Estimating Woody Vegetation Cover in an African Savanna using remote sensing and Geostatistics

By

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Declaration

This document describes study undertaken in fulfilment of a Master of Science Degree in the Discipline of geography and represents the original work of the author. Any source of information cited from other authors or institutions are duly acknowledged within the content of this document.

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Clement Adjorlolo

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Supervisor: Professor Onisimo Mutanga

Dedication

Dedicated to my dear son Selorm

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Abstract

A major challenge in savanna rangeland studies is estimating woody vegetation cover and densities over large areas where field based census alone is impractical. It is therefore crucial that the management and conservation oriented research in savannas identify data sources that provides quick, timely and economical means to obtain information on vegetation cover. Satellite remote sensing can provide such information. Remote sensing investigations, however, require establishing statistical relationships between field and remotely sensed data. Usually regression is the empirical method applied to field and remotely sensed data for the spatial estimation of woody vegetation variables. Geostatistical techniques, which take spatial autocorrelation of variables into consideration, have rarely been used for this purpose. We investigated the possibility of improving woody biomass predictions in tropical savannas using cokriging. Cokriging was used to evaluate the cross-correlated information between SPOT (Satellites Pour l'Observation de la Terre or Earth-observing Satellites)-derived vegetation variables and field sampled woody vegetation percentage canopy cover and density. The main focus was to estimate woody density and map the distribution of woody cover in an African savanna environment. In order to select the best SPOT-derived vegetation variable that best correlate with field sampled woody variables, several spectral vegetation and texture indices were evaluated. Next, variogram models were developed: one for woody canopy cover and density, one for the best SPOT-derived vegetation variable, and a cross-variogram between woody variables and best SPOT-derived data. These variograms were then used in cokriging to estimate woody density and map its spatial distribution. Results obtained indicate that through cokriging, the estimation accuracy can be improved compared to ordinary kriging and stepwise linear regression. Cokriging therefore provided a method to combine field and remotely sensed data to accurately estimate woody cover variables.

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Chapter 1. Introduction

1.1 Background

Savanna is a vegetation type defined by a mixture of trees and grasses that characterize vast areas of tropical landscapes. Savanna landscapes represent one of the largest biomes worldwide and are well known for their inherent dynamism (Sharp & Bowman 2004). Specifically, the dynamic vegetation composition and relative cover of the mixed trees and grasses that characterize savannas have important ecological effects such as their influence on density, diversity and distribution of wildlife (Mcnaughton & Banyikwa 1995; Mutanga *et al.* 2004; Mutanga & Rugege 2006). Savanna woody vegetation is also an important biophysical variable related to a wide range of other savanna ecosystem components, such as woody and herbaceous biomass, hydrological cycles, soil carbon and nitrogen pools (Hudak *et al.* 2003).

Research has shown that savanna woody vegetation do not only influence the density and distribution of wildlife species, but they are themselves susceptible to significant transformations due to complex ecological factors and varying land-management practices such as landuse changes (Hudak & Brockett 2004; Gillson & Duffin 2007). For example, prolonged variations in rainfall intensity, and altered fire regimes accompanied by shifts from one land-management system to another have had major and continuing impacts on savanna landscapes, and specifically on woody vegetation density and canopy cover distribution (Couteron 2002; Hudak & Brockett 2004). In this regard, information on the distribution and spatial variations in woody vegetation density and canopy cover in savanna environments is critical for making timely assessments of savanna ecosystem condition (Coops & Culvenor 2000).

Woody vegetation density and canopy cover assessment in savannas has been a major challenge to rangeland ecosystem managers and researchers. Ecosystem managers in South Africa, particularly in the Kruger National Park (KNP) use series of monitoring endpoints often denoted as *thresholds of potential concerns* (TPCs) to define the upper and the lower limits of acceptable changes in biodiversity (Gillson & Duffin 2007). The limits of acceptable changes in vegetation resource components of savanna biodiversity can be; spatial distribution, density and floristic composition. For instance, in the KNP it is suggested that TPC for woody vegetation density or cover in any landscape group should not drop by more than 80% of its highest ever value and the mean drop for the entire KNP is expected not to exceed 30% (Gillson & Duffin 2007). This technique views the conservation of biodiversity as the ultimate goal. Hence, it uses thresholds to determine an acceptable range along a continuum of patterned change for a selection of measurable vegetation variables to establish whether management is achieving its goals. However, if a component of the vegetation resources, e.g. bush encroachment or loss of woody vegetative cover exceeds its thresholds, then there is need for potential concern. It is therefore crucial that the management and conservation oriented research in savannas should identify data sources that provides quick, timely and economical means to obtain information on woody vegetation cover and its density estimations.

In the past, assessment of woody vegetation density and canopy cover in the vast arid to semiarid savanna environments has been limited to analysis of field data. The acquisition of field data for relatively large areas can be impractical, considering that longer time of fieldwork is required, and the related issues of accessibility, personnel, and cost constraints. In this respect, remote sensing applications can provide information that is quick, timely and economical for the estimation of vegetation resources over large and complex savanna environments. Satellite remote sensing measurements of vegetation reflectance, for example, SPOT5 (Satellites Pour l'Observation de la Terre or Earth-observing Satellites) and Multi-Spectral Scanner (MSS) have provided repetitive local to regional coverage data that is useful for vegetation studies (Hudak & Wessman 1998). Remotely sensed data such as SPOT5 image provides a means to extend the traditional techniques of ground-based vegetation survey by providing high resolution multispectral imagery useful to estimate the amount and the extent of vegetation distribution over large areas where field-based data alone could be insufficient.

Remote sensing is shown to play a critical role in acquisition of data, and have been widely used to model the spatial variability of vegetation density or cover in different vegetation types (Yang J. & Prince, 1997; Skidmore *et al* 1997; Moskal & Franklin, 2001; Hudak & Brockett, 2004; Olsson, 1984). However accurate remote sensing of vegetation in savannas has been prohibited by its complex stand structure and abundant vegetation species. Since savannas generally depict complex stand structure and abundant vegetation species, the development of remote sensing techniques to estimate vegetation has been biased toward savanna landscapes, as compared to other vegetation types such as forests. In addition, although several studies investigate the applications of remotely sensed data for vegetation estimation, identification of the remotely sensed data that best correlate with woody density or canopy cover variables have not been well-established for specific savanna landscapes. Only a handful of researches conducted in the African savanna ecosystems demonstrate analysis of spectral data, such as individual spectral bands, spectral vegetation indices (SVI), image spatial transformation by textural analysis, and spectral mixture analysis (SMA) at varying accuracies for the spatial estimation of woody vegetation cover and density in savanna woodlands (Hudak & Wessman 1998; Yang & Prince 2000; Hudak & Wessman 2001; Hudak *et al.* 2003; Small 2003; Ellis *et al.* 2006; Murwira & Skidmore 2006; Wessels *et al.* 2006). For example, Hudak & Wessman, (1998) characterized woody plant encroachment in the South African savanna by sampling several woody canopy structural traits (including density as well as percentage canopy cover) and correlates with few first order image texture indices. In the study the authors suggest that the application of textural indices to high resolution imagery has potential for estimating woody structural variables where spectral vegetation indices fail. To assess the potential of spectral vegetation indices such as the Normalized Difference Vegetation Index (NDVI) derived from the Advanced Very High Resolution Radiometer (AVHRR) data to estimate vegetation productivity in the KNP, Wessels et al, (2006) evaluated the influence of tree cover on NDVI-biomass relationship using woody vegetation density and canopy diameter variables.

Various image transformation techniques have been tested for the purpose of estimating woody density or cover in the African savanna environment (Hudak & Wessman 1998; Yang & Prince 2000; Hudak & Brockett 2004; Mutanga & Skidmore 2004; Wessels *et al.* 2006). However, none of them to our knowledge have compared the spectral approach using spectrally derived vegetation indices with that of spatial image transformation by texture analysis to determine the most suitable image variable for woody canopy cover and density estimation. Selection of the most suitable remotely sensed vegetation variable is critical for the reliability of vegetation modelling. In this respect, this study mainly focused on identifying suitable SPOT image data by establishing statistical relationships between woody vegetation density and canopy cover variables, using both SPOT5 vegetation and texture indices, as well as SPOT panmerged spectral bands. Other woody vegetation variables such as crown diameter, basal area of tree, height of tree, woody stem diameter and density of woody shrubs were also measured to evaluate how they relate to the remotely sensed SPOT derived vegetation and texture indices.

Research has revealed that studies of savanna ecological systems can be improved by integrating ecosystem modelling and remote sensing applications (Buyantuyev *et al.* 2007). Modelling ecological systems such as the savanna landscapes often requires the application of traditional methods of identifying statistical relationships between field and remote sensing data. Usually regression is the empirical method applied to field and remotely sensed data for the spatial estimation of woody vegetation variables. Ordinary regression method do not make maximum use of field and remotely sensed data because it ignores the spatial dependence of the two datasets (i.e. woody cover variable and derived SPOT vegetation data), and do not account for interdependence of the field and remote sensing data (Mutanga & Rugege 2006). Since ordinary regressions do not take into consideration the spatial autocorrelation in the vegetation and its radiation (Atkinson *et al.* 1994; Mutanga & Rugege 2006), the technique has resulted in either under estimation or over estimation of vegetation resources in the African savannas (Said 2003; Mutanga & Rugege 2006). In this respect, it is important for vegetation modeling to consider the fundamental principle that the vegetation natural groupings depicts spatial (data) distribution and spatial interdependence within vegetation communities and its radiation derived from remote sensing data, which are spatially correlated both to themselves (auto correlated) and to one another (cross correlated) (Atkinson *et al.* 1992; Mutanga & Rugege 2006).

Geostatistical techniques which take spatial autocorrelation of sparsely (e.g. woody canopy cover and density) and intensively sampled variables (e.g. SPOT data) into consideration can combine field and remote sensing data and model their interdependence simultaneously through cokriging. Cokriging is an extension of ordinary kriging which takes into consideration spatial dependency. The method has been applied to model herbaceous biomass distribution in the African savanna woodland (Mutanga & Rugege 2006), but so far this technique has not been tested for woody cover distribution and spatial estimation. The extension of the technique to estimate woody cover density and distribution is expected to improve the accuracy since it combines remotely sensed data, an intensively sampled auxiliary vegetation variable with sparsely sampled woody cover structural parameters.

This study investigated the suitability of intensively sampled SPOT satellite imagery and field sampled data for the estimation of woody vegetation cover in the KNP. The objective was to predict woody vegetation density and canopy cover distribution by establishing geostatistical relationships between the woody vegetation variables and remotely sensed SPOT data. In order to choose the best SPOT image variable for subsequent geostatistical analysis (co-kriging), preliminary analyses of the SPOT imagery were conducted. That included measures of texture analysis and spectral vegetation indices, as well as the raw multispectral and panmerged SPOT image data.The purpose was to evaluate the utility of a geostatistical technique (cokriging) to estimate woody vegetation cover with woody density serving as a dependent variable and the best SPOT derived spectral vegetation or texture index serving as independent variables. The results obtained from cokriging were validated and compared to those obtained from ordinary kriging using the field samples alone (ordinary kriging) as well as to those obtained using linear regression.

1.2 Aim and Objectives of the study

In the light of this background, the aim of this study was to investigate the utility of high-resolution satellite images in combination with geostatistics to assess the density and spatial distribution of woody vegetation cover in a semiarid African savanna. The study specifically aimed to employ geostatistical approaches to this investigation: cokriging with field and remote sensing data. An integration of remote sensing and geostatistics (particularly cokriging) was used to estimate woody vegetation density and spatial distribution in an experimental study area of Kruger National Park, South Africa. The aim of this study could be accomplished by considering the following objectives:

- Evaluate the utility of different vegetation indices and texture measures to characterise savanna woody vegetation cover.
- Compare the utility of SPOT5 multi-spectral and SPOT Panmerged imagery to estimate savanna woody cover.
- Predict woody vegetation canopy cover and density using geostatistical techniques (particularly cokriging) with the SPOT-derived spectral vegetation data or image texture measure that best correlates with the woody cover and woody density variables.

1.3 Key Research Questions

- Which image texture algorithm or spectral vegetation data is most appropriate to characterise savanna woody vegetation cover?
- Which spatial resolution of SPOT image is the most appropriate to characterise savanna woody vegetation cover?
- To what extent can geostatistical techniques (particularly co-kriging) improve estimation of savanna woody vegetation density and canopy cover?

1.4 Organisation of the Thesis

The overall organisation of this thesis is in two major sections. Section one is divided into two parts. Part one involved preliminary analysis of SPOT satellite imagery to extract spectral vegetation and texture indices, and the analysis of field sampled woody cover parameters. The second part of section one was to establish statistical relations between woody vegetation cover and density variables and SPOT derived vegetation and texture indices as well as the raw SPOT (multispectral and panmerged) imagery, with the purposes of identifying the best SPOT derived vegetation variable through simple linear correlation analysis.

The second section is modelling woody vegetation cover using regression and geostatistical techniques to estimate woody vegetation cover in the study area. Analysis in this section is three fold: first is stepwise multiple linear regression with the field sampled woody cover as well as woody density and the best SPOT derived vegetation or texture indices selected in section one. The second is ordinary kriging using field data alone for quantitative prediction of woody cover density, and cover. The third is cokriging with the woody vegetation cover and density variable serving as the dependent (primary) variables and the best SPOT derived vegetation or texture indices serving as independent variables, with the purpose to quantitatively predict the woody vegetation density and cover distribution. In order to draw conclusions, the results obtained from cokriging were validated and compared to those obtained from kriging using the field samples alone (ordinary kriging) as well as to those obtained using linear regression. Figure 1.1 illustrates the flow chart for the conceptual framework of the research.

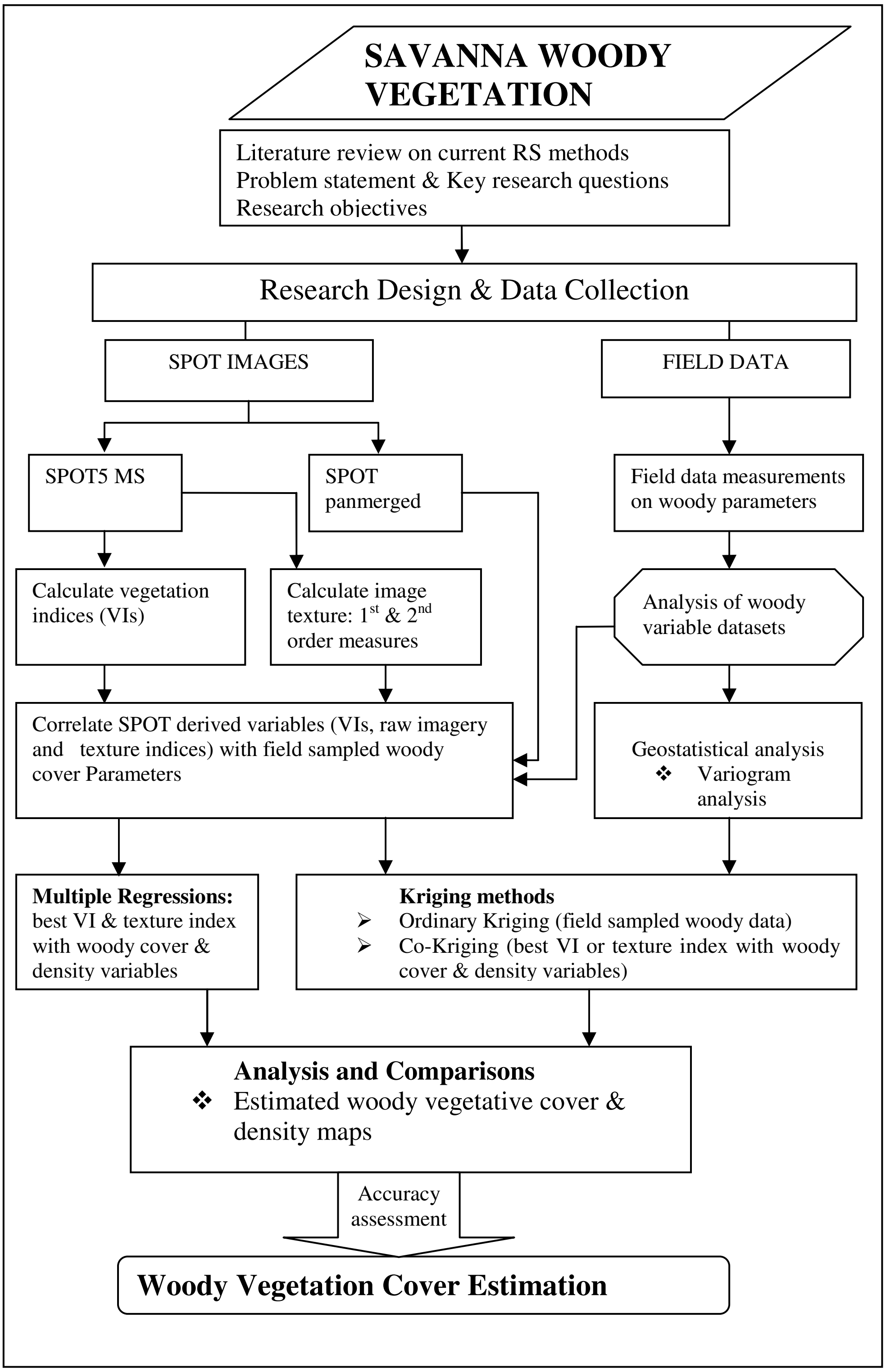

Figure 1.1: Flowchart for methods followed in this research
RS = remote sensing
SPOT = Satellites Pour l'Observation de la Terre,
MS = multispectral,VI = vegetation index

1.5 Study Area

The study area is located in Shingwedzi woodlands of the Kruger National Park (KNP). KNP is situated on the eastern side of Limpopo and Mpumalanga provinces of South Africa. Figure 1.2 shows the location of the study area. Geographically the KNP lies between 30^0 53' 18'' E, 22^0 19' 40'' S and 32^0 01' 59'' E, 25^0 31' 44'' S, covering a total area of 2 000 000 Ha and extends 360 km from north to south. The KNP falls within the savanna biome with a diverse landscape classified into significant environmental units for the purpose of conservation planning and management (Wessels *et al.* 2006). Thirty-five landscapes have been identified based on geomorphology, climate, soil, vegetation pattern and associated fauna (Gertenbach 1983). A simplified classification joined the 32 landscapes into 17 landscape groups.

Kruger National Park experiences 4 to 8 months hot, wet season (October to April) and a mild, dry winter (May to August). KNP is crossed by seven major river systems, all of which originate to the west of the KNP and drain a combined area of about 860 000 Ha (Mabunda *et al.* 2003). Estimated woody canopy cover in the northern woodlands ranges from 5 to 60% and is dominated by *Acacia spp., Combretum spp*. and *Colophospermum mopane* (here after refer as mopane) (Venter *et al.* 2003).The soils of the region are derived from the underlying undifferentiated metamorphic rock and amphibolite of the Swaziland system, as well as granite (Khomo & Rogers 2005). Away from the rivers the soils form shallow red clays becoming deeper with more recent alluvia adjacent to the river (Venter *et al.* 2003; Khomo & Rogers 2005). Tree size and tree density decrease with increasing distance from the riparian zone.

Generally, savannas are structurally heterogeneous at the local, landscape-level due to fine-scale floristic heterogeneity as well as the responses of individual species to underlying environmental variation (Hempson *et al.* 2007). However, in the Shingwedzi region of the Kruger National Park, the structure of mopane woodland which is an arid savanna of southern Africa, there is little local variation in the relative dominance of woody tress and shrubs forms of the dominant species, *Colophospermum mopane* across continuous environmental settings such soil forms and plant available moisture condition (Khomo & Rogers 2005 ; Hempson *et al.* 2007).

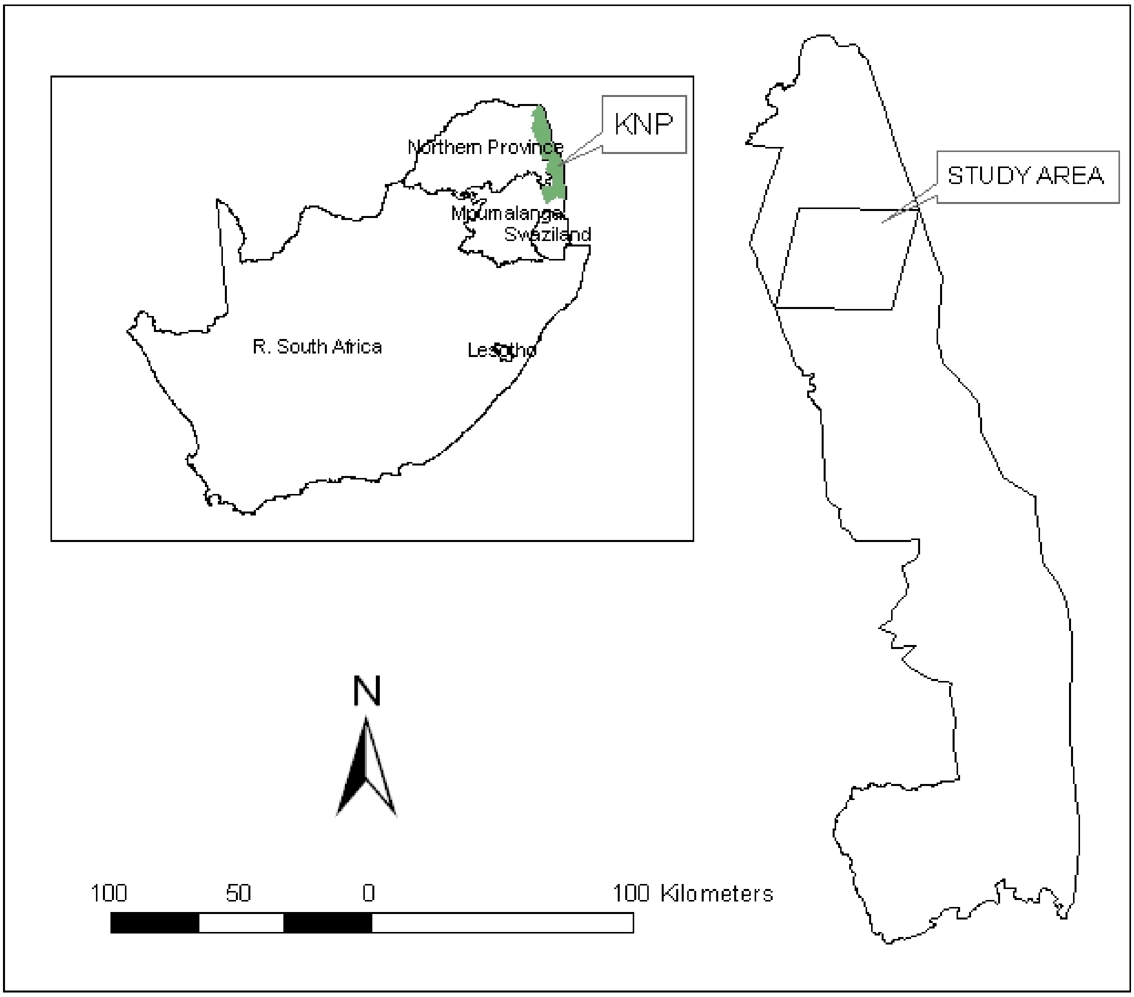

Figure 1.2: Location of the Study Area in the Kruger National Park (KNP)- South Africa

Chapter 2. Literature Review

Throughout sub-Saharan Africa, rainfall is highly seasonal and temperatures can rise as high as 45^{o}C or more. Arid and semiarid savannas are dominant ecosystems occupying this type of climatic region. It is common ecological knowledge that woody vegetation is an important characteristic of woodland savannas. However, characterizing the structure, composition and dynamics of the mixed trees and grasses in savanna areas has been a major challenge to savanna vegetation studies. Remote sensing data is often correlated with field sampled data to determine the relationships between biophysical variables such as woody vegetation cover and remotely sensed data with mixed results. However, until recently only a few studies have integrated remote sensing and other techniques such as spatial statistics for the spatial estimation of vegetation resources in savannas (Mutanga & Rugege 2006). This chapter reviews literature on three main approaches which are addressed in this study: the relationship between savanna woody vegetation variable and remote sensing data using image analysis methods based on (i) spectral vegetation and (ii) texture indices, and (iii) geostatistical techniques of interpolation

2.1 Remote sensing of vegetation density estimation and Savanna study

Increasingly, the application of remotely sensed data has proved to be the most efficient means to assess vegetation cover or density. Remote sensing-based vegetation estimation methods and assessment of existing issues influencing vegetation estimation are inevitable for improving estimation accuracy. However, vegetation canopy cover or density estimation remains a difficult task especially in areas with complex vegetation stand structures and heterogeneous environmental conditions. Various techniques based on integration of field measurement and remote sensing have been applied for vegetation modelling (Yang J. & Prince, 1997; Skidmore *et al* 1997; Moskal & Franklin, 2001; Hudak & Brockett, 2004; Olsson, 1984).

Savannas are described as tropical vegetation consisting of a continuous grass layer usually with a sparse canopy of either trees or woody vegetation. Savanna ecosystems worldwide occupy about 20% of the Earth's land surface (Stott 1991) and support a diverse community of species. At the regional or landscape level the savanna biome is estimated to occupy 46% of southern Africa and over one third of South Africa, making it the largest biome in southern Africa (Low & Rebelo 1998).

Savanna structure and dynamics are influenced by many factors that determine the vegetation structure and composition. These factors can be primary and secondary determinants. The primary determinants can be available plant moisture, available nutrients, soil types and geographical gradients. These factors influence the vegetation structural composition and vary spatially at both regional and local scales. The secondary determinants can be fire frequencies and intensity, as well as herbivory, which varies in spatial extent and intensity. The structure and dynamics of savannas are therefore a consequence of various disturbances acting within the constraints of the primary determinants (Mentis & Bailey 1990).

Although, savannas support a large community of species, most of them are extensively exploited for crop cultivation, livestock grazing, commercial forestry and infrastructure development. Due to the extensive human over-utilization or reckless exploitation caused by over-stocking, shorter fallow periods between crops, fuel-wood harvesting and changing fire patterns have specifically altered the African savanna landscapes and these continue to influence rapid changes in vegetation productivity, structure and biodiversity composition (Hudak & Brockett 2004). In this regard, the establishment of protected areas systems (PAs) and the biodiversity conservation status designated in some savanna rangelands ecosystems have so far helped to protect some savannas from further degeneration. However, vegetation resource dynamics in PAs are inherently unstable (McNaughton 1984; Scholes & Archer 1997), as well as the vegetation structure is influenced by both ecological factors (e.g. climate change, soil and available moisture) and effects of ecosystems management practices (e.g. vegetation resource burning and fire regimes, herbivory, desertification, and distribution of available watery sites). Several studies have revealed that the dynamics of woody cover density and distribution could specifically have serious implications on the savanna vegetation structure and floristic composition (Hudak & Wessman 2001; Hudak *et al.* 2003; Hudak & Brockett 2004; Hudak *et al.* 2004).

Given that savanna vegetation dynamics are inherently unstable, they variably, respond spatially to unpredictable disturbances (Hudak *et al.* 2004). For example, in a study on the assessment of habitat heterogeneity in a savanna environment using variance measures derived from remotely sensed images, Murwira and Skidmore (2006) found out that woody vegetation cover patterns in an African savanna ecosystem are spatially distributed and highly heterogeneous. In addition, several studies have indicated that spatial variation of vegetation cover in the savanna ecosystem is an important indicator of species habitat selection (Mcnaughton & Banyikwa 1995; Mutanga *et al.* 2004; Mutanga & Rugege 2006). The vegetation resource (woody cover) which is an important biophysical variable related to the structure of savannas is an important determinant factor of the savanna status (Gareth *et al.* 2007). In this regard, investigations into the spatial aspects of woody vegetation component of savannas have been considered as an important step towards improved understanding of the patterns and distributions of species habitat requirement since vegetation resources influence the density and diversity of wildlife species, and their habitat preference (Mcnaughton & Banyikwa 1995; Mutanga *et al.* 2004; Mutanga & Rugege 2006).

In a series of articles, it is increasingly recognized that assessment of variations in vegetation productivity and its spatial distributions is an important technique for understanding the factors (e.g. woody overstorey effects on soil carbon and nitrogen pools) driving local to global environmental change (Turner II *et al.* 1994; Hudak *et al.* 2003). In southern African, several studies have emphasized the importance of spatial estimation of vegetation resources in savanna environments and assessment of implications for global landcover change (Hudak & Wessman 1998; Yang & Prince 2000; Hudak & Brockett 2004; Murwira & Skidmore 2006). For example, Hudak & Wessman, (2001) noted that transformations in savannas, such as woody vegetation encroachment phenomenon have important habitat implications relating to significant shifts in the savanna ecosystem function. In addition, the spatial dynamics of savanna vegetation resources, particularly woody tree cover (reported to have negative relationship with herbaceous biomass (Wessels *et al.* 2006)influences the density and distribution of wildlife (Curran & Foody 1994; Mcnaughton & Banyikwa 1995; Mutanga & Rugege 2006) as well as influencing the occurrence and intensity of fire in savanna ecosystems (Hudak & Brockett 2004).

Current concerns about local and global environmental changes have lead to an increasing demand for spatial data on vegetation, particularly, for biodiversity planning and conservation. Satellite remote sensing is an efficient means to obtain such data in a timely, consistent, and economical manner. Remote sensing technologies, with its synoptic views and relatively frequent repeat times, have proved to be a key source of data for studying vegetation resources in savannas. Remote sensing methods have since provided important details of savanna composition and structure, as well as optimized field surveys targeted for local to regional scale vegetation estimation and mapping. However, remotely sensed vegetation data are not error-free, as they usually rely on regression of spectral responses of vegetation signal, often without accounting for interdependence factors (spatial autocorrelation and cross correlation) between ground data and the measured vegetation radiations. In this regard, studies of savanna ecology and vegetation assessment have investigated the applicability of integrated remote sensing and geostatistical techniques for the spatial estimation of vegetation resources (Mutanga & Rugege 2006). The combination of these techniques can enhance our understanding of the spatial dynamics of vegetation density and spatial distributions in the highly heterogeneous savanna environments, as well as allow for maximum use of remotely sensed vegetation data.

The following sections therefore introduce savanna vegetation studies and the applications of remote sensing to this regard. The main focus however, is on the utility of satellite remote sensing techniques for the spatial estimation of woody vegetation cover.

2.2 Savanna Woody Cover Estimation and Remote Sensing

Increasingly savanna environments transformed by a diverse range of land management systems and naturally occurring disturbances is cause of potential concern for ecosystem managers and researchers alike. Savanna landscapes set aside for biodiversity conservation (e.g. vegetation resources in PAs) play an important role in their capacity to function as carbon sinks for the reduction of global atmospheric carbon emission (Hudak *et al.* 2003), and their influences on the density, diversity and distribution of wildlife species (Mcnaughton & Banyikwa 1995; Mutanga & Rugege 2006). Woody vegetation cover is specifically an important component and a variable relating to the savanna ecosystem composition(Hudak 1999). Hence, the ability to quantify woody vegetation structural parameters can provide a measure of the underlying variation in savanna areas and enhance our understanding of the factors driving variability in the savanna environment. Remotely sensed vegetation data is an efficient means to obtain information on savannas.

Remote sensing has been utilised as a primary source of spatial data to characterize patterned woody vegetation density and canopy structure in the southern African savanna ecosystems (Hudak & Wessman 1998; Yang & Prince 2000; Hudak & Wessman 2001; Wessels *et al.* 2006). Remotely sensed data has also been used to develop updated vegetation maps and establish statistics about percentage woody canopy cover in semiarid savanna environment (Stuart *et al.* 2006; Wessels *et al.* 2006). In those studies, the researchers employed and tested different techniques to assess remote sensing data based on spectral measures or image texture analysis of both aerial photographs and satellite images, and assess how the remotely sensed vegetation variables relate with woody vegetation structure parameters. The various remote sensing techniques applied to woody cover assessment produced varying significant levels of correlation with the woody vegetation cover and their estimation accuracy (e.g. Hudak & Wessman, 1998; Yang & Prince, 2000; Hudak & Wessman, 2001; Wessels *et al*, 2006).

Although several image analysis techniques have been evaluated for vegetation remote sensing, one of the main challenges of using remotely sensed data to estimate woody vegetation cover in savanna ecosystems has been the identification of the best remote sensing derived vegetation variables that significantly relates with the ground surveyed vegetation data. In addition, unsatisfactory levels of estimation error arising from the use of traditional correlation or ordinary regression models that ignores the spatial autocorrelation factor in both field and remote sensing data (Atkinson *et al.* 1994; Mutanga & Rugege 2006)limits the full potential of remote sensing for vegetation resources estimation.

In this regard, the application of remote sensing techniques that explores the maximum use of information contained in remotely sensed vegetation coverage is crucial for the accurate delineation of the patches of vegetation cover (woody cover, a continuous variable) from other scene elements. The utility of spatial information such as auto and cross correlation factors, using applications of spatial statistics such as kriging interpolators which reduces interpolation error (Atkinson *et al.* 1994; Mutanga & Rugege 2006)can be beneficial for the estimation of woody vegetation cover. It is important to evaluate the utility of spatial statistical approaches in combination with remote sensing because fundamentally vegetation and its spectral measure (radiation) are spatially correlated, both to themselves (auto correlated) and to one another (cross correlated) (Atkinson *et al.* 1992; Acharya 1999; Mutanga 2000; Mutanga & Rugege 2006). In this respect, the spatial dependence between vegetation and its radiation obtained from remote sensing (e.g. spectral vegetation indices or image texture measures) can enhance the utility of using remote sensing techniques to extract woody canopy parameters.

Given that it is imperative for studies of savanna remote sensing to identify critical variables for modeling vegetation resources, the following two sections introduce satellite remotely derived vegetation data for the estimation of woody vegetation cover.

2.3 Vegetation indices and Remote Sensing of Woody vegetation Cover

Analysis of vegetation resources from spectral measurements is a remote sensing technique which is aimed at reducing spectral digital number (often denoted as DN data) to a single number which is related to physical characteristics of vegetation (e.g. leaf area, biomass, productivity, photosynthetic activity, and percent cover) (Baret & Guyot 1991; Gong *et al.* 2003; Mutanga & Rugege 2006; Wessels *et al.* 2006). The purpose of spectral evaluation of remotely sensed vegetation parameters is to minimize the effects of internal factors such as canopy geometry. In addition, vegetation spectral analysis often involves the combination of information from two or more spectral channels to retrieve vegetation signal, while minimizing external factors such as; soil, atmosphere, and solar irradiance effects on the spectral data (Huete & Warrick 1990; Baret & Guyot 1991; Jackson & Huete 1991; Gong *et al.* 1992; Li *et al.* 1993).

The Red (R) and Near Infrared (NIR) wavebands are the common bands used to compute various vegetation indices for acquiring precise estimation of vegetation abundance. There are several spectral vegetation indices relating to the abundance of vegetation. The spectral properties of vegetation resources, such as woody cover parameters are highly responsive to electromagnetic energy entering the tree canopy. Depending on the spectral properties, vegetation material can reflect or absorb light in precise regions of the electromagnetic spectrum. For example plant pigments such as chlorophyll will strongly absorb visible light between 400 to 700nm of the electromagnetic spectrum, and water content in plant leaves will absorb electromagnetic energy at longer wavelength regions of about 1400nm. This absorption and reflection characteristics of vegetation resources in specific wavelengths provides very useful information for the analysis of remotely sensed vegetation resources.

In semiarid savanna areas, the spectral behaviour of woody vegetation contrasts with that of other land surfaces and atmospheric features. This is an important factor which can be used to spectrally detect vegetation and the quantification of its abundance in the savanna environments. In this respect, a number of savanna studies have considered using satellite imagery data for the estimation and monitoring of woody vegetation cover pattern in semiarid savannas. Based on plant spectral properties, the following vegetation indices that account for the strong reflectance contrast between NIR and the red spectral channels of SPOT5 multispectral image are discussed for this study.

2.4 Description of SPOT5 derived Vegetation Indices

The ratio of NIR and red bands is the simplest vegetation index. As a Simple mathematical fraction, this index name is **Simple Ratio** (SR). SR indicates the amount of vegetation presence in an image by calculating the ratio of spectral values from the two spectral channels. In the output SR image, high ratios about 20 or more indicate dense vegetation and low ratios close to value of 1 indicate soil background or water body (Jackson & Huete 1991). One characteristic of SR worth consideration when it is being applied for the analysis of vegetation at landscape level is that it doesn’t give information that is related with landscape topography. This severely limits application of SR when quantitative measure of vegetation biomass is required. However, because SR primarily shows spectral information relating to the physical properties of vegetation it is useful for spectral class identification of vegetation resources (Huete & Warrick 1990). Closely related to the RS is the **square root of Simple Ratio** (sqrt-SR), which is developed to provid higher coefficient of determination for the presence of green vegetation.

Difference Vegetation Index (DVI) is another basic vegetation index, like the SR, it is also sensitive to the amount of the vegetation. It measures the differences between the NIR – R bands. DVI has the capability to distinguish soil and vegetation in non-shady scenes. In this regard, DVI can be limiting where noises such as topography, atmosphere or shadows affect the reflected vegetation signals.

The most common vegetation index, which is often applied to a wide range of vegetation types and in diverse environments, including savanna areas is the **Normalized Difference Vegetation Index** (NDVI). The NDVI explores the fact that vegetation is highly reflective in the NIR and strongly absorbing in the visible R due to chlorophyll absorption. The output NDVI image measure changes between -1 and 1 which is measure of vegetation property. For example, empirical results and theoretical explanation show that, if the resultant NDVI image value is 0.1 or less, it indicates an area of bare soils or rocks; if it is between 0.2 and 0.3, it indicates an area of shrubs or grasslands, if it is about 0.6 or higher it indicates an area of trees and woody vegetation (Tucker 1979).

Transformed Normalized Difference Vegetation Index (TNDVI) is the square root of the NDVI + 0.5. It has a higher coefficient of determination for vegetation than NDVI and this is the difference between the two closely related indices. The resultant formula of TNDVI ensures positive values and the variances of the ratio are proportional to mean values (Azzali & Menenti 2000). TNDVI generally indicates the amount of green biomass that is in a pixel. Azzali & Menenti, (2000) applied TNDVI in semiarid savanna environment by correlating the TNDVI measures with savanna woody canopy structure parameters and found significant correlation between percentage cover and TNDVI values.

As stated in the introductory section of this chapter, rainfall is highly seasonal and precipitation is low, as well as, temperatures can rise extremely high in arid and semiarid savannas. These climatic conditions can influence soil moisture content, as well as plant moisture content. The combination of plant water content deficient and other environmental variables can cause stress in the savanna vegetation status and composition. The fundamental principle is that both biophysical and biochemical aspects of plant functioning is influenced by moisture deficiency (Niemann & Visintini 2005). For remote sensing, both biophysical and biochemical component of plants is important since these relate to plant reflectance properties. For example, dry vegetation under water stress shows increased reflectance throughout the visible and middle infrared (1300 to 2500nm) (Aldakheel & Danson 1997), and a decreased reflectance in the NIR portion of the electromagnetic spectrum, due to reduced absorption in the chlorophyll active red edge band (Carter & Knapp 2001). Analysis of remotely sensed image data in the spectral domain usually takes advantage of contrast in spectral responses to enhanced vegetation presence and abundance. However, spectral analysis do not account for spatial arrangement of objects in an image. There is spatial dependence contained in vegetation and its radiation (Atkinson *et al.* 1992; Mutanga & Rugege 2006). In order to upscale or improve upon spectral analysis and develop alternatives that integrates spatial information, image (King 2000) texture analysis has been one of the techniques applied (King 2000; Dye *et al.* 2008). Transformation and analysis of remotely sensed imagery using texture measures is tested in this study. Spectral mixture analysis (SMA) (Small 2003; Ellis *et al.* 2006) is one of the vegetation transformation techniques that could be assessed and used but it was avoided in this study because of the complex structural nature of savanna vegetation.

2.5 Remote sensing of Savanna Vegetation and Image Texture analysis

Remote sensing investigations on tree canopy cover often follow the spectral or the spatial domains which are the two main approaches applied in vegetation studies (Jupp & Walker 1997). The first approach exploits the relationship between the vegetation structural and floristic parameters and the recorded spectral response. The second approach relies on the spatial variations in pixel intensities, which is defined as tonal variability in the spectral values of an image. In the later approach, the pixel size and the signal of its neighbouring pixels become a key factor for the successful retrieval of tonal information. In this respect, the fundamental concept is that remote sensing imagery are composed of two interdependent characteristics: the spectral information which is often denoted as the 'tone' and the image 'texture', also referred to as the 'tonal variability' in a scene (Harralick *et al.* 1973). The image texture characteristic is further defined as a function of the spatial variation in pixel intensities contained in an image, which is often signified as gray values. In addition, image texture response describes the fineness, coarseness, contrast, regularity, directionality and periodicity in an image (Harralick *et al.* 1973). For remote sensing investigations, the image texture response therefore contains important information about the spatial and structural arrangement of the remotely sensed objects (Tso & Mather 2001).

Texture information contained in remote sensing data has been very useful for a wide range of remote sensing applications. For example, to assess global landcover, image texture analysis has played important role in the classification of vegetation communities, which have been remotely sensed (Lark 1996; Miranda *et al.* 1998; Carter & Knapp 2001). Texture information extracted from high-resolution multispectral images has been intensively studied and considered useful for the discrimination of different landcover classes such as water bodies, urban areas and agricultural fields (Atkinson & Curran 1997; Chica-Olmo & Abarca-Hernândez 2000). However, the applications of image texture measures for savanna woody vegetation study is relatively not well established and studied by a handful of investigators who tested image texture information specifically in savanna areas to characterise woody vegetation cover. One outstanding application of texture as an efficient remote sensing variable is (Hudak & Wessman 1998, 2001) who considered image texture measures from the analysis of gray level values to characterize woody plant encroachment in a South African woody savanna environment.

Although, spectral analysis of image data can provide important information for savanna woodland assessment, using spectral information exclusively to assess vegetation pattern in sparsely heterogeneous savanna ecosystems can be limiting. This is because analysis of available satellite remote sensors with varying spectral resolutions (e.g. 10m spatial resolution, SPOT5, IKONOS, Quickbird, Orbview imagery) may not provide enough spectral variability, which can separate close reflectance response of scene elements. For example, per-pixel classification of the mixture of woody trees, shrubs, bushes, grass stratum, and other scene elements that characterise other landscapes often result in high probability of misclassification and lack of spatial consistency (Soille 1996; Woodcock *et al.* 2001; Wilson & Sader 2002; Maggi *et al.* 2007). To avoid these limitations, it is important therefore, to consider spatial information inherently contained in the input image data. Methodologies that emphasize the use of spatial information include image segmentation techniques such as texture analysis of remotely sensed images. In this regard, image texture measures can help quantify the tonal variability in the scene, where spectral measure alone cannot quantify variability in the image data (Hudak & Wessman 1998).

Texture analysis is used to retrieve spatial information contained in the scene that is related to the different object types in the scene for evaluation. For semiarid savanna studies, researchers have demonstrated that, structural and spectral information can lead to significant improvement in woody cover assessment. The output texture image generated can be correlated directly or used as an additional variable together with other multi-spectral raw or transformation landcover classification (Puissant *et al.* 2005). In this regard, the role remote sensing plays in dry land savanna environments can be enhanced when texture information is incorporated in the analysis. However, Hudak & Wessman, (1998) assessed the effect of spatial resolution of remotely sensed imagery and found out that, the accuracy at which texture measures can be use to assess woody cover depends in the image spatial resolution, as well as depending, on the objectives of the study. In the study, the authors found that the best spatial resolution suitable to assess woody cover in semiarid savanna environments is the remote sensors with 2m-20m spatial resolutions. In this study, woody cover estimation using texture information is assessed and integrated with alternative techniques such geostatistical methods of spatial interpolation.

2.6 Geostatistics and Remote Sensing of Savanna woody vegetation

Geostatistics is the term applied to a group of spatial statistical techniques which describes the correlation of spatial data by exploration, modeling and surface generation of local variables and their estimation at unsampled locations(Curran & Atkinson 1998). Geostatistical techniques are based on the Regionalized Variable Theory (Matheron 1971). Central to geostatistics is the modeled variogram which measures the spatial autocorrelation in the sampled data, arising from the underlying spatial structure in the variable (Curran & Atkinson 1998).

Until the past few decades, the synergy between geostatistics and remote sensing went un-utilized for landscape studies such as the assessment of biophysical variables (e.g. woody vegetation resources). Over the past few decades, geostatistical techniques increasingly aid researchers to explore and quantify the spatial information in remotely sensed data. In addition, geostatistical techniques are being used to design optimum sampling schemes for field and remotely sensed image data, and improve the accuracy with which image data in particular can be used to estimate biophysical variables (Hudak & Wessman 1998; Wallace *et al.* 2000).

Because in geostatistics, spatial autocorrelation is utilized to estimate optimally local values from data sampled elsewhere (Curran & Atkinson 1998) which is based on the techniques of regionalized variable theory (Matheron 1971), the extraction of information from field data and remotely sensed woody vegetated surfaces would greatly enhance the accuracy with which patterned savanna vegetation can be estimated. In geostatistics, the utility of spatial structure in image data becomes visible because the scenes contain discrete patches that are identifiable based on their spectral/spatial properties that are more homogeneous within the natural grouping of the vegetation composition than between them (Curran & Atkinson 1998). This spectral/spatial property can be measured using a series of geostatistical tools such as kriging and cokriging, which is increasingly applied in remote sensing of savanna vegetation studies (Atkinson *et al.* 1996; Hudak & Wessman 1998; Mutanga & Rugege 2006).

2.7 Geostatistical measures of spatial variation

The management and conservation oriented research in semiarid savanna woodland need to take advantage of the underlining spatial factor of vegetation density and distribution when making quantitative estimates of the savanna woody cover. It is important to consider the spatial aspects because in semiarid savanna environments, assessment of sample data from the patches of vegetation communities is spatially dependent on the natural grouping of the woody species.

As semiarid savanna environment are dynamic and inherently unstable (Hudak & Wessman 2001), the vegetation cover often exhibits poor correlation with the spectral characteristics of remotely sensed imagery, making vegetation cover estimation by simple statistical analysis result in high estimation error. Fortunately, savanna landscapes exhibits distinctly and measurable spatial variations in the vegetation patterning even where differences in the spectral values are unpredictable (Hudak & Wessman 1998). In this respect, geostatistical techniques such as ordinary kriging can spatially provide quantitative measures in estimating woody vegetation cover based on the regionalized variable theory. Regionalized variable theory share characteristics of both deterministic and absolute randomly sampled data, which is a critical element in the distribution of woody species in savanna areas. In this regard, kriging is considered as the most suitable interpolation technique for woody cover estimation and is a useful tool for mapping quantitative trends in woody vegetation cover density and distribution (Mutanga & Rugege 2006).

The variogram which is used to measure the strength of statistical correlation in both field and remote sensing data as a function of distance has been tested by kriging unsampled locations with data sampled from elsewhere. The variogram has three parameters, namely, *nugget*, *sill* and *range*. The *nugget* describes the intercept at some positive value on the variogram. For remotely sensed images, the nugget generally provides a reliable estimate of the measurement error (Atkinson 1993); *sill* is the value where the variogram levels out to a value equal to the variance of the dataset. The presence and magnitude of the sill are both important parameters. The lack of a sill in a variogram could be due to: (1) the existence of a trend in the data, or (2) very small spatial resolution compared to the scale of pattern in the data (Jupp *et al*., 1989). If it exists, the sill could relate to the proportion of the area covered by objects which is determined by their density (Woodcock *et al.* 1988a); and *range* is the lag or distance value (also referred to as range of influence) at which the variogram reaches the sill. This parameter is highly related to the size of objects in the sampled data (Woodcock *et al.* 1988a). For vegetation studies, the range relates to the size or density of the sampled trees, or for remotely sensed imagery, the range has been found to be highly related to the size of objects is the scene (Woodcock *et al.* 1988b; Hudak & Wessman 1998).

Essentially, kriging is method of local weighted averaging technique where the weights originate from the variogram parameters (Curran 1988; Curran & Atkinson 1998). The kriging estimates are therefore based on the spatial variation of the property (in this study; woody vegetation cover) under investigation. Several studies have demonstrated that Kriging is more robust and is the most reliable two-dimensional spatial estimator (Laslett *et al.* 1987; Laslett 1994) useful for multi-staged sampling designs that are intended to give reliable measure of the variogram to estimate woody cover.

Co-kriging is the logical extension of kriging in situations where two or more variables are spatially interdependent and the primary or dependent variable is undersampled (Curran & Atkinson 1998). Using ordinary co-kriging, the estimate is a weighted average of the available data with weights chosen so that the estimate is unbiased (Deutsch & Journel 1992). Cokring like the ordinary kriging has minimum variance, and in practice, utilizes the fundamental principle that near observations are likely similar, hence, carries more weight to have effect on the interpolation surfaces (Curran & Atkinson 1998). This principle explores the covariance and cross-variation to set sum of the weights applied to the primary variable (one of immediate interest) to one, and the sum of the weights applied to secondary (in this study, the SPOT imagery serving as independent variable) is set to zero (Deutsch & Journel 1992). The second condition tends to limit severely the influence of the secondary variable. For example, when cokriging is applied to estimate woody cover it is important that, since woody cover, covariance functions are required when image variables are considered, reduction in the variance will require additional modeling effort. This is because woody cover parameters are relatively under-sampled compared to the image, which is more sampled (Isaaks & Srivastava 1989). In addition, the linear model of co-regionalization provides a framework for modeling the auto- and cross-variogram of two or more variables so that the variance of any possible linear combination of these variables is always positive (Journel & Huijbregts 1978). In this regard, each variable is characterized by auto-variogram and each pair of variables by their own sample cross-variogram.

2.8 Lessons learnt from Literature Review

This section concludes on the main issues in the literature as regards the utility of remote sensing and geostatistics for vegetations studies. The section further highlights on what has been done and outlines questions that need to be answered.

It was evident in the literature that as demand for spatial information increases, it is crucial that spatial data acquisition must be quick, timely and economical. Remote sensing of vegetation resources was identified as an effective method of obtaining spatial information which is useful for species habitat monitoring and biodiversity assessment.

Spectral vegetation or image texture indices correlates with vegetation structural traits and are therefore remarkably used to characterize vegetation presence and abundance. However, each of these indices has its own merits and limitations.

It was therefore emphasized in the literature that an ideal vegetation index should be relatively insensitive to noise caused by canopy background and atmospheric effects while spectrally sensitive to the presence and abundance of vegetation resources. The literature also recommended that an ideal vegetation index useful for spatial estimation should be the one that is highly correlated to vegetation structural parameters. This study will investigate the image spectral or texture data that best correlates with specific woody structural parameter.

Although several authors (e.g. Mutanga & Rugege, 2006) have shown that vegetation and its radiation are spatially related and the spatial characteristics of vegetation traits can be estimated from its spectral reflectance properties, regression techniques (e.g., Gong et al., 2003; Wessels *et al.*, 2006) have been the typical method used to evaluate the relationship between spectral data and woody vegetation parameters for the spatial estimation of vegetation cover with limited results. The extent to which the integration of geostatistical techniques and spectral data can be use in vegetation assessment especially in the savannas have not been widely studied, yet they contain information that captures spatial autocorrelation which is useful to improve the accuracy of spatial estimation of vegetation resources. In this respect, this study will investigate the utility of geostatistical techniques such as cokriging to estimate the density and spatial distribution of woody vegetation cover.

Cokriging with sparsely sample field observations require that remotely sensed image data should be optimally sampled to ensure computational efficiency. Optimal sampling for image analysis has been usually done by the rule of a thumb (Mutanga & Rugege 2006) but there can be a statistical approach that can be developed to determine the optimal sampling scheme for image analysis. This study aims to determine the optimal image sampling lag distance using the application of experimental semivariogram parameters in this regard.

The selection of critical remote sensing variables to input in cokriging has been a subject of major concern in the literature. To account for the difficulties associated with selecting optimal remotely sensed data, this study will compare the performance of two set of imagery (multispectral and panmerged data) as well as various types of image transformation techniques.

Chapter 3. Materials and Methods

3.1 Introduction

Materials and methods consist in brief terms: pre-field and post-field processing of remote sensing data as well as the organization of ground survey mission for georeferenced data collection. In the pre-fieldwork stage, pre-processing of the SPOT imagery for further analysis was done. After this, the first step in the methods was to calculate spectral vegetation and texture indices. The second step was to carry out fieldwork in order to collect validation (i.e. training and test) data and all other information that could help improve our understanding of the savanna landscape (*mopane* woodland) under investigation. Figure 3.1 displays the overall outline of the methods, which included: fieldwork design, data collection and data compilation, as well as data analysis. The third step was to identify critical SPOT variables for geostatistical analysis. This was done by establishing statistical relationships between field (woody cover and density variables) and the remotely sensed datasets. The fourth step was to estimate woody density and cover using geostatistical techniques. At this stage, cokriging was considered as the most suitable technique (Mutanga & Rugege 2006), which could combine the critical variables (woody parameter and SPOT derived vegetation variable) identified in the previous step to predict or estimate woody cover. The final step (five) was to perform an accuracy assessment of the cokriging technique and compare the results to those obtained from ordinary kriging, as well as, results obtained from linear stepwise multiple regression method.

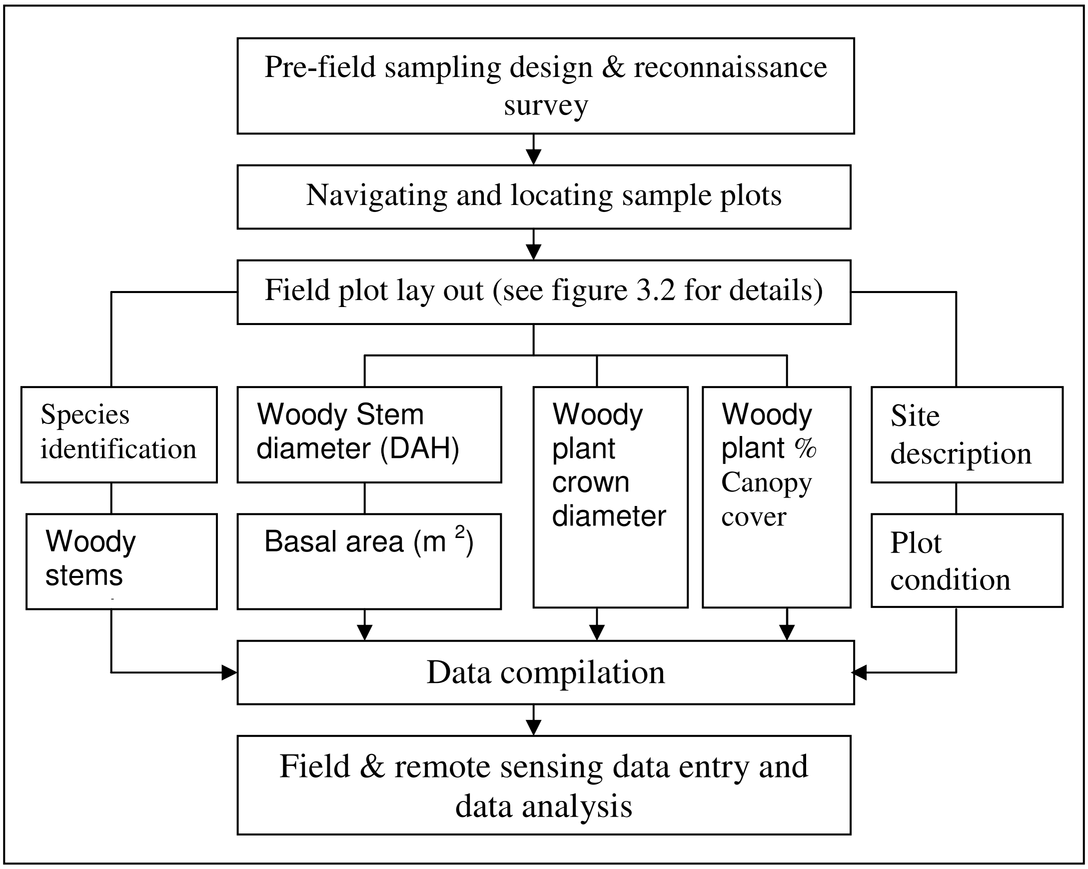

Figure 3.1: Field Design and Data Collection

3.2 Software and Field Materials

The image processing and GIS operations, as well as variogram modelling were performed using ERDAS imagine software version (v) 9.1, ArcGIS v9.2 respect5ively. Additional data analysis such as calculation of image texture measures and statistical tests were done using RSI ENVI v4.3. and Statistica 7 (StatSoft. Ltd. London. Inc) respectively. The materials and equipments used for this research are listed in table 3.1.

Table 3.1: List of materials

No.	Type of material
1.	Altimeter
2.	Diameter tape
3.	Calliper
4.	Meter tapes (30m and 50m lengths)
5.	Garmin 76CL GPS receiver
6.	Digital Photo camera
7.	Topographic maps (1:25 000)
8.	Field guide (plant species identification handbook)
9.	Field bag
10.	Plant specimen
11.	GIS shapefiles ('ecozone' maps of vegetation communities and study area boundary coverage)
12.	Four scenes of SPOT5 MS and SPOT panmerged satellite images (10m and 2.5m resolution respectively) of the KNP study area for 2005

3.3 Methods

Prior to starting the methods, few concepts have to be explained. The method explains and outlines the theoretical considerations, which are integrated in the techniques used for this study. For instance, issues relating to the description of savanna woodlands which was considered as a continuous landscape, that could be confused as a discrete savanna feature in their surroundings. An understanding of the nature of savanna landscape under investigation is central in the selection of appropriate techniques to apply for data collection and analysis. In this study, knowledge about such issues and how to treat them is mainly gathered from previous studies. For example, Hudak & Wessman (1998) characterized woody plant encroachment in a semiarid African savanna using texture analysis of high resolution imagery to map woody plant densities and monitor woody plant encroachment across savanna landscapes. In the study, dominant tree species in savanna woodland environments were considered as a continuous variable. The authors however, note that spatial heterogeneity introduced through the mixture of herbaceous and woody plant challenges quantitative assessments of woody plant densities using remote sensing, particularly, analysis in the spectral domain for vegetation cover assessment.

Several studies have indicated that significant changes in woody vegetation cover or density occur in decadal scales (Hudak & Wessman 1998; Yang & Prince 2000; Wessels *et al.* 2006). Given that changes in woody plant densities and cover distributions occur in decadal scales, field data which was collected in October, 2007 for this study was used to process remotely sensed woody vegetation variables derived from SPOT5 image data , acquired for October, 2005 hot but wet season. The fundamental principle is that vegetation and its radiation at any given time or season is correlated. Therefore it is important that time of field data collection must coincide with the season images were acquired with minimum time lapses.

3.3.1 Pre-Processing of Imagery and Auxiliary Data

Remote sensing and GIS applications for woodland savanna studies require that a pre-fieldwork should be carried out. In the pre-fieldwork stage of this study, GIS operations on auxiliary datasets were carried out. This involved analysis of shapefiles consisting of: boundaries, established Kruger National Park's (KNP) Veld Condition Assessment sites (VCAs), land classification groups (referred to as "Ecozones") and vegetation maps of the KNP (Trollope & Potgieter 1986; Mutanga & Rugege 2006; Wessels *et al.* 2006). In order to ensure best accuracy and circumvent any spatial or geometric distortions in the GIS databases, all shapefiles and imagery were geo-registered and where necessary re-projected to the original SPOT5 imagery projection. The initial GIS processing required definition of the study area, which involved selection of Mopane, dominated woodland area that matches the SPOT5 scenes. The next task was to use Hawths Analysis Tools for ArcGIS v9.2 to select well distributed and representative number of VCA points within the defined study area.

In the pre-fieldwork stage, all available information about the study area was collected and processed before commencing the actual field work. Assessment of appropriate sampling design (e.g. optimum sample size, plot size and the location of the sample plots) before commencing field-work gives a researcher great advantage to address any foreseen sampling difficulties as well as helps to establish an unbiased fieldwork sampling criteria. In this regard, availability of GIS spatial analytical capabilities has provided crucial tools, necessary for planning and designing of the fieldwork, which could have been otherwise difficult or inefficient

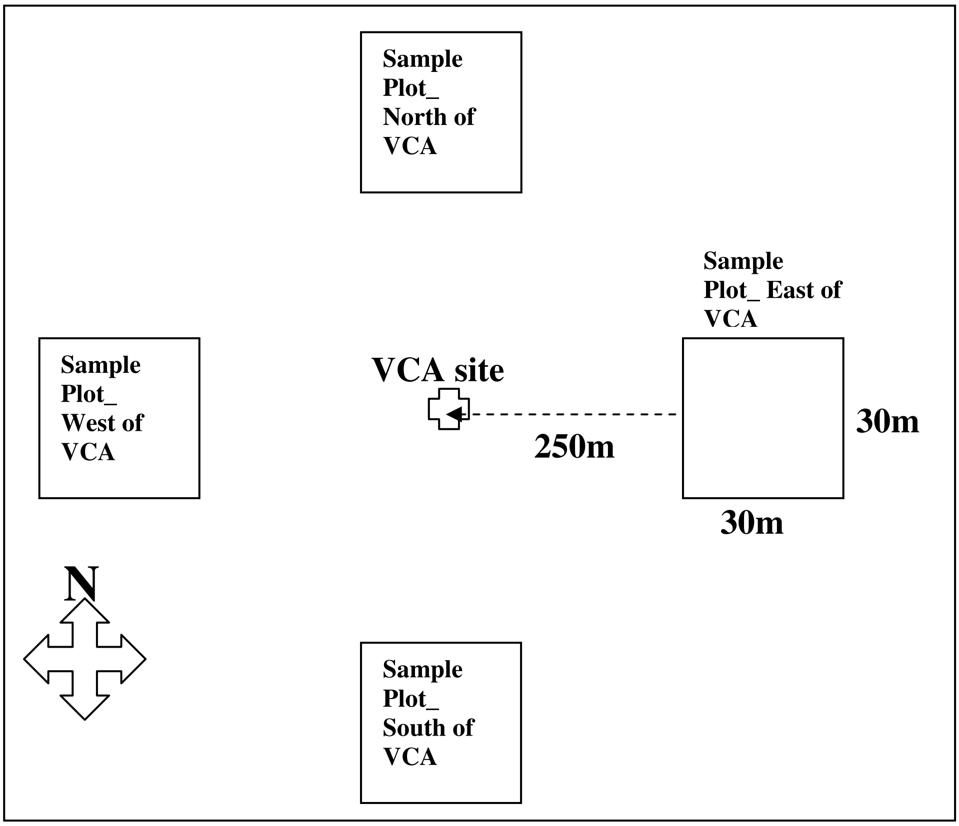

Figure 3.2: Cluster of 4 plots at VCA sites: For each sample plot, all trees with DAH > 2.5 cm are measured and counted, tree crown diameter measure in north- south, east-west directions as well as percentage tree canopy cover estimated for each sample plot

3.3.2 Sampling Design

In this study, a square plot of 30×30 meters (m) was used. All woody species completely inside the plot were identified and structurally assessed. Since a square plot has greater perimeter as compared with circular plots, the chances that a woody plant which is of primary interest fall completely in the plot is likely. Further, the square plot coincides with the square shaped remotely sensed image pixels, which enhances computational efficiency. In addition, the size of the sampling plots conform to the general guideline that, the spatial scale of object on the ground must be at least ×2 the spatial resolution of the remote sensing sensor (in this study SPOT5 MS and SPOT PM images are 10m and 2.5m resolution respectively), for spatial delineation of the woody plant traits to be reliable (Cowen *et al.* 1999). Previous experiments also recommended that plot size ranging from 20×20m up to 50×50m can be used for woody vegetation studies in savannas (Demisse 2006). The 30×30m (figure 3.2) plot was considered large enough to represent the surrounding woody plant properties, as well as optimum to retrieve spatial information contained in the respective, 2.5m panmerged and 10m multispectral spatial resolution images. The overall distribution of the sample plots is presented in figure 3.3. The sample plot distribution displayed in figure 3.3 depicts the distribution if sampled KNP's VCAs that fall completely within the extent of the study area. The backdrop in figure 3.3 shows the SPOT coverage data, which cover the entire study area. Because the SPOT image coverage is over the entire study area, the SPOT data selected for cokriging was sampled at a predetermined lag size (3000m) using a semivariogram model parameter. This was done to aid computational efficiency for cokriging analysis. Detailed explanation on this is presented in the geostatistical analysis section of this chapter.

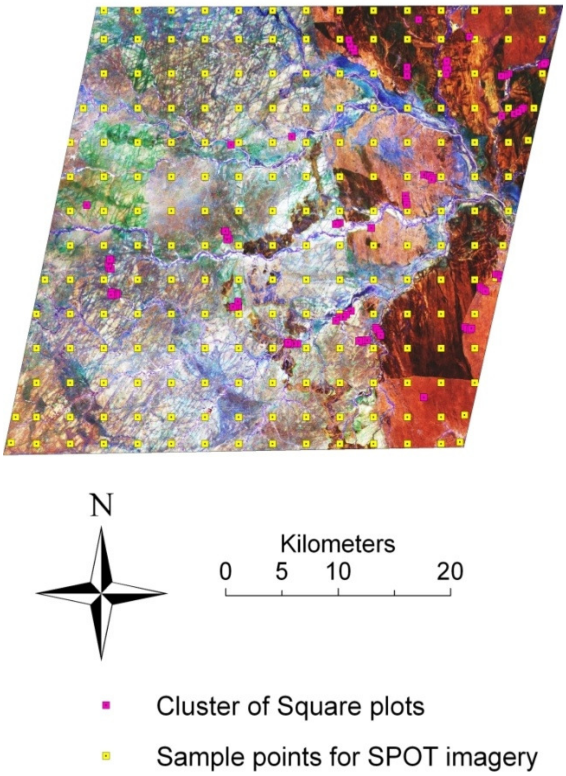

Figure 3.3: Distribution of sample locations in the study area. The pink squares display the cluster of field plots and the yellowish squares show the lag space (3000m) for image sample points. The backdrop is the SPOT multispectral image coverage of the study area.

3.3.3 Sample Plot Survey and Structural Data Collection

Georeferenced field data was collected by sampling at selected, already established VCAs. This approach was followed to ensure spatial consistency in vegetation assessment in the KNP. However, because the distance between VCA sites are very large (figure 3.3) and do not represent the range of spatial influence in the surrounding woody vegetation community, spatial interpolation of the KNP's VCA data does not provide reliable spatial vegetation maps (Wessels et al. 2006). Given that the main focus of this study was to predict estimate woody density and woody cover spatial distribution using an interpolation technique, sample plots were clustered around each selected VCAs sites. The VCA points were selected using the Hawths Analysis Tools for ArcGIS9 v9.2 and geo-registered in Decimal Degrees (DD) format. The DD data was saved as MS Excel comma delimited (CSV) and then imported into the GPS. The GPS together with field maps which were created using the VCA and road maps were then used to navigate to VCA sample points.

After a sample point has been successfully located and marked, a total of 4 sample plots at a distance of 250m (north, south, east and west directions) were clustered around each VCA site. Figure 3.2 illustrates the sampling plot layout in the four directions.

Table 3.2: List of field variables sampled

No.	Types of Woody vegetation structural traits
1.	Woody stem Diameter(m), measured at Ankle Height (DAH)
2.	Basal area of individual trees in a plot (calculated based on DAH)
3.	Height of individual trees per plot
4.	Number of woody tree stems (density per sample plot)
5.	number of woody shrubs (density per sample plot)
6.	Crown diameter of individual woody trees per plot
7.	Percentage woody tree canopy cover

The criterion for selecting woody species was to classify the woody plants as trees or shrubs. Trees in this study included all woody species with Diameter at Ankle Height (DAH) (10cm-15cm from the ground) greater than 2.5cm (Mueller-Dombois & Ellenberg 1974; Demisse 2006). Woody species attaining DAH less than 2.5cm were recorded as woody shrubs. Data sheets (see Appendix 1), which had been prepared already, were used to record woody trees structural parameters and total number of shrubs in each plot. Identification of woody species was done using field guides. As stated in the introduction chapter of this repot, the main woody variables considered for spatial estimation are density and cove (percentage canopy cover).

However, because woody density and cover variables relates to other vegetation parameters such as woody stem diameter, plant basal area, tree height, woody plant crown diameter or under storey shrub layer density, in this study these variables were also measured. This was done to check the performance of these variables as these variables could be of important to the ecologist. Table 3.2 displays the sample plot information consisting seven woody cover parameters which were measured in the field. The DAH for trees was measured using a standard caliper, as well as a 5m diameter tape. Percentage woody canopy cover per plot was assessed by estimating the total area covered by all trees in the plot. Crown diameter of trees was determined by measuring individual tree canopy in the north-south and east-west directions.

3.3.4 Data Processing and Analysis

3.3.4.1 Field Data processing

Field variables (table 3.2) measured at each sample plots were processed according to the study's objectives. Because the intent in this study was to evaluate woody structural parameters between plots and not within, the field variables measured were pooled for each plot. Woody stem diameter (variable1) measured at ankle height for all trees were averaged for each plot. Basal area of individual trees in a plot (based on DAH) was calculated using equation 1:

$$Ba = \left(\frac{1}{2} d \right)^2 * \pi \qquad \textbf{(1)}$$

Where *Ba* is basal area and *d* is diameter of individual plants measure at ankle height (DAH).

Variables 3-5 (Height of individual trees per plot, tree density per plot and shrub density per plot respectively) required no further processing, so were pooled by totalling the numbers for each plot (Mueller-Dombois & Ellenberg 1974; Hudak & Wessman 1998; Demisse 2006). Crown diameter of individual woody trees was pooled by calculating the average canopy diameter per plot. Percentage woody tree canopy cover was estimated using the plotless Bitterlich technique (Mueller-Dombois & Ellenberg 1974; Hudak & Wessman 1998) and the results averaged for each plot covering 900m^2.

The field data for all selected 25 VCA sites which consist of 4 clusters of sample plots was tallied to 100 samples, covering the study area. This approach of clustering helps to reduce the large distances (3km-12km) between VCA sites, which does not provide reliable spatial interpolation of the surrounding vegetation resources (Wessels et al. 2006) in the KNP. In addition, by clustering the sample plots in a systematic pattern, rather than randomly locating clusters as in simple random sampling, a regular pattern of sampling plots was insured. For spatial interpolation of vegetation resources, it is critical that the samples should be representative of the surrounding vegetation resources in the study area (Mutanga & Rugege 2006) as well as, follows a regular pattern, which also ensures that the maximum spatial interpolation (e.g. kriging) error is minimized (Webster & Oliver 2001).

In order to circumvent the problem of upwards bias in the estimation accuracy (Mcgarigal *et al.* 2000; Mutanga & Rugege 2006), a prediction error that is experienced when the same training samples are used for the model validation, the samples for this study were split into the ¼ and ¾, test and training data sets respectively using a geostatistical analyst tool for ArcGIS v9.2. This randomly divided the samples into training 75 samples for woody cover estimations and 25 samples for validating the results. The concept of the split criterion gives more weights to the training data set which provides reliable model building in vegetation studies (Kokaly & Clark 1999; Curran *et al.* 2001; Schmidt & Skidmore 2003; Mutanga *et al.* 2004; Mutanga & Rugege 2006). The split sample validation criterion was used in this study because the training ample size was large enough to compute variograms for spatial (geostatistical) analysis, as recommended by Webster & Oliver, (2001) who assessed the effect of different sample sizes on woody species spatial estimation. The authors suggested that 50 sample plots are the minimum samples needed for calculating variograms for plant density estimations. In those studies, the authors emphasized that the higher the number of samples, the more results of the predictions can be reliable.

3.3.4.2 Satellite Image Transformations, Analysis and Data Extraction

3.3.4.2.1 SPOT5 Imagery and Vegetation Indices

Table 3.3 displays the spatial and spectral properties of the SPOT multispectral (MS) and SPOT panmerged (PM) image datasets. The spectral reflectance values of all the four bands for both SPOT5 MS and panmerged were extracted to coincide with each 100 field sampled in the study area. The individual SPOT5 imagery bands were used in this study in order to test the potential of the very high spatial resolution (10m and 2.5m respectively) images for woody cover assessments. Usually the NIR and Red bands are the spectral regions where the signal of vegetation presence and abundance are strongest, and are generally considered as the best spectral regions for vegetation resource detection and mapping (Gong *et al.* 2003; Wessels *et al.* 2006). However, the blue/green and shortwave infrared (SIR) spectral regions have also received considerable and increasing attention by several authors for studying vegetation resources (Mutanga & Rugege 2006; Dye *et al.* 2008).

Table 3.3: Spectral bands and resolutions for SPOT 5 Multispectral (MS) & Panmerged (PM)

BAND No.	SPECTRAL RANGE	SPATIAL RANGE(m), MS/PM
1	**Blue/Green** (500-590nm)	10/2.5
2	**Red** (610-680nm)	10/2.5
3	Near Infrared-**NIR** (780-890nm)	10/2.5
4	Shortwave Infrared-**SWIR** (1580-1750nm)	10/2.5

A widely used spectral technique when evaluating the utility of remotely sensed imagery in vegetation studies is the assessment of differences in reflectance values from green healthy or dry vegetation in the visible and infrared (IR) wavelengths. The reflectance differs from around 10 % in the visible red band to over 50 % in near IR band (Rouse *et al.* 1973). This is a distinctive vegetation feature that no other naturally occurring land or atmospheric features show such significant differences in reflectance in the same spectral range (Rouse *et al.* 1974). For SPOT5 multispectral scanner (MS) system, this difference corresponds to the ratio or spectral differences between bands 3 and 2. Ratios of spectral bands are commonly used because they enhance the spectral contrasts between vegetation and other land surfaces, while decreasing the variations in surface brightness due to topography and atmospheric effects (Jackson & Huete 1991). In this regard, in addition to the four bands for the SPOT5 MS image, five vegetation indices were calculated as follows:

$$DVI = NIR - R \tag{2}$$

$$NDVI = \frac{NIR - R}{NIR + R} \tag{3}$$

$$TNDVI = \sqrt{\frac{NIR - R}{NIR + R}} + 0.5 \tag{4}$$

$$SR = \frac{NIR}{R} \tag{5}$$

$$sqrt\_SR = \sqrt{\frac{NIR}{R}} \tag{6}$$

Where: DVI= Difference Vegetation Index, NDVI = Normalized Difference Vegetation Index, TNDVI = Transformed Normalized Difference Vegetation index, SR = Simple Ratio, sqrt-SR = Square root of Simple Ratio, NIR = near infrared band, R = red band.The extraction of all individual spectral band reflectance values and all derived vegetation indices was done using the zonal statistics function in the spatial analyst tool for ArcGIS v9.2.

3.3.4.2.2 Texture Analysis

In a series of articles, the theory of image spatial transformation techniques such as texture analysis in remote sensing are outlined (Harralick *et al.* 1973; Carr 1996; Lark 1996; Atkinson & Curran 1997; Tso & Mather 2001; Woodcock *et al.* 2001). Image texture transformation was calculated in ENVI 4.3 (RSINC, 2007) and extracted (using ArcGIS zonal statistics tool) for all field sample plots locations.

There are two classes of texture measures: first order (occurrence) and second-order (co-occurrence) statistics as outlined by Harralick *et al.* (1973). The first class of texture measure, occurrence statistics are derived from the histogram of pixel intensities in a given neighborhood (i.e., a moving window), but ignores the spatial relationship between pixels (Harralick *et al.* 1973). The second class, co-occurrence statistics are calculated from grey-level co-occurrence matrix (GLCM). GLCM assume the probability that each pair of pixel values co-occur in a given direction and distance (Harralick *et al.* 1973). The co-occurrence statistics assumes that all pairwise combinations of the grey levels within a spatial window occur in conditionally combined probabilities. In that case, a set of grey level co-occurring probabilities (GLCP) are stored in the GLCM, and statistics are applied to the matrix. The centre pixel of the moving windows is then assigned with the resulting co-occurrence statistics which generate the texture measures (Jobanputra 2006). The second-order texture measures are comparatively more complex to compute than the first-order texture measures which are fast and easy to compute. Equations 7-9 show the best three image texture algorithms (measures) that correlates with the ground sampled woody cover parameters. The detailed description of all the first and second-order texture variables that were calculated in this study are in appendix 2.

Mean (first order texture index) calculates the average texture value at each plot or at each moving window (St-Louis *et al.* 2006) and is represented as:

$$AVG = \frac{\sum_k x_k}{K} \qquad (7)$$

Where *AVG* is mean texture index for first order statistics.

Mean (second order texture index) calculates average probability of grey-level co-occurrence, μ_i and μ_j (Lévesque & King 2003). It is represented as:

$$\mu_i = \sum_{i,j=0}^{N-1} i\,(p_{ij}) \qquad \mu_j = \sum_{i,j-0}^{N-1} j\,(p_{ij}) \tag{8}$$

Where i,j are the coordinates in the co-occurrence matrix space; p(ij) is the co-occurrence matrix value at the coordinates i,j.

Entropy (second order texture index) is a statistical measure of uncertainty. It is low if image texture is relatively smooth and high if the texture is structured. It can be used as a measure of the absence of a distinct structure or organization of image patterns (Yuan *et al.* 1991). It is represented as:

$$\sum_{i,j-0}^{N-1} P\,ij\,(-1n\,P_{i,j}) \tag{9}$$

Where i,j are the coordinates in the co-occurrence matrix space; p(i, j) is the co-occurrence matrix value at the coordinates i,j; n is the dimension of the co-occurrence matrix.

In this study both first and second order texture measures were evaluated based on the SPOT5 MS image data. The texture measures were calculated using 3×3 filter window, which is capable to capture the textural characteristics of individual objects such as trees in the scene (Moskal & Franklin 2001). Only 3×3 filter window was calculated as recommended by Hudak & Wessman, (1998). This window size was used in this study because in semiarid savanna environments larger filter windows exhibit an undesirable smoothing effect on the small-scale vegetation structural parameters (Hudak & Wessman 1998), which are the primary variable of interest in this study. Since the spatial resolution of the SPOT5 MS is 10m, using the 3×3 pixel (900m^2) moving window ensured spatial representation with the 30×30m (900m^2) ground sample plots.

3.3.5 Statistical Analysis

3.3.5.1 Stepwise linear regression

Stepwise linear regression is usually used to determine the relationships between remotely sensed data and ground surveyed vegetation variables (Cohen *et al.* 2003; Mutanga *et al.* 2004; Mutanga & Rugege 2006). In this study, stepwise linear regression was performed on the best SPOT5 derived vegetation variables that yielded significant correlation (significance level: $p < 0.05$) with woody canopy cover and density. Regression analysis was done for the texture indices, as well as the individual bands for SPOT5 MS, SPOT panmerged bands, and the SPOT5 derived vegetation indices.

Given specified criteria for the best fit model, stepwise linear regression analysis can be used to find subsets of the predictor variables that best predict responses on a dependent variable by a regression equation (Mutanga & Rugege 2006). However, to avoid over fitting a given stepwise regression model, the rule of thumb, as suggested by several authors (Skidmore *et al.* 1997; Serrano *et al.* 2002; Cohen *et al.* 2003; Mutanga *et al.* 2004; Mutanga & Rugege 2006) are that: (1) the number of predictor variables to enter the model be less than 1/3 the number of observations and (2) the number of steps in the stepwise linear regression analysis be 10 to 20 times less than the training data set. In this regard, the number of steps selected for this study was set at 6 on a training dataset of 75 samples. The authors recommended this ratio will circumvent the problem of predictions (regression line) being very unstable.

3.3.6 Accuracy assessment

An independent test dataset (n=25) was used to validate each spatial interpolation method. The predictive capability of the methods was determined using the root mean square error (RMSE) between the predicted and the measured test data. For ordinary kriging as well as cokriging, the RMSE was calculated as part of the modeling steps using the Geostatistical analyst tool for ArcGIS v9.2, and for stepwise linear regression, the RMSE was calculated as follows:

$$RMSE = \sqrt{SSE_i^2 / n} \tag{10}$$

Where SSE is sum of errors (observed-predicted values) and n is the number of pairs (Siska & Hung 2001).

3.3.7 Geostatistics

3.3.7.1 Exploring spatial structure of the data

After ground sampled woody data was pooled for all 100 sample plots, as well as the SPOT5 derived spectral vegetation and texture variables, which were extracted to match the ground sampled locations, preliminary statistical tests and analyses were performed using Statistica 7 (StatSoft. Ltd. London. Inc). Normality test was performed on all data sets using the Kolmogorov-Smirnov test. Once the normality test was completed and distribution of the datasets is known, the suitable statistical technique to use for further spatial-statistical analysis was then decided. Linear correlation analysis was performed on the datasets to assess the relationships between the ground sample woody vegetation variables and the SPOT5 derived variables. By taking this significance approach of testing the relationships between ground and remotely sensed data, a pursued goal of selecting critical variables required for modeling the woody cover in the savanna environment could be achieved. The identified, most suitable variables were then used in spatial statistical (geostatistical) analysis, as well as in forward stepwise linear regression analysis.

When constructing a linear model of coregionalization, it is imperative that isotropic variograms are applied. Examining the different pairs of sample (in this case woody cover) locations is an efficient means to assess the spatial structure in the regionalized variables. This is important because exploring the data gives a better understanding of the spatial autocorrelation among the measured values. This understanding helps to account for directional influences, known as anisotropy in the sampled data. The presence of anisotropy has an effect on geostatistical prediction methods, by imposing directional influence on the predicted surfaces. It is therefore, important to investigate anisotropy so that if directional differences are detected in the autocorrelation, it can be accounted for, by applying an affine transformation (ESRI Inc, 1999-2006). In this study, anisotropy was investigated using a semivariogram cloud tool in ArcGIS v9.2. The surface of the semivariogram values are calculated for each pixel (generated from a point map) and all pairs of locations that are in a certain distance apart. The pairs were selected by brushing all points at a search distance in the semivariogram cloud to visualize possible anisotropy of data and to determine the direction of the anisotropy axis (ESRI Inc, 1999-2006).

3.3.7.2 Sampling image data using the Variogram

The significant savanna woody vegetation density as well as percentage woody canopy cover and best selected SPOT data (identified from correlation analysis) were analysed using the basic geostatistical tool known as semivariogram (commonly referred to as the Variogram). The variogram is based on the theory of regionalization (Woodcock *et al.* 1988a).

The best selected SPOT5 texture measure data (i.e. pixels that coincided with the ground sample locations) was modeled using the variogram in order to determine the spatial range of influence in the samples. The range of spatial influence is an important parameter of the semivariogram (details of the theoretical features of the variogram was discussed in section 2 .7 of chapter2). The range has been found to be highly related to the size of objects in an image (Woodcock *et al.* 1988b). For vegetation studies, the range is found to be significantly related to tree density (Hudak & Wessman 1998).

The Range is an important feature of the semivariogram which represents spatial dependence as a function that relates semivariance to the lag distance (Atkinson 1993). The semivariance (γ) is half the expected squared differences between values of a property at a distance of separation which is generally referred to as the lag (h). The lag has two components, namely magnitude and direction. The semivariogram can be used to measure the strength of statistical correlation in both ground and remotely sensed data and generally takes the form:

$$\gamma(h) = \frac{1}{2} \mathrm{E}\left[\left\{Z_i^{'}(x) - Z_i^{'}(x+h)\right\}\right]^2 \qquad \textbf{(11)}$$

Where x and $x+h$ are two sample points, separated by distance h, and $\mathrm{E}[.]$ is the mathematical expectation and $Z_i^{'}(x)$ is the density of woody plants at sample location x (Isaaks & Srivastava 1989). Using the modeled lag value, the best SPOT5 derived images were sampled at 3000 m intervals in addition to the extracted pixel values that coincide with the field sampled locations (Mutanga & Rugege 2006).

3.3.7.3 The Experimental Variogram

The experimental variogram computed from both field and remotely sensed samples were assessed at different lag sizes before fitting a model. The variograms were calculated with varying lag spacing and visually determine the best resemble empirical variogram models. For this study because the data was acquired using an irregular VCA locations (although sampling scheme followed a regular pattern), the selection of a suitable lag size was determined using a basic rule of thumb. This rule suggests that multiplication of the lag size by the number of lags should be about half the largest distance among all sample points (ESRI Inc, 1999-2006).

The model fitting was performed for several empirical semivariogram (exponential, spherical, Gaussian, circular) models. The spherical model (equation 9) was the best closely resembled the experimental variogram model, which also happened to be the best model for woody plants spatial modeling (Isaaks & Srivastava 1989; Hudak & Wessman 1998; Wallace *et al.* 2000).

$$\gamma_s(h) = C_0 + C_1\left(\left(1.5\left(\frac{h}{a}\right) - 0.5\left(\frac{h}{a}\right)^3\right)\right) for\ h <= a$$
$$and\ \ \gamma_s(h) = C_0 + C_1\ for\ h > a \quad \textbf{(12)}$$

Where $C_0 = \text{nugget}$, $h = \text{distance}$, $C_1 = \text{sill}$, $a = \text{range}$ (Isaaks amd Srivastava, 1989)

3.3.7.4 *Kriging*

Two kriging techniques were evaluated for this study. The main focus was on cokriging method. However, ordinary kriging was assessed for the purposes of comparative analysis of the savanna woody cover prediction. These two kriging methods were computed using the geostatistical analyst tool for ArcGIS v9.2.

Kriging methods generally use the distance weighting factor and the spatial arrangement in the weights to quantify spatial autocorrelation in sample data. Ordinary kriging is thus based on the linear model of regionalization, which is fundamentally a weighting function approach which uses the variogram to estimate or predict variables. The variogram plots semivariance γ as a function of the distance between sample values of a property, usually called lag (*h*) distance. The semivariogram calculates *n* pairs of data locations, which is defined as follows:

$$\gamma(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} \{z(x_i) - z_u(x_i +)\}^2 \qquad \textbf{(13)}$$

Where $\gamma(h)$ is semivariance, h is lag distance, $n(h)$ is the number of data pairs separated by h, and z is the value at location x_i and (x_i+h) (Hudak *et al.* 2002; Mutanga & Rugege 2006).

In ordinary kriging the fitted model estimates a value U* (x) at unsampled location x based on the weights at measured points, the distance to the prediction location, and the spatial relationships among the measured values around the prediction location. Equation (10) shows how the ordinary kriging formula is used to estimate a value and create a map of the prediction surface:

$$U^*(x) = \sum_{\alpha_1=1}^{n_1(x)} \lambda_\alpha(x) U(x_\alpha) \qquad \textbf{(14)}$$

Where U(x_α) is the predicted primary variable and (λ_α) and (x_α) are the weights and locations, respectively of measured values around the prediction location (Isaaks & Srivastava 1989).

Cokriging is the multivariate extension of ordinary kriging to situations where two variables are spatially interdependent and the one of immediate interest is sparsely sampled. Cokriging computes estimations for the primary variable with the help of the secondary variable which is intensively sampled (Papritz & Stein 1999; Mutanga & Rugege 2006). In this study woody vegetation canopy cover and density sampled from the field are the variables of primary interest and the best sampled SPOT5 data is the secondary variable. The technique is based on the linear model of coregionalisation that provides a framework for modeling the spatial autocorrelation in the primary variable as well as the cross-correlation between the primary and the secondary variable (Hudak *et al.* 2002; Mutanga & Rugege 2006). Each regionalized variable is therefore characterized by its sample autocorrelation and each pair of variables by their sample cross-correlation. Since kriging uses the semivariogram to model spatial autocorrelation in the primary variable, then the cross-correlation between variable *u* and *v* can be graphically represented by the cross-semivariogram, defined as:

$$\gamma_{uv}(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} \{z_u(x_i) - z_u(x+h)\}\{z_v(x_i) - z_v(x_i+h)\} \quad \textbf{(15)}$$

Where $\gamma_{uv}(h)$ is the cross-semivariance between variables *u* and *v*, $n(h)$ is the number of pairs of data locations separated by lag distance *h*, z_u is the value of variable u at locations x_i and (x_i+h), and z_v is the data value of variable v at the same locations (Van Der Meer 1998; Hudak *et al.* 2002; Mutanga & Rugege 2006).

The technique uses the theory of linear co-regionalization and exploits the covariance between a primary variable U and a single secondary variable V to predict or estimate the unknown U variable at an unknown location *x*, which takes the form of $U^*(x)$:

$$U^*(x) = \sum_{\alpha_1=1}^{n_1(x)} \lambda_{\alpha_1}(x) U(x_{\alpha_1}) + \sum_{\alpha_1=1}^{n_2(x)} \lambda_{\alpha_2}(x) V(x_{\alpha_2}) \quad \textbf{(16)}$$

Where $\gamma_{\alpha 1}$ and $x_{\alpha 1}$ are the weights and locations, respectively, of the n_1 primary data, and $\gamma_{\alpha 2}$ and $x_{\alpha 2}$ are the weights and locations, respectively, of the n_2 secondary data (Hudak *et al.* 2002; Mutanga & Rugege 2006).

The cokriging estimator uses important conditions to satisfy positive definiteness constraint for the linear model of coregionalization. In this case the cross-semivariogram insures that the variance of the weights assigned to model at any possible linear combination of variables is positive (Atkinson *et al.* 1992). Thus, the sum of the weighted averages assigned to the primary variable *u* is forced to 1, and the sum of the weighted averages applied to the secondary variable is set to 0. These constraints avoid bias in the model prediction (Atkinson *et al.* 1994; Hudak *et al.* 2002). In this study, the cokriging estimator used operates under the two nonbias constraints:

$$\sum_{\alpha_1=1}^{n_1(x)} \lambda_{\alpha_1}(x) = 1; \qquad \sum_{\alpha_2=1}^{n_2(x)} \lambda_{\alpha_2}(x) = 0 \tag{17}$$

Using unbiased conditional constraints in the estimation of the primary variable ensures minimum variance which is very important because in practice near observations carry more weights to have effect (McBratney & Webster 1983). However, some studies suggest that the second condition tends to limit severely the influence of the secondary variable (Isaaks & Srivastava 1989; Hudak *et al.* 2002). In this study since the best selected SPOT5 data covariance functions is required when woody cover or density are considered, the reduction in estimation variance is worth the additional modeling effort because the primary variable (woody canopy cover and density) are sparsely sampled, relative to the secondary variable (SPOT5 vegetation indices or texture measures).

Chapter 4. Relationship between Spot image Data and Woody Vegetation

This chapter report results obtained from analysis of the relationship between savanna woody vegetation parameters and remotely sensed SPOT image data. Such a relationship was investigated using statistical analysis based on field data acquired on woody vegetation traits of the study area. Prior to determining the relationship between the field and remotely sensed data, analysis of the spatial structure (data distribution and normality testing) of the datasets is presented. The study examined the SPOT data in two analytical domains: (1) spectral domain, which included analysis of spectral vegetation indices and individual SPOT multispectral (MS) bands as well as individual SPOT panmerged bands; and (2) spatial domain, which involved spatial transformation of the SPOT MS image by calculating several image texture indices. Following an analysis of the relationship between the datasets, the chapter presents the results of the best woody vegetation correlates predicted using multiple independent SPOT variables. Finally, to accomplish the set objectives outlined in chapter one, the results presented in this chapter served to identify critical SPOT variables for geostatistical analysis.

4.1 Descriptive Statistics

Table 4.1 displays the descriptive statistics for selected sampled woody and image correlates per plot ($900m^2$) in the study area. Differences in intensity of herbivory, fire, fine-scale soil disparity, as well as site hydrology may have influenced local variation in tree densities and percentage woody canopy cover values in the sampling sites (see table 4.1), as observed within the study area (Hempson *et al.* 2007).

The null hypothesis formulated for a Kolmogorov-Smirnov test computed for one-sample test of normality was that the D statistic of the dataset under test are normally distributed if Ho: p= ns (i.e. D not significant). If the D statistic is not significant, then the alternate hypothesis that the data under test are not normally distributed (Ha: p = s (significant)) is rejected, where p is the significance of normality from the Kolmogorov–Smirnov D statistics. In this regard, the p values for the mentioned woody and SPOT variables were not significant. Therefore the null hypothesis could not be rejected. Results of the Kolmogorov–Smirnov D statistics test (K-S) which revealed that the datasets under test are normally distributed are displayed in table 4.1.

Because the selected datasets are normally distributed, parametric statistical methods, as well as geostatistical techniques were applied in subsequent analysis of the field sampled woody parameters, as well as the SPOT derived vegetation datasets. In this regard, testing for normality in the datasets is important for the selection of suitable statistical or geostatistical techniques which assume a normal distribution of the datasets.

Table 4.1: Descriptive statistics for best woody and SPOT variables (Total n = 100). K-S = Kolmogorov-Smirnov test, p=ns signify ‘p value is not significant.

No.	*Parameter*	*Woody tree density,900m-2*	*%Woody canopy cover*	*1st order Mean texture measure for SPOT MS Band3*	*Panm_band3*
1	Mean	53	56	119.95	130.41
2	Median	36	60	125.5	131.78
3	Minimum	4	6	0	98.05
4	Maximum	361	96	255	171.36
5	Standard deviation	56	22.87	64.23	15.07
6	Sum of individuals	5306	-	-	-
7	K-S (p = ns)	0.0342	0.0630	0.0625	0.0322

4.2 Relationship between SPOT5 Spectral Data and Woody Vegetation Cover

The relationship between ground sampled woody vegetation parameters (table 3.2) and SPOT derived vegetation indices, as well as individual SPOT MS and panmerged bands were assessed using a linear correlation analysis. The fitted linear relationship between woody parameters and SPOT5 MS datasets, as well as the SPOT panmerged bands is displayed in table 4.2.

The results of statistical analysis reveal a positive relationship between percentage canopy cover as well as tree density with all the SPOT derived data. The relationship largely showed average correlation coefficient for the individual SPOT bands. The spectral vegetation indices calculated on the SPOT MS imagery yielded weak correlations with all sampled woody parameters, including the tree density samples (table 4.2). Percentage canopy cover yielded strong correlation with SPOT panmerged band3. The highest correlation coefficients for SPOT MS (Band3) and SPOT panmerged (Band3) imagery were 0.37 and 0.58 respectively. The high correlation observed for the NIR (SPOT5 band3) can be associated with the multiscattering effects in the near infrared region of the electromagnetic spectrum (Kumar *et al.* 2001). Detailed explanation of spectral reflectance characteristics of vegetation and the related effects on vegetation radiation measurement is well documented in Kumar *et al.* (2001). In addition, stronger correlation coefficients recorded for woody parameters and the SPOT panmerged data can be attributed to the very high spatial resolution (2.5m) for the panmerged imagery compared to that of 10m resolution for the SPOT MS image data. The 2.5m panmerged image data is the product of 3 band SPOT MS fused with the SPOT panchromatic band (Cnes SPOT image, 2005) and has high spatial resolution capable of detecting small scale sparsely distributed woody stands more accurately at a panchromatic viewing geometry. This is indicated by the high correlation coefficient values recorded for the panmerged bands.

Spectral vegetation ratios such as NDVI and Simple ratio (SR) that have been formulated to enhance vegetation presence and abundance yielded low correlation coefficients with woody parameters as shown in table 4.2. Previous studies have suggested that low correlation coefficients observed for the vegetation indices such as NDVI can be attributed to the asymptotic nature of the NDVI–vegetation relationship (Mutanga & Skidmore

2004). For example NDVI calculated from multispectral images such as SPOT data is known to saturate in dense canopies as the growing season for vegetation progresses (Yang & Prince 1997; Mutanga & Skidmore 2004). The significance of the relationship between field and image data recorded for majority of the variables including the one with the highest correlation coefficient was at the 0.01 confidence limits (table 4.2).

Table 4.2: Relationship between woody vegetation parameters and SPOT multispectral (MS) and panmerged (Panm) bands (n=75)

Variables	*Tree density*	*% Canopy cover*
MS_band1	0.34**	0.25*
MS_band2	0.30**	0.44**
MS_band3	0.34**	0.53**
MS_band4	0.31**	0.39**
Panm_band1	0.29*	0.25*
Panm_band2	0.27*	0.44**
Panm_band3	0.37**	0.58**
Panm_band4	0.35**	0.49**
NDVI (equation 3)	0.21*	0.42**
TNDVI (equation 4)	0.21*	0.41**
DVI (equation 2)	0.20*	0.40*
SR (equation 5)	0.17	0.39**
sqrt_SR (equation 6)	0.2*	0.42**

Correlation coefficient: * Significance level: $p<0.05$.
** Significance level: $p<0.01$.

4.3 Relationship between Image Texture and Woody Vegetation Cover

Image texture measures were calculated on the SPOT5, 10m resolution Multispectral (MS) data. The relationship between field sampled woody structural parameters and SPOT5 derived texture indices were analyzed using correlation coefficient matrices. The resulting correlation coefficients between the best three texture algorithms and the woody correlates are displayed in Table 4.3. The highest correlation coefficients were 0.59 and 0.37 for percentage woody canopy cover and tree density respectively, using 1st order (occurrence) Mean texture measure for the SPOT MS Band 3. Appendix 3 displays the correlation matrices for all first and second order texture statistics and all field sampled woody vegetation parameters. As shown in appendix 3, correlation coefficients between some texture measures were very low or not significant. This can be attributed to the configuration of the texture algorithms on the image bands, as well as the effect of spatial resolution of the SPOT image bands. The results displayed in table 4.3 show that both first order (occurrence) and second order (co-occurrence) texture measures yielded high correlation with percentage woody canopy cover values, compared with that of woody tree density variant. This indicates that image texture measures performance is not only influenced by the type of image band but also dependent on the type of woody vegetation traits as is shown in this study. Other studies have suggested that performance of image texture to characterize vegetation is dependent on the spatial (pixel) resolution (Hudak & Wessman 1998).

Table 4.3: Relationship between woody parameters and top three SPOT MS texture variables

Rank	*Image Texture Variables*	*Percentage canopy cover*	*Woody tree density/plot*
1	1st order Mean texture measure for SPOT MS Band 3	0.59**	0.37**
2	2nd order Mean texture measure for SPOT MS Band 3	0.54**	0.33**
3	2nd order Entropy texture measure for SPOT MS Band 4	0.50**	0.34**

Correlation coefficient (R): ** Significant level: P<0.01

4.4 Predicting woody vegetation parameters using multiple independent SPOT variables

Forward stepwise linear regression analysis using the significant SPOT variables was carried out on percentage (%) woody canopy cover and tree density (training datasets n =75). The regression models calculated for the %woody canopy cover and the tree density variables resulted in R^2 = 0.58 and R^2 = 0.38 respectively (regression significance: $p < 0.00001$). Low R^2 values could have been the result of outliers that often have large impact on the strength of linear relationships determined from small datasets that may not be fully representative of the local variation (or fine scale heterogeneity) in the study area.

Betas of the SPOT variables (table 4.3) that were used in the stepwise linear regression equation were input to ArcGIS spatial analyst tool (raster calculator) to calculate the regression model equation using the selected SPOT data for the predictant variables. Figure 5.2 (c) and figure 5.3 (c) shows the respective estimated surfaces for the % woody canopy cover and tree density in the study area. The prediction accuracy of the models was calculated using the RMSE analysis on an independent %woody canopy cover and tree density (datasets n = 25). The resulting RMSE ($900m^{-2}$) values are displayed in table 5.2.

Table 4.4: Betas used in the forward stepwise multiple regression.

		Betas	
Parameter	*SPOT band*	%woody canopy cover	Tree density
Intercept		82.98658	-108.17087
1^{st} oder Mean texture	band 3	0.35061	-
1^{st}oder Mean texture	band 4	-	0.07566
2^{nd} order Mean texture	band 2	-0.23898	-
1^{st} oder skewness texture	band 1	-0.22257	-
1^{st} oder skewness texture	band 3	-0.10472	-
2^{nd} order correlation texture	band 3	-0.14905	-0.46453
2^{nd} order correlation texture	band 4	-	-0.20953
SPOT panmerged image	band 2	0.52197	-
SPOT multispectral image	band 1	-	0.32105
TNDVI (equation 4)	band 2&3	-	2468.69118
sqrt_SR (equation 6)	band 2&3	-	-1452.03648

Chapter 5. Geostatistical analysis

This chapter presents the results obtained using different geostatistical tools, such as the variogram modelling and the kriging methods, as outlined in chapter one. The results obtained in chapter four (i.e. assessment of the relationships between ground sampled and remotely sensed data) provided an efficient method to select critical variables for the geostatistical analysis. The chapter also examined the effects of sample plot layout on the kriging interpolators, and investigated the existence of directional influence or anisotropy in the optimal ground sampled woody data. Finally the results obtained from cokriging were evaluated and compared with the results obtained from ordinary kriging, as well as the results obtained from multiple regression analysis.

5.1 Selecting Optimal Field and Spot Derived Vegetation Variables for Cokriging

Correlation tests were calculated to determine the strength of the significant relationship between SPOT data and woody vegetation structural traits measured in the field (chapter 4). The results indicate that some woody plant parameters did not have significant correlation with the spectral vegetation indices and individual SPOT bands, as well as the texture measures. Percentage canopy cover and the number of trees per plot (tree density) were the woody parameters with highest significant correlation coefficients. The highest correlation coefficients were 0.59 and 0.37 (using first order image texture statistics for SPOT MS band3) for the percentage canopy cover and tree density respectively. In the spectral domain, the highest correlation coefficients were 0.58 and 0.37 (SPOT panmerged band3) for percentage canopy cover and tree density respectively. As shown in table 4.2 and table 4.3, first order image texture statistics for SPOT MS band3 yielded the highest correlation with both percentage woody canopy cover and woody tree density per plot, and was therefore selected for cokriging. It was important to use the best image texture correlate for cokriging because: (1) it recorded the highest correlation with the ground sampled woody data, and (2) texture measure is a good indicator of objects contained in an image, based on the spatial variability in an image, which is spatially correlated with vegetation radiation.

5.2 Investigating Directional Influence or Anisotropy in the Datasets

Anisotropy or directional influence in the datasets was investigated using the variogram surface. The resulting variogram surfaces reflected a gradual increase in the semi-variogram values from the centre into all directions (Figure 5.1) for both %woody canopy and tree density datasets. This shows that there is no anisotropy effect in the datasets, as suggested by Mutanga & Rugege, (2006). Figure 5.1 displays the pattern of the variogram surfaces for the datasets. Absence of anisotropy in the variogram surfaces measured for % woody canopy cover and tree density datasets makes it conducive to have a reliable linear model of coregionalization and accurate predictions using the two kriging interpolation techniques employed in this study. The fundamental principle is that when there is isotropy for spatial correlation, then the semi-variance, γ(h) depends only on the magnitude of h and not on its direction.

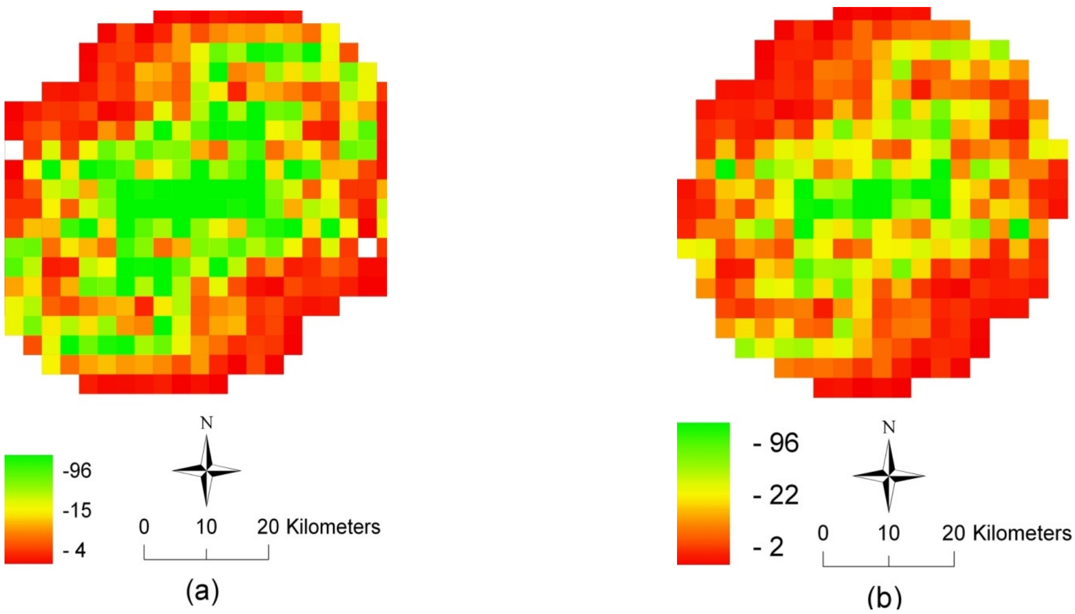

Figure 5.1: The isotropic variogram surfaces for measured %woody canopy cover (a) and tree density (b) datasets. The value in each cell represents a semi-variogram value.

5.3 Estimating Woody variables using ordinary kriging and Cokriging

Five variograms were constructed for the two selected woody parameters: one for percentage woody canopy cover data, one for woody tree density, one for the 1st order Mean texture measure for SPOT MS Band 3, and a crossvariogram between the 1st order Mean texture measure for SPOT MS Band 3 and the percentage woody canopy cover, as well as the tree density data. Figure 5.2 shows the fitted variograms using the spherical model with a nugget component.

The least square fitting for all the variograms is shown on each modeled variogram (figure 5.2), where as the parameters of all the variograms is displayed in table 5. 2. The variogram models were used to predict woody parameters using ordinary kriging and cokriging. Figures 5.3 and 5.4 show the distribution of the woody vegetation density and cover parameters respectively, using the three approaches evaluated in this study.

It is important to note that the cross-variogram models (for SPOT 5-derieved data and the woody variables) as shown in figure 5.2 d and e have very small nugget effect (nugget value closer to 0 or resembling the ideal variogram) suggesting that the measurement error (Atkinson, 1999; Curran, 1988) can be reduced when cross-correlation factor between intensively sampled SPOT 5 image data and woody variables are encompassed in cross-semivariogram modeling. An understanding of the nugget effect is therefore very important for cokriging interpolation which can be exact or smoothed depending on the measurement error model calculated from the cross-semivariogram.

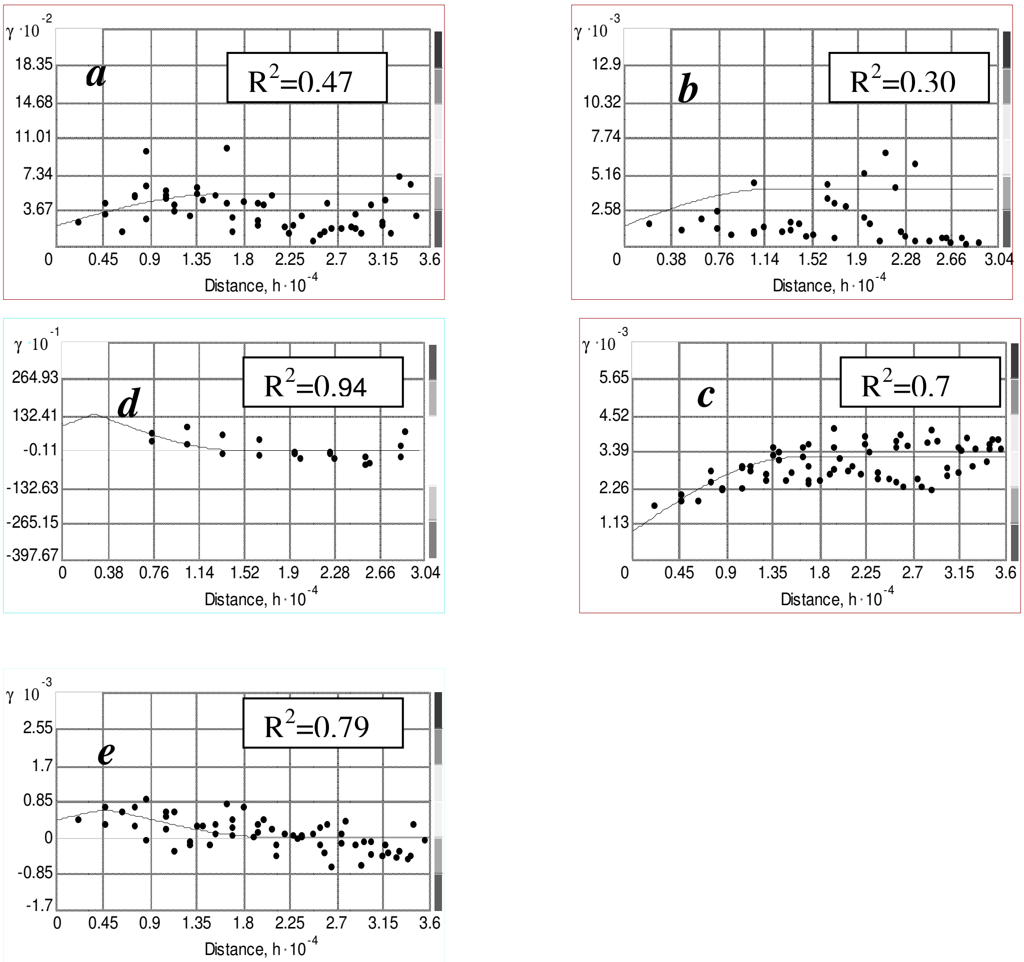

Figure 5.2: Isotropic variograms for predicted primary variables (woody tree density (a) and %woody canopy cover (b)), covariable (SPOT data (c)) and cross-variograms for a & c (d), and b & c (e); h is distance in meters and γ is the semi-variance values.

Table 5.1: Variogram parameters for predicted woody canopy cover and density vs the transformed SPOT variable

No.	Variable	Range (m)	Nugget	Sill
1	Woody tree density	12042	1412	2633
2	1st order Mean texture measure for SPOT MS Band 3	12042	687	2276
3	Cross-covariance for Woody tree density and the SPOT data	12042	-	1351
5	Percentage canopy cover	15 975	202	321
5	1st order Mean texture measure for SPOT MS Band 3	15 975	859	2329
6	Cross-covariance for percentage canopy cover and the SPOT data	15 975	-	718

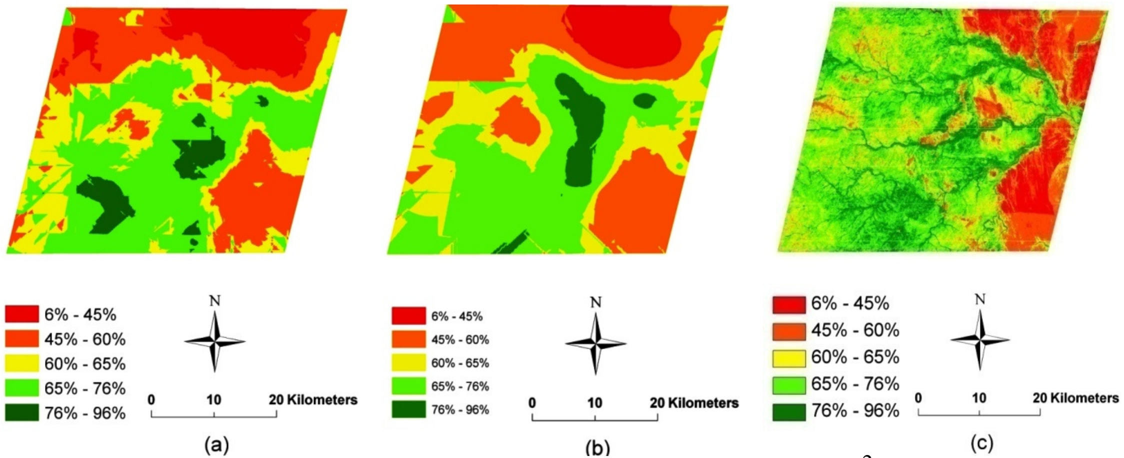

Figure 5.3: Predicted percentage canopy cover values ($900m^{-2}$) using cokriging (a), ordinary kriging (b) and linear regression (c).

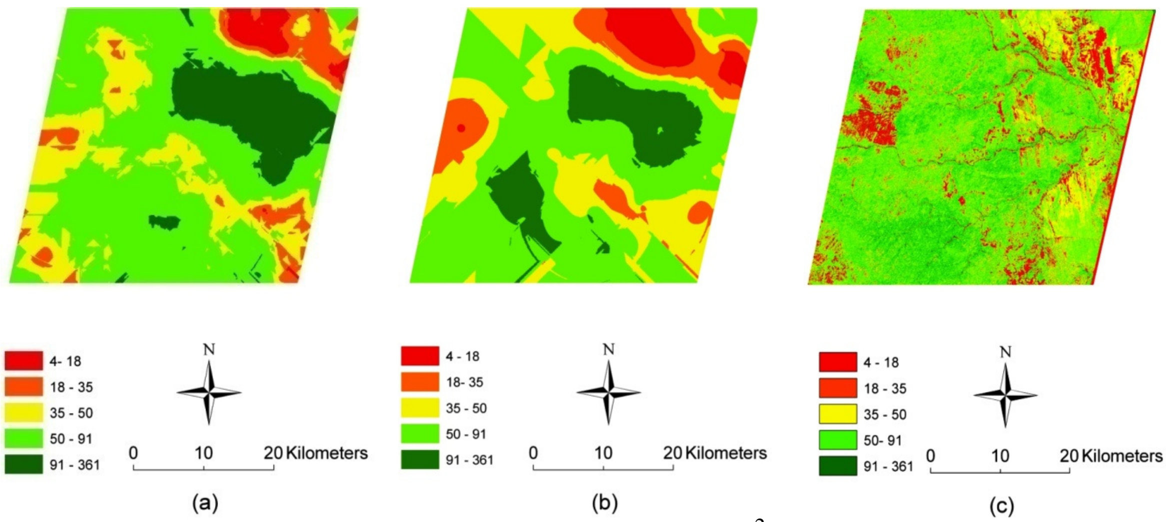

Figure 5.4: Predicted woody tree density values ($900m^{-2}$) using cokriging (a), ordinary kriging (b) and linear regression (c).

5.4 Evaluation of the prediction error of the kriging models

The fit model semivariogram for the %woody canopy cover as well as tree density prediction in the study area were both at 3000 lag size. At this lag size, the experimental model with a nugget effect yielded the best fit for the datasets sampled at $900m^2$ plots. The predictive performance of the models at the set lag for both datasets was identical (figure 5.5). The prediction error was less in the eastern part, through to the center of the study area. The highest prediction error values were at the north-western corner and the southern parts of the study area. The high error largely reflected the non-systematic sample plot layout in the study area. In this regard, it is important to note that high prediction error occurred in areas that were sparsely sampled. Figure 5.5 shows the prediction error map for the %woody canopy cover and tree density estimation in the study area.

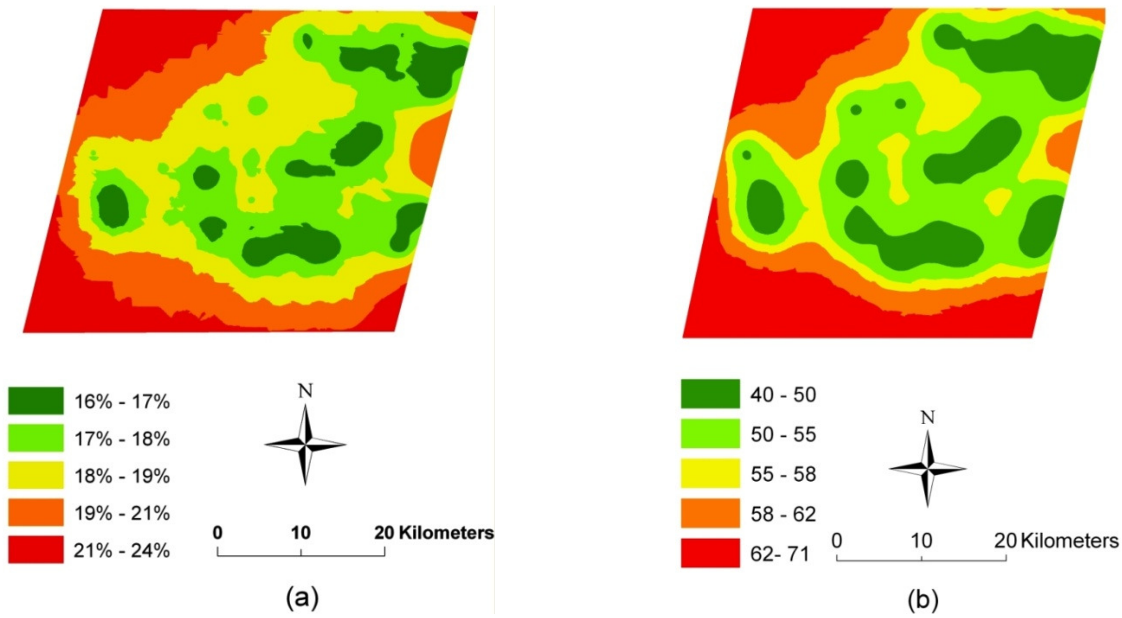

Figure 5.5: Prediction error for % woody canopy cover (a) and tree density (b), 900 m^{-2} of the study area

5.5 Comparing the cokriging method with ordinary kriging and regression approaches

The predictive capability of the approaches used in this study indicates that cokriging yielded the highest squares of linear fit: r^2 = 0.83 (predicted woody tree density) and r^2 = 0.66 (predicted % woody canopy cover) respectively. The predictive performance of the cokriging approach was further compared with that of ordinary kriging as well as stepwise linear regression using the 1st order Mean texture measure for SPOT MS Band 3 data. Table 5.2 shows accuracy assessment results obtained from the three approaches (regression model, ordinary kriging and cokriging) using the Root Mean Square Error (RMSE) of prediction. The RMSE between the measured and predicted woody parameter using cokriging on the independent test dataset is lower than that obtained using ordinary kriging and multiple linear regression methods.

Table 5.2: The Root-Mean-Square Error (RMSE) for predicting woody vegetation parameter on an independent SPOT-derived vegetation dataset.

Predictant Variable	RMSE measures		
	Cokriging	Ordinary kriging	Regression
Percentage woody canopy (%900m^{-2})	13	17	25
Woody tree density (individual plants 900m^{-2})	17	23	62

5.6 Summary of Results

Chapters four and five have shown the results of data analysis. Descriptive statistics of the datasets revealed normal distribution for the sampled woody correlates as well as remotely sensed datasets. Parametric statistical techniques that assume normal distribution of datasets were therefore performed in subsequent data analyses. Chapter four reported results obtained from analysis of the relationship between woody vegetation parameters and remotely sensed SPOT derived vegetation data. The results revealed that field sampled percentage woody canopy cover and tree density per plot were the best field measured woody correlates. SPOT panmerged band3 as well as first order (occurrence) image texture calculated on the SPOT5 multispectral image (band3) yielded the highest correlation coefficients (table 4.1 & 4.2) with the field sampled woody canopy cover and density. The individual SPOT5 bands as well as spectral vegetation indices calculated on the SPOT5 data yielded low correlations as compared to the best SPOT panmerged band and the best texture index.

Chapter five presented the results obtained from geostatistical (variogram modelling and the kriging interpolations) analysis of the woody canopy cover and density as well as the 1st order Mean texture measure for SPOT MS Band 3. The results show that there is no anisotropy (figure 5.1) in the datasets. However, the predictive error maps (figure 5.3) showed high prediction error in the upper and lower western corners of the study area. This was attributed to the effect of sample plots layout on the kriging interpolators. The best image texture measure (first order texture for SPOT band3) which recorded the highest correlation coefficient with the ground sampled percentage woody canopy and tree density data yielded the lowest RMSE (table 5.2) for the predictant variables using cokriging, as compared to the results obtained from ordinary kriging, as well as the results obtained from the simple linear multiple regression.

Chapter 6. Discussion

This chapter discusses the results obtained in chapter four and five in respect of the organization of the study as outlined in chapter one. The study was structured in two major parts and sections in order to effectively accomplish the set objectives of this study. Part one was to establish statistical relationships between woody vegetation variables and SPOT vegetation and texture indices for the purposes of identifying the best SPOT vegetation or texture indices. Analysis in part one also involved evaluating the effects of the sampling scheme employed, as well as evaluating the effects of the image spatial resolution and various image transformation methods on the relationship between the field and remotely sensed data.The second part was to model the woody canopy cover and density using cokriging and compared the results with those obtained using simple linear regression as well as ordinary kriging.

6.1 Comparison between the 10m SPOT5 MS and the 2.5m SPOT panmerged images used in Characterizing Woody cover and density

Several studies (e.g. Kumar *et al* 2001; Mutanga & Rugege, 2006) have shown that vegetation and its radiation are spatially correlated. Therefore, the ability to identify remote sensing data that strongly correlate with woody vegetation is an important step towards achieving high accuracy in woody cover estimation using remotely sensed data analysis procedures. An evaluation of the performance of the two SPOT images (SPOT5 multispectral and SPOT panmerged images respectively) to characterize woody cover and map its spatial distribution using remote sensing techniques has been demonstrated in this study.

The results obtained from analysis of the relationship between the two SPOT images and woody vegetation parameters yielded best correlation coefficients for percentage woody canopy cover, as well as tree density with the SPOT panmerged bands as compared to the 10m resolution SPOT multispectral bands. The high correlation coefficients observed for the SPOT panmerged data as compared to the SPOT5 multispectral data (table 4.2) can be attributed to the high spatial resolution, as well as the panchromatic view geometry of the SPOT panmerged image data. In semiarid savanna ecosystems, woody vegetation crown cover is highly reflective as well as the canopy background reflectance of actively growing herbaceous under storey. Hence, the surface reflectance recorded by the remote sensor is composed of mixture of signals from both woody over storey layer as well as noisy reflectance signals from underlying herbaceous layer for most pixels. Because actively growing or photosynthetic herbaceous under storey reflectance is contained in the recorded pixels, spectral saturation in the woody vegetation signals is expected (Mutanga & Skidmore 2004). Spectral saturation may have significantly influence the recorded signals which most likely resulted in weak correlation for the multispectral data. However, the high correlation coefficients observed for the SPOT panmerged bands indicate that high spatial resolution data is capable of reducing the effect of noise in the reflectance values recorded for woody structural parameters. In this regard, the SPOT panmerged image is better predictor of woody vegetation cover in the homogeneous mopane woodland savanna as shown in this study.

Although the SPOT5 multispectral bands yielded lower significant correlation coefficients with both percentage woody canopy and tree density parameter (table 4.2), it is important to note that the near infrared region (band 3) for both SPOT multispectral and SPOT panmerged images yielded the highest correlations coefficients respectively. Kumar et al. (2001) and Mutanga & Skidmore (2004) indicated that reflectance measurements for the NIR strongly correlate with vegetation structure due to multiscattering effects in the near infrared (NIR) region of the electromagnetic spectrum. In this respect the high correlation observed for band 3 can be attributed to the multiscattering in the band 3 for both SPOT multispectral as well as the SPOT panmerged images.

The results obtained from correlation analysis further revealed that percentage woody canopy cover yielded the highest correlation coefficient ($R = 0.58$) with both image data as compared to tree density ($R = 0.37$) (table 4.2). This result is very important for both biodiversity study (e.g. biomass prediction) as well as environmental monitoring studies (e.g. climate modeling). This is because studies have shown that there is a linear relationship between canopy cover estimates and vegetation biomass particularly in semiarid savannas (Olsson 1984; Tietema 1993). Therefore the high correlation obtained for percentage canopy cover means that further environmental or biodiversity predictions can be made based on the results of canopy measures of the study area. For example, Yang & Prince, (2000) have shown that canopy cover can be used as a critical input variable to simulate various climate and vegetation processes. Specific examples are net primary productivity and CO_2 pool modeling using biomass and canopy cover data as critical input parameters(Prince 1991; Sellers *et al.* 1996). In this regard, the high correlation coefficient observed for the percent woody canopy cover and the SPOT panmerged data in this study do not only help to improve the accuracy of estimating the density and distribution of woody cover in the study area but also provide great potential for quantitative measurement of environmental and biodiversity variables in savanna rangelands.

6.2 Relationship between SPOT5 multispectral vegetation indices and sampled Woody Variables

In the literature, the utility of remotely sensed spectral vegetation indices for vegetation study is well document. However, little is known about the effects of spatial resolution on multispectral vegetation indices for biomass estimations. By virtue of their purpose, vegetation indices are computed to combine spectral information contained in two spectral channels to produce a single value that indicates the presence and vigor (or abundance) of vegetation while being relatively insensitive to noise caused by canopy background or atmospheric effects (Yang & Prince 2000).

In this study, the results obtained from linear correlation analysis for field sampled woody vegetation parameters and 10m resolution SPOT5 derived vegetation indices have shown significant correlation coefficients (table 4.2). As stated in the description of the study area in chapter one, the Shingwedzi woodlands region of the Kruger National Park experiences four to eight months hot but wet season in October to April. In chapter three of this study, it was stated that the SPOT satellite images used in this study were acquired for October, 2005, hot but wet season. This means that at the time when the image was acquired, vegetation in the study area was actively high in photosynthesis.

In the literature, several studies have shown that vegetation indices computed from multispectral satellite remote sensing, using the red and near infrared bands may be of limited use as they asymptotically saturate in dense vegetation canopies (Skidmore *et al.* 1997; Mutanga & Skidmore 2004; Mutanga & Rugege 2006). It therefore possible to assume the both effect of resolution and saturation may have influence the strength of the correlation coefficients obtained from the analysis if the vegetation indices.

It is important to emphasize that, although this study did not setout to investigate the effect of pixel resolution on the relationship between woody vegetation parameters and spectral vegetation indices, the correlation results obtained suggests that spatial resolution of a remotely sensed vegetation index should not be ignored. In this study the assumption that resolution may have influence the performance of the raw multispectral bands as well as the vegetation indices is based on high correlation obtained for the 2.5m resolution SPOT panmerged data as compare to the 10m resolution SPOT5 multispectral data. In this regard, it can be suggested that finer resolution image provided better spectral data that is highly correlated with the ground sampled woody vegetation variables.

6.3 Image Texture Vs Woody Vegetation Cover and density Estimation

While high resolution multispectral satellite images may have adequate spatial resolution that is capable of detecting large landcover types such as forest stands or agricultural areas, they provide limited information that can be used to quantify densely distributed vegetation patches in open canopy savanna woodlands (Hudak & Wessman 1998). A number of studies (e.g. Hudak & Wessman, 1998) have shown that even relatively large trees in savannas are too small to be spectrally detected by most available high resolution multispectral remote sensing data.

In this study, analysis of the 10m resolution SPOT5 multispectral satellite imagery have shown significant correlation coefficients with field sampled woody parameters as shown in chapter four and further discussed in section 6.1. The application of texture algorithms to the raw 10m resolution SPOT5 multispectral bands yielded higher correlation coefficients with the best field sampled woody parameters: percentage woody canopy, R = 0.59 and tree density per plot, R = 0.37. The results obtained using image texture measures were relatively higher, as compared to the results obtained using the individual 10m resolution SPOT5 multispectral bands as well as the results obtained using spectral vegetation indices which was calculated on the 10m resolution SPOT5 multispectral image data. This shows that the application of suitable texture algorithm to multispectral data is an important step towards improving the accuracy of vegetation estimation where the performance of spectral data alone is insufficient.

The good correlation results obtained from texture analysis of the 10m resolution SPOT5 multispectral further confirms the recommendations made by a previous study (Hudak & Wessman 1998). In the study, the authors tested the performance of several image resolutions and found that texture measures calculated on simulated 20m resolution SPOT image was capable of characterizing savanna woody cover more accurately. And in this study, texture measures calculated on the 10m resolution SPOT5 multispectral image yielded the highest correlation with the field observations. Hence, the performance of texture measure is dependent on the spatial resolution of the original imagery that the texture index is calculated.

It is important to note that results obtained from the texture analysis were closely average with the results obtained for the 2.5m resolution SPOT panmerged data (table 4.2 and table 4.3). As stated earlier: we concluded that the 2.5m resolution SPOT panmerged data yielded higher correlation coefficients with selected woody parameters as compared with the 10m resolution SPOT5 multispectral image because the panmerged data has higher spatial resolution with a panchromatic geometry view. Therefore, higher correlation coefficients obtained for image texture calculated on the 10m resolution SPOT5 multispectral image data implied that image texture overcome the effect of spatial resolution, as well as highly insensitive to noisy reflectance which is attributable to woody canopy background in vegetation estimation processes.

6.4 Modeling woody vegetation cover

It has been evident in this study that to improve estimation accuracy, it is critical that correlation coefficient between primary (predictant) and secondary (an independent) variables should be highly correlated as suggested by Van Der Meer, (1998). In this study, the link between the primary and a secondary variable (in this case, SPOT derived vegetation correlate) for accurate prediction has been achieved through the selection of most strongly correlated ground and remotely sensed data. First order image texture measure for SPOT MS band 3 (r = 0.59) yielded the highest correlation coefficient (table 4.2) and was selected as the independent variable for modeling woody structural parameters. Cross-correlation information between the sparsely field sampled woody parameters and intensely sampled independent variable was exploited.

In order to model the cross-correlation factor as well as spatial dependence information in the variables, the semivariogram modeling was calculated. The semivariogram model calculations largely confirmed the results of the simple linear correlation analysis, by depicting more spatial auto and cross-correlation between the selected woody parameter and the highest correlated SPOT variable. The plot of cross-semivariance vs lag spacing yielded $R^2 = 0.94$ and $R^2 = 0.79$ for the predicted percentage woody canopy cover and tree density respectively (figure 5.2 c and e). This proves the existence of strong spatial autocorrelation in vegetation as well as its reflectance values and the cross-semivariogram modeling is a practical way of exploiting the spatial autocorrelation between ground sample and remotely sensed image data.

Cokriging which is a multivariate extension of ordinary kriging uses the well-sampled secondary variable derived from SPOT imagery to provide additional information about the primary data using the cross-semivariance information. Cokriging therefore yielded the highest accuracy of estimation of the primary variable (i.e. woody vegetation parameter) in this study. Analysis of the cokriging estimator yielded an average percentage woody tree cover of 49 % and varied between 16 % and 78 %, with a standard deviation of 21 %. In addition, woody tree density estimation in the study area using cokriging varied between 11 and 175 trees in $900m^{-2}$, with an average of 43 and a standard deviation of 42 trees in $900m^{-2}$.

6.5 Evaluation of the methods

A small field sampled woody test dataset (n= 25) was used for evaluation of all the methods tested. An integration of first order texture measure calculated for SPOT MS band 3 image data and field sampled woody variables in cokriging yielded a RMSE (table 5.3) of 17 woody trees in 900m^{-2} and 13% percentage tree canopy cover between the predicted and measured values for the tree density and percentage canopy cover respectively. As stated in few paragraphs above, the result is better than that obtained by ordinary kriging as well as the result obtained by stepwise linear regression on best correlated field sample and SPOT variables. The high RMSE's (25 % and 62 trees per 900m^{-2}) for simple linear regression model can be explained on account that the woody parameters were predicted by ignoring spatial arrangement of objects in the scene, as the variable at the ground is predicted from information in a given pixel and the information in the neighbouring pixel is ignored (Mutanga *et al.* 2004).

The results obtained in this study have shown that identification of the best woody parameter, by correlation analysis between field and remotely sensed woody variables do not only help improve the prediction when the utility of spatial dependence in field and remotely sensed datasets was incorporated through cokriging but also significant increase in accuracy can be achieved using only the best field sampled woody values through ordinary kriging as compared to the linear regression which do not take account for spatial dependence in the datasets for the spatial prediction of the predictant variable.

Results obtained from this study have shown that a combination of remotely sensed data and geostatistics can improve the accuracy of predicting woody vegetation density in complex savanna landscapes. The results compare well with a previous study by Mutanga & Rugege (2006) who evaluated the utility of remotely sensed and field data through cokriging to map herbaceous vegetation biomass quantities and distribution over large areas in the African savanna rangeland. Results in this study have therefore shown that the technique, with some refinement can be extended to woody density or percentage canopy cover prediction. The good result obtained in this study can be attributed to the capability of cokriging to utilize cross-correlation factor between a sparsely sample primary variable and a well sampled auxiliary (independent) variable. Cokriging therefore provided a method to combine field and remotely sensed data to accurately estimate woody cover variables and map its spatial distribution in respect to the results obtained in this study. The practical application of integrating remote sensing and geostatistical technique such as cokriging in this study presents a critical method for conservation managers and natural resource managers to spatially define the amount and extent of woody vegetation cover.

6.6 Remote sensing and Geostatistics for Savanna Woody Vegetation Estimation

Although savanna woody resources are spatially distributed (autocorrelation) and contain spatial dependence (cross-correlation) with remotely sensed data, vegetations studies in savannas rarely exploit the spatial aspects of woody cover in many attempts of woody cover quantification and mapping. Spatial techniques such as the semivariogram has been conventionally applied either to field observations alone or applied to remote sensing data in an attempt to estimate vegetation resources (e.g. Hudak & Wessman, 1998). However, an extension of this powerful tool to integrate field and remotely sensed data to predict vegetation resources has not been tested in the African savanna until recently. An integration of field and remote sensing data for herbaceous biomass prediction in the African savanna environment has been tested by Mutanga & Rugege, (2006). The study yielded good results when a cross-correlation factor was exploited by calculating a cross-semivariogram between field and remote sensing data through spatially engrained cokriging interpolation.

The utility of an integrated approach involving geostatistics and remote sensing to estimate woody vegetation cover in an African savanna rangeland has been demonstrated in this study. Remotely sensed SPOT5 satellite image data has provided a practical method of integrating geostatistics and remote sensing techniques to quantify woody vegetation cover and density in African savanna (mopane) woodland. The use of high spatial and temporal resolution SPOT5 imagery has therefore provided immense opportunity to intensively monitor savanna woodland for the benefit of both wildlife habitat studies and rangeland biodiversity assessment.

Chapter 7. Conclusion

This chapter reviews the aim and set objectives of the study, evaluate what has been achieved as regarding the set goals and provides a synthesis of the approaches adopted for this study. Conclusion as well as limitations and recommendations for future applications of remote sensing and geostatistical techniques for the estimation of savanna woody vegetation cover will also be provided.

7.1 Aim and Objectives re-examined

7.1.1 Aim reviewed

The main aim of this study was to investigate the utility of remote sensing data (high-resolution satellite images) in combination with geostatistical techniques (e.g. cokriging) to estimate density and map spatial distribution of woody vegetation in a *Colophospermum mopane* dominated woodland savanna. Cokriging was implemented as a novel geostatistical technique which combines field and remotely sensed data in an attempt to reduce error in estimating woody vegetation structural parameters.

This study has shown that there is a variation in the relationship between remotely sensing data and field measured woody vegetation structural parameters. In addition, the study revealed that the variation depends on the type of field sampled woody parameter and how it relates to both spectral and spatial characteristics of the remotely sensed image data.

The best field and image variable used in geostatistics is based upon the determined linear correlation coefficient values obtained for field and remotely sensed data. In this regard, the study has demonstrated that it is crucial that field and remotely derived vegetation data should be highly correlated in order to be useful input in geostatistical analysis procedures. This conclusion was reached following good results observed for geostatistical analysis of the best correlated field and remotely sensed data through cokriging.

While, previous studies have sampled remotely sensed images using a rule of thumb in an attempt to increase computational efficiency, this study has demonstrated the use of statistical approach of sampling the remotely sensed image data using the semivariogram modeling tool. The results showed that using semivariogram to sample image data for cokriging offer great potential for future studies within this niche of remote sensing to accurately estimate and map the spatial distribution of woody vegetation resources.

7.1.2 Objectives reviewed

The aim of this study as stated above was accomplished by considering the following set objectives**:**

1. Evaluate the utility of different vegetation indices and texture measures to characterise savanna woody vegetation cover.

The first specific objective was to investigate the extent to which spectral vegetation indices which included: NDVI, TNDVI, DVI, SR and sqrt-SR computed from the 10m resolution SPOT5 multispectral image data can predict woody cover density and distribution. The results obtained using correlation coefficient of determination showed very weak relationship (highest value, $R = 0.21$ and $R = 0.42$ for NDVI) with field sampled tree density and percentage woody canopy respectively. The low correlation observed for the spectral vegetation indices, particularly, the widely used NDVI was attributed to the effect of spatial resolution on a small scaled woody density, as well as attributed to the "saturation problem" suggested in a previous study by Mutanga and Skidmore, 2004.

The second specific objective was to investigate whether texture indices computed from the 10m resolution SPOT5 multispectral data can improve prediction of woody cover density and distribution. The correlation coefficients results obtained for the calculated texture measures (e.g. highest value, $R = 0.37$ and $R = 0.59$ for 1st order Mean texture measure for SPOT MS Band 3) with best field sampled tree density and percentage woody canopy respectively was higher than the results obtained from the vegetation indices. It has been shown in this study that the use spatial information contained in the10m resolution SPOT5 multispectral data in image textural analysis can overcome the effect of spatial resolution on small scaled woody density, as well as overcome the "saturation problem" which limit the performance of multispectral vegetation indices in estimating vegetation resources such as biomass densities (Mutanga & Skidmore 2004).

2. Compare the utility of SPOT5 multi-spectral and SPOT Panmerged imagery to estimate savanna woody cover.

Following objective one, the second set objective set to accomplish the main aim of this study was to compare the performance between the 10m resolution SPOT5 multispectral bands and 2.5m resolution SPOT panmerged dada. The results revealed that the 2.5m resolution SPOT panmerged data is a better predictor of the field sampled woody vegetation variables. This was shown by the high correlation coefficient measures (highest value, R = 0.37 and R = 0.58 for the panmerged spectral band3) with the best field sampled, tree density and percentage woody canopy cover respectively. This study has shown that cokriging with image textural index is capable to estimate woody cover structure. The main conclusion made on the high correlation is attributed to the finer spatial resolution (2.5m) at panchromatic view geometry for the panmerged band3 compared to the coarser spatial resolution (10) for the SPOT5 multispectral data.

3. Predict woody vegetation cover using geostatistical techniques (particularly cokriging) with the best SPOT derived spectral vegetation data or image texture measure.

As stated in the main aim, the final objective of this study was aimed at using the outcome of objectives 1 & 2, in an attempt to combine field sampled woody canopy cover, as well as density data and the best selected remotely sensed woody vegetation correlate in geostatistics (particularly cokriging) to estimate the density and map spatial distribution of woody vegetation cover in the study area. The 1st order Mean texture measure calculated from the 10m resolution SPOT multispectral Band 3 image yielded the highest correlation (R = 0.37 and R = 0.59) with the tree density and percentage woody canopy cover respectively. The best SPOT variable (i.e. 1st order Mean texture measure for SPOT5 MS

Band 3) was therefore selected for cokriging with both tree density and percentage woody canopy cover.

The performance of the cokriging method was validated by calculating a RMSE on an independent test dataset. The result obtained reviewed that RMSE for cokriging were lower than those obtained from ordinary kriging using the tree density and percentage woody canopy cover alone as well as to those obtained using linear regression. This study has demonstrated that the utility of a combination of the best SPOT derived vegetation data and geostatistics through cokriging improves the accuracy of estimation in savanna woody vegetation and spatial distribution.

7.2 Limitations and Recommendations

This section highlights important limitations of this study and suggests some recommendations for future studies aimed at utilizing remote sensing and geostatistical approaches to estimate woody vegetation resource components in savanna ecosystems.

7.2.1 Imagery spatial resolution

In the literature, it is has been established that vegetation and its reflectance are spatially correlated (Yang & Prince 2000; Mutanga & Rugege 2006). In this study, evaluation of the performance of two images of different spatial (10m SPOT5 multispectral as well as 2.5m SPOT5 panmerged) resolutions respectively re-affirms the position in the literature.

Differences in the strength of correlation analysis between the 10m and 2.5m images with woody vegetation cover and density has shown to what extent the effect of spatial resolution can determine the spatial correlation or relationship between vegetation and its reflectance. In this respect, this study showed that finer resolution image such as 2.5m SPOT5 panmerged image data presents high potential for spatial estimation of woody vegetation density in densely vegetated woody savanna rangeland. However, assessment of the effect of spatial resolution was limited by only two images. It could be ideal to resample the images in several spatial resolutions. Hence, for future studies it is recommended to sample different spatial resolutions for more accurate comparison as regard the effect of spatial resolution, something that was beyond the scope of this study since we mainly focused on understanding geostatistical relationships between image and field data.

7.2.2 Image transformation techniques

In order to explore the full potential of the 10m SPOT5 multispectral image data for assessment of relationship between woody vegetation and its reflectance data, various image transformation techniques are needed in addition to the use of the raw spectral bands. The best correlation results obtained for image texture measures demonstrate that applying textural indices to high resolution multispectral data has potential for accurate estimation of woody plant density as well as mapping the spatial distributions of woody cover where spectral vegetation indices are less effective.

7.2.3 Geostatistics

7.2.3.1 Sampling image Data For Cokriging

In the literature it is recommended that sampling image data in addition to the pixels that coincide with ground sampled locations enhances the computational efficiency within cokriging environment (Mutanga & Rugege 2006). Previous studies have therefore sampled image data conventionally using a rule of thumb. In this study, we have demonstrated that optimal image sampling can be done using a statistical approach such as the application of semivariogram modeling technique to determine optimum lag spacing for extraction of pixel values. It was important though, that caution has to be taken in the analysis of the experimental semivariogram to avoid overfitting of the model parameters.

In addition, the extraction of pixel values that coincide with the ground sample plots can be limited because the image resolution and field sample plots are different. In this study, the spatial resolution of the SPOT image data was 10 m resolution, while the sample plots size was 30 m × 30 m. In this respect, the individual SPOT5 image bands were resampled to a 3 × 3 pixels, as well as the image texture indices were calculated using 3 × 3 moving windows in order to ensure spatial match between the image data and the ground sample plots. It is therefore recommended that image resolution must match the field plot size to ensure spatial representation of the image scene to ground observation.

7.2.3.2 Modeling Vegetation and its reflectance value using Cokriging

As has been stated, vegetation and its reflectance are spatially correlated and this spatial reflectance characteristic can be modeled by combining ground sampled and remotely sensed vegetation data through cokriging. The application of semivariogram provided the means to model the cross-correlated information contained in ground sampled woody vegetation parameters and remotely sensed image data. However, semivariogram modeling (particularly for the remotely sensed covariable) was time consuming due to large amounts of data as compared to the size of field samples. Further research is therefore recommended in order to establish an understanding of optimal image sample size required to ensure reliable model building for the spatial prediction of woody density and canopy cover using cokriging interpolation method.

7.3 Concluding Remarks

The research reported in this thesis is intended both for biodiversity monitoring as well as wildlife habitat management aspects in the study area. The research output has shown direct practical application of the integration of remote sensing and geostatistics for up-scaling traditional vegetation assessment methods.

It is important to note that while the best correlated image datasets such as best image texture index or best SPOT5 panmerged data may be good predictors of woody plant density, as well as percentage woody canopy cover, they could be poor indicators of other woody structural parameters (e.g. tree basal area, tree height, etc.) which can be equally important to the ecologists.

The implication of this study showed that combination of remote sensing and geostatistics for woody vegetation density and cover estimation can offer great potential for improving semiarid savanna biophysical resources assessment as well as providing means to monitor wildlife habitat. However, the present research assessed the spatial aspects of savanna woody vegetation density and cover by combining remote sensing and geostatistics, it is important that, with availability of multi-temporal image data, future studies could extent the techniques employed in the current study for the assessment of temporal aspects of savanna woody cover and density.

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Chapter 9. Appendices

Appendix 1: Woody Tree/Shrub Data Collection Form

<table>
<tr><td colspan="6">Section Name:</td><td colspan="3">Date:</td></tr>
<tr><td colspan="6">VCA_ID:</td><td colspan="3" rowspan="5"></td></tr>
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<tr><td rowspan="2">Plot_ID</td><td rowspan="2">Scientific name</td><td rowspan="2">No. of stem</td><td rowspan="2">DAH (m)</td><td colspan="2">Crown Diameter (m)</td><td rowspan="2">Height Of stem (m)</td><td rowspan="2">% canopy cover</td><td rowspan="2">Remark</td></tr>
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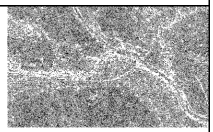
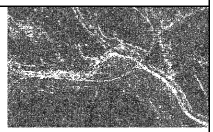
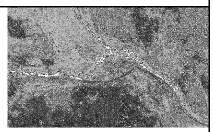
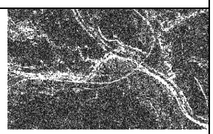
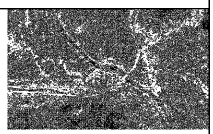
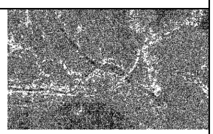
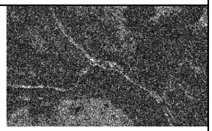
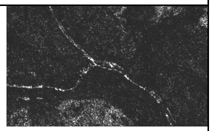
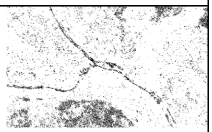
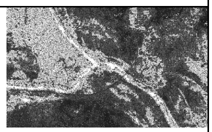
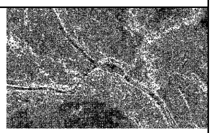
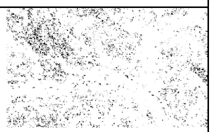
</table>

Checklist: woody vegetation traits measured at each sampling plot

- Identify number of woody species per plot
- Woody Stem basal diameter (m), measured at ankle height (DAH)
- Woody stem height approximated to the nearest meter
- Number of woody stems (density per sample plot)
- Crown diameter of woody trees and shrubs
- Percentage canopy cover of trees and shrubs

Appendix 2: Texture algorithms calculated from the high resolution SPOT5 MS satellite image Adapted from Dye *et al.* (2008)

Type of Measure	Measure	Formula	Description	Example: NIR band (3x3 window)
First-order	**Entropy**	$\sum_{i=0}^{G-1} p(i)\log_2[p(i)]$ Where G is the total number of intensity levels	Entropy is a measure of histogram uniformity (Materka & Stralecki 1998).	
	Data Range	$\max\{X\}-\min\{X\}$ Where $X = x_1, x_2, ..., x_k$	Measures the range of the pixel data(St-Louis *et al.* 2006)	
	Mean	**AVG =** $\dfrac{\sum_k x_k}{K}$	The mean calculates the average texture value at each plot (St-Louis *et al.* 2006).	
	Skewness	$\mu_3 = \sigma^{-3}\sum_{1=0}^{G-1}(i-\mu)^3 p(i)$ Where G is the total number of intensity levels	Measures the skewness of the data set, if the skewness is 0 the histogram is equal about the mean (Materka & Stralecki 1998).	
	Variance	$\dfrac{\sum (x_{ij}-M)^2}{n-1}$ Where x_{ij} is the digital number of the pixel (i, j), and n is the number of pixels in the moving window (ERDAS, 1997).	The variance texture measure accounts for the variability of the spectral response of pixels	
Second-order	**Contrast**	$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$	Contrast is a measure of the overall amount of local variation in a window (i.e., it is proportional to the range of grey levels) (Yuan *et al.* 1991).	
	Dissimilarity	$\sum_{i,j=0}^{N-1} P_{i,j}\lvert i-j\rvert$	The Dissimilarity measure is similar to the contrast measure. However, where contrast weights increase exponentially (0, 1, 4, 9, etc.) as one moves away from the diagonal, dissimilarity weights increase linearly (0, 1, 2, 3 etc.)(Hall-Beyer 2007).	

Type of Measure	**Measure**	**Formula**	**Description**	**Example: NIR band (3x3 window)**
Second-order	**Homogeneity**	$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$	Homogeneity measures the smoothness of image texture. Large changes in spectral values will result in very small homogeneity values, while small changes will result in larger homogeneity values (Tuttle *et al.* 2006).	
	Second Moment	$\sum_{i,j=0}^{N-1} P_{i,j}{}^2$	Second moment or angular second moment is a measure of homogeneity. A small second moment value indicates contrast in image texture while a large second moment value shows that the image is quite homogeneous (Yuan *et al.* 1991).	
	Entropy	$\sum_{i,j=0}^{N-1} P_{i,j}\left(-\ln P_{i,j}\right)$	Entropy is a statistical measure of uncertainty. It is low if image texture is relatively smooth and high if the texture is structured. It can be used as a measure of the absence of a distinct structure or organization of image patterns (Yuan *et al.* 1991).	
	Mean	$\mu_i = \sum_{i,j=0}^{N-1} i\left(P_{i,j}\right)$ $\mu_j = \sum_{i,j=0}^{N-1} j\left(P_{i,j}\right)$	Average probability of grey-level co-occurrence (Lévesque & King 2003).	
	Variance	$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}\left(i-\mu_i\right)^2$ $\sigma_j^2 = \sum_{i,j=0}^{N-1} P_{i,j}\left(j-\mu_j\right)^2$	Accounts for the variability of the spectral response of pixels but considers the pairwise combinations of variability.	
	Correlation	$\sum_{i,j=0}^{N-1} P_{i,j} \left[\frac{\left(i-\mu_i\right)\left(i-\mu_j\right)}{\sqrt{\left(\sigma_i^2\right)\left(\sigma_j^2\right)}}\right]$	The correlation texture algorithm measures the grey level linear-dependency within the image (Kayitakire *et al.* 2006).	

Appendix 3: Relationship between woody parameters and first order (1^{st}) as well as second order (2^{nd}) texture indices or SPOT Multispectral image bands (B).

1^{st} & 2^{nd} order Texture Variables	NO_SHRUBS	NO_TREES	DAH	BASAL_AREA	CROWN_D	TREE_H	CANOPY_C
1^{st} B3_Mean	-0.25*	0.36**	0.08	0.02	0.15	-0.01	0.59**
2^{nd}B3_Mean	-0.28*	0.33**	0.11	0.04	0.17	0.00	0.54**
2^{nd}B4_Entropy	-0.10	0.34**	-0.09	-0.14	0.04	-0.08	0.50**
1^{st}B4_Mean	-0.24*	0.36**	-0.07	-0.11	0.05	-0.10	0.49**
2^{nd}B4_Dissimilarity	-0.32**	0.25*	0.09	0.06	0.29*	0.02	0.48**
2^{nd}B2_Dissimilarity	-0.26*	0.23*	0.09	0.07	0.31**	0.24*	0.46**
2^{nd}B1_Dissimilarity	-0.26*	0.09	0.14	0.11	0.33**	0.29*	0.41**
2^{nd}B1_Contrast	-0.25*	0.10	0.17	0.13	0.38**	0.31**	0.41**
2^{nd}B4_Variance	-0.28*	0.25*	0.14	0.13	0.38**	0.09	0.41**
2^{nd}B4_Contrast	-0.31**	0.18	0.17	0.14	0.40**	0.10	0.41**
2^{nd}B2_Contrast	-0.28*	0.14	0.14	0.11	0.36**	0.27*	0.40**
2^{nd}B3_Entropy	0.10	0.24*	-0.07	-0.09	0.01	0.06	0.40**
2^{nd}B2_Entropy	-0.10	0.27*	-0.03	-0.01	0.09	0.00	0.39**
2^{nd}B3_Dissimilarity	-0.12	0.05	0.12	0.07	0.21	0.13	0.38**
2^{nd}B2_Variance	-0.24*	0.19	0.07	0.04	0.20	0.21	0.38**
1^{st}B2_Range	-0.24*	0.05	0.24*	0.19	0.31**	0.28*	0.37**
1^{st}B3_Range	-0.12	0.05	0.23*	0.18	0.31**	0.19	0.37**
1^{st}B2_Mean	-0.22	0.23*	0.06	0.01	0.07	-0.12	0.37**
1^{st}B1_Entropy	-0.27*	0.14	0.08	0.06	0.16	0.12	0.36**
2^{nd}B4_Mean	-0.31**	0.30*	-0.03	-0.08	0.02	-0.11	0.36**
1^{st}B3_Variance	-0.10	0.07	0.27*	0.23	0.37**	0.22	0.36**
1^{st}B1_Range	-0.25*	0.09	0.16	0.11	0.18	0.19	0.35**

Correlation coefficient: * Significance level: $p<0.05$.
** Significance level: $p<0.01$.

Appendix 3 continued

1st & 2nd order Texture Variables	NO_SHRUBS	NO_TREES	DAH	BASAL_AREA	CROWN_D	TREE_H	CANOPY_C
1stB2_Variance	-0.22	0.00	0.27*	0.22	0.36**	0.28*	0.34**
1stB1_Variance	-0.22	0.08	0.18	0.13	0.21	0.23*	0.33**
2ndB2_Mean	-0.25*	0.26*	0.02	-0.04	0.04	-0.13	0.32**
2ndB3_Contrast	-0.14	-0.05	0.18	0.13	0.27*	0.17	0.31**
2ndB3_Variance	-0.14	-0.02	0.24*	0.19	0.30**	0.16	0.31**
1stB3_Entropy	-0.12	0.02	0.11	0.06	-0.05	0.06	0.31**
1stB4_Range	-0.03	0.06	0.21	0.18	0.34**	0.18	0.31**
2ndB1_Variance	-0.16	0.11	0.11	0.07	0.14	0.20	0.29*
1stB2_Entropy	-0.23*	0.07	0.17	0.15	0.18	0.09	0.28*
1stB4_Entropy	0.11	0.02	0.17	0.12	0.19	0.18	0.22
1stB1_Mean	-0.05	0.29*	-0.14	-0.14	0.00	-0.18	0.22
2ndB1_Mean	-0.03	0.31	-0.20	-0.19	-0.04	-0.19	0.20
2ndB2_Corre	0.02	0.12	0.11	0.09	-0.03	0.07	0.19
1stB2_Skewness	-0.06	-0.05	0.09	0.09	0.01	0.08	0.07
2ndB1_Entropy	0.13	0.19	-0.22	-0.19	-0.04	0.00	0.06
2ndB1_Correlation	-0.03	-0.17	0.17	0.13	0.07	0.15	-0.02
1stB3_Skewness	-0.23	0.04	-0.18	-0.14	-0.22	-0.28*	-0.09
2ndB1_Second Moment	-0.14	-0.18	0.15	0.13	0.00	-0.06	-0.12
1stB4_Skewness	-0.03	0.13	-0.40**	-0.41**	-0.16	-0.18	-0.13
2ndB3_Correlation	0.07	-0.33*	0.11	0.08	0.02	0.16	-0.16
1stB1_Skewness	0.18	-0.01	-0.04	-0.08	0.02	0.03	-0.18
2ndB1_Homogeneity	0.15	-0.12	0.04	0.03	-0.04	-0.09	-0.25*
2ndB4_Correlation	0.10	-0.33*	0.05	0.04	-0.08	-0.11	-0.27*
2ndB3_Second Moment	-0.12	-0.24*	0.06	0.08	-0.03	-0.07	-0.38**
2ndB2_Second Moment	0.09	-0.25*	0.01	0.00	-0.11	-0.03	-0.38**
2ndB3_Homogeneity	0.02	-0.23*	0.07	0.11	-0.01	0.00	-0.42**
2ndB2_Homogeneity	0.14	-0.33*	0.05	0.04	-0.14	-0.04	-0.46**
2ndB4_Second Moment	0.08	-0.34*	0.08	0.13	-0.06	0.06	-0.48**
2ndB4_Homogeneity	0.25*	-0.27*	-0.02	0.02	-0.15	0.03	-0.50**