

**THE USE OF HIGH-RESOLUTION SATELLITE IMAGERY  
IN FOREST INVENTORY: A CASE OF HANS KANYINGA  
COMMUNITY FOREST - NAMIBIA**

by

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## **DECLARATION**

I, the undersigned, declare that the work contained in this thesis is my own original work and has not previously in its entirety, or in part, been submitted at any University for a degree.

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J. M. Kamwi

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Date

## UITTREKSEL

Die studie het die gebruik van dubbel bemonstering met regressie skatters in Namibiese bosse ondersoek, in 'n soeke na effektiewe bosopnames. Bykomstige data is verkry vanaf QuickBird satelliet beelde (fase 1) gedurende Oktober en November 2004, vir die Hans Kanyinga Gemeenskapsbos wat 'n area van 12,107 hektaar beslaan. Hierdie data is getoets teen 'n veldopname van 2002 (fase 2). Die verwantskappe tussen bykomstige en veld veranderlikes word beskryf en voorspellings modelle is geskep. Volgens die resultate van die stapsgewyse prosedure en Mallow se Cp statistiek as keuse maatstaf, is gevind dat fotogrammetriese opstandsdigtheid en 'n samestelling van fotogrammetriese kroon area en fotogrammetriese opstandsdigtheid die beste kandidate vir geskatte opstandsvolume is. Die volume model wat verkry is verklaar 56% van die variasie. Fotogrammetriese opstandsdigtheid is goed gekorreleer met die veldopname opstandsdigtheid en verklaar 81% van die variasie. Fotogrammetriese kroondeursnit is gekorreleer met deursnit op borshoogte wat verkry is tydens 'n veldopname om ruimtelike posisies van bome te bepaal asook om 'n deursnit verspreiding te kry. Die deursnit verspreidings model verklaar 43% van variasie. Die GPS posisies wat in die proses bepaal is, is ook met opmetingstegnieke, wat afstand en rigting behels, vergelyk en 'n verplasing van 8.67m is in GPS posisies gevind. Slegs die meet van afstande van bome van die middel van die perseel tydens veld opmeting is meer aanvaarbaar as dit gevind. Foute in bepaling van boomposisie is nie van groot belang in die tydelike steekproef plote wat gewoonlik in Namibiese bosinventarisasie gebruik word nie. Die vermindering in koste van opname met die metode is 24% (N\$25.79 teenoor N\$19.67 per hektaar). Die resultate van die studie kan as haalbaar gesien word vir die Kavangostreek en ander streke met soortgelyke fisiese en klimaatstoestande, maar versigtigheid moet aan die dag gelê word in die gebruik van resultate in ander omgewingstoestande.

**Sleutelwoorde:** Afstandswaarneming, QuickBird, dubbele bemonstering, regressie, effektiwiteit, posisionele akkuraatheid, opstandsvolume, opstandsdigtheid, deursnit, model.

## **ABSTRACT**

The present study investigated double sampling with regression estimators as a quest for efficiency and effectiveness in forest inventory in Namibian woodlands. Auxiliary data used were obtained from Standard QuickBird satellite scenes (phase 1) for Hans Kanyinga Community Forest from October and November 2004 covering an area of 12,107 hectares, amplified with terrestrial data (phase 2) of 2002. The relationships between auxiliary and terrestrial variables are described and prediction models were constructed. According to the results of the stepwise procedure with the Mallow's Cp statistic as the selection criteria, photogrammetric stand density and a combination of the photogrammetric crown area with photogrammetric stand density were the best candidates for predicting the stand volume. The resulting volume model explains 56% of the variation. Photogrammetric stand density was found to be highly correlated to the terrestrial stand density with the resulting model explaining 81% of the variation. Photogrammetric crown diameter was found to be correlated with the diameter at breast height measured from the plots which were assessed for spatial tree positions, which enabled the derivation of the diameter distribution. The diameter distribution model explains 43% of the variation. In addition, the actual tree positions were determined using the GPS and surveying techniques (polar positions) involving distance and bearings. GPS tree positions showed a considerable shift of up to 8.67 m. However, only the distance measurements of trees from the plot centre using the infield surveying methods were more reliable. Nevertheless, the influences of the tree positional errors are not of high concern for temporary based sample plots which are normally used in Namibian forest inventories. A reduction in inventory cost was found to be 24% i.e. N\$25.79 to N\$19.67 per hectare. The results of this study are valid for Kavango region or any other region with similar set of physical and climatic conditions, but caution must be exercised in implementing these results elsewhere under different physical and environmental conditions.

**Keywords:** Remote sensing, QuickBird, double sampling, regression, efficiency, effectiveness, positional accuracy, stand volume, stand density, diameter, model.

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**In God I trust**

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## ACRONYMS, ABBREVIATIONS AND DEFINITIONS

### Acronyms

ESRI	Environmental Systems Research Institute
FAO	Food and Agriculture Organization
GIS	Geographic Information System
GPS	Global Positioning System
N\$	Namibian Dollar
NFI	National Forest Inventory
NRSC	National Remote Sensing Centre (in Namibia)

### Abbreviations

DBH	Diameter at breast height (1.3 m)
ha	Hectare
n	Sample size
SE	Standard error
R <sup>2</sup>	Coefficient of determination
s.a.	sans annum ( <i>undated</i> )

### Definitions

There can be much confusion about the terminology used in this investigation. In order to facilitate the description and avoid misunderstanding, the terms accuracy, auxiliary, crown area, crown cover percent, double sampling, effectiveness, efficiency, monitoring, precision, stand density, terrestrial, traditional inventory, and trees are defined here:

Accuracy implies the success of estimating the true value of the inventory variable.

Auxiliary sample refers to the measurements carried out on the satellite image. In this investigation, it is used interchangeably with the term phase 1.

Crown area is the area in m<sup>2</sup> which is covered by the tree crown. When this is expressed in percent of the total area of the sample plot, it gives rise to the crown cover percent.

Crown cover percent is the percentage of the total area of a sample plot which is covered by the horizontal projection of the tree crown.

Double sample refers to the measurements carried out on the image combined with few samples collected in the field (phase 1 + phase 2). This term also encompasses the costs involved in collecting both samples.

Effectiveness implies that the estimates obtained are within a tolerable limit of error and can be used to make decisions. This term is also used to express the logistical and time requirements for fieldwork.

Efficiency implies that stand volume, stand density and diameter distribution estimation can be possible with few inputs leading to financial, time and productivity gain in terms of laborious fieldwork.

Monitoring refers to the data sampling which is repeated at certain intervals of time for management purposes and decisions. Monitoring is distinguished from surveys by emphasizing repeated and replicable measurements over an extended period of time and by focusing more on the rates and magnitude of change (Danielsen *et al.* 2000).

Precision implies the clustering of the sample values around the mean or average.

Stand density refers to the number of stems per hectare. These terms are sometimes used interchangeably.

Terrestrial sample (phase 2) refers to the trees/stems measured in the field, but not necessarily referring to traditional inventory.

Traditional inventory refers to the inventories which are carried out only terrestrially (or phase 2) without the amplification of data by other sources (such as satellite images).

## 1. INTRODUCTION

The ultimate purpose of this study is to investigate how remote sensing can support traditional forest inventories by enabling the collection of forest stand parameters instantly, and to efficiently obtain stand volumes, number of trees and diameter distribution. The study represents a quest for efficiency and effectiveness of forest inventory in Namibia. To the author's knowledge, this is the first time that double sampling with regression estimators aimed at reducing inventory costs is investigated in open savannah woodlands of Southern Africa. This can also be substantiated by the lack of relevant literature regarding efficient inventory concepts such as double sampling in the open savannah woodlands of Southern Africa.

In Namibia, forests are an important national legacy and are described as key resources because they play a crucial role in productive and protective functions i.e., their role in climate, biodiversity, human livelihood and recreation. Therefore, forests are appreciated as one of the close-to-nature landscapes (Brassel and Lischke, 2001). Of late, exchanging, sharing and integrating forest spatial data from various sources has become increasingly important (Noongo *et al.* 2003). This is due to the growing environmental concerns and pressure on the Namibian government to perform more efficiently under budgetary constraints. Other phenomena such as deforestation and forest change are monitored because forest resources and products are used for political and management decisions and also supports the need for a consistent view of forest rehabilitation (Apan, 1997).

Forestry development in Namibia started at the beginning of the 20<sup>th</sup> century when the role of woody vegetation in environmental protection was recognized by the German colonial government (FAO, s.a.). However, the forest resource suffered a great deal during the liberation struggle for independence when the forest policy was not effectively enforced, especially in the communal areas of the North and North East of the country. From 1995, donor support was received from the government of Finland to support the

Directorate of Forestry. This support became known as the Namibia-Finland Forestry Programme. The aim of the support was to build the capacity of the Directorate of Forestry to carry out forest inventories for sustainable management and utilization of the forest resource. This support was extended to cater for forest inventories needs and since then a substantial amount of forest inventories were carried out. The support came to an end in 2004 and from that year, it became a too heavy load for the Directorate of Forestry to sustain these forest inventories. Consequently, a cost effective and efficient method of carrying out forest inventories and sampling is needed to satisfy the increasing and diverse informational demands, in view of ensuring sustainable forest management in Namibia. This method should be conducted with the up-to-date technologies and should provide scientifically sound estimates of the target parameters necessary for sustainable forestry (Lund, 1998). This requirement is in line with the mission statement of the Directorate of Forestry in Namibia which aims:

*“To practice and to promote sustainable and participatory management of forest resources and other woody vegetation to enhance the socio-economic development and environmental stability in Namibia”* (Directorate of Forestry, 2001 cited in Julin, 2002).

Before the phasing out of the Namibia-Finland Forestry Programme in 2004, a woody vegetation inventory based upon detailed field sampling of tree parameters was conducted in Northern Namibia in 2002. The ultimate goals were to investigate the extent to which Landsat TM satellite imagery could be used to reduce inventory costs, to model woody resources in areas which were not yet covered by an inventory and to monitor changes in woody vegetation resources over time (Verlinden and Laamanen, 2006). This woody resource monitoring method developed is good for forest cover, biomass and stand volumes. However, the recent shift from regional inventories to local level (community forests) inventories requires additional information such as the number of trees and diameter distribution.

Similarly, investigations of this nature have been carried out in many countries in the Northern Hemisphere and to a limited extent in Southern Africa's natural forests and woodlands. This widens the information gap since the sharing of experiences among countries is limited and the methods applied in the Northern Hemisphere cannot be sufficiently applied in the Southern Hemisphere due to the manifold growth and structural characteristics of trees. For instance, most of the existing literature on this subject is from homogeneous forests, where the application of remote sensing may be relatively easier than in natural woodlands where a mixture of plant species is found with their different growth and recognition characteristics. Therefore, this study is aimed at highlighting the situation in using remote sensing in Southern African savannah woodlands and at the same time uses the recent technologies of high resolution satellite imagery and new advances in image processing. The results of this investigation will hopefully become a major milestone to ensure the acquisition of the inventory data needed for forest management planning taking the cost implications into account. The knowledge generated will serve as a basis for most inventory concepts to be developed in the future and the modification of readily available concepts in Namibia and other countries in Southern Africa with the same conditions. The target beneficiary of this investigation is the Directorate of Forestry in Namibia or any entity dealing with resource assessments.

The hypothesis that inspired this study is that the use of QuickBird satellite imagery can provide the inventory information pertaining to Namibian woodlands, efficiently and effectively. For this hypothesis to be tested, two things have to be demonstrated, firstly, QuickBird satellite imagery has to be effective in providing the required inventory parameters and, secondly, it should deliver the parameters at a lower cost than the traditional method, by reducing costly inventory activities and expenses i.e. amount of field work without risking the precision and accuracy of the information.

## 2. STATE OF THE ART

This investigation deals with different fields such as remote sensing and forest inventory in the open savannah woodlands of Namibia. This chapter highlights the work that has been done or is still ongoing in remote sensing as far as its application in forest inventory is concerned in various forest types. The discussions in this chapter are limited for Southern African natural forests since there have been few investigations of this nature. Nonetheless, the principles and basics remain applicable elsewhere in different forest types and conditions.

### Inventory concept: Double sampling with regression estimators

Double sampling as described in most of the literature is dominated by double sampling with regression estimators and its suitability has been investigated extensively in the small regions and relatively homogenous forests of the Northern Hemisphere. This forest inventory concept includes a terrestrial phase on a smaller number of sample plots taken in the field and a big sample measuring auxiliary variables from a set of different imagery (e.g. Kättsch, 2006a; Kättsch and Van Laar, 1994; Akça *et al.* 1993; Avery and Burkhart, 1988; Cochran, 1977; Hildebrandt, 1996).

Multiphase sampling is another important inventory concept which is an extension of double sampling. This makes use of different sources of data (more than two) which are linked by mathematical models (Kättsch, 2006a; Lötsch, F and Haller, K.E, 1964). This concept is also aimed at replacing expensive terrestrial measurements by taking auxiliary variables from images at different scales. Based on the investigations carried in the Northern Hemisphere, the multiphase concept is very efficient than full terrestrial inventories without compromising the accuracy (Kättsch, 1990; Scheer *et al.* 1997 cited in Kättsch, 2006a). Therefore, when satellite images are used for determining variables that are known to be related to timber volume, a two-phase (double sampling) sampling design with regression estimators is an appropriate choice (Kättsch, 1991 cited in Stellingwerf and Hussin, 1997).

Aerial regression equations are composed of a dependent y- variable (such as volume) and one or more independent x- variables such as tree height, crown diameter or crown area for single trees, maximum or mean tree height and mean crown diameter of trees per plot (Kätsch, 1991 cited in Stellingwerf and Hussin, 1997). In all the techniques, the variable of interest (the y- variable) must be determined in the field and the x- variables on the satellite image. The resultant equations are obtained by carrying out multiple regression procedures and the usual regression assumptions applies.

#### Applications of remote sensing in forest inventory

Little work has been published regarding the employment of remote sensing in forestry in the natural woodlands of Namibia. Some of the pioneering work in Namibia was done by Tokola *et al.* (1999) which was based on the calibration of Landsat TM images for forest cover and change detection. Erkkilä and Löfman (1999) cited in Verlinden and Laamanen (2006) used Landsat TM and aerial photographs to assess forest cover change. Recently, Verlinden and Laamanen (2006) developed a woody resource monitoring system based on the on numerical analysis of Landsat TM images with limited field work. This woody resource monitoring system was aimed at reducing the inventory costs, to model woody resources in areas which were not yet covered by inventories and to monitor changes over time. In plantation forests, several authors provide good examples of their work in which the potential of remotely sensed data was demonstrated. For instance, Norris-Rogers (2004) demonstrated that remote sensing technology can be used for change detection in plantations for reporting and planning future forest management operations. Therefore, Apan (1997) concluded that remote sensing is a powerful tool that could be used to address the problem of out-dated thematic maps which may be used for land cover mapping.

In view of the above, Kätsch (2006a) grouped the uses of remote sensing in forest inventory into four intensity levels, namely:

- Level I in which the remotely sensed data is used as an aid for orientation in the forest aimed at reducing the time lags in activities such as fieldwork planning.
- In level II, remotely sensed data is used with a simple forest inventory to yield a basis for stratification, forest type mapping etc. This level was also mentioned by Newton and Kapos (2003) and Skidmore *et al.* (s.a.) that remote sensing images can provide a basis for stratifying the forests as well as for mapping distributions of species that are closely associated with distinctive vegetation types. Although remote sensing may provide indications of ecosystem-level diversity as indicated by spatial distribution of different vegetation types, it cannot yet provide direct information on species-level diversity (Newton and Kapos, 2002; Norris-Rogers, 2004). This may however be overcome in the near future with the rapid development of remote sensing technologies, such as the development of the new generation imaging sensors such as the hyperspectral technology (Kätsch, 2006b).
- Level III combines remotely sensed data with terrestrial measurements using photogrammetric variables, grey scale values as auxiliary variables etc.
- Level IV includes automatization of the forest inventory, which is completely based on remotely sensed data and a model based estimation of forest tree and forest stand data.

Apart from the applications of remote sensing in forest inventory, remote sensing has been used in other fields. Aplin (s.a.) mentioned that remote sensing has been an important tool in ecological research such as habitat monitoring in National parks such as the Kruger National Park. In a Zambian study, Scanlon and Albertson (2003) cited in Aplin (s.a.) processed satellite imagery to define the leaf area index (LAI) and vegetation canopy structure to monitor the changes between vegetation and the atmosphere. A similar study was conducted by Scholes *et al.* (2004) in the Kalahari Sands and there was good agreement in the estimations of the LAI in the field and remote sensing imagery.



### Cost implications of remote sensing in forest inventory

Linked to all of the above, but also of separate concern is to note that the current traditional forest inventory methods used in Namibia are very expensive and raise a concern for carrying out forest inventories. Government funding is not enough to cater for forest inventories due to high costs and problems associated with carrying out the inventories despite the readily available manpower. To alleviate this situation, Diedershagen *et al.* (2002) suggested that it is necessary to automate forest inventory methods and to analyze them with the use of remote sensing. Also, many attempts have been made to find equilibrium between the desired information and the cost (Kätsch, 2002). A number of investigations indicated a massive reduction in inventory costs by using remote sensing. For instance, Edwards (1975) cited in Paine and Kiser (2003) used a combination of photogrammetric measurements with some ground variables and subsequently encountered an estimated reduction of the inventory costs by up to 35 percent for mapping, inventorying and planning in forest management. This reduction in the costs is an important aspect on which this study focuses in order to ensure sustainability of carrying out forest inventories in countries such as Namibia.

### Limitations of remote sensing in forest inventory

Remote sensing as depicted elsewhere in literature is an ideal tool for carrying out forest inventories, but may be difficult to apply in heterogeneous woodlands of Namibia. In their work, Bodmar (1993) and Kellenberger (1996) cited in Brassel and Lischke (2001) mentioned that the use of remotely sensed data still needs to overcome some obstacles mostly in different forest types. Similarly, it was found that there is a limitation in the use of remote sensing data for detailed forestry application due to its coarse spatial resolution (Hamzar, 2001). This limitation is being alleviated by the increasing availability of high resolution satellites such as IKONOS and QuickBird which enables the view of single trees with less effort. Over the past decades, remarkable advancement has been made in indicating the potentials and limits for identifying and mapping various earth surface features and that these limitations prompt the repeated improvement and

concentration to sensors that can obtain data at wavelengths beyond the optical portion of the spectrum (Stellingwerf and Hussin, 1997).

In view of the above, Kätsch (2006a) recommended that sophisticated inventory concepts are required to combine some terrestrial measurements with image analysis and spatial modelling approaches provided by the contemporary geo-informatics. Otherwise, the use of remote sensing unaided cannot be fully realized. Nevertheless, the technology of remote sensing is currently developing so fast that it might be a fully operational tool even in the heterogeneous woodlands of Namibia and elsewhere with similar forest conditions.

Accuracy of remotely sensed data in forest inventory also poses a serious limitation. In their recent study, Kätsch and Kunneke (2006) developed an automatic tree counting system for *Pinus patula* stands using aerial photographs and found that there is a systematic underestimation of the actual number of stems. Their reason for the underestimation was due to the fact that not all trees were visible from above, meaning that some trees were covered by others. The remedy for the underestimation of the number of stems could be corrected using simple linear regression models. Under normal conditions, reasonably accurate tree counts can be made. For instance, Dilworth (1956) cited in Paine and Kiser (2003) using 1:12,000-scale photographs conducted crown counts on Douglas-fir and the average difference between the visible count from the photos and dominant and co-dominant trees on field plots was +1.0, with an average deviation of 2.02 trees.

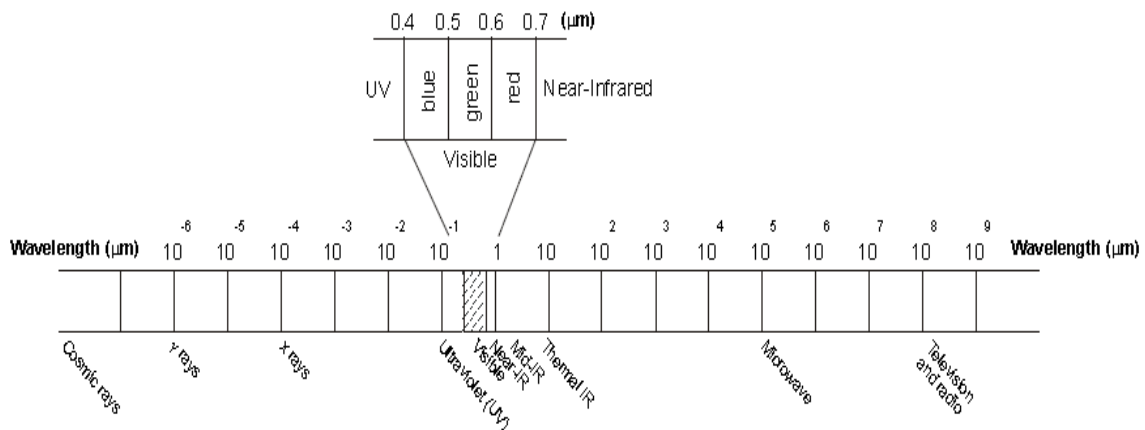
Two factors that contribute to the accuracy of tree counts are photo scale and stand density (Paine and Kiser, 2003). It is also important to note that the success and accuracy of using remotely sensed data also depends on the sensor's spectral and spatial characteristics (Kätsch, 2006a). Coupled with the later, is the image analysis and processing, which are crucial in ensuring the reliable extraction of tree parameters. Contemporary statistics and geo-statistics facilitate the procedural structure for assessing

the precision of sample parameters and for calculating indices describing the forest situation.

With regard to positional errors, the work of Imfeld *et al.* (s.a.) indicated that the positional accuracy of the centre of photo and the terrestrial plots is low even with the aid of relatively sophisticated instruments such as Ortho-photos. A mean positional distance of 5.2 meters apart was encountered and the authors warn of a possibility of further distances.

## 2.1 ASPECTS OF REMOTE SENSING

The aspects of remote sensing are fully described in remote sensing textbooks and publications and it is the contention of the author that they are not repeated in detail in this thesis. Important sensor specifications relevant to this study are discussed in Chapter 4. Nevertheless, it is important to mention that remote sensing enables the acquirement of information from a distance without being in physical contact with the object. Remote sensors in space borne and airborne platforms use the electromagnetic spectrum (figure. 1).



**Figure 1.** The electromagnetic spectrum (Lillesand and Kiefer, 1979)

The electromagnetic radiation from the sun will hit the object on the earth's surface, resulting in one of the following interactions (Clevers, 1986);

- Transmission of radiation because the object is wholly or partly transparent to the radiation;
- Absorption of radiation by the object, i.e. radiation is retained by the object and may be used for certain internal processes (e.g. photosynthesis); and
- Reflection of radiation at or near the surface of the object. The radiation reflected or emitted by an object on the earth's surface may be remotely sensed.

The energy interaction is often specific for a certain object. This may be used for distinguishing objects or ascertaining characteristics of an object. The atmosphere may modify or contribute to the radiation from the earth's surface. It is important to note that there are different kinds of particles present in the atmosphere that scatters and absorb the radiation that passes through them. Also, it should be remembered that the atmosphere has limited transparency in certain parts of the electromagnetic spectrum (bands) because there is a strong absorption of energy by the atmosphere in those bands, thus restricting the application of remote sensing to certain windows in the electromagnetic spectrum.

### **3. INFORMATION NEEDS AND EARLY FOREST INVENTORIES**

#### **3.1 INFORMATIONAL NEEDS**

Because of their diverse uses and cultural values, woodlands are one of the most important natural resources in Namibia. The variable quantity and quality of these woodlands requires that continuous assessment and monitoring is carried out due to the fact that they are used to meet demands of communities, whose population continues to increase. However, the assessment of forests to support decision making in forest policy and management presents a number of challenges. First, because of the complexity of the forests in time and space, information about it needs to be assembled and expressed based on simplified variables (Noss, 1990; 1999 cited in Neuton and Kapos, 2002). Second, since decisions relating to forests are made at a variety of scales, forest data need to be aggregated across different scales for monitoring and reporting purposes (Noss, 1990; Turner, 1995 cited in Neuton and Kapos, 2002).

In Namibia, forest inventories are carried out to determine the location of forest resources, their quantity by species and the potential of harvesting them. Resource assessments are also carried out to provide a foundation for both political and management decisions. Management and planning decisions require mapped or pinpointed information on the availability of the resources, both in quantities and qualities when possible. This investigation deals with the estimation of stand volume, diameter distribution and the number of stems. These parameters are pivotal for resource assessment and management decisions for the Directorate of Forestry. Timber quality is usually assessed during the terrestrial inventories.

The informational changes and needs are recognized by various administrative levels which are concerned with the woodland resource, namely the lower (community) and higher (Directorate of Forestry) level. However, the information changes are increasingly linked to the costs involved in obtaining the required information particularly for the higher level. Furthermore, this change in information needs is

reflected, for instance in the type of data collected from the onset of the forest inventories to date (section 3.2).

In view of the above, it is also important to note that the basic information required to satisfy management plans and decisions differs only on the finest details needed by higher and lower level planners. This difference is mainly on the parameters measured and the way the data are analyzed and reported. For instance, at the community level, the volume parameter is not very important since the community is mainly interested in the number of stems and sizes in specific areas of their community forests. The above information is also required by the higher level but on a broader scale (region) and additional information regarding the forest roads and trails is crucial for the higher level to enable prior knowledge of accessibility to the remotest areas while carrying out routine forest management and protection.

The paradigm shift from regional inventories to the community forestry approach is in line with the current demand for reliable and location specific information by communities, which applies not only to forest resources but also include woody plants in agricultural fields, grazing grounds and in other land-use areas not traditionally considered being forests (FAO, 2000 cited in Erkkilä, 2001). Hence, in order to be able to satisfy the increasing and diverse informational needs, an efficient and effective method of collecting and analyzing of the information is required in Namibia.

### **3.2 EARLY FOREST INVENTORIES**

Early forest inventories in Kavango started as early as 1975. The mapping of the forest was done using aerial photographs (1:75 000) and topographic maps (1:250 000). Initially, four forest types were defined over an area of 2.4 million hectares, which is about half of Kavango (see map 1 for the location of Kavango region). After the field survey, five forest types were defined and consisted of 14 different species groups. In total, 194 cluster points were selected for data collection. Each cluster consisted of four circular sample plots, each with a radius of 30 m (0.283 ha). All trees with DBH >10 cm

were enumerated by species and DBH. Volumes of saw logs were estimated for the main species namely *Baikiaea plurijuga*, *Pterocarpus angolensis*, *Guibourtia coleosperma* and *Burkea africana* (Geldenhuys, 1975).

Another inventory was conducted in 1986 on an area of 10,000 ha at Mile 30 (an area popularly known to be inhabited by wood carvers). A systematic line plot inventory was carried out using 0.5 ha sample plots (total 128 plots). All *Pterocarpus angolensis* trees over 10 cm DBH were measured and vitality was classified. No estimation of volumes was done (Hilbert, 1986).

Of late, woody vegetation inventories based upon detailed field sampling of tree parameters were initiated by the Namibia Finland Forestry Programme. The aim was to obtain tree cover, basal density and volume estimates in northern Namibia (Verlinden and Laamanen, 2006). It was hoped that the approach would result in regional level inventories useful for strategic planning.

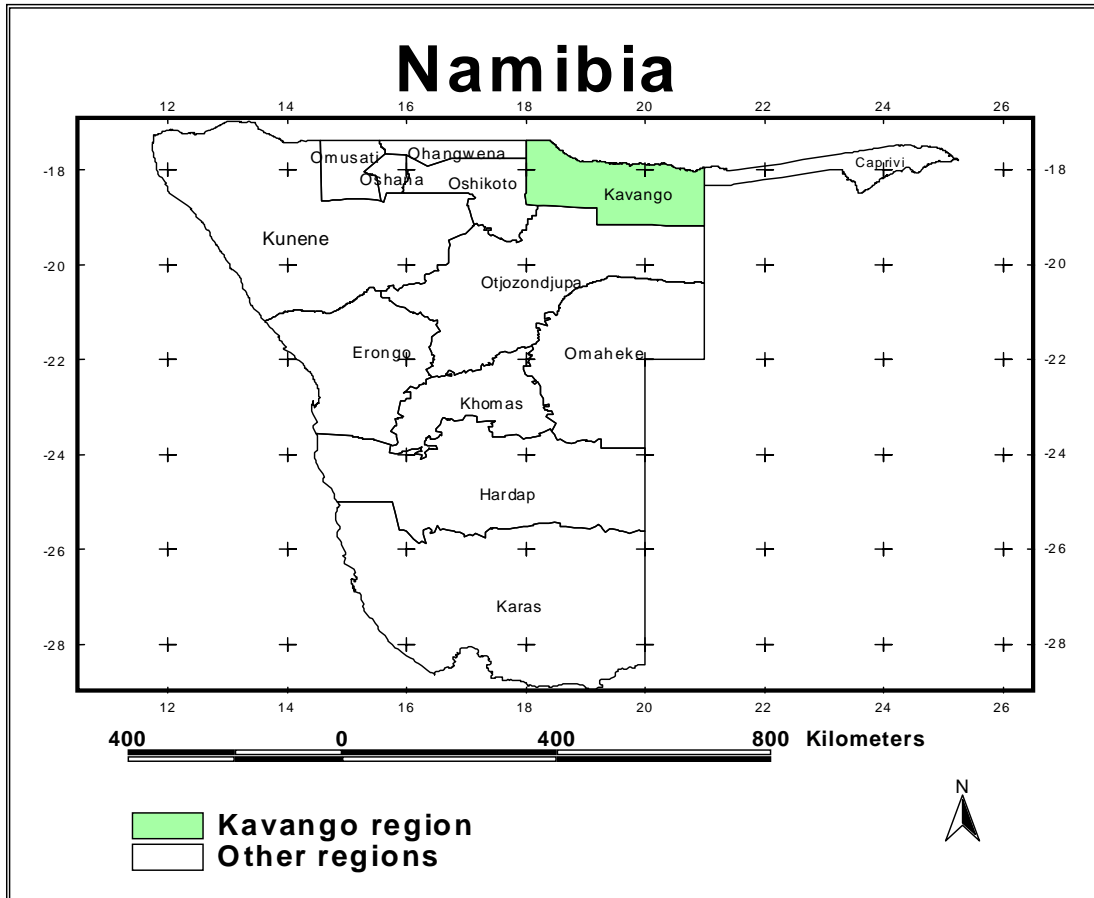
A common drawback of these early inventories is that they have been species specific and biased towards timber industrial development. This entails that the focus was woody species with commercial value. Another shortfall of these early inventories is their inadequate value in monitoring and prediction of the forest stand parameters. However, the need for monitoring woody resources was deemed necessary and was included in the latest woody resource monitoring system (Verlinden and Laamanen, 2006).

## 4. MATERIALS AND METHODOLOGY

### 4.1 THE TEST AREA

#### 4.1.1 Location

Kavango is one of the 13 regions of Namibia which lies in the north eastern part of the country and is bordered by the Caprivi, Oshikoto, Ohangwena and Otjozondjupa regions (see map 1 below).



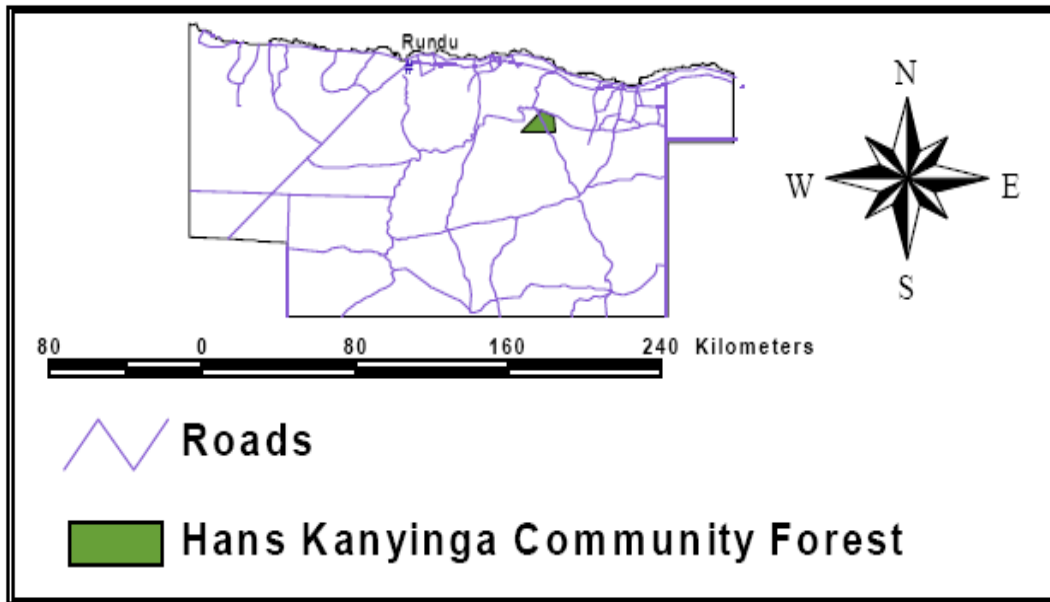
**Map 1.** Map showing the Location of Kavango region

Hans Kanyinga Community Forest lies between latitudes  $18^{\circ} 08'26''$  S and  $18^{\circ} 18'21''$  S and longitudes  $20^{\circ} 11'54''$  E and  $20^{\circ} 27'46''$  E within Ndiyona Constituency of the Kavango region (see map 2). The study area covers 12,107 hectares. It lies about 900 m above sea level and approximately 115 km South-east of Rundu<sup>1</sup> and is further described in Kamwi (2003). The study area was selected due to the availability of QuickBird

<sup>1</sup> Regional town for Kavango region



satellite scenes with less clouds and the availability of terrestrial data which was collected shortly before the scenes were captured (2 years). Adding to the selection of the study area on a larger scale, Kavango region is the main source of wood-carving materials in Namibia, thus requires regular assessment of the resources to enable sound decisions for sustainable harvesting. The study area is typical of the entire Kavango region.



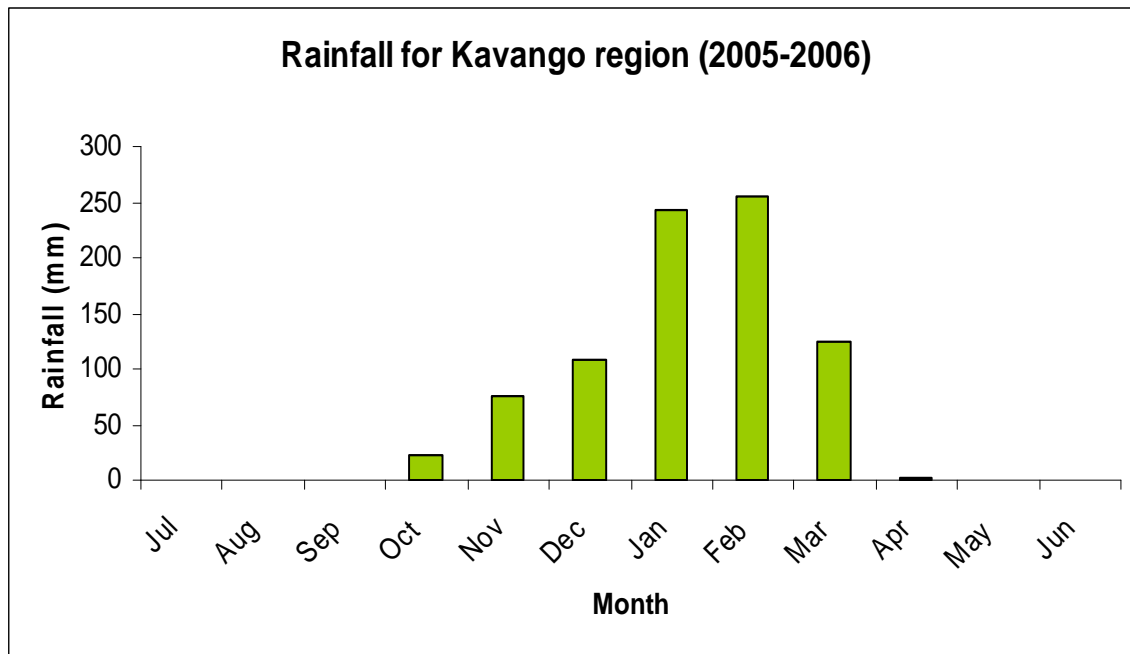
**Map 2.** Map showing the Location of Hans Kanyinga community forest (Courtesy of Kamwi, 2003).

#### **4.1.2 Ownership**

Hans Kanyinga Community Forest belongs to four villages namely Vikota, Tara Tara, Shinunga and Kapupa Hedi in the VaGciriku district of Kavango east. The people settled in the area in 1958 having come from Mabushe, Ngona, Shitemo, Cavazi, Ndonga Linena, Makendu and Kayengona areas along the Kavango River. The main reason for this settling pattern was to find space where the community could cultivate and graze their livestock. The population is estimated at 1,300 with 112 households (Otsub *et al.* 2004).

### 4.1.3 Climate

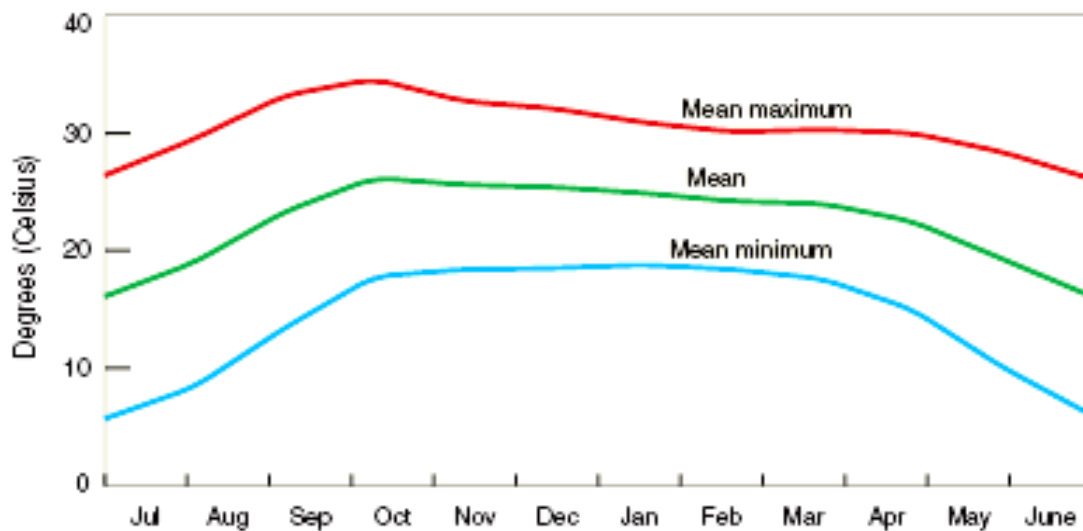
Compared to other regions in Namibia, and Botswana, Kavango has a climate that is comparatively sub-tropical because it receives more rain than the south and the west of the country. The rainfall increases slightly from southwest to northeast. The average annual rainfall is 500-600 mm. The first rains are expected in September or October and the last ones in April or May. Most of the rain falls between December and March although there are marked fluctuations from year to year.



**Figure 2.** Rainfall for Kavango region

Furthermore, there are no rains between May and September (see figure 2 above). This is attributed to the fact that there are high rates of solar radiation and evaporation, relatively low cloud cover and a limited amount of rainfall.

The long-term average monthly temperature varies from 16°C in June-July to 25-26°C in October-January (figure 3). The corresponding maximum and minimum temperatures are 30°C and 7°C respectively. There is a slight possibility of a few nights with frost in June. The absolute minimum temperature measured in Rundu is – 4°C and the absolute maximum temperature measured is 41°C (Erkkilä and Siiskonen, 1992).



**Figure 3.** Temperature for Kavango region (Obeid and Mendelsohn, 2001)

#### 4.1.4 Forest types and structure

Forest types and their structures are manifold in Namibian woodlands. The forest structure is very uneven with a mixture of different species (about 26 tree species). This is important when employing remote sensing for the reason that apart from the sensor's characteristics, forest structure determines the success of obtaining meaningful remotely sensed data. The vegetation in Kavango can generally be described as tree savanna and woodland and along the Kavango River, riverine woodlands are found.

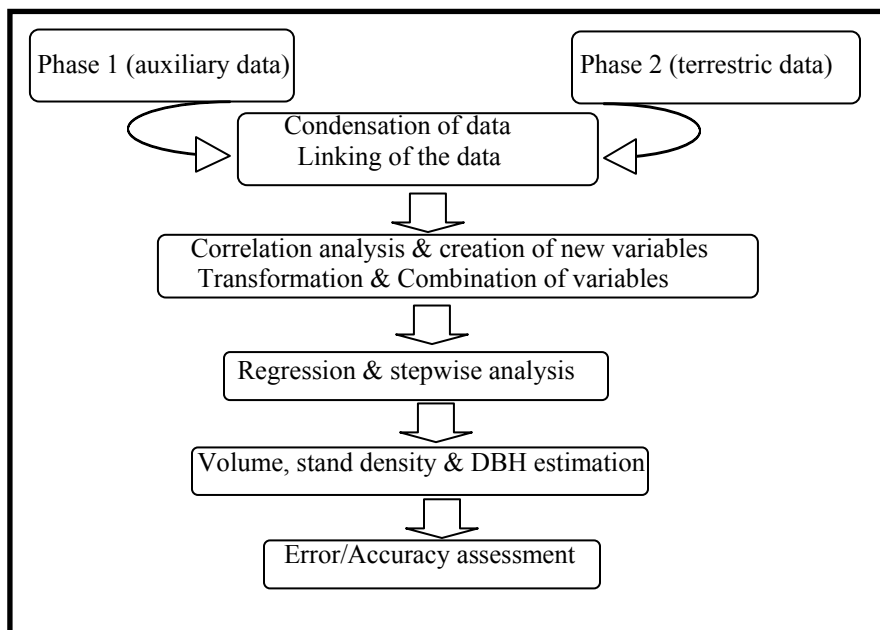
Tree density increases from south to north and from west to east respectively, following the precipitation patterns. The dominant tree species are mainly *Baikiea plurijuga*, *Guibourtia coleosperma*, *Pterocarpus angolensis*, *Burkea africana* and *Dialium engleranum* (Kamwi, 2003).

#### 4.1.5 Edaphic situation

Kalahari sandy soils predominate in the eastern parts of the country including Hans Kanyinga Community Forest. Ferralic Arenosols<sup>2</sup> dominate these sands (Mendelsohn *et al.* 2002). Variations in vegetation are mainly due to soil depth and topography (Kamwi, 2003). The landscape is rather uniform with isolated valleys, called the Omirambas.

#### 4.2 DATA

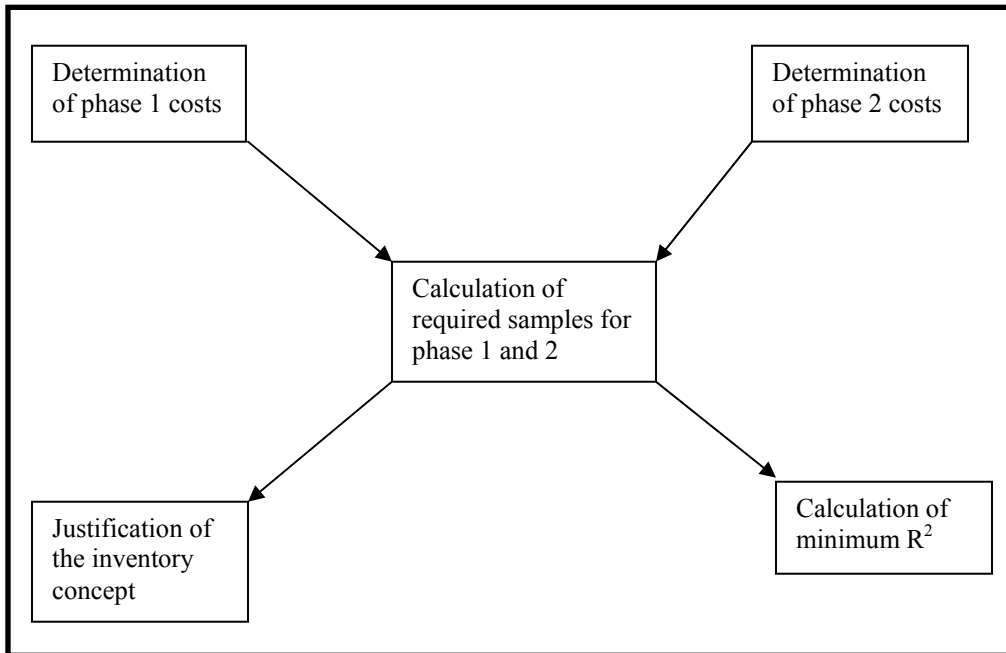
Double sampling with regression estimators investigated in this thesis utilizes two different data sets namely auxiliary data, which is data emanating from the satellite imagery and terrestrial data, which emanates from the field inventory. The manner in which these data sets were collected is described in detail in this section, including the costs involved. Figure 4 shows the flowchart indicating the steps taken during inventory data handling in phase 1 and 2 respectively.



**Figure 4.** Work flowchart (inventory data handling)

Figure 5 shows the flowchart for the inventory cost examination in phase 1 and 2.

<sup>2</sup> Soils formed by deposition of sand and can be 1 m deep hence increasing drainage of water to depths to which most plant roots cannot reach



**Figure 5.** Work flowchart (inventory cost examination)

#### **4.2.1 Overview of the inventory concept**

Double sampling with regression estimators applies when tree parameters are estimated e.g. from satellite images or aerial photographs, or when variables are estimated which are correlated with the growing trees and are further related to the measured standing trees in the forest sample plots via regression estimation (Brassel and Lischke, 2001). In simple terms, a larger sample is collected from the satellite image and a smaller one is collected terrestrially, with the same plots in both cases i.e. the plots measured terrestrially are again measured on the image. The ultimate idea of the concept is to combine the accuracy of the terrestrial data with the economy of obtaining auxiliary data.

By nature of its underlying theory, auxiliary variables in double sampling are assessed in the first phase (from the image). In the second phase, the survey of tree volume takes place by measuring individual tree parameters on the forest plots (terrestrial). Auxiliary variables are usually easier and more cost efficient to measure than the target variable since more samples are taken in the first phase than in the second phase. Therefore, double sampling permits a more cost efficient assessment of the variables of interest than

the simple terrestrial inventory for the same level of precision (Brassel and Lischke, 2001).

The size of the photogrammetric sample plot corresponded to 50 m radius (0.7855 ha) and terrestrial sample plots to 30 m (0.2828 ha). A relatively larger plot size for the photogrammetric plots was used to cater for possible errors in plot locations. These different plot sizes were expressed in hectares before further calculations were done. Hundred photogrammetric and 50 terrestrial plots out of the 203 plots from the earlier traditional inventory were systematically selected and used in this investigation. The illustrations of the costs based on the inventory carried out in this investigation and the actual two phase for planning purposes are given in Chapter 5.

#### **4.2.2 Auxiliary data (image/phase 1)**

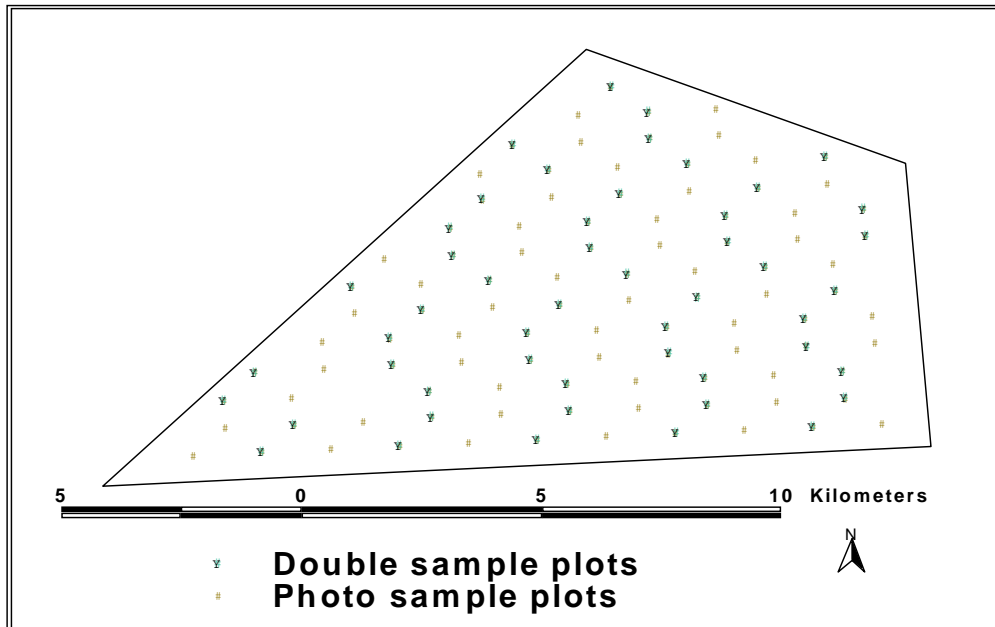
As presented by DigitalGlobe Inc., QuickBird satellite imagery is the highest-resolution satellite imagery currently commercially available. The QuickBird imaging system concurrently gathers 60-70 centimeter resolution for panchromatic and 2.44-2.88 meter resolution for multi-spectral images. DigitalGlobe provides three types of QuickBird products using different processing levels: Basic Imagery, Standard Imagery and Orthorectified Imagery (DigitalGlobe, 2002). In this investigation, a Standard QuickBird bundle (Panchromatic and Multispectral images) was used to extract the auxiliary variables of interest since it was the only QuickBird scene available in the archive at reasonable cost for the study.

The two software environments used in this investigation are the geographic imaging software Erdas Imagine 8.7 and ArcView 3.2. Erdas Imagine 8.7 software includes a broad tool set incorporating enhanced image mosaicing and 3-D visualization feature along with the tools for advanced modeling, vector and raster support, surface interpolation, image interpretation, ortho-rectification and GIS spatial analysis. ArcView 3.2 is a powerful GIS and mapping software, provided by ESRI. It is a tool used to display spatial information and to read information in tables from different data formats and was used for the production of maps.

The Standard QuickBird satellite scenes (Panchromatic and Multispectral) used were acquired in October (P0002) and November 2004 (P0001), with all channels present namely; blue (0.45-0.52  $\mu\text{m}$ ), green (0.52-0.60  $\mu\text{m}$ ), red (0.63-0.69  $\mu\text{m}$ ) and near infrared (0.76-0.89  $\mu\text{m}$ ) in the Multispectral image and a Panchromatic channel (0.45-0.90  $\mu\text{m}$ ) in the Panchromatic image from GISCOE South Africa (Pty) Ltd at a cost of N\$26,900.00. The image acquired in October was cloud free, while the one acquired in November 2004 had cloud cover of 9%. It is important to note that the only QuickBird satellite scenes available in the archive for the study area were from October and November 2004. Due to high altitudes (which may result in some sort of displacement and noise) at which these scenes were taken, it was essential to register them for consistency. Therefore, the images were geo-referenced by the supplier. The satellite images were projected using the Universal Transverse Mercator (UTM) as the coordinate system with WGS 84 as the spheroid and datum name with the scale factor of 1 in zone 34. Since the two images were taken at different dates and time; they appeared slightly different because of the sun or atmospheric effects. The two images (P0002 and P0001) were mosaiced to obtain a single image with panchromatic and multispectral layers.

As one would expect, image enhancement modifies the image to make it more suited to human vision (Sabins, 1978). The optimization of the Image brightness and contrast were carried out before the actual analysis began. Panchromatic and multi-spectral images were overlaid and fused together using the multiplicative as the merging method and the nearest neighbour as the resampling technique to derive a single image which was clear and enabled the vision of a single tree crown. The multiplicative merging method uses a simple multiplicative algorithm which integrates the Panchromatic and Multispectral images. This merging method was selected because it allows the quick movements (scrolling) on the images since it requires least computer system resources. The aim of fusion was to obtain a new image from the original ones in order to increase the amount of information that could be interpreted visually. On the image, it was assumed that tree crowns were ellipsoidal geometric shapes and were measured using the measuring tool offered by Erdas Imagine 8.7 by measuring the longest portion of the

crown and the narrowest axis of the crown. The two measurements were averaged to obtain the mean crown diameter. Tree counts were made by counting the visible tree crowns.



**Figure 6.** Photogrammetric and terrestrial layout of sample plots

A systematic layout of sample plots was used to ensure a full coverage of the whole inventory area. Every second photogrammetric sample plot from the random starting point was selected for the double assessment (figure 6). All the sample plots were assessed photogrammetrically while the dark coloured sample plots were assessed also during the terrestrial phase as depicted in figure 6 above. The sample plots which fell directly under the cloud were omitted and removed from the data set since no measurements could be obtained from them. Photogrammetric plot coordinates are given in Appendix 5.

In order to determine the extent to which the satellite imagery could be used to predict the diameter distribution of trees, 2 plots out of the 100 photogrammetric plots (figure 8) were accurately measured in the field. These plots were selected subjectively due to their closeness to the road and the visibility of individual tree crowns on the satellite image. The spatial tree positions in these 2 plots were determined from the field measured

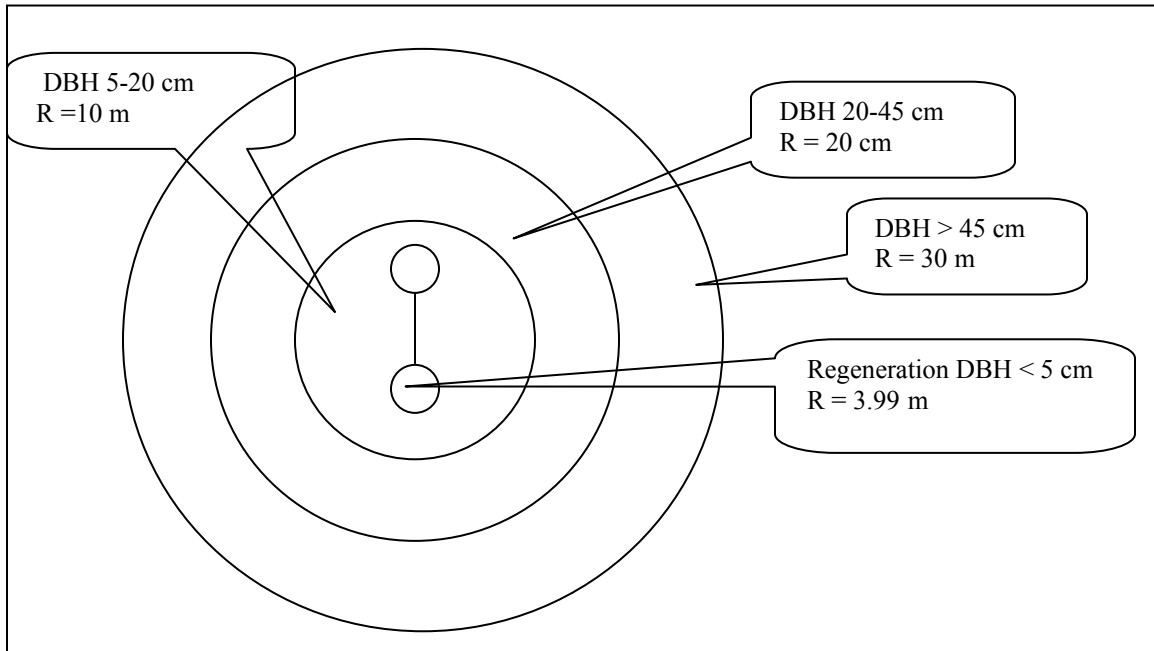


distances and bearings (surveying method). The DBH measurements collected from these two plots was correlated to the corresponding photogrammetric crown diameters. The resultant model was then used to predict the DBH of trees in the fitting set (photogrammetric crown diameters of trees in 100 plots measured). Trees which were in clusters were removed from the sample for diameter distributions, as their crowns could not be assessed accurately from the satellite image.

#### **4.2.3 Terrestrial data (phase 2)**

The terrestrial data used in this study was collected by the National Forest Inventory (NFI) team in 2002. Depending on the tree size and distance from the plot centre, trees inside the plot with at least 5 cm DBH were measured. The plot consisted of three concentric circles (Selanniemi and Chakanga, 2001). This is because of the spatial variability of trees and their sizes in the forest. In Namibia, big trees are not very frequent and in order to be able to get one or more on a plot, the plot size must be big enough although there is a practical limit of using very large plots. The size of the plot depended on the size of the tree so that the radius of the plot is 30 m for trees with a breast height diameter (DBH) more than or equal to 45 cm; 20 m for trees with  $20 \leq \text{DBH} < 45$  cm; and 10 m for trees with  $5 \leq \text{DBH} < 20$  cm (see figure 7). The DBH were measured with sliding callipers. A Vertex hypsometer was used to measure distance, length of possible saw log, height, canopy diameter and crown height. Other recordings taken included species, crown class, quality and phenology.

In addition, shrubs and regeneration were measured using two circular sub plots of 3.99 m radius. Woody plants with a diameter at breast height less than 5 cm were recorded accordingly. Several variables describing the site, soil and tree cover were observed and recorded for each plot. All these measurements are described in more detail in the field instructions (Selanniemi and Chakanga, 2001).



**Figure 7.** Plot design of terrestrial sample plots (Adapted from Selanniemi and Chakanga, 2001)

In the field, a systematic grid of terrestrial sample plots with a random starting point was laid. The sample plots were located using Garmin GPS II plus. For this project, sample plot selection for phase 2 sample was done by systematically taking every second plot of the photogrammetric sample plot, thus remaining within the systematic grid of the photogrammetric sample plots (see figure 6). It is important to mention here that if the grid was not maintained, everything could be wrong because it would mean that correlations were being carried out away from actual subject-trees with different correlation characteristics (plot pairing was the aim). Measuring instruments were checked for accuracy and consistency from time to time and re-calibrated when necessary before data collection.

With regard to the layout of the terrestrial sample plots onto the satellite image, the coordinates of the sample plots were captured in Microsoft Excel and saved in a database file (dbf) format which was imported into ArcView 3.2 and converted to a shape file. The shape file was registered in the same manner as the QuickBird satellite imagery to allow the compatibility with the already projected QuickBird satellite scene. The coordinates were later imported to Erdas Imagine in a vector format where they were

superimposed on the fused image and measurements of the crown diameters taken. Terrestrial plot coordinates are given in Appendix 6. The volume functions used to calculate tree volumes in the database were general functions designed for use in the whole of Namibia. These functions are further described and given by Verlinden and Lamaanen (2006).

### **4.3 DATA ANALYSIS, ACCURACY ASSESSMENT AND COSTS**

#### **4.3.1 Data analysis**

In general, the knowledge regarding the relationship between tree parameters and remote sensing data was deficient in Hans Kanyinga Community Forest. Therefore, linear regression procedures were used for the relationship between photogrammetric and terrestrial tree parameters. The premise for double sampling with regression estimators is that the photogrammetric data need to be significantly correlated to the target variables such as volume, terrestrial number of trees and DBH. Data were analyzed using Microsoft Excel and SAS enterprise guide 3.0. It was also important to check whether the populations from which the samples were taken were normally distributed. For example, the photogrammetric samples should be normally distributed, or if not, there should be a sufficiently large number of sample plots to obtain precise estimates. Therefore, the test for normality was important for statistical inference and in obtaining reliable measures of precision (Stellingwerf and Hussin, 1997). The test was carried out using SAS enterprise guide 3.0. It was therefore hypothesized that:

*H<sub>0</sub>: The data follows the Gaussian distribution.*

The first step was to analyze the relationship between the photogrammetric and terrestrial variables. When necessary, combined variables were developed to improve the correlations. After obtaining a set of variables that correlated with the volume, a stepwise selection regression analysis which included Mallows' Cp statistic as the selection criteria was used to optimize the model selection at 0.1000 significant level to minimize the number of terms. Mallows' Cp statistic is based on the goodness of fit for the selection of explanatory variables (Lakshminarayan and Moore, 2001). In this investigation, the selected variables were described as having "behaved" themselves, and

they appear in the equation-sequence from the best to the least behaved variable. Furthermore, it was noted that the inclusion of many interconnected variables as anticipated tends to produce “inflated estimates of the regression estimates” (Kätsch and Van Laar, 2002). Since the procedure of double sampling with regression estimators in this investigation is the relationship between photogrammetric variables and volume, stems per hectare and DBH, all the terrestrial variables were removed from the regression analysis. The correlation matrix reflecting the degree of linear interrelationship among the variables is given in Appendix 1a.

The second step was to test the degree to which the regression assumptions were met by the models based on the display of standardized residuals and using the non parametric Shapiro-Wilk *W* statistic because it is regarded to be one of the best omnibus tests for normality (Royston, s.a.). It can be used in samples as large as 2,000 or as small as 3 since some of the samples used in this investigation (such as diameter distribution model) were small.

#### **4.3.2 Accuracy assessment**

##### Inventory data evaluation and assessment

Inventory result evaluation and assessments determine the quality of the information in terms of estimates derived from the inventory data (Stellingwerf and Hussin, 1997). The likelihood that errors occurred in the data collected were almost unlimited during the traditional inventory. It was absolutely important that the data collected was checked with respect to its plausibility before entering it into the NFI data entry and analysis program. Usually, the first check was done in the field by the field team supervisor while collecting the data. For this project, a database for Hans Kanyinga was obtained from the NFI within the Directorate of Forestry. In this database, dead trees were removed from the data set because their crowns were not measured (see plate 1).



**Plate 1.** Live tree standing alongside a dead tree (Plot 94)

In this investigation it was important to focus on the actual number of stems not only the number of trees because trees tend to grow in clusters or one stem may have several forks. When the forks are below 1.3 m, they were considered to be several trees, in which one tree represents many individuals per hectare. If this was not attended to, it could lead to the underestimation of the stems per hectare and the results could not correlate with other variables investigated, as it was the case at the beginning of the terrestrial data analysis.

The standard error of the mean volume was calculated using the formula given by Kättsch (1991).

$$S_{y_{ds}}^2 = \frac{S_y^2 \times (1 - R^2)}{n_t} \times \left[ 1 + \frac{n_p - n_t}{n_p} \times \frac{p}{n_t - p - 2} \right] + \frac{R^2 \times S_y^2}{n_p} - \frac{S_y^2}{N} \quad (1)$$

*Where:*

$S_{y_{ds}}^2$  = standard error of the mean volume

$S_{y_2}^2$  = variance of terrestrial volume

$R^2$  = coefficient of determination of the model used

$n_p$  = number of photo-measured plots

- $n_t$  = number of field-measured plots  
 $p$  = number of auxiliary variables  
 $N$  = total possible number of plots in the population without replacement

It is important to note that the correction factor in formula 1 was not used in the calculations because the area under investigation is very large and the true population was not known. The confidence limit for the mean volume was calculated using a formula by Paine and Kiser (2003).

$$CI = \bar{y} + t \times SE_{\bar{y}} \quad (2)$$

Where

$CI$  = confidence interval

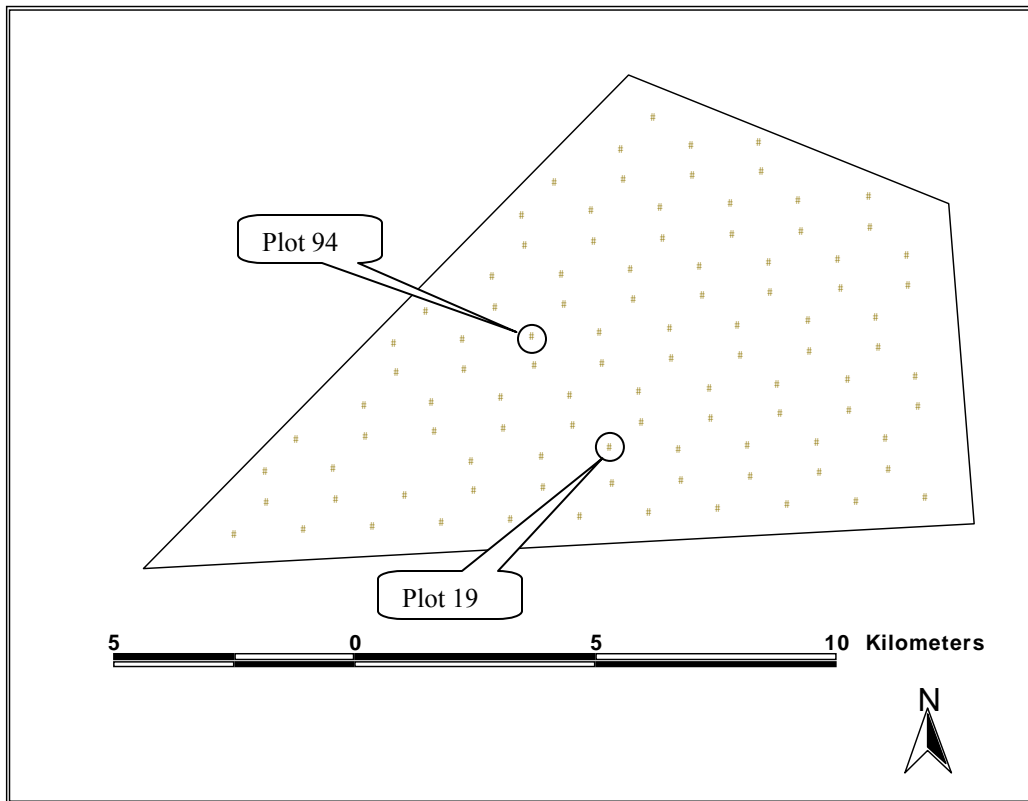
$\bar{y}$  = mean volume

$t$  =  $t$  statistic for probability level

$SE_{\bar{y}}$  = Standard error of the mean volume

#### Evaluation of tree spatial position

The central question under the evaluation of tree spatial positions was to find out if the trees on the image are correctly located in relation to the actual trees in the field and whether it is necessary to have a higher accuracy in the spatial positions of the trees. In order to answer this question, the accuracy of the GPS tree spatial positions was evaluated through a comparison of the actual distances and bearings (surveying method) of trees away from the plot centre and the GPS positional readings. Figure 8 shows the 2 plots which were selected for positional accuracy assessment. These sample plots were measured as accurately as possible terrestrially. Plot and tree position coordinates were obtained from the Garmin GPS II plus and distances of trees from the centre of the plot and their respective bearings were measured using Vertex hypsometer and a compass respectively. The specifications of the Garmin GPS II plus device are given in Appendix 8. The tree spatial positions from both methods were superimposed on the Standard QuickBird satellite scene to determine the relationships between the GPS and surveyed distances and to visualize the individual tree positions.



**Figure 8.** Positional accuracy assessment sample plots

### 4.3.3 Cost analysis (phase 1 and 2)

The expenditure composed of satellite image costs; personnel expenditures (salaries, travels, daily subsistence allowances and overtime payments); fuel, and equipment perishables (batteries for GPS and torches). The labour cost in the first phase was associated with a forester, one who has specialized skills in statistics, GIS and remote sensing.

For the estimation of the expenditure, several different bases and empirical figures were available for phase 2 from the initial traditional inventory. From the initial traditional inventory, the numbers of sample plots were known. The cost for the terrestrial sample was derived from adding the cost of all the activities and expenses required in collecting data in a sample plot for a given period of time, e.g. salaries of the staff, daily subsistence allowances and fuel for guard bikes and cars used during the inventory. The cost also

includes the allowances and man-hour remuneration for the technical advisors to the NFI, and staff of the NRSC including their accommodation during the field work. The man-hours of the district forest officials who provided logistical support from the nearby forestry office are included. However, the depreciation of vehicles and equipment is not included in the calculations.

The justification (optimum ratio) of double sampling with regression estimators was calculated based on the formula given by Kättsch and Van Laar (2002).

$$K = \frac{n_t}{n_p} \geq \frac{R^2}{(1 - \sqrt{1 - R^2})^2} \quad (3)$$

Where:

- $R^2$  = coefficient of determination of the model used
- $n_t$  = cost per sampling plot of terrestrial sampling
- $n_p$  = cost per sampling plot on the satellite imagery
- $K$  = cost ratio of terrestrial to photo plot

The minimum value of the coefficient of determination required to render double sample sampling efficient was calculated using the formula given by Kättsch (1991).

$$R^2 = \frac{(4 \times n_t \times n_p)}{(n_t + n_p)^2} \quad (4)$$

The number of required sample plots was calculated using the formulae given Kättsch (1991).

$$n_p = \frac{S_y^2 \times t^2}{S_{y ds}^2} \times \left[ \sqrt{K \times R^2 \times (1 - R^2)} + R^2 \right] \quad (5)$$

$$n_t = n_p \times \sqrt{\frac{1 - R^2}{R^2} \times \frac{1}{K}} \quad (6)$$

Where:

- $n_p$  = number of photo plots



$n_t$  = number of terrestrial plots

$S_y^2$  = variance of mean terrestrial volume

$S_{y_{ds}}^2$  = sampling error in %

$t$  = t statistic for confidence level

$t = 1$  for 68.3%

$t = 2$  for 95.4%

$R^2$  = coefficient of determination of the model used

$K$  = cost ratio of terrestrial plot to photo plot

## 5. RESULTS

### 5.1 REGRESSION AND CORRELATION ANALYSIS

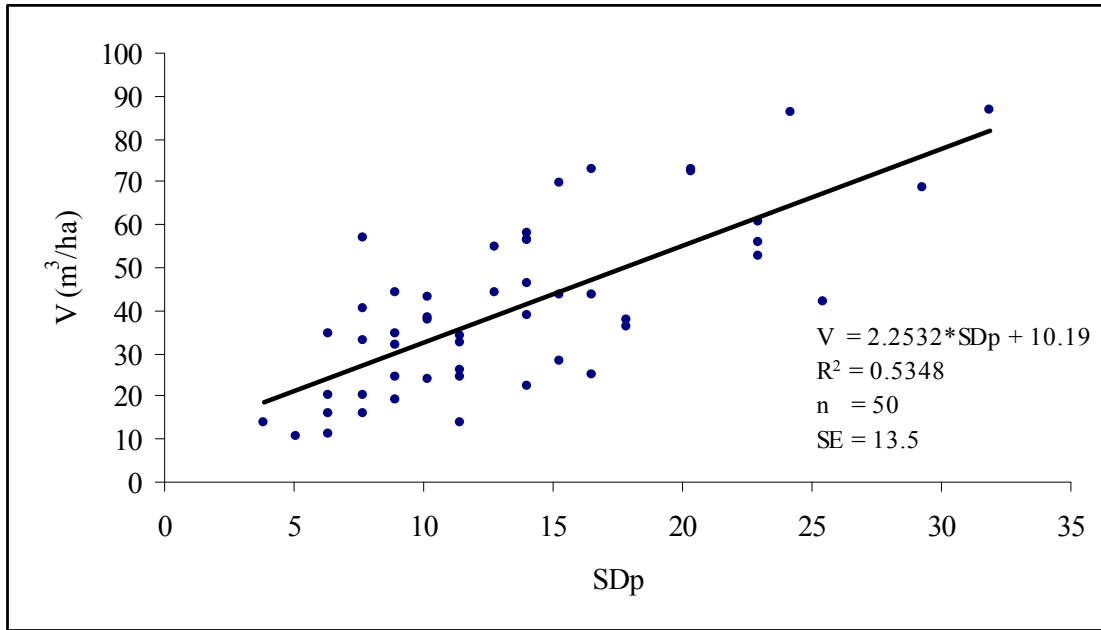
Table 1 below summarizes the explanatory variables used in the statistical analysis. It is important to note that the photogrammetric, terrestrial and volume estimates were not absolute values, but were average values per plot. Absolute values were only used for the plots which were assessed for positional accuracy since the tree positions were known.

**Table 1.** Summary of explanatory variables

<b>Variable</b>	<b>Description</b>
BA	Basal area (cm <sup>2</sup> )
DBH	Diameter at breast height (cm)
CAP	Photogrammetric crown area (m <sup>2</sup> )
CAP*SDp	Combination of Photo crown area and Photo number of stems per hectare
CAt	Terrestrial crown area (m <sup>2</sup> )
CCp	Photogrammetric crown cover (%)
CCt	Terrestrial crown cover (%)
CDp	Photogrammetric crown diameter (m)
CDt	Terrestrial crown diameter (m)
SDp	Photogrammetric number of stems or stand density (per hectare)
SDt	Terrestrial number of stems or stand density (per hectare)
SDp*CCp	Combination of Photo-stems per hectare and Photo crown cover percent
V	Stand volume (m <sup>3</sup> per hectare)

#### Stand volume

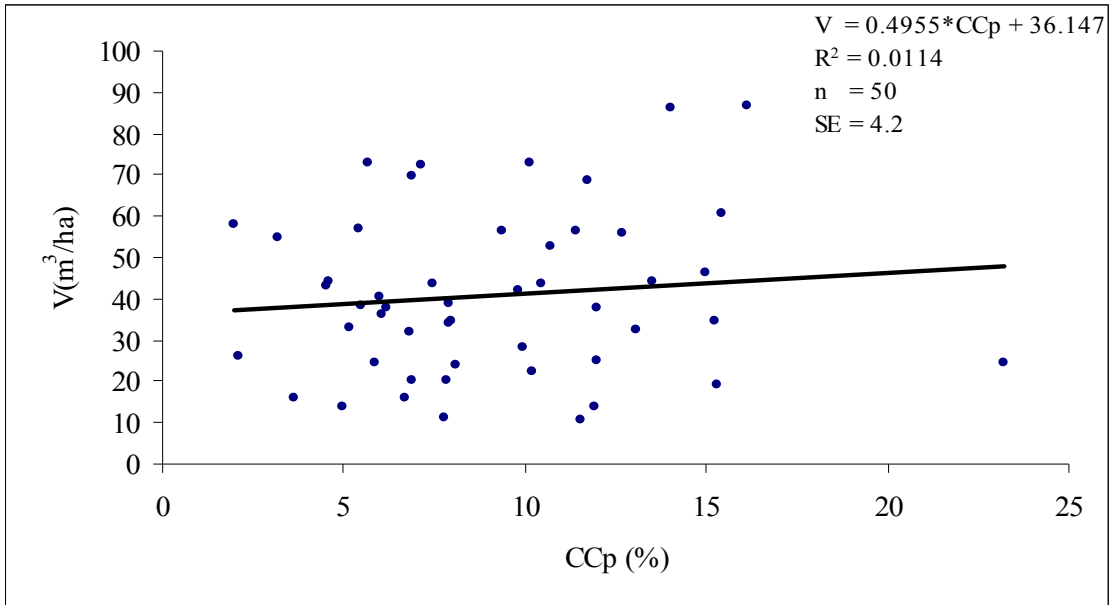
Potential explanatory variables for the model were analyzed individually to determine their relationship with the stand volume.



**Figure 9.** Linear regression between SDp and V(m<sup>3</sup>/ha)

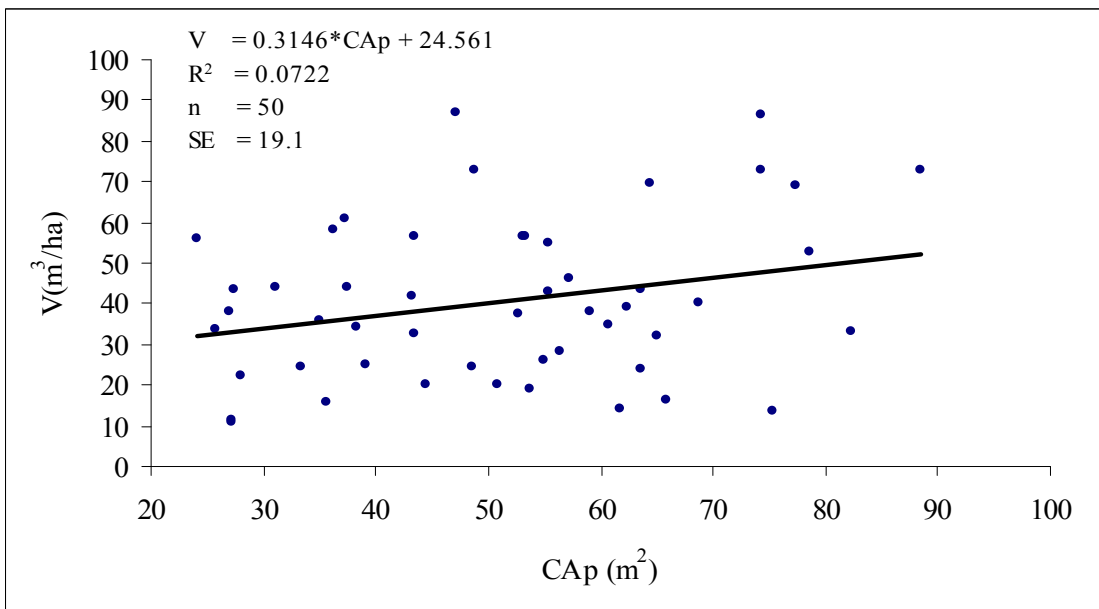
From figure 9, it is apparent that the volume per hectare increased with an increase in the number of stems counted on the image. In other words, the higher the number of stems per hectare counted on the image, the higher the volume per hectare. The corresponding  $R^2$  value is 0.53, indicating that 53% of the variation in volume V(m<sup>3</sup>/ha) can be explained by the linear relationship with SDp. The trend depicted in figure 9 may be different from other forest types, where the volume increases as the number of stems decreases due to growing space availability (Kätsch, 2006b).

Figure 10 shows that the volume per hectare had a relatively flat relationship with the photogrammetric crown cover percent. The low value of  $R^2$  (0.011) was a clear indication of the poor correlation between volume and the photogrammetric crown cover percent. This was expected because there are many small sized trees per unit area in Hans Kanyinga Community Forest with little contribution to the stand volume.



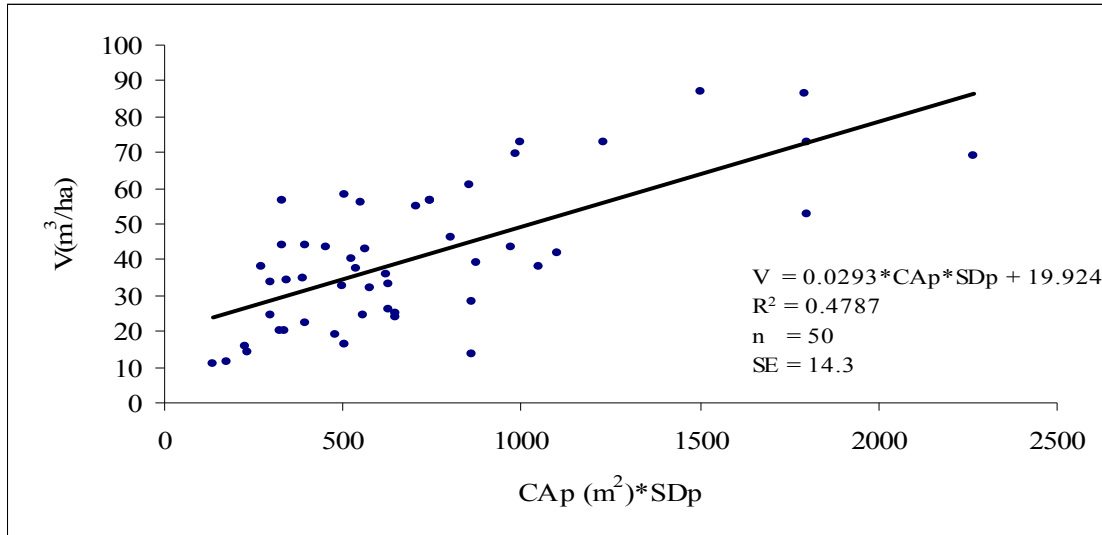
**Figure 10.** Linear regression between CCp and V(m<sup>3</sup>/ha)

Figure 11 shows that the relationship between photogrammetric crown area and stand volume was weak. The R<sup>2</sup> value of 0.072 was a clear indication of the weak correlation between the photogrammetric crown area and stand volume.



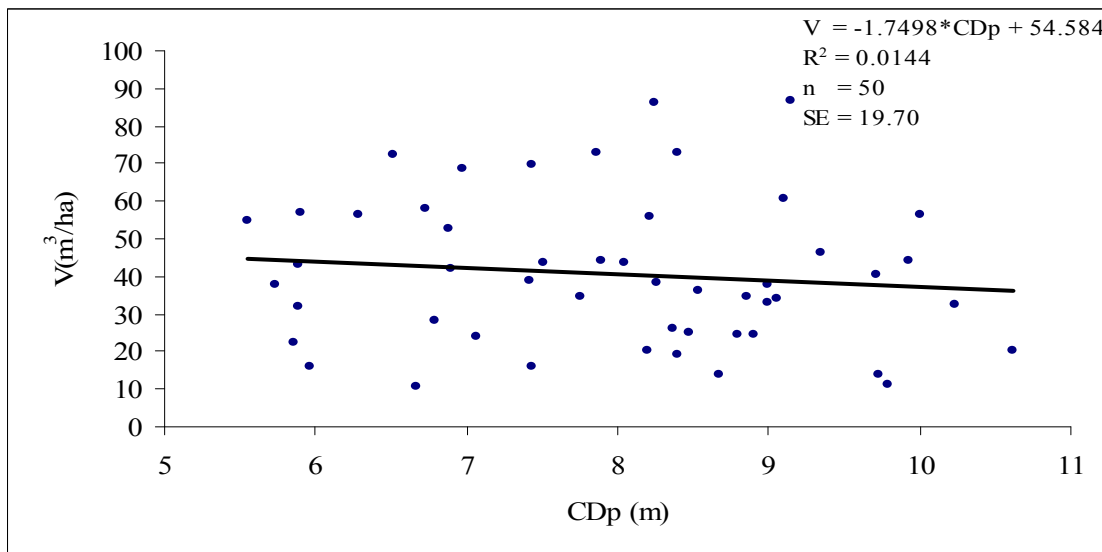
**Figure 11.** Linear regression between CAp and V(m<sup>3</sup>/ha)

Figure 12 below shows that a combination of the photogrammetric crown area and stand density was a function of the stand volume. This combination was made deliberately to improve the prediction capability of the model. The resultant  $R^2$  value was 0.479. Appendix 4 shows the relationship between the stand volume and some terrestrial variables as well as the combined variables.



**Figure 12.** Linear regression between  $CAp*SDp$  and  $V(m^3/ha)$

Figure 13 below shows that the relationship between volume and photogrammetric crown diameter is very weak ( $R^2$  value of 0.011).



**Figure 13.** Linear regression between  $CDp$  and  $V(m^3/ha)$

## Multiple regression

The results obtained from the stepwise regression procedure are shown in Table 2 below:

**Table 2.** Stepwise procedure

Summary of Stepwise Selection									
Step	Variable	Variable	Label	Number	Partial	Model	C(p)	F	Pr > F
	Entered	Removed		Vars In	R-Square	R-Square		Value	
1	SDp		SDp	1	0.5348	0.5348	3.815	55.18	<.0001
2	CAP*SDp		CAP*SDp	2	0.027	0.5618	2.921	2.9	0.095
3	SDp*CCp		SDp*CCp	3	0.0172	0.579	3.079	1.88	0.177
4		SDp*CCp	SDp*CCp	2	0.0172	0.5618	2.921	1.88	0.177

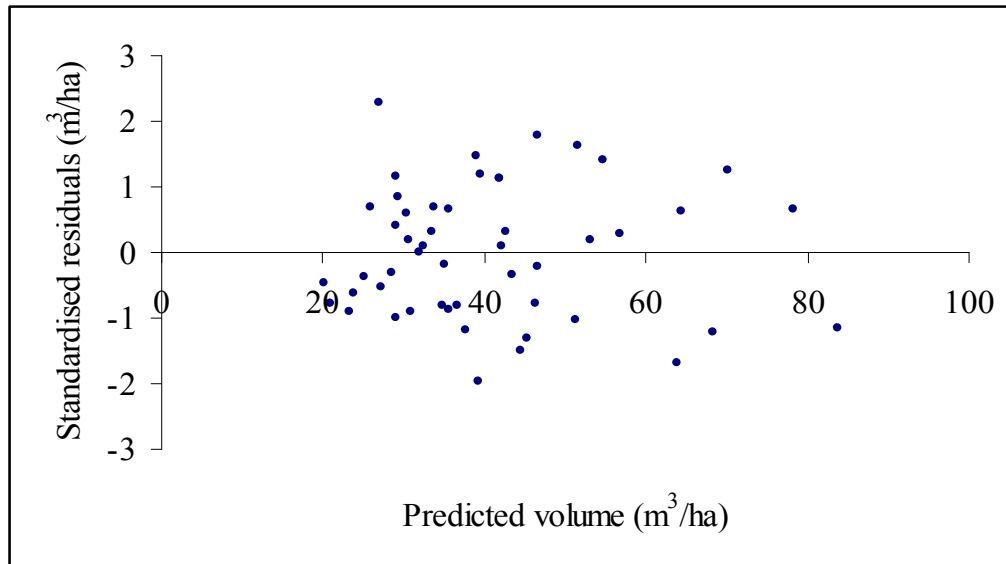
The first variable to be selected by the step wise procedure was SDp. It can be seen that the relationship between the stand volume and SDp already accounted for 53% ( $R^2 = 0.5348$ ) of the variation in the data set. The second variable to be selected was CAP\*SDp. The  $R^2$  value has increased to 56% ( $R^2 = 0.5618$ ). This means that the two variables alone account for almost the same amount of variation as the full model would. Therefore, 56% of the variation in the total volume per hectare can be explained by the linear relationship with SDp and a combination of CAP with SDp. In the statistical context, SDp\*CCp was removed because it was not significant at 0.1000 significant level. For this reason, SDp was found to be the best behaved photo variable to be used for volume estimation per hectare, followed by CAP\*SDp. Already, it can be seen that a combination of explanatory variables (CAP with SDp) resulted in the following regression model:

$$\text{Total vol/ha (m}^3\text{)} = 11.33865 + 1.53760 * \text{SDp} + 0.012054 * \text{CAP} * \text{SDp}$$

$$R^2 = 0.56, n = 50, SE = 13.3$$

### *Plausibility check of the stand volume model*

Regression diagnostics were used to check the goodness of fit, the ability of the model to predict the stand volume and whether the assumptions of multiple linear regression were satisfied. This check, using residual plots is shown in figure 14 below.



**Figure 14.** Residuals of the stand volume per hectare model

With the visual analysis of figure 14, it can be clearly seen there was no distinct pattern of residuals depicted, hence making it a good model to predict stand volume. In addition, figure 14 shows a relatively even scatter of the residuals, which satisfies one of the important assumptions of the multiple linear regression procedure. The figure above shows that almost all the standardized residuals are below 2 (or 1.96). This means that there is 95% probability that most of the residuals do not violate the good fit of the linear model. However, one observation with the size of 2.5 m<sup>3</sup>/ha was unusual to the entire population. This unusual observation was checked and was attributed to measurement errors. Therefore, there is only 5% chance (probability) that this unusual observation belongs to the entire population. The corresponding value for normality of residuals based on Shapiro-Wilk W statistic was 0.5734. This means that there is insufficient evidence to reject the null hypothesis that the data were normally distributed. The estimated stand volume in the initial traditional inventory was 40.399 m<sup>3</sup>/ha, which is

close to 35.728 m<sup>3</sup>/ha in the present investigation. The stand volume model was used for further analysis and calculations in this investigation.

### Stand density

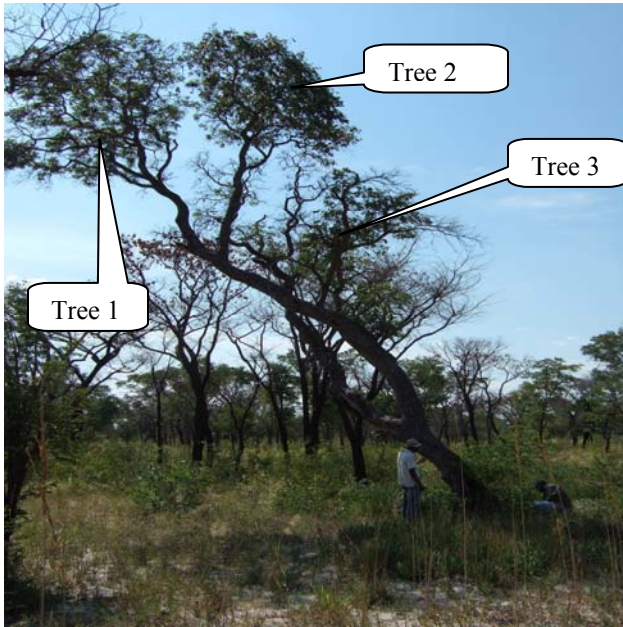
As indicated earlier, the sample plots in which the numbers of trees were counted comprised of different dimensions (50 m photogrammetric and 30 m terrestrial). Relatively big plot sizes of 50 m radius were used on the image to cater for spatial positional shifts of the plots, while 30 m radius of the terrestrial plot was based on the practicality of measuring trees on the ground. To avoid misunderstandings, these dimensions were standardized to a per hectare basis before deriving these results. Therefore, in this investigation, the results of the number of stems are accounted for on a per hectare basis. It is important to note that the terrestrial number of stems per hectare may include trees in clusters, but these were regarded as different stems during the traditional inventory. Plate 2 shows a cluster of *Baikea plurijuga* trees. Counting individual trees on the satellite imagery was sometimes unrealistic and contributed to the underestimation of the tree counts.



**Plate 2.** Tree cluster (plot 19) causing the underestimation of tree counts

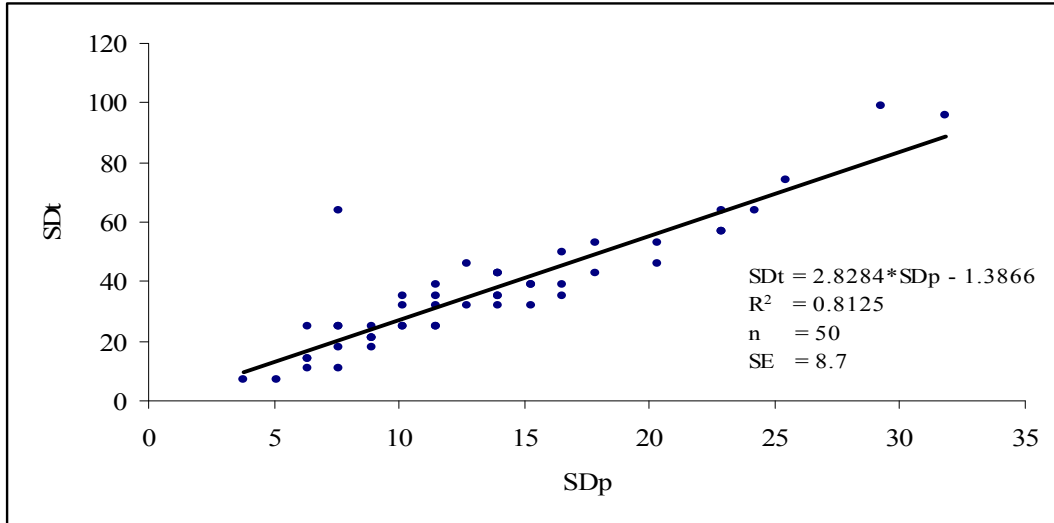


In many cases, the likelihood that leaning stems with their extended branches have comprised a serious inconsistency on stem counts on the satellite image (see plate 3) should not be excluded. That is, a single stem may also appear as numerous stems on the image, thus leading to inconsistency in tree counts.



**Plate 3.** Leaning tree (Plot 19) which may be regarded as several trees on the satellite image

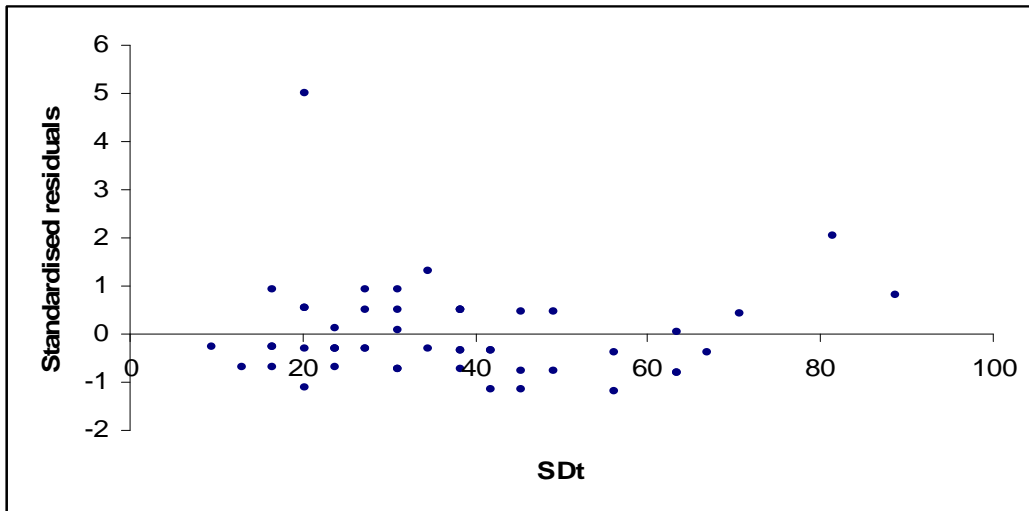
Figure 15 shows that the photogrammetric number of stems per hectare and terrestrial stems per hectare follows a similar pattern when plotted against each other, with the  $R^2$  of 0.81%, which was very satisfactory giving the characteristics associated with natural woodlands a merit.



**Figure 15.** Linear regression between SDt and SDp (with the unusual observation)

*Plausibility check of the terrestrial stand density model*

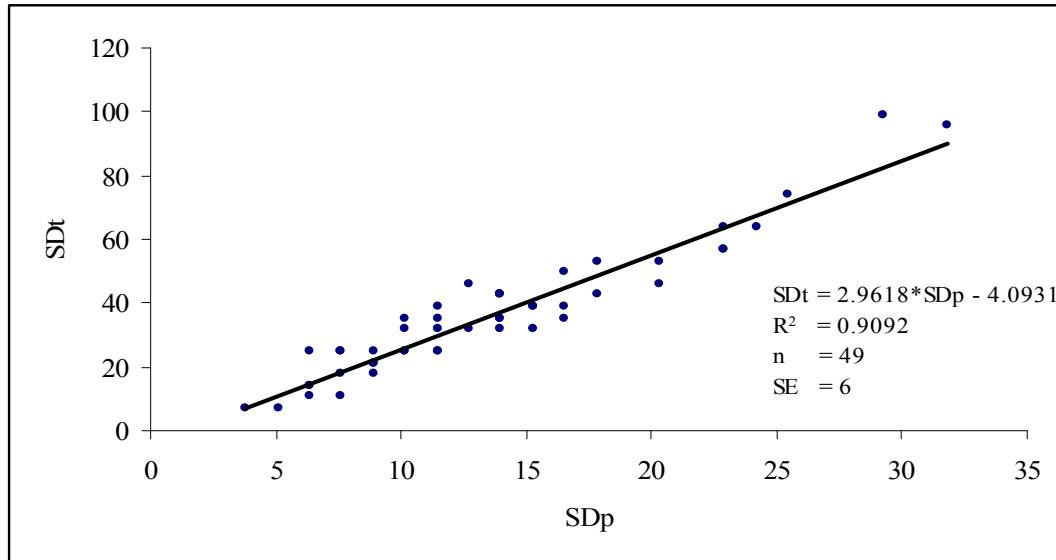
The goodness of fit and the predictive ability of the model (in figure 15) to predict the terrestrial number of stems per hectare was assessed in figure 16 below.



**Figure 16.** Residuals of the terrestrial stand density model (with the unusual observation)

The Shapiro-Wilk *W* statistic for normality is highly significant ( $p < 0.0001$ ), indicating that there is sufficient evidence to reject the null hypothesis that the terrestrial data are normally distributed. The histogram (Appendix 3) shows that the data are asymmetrical with right skewness. The Shapiro-Wilk *W* statistic was found not to be significant ( $p =$

0.8568), indicating that the data were indeed lognormal. Figure 16 also indicates one big unusual value with a value of 5 which was attributed to counting or recording errors. For indication purposes, this unusual value was removed and the resulting figures were inspected for improvement in the  $R^2$  value. The regression with the removed observation is shown in figure 17.



**Figure 17.** Linear regression between SDt and SDp (without the unusual observation)

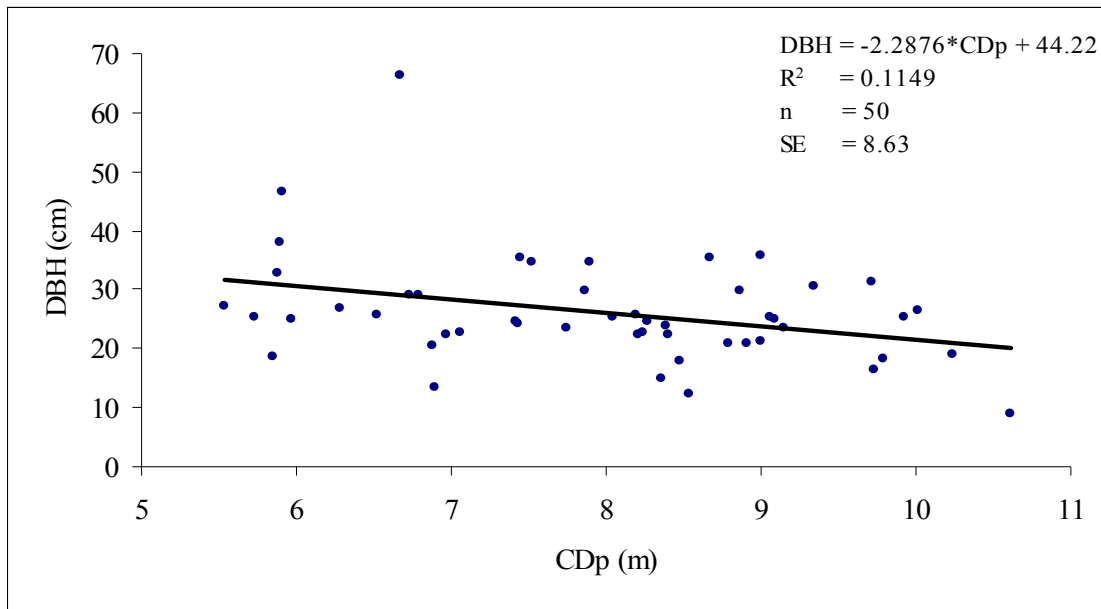
Figure 17 above reveals that the coefficient of determination has improved considerably to 0.91.

### Diameter distribution

The question whether the diameter distribution could be obtained from the QuickBird satellite imagery using the well known and much publicized relationship (e.g. Hemery *et al.* 2005; Smith and Gibbs, 1970) between tree crown diameter and stem diameter was investigated. Whether such a relationship existed in the natural woodlands of Namibia was investigated by regression before and after assessing the tree spatial positions in two sample plots.

Figure 18 shows the linear relationship between DBH and photogrammetric crown diameter. The resultant  $R^2$  value of 0.115 is a clear indication of the weak correlation

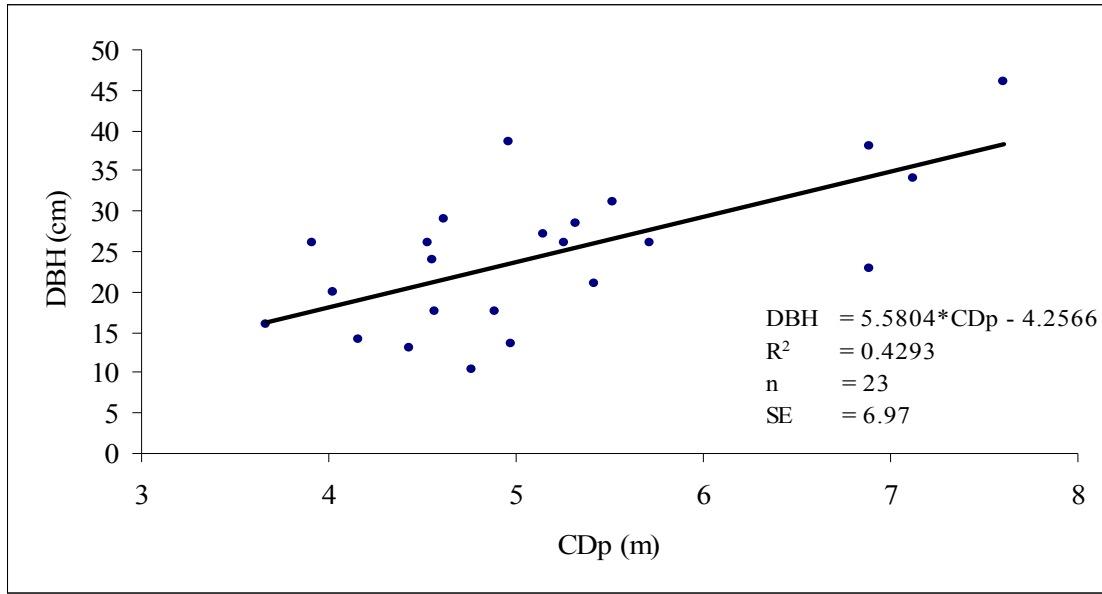
between DBH and CDp. This indicates that only 0.115% of the variation in the mean DBH can be explained by the linear relationship with the CDp. Normally, a positive slope of the trend line would have been expected as opposed to the negative slope of the trend line shown in figure 18.



**Figure 18.** Linear regression between DBH and CDp

Figure 18 further shows indicated one big unusual observation with a value of 66.2 cm. This is expected because bigger sized trees are not frequent in Hans Kanyinga Community Forest.

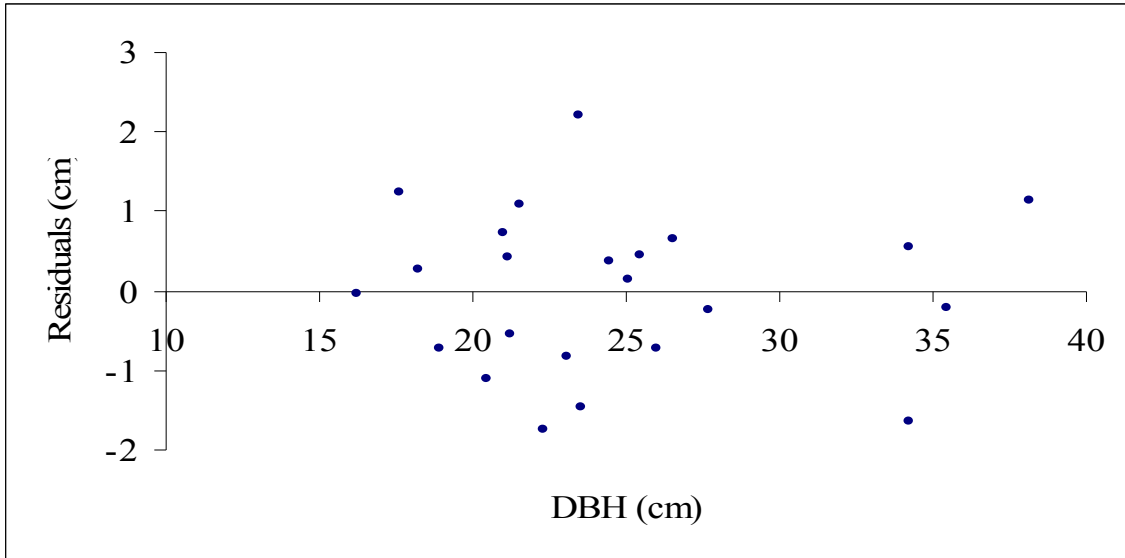
The terrestrial data obtained from the 2 plots which were assessed for spatial tree positions was referred to as the validation set. This is because the data could be paired, meaning that the same trees measured on the image were the same ones measured in the field. The validation set indicated an improvement in the  $R^2$  value to 0.43. This improvement means that 43% of the variation in DBH can now be explained by the linear relationship with the photogrammetric crown diameter, instead of 11.5% when spatial positions were not assessed. Appendix 1b shows the correlation matrix based on the plots which were assessed for spatial positional accuracy.



**Figure 19.** Linear regression between DBH and CDp (plots assessed for positional accuracy)

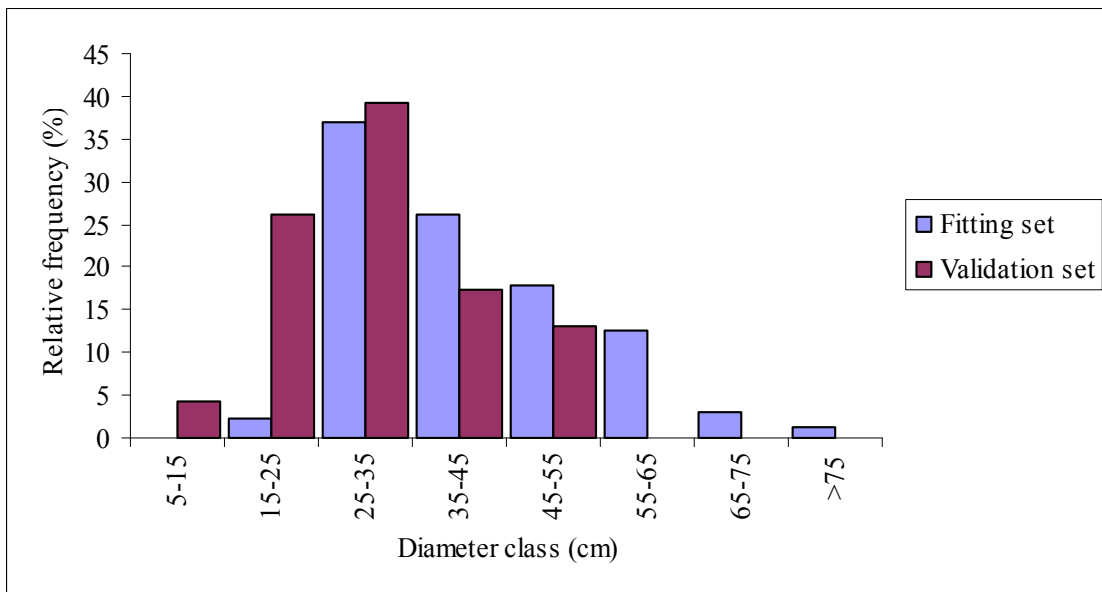
The coefficient of determination in the plots which were assessed for spatial positions was considered to be high enough, taking the positional errors of the measuring devices into account, to further consider the correlation between DBH and photogrammetric crown diameter as a potential candidate of the regression estimator for the diameter distribution. Subsequently, a rule of thumb was developed based on the linear relationship in figure 19 that the tree diameter in cm equals 5 times the average photogrammetric crown diameter in meters.

The value for Shapiro- Wilk  $W$  statistic was found to be 0.8733. This means that there is insufficient evidence to reject the null hypothesis that the data were normally distributed. The full regression diagnostics are shown in appendix 7. The standardized residuals of the model indicate that there was 95% probability that most of the residuals do not infringe the good fit of the linear model (figure 20).



**Figure 20.** Residuals of the diameter distribution model

The model in figure 19 was used to predict the DBH distribution of trees based on the photogrammetric crown diameters (shown in figure 21). The fitting data set emanates from all the crown diameters measured on all photogrammetric plots (100 plots).



**Figure 21.** Diameter distribution

From figure 21, it can be clearly seen that the bulk of trees were in the small and medium diameter classes (<50 cm). However, big trees were not very frequent. This trend was

also depicted in Kamwi (2003). It also important to note that smaller sized trees may have not been sufficiently represented in the sample due to the effect of fires and the usage of small diameter trees for fencing and kraals. Overall, figure 21 indicates that despite the effect of the fire and usage, there are a relatively good number of trees entering the medium to large diameters (>35 cm) which are exploited for timber.

## 5.2 ACCURACY ASSESSMENT

### Inventory data evaluation

The estimated volume for Hans Kanyinga Community Forest was 35.728 m<sup>3</sup>/ha. For the full regression diagnostics, see appendix 2. The standard error of the mean volume based on formula 1 is:

$$\text{Variance of estimated mean} = \frac{385.6 \times (1 - 0.56)}{50} \times 0.54 + \frac{0.56 \times 385.6}{100} = 3.991$$

Where:

$$S_{y_2}^2 = 385.6 \text{ m}^3/\text{ha} \text{ (variance of mean terrestrial volume)}$$

$$R^2 = 0.56 \text{ (coefficient of determination of the model used)}$$

$$n_p = 100 \text{ (number of photo-measured plots)}$$

$$n_t = 50 \text{ (number of field-measured plots)}$$

$$\text{Adjusted } R^2 = 0.54 = \left[ 1 + \frac{n_p - n_t}{n_p} \times \frac{p}{n_t - p - 2} \right]$$

$$\text{Standard error of mean volume} = \sqrt{3.991}$$

$$= 1.998 \text{ m}^3/\text{ha}$$

The standard error of the mean volume per hectare was found to be 1.998 m<sup>3</sup>/ha. This means that 68 percent of all sample means in Hans Kanyinga Community Forest lie between 33.730 m<sup>3</sup>/ha and 37.726 m<sup>3</sup>/ha. The standard error as a percentage of the mean volume was:

$$\text{Standard error of the mean volume in \%} = \frac{1.998 \text{ m}^3 / \text{ha}}{35.728 \text{ m}^3 / \text{ha}} \times 100 = 5.59\%$$

Based on formula 2, the confidence interval for the estimated mean volume was:

$$\text{Confidence interval} = 35.728 \text{ m}^3 / \text{ha} \pm 1.96 \times 1.998 \text{ m}^3 / \text{ha}$$

$CI$  = confidence interval

$$\bar{y} = 35.728 \text{ m}^3 / \text{ha} \text{ (mean volume)}$$

$$t = 1.96 \text{ (} t \text{ statistic for probability level)}$$

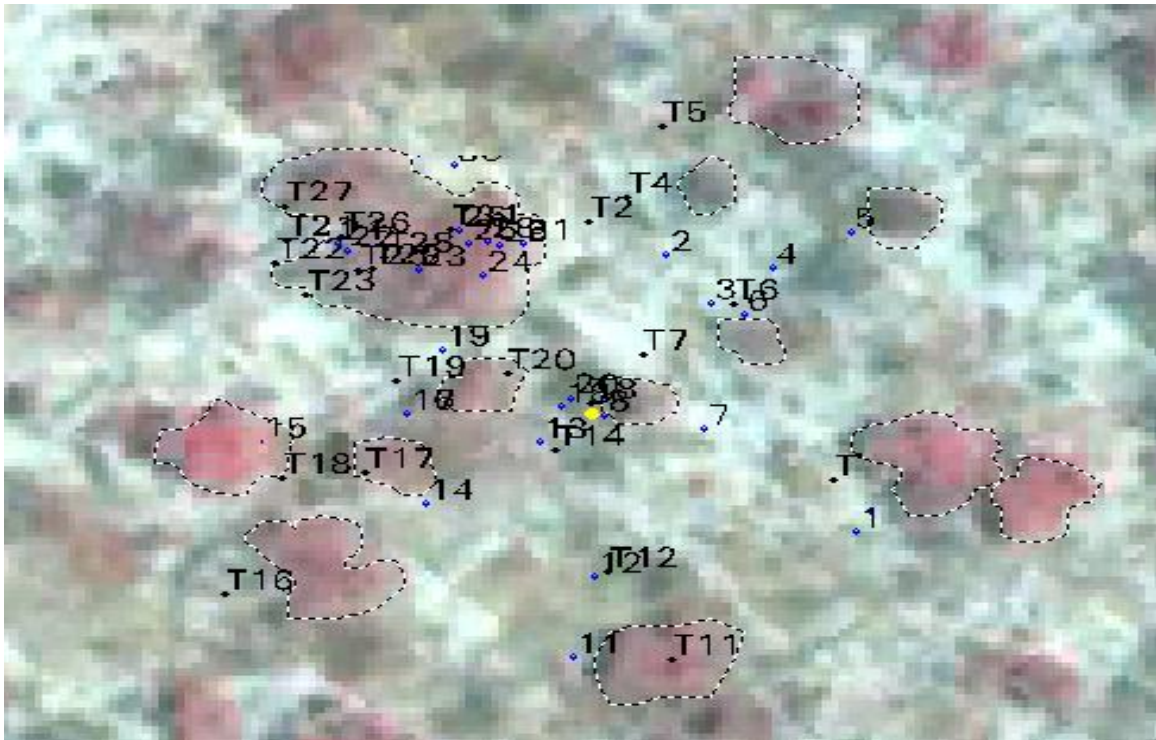
$$SE_{\bar{y}} = 1.998 \text{ m}^3 / \text{ha} \text{ (standard error of the mean volume)}$$

It is therefore, expressed with 95 percent confidence that the true mean volume is somewhere between 31.812 m<sup>3</sup>/ha and 39.644 m<sup>3</sup>/ha.

#### Evaluation of tree spatial position

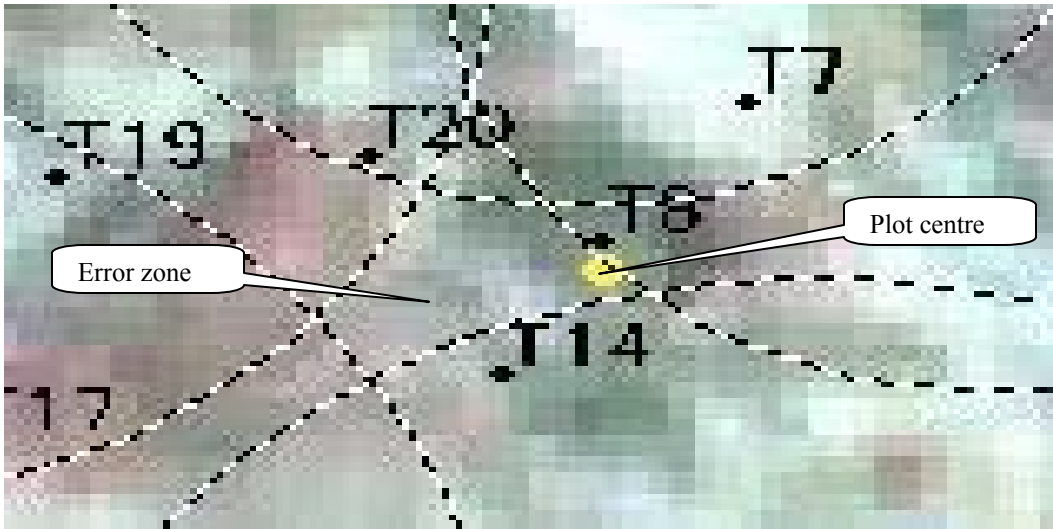
Individual spatial tree positions emanating from the GPS and surveying (distance and bearing measured positions) method is indicated in plate 4. GPS positions are denoted with a T (tree) in front of a specific number (black dots); surveyed positions (blue dots) are not denoted by any letter and the yellow point represents the plot centre. The reddish colour on the image denotes tree crowns (polygons represent tree crowns); brownish colour represents the shrubs and other small vegetation while the whitish colour represents soil with grass.



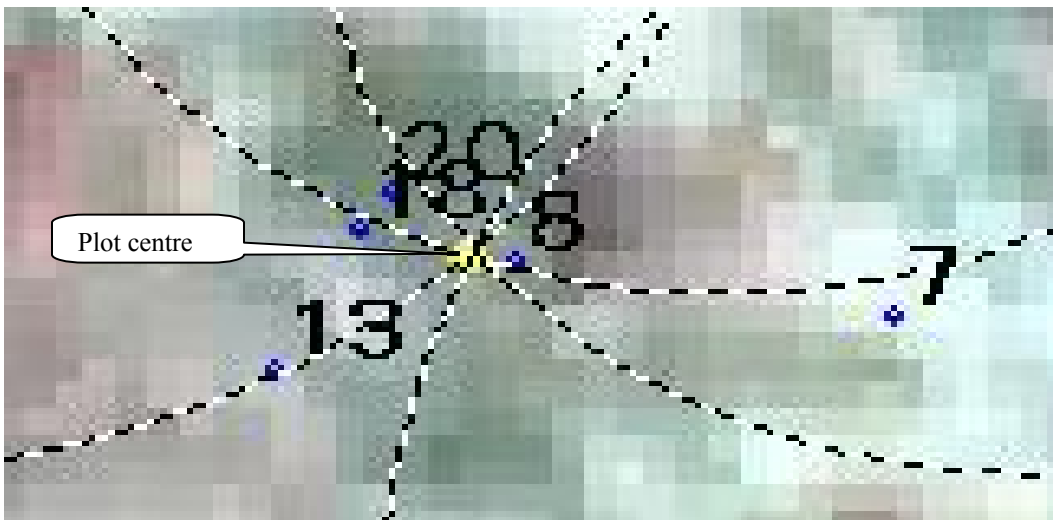


**Plate 4.** Tree positions in plot 94 (GPS and surveyed positions)

It is apparent from plate 4 above that individual trees behave erratically by assuming two positions depending on the method of spatial positional determination. Plate 5 shows the portions of circular peripherals of the measured distances of individual trees (using GPS) from the centre of the plot. That is, each circle represents the actual measured distance of an individual tree from the plot centre. Looking at these circles in plate 5, they do not fit with the centre of the plot indicating that the measured distances were either more or less than the GPS distances. The spatial positional error was found to be up to 8.67 m. GPS positions are denoted with a T (tree) in front of a specific number. The reddish colour on the image denotes tree crowns; brownish colour represents the shrubs and other small vegetation while the whitish colour represents soil with grass. It is important to note that the plot centre itself is also prone to positional errors, so the true plot centre is somewhere within the error zone formed by the circles representing tree peripherals around the plot centre.



**Plate 5.** Tree positions using GPS (plot 94)



**Plate 6.** Distance measurements (surveyed tree positions, plot 19)

Plate 6 shows the surveyed spatial tree positions based on the distance and bearing. It is noticeable that the peripherals of the portions of the circles representing the distances of individual trees passes through the centre of the plot indicating that the measured distances from the plot centre were reliable. The yellow dot represents the plot centre and surveyed tree positions are the blue points with a corresponding tree number. The reddish colour on the image denotes tree crowns; brownish colour represents the shrubs and other small vegetation while the whitish colour represents soil with grass.

### 5.3 COSTS

In Namibia, foresters are paid N\$400 per man-day (N\$8,400 divided by 21 working days). Experience has shown that it takes 15 minutes to measure crown diameters and count trees on the image, which is N\$12.50 per photogrammetric sample plot. The total cost of the initial traditional inventory was N\$131,950.00 (N\$10.90/ha), which is N\$650.00 per plot. Experience has also shown that 30 minutes is required to measure a traditional sample plot. The costs of the traditional inventory were derived from the expenses described in 4.3.3. The costs of the inventory carried out in this investigation using the background data from the initial traditional inventory and the two phase approach based on planning a new inventory are elaborated fully in this section.

The cost for double sampling in the current inventory was:

<i>Phase 1</i> (100 plots), fixed costs	Expenditure	N\$	N\$/ha
	Satellite image	26,900	2.22
	Software renewal	2,000	0.17
	Hardware	6,000	0.50
Variable cost	Labour per plot (N\$12.5)	1,250	0.10
<i>Phase 2</i> (50 plots)	Cost per plot (N\$650)	32,500	2.68
<b>Total</b>		<b>68,650</b>	<b>5.67</b>

The costs for the hardware and software, including its associated annual license fees are estimates. The cost for double sampling in relation to the direct sampling approach for planning purposes is:

<i>Double sampling</i>	Expenditure	N\$	N\$/ha
<i>Phase 1</i> (903 plots), fixed costs	Satellite image	26,900	2,22
	Software renewal	2,000	0,17
	Hardware (Depreciation)	6,000	0,50
Variable costs	Labour per plot (N\$24.35) incl. Support from remote sensing centre & logistics	21,989	1,82
<i>Phase 2</i> (223 plots)	Terrestrial (N\$813/plot) incl. Transport & logistics	181,299	14,97
<b>Total</b>		<b>238,188</b>	<b>19,67</b>

<i>Direct sampling</i>	Expenditure	N\$	N\$/ha
Terrestrial (384 plots)	Terrestrial (384 plots)	312,192	25,79
<b>Total</b>		<b>312,192</b>	<b>25,79</b>

In Namibia, experience has shown that phase 2 requires more time (about 2 hours), which can be attributed to extra time for geo-referencing with GPS, and longer traveling time from plot to plot. Therefore, the cost in phase 2 increased by a quarter of the traditional cost per plot. Subsequently, the cost per sample plot in phase 2 became N\$813.00. The cost of phase 2 is N\$181,299.00 which was obtained by multiplying the required 223 terrestrial plots by the cost per plot (N\$813.00). Therefore, the total cost of the double sample was N\$238,188.00 (N\$19.67/ha). The corresponding cost for the direct sample is N\$312,192.00 (N\$25.79/ha). For planning purposes, the actual costs for the two phase sample using the above parameters of this study are graphically scrutinized in figure 22 and 23.

The cost of carrying out double sampling makes sense and is justifiable if the total sampling cost for a given precision of the estimated parameter is below that associated with direct estimates (Kätsch and Van Laar, 2002). The justification was evaluated using the optimum ratio based on formula 3:

$$\begin{aligned} \text{Optimum ratio} &= \frac{813}{63} \geq \frac{0.56}{(1 - \sqrt{1 - 0.56})^2} \\ &= 12.9 \geq 4.8 \end{aligned}$$

Where:

$R^2 = 0.56$  (coefficient of determination of the model used)

$n_t = \text{N\$}813.00$  (cost per sampling plot of terrestrial sampling-planning purposes)

$n_p = \text{N\$}63.00$  (cost per sampling plot on the satellite imagery-planning)

From the calculation above, it can be seen that the two phase approach is justifiable for carrying out inventories in Hans Kanyinga Community Forest. In addition, underlining the advantages and uses of the satellite imagery in forest inventory justifies the inventory concept further as elaborated in Chapter 6. It is also important to understand that the efficiency of double sampling depends on the cost relationship between the assessment in the first and second phase and it also depends on how close the relationship is between the variable of interest (volume) and the auxiliary variable (Kätsch, 1991). The minimum value of the coefficient of determination that should be exceeded to render double sampling efficient in this investigation based on formula 4 was found to be:

$$R^2 = \frac{4 \times 813 \times 63}{(813 + 63)^2} = 0.27$$

The costs involved in double sampling are handsomely related to the number of samples and the desired standard error. This subsection shows the calculations based on the formulae given by Kättsch (1991) which were used to derive the required number of sample plots. The desired sampling error was 5% and the coefficient of variation was 49% (from the previous inventory in Hans Kanyinga Community Forest). The coefficient of determination of the model used was 56%. Based on formula 5 and 6, the number of photogrammetric and terrestrial sample plots for the actual planning of the two phase sample are:

$$n_p = \frac{385.6 \times 1.96^2}{2^2} \left[ \sqrt{12.9 \times 0.56 \times (1 - 0.56)} + 0.56 \right] = 903 \text{ plots}$$

$$n_t = 903 \times \sqrt{\frac{1 - 0.56}{0.56} \times \frac{1}{12.9}} = 223 \text{ plots}$$

Where:

$n_p$  = number of photo plots

$n_t$  = number of terrestrial plots

$S_y^2$  = 385.6 (variance of terrestrial mean volume)

$S_{y_{ds}}^2$  = 2 (5% of 40.399 m<sup>3</sup>/ha) = sampling error

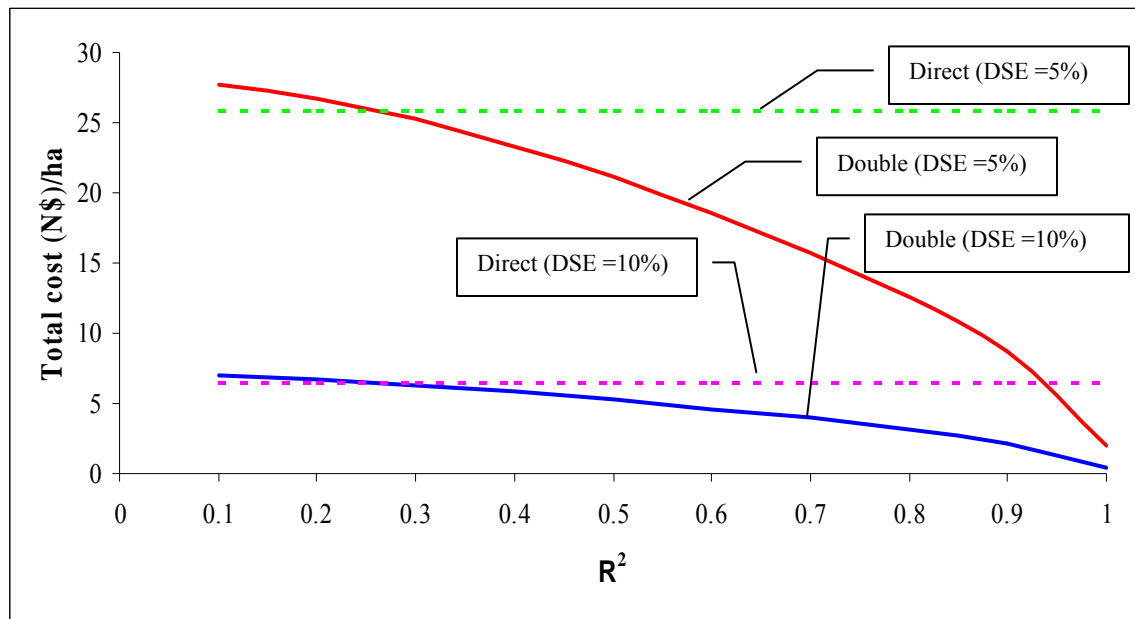
$t^2$  = 1.96 (t statistic for 95% confidence level)

$R^2$  = 0.56 (coefficient of determination of the model used)

$K$  = 12.9 (cost ratio of terrestrial plot to photo plot)

The number of sample plots also determines the sampling error to be tolerated in an inventory. This has a marked influence on the precision of the results and the cost. There are many ways of defining sampling error with distinctions made upon its applicability. FAO (s.a.) defined it as the inaccuracy of the expected inventory results. However, Kättsch (1991) defined it as the cost incurred per hectare because high sampling error leads to high costs and low sampling error leads to low costs. In this study, Kättsch (1991)'s definition of sampling error has been adopted using the inventory

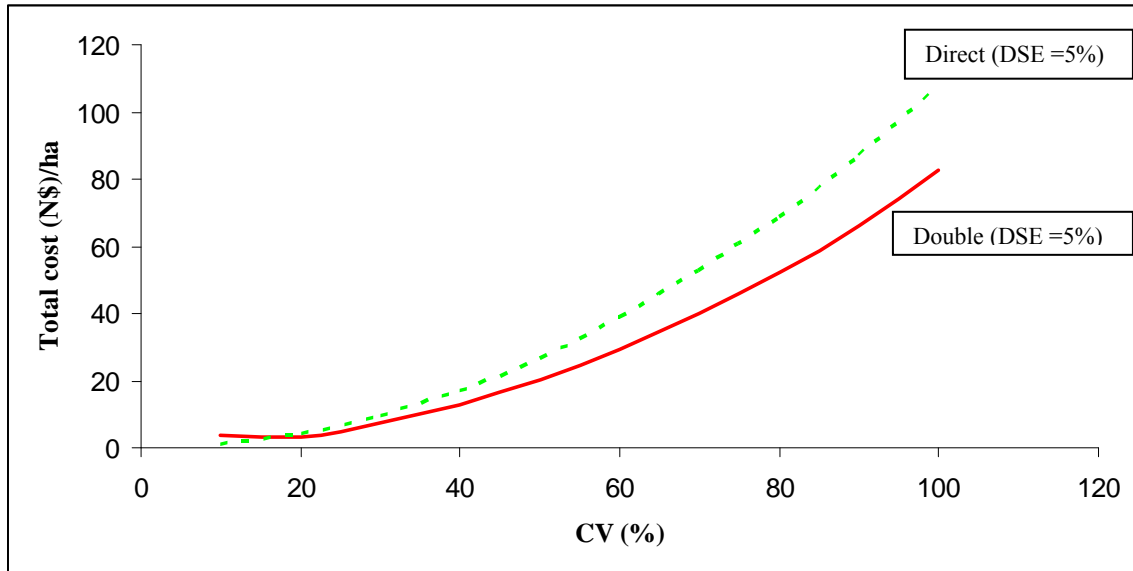
costs and parameters of this investigation. Kättsch (1991)'s definition was adopted because the current study also deals with inventory cost optimization. It is also important to note that the desired sampling error (DSE) is always a compromise between the available time, funds, manpower and required precision of the information (Lötsch *et al.* 1973). The relationship between the costs per hectare and coefficient of determination at different desired sampling errors is depicted in figure 22.



**Figure 22.** Total cost (N\$/ha) above the  $R^2$  for planning purposes using different sampling errors (DSE =  $\pm$  5% and DSE =  $\pm$  10%)

Figure 22 above shows that the total cost for double sampling is higher than the direct sampling approach but reduces as the correlation of determination increases. That is, double sampling gets more efficient as the relationship between the auxiliary and variable of interest becomes tight. This trend was also depicted by Kättsch (1991) in Germany. Higher costs in double sampling than the direct sampling approach are attributed to high investment costs, involving, software, hardware and satellite images. Other costs may include training, planning and organizational restructuring. On the other hand, the cost of direct sampling remains constant regardless of how small or big the  $R^2$  becomes. The point where these two approaches cross indicates the minimum  $R^2$  for double sampling to be efficient (0.27 from equation 3). Figure 22 further shows that the total cost per hectare is reduced as the sampling error gets smaller in both

approaches since few samples are taken. Figure 23 shows the relationship between the cost per hectare and the coefficient of variation.



**Figure 23.** Total cost (N\$/ha) above the CV for planning purposes using different sampling errors (DSE =  $\pm 5\%$ )

It is important to note that a high coefficient of variation means that there is high variability within the variable of interest i.e. stand volume in the forest. In this investigation, the coefficient of variation in stand volume is 49% obtained from the initial traditional inventory. Figure 23 above shows that the total cost of double sampling is higher than that of the double sample below the CV of 18% due to high investment costs. The double sampling approach break-evens with the total cost per hectare at the CV of 18% and beyond the break-even point both double and direct sampling approaches increase with an increase in the coefficient of variation. However, the total cost for double sampling becomes lower than for a direct sampling approach after the break-even point. It is important to observe that the total cost per hectare increases with an increase in the coefficient of variation because more plots and effort leading to higher costs is needed to sufficiently obtain a representative sample in a more diverse and variable stand.

## **6. DISCUSSION**

### **6.1 THE NECESSITY TO DEVELOP A NEW INVENTORY CONCEPT**

Traditional timber inventory methods used in Namibia are no longer appropriate for the Directorate of Forestry in Namibia. These methods provide detailed forest inventory information i.e. volume, number of stems, diameter distribution and species diversity as this information is needed for higher and lower level decision making on the management of the forest resource. However, the costs involved in collecting this information is enormous for the Government of Namibia, hence a new concept which can be used to collect the inventory information under the constraint of the budget is deemed necessary. Remotely sensed data has potential to be one of the main sources of forest information and future inventories in Namibia. At this moment, it is naïve to make a statement about the full employment of remote sensing, since this depends decisively on the inventory objectives, which are highly dynamic from area to area. This calls for a critical definition of the inventory information needs by forest managers and balance the required information with the corresponding costs of acquiring this information.

As indicated earlier, an investigation to the extent to which Landsat TM satellite imagery could be used to model woody resources, aimed at a reduction in the cost was conducted in 2002 (Verlinden and Laamanen, 2006). The results of the investigation were satisfactory for forest cover, biomass and stand volumes. However, it does not provide inventory information necessary for the local level inventories since the forest inventory focus has been shifted from regional to local level inventories. Although crown cover can be assessed from the woody monitoring system, it does not sufficiently provide information on the number of stems and diameter distributions, which are important parameters at the local level. This is due to the low spatial resolution (30 m) of the Landsat TM satellite imagery used in which distinguishing features in detail such as individual tree crowns is not possible. Therefore, in a quest for efficient and effective inventory information, the spectral characteristics of QuickBird satellite imagery are useful for identifying features such as trees, as single tree crowns.



In line with the quest for a new inventory concept, double sampling with regression estimators was investigated to determine the degree to which it can provide inventory information efficiently than the traditional inventory approach. The main aim of double sampling with regression estimators is to reduce the costs of collecting forest inventory information amplified with the multipurpose use of the concept inputs, such as the satellite image for many other purposes. Further justification of the new concept is dealt in detail in the forthcoming sections of this investigation.

## **6.2 MEASURED DATA**

### General

Looking for trees on the image requires very different and sophisticated approaches in digital image processing (Kätsch and Kunneke, 2006). In this investigation, the auxiliary attributes which were measured on the QuickBird satellite scene were used as explanatory variables to estimate tree volume, number of stems and diameter distribution. A major disadvantage encountered was that some of the explanatory variables could only be measured in sometimes unrealistic conditions. For instance, in dense, clustered and multilayered plots the assessment of the number of trees or individual crown diameters was difficult since the trees appeared fairly different on the image. Moreover, tree height, being an important variable in estimating tree volume was un-obtainable from the image because to some extent hotspots were created by the sun when the images were acquired before 9 am. Simply stated, the sensor appeared to be directly in front of the sun, thus no sun-angle could be determined. The influence of the shadows emanating from the sun angles was also depicted in an investigation by Verlinden and Laamanen (2006).

### Relationship between auxiliary and response variables

#### *Stand volume*

A detailed analysis of the photogrammetric variables indicated that the volume per hectare is mainly explained by the variables photogrammetric stems per hectare and a combination of the photogrammetric crown area and photogrammetric stems per hectare. This investigation further revealed that auxiliary variables obtained from

QuickBird satellite images are suitable and reliable in predicting stand volume. This is attributed to the good quality of the satellite image and its spectral characteristics such as the ability to see tree crowns clearly. For instance, the mean stand volume increased with an increased number of stems per hectare counted from the image. In other words, the higher the number of stems per hectare counted on the image, the higher the stand volume. This relationship made sense because an accumulation of the number of trees means an accumulation of volume as well. On the other hand, there is a weak relationship between the mean stand volume and the photogrammetric crown cover. This was possibly because there were few big sized trees and many small sized trees in the study area covering a large area with little contribution to volume. However, this result is different from other forest situations. For instance, Stellingwerf and Hussin (1997) found a positive relationship between volume and crown cover percent in beech stands.

The relationship between the photogrammetric crown area and stand volume per hectare was weak. In the case of Hans Kanyinga Community Forest, this was possible because there were many different trees with different crown growth characteristics whereby some individuals may comprise wide crowns but with relatively small bole diameters. However, this was in line with what was expected in natural woodlands where there are many small individuals with little contribution to the volume.

The relationship between the photogrammetric crown diameter and volume per hectare was very weak. This is in contrast to the findings by Kätsch (2002) in even-aged spruce stands where the coefficient of determination was high. The weak relationship between the photogrammetric crown diameter and stand volume per hectare was anticipated because of the unevenness of the forest and the highly irregular shapes of tree crowns in Hans Kanyinga Community Forest.

#### *Stand density*

Photogrammetric stand density was found to be highly correlated to the terrestrial stand density. Similarly, Stellingwerf and Hussin (1997) found this relationship in Norway spruce. However, the photogrammetric stand density was lower than the terrestrial stand

density. The low photogrammetric stand density was attributed to the growth character of natural woodlands in which some stems tend to grow under large trees hence making it impossible to see them from the satellite image. This scenario was also encountered by Tandon (1973) cited in Stellingwerf and Hussin (1997), where a higher number of trees in the understorey created an underestimation of the number of trees on the aerial photograph.

Another reason for the underestimation of the number of trees was due to the fact that some stems tend to grow in clusters, which may be judged as a single stem on the satellite image while judged as several stems during the terrestrial inventory, depending on the origin of the boles. These clusters may have been interpreted on a satellite image as single stems while in reality there were several stems and some of them may not emanate from the same stump per se, leading to a loss in the number of individuals which may translate to many stems per hectare. In other words, a cluster of several individuals may have been regarded as a single stem on the image. This was because it was difficult to make these distinctions on the satellite image since the individual stems in the clusters and stumps may not have been seen clearly.

The forking behaviour of trees also contributed to the underestimation of photogrammetric stand density. Stems which have forks below 1.3 m were regarded as individual trees (Selanniemi and Chakanga (2001)). This forking behaviour may not be seen from the satellite image, consequently leading to the assignment of the forked stems as single stems while they were regarded as several stems during the terrestrial inventory.

#### *Diameter at breast height*

Diameter distribution is important because it gives a clue of the tree sizes expected to enter useable diameter classes in the stand. It also gives an indirect clue of the forest stand age (Paine and Kiser, 2003). It is important to note that the growth phenomenon of the trees in which they have a tendency of clustering creates unrealistic situations for predicting the DBH because the visible crown diameter may be assigned to a single crown regardless of the numerous stems present in a cluster with different

diameters. The wrong positional orientation of trees in plots also meant that the paired observations of trees on the photo and in the field were not achieved. This resulted in a negative and very weak correlation between the DBH and photogrammetric average crown diameter in plots which were not assessed for positional accuracy. By contrast, the two plots which were assessed for spatial positional accuracy demonstrated a good improvement in the correlation between the DBH and photogrammetric average crown diameter. Most of the variation which was not explained by the model was chiefly attributed to the positional shift due to the GPS devices (Chapter 5) and the co-registration between satellite and terrestrial data.

Finally, the relatively low level of explanation of variation by the models in the measured data should be expected in natural and heterogeneous woodlands. This is attributed to the variable structure and species composition of the Namibian woodlands.

### **6.3 ACCURACY ASSESSMENT**

#### Error sources and their influence on the results of the study

Making errors is not needed and to believe that no errors can occur is naïve (Brassel and Lischke, 2001). Therefore, despite the efforts to achieve high quality data and to use efficient statistical estimators, the results of this study were not free of errors. Initially, a complete census of Hans Kanyinga Community Forest was impossible due to the costs, available personnel and the required time from the beginning of the inventory up to the end, including the presentation of the results. Therefore, there was no other alternative to a sample based approach.

In this sample based inventory, a small portion (sample) was selected from the entire forest stand and precisely assessed. The variables included in the sample were then used to draw an inference about the entire forest of Hans Kanyinga Community Forest. Inference to the whole forest means that the probabilities within which the individual forest elements selected for the sample are taken into account during the derivation of the statistical parameters such as mean volumes, number of stems and

diameter distribution (Brassel and Lischke, 2001). Therefore, the statistical parameters that were calculated using the sample data were applied to the entire Hans Kanyinga Community Forest.

Since only some of the tree variables were used for the derivation of the statistical parameters, the derived values for the resources in Hans Kanyinga Community Forest were not absolute values, but rather estimates. These estimates were subject to sampling errors. The calculation of the standard error was based on the assumption that an observation of the estimated volume per hectare corresponds to its actual or true value. The standard error of the mean stand volume estimate per hectare in the present investigation was found to be 5.59% and in the initial traditional inventory was 3.43%. The standard error of the mean volume estimate in the present investigation could further be reduced by increasing the number of photogrammetric sample plots which are measured at a low cost, thus becoming more cost efficient and effective. It is important to note that this estimate of the standard error of the mean volume was obtained using the formula applicable for random sampling. Usually, the formula for random sampling provides an overestimate of the sampling error for the systematic sampling (Kätsch, 2006c). As a result, it is safe to use the derived estimates of this investigation. Deviations of observed and true value occurred due to measurement errors or the wrong assignment of tree attributes such as the number of stems. Finally, the magnitude of prediction errors that occurred because the forest parameters such as the terrestrial volume were derived with the help of general functions which were not assessed in this study.

#### Evaluation of spatial tree positions

It is important to assess accuracy in remote sensing; otherwise the derived results may be misleading (Achard *et al.* 2001). The major consideration in this investigation was if the trees were mapped correctly on the satellite image. The visual display of trees on the satellite image showed the positional shift of up to 8.67 m (Chapter 5). This shift is substantial and may have resulted in the low correlations obtained in this investigation. This was also found by Verlinden and Laamanen (2006) in

Namibia. According to the specifications of the Garmin GPS II plus device used in this investigation, the error limit expected is up to 15 meters.

Other factors influencing spatial positional errors are inseparable e.g. the orientation of the satellite image. This factor was also encountered by Verlinden and Laamanen (2006) using Landsat TM satellite imagery. The Standard QuickBird satellite image used in this investigation was geo-referenced by the supplier. Geo-referencing by suppliers of satellite imagery is usually based on general analytic models, which may not provide the finest accuracy for small areas. Also, Standard QuickBird satellite images cannot be aimed for very accurate geometric positioning since the image has been naturally distorted in an irreversible way by using the coarse digital elevation models (Volpe, s.a.). However, since the terrestrial sample plots were located and measured with high expenditure, it is reasonable to assume that the positional shifts achieved here are the lowest limit possible under the practical conditions. Further positional shifts should be expected in other plots due to measurement and equipment error.

To minimize the problems associated with the shifts in positions, differential GPS may be necessary. However, the question of whether higher accuracy is necessary (such as measuring the location of each and every tree) and the questions of cost implications of such investments in various differential installations need to be addressed. Huge distances between Namibian forest areas also raise logistical problems due to the fact that more differential stations maybe necessary, leading to uplift in the cost.

#### **6.4 COST-EFFICIENCY AND QUICKBIRD APPRAISAL**

The efficiency of double sampling depends on the cost relationship between the assessment in the first and second phase and it also depends on how tightly the relationship is between the variable of interest and the auxiliary variables. The present study showed that the measurement of one sample plot on the image takes less than 15 minutes, although this varies with the tree density of a given area. From the cost efficiency calculations, it was clearly seen that the total cost of a traditional inventory in Hans Kanyinga is N\$312,192.00 (N\$25.79/ha) and for a double sample is N\$238,188

(N\$19.67/ha) which is a reduction in the inventory costs by 24%. This is insufficient evidence to reject the null hypothesis that double sampling using QuickBird satellite imagery can provide the inventory information pertaining to Namibian woodlands, efficiently and effectively since the time delivery of the inventory results is also reduced (a number of days against several months or years) and the estimates fell within 95% confidence limits. This is in line with the need to focus on more cost efficient and effective methods of collecting forest inventory information in Namibia as there is a constraint of funding. However, this is factual when the area to be inventoried is large and when the relationship between the photo and field plots parameters is high.

Caution must be exercised in estimating the costs for the terrestrial phase because the cost of a traditional or direct inventory is highly variable as it depends on the number of the inventory teams with their crews, their man-days and allowance rates. It is important to note that the motivation of the field teams is crucial for the quality of the data. As a result, good working conditions have to be created for the field teams which lead to an increase in the cost of the terrestrial inventory. Of particular interest is to compare the results of the volume estimates of double sampling to the traditional inventory. The estimated volume from this investigation was 35.728 m<sup>3</sup>/ha and the estimated volume in the traditional inventory was 40.399 m<sup>3</sup>/ha. It is important to understand that these terrestrial volumes are also error prone due to many reasons such as poor volume estimators and measurement errors. The precision of the results can be improved, but it is important to weigh the benefits of the high precision with the corresponding investment cost of obtaining the “very precise” results. It has also been demonstrated that the total cost of an inventory per hectare increases as the desired sampling error reduces. This is attributed to the fact that more sample plots are taken to ensure higher precision of the inventory results. In addition, the total cost was found to decrease as the desired sampling error increases, due to a low number of required sample plots. Furthermore, the total cost per hectare of direct sampling remained constant regardless of the increase in the coefficient of determination while the double sampling approach decreased as the coefficient of determination increased. Double sampling became more efficient when 27% of the variation could be explained by the linear model

used. The relationship between the cost per hectare and the coefficient of variation showed that double sampling becomes efficient beyond the coefficient of variation of 18% due to high investment costs. The total cost per hectare increases with an increase in the coefficient of variation because more plots and effort is required to obtain a representative sample in more variable forest stands.

The optimum ratio indicated that double sampling is an efficient means of carrying out forest inventories in Namibia. Further justification of the use of QuickBird satellite imagery in forest inventory is the relative short period of time in which most of the required forest information can be obtained, subsequently leading to lower costs as compared to traditional inventory methods where trees have to be measured for different parameters individually which in turn can be very labour intensive. One way of further reduction in cost in double sampling is to increase the extensive use of the QuickBird satellite data for other costly purposes. For example, the images can also be used for mapping, change detection and updating of existing inventory maps (Tokola *et al.* 1999; Norris-Rogers, 2004).

On the other hand, acquiring data from satellite images poses difficulties due to the fact that the information cannot be obtained at every desirable moment because it depends on the weather and on the service providers of the satellites. Satellite orbits cannot be controlled by the Department of Forestry, which means that the information can only be obtained at the moment the satellite passes over the area of interest. Furthermore, despite the long and dry cloudless seasons in Namibia, when purchasing a new satellite image tasking, it may not be possible to have a quick look of the image, this means accepting an image with at least 20% cloud cover which can be exactly on the area of interest. Special requests of images with less cloud cover may be made to the supplier of the image although there may be a significant uplift in price.

Comparing QuickBird satellite imagery with other sources of data in terms of spatial resolution, the apparent limit is the resolution (lower than aerial photographs usually at scales of about 1:20 000), but the advantage is that the different bands available on



QuickBird can be selected and combined to improve the resolution (table 3). Conversely, the availability and access to recent aerial photographs is often limited and new aerial surveys are time consuming, low frequency of obtaining photographs, costly and difficult to organize in developing countries (Holland and Marshall, s.a.). However, this limitation may be compensated by the advantages of the frequent re-visit prospects of the satellite which enables the monitoring of forest resources, fast processing of the image data and the possibility of covering large areas.

The limited area coverage of individual aerial photographs leads to a practical disadvantage whereby large area coverage of aerial photographs may need to be mosaiced from geometrically corrected and mosaiced aerial photographs. This task is far more time consuming than correcting a single satellite image scene and is prone to registration errors where expertise is inadequate.

**Table 3.** Technical comparison between QuickBird and other auxiliary data sources (Adapted from Timmerman and Strydom, 2004)

Sensor	Spectral bands	Pixel size	Special features	Radiometric resolution	Footprint	Temporal resolution	Costing (R/ha)
Aerial photography	1 and 3	Depends on flight height. Usually 10 cm to 1.5 m	Stereo capability	Depend on scan, normally 8 bits	Depends on flight height. Usually from 1 to 25 km <sup>2</sup>	Depend on weather, fuel & logistics	R1.98 to R2.10 per ha
Landsat 7 ETM+	7	15 m pan, 30 m multi-spectral	Limited stereo capability	8 bits	180 x 180 km	16 days	R0.14 per ha
SPOT5	5	2 m pan, 10 m multi-spectral	Stereo capability	8 bits	60 x 60 km	2-3 days	R0.7 to R0.25 per ha
IKONOS	Blue, Green, Red, Near infrared, Pan	0.82 m pan, 3.2 m multi-spectral	Stereo capability	11 bits	11.3 x 11.3 km	Every 3 days at 40° off-nadir	R1.90 to R2.10 per ha
QuickBird	Blue, Green, Red, Near infrared, Pan	0.61 m pan, 2.44 m multi-spectral	Stereo capability	11 bits	16.5 x 16.5 km	2-3 days	R1.54 to R1.96 per ha

Finally, in spite of the good achievements of some remote sensing techniques, the use of remote sensing within the National Forest Inventory (NFI) in Namibia has been slow. This may be due to reluctance to move away from traditional inventory methods and the limited understanding of recent developments. There is also a high rate of staff turnover in Forestry, i.e. skills loss to greener pastures such as non-governmental organizations. The apparent high cost of satellite imagery and the bureaucratic procedures for investment in satellite imagery by the government also makes the employment of remote sensing in forest inventory to move at a slow pace.

## 7. CONCLUSIONS

Traditional forest inventories operational in Namibia are increasingly becoming inappropriate. They should pave a way to integrated and multiple data collection inventory concepts to produce more comprehensive information of the forests efficiently and effectively. In this view, the recent application and scientific advances in the use of remote sensing in forest inventories have produced methods which may be useable in carrying out forest assessment. However, these methods are not universally applicable due to different forest conditions where they have been tested. It was deduced that remotely sensed data allows the updating of GIS data and improve the practical arrangements required for the fieldwork. However, the decrease in the amount of the fieldwork using remotely sensed data creates arguments with the current and possibly future informational needs since they require detailed woodland observation e.g. species diversity and regeneration information.

The results of this investigation are quite satisfactory and a plausible fit of the models to the data was obtained. The comparison of results from regression equations with the results from the traditional inventory in the same area indicated that the equations yield comparable estimates of stand volume, diameter distribution and stand density. Especially, stand volume and stand density estimates were close to the average obtained by field inventories. The trend depicted from the diameter distribution obtained in this investigation is comparable to the diameter distribution derived using traditional inventory method. Although traditional inventory method gives an indication of species composition but limited indication of spatial distribution, the inventory concept investigated here gives comprehensive high resolution distribution information but without information regarding species composition. Therefore, this concept will permit a raw inventory in Namibia which will be adequate because there are no strict schedules of activities such as thinning and other silvicultural operations.

This investigation also showed that correlating terrestrial data with satellite image data which were not measured at the same time (about less than 5 years) is not usually likely

to cause great error in Namibian woodlands because these woodlands do not change quickly (Mwiikinghi<sup>3</sup>, 2007). The change in a short period of time (less than 5 years) may be observed when there is moderate to heavy cutting or when the stand is subjected to incidences such as fire or elephant damage, which lead to a reduction in tree individuals. Moreover, for the improvement of the correlations among the variables from the image and the target variable, it is important that the size of the sample plot on the image is not too large since the counting of too many trees will unquestionably reduce the accuracy (Stellingwerf and Hussin, 1997). Small sample plots may jeopardize the statistical representation of the results due to high variations among sample plots. Therefore, a balance must be found to include an optimum number of sample plots and sizes with the required precision taking the available budget into consideration.

Furthermore, double sampling is not necessarily a separate inventory technique for obtaining forest inventory information, but it is a valuable and valid inventory concept that can be adopted in view of reducing forest inventory costs which are relatively high in Namibia. The cost calculations indicated that the inventory costs may be reduced when double sampling is used compared to traditional forest inventory. It was therefore articulated that if double sampling with its different data sources can be used for numerous purposes e.g. forest mapping and monitoring, then it becomes a much more cost effective option for financial stricken departments such as the Directorate of Forestry in Namibia.

Despite the favorable environmental conditions and the structure of the trees in using the GPS devices in Namibia, the surveying method used in this investigation is promising in obtaining accurate spatial tree positions than the GPS. The use of GPS alone may not provide exact research positions for the trees. This is chiefly attributed to the high range of positional errors to be accepted when using GPS. Therefore, there is potential to derive diameter distributions from the QuickBird imagery if the actual tree positions in the plots are known.

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<sup>3</sup> Forester in charge of Hans Kanyinga Community Forest

## 8. RECOMMENDATIONS

Future inventory concepts should focus on the information needs and technical issues of forest inventory to promote efficiency and effectiveness, being important aspects in ensuring the continuity of carrying out forest inventories. Also, future inventory concepts should be fully adapted to the information needs. Since there are increasing needs to obtain detailed and specific forest resource information in small community forest areas of Namibia, the use of the K-nearest neighbour (K-nn) concept should be explored. This concept uses satellite data or digital maps aided with field sample plot data to produce thematic maps and detailed small area inventory information (Tomppo, s.a.). The K-nn method could be used as an expansion of double sampling in the estimations with very low additional costs to the double sampling design.

In addition, multiphase approaches should also be thought of in further investigations to improve the correlations among variables. Tree height, being an important variable in volume estimation could not be obtained from the QuickBird satellite scene alone as it is dependent on the time the image was acquired. Also, trees have different growth patterns and forms therefore the use of stereo images should be thought of in the future where height is expected to have a significant contribution to the overall estimates of the target variables. These stereo images will allow the observation of the differences between trees and crown heights, leading to a fairly accurate estimation of the tree height.

Further investigations should attempt to measure a coarse network of terrestrial plots using surveying methods to determine the exact spatial position of trees in plots. Without the accurate positions of trees in sample plots, QuickBird data's utility for the determination of the diameter distributions is considered very minimal. In situations where accurate satellite imagery data is required to be linked to terrestrial data, surveying methods involving the accurate determination of distances and bearings should be carried out. GPS positions alone may not be sufficient due to the positional errors which should be tolerated and hence attracting risks of incorrect inventory results emanating from inaccurate spatial data.

Further investigations which are aimed at modeling the number of stems likely to be in a “mob” of trees observable from the satellite imagery should be carried out to improve the accuracy of tree counts. These further investigations should be coupled with the development of reference spectra to enable species recognition from the satellite image.

Finally, in order to fully convince potential users of the remote sensing technology, further investigations would be needed to determine whether the benefits of using QuickBird satellite imagery would be economically accepted in Namibia.

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## APPENDICES

### Appendix 1a. Correlations among predictor variables

	BA (cm <sup>2</sup> )	DBH (cm)	CAP (m <sup>2</sup> )	CAP*SDp	CAt (m <sup>2</sup> )	CCp (%)	CCt (%)	CDp (m)	CDt (m)	SDp	SDt	SDp*CCp	V (m <sup>3</sup> /ha)
BA (cm <sup>2</sup> )	1												
DBH (cm)	0.958	1											
CAP (m <sup>2</sup> )	-0.108	-0.036	1										
CAP*SDp	-0.246	-0.222	0.641	1									
Cat (m <sup>2</sup> )	0.257	0.290	-0.083	0.276	1								
CCp (%)	-0.092	-0.123	-0.074	0.249	0.351	1							
CCt (%)	-0.043	-0.015	0.001	0.467	0.890	0.357	1						
CDp (m)	-0.297	-0.339	-0.100	-0.116	0.082	0.358	0.137	1					
CDt (m)	0.764	0.769	-0.149	-0.152	0.638	0.152	0.419	-0.132	1				
SDp	-0.314	-0.311	0.150	0.816	0.451	0.381	0.635	-0.036	-0.163	1			
SDt	-0.370	-0.406	0.122	0.741	0.397	0.246	0.609	0.047	-0.251	0.901	1		
SDp*CCp (%)	-0.248	-0.254	0.061	0.661	0.550	0.755	0.673	0.191	-0.004	0.862	0.739	1	
V (m <sup>3</sup> /ha)	-0.059	0.046	0.269	0.692	0.598	0.107	0.689	-0.120	0.103	0.731	0.702	0.553	1

### Appendix 1b. Correlations among DBH predictor variables (position assessed plots)

	CDp (m)	DBH (cm)	CDt (m)
CDp (m)	1		
DBH (cm)	0.655	1	
CDt (m)	0.494	0.735	1

## Appendix 2. Regression diagnostics of the Stand volume model

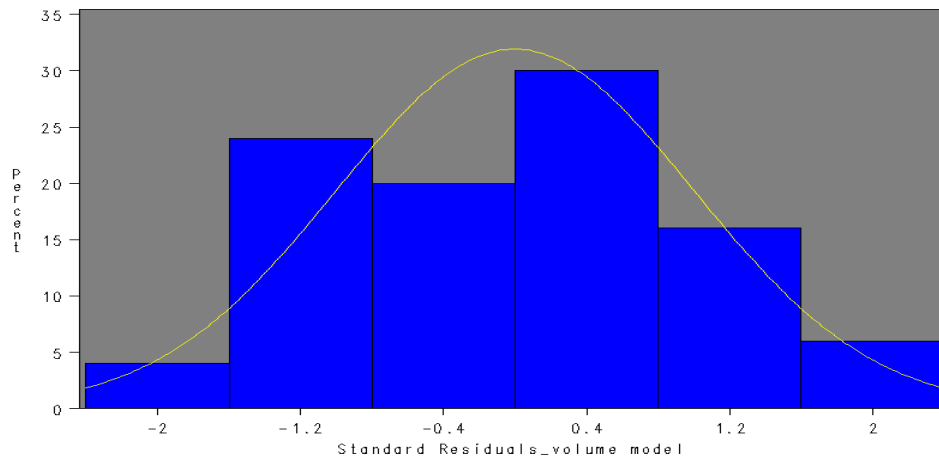
<i>Regression Statistics</i>	
Multiple R	0.750
R Square	0.562
Adjusted R Square	0.543
Standard Error	13.272
Observations	50

### ANOVA

	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	2	10615.645	5307.822	30.131	3.7915E-09
Residual	47	8279.421	176.158		
Total	49	18895.066			

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	11.339	4.490	2.525	0.015	2.306	20.371	2.306	20.371
CAp*SDp	0.012	0.071	1.703	0.095	-0.022	0.263	-0.022	0.263
SDp	1.538	0.515	2.986	0.004	0.502	2.573	0.502	2.573

<b>Tests for Normality</b>			
<b>Test</b>	<b>Statistic</b>		<b>p Value</b>
<b>Shapiro-Wilk</b>	<b>W</b>	0.980504	<b>Pr &lt; W</b> 0.5734
<b>Kolmogorov-Smirnov</b>	<b>D</b>	0.102601	<b>Pr &gt; D</b> >0.1500
<b>Cramer-von Mises</b>	<b>W-Sq</b>	0.060964	<b>Pr &gt; W-Sq</b> >0.2500
<b>Anderson-Darling</b>	<b>A-Sq</b>	0.365688	<b>Pr &gt; A-Sq</b> >0.2500



### Appendix 3. Regression diagnostics of the photogrammetric Stand density model

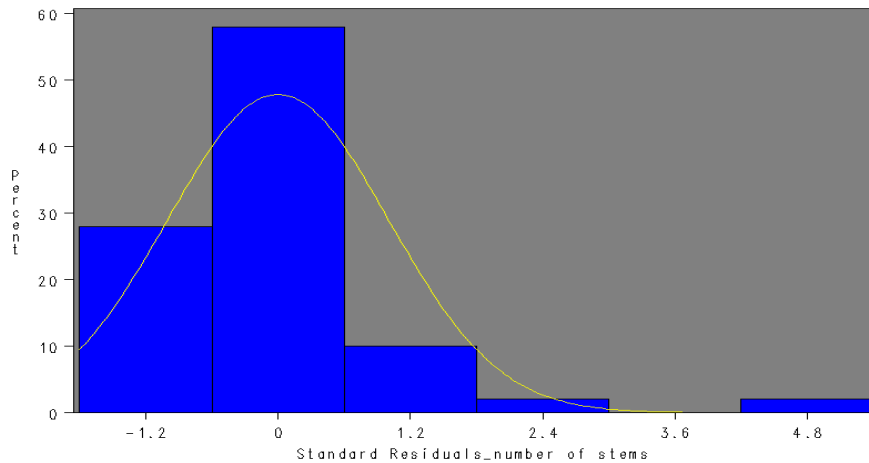
<i>Regression Statistics</i>	
Multiple R	0.901
R Square	0.813
Adjusted R Square	0.809
Standard Error	8.748
Observations	50

#### ANOVA

	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	15923.290	15923.290	208.050	4.48918E-19
Residual	48	3673.730	76.536		
Total	49	19597.021			

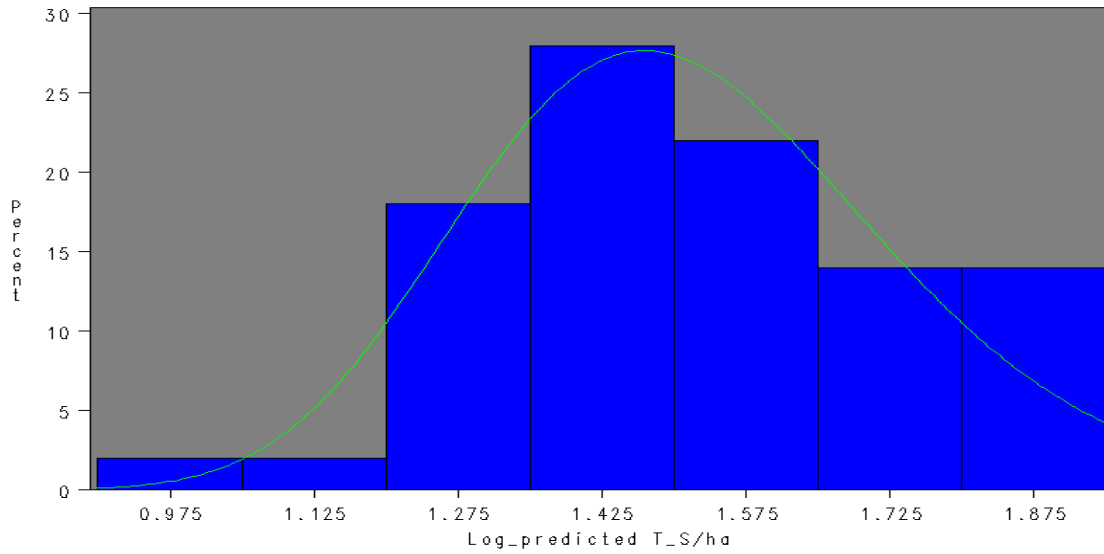
	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	-1.387	2.926	-0.474	0.638	-7.270	4.496	-7.270	4.496
SDp	2.828	0.196	14.424	0.000	2.434	3.223	2.434	3.223

<b>Tests for Normality</b>				
<b>Test</b>	<b>Statistic</b>		<b>p Value</b>	
<b>Shapiro-Wilk</b>	<b>W</b>	0.760566	<b>Pr &lt; W</b>	<0.0001
<b>Kolmogorov-Smirnov</b>	<b>D</b>	0.206633	<b>Pr &gt; D</b>	<0.0100
<b>Cramer-von Mises</b>	<b>W-Sq</b>	0.390019	<b>Pr &gt; W-Sq</b>	<0.0050
<b>Anderson-Darling</b>	<b>A-Sq</b>	2.423798	<b>Pr &gt; A-Sq</b>	<0.0050



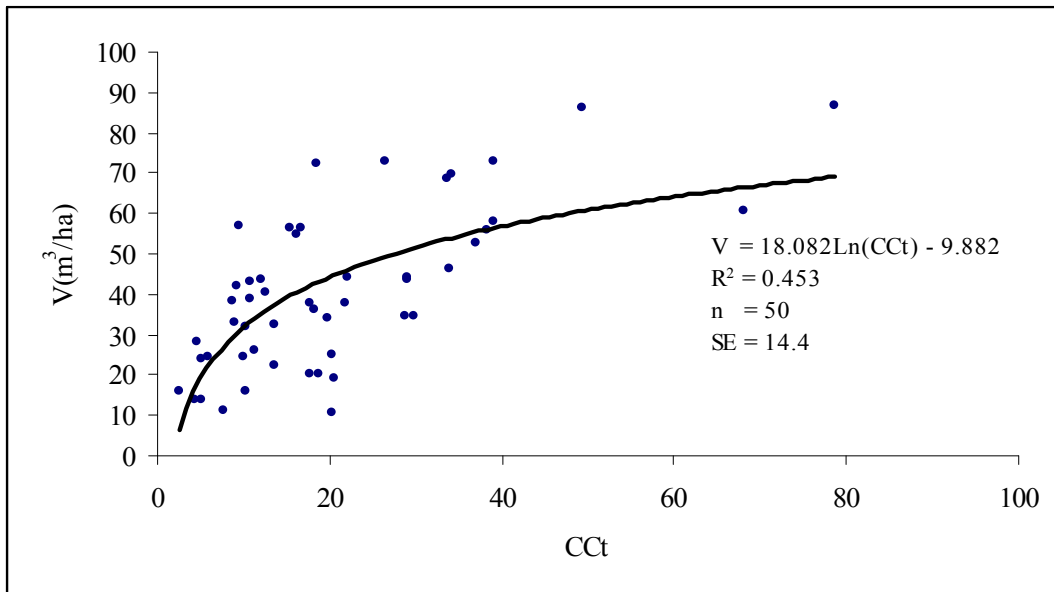
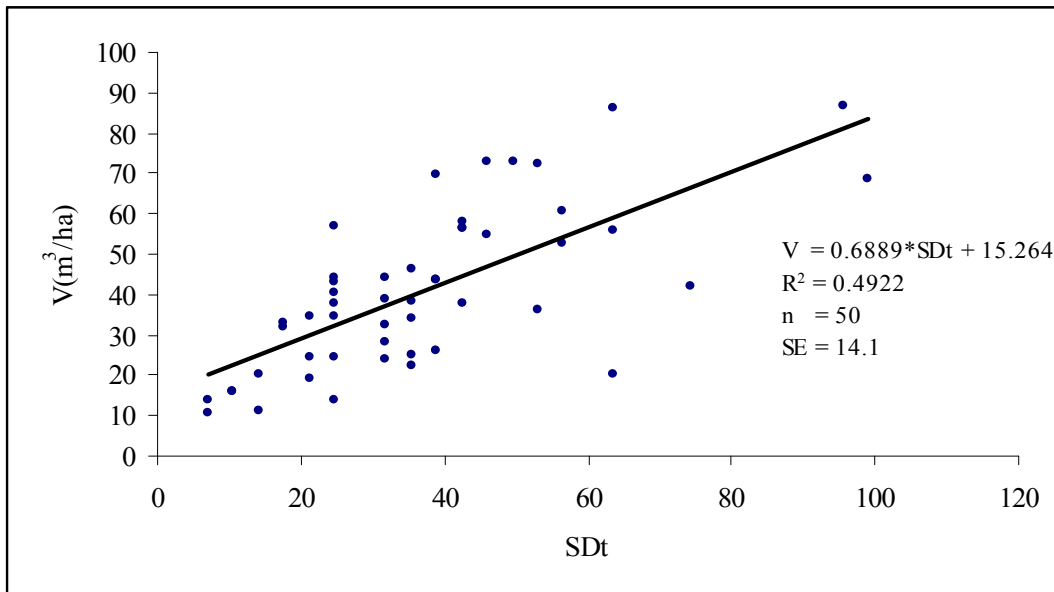
**Appendix 3 cont.** Regression diagnostics of the photogrammetric number of stems model: Lognormality test

Tests for Normality			
Test	Statistic	p Value	
Shapiro-Wilk	W 0.987103	Pr < W	0.8568
Kolmogorov-Smirnov	D 0.081044	Pr > D	>0.1500
Cramer-von Mises	W-Sq 0.035343	Pr > W-Sq	>0.2500
Anderson-Darling	A-Sq 0.230158	Pr > A-Sq	>0.2500





**Appendix 4.** Relationship between the volume and some terrestrial variables



## Appendix 5. Photogrammetric plot coordinates

PLOT	LONGITUDE	LATITUDE	PLOT	LONGITUDE	LATITUDE
2	20.40663	-18.16737	103	20.36006	-18.20722
5	20.39992	-18.17408	104	20.35334	-18.21394
7	20.41334	-18.17408	106	20.36656	-18.21394
9	20.42656	-18.17408	108	20.37999	-18.21394
11	20.39320	-18.18730	111	20.40663	-18.21394
12	20.39320	-18.19401	113	20.41985	-18.21394
15	20.39320	-18.21394	115	20.43327	-18.21394
16	20.39320	-18.22065	117	20.44649	-18.21394
19	20.39320	-18.24058	119	20.35334	-18.22044
20	20.39320	-18.24729	121	20.36656	-18.22044
23	20.31990	-18.25380	123	20.37999	-18.22044
25	20.33320	-18.25380	126	20.40663	-18.22065
27	20.34663	-18.25380	128	20.41985	-18.22065
29	20.35985	-18.25380	130	20.43327	-18.22065
31	20.37327	-18.25380	132	20.44649	-18.22065
33	20.38649	-18.25401	134	20.34663	-18.22715
34	20.39992	-18.25401	136	20.35985	-18.22715
36	20.41334	-18.25401	138	20.37327	-18.22715
38	20.42656	-18.25401	140	20.38649	-18.22736
40	20.43999	-18.25401	141	20.39992	-18.22736
42	20.45320	-18.25401	143	20.41334	-18.22736
45	20.45320	-18.23408	145	20.42656	-18.22736
46	20.45320	-18.22736	147	20.43999	-18.22736
49	20.45320	-18.20722	149	20.33320	-18.23387
50	20.45320	-18.20072	151	20.34663	-18.23387
52	20.44670	-18.19401	153	20.35985	-18.23387
54	20.43327	-18.19401	155	20.37327	-18.23387
56	20.42006	-18.19401	157	20.38649	-18.23408
58	20.40663	-18.19401	158	20.39992	-18.23408
61	20.37999	-18.19380	160	20.41334	-18.23408
64	20.40663	-18.18730	162	20.42656	-18.23408
66	20.42006	-18.18730	164	20.43999	-18.23408
68	20.43327	-18.18730	166	20.32670	-18.24058
71	20.44670	-18.18730	168	20.33992	-18.24058
72	20.37999	-18.18730	172	20.36656	-18.24058
73	20.39992	-18.18058	174	20.37999	-18.24058
75	20.41334	-18.18058	177	20.40663	-18.24058
77	20.42656	-18.18058	179	20.41985	-18.24058
80	20.37327	-18.20051	181	20.43327	-18.24058
82	20.38670	-18.20072	183	20.44649	-18.24058
83	20.39992	-18.20072	185	20.32670	-18.24729
85	20.41334	-18.20072	187	20.33992	-18.24729
87	20.42656	-18.20072	189	20.35334	-18.24729
89	20.43999	-18.20072	191	20.36656	-18.24729
92	20.37327	-18.20722	193	20.37999	-18.24729
94	20.38670	-18.20722	196	20.40663	-18.24729
95	20.39992	-18.20722	198	20.41985	-18.24729
97	20.41334	-18.20722	200	20.43327	-18.24729
99	20.42656	-18.20722	202	20.44649	-18.24729
101	20.43999	-18.20722	203	20.38670	-18.18058

**Appendix 6.** Terrestrial plot coordinates

PLOT	LONGITUDE	LATITUDE	PLOT	LONGITUDE	LATITUDE
2	20.40663	-18.16737	166	20.32670	-18.24058
7	20.41334	-18.17408	172	20.36656	-18.24058
11	20.39320	-18.18730	179	20.41985	-18.24058
16	20.39320	-18.22065	183	20.44649	-18.24058
19	20.39320	-18.24058	187	20.33992	-18.24729
20	20.39320	-18.24729	191	20.36656	-18.24729
25	20.33320	-18.25380	198	20.41985	-18.24729
29	20.35985	-18.25380	202	20.44649	-18.24729
33	20.38649	-18.25401	203	20.38670	-18.18058
36	20.41334	-18.25401			
40	20.43999	-18.25401			
49	20.45320	-18.20722			
50	20.45320	-18.20072			
54	20.43327	-18.19401			
58	20.40663	-18.19401			
61	20.37999	-18.19380			
66	20.42006	-18.18730			
71	20.44670	-18.18730			
75	20.41334	-18.18058			
80	20.37327	-18.20051			
83	20.39992	-18.20072			
87	20.42656	-18.20072			
92	20.37327	-18.20722			
95	20.39992	-18.20722			
99	20.42656	-18.20722			
104	20.35334	-18.21394			
108	20.37999	-18.21394			
111	20.40663	-18.21394			
115	20.43327	-18.21394			
121	20.36656	-18.22044			
128	20.41985	-18.22065			
132	20.44649	-18.22065			
136	20.35985	-18.22715			
140	20.38649	-18.22736			
143	20.41334	-18.22736			
147	20.43999	-18.22736			
149	20.33320	-18.23387			
153	20.35985	-18.23387			
157	20.38649	-18.23408			
160	20.41334	-18.23408			
164	20.43999	-18.23408			

**Appendix 7.** Regression diagnostics of the photogrammetric crown diameter and DBH

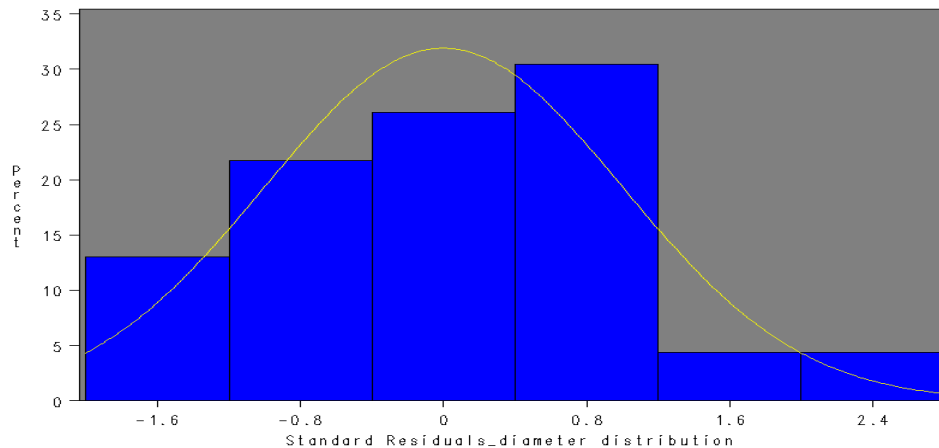
<i>Regression Statistics</i>	
Multiple R	0.655
R Square	0.429
Adjusted R Square	0.402
Standard Error	6.973
Observations	23

ANOVA

	<i>df</i>	<i>SS</i>	<i>MS</i>	<i>F</i>	<i>Significance F</i>
Regression	1	767.969	767.969	15.796	0.001
Residual	21	1021.009	48.619		
Total	22	1788.978			

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	-4.257	7.407	-0.575	0.572	-19.660	11.147	-19.660	11.147
CDp	5.580	1.404	3.974	0.001	2.660	8.500	2.660	8.500

<b>Tests for Normality</b>				
<b>Test</b>	<b>Statistic</b>		<b>p Value</b>	
<b>Shapiro-Wilk</b>	<b>W</b>	0.978198	<b>Pr &lt; W</b>	0.8733
<b>Kolmogorov-Smirnov</b>	<b>D</b>	0.08062	<b>Pr &gt; D</b>	>0.1500
<b>Cramer-von Mises</b>	<b>W-Sq</b>	0.026498	<b>Pr &gt; W-Sq</b>	>0.2500
<b>Anderson-Darling</b>	<b>A-Sq</b>	0.189355	<b>Pr &gt; A-Sq</b>	>0.2500



**Appendix 8.** Specifications of the GPS used in this investigation  
 Source: [Online] [www4.shopping.com/xPF-Garmin-GPS-II-Plus](http://www4.shopping.com/xPF-Garmin-GPS-II-Plus)

**Garmin GPS II Plus GPS Receiver**



**Specifications and Features**

Designation	Outdoor
Receiver type	Parallel-Channel (12)
Resolutions	100 X 64
Trip calculator	Maximum speed
Grids	Irish, Lat/Lon, Swedish, Swiss, User Grid, UTM, Maidenhead, Taiwan
Acquisition time - cold	45 sec
Acquisition time - warm	15 sec
Update rate	1 per second, continuous
Max. Horizontal accuracy	< 49 feet (15 meters)
Differential standards	DGPS Ready
Number of routes	20
Waypoints	500