degradation, sun angle, earth sun distance (Space Imaging, 2005; Thenkabail, 2004). This was done using ATCOR 2 for IMAGINE 8.7. ATCOR 2 is a fast atmospheric correction algorithm for imagery of medium and high spatial resolution satellite sensors such as Landsat TM, SPOT, ASTER, IKONOS or QuickBird (ATCOR, 2004).

Calculating vegetation indices maps
The calculations of vegetation indices maps using relevant band data of IKONOS image was done as follows;

\[
NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}}
\]

Thenkabail (2004) found that NDVI calculated from IKONOS imagery is relatively sensitive to soil background effects due to the small pixel size of IKONOS compared with Landsat ETM+ NDVI. Based on the fact that the study area is characterised by open woodlands frequented by bare soil due to effects of cattle herding, Perpendicular Vegetation Index (PVI) was introduced to take care of soil background. It is an index that is independent of soil influence, Wiegand and Richardson (1987) as cited by Casanova (1998). Therefore reflectance of the soil has to be known. Since areas with bare soil especially around cattle posts were found in the field, it was easy to locate them on the image hence reflectance of bare soil was easily found and PVI was calculated as follows;

\[
PVI = \sqrt{[\rho_r - \rho_{r,s}]^2 + [\rho_i - \rho_{i,s}]^2 + [\rho_s - \rho_{s,s}]^2}
\]

Where \( \rho_r \) = red reflectance; \( \rho_i \) = near infra-red reflectance; \( \rho_s \) = red reflectance of bare soil;
\( \rho_{\text{nir},s} \) = near infra-red reflectance of bare soil.

The other vegetation index which could take care of soil background effect is the Soil Adjusted Vegetation Index (SAVI). It is a transformation technique that minimises soil brightness influences from spectral vegetation indices involving red and near-infrared wavelengths. SAVI is similar to NDVI except for an additive term to correct for soil background (De Jong et al., 2003b). The correction factor varies between 0 for very high densities to 1 for very low densities. The standard value typically used in most applications is 0.5 which is for intermediate vegetation densities.

\[
SAVI = \left( \frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + \rho_{\text{red}} + F} \right)(1 + F)
\]

Where F is a correction factor which ranges from 0 for very high vegetation cover to 1 for very low vegetation cover and F is the canopy background adjustment that addresses nonlinear. The correction factor used is 0.75 because the vegetation cover of the study area cannot be said to be intermediate but somewhere between intermediate and very low.

Enhanced Vegetation Index (EVI) was also used. Like the SAVI, EVI minimises the soil background effect and enhances the capability of the vegetation index to respond to vegetation abundance. However, difficulties may arise in that, by minimizing the sensitivity of an index to one extraneous factor, the index may then become insensitive to the factor of interest, or sensitive to other extraneous factors (Gemmell and McDonald, 2000).

\[
EVI = G \frac{\rho_{\text{nir}} - \rho_{\text{red}}}{\rho_{\text{nir}} + C_1 \times \rho_{\text{red}} - C_2 \times \rho_{\text{blue}} + L}
\]

where \( G \) is atmospherically corrected (rayleigh and ozone absorption) surface reflectances, \( L \) is the canopy background adjustment that addresses nonlinear, differential NIR and red radiant transfer through a canopy, and \( C_1, C_2 \) are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band (Huete et al., 2002). The coefficients in the EVI algorithm are, \( L=1, C_1=6, C_2 = 7.5 \), and \( G \) (gain factor) = 2.5 (Huete et al., 2002). These coefficients were applied with the assumption that they were developed in an environment similar to the one described in this study. Furthermore, EVI had to be normalised by converting it to a scaled up value EVI* (Nagler et al., 2005) using the following formula:

\[
EVI^* = 1 - \left( \frac{EVI_{\text{max}} - EVI}{EVI_{\text{max}} - EVI_{\text{min}}} \right)
\]

2.4. Sampling design for field data collection

Plot size selection

De Gier (1989) investigated how plot size affects the coefficient of variation (CV) for the vegetation type concerned in order to determine suitable plot size. This was done in a forest type most similar to the savanna type; in a naturally established open forest on dry areas comparable to the vegetation type described in this study. He found that CV decreases rapidly as plot size increases to approximately 400m², after which the rate of decrease becomes less. This value indicates that 400m² should be the right plot size. However the same source warns that in addition to these theories, practical aspects must be borne in mind because by increasing the plot size, one runs the risk of omitting or double
counting elements when enumerating. This is important in dense vegetation types where marking the stems and visibility from the centre are very difficult. Moreover, reliability of the determination of the plot boundary decrease with increasing plot size and the chance of varying relief within the plot increases as well, hence making proper plot lay-out more complicated. De Gier (1989) suggested a compromise plot size of 500m$^2$ based on the CV analysis and practical considerations. Based on this reasoning, circular plot sizes of 500 m$^2$ were selected. The 169 plots were clearly marked on the IKONOS image. The coordinates of the centres of the plots were entered into a GPS as waypoints in the field. The image was printed on A3 size paper to help in locating sampling plots as precise as possible. Using the GPS waypoints for navigation, the plots were located in the field.

**Systematic sampling**

Systematic sampling was used in this study. This method was preferred over simple random sampling because with it; (1) the location of sample units in the field is often easier and cheaper as it requires the researcher to walk straight lines and install sample plots at a constant interval; (2) since a sample is deliberately spread over the entire population, the method is more representative as coverage of the entire study area was guaranteed; (3) it is less time consuming and more cost efficient to install plots systematically rather than randomly (Freese, 1984).

The disadvantages of this method are that; (1) it is not always applicable; (2) it is difficult to assess the true amount of variability between the plots. However, these will not have implications for this work because vegetation in the study area was observed to be relatively homogenous; the landscape is relatively flat and predominantly covered by sandy soils.

**Map with sampling plots**

![Sample Plot Layout for Serowe](image-url)

*Figure 2-7  A map showing the plot layout*
In this study, data collection was done in two parts. The first part was a forest inventory (pink stars in figure 2-7) involving 169 sample plots. For every 5th plot (green triangles in figure 2-7) trees were sampled for biomass estimation. These are the plots where biomass data (kg/tree) were obtained from. At least one tree was felled from the 34 green plots.

Tree felling selection for regression equations
Cited by Stewart et al., (1992) MacDicken et al., (1991) recommends that trees to be felled should not be selected at random because it is important to include individuals which cover the whole size range/class for purposes of individual tree species being equally representative across the size range. But first identification and measuring of all trees and shrubs with the relevant diameter range was done. The tree species involved were *Terminalia sericea, Dichrostachys cinerea, Ochna pulchra, Burkea africana, Lonchocarpus nelsii, Boscia albitrunca* and *Acacia fleckii*. As for the diameter of stems and branches of trees and shrubs, it is necessary to define a lower limit of the diameter under which wood should not be considered to be fuelwood. Therefore a minimum diameter of 2.5 cm for any wood component of a tree or shrub appears reasonable (de Gier, 1989). The tree component included aboveground woody biomass (stems and branches). The diameters of stems and or branches smaller than 2.5 cm and foliage were excluded. For this study, only trees falling between the diameters of 2.5 cm to 22.8 cm were considered. This was because it was found that 99% of trees (3555 trees out of 3577) fell within the range of 2.5 cm to 22.8 with some tree species like *D. cinerea* and *A. fleckii* hardly ever reaching the 15 cm diameter. The maximum diameter at ankle height recorded on the field was 107 cm. Therefore, the diameter range (2.5 -22.8 cm) was divided into 3 classes of ‘1’, ‘2’, and ‘3’ (table 2-1), representing small, medium and large respectively. Then a tree or trees for felling were identified and photographs of those trees taken in order to process them later in the office through model stem method. A tree was then felled and the sub-sampling method applied on it after which the weight of the entire tree was taken through complete harvesting method by use of a balance scale. The following table shows the diameter distribution of the sampled trees.

<table>
<thead>
<tr>
<th>Class</th>
<th>Diameter at ankle height (dah) in cm</th>
<th>Number of sample trees</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.5-8.0</td>
<td>21</td>
</tr>
<tr>
<td>2</td>
<td>8.1-14.0</td>
<td>21</td>
</tr>
<tr>
<td>3</td>
<td>14.1-22.8</td>
<td>21</td>
</tr>
</tbody>
</table>

Within each size class the sampled trees were purposively selected based on the diameters recorded on the data collection sheet. By using this technique, the sampled trees could be selected plot by plot, hence it was not necessary to complete diameter measurements for the whole experiment before starting the biomass study. Stewart et al., (1992) recommends that at least twelve trees of each species should be felled to provide data for regression analysis. For this study, three trees were systematically selected in each class, making 9 trees per species of differing diameter. Only 7 main tree species in the study area have been selected because of limited resources like manpower, budget and time, however, the overall 63 trees were adequate.

Time cost
One aim of this study is a comparative time analysis since field work is the most expensive part in a research. The idea is to come up with a method that is rapid in terms of time requirement (duration) for a given quality of estimates and to assess its practicability and applicability in the study area. The
duration of time required to apply a particular method on the field is therefore of paramount importance. Fixed time costs such as the preparatory work for field data collection like familiarisation with field work equipment, map productions, field data collection simulation, reconnaissance of the study area, travel time from the camping site to the study area, navigation to the plot centre, delineation of the plot and general inventory were not considered. Time recording started as soon as the decision to include a particular tree has been taken and that tree identified. Although complete harvesting method was used for validation, time was also recorded during its application. A detailed description of how each method was approached can be seen on appendix 8-5.

2.5. Variables measured in the field

**Stem diameter (cm)**
Tree stem diameter was measured at ankle (dah) (Tietema, 1993) and breast (dbh) heights i.e. 10 cm and 130 cm from the ground, respectively. Most researchers (Barnes et al., 1996; Boyd et al., 1999; de Gier, 1989; de Gier, 1995; De Jong et al., 2003a; Lu et al., 2004; Porte et al., 2002; Sah et al., 2004; Vann et al., 1998) use the traditional dbh as an easily measurable tree variable. However, the majority of the trees in the study area were of height 3 to 5 m, often low branching multi-stemmed trees. In such vegetation measuring dah is more practical than dbh (Sekhwela, 1997; Tietema, 1993) It is because of this reason that dah was used together with the traditional dbh, to find out which one is a good predictor of total tree fresh weight in the study area. The dah and dbh were measured using a tree calliper and readings were rounded up to the nearest millimetre. The dbh was measured only when practical i.e. when a tree was tall and branching above dbh. Two readings were taken along the north-south (d1) and west-east (d2) axis providing the average diameter (d). As for the trees with multiple stems branching below the dah, the individual stems were measured at dah. Stem basal area was calculated using the following formula as used by Rosenschein et al, (1999)

\[ BA = \left( \frac{\pi}{4} \right) d^2 \]

Where BA is the stem basal area and d is the diameter (cm).

**Height (h)**
The total tree height (h) for sampled trees was measured using a 30 m measuring tape. The measurement was taken after the tree was felled. As for the inventory, tree height was determined using a haga altimeter. It consists of a gravity-controlled, damped, pivoted pointer and a series of scales on a rotatable, hexagonal bar in a metal, pistol-like shape (Husch et al., 2003). Heights were taken through a gun-type peeping sight and pulling a trigger to lock the indicator needle and observed reading taken on the scale.

**Crown diameter**
Crown diameter was measured to the tips of the longest branch with a tape measure to the nearest 10 cm along the north-south (K1) and west-east (K2) axis as per Rosenchein (1999). These provided an average diameter (K) which can be used to calculate crown area (a_c) as follows:

\[ a_c = \left( \frac{\pi}{4} \right) K^2 \]
### 2.6. Statistical analyses

Fresh aboveground biomass (kg/tree) was estimated using the tree sub-sampling method. Simultaneously, fresh aboveground biomass (kg/tree) was measured on the field using complete tree harvesting method. This method was applied to every tree sampled. It was used as a validation data set to test the reliability of the two methods (model stem and sub-sampling). Before any cutting could be done, the sampled trees were photographed and later processed in the office using the model stem method to obtain the estimated fresh biomass (kg/tree). Though it is advantageous to have a rapid method for data collection, as it ultimately reduces the time spent in the field, reliability of the results was of essence. Reliability was evaluated on the basis of overall effectiveness of a particular method through the coefficient of determination and the confidence limits. A graph was plotted with models stem estimates on the Y-axis and complete harvesting measurements (validation) on the X-axis. It was assumed that complete harvesting measurements were error free hence used for validation. The same was done for sub-sampling estimates and the coefficients of determination for both methods noted. A one to one linear relation between model stem versus complete harvesting and sub-sampling versus complete harvesting was expected. This would satisfy the equation: \( y = a + bx \); Where \( y \) = either model stem or sub-sampling estimates; \( x \) = complete harvesting measurements; \( a \) (intercept) = 0 and \( b \) (slope) = 1. The confidence limits at 95% confidence level were used to accept or reject the hypotheses that \( a = 0 \) and \( b = 1 \) for both methods. One equation was expected to be better than the other.

**Development of biomass equations**

The mostly used statistical method for determining biomass equation from a set of data is the least squares method of regression (Cunia, 1964; de Gier, 1989). This method has main shortcoming in that the tree biomass variable does not satisfy the homogeneity of the variance. However, one way of addressing the non homogeneity of variance is to use the log transformed data (Brown, 1997; Cleemput et al., 2004; Cunia, 1964; FRA, 2000; Tietema, 1993; Vann et al., 1998). This method has its own problems in that by taking the logarithms, the estimation of the arithmetic mean is automatically replaced by the estimation of the geometric mean; since the former is always larger than the latter, therefore the estimated biomass becomes biased (Cunia, 1964). Yet another way of correcting for the non homogeneity of the variance and apparently a better one since it is unbiased, is to estimate the regression coefficients by the method of weighted least squares (Chave et al., 2004; Cunia, 1964; de Gier, 1989).

Therefore, polynomial equations of the following form was used: \( y = b_0 + b_1x + b_2x^2 + b_3x^3 \) where \( y \) = the dependent variable (estimated biomass), \( x \) = the independent variable (diameter at ankle height) having different degree of polynomial function, \( b_0 \) to \( b_n \) = regression coefficients. The equations were developed using the POLYREG (short for Polynomial Regression) program (de Gier, 2000) as a weighted linear polynomial regression analysis using 1st, 2nd or 3rd degree polynomial with backward elimination. POLYREG program is designed to be used in combination with the Excel workbook named REGDAT (short for Regression Data). It is an easy to use program which comes with straight forward help text. Weighting was done only when the residuals indicated that they were not constant i.e. they were forming a funnel like shape indicating that variance increases as one moves along the Y-axis.
The biomass equation was used to calculate biomass per plot (kg/m²) using the 169 plot inventory data. The plot biomass was then correlated with mean vegetation index per plot for all the 4 VI’s (NDVI, SAVI, EVI and PVI). The VI’s maps were calculated using the model maker in ERDAS IMAGINE software. The mean VI per plot was obtained through the use of block statistics under spatial analyst tools in ArcMap. The correlation coefficients of all the 4 vegetation indices and aboveground biomass were low and proceeding with them was found to be unnecessary.
3. Results

3.1. Tree species mean stem diameter

Table 3-1  Tree species mean stem diameter

<table>
<thead>
<tr>
<th>Tree species</th>
<th>Local name</th>
<th>n</th>
<th>Minimum \textit{dah} (cm)</th>
<th>Maximum \textit{dah} (cm)</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Terminalia sericea</td>
<td>Mogonono</td>
<td>9</td>
<td>5.5</td>
<td>18</td>
<td>10.8</td>
<td>4.5</td>
</tr>
<tr>
<td>Acacia fleckii</td>
<td>Mhahu</td>
<td>9</td>
<td>3.4</td>
<td>14.3</td>
<td>9.4</td>
<td>3.7</td>
</tr>
<tr>
<td>Lonchocarpus nelsii</td>
<td>Mhata</td>
<td>9</td>
<td>6</td>
<td>19.9</td>
<td>12.1</td>
<td>5.1</td>
</tr>
<tr>
<td>Ochna pulchra</td>
<td>Monyelenyele</td>
<td>9</td>
<td>5.8</td>
<td>21.7</td>
<td>12.5</td>
<td>6</td>
</tr>
<tr>
<td>Burkea africana</td>
<td>Monato</td>
<td>9</td>
<td>4.8</td>
<td>20.6</td>
<td>10.6</td>
<td>4.9</td>
</tr>
<tr>
<td>Dichrostachys cinerea</td>
<td>Moselesele</td>
<td>9</td>
<td>7.4</td>
<td>22.3</td>
<td>12.6</td>
<td>5.6</td>
</tr>
<tr>
<td>Boscia albitrunca</td>
<td>Motlopi</td>
<td>8</td>
<td>7.4</td>
<td>22.8</td>
<td>13.4</td>
<td>5.4</td>
</tr>
</tbody>
</table>

When the initial analysis of the data commenced, it was found that there was an anomaly with one tree despite the fact that the data were checked vigorously for errors. No obvious explanation could be attached to the anomaly of this tree. The Chebyshev theory (Appendix 8-8) of detecting outliers was implemented and indeed confirmed that the tree was an outlier, consequently it was discarded from subsequent analyses. The data indicates that \textit{Boscia albitrunca} is predominantly the tree species with the largest mean stem diameters (13.4 cm) measured at ankle height (\textit{dah}), whereas \textit{Acacia fleckii} was characterised by small stem mean diameters (mean = 9.4) at \textit{dah}. Analysis of variance (one way ANOVA) shows that there is no significant difference among the mean stem diameters of the seven species as illustrated by an F value of 0.898 and p value of 0.630.

3.2. Reliability and Time cost analyses

3.2.1. Reliability assessment

Reliability of the two methods was validated by the fresh weights (measured biomass) obtained in the field through the complete harvesting method on the basis of overall effectiveness of a particular method through the coefficient of determination (R$^2$) and the confidence limits using the confidence level (1-$\alpha$), where $\alpha$ is 0.05. Plotted against the complete harvesting method, the model stem method displayed an R$^2$ of 0.74 (figure 3-1) with statistical significance (p < 0.05), whereas sub-sampling against complete harvesting was 0.94 (figure 3.2) at the same significance level. This was based on the assumption that the measured biomass was flawless, then, Y (response variable) should always be equal to X (explanatory variable) representing a 1:1 relation between the two variables with an equation of the form; \(Y = a + bX\); where Y = estimated biomass (kg/tree) through either model stem or sub-sampling methods and X = measured biomass (kg/tree), a (intercept) is the value of Y when X = 0 and b (slope) is the amount by which Y changes when X increases by one unit. Table 3-2 presents the summary of statistics for the two methods against the measured biomass (complete harvesting method).
Table 3-2  Summary of statistics for the two methods versus complete harvesting

<table>
<thead>
<tr>
<th>Model stem method</th>
<th>Sub-sampling method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>Lower 95%</td>
</tr>
<tr>
<td>a</td>
<td>14.59467</td>
</tr>
<tr>
<td>b</td>
<td>1.112577</td>
</tr>
</tbody>
</table>

Model stem Method

![Figure 3-1 Biomass estimated through stem model method (kg/tree) against measured biomass (kg/tree)](image)

The scatter plot (figure 3-1) shows that the model stem method tends to overestimate biomass as shown by the points predominantly above the 1:1 line. The model \( Y = a + bX \) was used. This model describes how \( Y \) (estimated biomass – kg/tree) changes as \( X \) (measured biomass – kg/tree) changes. It shows that the estimated biomass (\( Y \)) increases by 1.1 kg for every one kg increase of measured biomass (\( X \)). The intercept \( a = 14.6 \) kg shows that when there is no measured biomass (\( X = 0 \)) then estimated biomass is 17.8 kg. The following hypotheses were developed:

**Hypothesis 1**

**H0**: The intercept of measured biomass (complete harvesting method) versus estimated biomass (model stem method) does not differ from zero i.e. \( a = 0 \)

**Ha**: The Intercept of measured biomass (complete harvesting method) versus estimated biomass (model stem method) differs from zero i.e. \( a \neq 0 \)

**Conclusion**

The null hypothesis \( H_0 \) is rejected and the alternative accepted because in this case \( a = 14.6 \) and it falls within the confidence limit of 8.0 and 21.1 which does not in anyway include 0 at 95% confidence level.

**Hypothesis 2**

**H0**: The slope of measured biomass (complete harvesting method) versus estimated biomass (model stem method) does not differ from one i.e \( \beta = 1 \)

**Ha**: The slope of measured biomass (complete harvesting method) versus estimated biomass (model stem method) differs from one i.e \( \beta \neq 1 \)
Conclusion
The null hypothesis $H_0$ is accepted and the alternative rejected because $b = 1.1$ and falls within the confidence limit of 0.92 and 1.3 which includes 1 at 95% confidence level. Although this means that at one stage, $b$ could be 1 at 95% confidence level satisfying the condition of a 1:1 relation, $a$ could never satisfy the condition that $a=0$, the closest $a$ can be to 0 is 8 kg. Therefore the model stem method is rejected on the grounds that the null hypothesis for $a$ was rejected even though $b$ was accepted 95% confidence limit.

Sub-sampling method

![Figure 3-2 Biomass estimated through sub-sampling method (kg/tree) against measured biomass (kg/tree)](image)

The scatter plot (figure 3-2) shows that sub-sampling method tends to slightly underestimate biomass. Still using the model $Y=a+bX$ which in this case translates to $Y=-0.92+0.93X$, this model shows that the estimated biomass ($Y$) increases by ca 1 kg for every one unit increase of measured biomass ($X$).

The intercept $a=-0.92$ kg tells us that when there is no measured biomass ($X=0$) then estimated biomass is -0.92 kg. The following hypotheses were developed;

**Hypothesis 1**

$H_0$: The intercept of measured biomass (complete harvesting) versus estimated biomass (sub-sampling) does not differ from zero i.e. $a = 0$

$H_a$: The Intercept of 1 measured biomass (complete harvesting) versus estimated biomass (sub-sampling) differs from zero i.e. $a \neq 0$

**Conclusion**

The null hypothesis $H_0$ is accepted and the alternative rejected because in this case $a = -0.92$ and it falls within the confidence limit of -3.01 and 1.17 which includes 0 at 95% confidence level.

**Hypothesis 2**

$H_0$: The slope of measured biomass (complete harvesting method) versus estimated (sub-sampling method) does not differ from one i.e. $\beta = 1$

$H_a$: The slope of measured biomass (complete harvesting method) versus estimated (sub-sampling method) differs from one i.e. $\beta \neq 1$
Conclusion

The null hypothesis $H_0$ is accepted and the alternative rejected because $b = 0.93$ and falls within the confidence limit of $-0.88$ and $1.00$ which includes $1$ at 95% confidence level. Therefore, sub-sampling method was selected based on the evidence that indeed, at one stage, $a$ could be $0$ and $b$ could be $1$ at 95% confidence level, since both $a=0$ and $b=1$ fall within the confidence limits.

3.2.2. Time cost analysis

The traditional way of collecting aboveground woody biomass data is through manual, field based observation. This approach has the benefit of generating reliable measurements, but due to its high cost associated with the length of time spent in the field, many organisations in Botswana are finding it difficult to invest a lot of time and money on this activity, hence non existence or outdated data on the resource in Botswana. Therefore, one aim of this study is a comparative time analysis of the two approaches used. The duration of time required to apply a particular method in the field is therefore of paramount importance as it tremendously reduces the costs of data collection and this also increases the chances of collecting adequate data. Time was therefore, recorded for both methods as per the description given on Chapter 2.4 and appendix 8-5.

Model stem method

![Figure 3-3 Time required by Model stem method per tree](image1)

The bar graph (figure 3-3) indicates that time requirement for the model stem method is almost the same for all the trees. The procedure required between 10 and 36 minutes per tree. This translates to an average of 20 minutes for a single tree to be processed and volume and biomass of that tree estimated based on a single photograph.

Sub-sampling method

![Figure 3-4 Time required by Sub-sampling method per tree](image2)

Figure 3-4 shows that time requirement for Sub-sampling method varies from 10 to 72 minutes per tree. This variation in time was dependent on the size of a tree, the difficulty or ease in felling the tree, preparing the tree for path selection, importance sampling, and disk removal.
On average it took 25 minutes for a single tree to be processed and volume and biomass of that tree obtained.

**Complete harvesting method**

Time requirement for complete harvesting method was also recorded. This entailed felling the tree and sub-dividing it into smaller components for ease of taking weights. It took an average of 23 minutes (ranging from 4 to 72 minutes) for one tree to be processed and fresh weight obtained.

**Time dependency on tree size**

The relationship between time requirement (minutes) and $d_{ah}$ (cm) for all the methods was also investigated. The general pattern displayed by the scatter plot in figure 3-6 indicates that for the model stem method, there is no relationship between the diameters and time requirement. This is also verified by the poor correlation coefficient of 0.16. This is largely because the method uses a single spreadsheet as a platform for all the trees, therefore, the difficulty contributing to more time depends on whether the outline of the tree is clear or not but not on diameter size. As for sub-sampling and complete harvesting methods in figures 3-7 and 3-8 respectively, the scatter plots show that indeed a relationship does exist between $d_{ah}$ and time requirement. The methods gave correlation coefficients of 0.69 for sub-sampling and 0.74 for complete harvesting method, indicating that the bigger diameters tend to require more time.

**Model stem method**

![Figure 3-6](image-url)  
**Figure 3-6**  Relationship between time requirement (minutes) and $d_{ah}$ (cm) for model stem method
3.3. Development of biomass equations using Sub-sampling method

First, it was determined whether it was necessary to develop species-specific or mixed-species biomass equations for the study area. After looking at the seven scatter plots (figure 3-9 to 3-15) of seven different tree species, it was decided that separate biomass equations for individual tree species were not necessary as the points of individual tree species appeared to fall pretty much at random among other tree species. However, the scatter plot for *D.cinerea* (figure 3-14) appeared to be following a different pattern, but that was not outright clear by the look of the eye. At this point the strength of the relationship between *dah* (cm) and estimated biomass (kg/tree) for *D.cinerea* was examined and gave correlation coefficient of 0.53. This indicated that a relationship does exist between the two variables, though it was relatively weak compared with the other tree species which displayed high correlation coefficients ranging from 0.86 for *T.sericea* to 0.98 for *L.nelsii*. 

Figure 3-7 Relationship between time requirement (minutes) and *dah* (cm) for sub-sampling method

Figure 3-8 The relationship between time requirement (minutes) and *dah* (cm) complete harvesting method
Figure 3-9  Distribution of *O. pulchra* among other tree species

Figure 3-10  Distribution of *A. fleckii* among other tree species

Figure 3-11  Distribution of *T. sericea* among other tree species
Figure 3-12  Distribution of *L. nelsii* among other tree species

Figure 3-13  Distribution of *B. africana* among other tree species

Figure 3-14  Distribution of *D. cinerea* among other tree species
Therefore, a decision was taken that *D. cinerea* which was observed in the field to be predominantly multi stemmed, be discarded from the mixed-species equation, since the species could be contributing to the lower $R^2$ of 0.72 ($F_{\text{test}}$, $F_{\text{stat}}$ > $F_{\text{tab}}$, $p = 0.01$, df = 3, 58; $F_{\text{stat}}$ > 4.16). Indeed, the results shows that when *D. cinerea* was discarded from the rest of the species, the $R^2$ of the mixed-species equation improved significantly from 0.72 to 0.76 statistically significant ($F_{\text{test}}$, $F_{\text{stat}}$ > $F_{\text{tab}}$, $p = 0.01$, df = 3, 49; $F_{\text{stat}}$ > 4.20).

**Determination of easily measurable tree dimensions**

The coefficient of determination ($R^2$) for biomass and easily measurable tree dimensions (diameters at ankle height- *dah* and breast height- *dbh*) were explored to find which one is the best predictor of biomass (figure 3-16). $R^2$ values for both *dah* and *dbh* were high at 0.76 highly significant ($F_{\text{test}}$, $F_{\text{stat}}$ > $F_{\text{tab}}$, $p = 0.01$, df = 3, 49; $F_{\text{stat}}$ > 4.20) and 0.72 also highly significant ($F_{\text{test}}$, $F_{\text{stat}}$ > $F_{\text{tab}}$, $p = 0.01$, df = 1, 50; $F_{\text{stat}}$ > 7.17) respectively. The *dah* proved to be the most objective prediction variable in the study area compared with the traditional *dbh*. Other tree dimensions measured were total tree height and average crown diameter (appendix 8-12). They were also explored to find how well they can predict biomass. They displayed the $R^2$ of 0.68 statistically significant ($F_{\text{test}}$, $F_{\text{stat}}$ > $F_{\text{tab}}$, $p = 0.01$, df = 3, 58; $F_{\text{stat}}$ > 4.16) and 0.41 also statistically significant ($F_{\text{test}}$, $F_{\text{stat}}$ > $F_{\text{tab}}$, $p = 0.01$, df = 3, 58; $F_{\text{stat}}$ > 4.16) respectively. Though the $R^2$ for total tree height was satisfactory, this tree dimension was not used because the height of the tree was obtained as accurately as possible from a felled tree to be used for sub-sampling. Therefore the height of a standing tree was found to be difficult to measure, hence to avoid distortions; it was decided to leave total tree height out.
The biomass equation for this study was developed using the POLYREG program (de Gier, 2000) as a weighted linear polynomial regression analysis using 1\textsuperscript{st}, 2\textsuperscript{nd} or 3\textsuperscript{rd} degree polynomial with backward elimination. Plotting of residuals indicated that they were not constant i.e. they were heteroscedastic as shown in figure 3-18 i.e. they formed a funnel like shape indicating that variance increases as one moves along the Y-axis. This is not required for curvilinear regression analysis. Therefore weighting was deemed necessary, hence implemented. It was also found that when fitting the model, the curve dips below zero after reaching the minimum diameter resulting in negative biomass values. These problems were overcome by using a third degree polynomial in concert with weighting to obtain constant residual variance.

Using REGDAT program (de Gier, 2000), the procedure for obtaining weights is semi-automatic. Different weights are tried until the variance of the residual error is reduced (homoscedastic) throughout the range of the estimated biomass as can be seen in figure 3-19. Then the entire regression procedure was repeated and the significance test for the coefficients carried out. It has been found that this procedure provides a better fit than the un-weighted model hence increasing the coefficient of determination significantly. For example, for the mixed-species equation, the $R^2$ of the polynomial regression analysis was 0.66 before weighting, and after weighting it increased to 0.76. This means that 76 % of all variation is explained by the model. A fresh weight equation in the form of $Y = 15.366 - 5.807X + 0.721X^2 - 0.016X^3$ relating aboveground woody biomass with tree $dah$
was developed. Where $Y = \text{estimated fresh biomass (kg/tree)}$ and $X = \text{diameter at ankle height (dah)}$ measured 10 cm from the ground. All coefficients were significant as shown in appendix 8-11a. Since sub-sampling method gives on-the-spot estimates of both volume and fresh weight, dry weight was also calculated after oven drying the wood sub-samples. The regression equations for volume and dry weight were also developed. For volume, weighted curvilinear regression analysis using backward elimination technique showed that in the presence of third degree polynomial, the second degree and first degree polynomials were not significant (appendix 8-11b). Hence the model:

$$Y = 0.003295 + 0.00001272X^3$$

with an $R^2$ of 0.91 highly significant ($F_{\text{test}}, F_{\text{stat.}} > F_{\text{tab.}}, p=0.01$, df=1, 51; 535>7.17). Where $Y = \text{estimated tree volume (m}^3/\text{tree)}$ and $X = \text{diameter at ankle height (dah)}$.

Whereas for dry biomass, all the coefficients were significant (appendix 8-11c) with the resultant model:

$$Y = 9.92 - 3.77X + 0.468X^2 - 0.1021X^3$$

with an $R^2$ of 0.77 also highly significant ($F_{\text{test}}, F_{\text{stat.}} > F_{\text{tab.}}, p =0.01$, df=3, 49; 54.9>4.22). Where $Y = \text{estimated dry biomass (kg/tree)}$ and $X = \text{diameter at ankle height (dah)}$.

**Figure 3-17** The curvilinear relationship between *dah* and estimated fresh biomass

**Figure 3-18** Un-weighted residual plot showing the non-constant residuals
3.4. Measured against estimated biomass using Brown, Tietema and sub-sampling equations

Figure 3-19  Weighted residual plot showing the constant residuals

Figure 3-20  Measured biomass (kg/tree) against estimated biomass (kg/tree) using Brown (top left), Tietema (top right) and sub-sampling equations (bottom left)
A comparison was made between measured aboveground woody biomass and estimated woody biomass using Tietema, sub-sampling and Brown’s mixed-species equations. Tietema’s equation was developed in Botswana but in a different study area. The equation is as follows: 

\[ B = 0.1936 \times BA^{0.1654} \]

where \( B \) = aboveground fresh biomass and \( BA \) = basal area calculated from the \textit{dah}. Brown’s equation was developed for dry zones with rainfall less than 900 mm/year (Brown, 1997). The equation was revised by (Brown, 1997) from Martinez-Yrizar et al., 1992 for dry forest in Mexico. The equation is:

\[ Y = 10^{\left(-0.535 + \log_{10}(BA)\right)} \]

where \( BA \) = basal area calculated from \textit{dbh}.

By visually comparing the three scatter plots (figure3-20), biomass (kg/tree) estimated through Brown and sub-sampling equations appear to follow the 1:1 relationship line. That is, all of the variation in estimated biomass is explained by the linear relationship between estimated biomass and measured biomass. All the three models gave a similar high \( R^2 \) of 0.87, 0.88 and 0.87 (p<0.05) for Brown, Tietema and sub-sampling equations respectively. However, the means of biomass estimated through the three equations were compared with the mean of biomass measured on the field. Table 3-3 shows these comparisons through the confidence intervals at 95% confidence limit.

### Table 3-3  The means of biomass estimated through sub-sampling, Brown and Tietema’s equations and their confidence intervals

<table>
<thead>
<tr>
<th></th>
<th>95% confidence interval for mean</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>Measured biomass (kg/tree)</td>
<td>23.1</td>
</tr>
<tr>
<td>Biomass estimated using sub-sampling equation (kg/tree)</td>
<td>19.1</td>
</tr>
<tr>
<td>Biomass estimated using Brown's equation (kg/tree)</td>
<td>30.3</td>
</tr>
<tr>
<td>Biomass estimated using Tietema's equation (kg/tree)</td>
<td>45.6</td>
</tr>
</tbody>
</table>

Table 3-3 shows that the mean for biomass estimated using sub-sampling method (19.1 kg/tree) has a probability of 0.95 within +/- 4.8 kg/tree deviations of the mean overlapping with the range of the measured biomass mean at the lower bound, indicating underestimation. The confidence intervals for mean biomass estimated using Brown’s equation overlap with the confidence interval for measured biomass at the upper bound, depicting overestimation of biomass. However, the confidence interval for biomass estimated using Tietema’s equation is way beyond that of measured biomass, also indicating overestimation of biomass. The box plot (figure 3-21) shows the visualisation of this explanation, but this time with the median.
The absolute estimates from these equations and the visual interpretation of the scatter plots (figure 3-20) indicates that Brown and Tietema’s equations tend to over estimate aboveground woody biomass from measured biomass. The error in estimated biomass from the two sets of equations is very high ranging from as low as 7 to 412 % per tree for Brown’s equation (averaging of 89 %) to 11-749 % per tree for Tietema’s equation with an average of 147 % error.

Comparison of sub-sampling equation with Tietema’s equation
Since Tietema’s equation was developed in Botswana though in a different study area, the equation was further compared with sub-sampling equation using the inventory data obtained from the field. Using Tietema’s biomass equation for mixed-species, biomass per plot (kg/m$^2$) was calculated and compared with the biomass per plot (kg/m$^2$) obtained by using the sub-sampling equation developed in this study. The results showed that Tietema’s equation tend to over estimate aboveground woody fresh biomass from sub-sampling by almost 100 %. The difference in estimated biomass from the two sets of equations is very high ranging from as low as 1.6-250 %.

To demonstrate this difference, biomass obtained through Tietema and sub-sampling equations were plotted on a 1:1 relation (figure 3-22) between the two models. A simple linear regression in the form $Y = X$ was used with a model $Y = 1.8946X$. This model shows that for every 1 kg/m$^2$ of biomass estimated using sub-sampling equation, Tietema's equation estimates by 1.89 kg/m$^2$. The relationship yielded an $R^2$ of 0.78 statistically significant (p<0.05).
3.5. Relating biomass to satellite image (IKONOS) data

The relationship between estimated aboveground woody biomass and spectral vegetation indices derived from IKONOS image showed poor correlation coefficient (R) of NDVI = 0.024, EVI = 0.083, SAVI = 0.077, and PVI = 0.060 as shown on table 3-4. The visual evidence of the scatter plots (appendix 8-13 a,b,c,d) do not depict any form of relationship between biomass estimated from the field and these image variables. All the four VI’s maps can be seen in appendix 8-14.

Table 3-4 Statistics of aboveground biomass and VI’s

<table>
<thead>
<tr>
<th>Index</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Range</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>NDVI</td>
<td>0.323</td>
<td>0.066</td>
<td>0.028-0.665</td>
<td>0.023</td>
</tr>
<tr>
<td>SAVI</td>
<td>0.187</td>
<td>0.036</td>
<td>0.022-0.436</td>
<td>0.076</td>
</tr>
<tr>
<td>EVI</td>
<td>0.287</td>
<td>0.066</td>
<td>0.032-0.756</td>
<td>0.082</td>
</tr>
<tr>
<td>PVI</td>
<td>0.29</td>
<td>0.029</td>
<td>0.021-0.432</td>
<td>0.059</td>
</tr>
</tbody>
</table>

Relationship between aboveground woody biomass and vegetation indices derived from Landsat ETM and MODIS

Statistical analysis revealed that there was a poor relationship between woody biomass and spectral vegetation indices (NDVI, PVI, SAVI and EVI) derived from high spatial resolution IKONOS imagery. Hence, it was decided that the relationship between biomass and spectral vegetation indices derived from medium spatial resolution imagery such as Aster (15 m spatial resolution); Landsat ETM (30 m spatial resolution) and low spatial resolution imagery such as Moderate Resolution Imaging
Spectro-radio meter (MODIS) also be sought. The MODIS image used was downloaded from NASA and was already processed. Its spatial resolution is 250 m. The description of image processing for Landsat ETM and MODIS data can be found in appendix 8-15 and 8-16 respectively. However, the two Aster images available for the greater Kalahari Research Project were not used since they did not cover the study area delineated by the IKONOS image within which field data collection for this study was done.

The hypothesis was that, in spite of the fact that when the spatial resolution of the imagery increases, the level of detail sufficient for meaningful and accurate forest investigation also improves; the detail may be too much that extraction of the right information is difficult. Table 3-5 shows correlation coefficients between aboveground woody biomass and spectral vegetation indices derived from Landsat ETM of October and September 2000 and 2001 respectively as well as MODIS (16 day average) for September 2005. As depicted by the table, there is still considerable evidence that aboveground woody biomass is poorly associated with spectral vegetation indices.

<table>
<thead>
<tr>
<th>Vegetation Index</th>
<th>Landsat 7 ETM+ October 2001</th>
<th>Landsat 7 ETM+ September 2002</th>
<th>MODIS (16-Day) September 2005</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>30 m spatial resolution</td>
<td>250 m spatial resolution</td>
<td></td>
</tr>
<tr>
<td>NDVI</td>
<td>0.248</td>
<td>0.333</td>
<td>NDVI</td>
</tr>
<tr>
<td>SAVI</td>
<td>0.23</td>
<td>0.334</td>
<td>SAVI</td>
</tr>
<tr>
<td>EVI</td>
<td>0.267</td>
<td>0.33</td>
<td>EVI</td>
</tr>
<tr>
<td>PVI</td>
<td>0.019</td>
<td>0.105</td>
<td>PVI</td>
</tr>
<tr>
<td>TM 4</td>
<td>0.056</td>
<td>0.046</td>
<td>Red</td>
</tr>
<tr>
<td>TM 5</td>
<td>0.08</td>
<td>0.153</td>
<td>NIR</td>
</tr>
<tr>
<td>TM 7</td>
<td>0.065</td>
<td>0.163</td>
<td>MIR</td>
</tr>
</tbody>
</table>
4. Discussion

4.1. Tree species mean stem diameter

As illustrated by table 3-1, the large mean stem diameter species such as *Boschia albitrunca* (mean = 13.4 cm) may be attributed to scarcity of water in the study area. Ground water in the sandveld area is generally at deep levels (Obakeng and Lubczynski, 2004; Stephenson et al., 2004). Therefore *B. albitrunca*’s deep root characteristic of tapping groundwater at deep levels of up to 70 m (Obakeng and Lubczynski, 2004) may be contributing to its large mean stem diameter. Whereas the small mean stem diameter species such as *Acacia fleckii* (mean = 9.4 cm) can be ascribed to the shallow rooting systems of the tree species which does not allow them to tap water at deep levels. Other factors could be that the poor Kalahari sands do not support the tree species diameter growth.

4.2. Comparison of biomass estimation methods (model stem and sub-sampling)

4.2.1. Reliability (Quality)

Reliability of the two methods was validated by the measured biomass (kg/tree) obtained in the field through complete harvesting method on the basis of overall effectiveness of a particular method through the coefficient of determination ($R^2$) and the hypotheses tested using the confidence limits and the confidence level. This was based on the assumption that the measured biomass is free of errors. Using a straight line relating $Y$ to $X$ in the form: $Y=a+bX$, then, $Y$ (response variable) should always be equal to $X$ (explanatory variable) representing a linear relationship between the two variables. Where, $Y$ represents estimated biomass (kg/tree) through either model stem or sub-sampling methods and $X$ represents measured biomass (kg/tree) obtained through complete harvesting method, $a$ (intercept) is the value of $Y$ when $X$ is 0 and $b$ (slope) is the amount by which $Y$ changes when $X$ increases by one unit.

Plotted against complete harvesting method, the model stem method displayed an $R^2$ of 0.74 with statistical significance ($p<0.05$), for the equation $Y=14.6+1.1X$. This tells us that the estimated biomass ($Y$) increases by ca 1 kg for every 1 kg increase of measured biomass ($X$) at 95 % confidence level. The data shows that the range here is not necessary since $Y$ is almost equal to $X$. The intercept $a=14.6$ kg means that when there is no measured biomass ($X=0$) then estimated biomass ($Y$) is 14.6 kg. Using the confidence limit for $a$ (ranging from 8.02 to 21.15) which is far from 0, at 95 % confidence level, the data tells us that when there is no measured biomass, the nearest estimated biomass could be to 0 is at least 8 kg. Therefore the model stem method was rejected on the grounds that the null hypothesis for $a$ was rejected even though $b$ was accepted 95 % confidence limit. A conclusion was drawn that the model stem method appears to be unreliable.
With regard to sub-sampling method plotted against the complete harvesting method, an $R^2$ of 0.94 ($p<0.05$) for the equation $Y=-0.92+0.93X$ was achieved. This model shows that the estimated biomass ($Y$) increases by 0.93 kg for every one kg increase of measured biomass ($X$). Using the confidence limit for $b$ ranging from -0.88 to 1.0, which includes one, the data shows that $b$ can be one at 95% confidence level, satisfying the condition of a 1:1 relation between $Y$ and $X$. As for the intercept $a =-0.92$ kg, it explains that when there is no measured biomass ($X=0$) then estimated biomass is -0.92 kg. Although this shows that when $X=0$ then $Y = -0.92$ kg which is not possible, but still it includes 0 which falls within the 95% confidence limit for $a$ ranging from -3.0 to 1.17 kg. Hence this satisfies the condition that when there is no measured biomass ($X = 0$), there is no estimated biomass ($Y$ is also 0). Therefore, a conclusion was drawn that sub-sampling method is more reliable than model stem method based on the evidence that indeed, at one stage, $a$ could be 0 and $b$ could be 1 at 95% confidence level, since both $a=0$ and $b=1$ fall within the respective confidence limits. The sub-sampling method was further used for the construction of biomass equations.

The non-reliability of the model stem method can be linked to a number of reasons; Firstly, the size of the grid cells could have contributed to this scenario. Time constraint was the main reason for not trying the different grid sizes. However the grid cell of 3 mm tested and found to be adequate by Adhikari (2005) was used. Other grid cells sizes tested by the same source were 2 by 2 mm and 4 by 4 mm. Adhikari (2005) concluded that the smaller the grid cell the better the results but for practical reasons, 3 mm was found to be adequate.

Secondly, as it was also observed by Montes (2000), the main limitation of this method is the requirement for a complete tree outline on the photograph. This therefore means that if the outline of the tree is not clear on the photograph then the user may introduce bias which may lead to either over-estimation or underestimation. Over-estimation would be introduced when grid cells which are supposed to be left out, are counted as falling within the tree boundary. Under-estimation would be when the grid cells which should be included in the counting are left out. The other reason can be linked to a situation where a grid cell does not entirely cover part of the tree. For this study a condition was set that if a grid cell does not entirely cover part of the tree, it will be included or excluded in alternates i.e. first time in, second time out, third time in, fourth time out etc.

Thirdly, when taking tree photographs in the field, the same distance of 5 m was maintained as far as possible for all the trees sampled. This was done to avoid discrepancies between scale calculations for the same tree which plays an important role in the ultimate biomass estimation. However, human errors in the form of variations in the distance between the tree and the camera as well as the tilt angles (either backwards or forward) of the camera could have been introduced in the field.

Lastly, since this study was focussing on woody biomass component of the tree, it was very difficult to locate the boundaries of stems and or branches covered by leaves. Therefore an error could have been introduced leading to the method’s overestimation of biomass.

Although Adhikari (2005) concluded that the model stem method appears to be a reliable method for the study of aboveground biomass of isolated trees and tree stands in open woodlands, the results of this study suggests sub-sampling to be the most reliable. In fact the results suggest that sub-sampling...
is the most reliable method (other than the model stem method) for the study of aboveground biomass of tree stands in open woodlands. The sub-sampling method was first developed and demonstrated by Valentine et al., (1984), adopted, improved and used by de Gier in several of his researches (de Gier, 1989; de Gier, 1995; de Gier, 1999; de Gier, 2003) in the Netherlands, Africa and central America. All the researchers came to the same conclusion that the approach is efficient, provides unbiased estimates, and avoids the time consuming and laborious task of weighing the whole tree. All these are consistent with the findings of this study. The method worked well for the different trees species in the study area, proving its applicability and that the form of the tree species is not relevant.

4.2.2. Time analysis

One aim of this study was to evaluate the different biomass estimation methods which can provide timely and cost effective source of information with limited resources for careful planning and management of the woody biomass resource. Based on the results of this study, time analysis revealed a very close tie between model stem and sub-sampling methods in terms of time requirement per tree in the field, and in the office. However, analysis shows an unfavourable position of sub-sampling method against model stem method.

It requires an average of 20 minutes (ranging from 10 – 36 minutes) for a single tree to be processed and biomass obtained using model stem method while an average of 25 minutes (ranging from 10-72 minutes per tree) is required for the same process using sub-sampling method. This difference which favours model stem method can be attributed to the fact that one spread sheet is designed as a calculation platform for all the trees used for the method. This improved the processing time and hence the relatively low average time per tree hence its low cost. However, the method requires that different grid cell sizes be tried for optimal output, but due to time constraints this was not done and the grid square size of 3 mm found by Adhikari (2005) to be adequate was used. Therefore, if different grid cell sizes could have been tried, the time requirement could have been different. Unfortunately the originator, i.e. (Montes et al., 2000) and the proponent of the model stem method, i.e. (Adhikari, 2005) did not include the time cost analysis in their studies therefore, it is assumed that this is the optimal time requirement for this method.

For the sub-sampling method, the findings indicate that time in the range of 10 – 72 minutes averaging 25 minutes is required for processing one tree. The process entails felling the tree, path selection importance sampling and disk removal and weighing the removed disk. The results are in line with those by de Gier (1989) who implemented the method in a similar type of vegetation but in the Netherlands. The time requirement found by de Gier ranged from 10 minutes to two hours (depending on the tree size) for a crew of two with an average of 30 minutes per tree. The slightly lower time revealed by this study can be associated with the on-average smaller tree diameters characterising the study area. Though the sub-sampling method (for one path) was 5 minutes on average slower than the model stem method, the former is still very efficient with regard to time usage cited in literature (de Gier, 1989). The sub-sampling method will provide an alternative method for estimating aboveground woody biomass timeously and with high levels of reliability and low cost. The estimation of quantities of the resource would be possible hence informed and guided decision making process would be possible.
Time was also recorded for complete harvesting method and the results show that average time per tree was only 23 minutes ranging from 4 – 72 minutes (depending on the tree size). This results are not consistent with the results of many researchers (Brown, 1997; de Gier, 1989; de Gier, 2003; Stewart et al., 1992; Vann et al., 1998). For example, Stewart et al., (1992) observed that this method is prohibitively time consuming and generally impractical (Vann et al., 1998) such that even with several workers it is often difficult to fell and weigh more than 30 trees per day. De Gier (1989) points out that heavy weighing scales are necessary requiring a lot of time for set up.

However, the results in this study are due to the fact that trees in the study area are predominantly small, hence felling the tree and dividing it into components for taking the weight was easy and fast. For example, in the inventory, 3577 trees were measured. Of this, 3548 were of the dah between 2.5 cm and 22.8 cm and only 29 trees fell in the dah between 22.9 and 107 cm. Most of the time, it was not necessary to divide a tree into components. Even when the tree was thorny, for example in the case of D. cinerea and A. fleckii, it was still easy to measure and remove the unwanted components (leaves and branches less than 2.5 cm diameter) and weigh the tree as a whole. A spring scale of 50 kg was used for weights measurements, hence smaller tree were not divided into components.

4.3. Development of biomass equations

Determination of easily measurable tree dimensions

The results from this study indicate that dah had a higher coefficient of determination (R^2) of 0.76 (F_{test}, F_{stat}>F_{tab}, p=0.01, df=3, 49; 52>4.20) compared with dbh’s R^2 of 0.72 (F_{test}, F_{stat}>F_{tab}, p=0.01, df=1, 50; 130>7.17). Hence dah proved to be the most objective prediction variable in the study area compared with the traditional dbh. These results are consistent with those presented by Tietema (1993). However, the dah should only be used in a situation similar to the study area where majority of the woodlands are of height 3-5 m and often low branching at heights lower than the standard breast height which is 1.3 m. This is because dah can be impractical when it comes to kneeling down and taking the measurements. This may introduce human error when the user swiftly takes the measurement to avoid the inconveniences of kneeling. Dbh is definitely more practical compared with dah, because one does not have to kneel down, the measurement is taken while standing.

Elsewhere, many researchers (Barnes et al., 1996; Boyd et al., 1999; Brown, 1997; de Gier, 1989; de Gier, 1995; de Gier, 1999; De Jong et al., 2003a; Lu et al., 2004; Porte et al., 2002; Sah et al., 2004; Stromgaard, 1985; Vann et al., 1998) have found satisfactory relationship between aboveground biomass as the dependant variable and dbh as the independent variable. However, in another study in a similar environment in Zimbabwe, ankle height and breast height diameters were found to be equally precise predictors of biomass with R^2 of 0.933 and 0.963 respectively, both statistically significant (p<0.05) (Gourlay et al., in press). The basis for the consistency in the relation between dah/dbh and biomass could be purely mechanical, i.e. a certain size range of the stem is required to support a certain weight of the tree, or that a given phloem and xylem capacity is required which itself is dependent on the stem basal area (Tietema, 1993). Based on the results of this study, adequate algorithms were developed using dah as an independent variable to predict aboveground biomass.
Mixed versus species-specific equations
After looking at the scatter plots of different tree species (figure 3-9 to 3-15), it was found that species-specific biomass equations were not necessary based on the random nature of scatter per individual tree species among the rest of the tree species. This shows that there is a great similarity between regression models of a range of trees in the study area, a mixed-species equation using ¯dah to predict biomass can be used in a normal diverse forest or woodland. This is consistent with the findings by Tietema (1993) in a study; biomass determination of fuelwood trees and bushes in Botswana and de Gier (1989) in a similar type of vegetation in the Netherlands. This is an important finding in the sense that it simplifies all subsequent work of having to develop species-specific equations. Moreover, species identification in the field which is often problematic hence a potential source of error, is not necessary, therefore this would eliminate this potential error source and also add to time savings in the field.

However, there was one exception with D. cinerea which appeared to take a different pattern from the rest of the species. The species was discarded from the rest of the tree species after it was found that D. cinerea displayed a low $R^2$ of 0.29 ($p<0.05$). D. cinerea is predominantly a multi-stemmed tree with a single stem diameter hardly above 15 cm (¯dah) as observed in the field. These results were not consistent with the findings by Tietema, (1993) and de Gier (1989) who did a comparison between single stemmed trees and multi-stemmed trees and found no significant difference in the regression between the two growth forms. However, elsewhere in Northern Ethiopia, in a vegetation type similar to that described in this study, Cleemput et al (2004) using the stem section as part below 30 cm, got rather a poor low correlation with the D. cinerea as compared with the rest of the species considered. The weak relationship between ¯dah and estimated biomass for D. cinerea in this study is not yet understood, but could be traced back to the approach used for measuring multi-stemmed trees. The approach was based on Tietema’s (1993) approach of obtaining stem basal area by adding individual single-stem basal areas. Conversely, de Gier (1989) defines the reference diameter of multi-stemmed trees, at any height, as the square root of the sum of the diameters squared. However, since the reason for D. cinerea to be behaving differently is not obvious in this case, there is need for further research in the study area regarding the same.

The biomass equations
The biomass equation for this study was developed from sub-sampling estimates using the POLYREG program (de Gier, 2000) as a weighted linear polynomial regression analysis using 3rd degree polynomial with backward elimination. However, the entire first, second and third degree components were significant (appendix 8-11a) hence they were not eliminated. Aboveground woody biomass was related to diameter at ankle height and found to be satisfactory. Weighting was found to be necessary as it was one way of correcting for the non-homogeneity of variance, and apparently a better one since it is unbiased (Cunia, 1964; de Gier, 1989) in estimating the regression coefficients by the method of weighted least squares. Weighting also had an added advantage in that the weighted model provided a better fit than the unweighted model. For example, the mixed-species model gave a lower $R^2$ value of 0.66 before weighting, and after weighting it increased to 0.76. Similar results were also found by de Gier (1989).
The sub-sampling equation developed in this study will be used by the interested institutions, organisations and academics for research purposes as well as relevant authorities for estimating the current standing stock of the resource and whether the standing woody biomass can meet local demands. As a result, informed decision making which is necessary for the effective use of the limited available resources for their sustainability will be effected. Moreover, this study will contribute immensely in addressing the problem of unreliable data as well as the reduction of the information gap existing in Botswana.

In the global perspective, understanding the rates at which different forest ecosystems change, grow, and add new biomass is important in developing more accurate estimates of factors contributing to changes in the atmospheric concentration of carbon dioxide and other greenhouse gases (Houghton, 1996) cited by Kasischke (1997) and also necessary for better understanding the deforestation impacts on global warming and environmental degradation. This will also be contributing to the Kyoto protocol of the United Nations Framework Convention on Climate Change (UNFCCC) which represents an international effort in mitigating global warming by reducing the continued release of greenhouse gases into the atmosphere to 95% of 1990 levels by 2012. The UNFCC stipulates mechanisms whereby storage of carbon in terrestrial sinks may be allowable for inclusion in national greenhouse gas inventories. However, this can only be achieved if information on the quantities of biomass available in the earth’s terrestrial biomes is available.

4.4. Comparison of measured against estimated biomass using different equations

Using measured aboveground biomass for validation based on the assumption that the data was flawless; a comparison was made with estimated biomass obtained using Brown, Tietema and sub-sampling equations. The data from these equations and the visual interpretation of the scatter plots (figure 3-20) and box-plots (figure 3-21) indicate that Brown and Tietema’s equations tend to over estimate aboveground woody biomass from measured biomass. The difference in estimated biomass from the two models was found to be very high ranging from as low as 7 - 412 % per tree for Brown equation with an average error of 89 % to 11- 749 % per tree for Tietema’s equation with an average error of 147 %.

The over estimation of biomass by Brown and Tietema’s equations can be linked with the field measurement approaches used. For example, Tietema (1993) did not divide trees into components of interest. The entire tree including branches and leaves were measured. Whereas in this study, components such as leaves and branches less than 2.5 cm in diameter were not included. The other reason can be linked to the fact that the equations were developed in different environments. For example, during the construction of the Brown’s equation, a total of 371 trees of many species with dbh ranging from 5 to 148 cm from ten different sources and all the three tropical regions were used (Brown, 1997) for the construction of biomass equation. Though climate in tropical regions might be similar, the local climate, soils and vegetation may differ significantly. Hence the use of data from many sources and different regions could have contributed immensely to the error in construction of the model hence the overestimation of biomass. It is also not clear which tree components were measured on the field for the Brown data set. This makes meaningful conclusion very difficult.
Moreover, both equations were constructed using a regression based on the log-transformed data. However, Cunia (1964) pointed out that by taking the logarithms, the estimation of arithmetic mean is automatically replaced by the estimation of the geometric mean, which is always smaller than the first mean, hence introducing bias in biomass estimation. Chave et al., (2004) observed that using a regression on the log-transformed data represents the departure from a perfect allometry by the residuals which are normally distributed. The same author contends that these residuals represent the uncertainty in the biomass estimation due to the allometry itself. Harrel et al., (1997) found that the use of logarithmic transformation mask the true levels of ambiguity. Sprugel, (1983) cited by Cleemput et al., (2004) found that equations developed with transformed data have the potential for bias. Sah, et al., (2004) on the other hand found that logarithmic models generally give under predictions and as such a correction factor has to be applied in the back transformation of the data. The log-transformation of data could also be responsible for the overestimation of biomass by these equations (Brown and Tietema).

Although the data shows that the equation from sub-sampling method provides a more reliable estimation of biomass than the Brown and Tietema’s equations, the 1:1 relationship line (figure 3-20) and the scatter plot show that this equation tends to underestimate aboveground woody biomass by an average of 32% ranging from 0.07% to 96%. The reason for underestimation of biomass by the equation developed from sub-sampling data is not readily known, this may call for further research on the method to determine this shortcoming and improve on it.

In a nutshell, the findings of this study reveal that existing biomass equations show large differences especially when developed in different geographical areas regardless of whether it is the same country or not. Therefore they should not be used outside their areas of origin without validation. It should be borne in mind that validation entails tree felling, for which Chave et al., (2004) recommends 50 trees whereas de Gier (1999) recommends at least 25 trees for validation. Such a number of felled trees are sufficient to develop new biomass equations for the area concerned. This would therefore call for a very efficient method in terms of time usage and reliability of estimation. Sub-sampling method is therefore recommended for this purpose since it is time efficient and reliable, it provides on the spot estimates of volume and fresh weight, it requires light weight equipment and can resourcefully be carried out by two people.

4.5. Relating biomass to satellite image data

One of the objectives of this study was to establish a relationship between aboveground woody biomass and different spectral vegetation indices (VI’s) such as Normalised Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Perpendicular Vegetation Index (PVI) and Enhanced Vegetation Index (EVI). As mentioned in chapter 1-3, VI’s have been very widely applied to multi-spectral data (Gemmell and McDonald, 2000). The most popular ones using the red and near infrared wavelengths to emphasize the difference between the strong absorption of red electromagnetic radiation and the strong scatter of near infrared radiation (Lu et al., 2004). NDVI is one of the most commonly used vegetation index in many applications relevant to the analysis of the biophysical parameters. Since the study area is open woodland with clearly visible soil patches on the ground, SAVI, EVI and PVI were selected because they minimize soil background effect.
Subsequently, to use a VI which gives a higher correlation than others with aboveground woody biomass and to use this relationship to estimate aboveground woody biomass of the entire study area.

However, the results revealed low correlation coefficient between estimated aboveground biomass and different vegetation indices (NDVI = 0.024, EVI = 0.083, SAVI = 0.077 and PVI = 0.060) derived from IKONOS imagery. These results suggest that the relationship between aboveground fresh biomass and these vegetation indices is poor. These results are almost consistent with the results of previous studies done in Botswana, though the satellite system used was different. Using Landsat TM, Moleele et al., (2001) found low correlation between mean VI’s and measured biomass. For example correlation coefficients of 0.52 for NDVI ($p=0.01$) and 0.31 for PVI ($p=0.01$) were obtained. However, Thenkabail, (2004) concluded that satellite data derived from IKONOS imagery provides a more detailed depiction of vegetation and related factors such as biomass. Gemmell and McDonald (2000) concluded that the potential of the VI’s for discriminating forest cover was low probably because of nonlinear relationships with cover. In support of this, Rundquist (2002) using Landsat TM concluded that VI’s (NDVI and SAVI) tested are strongly related to green vegetation and the relationship tends to be linear, approximating a 1:1 line. Whereas Gemmell and McDonald (2000) concluded that, although remote sensing can provide timely and cost effective source of information, a robust method for extracting forest characteristics from remotely sensed data is yet to be fully developed.

Furthermore, the relationship between aboveground woody biomass and spectral vegetation indices derived from medium resolution imagery such as Landsat ETM (30 m spatial resolution) and low resolution imagery such as Moderate Resolution Imaging Spectro-radio meter (MODIS) with 250 m spatial resolution was also investigated. The difference was still the same. The relationship between biomass and vegetation indices was still found to be poor. For example, correlation coefficient values of 0.25, 0.33 and 0.22 were obtained when using NDVI derived from Landsat ETM (October 2001), Landsat ETM (September 2002) and MODIS 16-day (September 2005) respectively. In general terms, a number of reasons may be responsible for the low correlation depicted in this study.

(I) First and foremost, this study is concerned with the woody material of biomass and excludes foliage grass and small trees and shrubs which are photosynthetically active material. This material may have contributed to the poor relationship observed. For example, as it was observed in the field, a plot would contain two trees eligible for biomass estimation, and the rest would be grass, herbs and small trees with diameter less than 2.5 cm. Therefore that plot would have a small quantity of woody biomass whereas the photosynthetic activity of vegetation in the same plot is high, hence high vegetation index. Similarly, the satellite sensor directly measures the reflectance of the crown and not the woody portions of the tree. Woody biomass does not contribute much to spectral reflectance. As such a relationship between woody biomass and crown has to be sought first before biomass could be related to spectral reflectance. However, this relationship is very difficult to find. Nevertheless, some tree species have a strong correlation between woody biomass and crown area. This was found among species like *B. albitrunca, L. nelsii, B. Africana* and *O. pulchra* with correlation coefficients of 0.72, 0.75, 0.77, and 0.94 correspondingly. These relationships can be used to seek for the relationship between biomass and spectral reflectance.
(II) Where there is more biomass, one would expect high photosynthetic activity but this is not really the case because woody biomass accumulates or is made over time and photosynthetic activity is measured at an instant, hence low correlation between aboveground woody biomass and vegetation indices. With increase in age of forest or woodlands there is a steady decrease in chlorophyll accumulation (Thenkabail 2004). For example, a maize field may have high photosynthetic activity and low biomass whereas a fully grown forest or woodland may have a low photosynthetic activity and high biomass.

(III) Approximately 0.8% of inventoried trees had large \textit{dah} (> 22.8 cm) which is the maximum range of the original data set. The 0.8% of trees had \textit{dah} ranging from 22.9 cm to 108 cm. Therefore they were not included in the calculation of plot biomass because most of them were well beyond the valid diameter range of the data set used to develop the biomass equation for this study. However, Brown., (1997) contends that it is important that biomass of trees with large \textit{dah} be estimated as accurately as possible because their contribution to the biomass of a forest stand is much more than their number suggests. Since large \textit{dah} trees were not included, this could be one contributing factor to the poor correlation between the VI’s and estimated fresh biomass.

(IV) Existing models of VI’s were primarily developed for agricultural applications which tend to be characterised by homogenous vegetation canopies than those typically found in semi arid areas like Botswana (Moleele et al., 2001). Vigorously growing crops reflect far more energy in the NIR than primary or secondary forests. This is due to the rate of accumulation of chlorophyll per unit area of leaf, which is far greater in younger regrowth than older regrowth (Thenkabail, 2004). Dry areas have a wide variety of different vegetation complexes including woody species with different canopy closures. These characteristics pose problems in the spectral discrimination of vegetation in semi-arid environments (Ringrose et al., 1990; Ringrose et al., 1999; Ringrose et al., 1996). Moreover, Verstraete and Pinty, 1992 cited by Gemmell and McDonald (2000) contend that using VI’s is theoretically the same as solving an inverse problem where all variables are assumed to be constant. However, this can be a disadvantage if the index is applied under conditions evidently different to those for which the index was developed (Gemmell and McDonald, 2000).

(V) In semi-arid environments, problems are known to arise in the interpretation of vegetation indices particularly NDVI due to the lack of effective NIR radiance especially when single date imagery is used (Moleele et al., 2001), as in this study.

(VI) The timing of data collection in relation to the acquisition date of the imagery was not good. For example, all the imagery except for MODIS were acquired in 2001 and 2002 whereas the data collection was done in September of 2005, more than three years in between and totally different seasons for IKONOS imagery (February). Though there was no evidence of disturbance in terms of recent fires or massive tree harvesting, biomass definitely increased over the last three years. Furthermore, satellite imagery acquired in the late summer as in this study (for IKONOS), maximise the spectral contrast between some green tree crowns and dry herbaceous background (Carreiras et al., 2005 In press). Nonetheless, the study area is still characterised by enormously variable under-story containing bare soil, dry grass and some green shrubs. In addition, rains in Botswana starts from late September to March and the different vegetation species are fully green by January and February.
(Ringrose et al., 1990). Therefore, it is assumed the image was acquired when vegetation in the study area was fully green, and data collection was collected when trees were recovering from the dry season hence shed all their leaves. However, it must be noted that although the IKONOS image was not the most optimal, it was the best available for this study.

(VII) Lastly, navigation to the centre of the plots was done using the Garmin GPS with a positional error of approximately 4 meters. Therefore, it is most likely that, the enumerated plots in the field were not exactly overlaying the image plots where the mean spectral vegetation indices were obtained. Moreover, the field plots were circular whereas the image pixels were square hence there was an overlap.

It appears like the method used to relate the biophysical parameters to IKONOS and or Landsat and MODIS data in this study is not the right one to use. Other methods like relating canopy cover to biomass especially when using the IKONOS image could be used instead of vegetation indices. In addition, spectral reflectance of different tree species is different even among the same tree species, therefore to relate aboveground biomass to image data especially high resolution IKONOS data canopy cover could be the answer. But first, a relationship between woody biomass and canopy cover on specific species could be explored though this relationship is difficult to come by. If found it could be possible to use the relationship to estimate biomass only for particular tree species.
5. Conclusions

With respect to the aboveground woody biomass estimation methods, which is the most effective in terms of time cost and reliability among the two methods? Even though the method is timeous and reliable, is it practical in terms of applicability on the field?

- The model stem method to estimate aboveground biomass was not reliable based on the validation data set used.
- Sub-sampling method can be used to estimate aboveground biomass of shrubs and wood lands with high reliability and within the required time.
- In order to estimate biomass for species for which no regression equation has been developed, the mixed-species biomass equation developed in this study can be used. However, caution should be taken when using this biomass equation more especially when extrapolating beyond the range of the data. Similarly, caution should be applied when using the equation in the environment different from the one it was developed in. Therefore, validation of this equation needs to be carried out. Since validation requires up to 50 trees as recommended by different researchers, it is only practical that new equations are developed for the study area in question, therefore sub-sampling is recommended for that purpose.

What is the relationship between easily measurable tree dimension and estimated aboveground woody biomass?

- The regression of diameter at ankle height against aboveground fresh/dry woody biomass and tree volume as described by the mixed-species equations can be used to determine the standing fresh/dry biomass and tree volume in a mixed woodland/forest in Botswana. However, there is need for further research regarding the differentiation of single versus multi-stemmed species in the study area.

How strong is the relationship between spectral vegetation indices (NDVI, SAVI, PVI, and EVI) derived from satellite imagery and estimated aboveground woody biomass? Which of the above mentioned vegetation indices gives a higher correlation with estimated aboveground woody biomass compared to the others?

- Estimating aboveground woody biomass from spectral vegetation indices derived from satellite imagery particularly IKONOS has proven to be very difficult. The poor correlation between estimated aboveground woody biomass and spectral vegetation indices (NDVI, PVI, SAVI and EVI) indicate that these vegetation indices are not appropriate for estimating aboveground woody biomass in the study area.

Finally, it can be concluded that even though the potential of ground based biomass estimation combined with satellite based remote sensing proved difficult, the practical use of this thesis work can be found in providing adequate and reliable information regarding the woody biomass resource particularly fuelwood, through the biomass equations developed therein. Such information will guide
the decision making process hence providing a profound basis for the development of sound policies for the protection and conservation of our natural woodlands. In the universal perspective, understanding the rates at which different forest ecosystems change, grow, and add new biomass is important in developing more accurate estimates of factors contributing to changes in the atmospheric concentration of carbon dioxide and other greenhouse gases.
6. Recommendations

Aboveground woody biomass estimation

- The mixed-species equations developed in this study are recommended where particular tree species are threatened or where cutting of trees is totally forbidden.
- Since the reason for *D. cinerea* behaving differently is not yet understood; there is need for further research in the study area regarding the same.
- The biomass equations developed in this study can be used by the interested institutions, organisations and academics for research purposes as well as relevant authorities particularly EAD for estimating the current standing stock of the biomass resource and whether the standing woody biomass can meet local demands. As a result, informed decision making which is necessary for the effective use of the limited woody biomass resources for their sustainability will be effected.
- Sub-sampling method is recommended particularly in areas where big trees are encountered. However, the systematic underestimation of biomass through sub-sampling method needs to be investigated.

Relationship between aboveground woody biomass and spectral vegetation indices

- If remote sensing data is to be used in concert with field observations, then it is recommended that seasonality should be taken in consideration.
- Though a variety of spectral vegetation indices have been developed in the past for different purposes, more research focussing on vegetation indices which can be used to estimate aboveground woody biomass is necessary in the future. By the same token, if spectral reflectance derived from IKONOS image is to be used to predict woody biomass, then two options are recommended;
  - First of all, since the relationship between *dah/dbh* and weight of the tree (woody biomass) has been established, further relationship between the stem and the branches holding crown has to be established. If the relationship is strong then the relationship between the branches and the crown can be sought. Using these relationships, then the relationship between crown and spectral reflectance through vegetation indices can be sought.
  - Secondly, a strong relationship has been established between woody biomass and crown area among four tree species (*B. albitrunca, L. nelsii, B. Africana and O. pulchra*) in the study area. This relationship can be used to seek for the relationship between woody biomass and spectral reflectance. However, classification of individual tree species which is possible with high resolution imagery has to be done first. Next, tree species which do not show a good association between woody biomass and crown area are masked out, so that a map of ‘wanted’ tree species is produced. This map can be used to derive spectral reflectance which can then be
correlated with woody biomass. Therefore with these two options, a strong relationship between wood biomass and vegetation indices can be obtained.
7. References

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8. Appendices

Appendix 8-1 Definition of concepts

Woodland is defined in this study as natural habitat including all grass, shrub, bush and other wooded land categories.

Biomass is defined by Brown (1997) as the total amount of above ground living organic matter expressed as oven dry tons per unit area. The European Biomass Association - AEBIOM (2004) (webpage) defines biomass as renewable vegetable and animal matters that can be used for industrial (fibre, chemicals) or energy production (heat, electricity, fuel). However, since this study deals with aboveground woody biomass as a source of energy in the form of wood, biomass is defined as above ground woody material including stem, branches and twigs of dimensions more than 2.5 cm. This definition excludes other biomass components like grass, leaves, roots and small twigs.

Wood is a biological tissue made of cells, or tracheides, and walls of composed lignin. The tracheides are like pipes, that transport the sap along the stem, they are filled by water (Chave, 2005)

Wood fuel; it has a broader meaning which includes both charcoal and fuelwood.

Tree component; most researchers have worked with tree components rather than with the entire tree, standardization of terms was found to be a problem (de Gier, 1989). After being felled, trees are usually subdivided into different components depending on the research aims. Stem wood is usually measured for volume and/or fresh weight, branches, twigs and leaves for fresh weight only (de Gier, 1989). Large pieces are then sectioned and the total fresh weight is determined for each component. However, in this study, only one tree component was considered (stem wood and branches greater than 2.5 cm in diameter excluding foliage, stems and branches smaller than 2.5 cm in diameter

Fuelwood; de Gier (1989) observed that fuelwood dimensions are not erratic, e.g. the length of a single piece is often an arm’s length and the diameter about an arm’s thickness, and this diameter is rarely under 2.5 cm. Therefore, for the purpose of this study, fuelwood is defined as above ground woody material including stem, branches and twigs with diameter greater than 2.5 cm.

Density; density is mass per unit volume expressed in kg/m$^3$. Wood density is generally expressed as the dry mass of wood substance per unit of green volume (Husch., et al 2003).

\[ D = \frac{W_d}{V_g} \]

Where \( D \) = wood density (kg/m$^3$), 
\( W_d \) = oven-dried weight of wood (kg),
\( V_g \) = fresh volume (m$^3$).
Appendix 8-2  Fine spatial resolution sensors

<table>
<thead>
<tr>
<th>Year of launch</th>
<th>Satellite sensor</th>
<th>Spatial resolution (m) Panchromatic</th>
<th>Multispectral</th>
</tr>
</thead>
<tbody>
<tr>
<td>1995</td>
<td>IRS-1C</td>
<td>5.8</td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>IRS-1D</td>
<td>5.2</td>
<td></td>
</tr>
<tr>
<td>1999</td>
<td>IKONOS</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>2000</td>
<td>Eros-A1</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2001</td>
<td>QuickBird</td>
<td>0.61</td>
<td>2.44</td>
</tr>
<tr>
<td>2002</td>
<td>SPOT HRG</td>
<td>2.5, 5</td>
<td>10</td>
</tr>
<tr>
<td>2003</td>
<td>OrbView-3</td>
<td>1</td>
<td>4</td>
</tr>
</tbody>
</table>

IRS = Indian Remote sensing satellite
SPOT = Systeme Pour l’Observation de la Terre
HRG = High Resolution Geometry

Appendix 8-3  The Electromagnetic spectrum; adopted from (ITC, 2004)

Appendix 8-4  An ideal spectral reflectance curve of green vegetation (ITC, 2004)
### Appendix 8-5 Time cost

<table>
<thead>
<tr>
<th>Method</th>
<th>Activity</th>
<th>Time requirement</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model stem</td>
<td>Measuring of tree diameter at breast height, diameter at ankle height &amp; crown diameter.</td>
<td>TR 1</td>
</tr>
<tr>
<td></td>
<td>Clearing small bushes around a tree. Since trees in Botswana are mainly of height 3 to 6m, a consistent 5 m distance from the tree was maintained. Taking tree pictures</td>
<td>TR 2</td>
</tr>
<tr>
<td></td>
<td>Photograph processing in the office until tree fresh biomass is produced. It starts from inserting the tree as background on the excel spreadsheet, then, working out the scale and coding pixels covering the stem and branches. Pixels which are not entirely covering the parts of the tree will be included only if they occupy 50 % or more of the tree part. Preparation of excel spreadsheet was not timed because it is common to all trees.</td>
<td>TR 3</td>
</tr>
<tr>
<td>Sub-sampling</td>
<td>TR 1 time applies since activity is the same</td>
<td>TR 1</td>
</tr>
<tr>
<td></td>
<td>Felling the entire tree at butt level (as low as possible, mostly at ankle height though in most cases this was not convenient to the person felling the tree)</td>
<td>TR 4</td>
</tr>
<tr>
<td></td>
<td>Path selection and importance sampling of path</td>
<td>TR 5</td>
</tr>
<tr>
<td></td>
<td>Estimating tree woody biomass</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Locating the point for disk removal</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Estimating tree woody fresh weight</td>
<td></td>
</tr>
<tr>
<td>Complete</td>
<td>TR1 and TR4 times applies</td>
<td>TR 1 &amp; TR 4</td>
</tr>
<tr>
<td>harvesting</td>
<td>Subdividing tree into manageable components where necessary</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Removing the small branches</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Weighing all the components</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Total fresh weight obtained</td>
<td></td>
</tr>
</tbody>
</table>

**Model stem method**
Time cost/efficiency for this method (TM) was therefore be calculated as follows:

\[
TM = TR1 + TR2 + TR3
\]

Where TR = time requirement

**Sub-sampling Method**
Time cost/efficiency for this method (TS) was therefore be calculated as follows:

\[
TS = TR1 + TR4 + TR5
\]

**Complete Harvesting Method**
Time cost/efficiency for this method (TF) was therefore be calculated as follows:

\[
TF = TR1 + TR4 + TR6
\]
### Materials used for the field survey

<table>
<thead>
<tr>
<th>Biomass estimation method</th>
<th>Equipment</th>
<th>Purpose</th>
<th>Quantity</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sub-sampling</strong></td>
<td>Diameter tape/callipers**</td>
<td>For dbh and dah measurements</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Suunto Compass**</td>
<td>For direction incase the GPS does not work</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>GPS (Garmin 12XL model)**</td>
<td>For navigation</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Electric scale (2000g) I-paq**</td>
<td>For weighing disks</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Panga**</td>
<td>For data recording</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Hand saw*</td>
<td>For clearing small bushes around the tree</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Note book**</td>
<td>For felling trees and removal of discs</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Chissel</td>
<td>For data recording as back up</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Markers</td>
<td>For smoothning the bark</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Digital Camera</td>
<td>For taking tree photographs</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Stop watch**</td>
<td>For measuring duration of time required for each method</td>
<td>1</td>
</tr>
<tr>
<td><strong>Model stem</strong></td>
<td>Measuring tape (30 m length)***</td>
<td>For plots measurement and tree height</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Weighing spring scale (25 kg)</td>
<td>For full tree weight</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Weighing spring scale (50 kg)</td>
<td>For full tree weight</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Plastic rope (100 m long)**</td>
<td>For demarcating the plot</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Ribbon*</td>
<td>For marking the tree</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Ikonos image printout**</td>
<td>For locating the plots</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>Field Vehicle (Van)**</td>
<td>For transportation</td>
<td>1</td>
</tr>
</tbody>
</table>

* = common to both sub-sampling and full tree harvesting methods.

** = Common to all the three methods
Human Resources
Researcher = 1; Botanist = 1; Support staff = 1
Total number of sample plots = 169 plots (34 for biomass estimation and the rest for the inventory)
Plot size = 500 m² (circular).

Appendix 8-7  Field work in pictures
Appendix 8-8  Method for detecting outliers

An outlier is an observation or data point that comes from a distribution different (in location, scale, or distributional form) from the bulk of the data. In the real world, outliers have a range of causes, from as simple as; operator blunders, equipment failures, day-to-day effects, batch-to-batch differences, anomalous input conditions and warm-up effects. Checking for outliers should be a routine part of any data analysis. All outliers should be taken seriously and should be investigated thoroughly for explanations. If the data point is in error, it should be corrected if possible and deleted if it is not possible. If there is no reason to believe that the outlying point is in error, it should not be deleted without careful consideration.

Method of using z-score:

Chebyshev’s outlier theorem was used to remove outliers in the data set. It states that almost all the observations in a data set will have z-score less than 3 in absolute value i.e. fall into the interval \((\bar{x} - 3\sigma, \bar{x} + 3\sigma)\), where \(\bar{x}\) is the mean and \(\sigma\) is the standard deviation of the sample. Therefore, the observations with z-score greater than 3 will be outliers (http://www.netnam.vn/unescocourse/statistics/37.htm).

Appendix 8-9  Processing of IKONOS image

Earth-sun distance in Astronomical Units as taken from Space Imaging (2005)

<table>
<thead>
<tr>
<th>Julian Day</th>
<th>Distance</th>
<th>Julian Day</th>
<th>Distance</th>
<th>Julian Day</th>
<th>Distance</th>
<th>Julian Day</th>
<th>Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.9832</td>
<td>74</td>
<td>0.9945</td>
<td>152</td>
<td>1.014</td>
<td>227</td>
<td>1.0128</td>
</tr>
<tr>
<td>15</td>
<td>0.9836</td>
<td>91</td>
<td>0.9993</td>
<td>166</td>
<td>1.0158</td>
<td>242</td>
<td>1.0092</td>
</tr>
<tr>
<td>32</td>
<td>0.9853</td>
<td>106</td>
<td>1.0033</td>
<td>182</td>
<td>1.0167</td>
<td>258</td>
<td>1.0057</td>
</tr>
<tr>
<td>46</td>
<td>0.9878</td>
<td>121</td>
<td>1.0076</td>
<td>196</td>
<td>1.0165</td>
<td>274</td>
<td>1.0011</td>
</tr>
<tr>
<td>60</td>
<td>0.9909</td>
<td>135</td>
<td>1.0109</td>
<td>213</td>
<td>1.0149</td>
<td>288</td>
<td>0.9972</td>
</tr>
</tbody>
</table>

IKONOS Band-dependant Parameters also taken from Space Imaging (2005)

<table>
<thead>
<tr>
<th>IKONOS Band ((\lambda))</th>
<th>(\text{CalCoef}_{\lambda}) Pre 2/22/2001* (DN/(mWcm}^{-2}\text{-sr})</th>
<th>(\text{CalCoef}_{\lambda}) Post 2/22/2001* (DN/(mWcm}^{-2}\text{-sr})</th>
<th>(\text{Bandwidth}_{\lambda}) (nm)</th>
<th>(E_{\text{SUN}\lambda}) (W/m}^2/\mu\text{m})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pan</td>
<td>161</td>
<td>161</td>
<td>403</td>
<td>1375.8</td>
</tr>
<tr>
<td>Blue</td>
<td>633</td>
<td>728</td>
<td>71.3</td>
<td>1930.9</td>
</tr>
<tr>
<td>Green</td>
<td>649</td>
<td>727</td>
<td>88.6</td>
<td>1854.8</td>
</tr>
<tr>
<td>Red</td>
<td>840</td>
<td>949</td>
<td>65.8</td>
<td>1556.5</td>
</tr>
<tr>
<td>NIR</td>
<td>746</td>
<td>843</td>
<td>95.4</td>
<td>1156.9</td>
</tr>
</tbody>
</table>

* is Image production date. The coefficients are for the 11-bit products.

The process of how radiometric correction of IKONOS satellite image was done:

1. Digital number (DN) values recorded by the sensor
2. Conversion of DN values to spectral radiance (at sensor)
3. Conversion of spectral radiance to apparent reflectance (at sensor)
4. Removal of atmospheric effects due to scattering and absorption
5. Reflectance of pixels at the earth’s surface
### Appendix 8-10  Biomass data and tree variables for 62 trees

#### Summary of tree data used for regression analysis; Part 1

<table>
<thead>
<tr>
<th>Plot #</th>
<th>Scientific name</th>
<th># of stems</th>
<th>DAH @ 10 cm from ground</th>
<th>DBH @ 1,3m from ground</th>
<th>Tree Height</th>
<th>Crown Diameter (avrg)</th>
<th>Estimated fresh Weight (avrg)</th>
<th>Time taken</th>
<th>Measured fresh weight</th>
<th>Time taken</th>
<th>Estimated fresh weight</th>
<th>Time taken</th>
</tr>
</thead>
<tbody>
<tr>
<td>14</td>
<td>Terminalia sericea</td>
<td>1</td>
<td>5</td>
<td>2.2</td>
<td>2.65</td>
<td>2.9</td>
<td>18</td>
<td>5.2</td>
<td>20</td>
<td>8.8</td>
<td>28</td>
<td>11</td>
</tr>
<tr>
<td>17</td>
<td>Acacia fleckii</td>
<td>1</td>
<td>3</td>
<td>1.5</td>
<td>2.25</td>
<td>3.5</td>
<td>19</td>
<td>2.9</td>
<td>11</td>
<td>2.8</td>
<td>30</td>
<td>11</td>
</tr>
<tr>
<td>22</td>
<td>Dichrostachys cinerea</td>
<td>1</td>
<td>9.9</td>
<td>4</td>
<td>6</td>
<td>13.1</td>
<td>28</td>
<td>20.0</td>
<td>24</td>
<td>22.6</td>
<td>32</td>
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<td>1.65</td>
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<td>1.1</td>
<td>16</td>
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<td>4</td>
<td>24.6</td>
<td>29</td>
<td>4</td>
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<tr>
<td>30</td>
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<td>10.3</td>
<td>4.5</td>
<td>4</td>
<td>23.9</td>
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<td>24.6</td>
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<td>11</td>
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<td>4</td>
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<td>31</td>
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<tr>
<td>26</td>
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<td>3.7</td>
<td>2.75</td>
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<td>11</td>
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<td>26</td>
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<td>2.7</td>
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<td>7.5</td>
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<td>39.2</td>
<td>18</td>
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<td>3.9</td>
<td>2</td>
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<td>32</td>
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<td>27</td>
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<td>20.6</td>
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<td>52.3</td>
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<td>Dichrostachys cinerea</td>
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<td>3.9</td>
<td>3</td>
<td>7.4</td>
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<td>23</td>
<td>25</td>
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<td>11.5</td>
<td>3.9</td>
<td>2.5</td>
<td>17.5</td>
<td>17</td>
<td>20.0</td>
<td>21</td>
<td>27.7</td>
<td>18</td>
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<td>6.8</td>
<td>1.76</td>
<td>0.75</td>
<td>0.6</td>
<td>15</td>
<td>1.5</td>
<td>11</td>
<td>14.5</td>
<td>18</td>
<td>10</td>
</tr>
</tbody>
</table>
### Biomass data and tree variables … continued…

#### Summary of tree data used for regression analysis; Part 2

<table>
<thead>
<tr>
<th>Plot #</th>
<th>Scientific name</th>
<th># of stems</th>
<th>DAH @ 10 cm from ground</th>
<th>DBH @ 1.3m from ground</th>
<th>Tree Height</th>
<th>Crown Diameter (avg)</th>
<th>Estimated fresh Weight (avg)</th>
<th>Time taken</th>
<th>Measured fresh weight</th>
<th>Estimated fresh weight</th>
<th>Time taken</th>
</tr>
</thead>
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Appendix 8-11 Summary of weighted linear regression analyses using sub-sampling method

(a) Estimated biomass (kg/tree) regressed against diameter at ankle height (cm)

NAME OBJECT : Estimated Biomass and dah
# DATA SETS : 53
MODEL: \( Y = B_0 + B_1 \times X_1 + B_2 \times X_2 + B_3 \times X_3 \)

\[
\begin{align*}
Y & = \text{estimated biomass (kg)} \\
X_1 & = \text{dah (cm)} \\
X_2 & = \text{dah}^2 \\
X_3 & = \text{dah}^3 \\
\text{WEIGHT} & = \left(\frac{1}{X_1^2}\right)^2
\end{align*}
\]

COEFFICIENTS

\[
\begin{align*}
B_0 & = 1.5365804579 \times 10^1 \\
B_1 & = -5.8069294656 \times 10^0 \\
B_2 & = 7.2121508505 \times 10^{-1} \\
B_3 & = -1.5596751573 \times 10^{-2}
\end{align*}
\]

ANALYSIS OF VARIANCE

\[
\begin{array}{ccc}
\text{SS} & \text{df} & \text{MS} \\
\text{REG.} & 6.86647 \times 10^{-2} & 3 & 2.28882 \times 10^{-2} \\
\text{RES.} & 1.83865 \times 10^{-1} & 49 & 3.75236 \times 10^{-3} \\
\text{TOT.} & 2.52530 \times 10^{-1} & 52 & 4.85635 \times 10^{-3}
\end{array}
\]

VAR. RATIO (F) = 5.2137E+01

RES. MEAN SQUARE = 6.1256E-02

MEAN X_1 = 1.1297E+01
MEAN Y = 2.2642E+01

MULTIPLE CORRELATIONS

\[
\begin{align*}
R^2 & = 7.6150 \times 10^{-1} \\
R & = 8.7266 \times 10^{-1}
\end{align*}
\]

SIGNIFICANCE COEFFICIENTS

\[
\begin{array}{cccc}
\text{Coeff.} & \text{St.Error} & \text{t} & \text{significance} \\
B_0 & 4.3108E+00 & 3.5645E+00 & >0.1\% \\
B_1 & 1.7775E+00 & -3.2670E+00 & >1\% \\
B_2 & 2.1343E-01 & 3.3791E+00 & >1\% \\
B_3 & 7.3729E-03 & -2.1154E+00 & >5\%
\end{array}
\]

(b) Estimated biomass volume (m³/tree) regressed against diameter at ankle height (cm)

NAME OBJECT : Biomass volume
# DATA SETS : 53
MODEL: \( Y = B_0 + B_1 \times X_1 \)

\[
\begin{align*}
Y & = \text{Biomass volume} \\
X_1 & = \text{dah}^3 \\
\text{WEIGHT} & = \left(\frac{1}{X_1}\right)^2
\end{align*}
\]

COEFFICIENTS

\[
\begin{align*}
B_0 & = 3.2947352781 \times 10^{-3} \\
B_1 & = 1.2720552804 \times 10^{-5}
\end{align*}
\]
### Analysis of Variance

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**Var. Ratio (F) = 5.3598E+02**

RES. Mean square = 1.1199E-02

Mean X1 = 1.1297E+01

Mean Y = 3.2454E-02

### Multiple Correlations

- \( R^2 = 9.1316E-01 \)
- \( R = 9.5562E-01 \)

### Significance Coefficients

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(c) Estimated dry biomass (kg/tree) regressed against diameter at ankle height (cm)

**NAME OBJECT:** Dry weight analysis

**# DATA SETS:** 53

**MODEL:** \( Y = B_0 + B_1 X_1 + B_2 X_2 + B_3 X_3 \)

- \( Y = \) Dry weight (kg/tree)
- \( X_1 = \) dah (cm)
- \( X_2 = dah^2 \)
- \( X_3 = dah^3 \)

**WEIGHT = \( (1/X_1)^{1.5} \)**

**COEFFICIENTS**

| B 0 | 9.180434037E+00 |
| B 1 | -3.7744335808E+00 |
| B 2 | 4.6806731012E-01 |
| B 3 | -1.0211900745E-02 |

**Analysis of Variance**

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**Var. Ratio (F) = 5.4903E+01**

RES. Mean square = 1.4017E-01

Mean X1 = 1.1297E+01

Mean Y = 1.4358E+01

**Multiple Correlations**

\( R^2 = 7.7077E-01 \)

\( R = 8.7795E-01 \)

**Significance Coefficients**

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<td>1.4525E+00</td>
<td>-2.5986E+00</td>
<td>&gt;5%</td>
</tr>
<tr>
<td>B 2</td>
<td>1.5791E-01</td>
<td>2.9642E+00</td>
<td>&gt;1%</td>
</tr>
<tr>
<td>B 3</td>
<td>5.0073E-03</td>
<td>-2.0394E+00</td>
<td>&gt;5%</td>
</tr>
</tbody>
</table>
(d) Estimated biomass (kg/tree) regressed against diameter at breast height (cm)

NAME OBJECT  : Fresh biomass and dbh
# DATA SETS  : 52

MODEL: \( Y = B_0 + B_1 \times X_1 \)
\( Y \)  = Biomass (kg)
\( X_1 \)  = dbh^2

WEIGHT = \( (1/X_1)^2 \)

COEFFICIENTS
B 0 = -3.5452016548E-01
B 1 = 2.2880851094E-01

ANALYSIS OF VARIANCE
SS       df       MS
REG.    3.68015E-03     1   3.68015E-03
RES.    5.11842E-01    50   1.02368E-02
TOT.    5.15522E-01    51   1.01083E-02

VAR. RATIO (F) = 1.3143E+02
RES.MEAN SQUARE= 1.0118E-01
MEAN X1        = 8.9231E+00
MEAN Y         = 2.2538E+01

MULTIPLE CORRELATIONS
\( R^2 = 7.2446E-01 \)
\( R = 8.5117E-01 \)

SIGNIFICANCE COEFFICIENTS
Coeff. St.Error          t       significance
-----  --------          -       -----  
B 0    5.9127E-01   -5.9959E-01    -
B 1    1.9958E-02    1.1464E+01   >0.1%

(e) Estimated biomass (kg/tree) regressed against total tree height (m)

NAME OBJECT  : Fresh Biomass and height
# DATA SETS  : 62

MODEL: \( Y = B_0 + B_1 \times X_1 + B_2 \times X_2 + B_3 \times X_3 \)
\( Y \)  = Bio (kg)
\( X_1 \)  = h (m)
\( X_2 \)  = h^2
\( X_3 \)  = h^3

WEIGHT = \( (1/X_1)^2 \)

COEFFICIENTS
B 0 = -1.1489972531E+01
B 1 = 1.6931573382E+01
B 2 = -6.8091934904E+00
B 3 = 1.0457335182E+00

ANALYSIS OF VARIANCE
SS       df       MS
REG.    8.15573E+00     3   2.71858E+00
RES.    2.21768E+01    58   3.82358E-01
TOT.    3.03325E+01    61   4.97254E-01
VAR. RATIO (F) = 4.3358E+01
RES.MEAN SQUARE= 6.1835E-01
MEAN X1 = 3.9832E+00
MEAN Y = 2.1390E+01

MULTIPLE CORRELATIONS
R^2 = 6.9166E-01
R = 8.3168E-01

SIGNIFICANCE COEFFICIENTS
Coeff. St.Error          t       significance
-----  --------          -       -----  
B 0    1.3792E+01   -8.3307E-01    -
B 1    1.4902E+01    1.1362E+00    -
B 2    4.8901E+00   -1.3924E+00    -
B 3    4.9500E-01    2.1126E+00   >5%

(f) Estimated biomass (kg/tree) regressed against Crown diameter (m)

NAME OBJECT : Fresh Biomass and Crown diameter
# DATA SETS : 62

MODEL: Y=B0+B1*X1+B2*X2+B3*X3

Y   = Biomass (kg)
X 1 = CD (m)
X 2 = CD^2
X 3 = CD^3

WEIGHT = (1/X_1^2)

COEFFICIENTS
B 0 = -1.6072140691E+00
B 1 =  8.6950208741E-01
B 2 =  6.675850635E+00
B 3 = -8.8197658504E-01

ANALYSIS OF VARIANCE
SS         df       MS
REG. 4.28712E+01     3   1.42904E+01
RES. 7.84561E+02    58   1.35269E+01
TOT. 8.27432E+02    61   1.35645E+01

VAR. RATIO (F) = 1.5025E+01
RES.MEAN SQUARE= 3.6779E+00
MEAN X1 = 2.2024E+00
MEAN Y = 2.1390E+01

MULTIPLE CORRELATIONS
R^2 = 4.3736E-01
R = 6.6134E-01

SIGNIFICANCE COEFFICIENTS
Coeff. St.Error          t       significance
-----  --------          -       -----  
B 0    9.6345E+00   -1.6682E-01    -
B 1    1.6588E+01    5.2418E-02    -
B 2    7.8616E+00    8.4917E-01    -
B 3    1.0739E+00   -8.2130E-01    -
Appendix 8-12 The relationship between total tree height (A) / average crown diameter (B) and estimated fresh biomass

\[ R^2 = 0.68 \]

\[ R^2 = 0.41 \]

Appendix 8-13 The scatter plots of vegetation indices derived from IKONOS image against estimated aboveground fresh biomass (kg/m²)

(a) The scatter plot of NDVI against estimated aboveground fresh biomass (kg/m²)
(b) The scatter plot of PVI against estimated aboveground fresh biomass (kg/m$^2$)

(c) The scatter plot of SAVI against estimated aboveground fresh biomass (kg/m$^2$)

(d) The scatter plot of EVI against estimated aboveground fresh biomass (kg/m$^2$)
Appendix 8-14  Spectral vegetation indices maps derived from IKONOS image
Appendix 8-15  Processing of Landsat 7 ETM + images

The landsat programme is the oldest civil Earth observation programme which started in 1972 with the Landsat 1 satellite (ITC, 2004). In April 1999 Landsat 7 was launched carrying the Enhanced Thematic Mapper (ETM) scanner.

Table 8-1 Spatial resolution of Landsat ETM

<table>
<thead>
<tr>
<th>Bands</th>
<th>Spectral range (µm)</th>
<th>Spatial resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.45 - 0.52</td>
<td>30 m</td>
</tr>
<tr>
<td>2</td>
<td>0.52 - 0.6</td>
<td>30 m</td>
</tr>
<tr>
<td>3</td>
<td>0.63 - 0.69</td>
<td>30 m</td>
</tr>
<tr>
<td>4</td>
<td>0.76 - 0.9</td>
<td>30 m</td>
</tr>
<tr>
<td>5</td>
<td>1.55 - 1.75</td>
<td>30 m</td>
</tr>
<tr>
<td>6</td>
<td>10.4 - 12.5</td>
<td>60 m</td>
</tr>
<tr>
<td>7</td>
<td>2.08 - 2.34</td>
<td>30 m</td>
</tr>
<tr>
<td>Pan</td>
<td>0.5 - 0.9</td>
<td>15 m</td>
</tr>
</tbody>
</table>

Today only Landsat 5 and 7 are operational though Landsat 7 is currently experiencing some technical problems regarding line stripping. The applications of Landsat TM entails landcover mapping, land use mapping, soil mapping, geological mapping, sea surface temperature mapping, etc. (ITC, 2004).

Landsat 7 ETM operates in the following spectral bands (table 8-1).

Calculation of spectral reflectance

\[
\rho_p = \frac{\pi L_\lambda d^2}{ESUN_\lambda \cos \theta_s}
\]

Where \( \rho_p \) is the unitless planetary reflectance, \( \pi \) is a constant value (3.142), \( L_\lambda \) is spectral radiance measured by the sensor (W m\(^{-2}\) sr\(^{-1}\) µm\(^{-1}\)), \( d \) is relative earth sun distance in astronomical unit, \( ESUN_\lambda \) is the mean solar exo-atmospheric irradiance for particular band (table 8-83), and \( \theta_s \) is solar zenith angle in degree (calculated as 90 degree minus sun elevation angle).

Calculation of spectral radiance

\[
L_\lambda = L_{MIN,\lambda} + \left( \frac{L_{MAX,\lambda} - L_{MIN,\lambda}}{QCALMAX - QCALMIN} \right) \times (QCAL - QCALMIN)
\]

Where \( L_\lambda \) is the spectral radiance for a particular band, \( QCAL \) is the quantized calibrated pixel value in digital number (DN), \( QCALMIN \) is the minimum quantized calibrated pixel value corresponding to \( L_{MIN} \) in DN value (equal to 1 and 0 for LPGS and NLAPS products respectively) \( QCALMAX \) is the maximum quantized calibrated pixel value corresponding to \( L_{MAX} \) in DN value, \( L_{MIN} \) and \( L_{MAX} \) are the corresponding radiance that are scaled to \( QCALMIN \) and \( QCALMAX \) (W m\(^{-2}\) µm\(^{-1}\)) and different for low and high gains. \( L_{MIN} \) and \( L_{MAX} \) for Landsat 7 ETM + are presented in table 8-82.

The relative earth-sun distance \( d_{jx} \) in astronomical unit for a particular image acquisition date can be interpolated from table 8-81 as follows;

\[
d_{jx} = \left( \frac{J_x - J_2}{J_1 - J_2} \right) d_{j1} - \left( \frac{J_x - J_1}{J_1 - J_2} \right) d_{j2}
\]

Where \( J_x \) is the Julian day of the image, \( J_1 \) and \( J_2 \) are lower and upper Julian day in table 8-81., \( d_{j1} \) and \( d_{j2} \) are lower and upper earth sun distance in table 8-81. The study area was cut from the Landsat images using the area of interest (AOI) delineated from the IKONOS image. The subset image was overlaid with the plot shapefile and the VIs values were extracted and correlated with the aboveground plot biomass (kg/m\(^2\)).
Table 8-81 Earth-sun distance in astronomical units

<table>
<thead>
<tr>
<th>Julian Day</th>
<th>Distance (Julian Day)</th>
<th>Distance (Julian Day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.9832</td>
<td>0.9945</td>
</tr>
<tr>
<td>15</td>
<td>0.9836</td>
<td>0.9993</td>
</tr>
<tr>
<td>32</td>
<td>0.9853</td>
<td>1.0033</td>
</tr>
<tr>
<td>46</td>
<td>0.9878</td>
<td>1.0076</td>
</tr>
<tr>
<td>60</td>
<td>0.9909</td>
<td>1.0109</td>
</tr>
</tbody>
</table>

Table 8-82 Landsat 7 ETM+ spectral radiance range

<table>
<thead>
<tr>
<th>Band</th>
<th>Before 1 July 2000</th>
<th>After 1 July 2000</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low gain</td>
<td>High gain</td>
</tr>
<tr>
<td></td>
<td>Lmin</td>
<td>Lmax</td>
</tr>
<tr>
<td>1</td>
<td>-6.2</td>
<td>297.5</td>
</tr>
<tr>
<td>2</td>
<td>-6</td>
<td>303.4</td>
</tr>
<tr>
<td>3</td>
<td>-4.5</td>
<td>235.5</td>
</tr>
<tr>
<td>4</td>
<td>-4.5</td>
<td>235</td>
</tr>
<tr>
<td>5</td>
<td>-1</td>
<td>47.7</td>
</tr>
<tr>
<td>6</td>
<td>0</td>
<td>17.04</td>
</tr>
<tr>
<td>7</td>
<td>-0.35</td>
<td>16.6</td>
</tr>
<tr>
<td>8</td>
<td>-5</td>
<td>244</td>
</tr>
</tbody>
</table>

Table 8-83 Mean solar exo-atmospheric irradiance for particular band in Landsat 7 ETM+ (ESUN)

<table>
<thead>
<tr>
<th>Band</th>
<th>ESUN (Wm⁻²μm⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1969</td>
</tr>
<tr>
<td>2</td>
<td>1840</td>
</tr>
<tr>
<td>3</td>
<td>1551</td>
</tr>
<tr>
<td>4</td>
<td>1044</td>
</tr>
<tr>
<td>5</td>
<td>225.7</td>
</tr>
<tr>
<td>7</td>
<td>82.07</td>
</tr>
<tr>
<td>8</td>
<td>1368</td>
</tr>
</tbody>
</table>

Appendix 8-16 Processing of MODIS image

The Moderate Resolution Imaging Spectro-radiometer (MODIS) instrument is operating on both the Terra and Aqua spacecraft. It has a viewing swath width of 2,330 km and views the entire surface of the Earth every one to two days. Its detectors measure 36 spectral bands between 0.405 and 14.385 μm, and it acquires data at three spatial resolutions - 250m, 500m, and 1,000m (http://modis.gsfc.nasa.gov/data/). The MODIS images used (250 m spatial resolution) were downloaded from NASA Land Processes Distributed Active Archive Center and were already processed to spectral reflectance. NDVI and EVI were already calculated. Relevant band data (Red and NIR bands) were derived to calculate SAVI and PVI. The study area was cut from the MODIS image using the area of interest (AOI) delineated from the IKONOS image. The subset image was overlaid with the plot shapefile and the VIs values were extracted and correlated with the aboveground plot biomass (kg/m²).