USING REMOTE SENSING INDICES TO EVALUATE HABITAT INTACTNESS IN THE BUSHBUCKRIDGE AREA: A KEY TO EFFECTIVE PLANNING

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DECLARATION

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ABSTRACT

Anthropological influences are threatening the state of many savanna ecosystems in most rural landscapes around the world. Effective monitoring and management of these landscapes requires up to date maps and data on the state of the environment. Degradation data over a range of scales is often not readily available due to a lack of financial resources, time and technical capabilities. The aim of this research was to use a medium resolution multispectral SPOT 5 image from 2010 and Landsat 8 images from 2014 to map habitat intactness in the Bushbuckridge and Kruger National Park (KNP) region. The images were pre-processed and segmented into meaningful image objects using an object based image analysis (OBIA) approach. Five image derivatives namely: brightness, compactness, NIR standard deviation, area and the normalised difference vegetation index (NDVI) were evaluated for their capability to model habitat intactness. A habitat intactness index was generated by combining the five derivatives and rescaling them to a data range of 0 to 10, with 0 representing completely transformed areas, 10 being undisturbed natural vegetation. Field data were collected in October 2014 using a field assessment form consisting of 10 questions related to ecosystem state, in order to facilitate comparisons with the remote sensing habitat intactness index. Both satellite data sets yielded low overall accuracies below 30%. The results were improved by applying a correction factor to the reference data. The results significantly improved with SPOT 5 producing the highest overall accuracy of 62.6%. The Landsat 8 image for May 2014 achieved an improved accuracy of 60.2%. The SPOT 5 results showed to be a better predictor of habitat intactness as it assigned natural vegetation with better accuracy, while Landsat 8 correctly assigned mostly degraded areas. These findings suggest that the method was not easily transferable between the different satellite sensors in this savanna landscape, with a high occurrence of forest plantations and rural settlements too. These areas caused high omission errors in the reference data, resulting in the moderate overall accuracies obtained. It is recommended that these sites be clipped out of the analysis in order to obtain acceptable accuracies for non-transformed areas. The study nevertheless demonstrated that the habitat intactness index maps derived can be a useful data source for mapping general patterns of degradation especially on a regional scale. Therefore, the methods tested in this study can be integrated in habitat mapping projects for effective conservation planning.

KEY WORDS AND PHRASES

SPOT 5, Landsat 8, OBIA, image derivatives, habitat intactness index, segmentation.

OPSOMMING

Antropologiese invloede bedreig die toestand van savanna-ekostelsels in die meeste landelike landskappe regoor die wêreld. Doeltreffende monitering en bestuur van hierdie landskappe vereis op datum kaarte en inligting oor die toestand van die omgewing. Agteruitgangsdata van verskillende skale is dikwels nie geredelik beskikbaar nie weens 'n gebrek aan finansiële hulpbronne, tyd en tegniese vermoëns. Die doel van hierdie navorsing was om ‘n hoë resolusie multispektrale SPOT 5 beeld van 2010 en Landsat 8 beelde van 2014 te gebruik om die habitatongeskondenheid in die Bushbuckridge en Kruger Nasionale Park (KNP) streek te karteer. Die beelde is voorverwerk en gesegmenteer om sinvolle beeldvoorwerpe te skep deur die gebruik van ‘n voorwerp gebaseerde beeldanalise (OBIA) benadering. Vyf beeldafgeleides naamlik: helderheid, kompaktheid, NIR standaardafwyking, area en die genormaliseerde verskil plantegroei-indeks (NDVI) is geëvalueer vir hul vermoë om habitat ongeskondenheid te modelleer. ‘n Habitatongeskondenheidsindeks is gegenereer deur die kombinasie van die vyf afgeleides wat herskaal is na 'n datareeks van 0 tot 10, met 0 om totaal getransformeerde gebiede te verteenwoordig en 10 om ongestoorde natuurlike plantegroei voor te stel. Velddata is versamel in Oktober 2014 met gebruik van 'n veldassesseringsvorm, bestaande uit 10 vrae wat verband hou met die toestand van die ekostelsel, om vergelykings met die afstandswaarneming habitatongeskondenheidsindeks te fasiliteer. Beide satellietdatastelle het lae algehele akkuraatheid onder 30% opgelewer. Die resultate is deur die toepassing van 'n regstellingsfaktor tot die verwysing data verbeter. Die resultate het aansienlik verbeter met SPOT 5 wat die hoogste algehele akkuraatheid van 62.6% gelewer het. Die Landsat 8 beeld vir Mei 2014 bereik 'n verbeterde akkuraatheid van 60.2%. Die SPOT 5 resultate het geblyk om ‘n beter voorspeller van habitatongeskondenheid te wees as gevolg van ‘n beter akkuraatheid vir natuurlike plantegroei, terwyl Landsat meestal gedegradeerde gebiede kon voorspel. Hierdie bevindinge dui daarop dat die metode nie maklik oordraagbaar was tussen die verskillende satelliet sensors in hierdie savanna landskap nie, veral as gevolg van ‘n hoë voorkoms van bosbouplantasies en landelike nedersettings. Hierdie gebiede veroorsaak hoë weglatingsfoute in die verwysing data, wat lei tot gematigde algehele akkuraatheid. Dit word aanbeveel dat hierdie areas gemasker word tydens die ontleding om aanvaarbare akkuraatheid te verkry vir nie-getransformeerde gebiede. Nogtans het die studie getoon dat die afgeleide habitatongeskondenheidsindekskaarte ‘n nuttige bron van data kan wees vir die kartering van algemene patrone van agteruitgang, veral op 'n plaaslike skaal. Daarom kan die getoetsde metodes in die studie in habitatkarteringsprojekte vir doeltreffende bewaring beplanning geïntegreer word.

TREFWOORDE EN -FRASES

SPOT 5, Landsat 8, OBIA, beeld afgeleides, habitatongeskondenheidsindeks, segmentasie.

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ACRONYMS AND ABBREVIATIONS

CBD	Convention on Biological Diversity
EMS	Electromagnetic spectrum
EVI	Enhanced vegetation index
EVI_2	Enhanced vegetation index 2
GIS	Geographic information system
GPS	Global positioning system
K2C	Kruger to Canons Biosphere Reserve
KNP	Kruger National Park
LAI	Leaf area index
LiDAR	Light Detection and Ranging
MRS	Multi-resolution segmentation
NDVI	Normalised difference vegetation index
NIR	Near infrared
OBIA	Object based image analysis
SAVI	Soil-adjusted vegetation index
SPOT	Satellite Pour l'Observation de la Terre
TM	Thematic Mapper
VHR	Very high resolution sensors
VI	Vegetation index
VI	Vegetation index

CHAPTER 1 INTRODUCTION

1.1 BACKGROUND TO THE STUDY

There is a growing concern globally amongst conservationists about the persistence and extensive decline in habitats of plant and animal species in ecosystems (Rouget et al. 2006; Scholes & Biggs 2005). This has resulted in biodiversity being threatened as species extinction rates have gone up (Brooks et al. 2006). Habitat degradation is described by many researchers as the reduction in ecosystem function due to anthropological activities (Grifitths, Lee & Eversham 2000; Stocking & Murnaghan 2001; Foster 2006; Brooks et al. 2006; Duro et al. 2007; Bai et al. 2008; Oldeland et al. 2010). Alterations in the environment has many consequences such as soil erosion, loss of nutrients from soils, poor water quality, increased flooding severity and most importantly, the loss of suitable habitat for wild life. Habitat degradation effects can also negatively impact a nation's economy due to reduced tourism prospective of the land.

Scientists also define habitat degradation as a negative environmental modification caused by natural factors, which are in most cases a result of human influences (Sahney, Benton & Falcon-Lang 2010). The invasion of foreign species, volcanism, fire and climatic variations are a few natural factors that contribute to habitat degradation (Sahney, Benton & Falcon-Lang 2010). Subsequently, the state of our ecosystems is negatively changing mainly due to land use practices (Foley et al. 2005; Zhao et al. 2006) and to a certain degree, natural factors. It is important that ecosystems stay intact, for instance to provide critical ecosystem services such as plant species fixing carbon through the process of photosynthesis (Geider et al. 2001), clean water, food, wildlife and aesthetic values to society (Chapin et al. 2000).

In the South African context, social elements such as demographics, socio-economic status and past land management policies contributed highly to the vulnerable state in which our habitats are currently in (Fisher et al. 2014). Savanna rural landscapes in South Africa are inhabited by well over 9.2 million residents (Shackleton 2000). A large percentage of rural inhabitants in these landscapes live below the poverty line, and consequently rely largely on the natural environment to sustain their livelihoods (Griffin et al. 1993; Shackleton and Shackleton 2000;

Kirkland, Hunter & Twine 2007). Habitat destructions are mainly for the purpose of human settlements, cultivation and grazing by livestock (Wessels et al. 2004) and also the cutting down of live trees (Kirkland, Hunter & Twine 2007).

Savanna woodlands in particular are mainly used for fuel wood harvesting by rural inhabitants due to high electricity and paraffin prices, and unemployment in these areas (Banks et al. 1996; Dovie, Witkowski & Shackleton 2004; Kirkland, Hunter & Twine 2007). A study done by Dovie, Witkowski & Shackleton (2004) in Thordnale, a village in a savanna landscape showed that 96% of households in that region harvested fuelwood mainly for income and domestic purposes. Although traditional authorities have designed laws aimed at protecting savanna woodlands from deforestation, these laws are ineffective as residents heavily rely on fuelwood as their main source of energy (Kirkland, Hunter & Twine 2007). In recent times, people have quicker means of transportation, which implies that woodlands are easily overexploited than previously. In addition, the growing population in rural landscapes has placed even more threat to the environment. Consequently, human dependency on natural resources has resulted in extreme land use change to habitats (Foley et al. 2005) and the scarcity of resources over the years has resulted in deforestation of savanna woodlands (Kirkland T, Hunter M & Twine W 2007).

Considering the high rates at which habitats are degraded, monitoring of biodiversity is crucial (Nagendra 2001). Conservation managers need to develop rapid assessment tools that can be used to measure and re-evaluate the rate of change in habitats (Luck-Vogel, O'Farrell &Roberts 2013), and develop management strategies that will be of benefit to both human kind and biodiversity. Dovie, Witkowski & Shackleton (2004); Giannecchini, Twine, Vogel (2007) caution that understanding the underlying factors of human need and rural livelihoods is crucial when designing effective conservation policies, there should be linkages between rural inhabitants and their environment.

Monitoring biodiversity is also a great scientific challenge Rouget et al. (2006), as reporting on the state of biodiversity requires a lot of detailed, reliable data. Furthermore, an extensive knowledge on habitat distribution at a range of scales is required (Turner et al. 2003; Borre et al. 2011). The availability of biodiversity monitoring data is often limited in most countries throughout the world Grifitths, Lee & Eversham (2000) which inhibits biodiversity monitoring progress (Pettorelli et al. 2005). Monitoring experts have tried to address this issue by conducting intensive field mapping surveys over the years (Borre et al. 2011). However, field surveys are still a limited means of acquiring data because they are usually lengthy and expensive tasks, which are often done at a local scale (Pettorelli et al. 2005; Borre et al. 2011). This is particularly problematic because the extent in which field information exists is often limited when predicting large scale changes (Pettorelli et al. 2005). In addition, the level of detail in which data is captured in the field can vary from one expert to the other (Griffiths, Lee & Eversham 2000; Pettorelli et al. 2005). Accessibility and safety are inhibiting factors when conducting field surveys in areas such as mountainous terrains, large wetlands and rain forests.

Due to rising concerns of anthropogenic effects on ecosystem intactness, scientists have been prompted to develop new approaches to monitoring biodiversity globally (Griffiths, Lee & Eversham 2000). Scientists however, should focus on developing monitoring methods that are simple but yet practical (Rouget et al. 2006). The spatial technologies of remote sensing and geographic information systems (GIS) provide conservationists with the necessary practical and cost-effective tools to quantitatively map, capture and update habitat maps over time (Turner et al. 2003; Lucas et al. 2011).

Remote sensing data can effectively be used to map the distribution and composition of vegetation (Pettorelli et al. 2005). Vegetation distribution and composition influence the distribution and movement of animals. Therefore, researchers can derive key information on animal species distribution by integrating remote sensing data into their analysis (Pettorelli et al. 2005). Remote sensing is a vital tool not only for mapping where vegetation occurs but also vegetation intactness as it has the capability to detect vegetation variations within habitats from satellite imagery (Nagendra et al. 2010). It has a fair advantage in comparison to field data, as it provides a systematic and synoptic means of acquiring data. It offers repeat coverage frequently, which can be useful in mapping and detecting changes in habitats repeatedly (Nagendra 2001; Biggs & Scholes 2002). For decades researchers have used remote sensing imagery to monitor land cover change in important ecological regions (Borre et al. 2011). This was done by visual interpretation from aerial photography, which can also be labour intensive and expensive like collecting field data (Lillesand et al. 2008). The field of remote sensing has developed significantly over the years as computer supported analytical techniques have been created to extract information from satellite imagery (Borre et al. 2011). Additionally, improvements in the spatial, spectral, and temporal resolution of sensors have made monitoring of ecological regions even more progressive (Borre et al. 2011).

Various researchers such as (Lee & Eversham 2000) and (Grifitths & Aplin 2005) devised techniques for evaluating habitat intactness using remote sensing data. These techniques are focused on exploiting the spectral information contained within a satellite images bands. Pixel-based image classification techniques using hard classifiers such as maximum likelihood classifier are one of the most widely used remote sensing techniques in habitat mapping (Munyati, Ratshibvumo & Ogola 2009). Although there are different remote sensing concepts of determining habitat intactness, Borre et al. (2011) identified that in recent years, object-based image analysis (OBIA) techniques are being explored in habitat mapping projects. OBIA makes use of the spectral, spatial and textural attributes of image objects in digital image classifications.

Mehner et al. (2004) and Gross, Goetz & Cihlar (2009) pointed out that conservationists even though aware of the potential use of remote sensing to model habitat intactness, are however still lagging behind with respect to adopting more advanced computer supported remote sensing techniques. Aplin (2005) explains that the reason for this lag is because ecologists are hesitant to adopt remote sensing approaches as they are perceived to be of a very course spatial scale. On the other hand Turner et al. (2003) expresses that remote sensing specialists are also responsible for this lag as they are focused on technical issues rather than ecological issues. This study will test the ability of remote sensing techniques to model habitat intactness in the Bushbuckridge region, thus bringing together remote sensing and ecology.

1.2 RESEARCH PROBLEM

Savanna ecosystems in Africa have experienced major transformations over the years, more specifically in South African rural landscapes. Savanna ecosystems are richly endowed with a diversity of plant and animal species, thus they are of great economic and ecological importance. However, they are under threat from an array of uncontrolled human activates such as uncontrolled agricultural practices, expanding settlements and deforestation of live trees for firewood. Consequently, the need to monitor these landscapes is of importance.

Due to the extensive and complex nature of savanna ecosystems, they present a great monitoring challenge to conservation managers and policy makers in these regions. Thus, more effective methods to monitor habitat intactness in savanna regions at both regional and local scales are needed. There is a direct connection between biodiversity and habitat intactness (Luck-Vogel, O'Farrell & Roberts 2013). Therefore, by implementing tools that can assess the state of habitats, valuable information on biodiversity can be provided.

Remote sensing is a vital tool in mapping habitat intactness as it has the capacity to detect vegetation composition within habitats from satellite imagery. To evaluate the efficacy of remote sensing for mapping habitat intactness in the Bushbuckridge region as a key to effective conservation planning in Southern Africa, an evaluation of various remote sensing based indices will be undertaken. The Bushbuckridge area supports a variety of landscapes, which have undergone different stages of transformation.

Medium resolution satellite imagery from SPOT 5 and Landsat 8 were used for this study as they allow for the assessment of large areas, and provide adequate spatial resolutions to aid in biodiversity monitoring (Luck-Vogel, O'Farrell & Roberts 2013). In addition, the methods implemented were expected to allow for repeatability of results when implemented to a multi-temporal series of imagery.

1.3 RESEARCH AIM AND OBJECTIVES

The aim of this study is to evaluate the efficacy of existing and recently developed remote sensing derivatives and indices to model habitat intactness in the Bushbuckridge area, using Landsat 8 and SPOT 5 satellite imagery. These indices will serve as rapid assessment tools which can be used by conservation managers to map habitat quality based on vegetation composition. The effectiveness of these indices will be measured on a basis of the range of imagery to which they can be applied. If they are applicable to a wide range of imagery, the more robust and effective they are as tools for conservation management.

To achieve the research aims, the following objectives have been set:

1. Review of relevant literature on appropriate remote sensing indices derived for ecological studies;
2. Acquire and pre-process satellite imagery;
3. Derive habitat intactness indices using a time series of SPOT 5 and Landsat 8 satellite imagery in eCognition Developer;
4. Collect ground truth data using a field validation questionnaire;
5. Evaluate the effectiveness of SPOT 5 and Landsat 8 data in mapping habitat intactness.

1.4 RESEARCH METHODOLOGY AND RESEARCH DESIGN

The methodology implemented in this study was adapted from Luck-Vogel and co-workers (Luck-Vogel, O'Farrell & Roberts 2013), thus enabling replication of the methodology across different landscapes. This methodology focuses on developing a remote sensing habitat intactness index based on spectral, structural and textural properties of land cover features. In addition, the normalised difference vegetation index (NDVI) is also be derived. NDVI has been used widely in ecological studies to monitor vegetation cover and distribution from satellite imagery (Wessels, Reyers & Van Jaarsveld 2000; Chen 2002; Stillwell & Clarke 2004; Falcucci, Maiorano & Boitani 2007) and due to its previous successes and general applicability in other studies, NDVI thus serves as reliable measures of habitat intactness as it positively correlates with plant abundance (Nagendra et al. 2010). Multispectral satellite (MS) imagery will be used to evaluate the efficacy of the selected remote sensing derived indices in mapping habitat intactness. The selection of MS imagery for this study is for their ability to capture large areas and their appropriate spatial resolution for biodiversity monitoring (Luck-Vogel, O'Farrell & Roberts 2013).

The research design is provided in Figure 1.1. It groups the processes followed in this research into respective objectives as listed in Section 1.3.

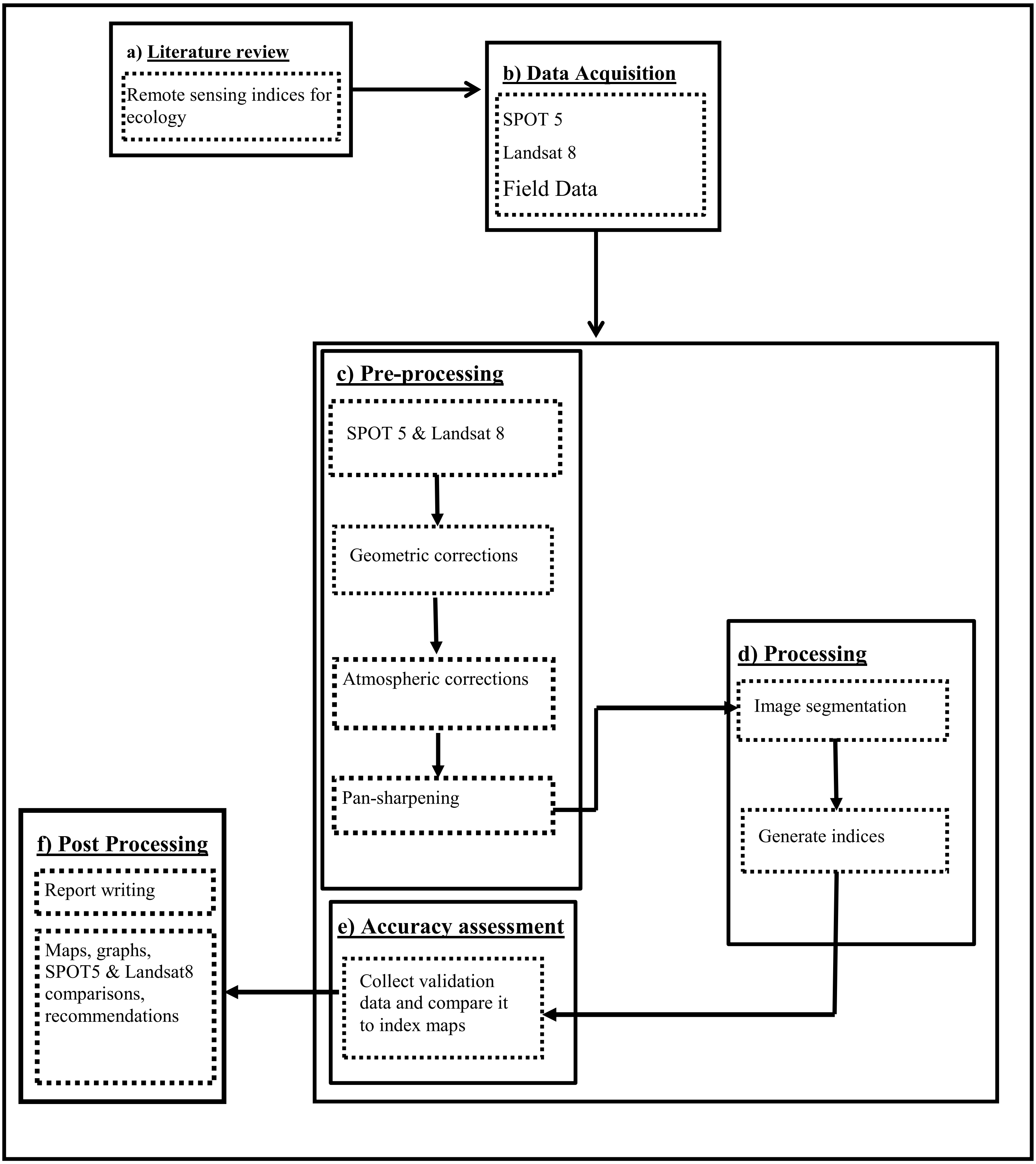


Figure 1.1 The research design implemented in this study

1.5 THESIS OUTLINE

The structure of this document is divided into 5 chapters. A short description of the following chapters is given below. Chapter 1 gave a brief background to the study, including the aim and objectives established. Chapter 2 provides a detailed assessment of existing literature on the use of remote sensing in ecological studies. Chapter 3 briefly gives a description of the study area, and in detail explains the methods and techniques implemented to achieve the final results. Chapter 4 gives a report of the findings achieved from the remote sensing based indices. In addition, a qualitative assessment of interpreting the results is also given. Chapter 5 is the closing chapter and provides deductions and recommendations for future research.

CHAPTER 2 LITERATURE REVIEW

This chapter gives a review of existing literature on studies conducted using remote sensing data for biodiversity monitoring. First, a range of satellite images are compared for their usefulness in monitoring biodiversity, with specific emphasis on their spatial, spectral and temporal resolutions. Secondly, various remotely sensed vegetation analytical methods are reviewed. Lastly, a brief discussion on the implications of using the object-based approach versus a pixel-based approach is given.

2.1 BIODIVERSITY MONITORING IN A SAVANNA ECOLOGY

The term biodiversity can be used to refer to the variation in both animal and plant species within a specific ecosystem (Stoms & Estes 1993; DeLong 1996; Swingland 2001). Globally, biodiversity loss has been recorded as increasing at an alarming rate (Van den Borre et al. 2011; Scholes & Biggs 2005; Rouget et al. 2006). The loss in habitats and species is a cause for concern, as species extinction rates have gone up Brooks et al. (2006) and researchers agree that losses in natural resources reduces ecosystem functioning (Omuto, Balint & Alim 2011). As a result, the need to monitor changes in biodiversity has increasingly become necessary over the years. In order for biodiversity monitoring to be useful in the implementation of effective policies, it needs information on: the spread of invasive alien species at an appropriate temporal resolution (Nagendra 2001), increase in land uses such as urbanisation, mining, as well as on agriculture, grazing, fire, drought, hunting and logging (Wessels et al. 2004; DeFries et al. 2005; Nagendra 2008; Sahney, Benton & Falcon-Lang 2010).

The Convention on Biological Diversity (CBD) has set out targets to reduce the decline in biodiversity by 2014 (Chape et al. 2005). Immediate interventions such as establishing protected areas, land use management strategies and species recovery programmes are a few strategic actions implemented to measure and conserve biodiversity in critical ecosystems (GEO BON 2011), in order to meet the CBD targets. Historically there's been an absence in adequate measures and explicit information on biodiversity (GEO BON 2011). This lack can be attributed to the challenges of gathering biodiversity information on larger scales faced by monitoring experts (Turner et al.

2003; Rouget et al. 2006; Vanden Borre et al. 2011), in addition to a lack of human skills and financial resources required to effectively monitor biodiversity. Information on biodiversity often requires intensive field surveys to be conducted, which are often expensive and time consuming as they sometimes take up to several months or years (Pettorelli et al. 2005; Vanden Borre et al. 2011). Furthermore, field surveys require a substantial amount of expert knowledge in the fields of conservation and biodiversity (Yichun, Zongyao & Mei 2008). This complements Heywood (1995) who argued that it is nearly impossible to gather all the necessary information on biodiversity, solely based on field work. Researchers are under pressure to find methods which are time and cost-effective, and also capable of gathering biodiversity monitoring data at rates faster than the decrease in important habitats and species (Nagendra 2001).

Nagendra et al. (2012) mention four important areas of focus that need to be considered when monitoring changes in biodiversity within protected areas. These are changes in habitat extent and landscape structure, degradation in habitats, alterations in biodiversity and tracking of pressures and threats within and outside protected areas. Remote sensing can provide researchers with this kind of information as it has the ability to capture data systematically, at regular intervals (Debinski & Humphrey 1997; Innes & Koch 1998). By utilising remote sensing data, persistent patterns that occur within habitats over time at different spatial scales can be monitored. This is because remote sensing provides a synoptic means of observing the earth's surface, thus making it ideal for biodiversity monitoring (Debinski & Humphrey 1997; Innes & Koch 1998). In addition, temporal remote sensing imagery provides biodiversity monitoring experts with the ability to assess changes caused by climatic and human influences over time (Nagendra et al. 2012). Land use effects on biodiversity, such as burn scars and urbanization can now be studied in more detail and accuracy than previously thought (Fuller 2007). Remotely sensed data can be integrated with GIS datasets such as roads, rivers and human population densities to further support land use management, while in the process providing effective conservation policies (van Lynden & Mantel 2001).

2.2 HABITAT MAPPING

A key to effectively maintaining good habitats is to minimise habitat destruction, particularly that which is a result of anthropological developments as much as possible (Liaoa et al. 2013). It is important to detect degradation in important habitats at an earlier stage, so that it can be stopped or reversed. Habitat degradation can disrupt connectivity between populations of a species (Nagendra et al. 2012). A disturbance in habitat connectivity can prevent the dispersal of species between habitats, which results in a decline in gene flow within a population (Dixo et al. 2009). In addition, species reproduction rates start decreasing, ultimately resulting in high mortality rates.

By mapping natural vegetation intactness or degradation across various habitats, information on the locations of vulnerable habitats can be provided (Nagendra et al. 2010). Rates of change in vegetation cover can also be monitored over time from degradation maps. According to Joseph et al. (2011), measuring habitat transformation is more difficult than mapping habitat transformation. This is because measuring habitat transformation requires the detection of changes in sub-canopy structure, species composition and species structure, which are all difficult to distinguish. By mapping habitat intactness, researchers can illustrate the extent in which degradation has taken place in key biodiversity landscapes. Consequently, researchers need to develop effective methods to quantifying the extent of habitat degradation. Due to the limited number of studies that have been done on mapping habitat transformation, biodiversity monitoring progress is moving at a slow rate (Nagendra et al. 2012). Remote sensing offers a potential solution in studies based on mapping habitat degradation as it has the capability to detect changes in the spatial and temporal patterns of vegetation (Garbulsky & Paruelo 2004).

2.3 ECOLOGICAL REMOTE SENSING

Vegetation mapping studies are based on the identification of various vegetation classes and are commonly carried out by means of ground based methods (Oldeland et al. 2010). Monitoring biodiversity by means of field mapping approaches has presented a number of challenges. For example, field surveys are time consuming, labour intensive, expensive and also present complicated logistics (Oldeland et al. 2010). Remote sensing on the other hand provides monitoring experts with the means to generate vegetation maps rapidly, which can further be used to support management decisions within protected areas. Furthermore, monitoring experts can use their time as effectively as possible when monitoring large areas. Remote sensing complements biodiversity monitoring were field approaches cannot provide essential information in regions with mountainous terrains (Cho et al. 2012) for example. Researchers can now map the spatial distribution and patterns of different vegetation units by using satellite data in combination with floristic data at various scales (Aragon & Oesterheld 2008).

Remote sensing is based on the knowledge that different materials on the earth's surface have distinctive spectral signatures (Campbell 2007). An objects spectral signature is reflected or absorbed by electromagnetic radiation at a certain wavelength. Vegetation spectral signatures are associated with distinctive biochemical and biophysical characteristics (Asner & Martin 2009; Clark et al. 2005). Savanna ecosystems are complex in nature as they are characterised by a grass layer, shrubs and isolated trees (Fisher et al. 2013). This complexity results in a confusion of spectral signatures between trees of varying heights and variations in plant species types (Cho et al. 2012). Furthermore, trees at different phenological stages will have varying spectral responses. Therefore, the interpretation of remote sensing derived maps needs to be done with much care and skill, especially when mapping complex ecosystems. Holm et al. (2003); Thiam (2003); Nagendra et al. (2012); used remote sensing to measure the extent of degradation and recovery of habitats, including the events which contribute to land cover change

Researchers can assess transformations in vegetation patterns and structure through the use of remote sensing data. Studying the spatial patterns of fragments on satellite imagery, researchers can effectively determine whether degradation is human induced or caused by nature (Nagendra et al. 2012). In the past, remote sensing was used in vegetation mapping studies by visually interpreting aerial photos (Lillesand et al. 2008). Presently, the availability of high resolution sensors such as Thematic Mapper (TM) and SPOT High Resolution Visible (HRV) are used in vegetation mapping applications by implementing computer automated classifications. According to Yu et al. (2006), medium resolution sensors have proven unsatisfactory in studies were vegetation species are discriminated in detail at species-level. Czaplewski & Patterson (2003) obtained an accuracy of less than 40% when using Landsat data to classify vegetation in detail. The increasing availability of high spatial resolution imagery has made detailed vegetation mapping studies even more progressive (Yu et al. 2003).

Recently, the advancement in computer assisted techniques such as supervised classifiers have made remote sensing a more effective tool in ecological studies (Vanden Borre et al. 2011). Remote sensing measures the extent of degradation caused in habitats by using signals to detect changes in the distribution of vegetation species (Nagendra et al. 2012). Various remote sensing data sets have increasingly become available, ranging from free and inexpensive satellite data such as Landsat, MODIS and SPOT to more expensive satellite data such as IKONOS and QUICKBIRD (Nagendra & Rocchini 2008). Landsat and SPOT data sets are ideal for habitat mapping studies due to their high temporal resolution which makes it possible to study change patterns over several decades (Eva et al. 2010). Additionally, their moderately high spatial resolution makes them ideal for detecting changes in land cover over large regions (Hansen et al. 2008). Very high resolution (VHR) sensors such as Quick bird and IKONOS have since become affordable and easier to acquire than previously. Coupled with their much finer spatial resolution, VHR sensors provide a better opportunity to study vegetation species structure and composition within habitats in greater detail (Nagendra et al. 2012).

According to Jump, Cavin & Hunter (2010), remote sensing data needs to be used in combination with field data for it to be effective in conservation planning. A lack of field data in many countries has made this integration limited, especially when mapping vegetation at a regional scale (Grifitths, Lee & Eversham 2000; Feld et al. 2010).

Habitat mapping using remote sensing is much more complicated than other studies that integrate remote sensing Nagendra et al. (2012) such as mapping urban settlements for example. Studies that focus on using change detection to map habitats for example, need to take into account physical changes that occur within the environment such as climatic and phenological events that vegetation experiences. A change detection study can only be effective if the images used are from the same season for several consecutive years (Nagendra et al. 2012). Additionally, field verification used to facilitate remote sensing interpretation needs to be collected in the same period as the acquisition date of satellite images so that the detection of change within habitats is enhanced.

This section demonstrated the usefulness of remote sensing as a tool for monitoring important habitats. However, it was noted that remote sensing has not been used to its maximum capacity in most ecological studies due to its technical complications. Problems experienced by users varied from conducting analysis using complicated software and correctly interpreting the results obtained from the analysis (Nagendra et al. 2012). Furthermore, a lack of integration of field data with remote sensing derived products has limited monitoring progress. Problems experienced by monitoring experts with using remote sensing data can be bridged by providing basic technical skills which can help improve the integration of remote sensing data in conservation policies (Nagendra et al. 2012).

2.4 SELECTING APPROPRIATE REMOTE SENSING IMAGERY FOR HABITAT DEGRADATION MAPPING

Selecting appropriate satellite imagery is vital when mapping habitat degradation. The type of imagery selected will determine the amount of information that can be extracted, from the satellite image (Nagendra 2001). There are three important factors that need to be considered when selecting the sensor to be used to detect habitat fragmentation. These are spatial, spectral and temporal resolution.

2.4.1 Spatial resolution

Spatial resolution can be defined as the amount of detail contained in a satellite image (Campbell 2006). The higher the spatial resolution, the more information can be discerned from a satellite image. The spatial resolution of an image is dependent on the characteristics of the sensor creating the image (Nagendra 2001). However, the level of detail required in any specific study determines whether fine or course spatial resolution imagery is required. In a vegetation classification study, for example, choosing the correct spatial resolution will ensure that adequate classification accuracies are obtained. In most instances, a low spatial resolution results in low classification accuracies because the classifiers ability to distinguish between different object groups is lowered. A high spatial resolution can result in orders of magnitude smaller than that of the objects classified, and thus a decrease in classification accuracy. This produces a “salt and pepper” effect (Meyer et al. 1996). Therefore, spatial resolution is directly related to the dimensions of the feature being categorised. Classifying single plant species might require a very high spatial resolution whereas a medium to high resolution might be adequate to separate patches of plant species in a classification.

In 1999, the field of remote sensing was complemented by the development of VHR sensors like IKONOS, Quickbird, Worldview and Orb View-3. VHR sensors have presented researchers with the possibility of studying habitats of high ecological importance with better detail than previously possible (Mumby & Edwards 2002; Boggs 2010). However, their very high spatial resolution comes with a few shortfalls. For example, using VHR imagery in habitat mapping might not be ideal, as individual pixels can be smaller than the size of individual tree crowns, thus decreasing the intra-class variability significantly (Nagendra et al. 2001). In addition, shadowing and mixed pixels of ground features can reduce mapping accuracy (Hsieh et al. 2001; Su et al. 2004). VHR sensors are expensive and require longer processing times.

A general remote sensing problem related to spatial resolution is the inability to discern individual shrubs and any minute object at a species level from earth observation (Verbyla 1995). This shortcoming has some ecologists doubting the potential of remote sensing as a tool for mapping important ecological regions such as deserts (Aplin 2005). Most satellite sensors lack the capability to detect animal species (Nagendra 2001).The shortfalls in VHR sensors highlights that a very high spatial resolution does not always guarantee better results (Oldeland 2010; Nagendra et al. 2012). Landsat and SPOT have been used extensively in vegetation mapping studies (Aplin 2005; Yu et al. 2006; Nagendra et al. 2012). Their coarse resolution might be an inhibiting characteristic when mapping single habitat patches at a local scale. Most multispectral satellite sensors are still limited in their capacity to penetrate through vegetation cover to acquire data from beneath the ground, however, the invention of microwave imagery has made this a possibility (Nagendra 2001). O'Neill et al. (1996) suggested as a general rule based on experience, that the spatial resolution selected for a certain application must be two to five times smaller than the object of interest.

2.4.2 Spectral resolution

Mapping plant species using remote sensing is based on the knowledge that different plants have distinctive spectral signatures (Campbell 2007). This is due to different responses to light in the electromagnetic spectrum, linked to a plants characteristic biochemical and biophysical properties (Mlark et al. 2005; Asner & Martin 2009; Cho et al. 2010). Based on the fundamental principles of remote sensing, datasets with sufficient spectral resolution can successfully identify differences between various plant species (Nagendra 2001). Selecting the correct spectral bands to distinguish the object of study is a rather complex task as the researcher has to consider the spectral characteristics of the object being studied. When mapping plants, the characteristic biochemical properties of a plants leaf would serve as a basis for the exact bands to be used (Nagendra 2001).

A level of compromise has to be taken into consideration when selecting the appropriate satellite dataset (Nagendra et al. 2012). For example, VHR sensors such as Quickbird, GeoEye and IKONOS might have the ideal spatial resolution. However, they are limited in their capacity to discriminate some vegetation types, due to their lack of a shortwave and thermal infrared band, which have proved beneficial in vegetation classification studies. A study done to map tree species in a dry tropical forest in India by Nagendra et al. (2010a) compared a high spatial resolution Landsat image, to a VHR IKONOS image. The results showed that Landsat outperformed IKONOS. This was because Landsat contains a shortwave infrared band which IKONOS lacks. Other studies confirm that multispectral sensors with a high spatial resolution such as Landsat have proven more useful for vegetation mapping than VHR sensors because Landsat is more spectrally advanced.

Gao (1999) did a study in which Landsat datasets with a spatial resolution of 30 m were compared with 10 m SPOT datasets to classify a mangrove forest in New Zealand. Based on the classification accuracy received, the study showed that Landsat dataset achieved higher classification accuracy than SPOT due to the presence of the thermal infrared band in the Landsat dataset, although Landsat has a third of the SPOT images spatial resolution. This study clearly shows that a higher spatial resolution does not necessarily guarantee higher classification accuracy.

Unlike multispectral imagers, hyperspectral imagers collect information in more narrow spectral bands over a continuous spectral range (Campbell 2007). Hyperspectral imagers have been successfully applied in an array of applications such as agriculture (Thenkabail, Smith & De Pauw 2000) and forestry (Clark, Robert & Clark 2005). Nagendra et al. (2012) mentions that hyperspectral datasets are technically challenging to process. Nonetheless, they have the potential to map changes that occur within habitats with a much higher accuracy than multispectral datasets. Oldeland et al. (2010) achieved a very high classification accuracy of 98% while testing the capability of HyMap hyperspectral data to discriminate variations in plant species within a semi-arid rangeland in Namibia. HyMap has a very high spatial resolution of 5m, however, the high classification accuracy can also be attributed to HyMap having 126 bands, which make it more spectrally advanced than most commercial sensors. This study shows that a high spectral resolution can result in high classification accuracies.

Thenkerbail et al. (2004) did a comparison study to evaluate the efficacy of various optical sensors to differentiate between forest classes in Congo. Landsat ETM+ with a spatial resolution of 30m, and contains six bands was tested against IKONOS, which has a 4m spatial resolution but has only four bands, Hyperion hyperspectral imager with a spatial resolution of 30m and consists of 196 bands; lastly Advanced Land Imager (ALI) with a spatial resolution of 30 m and consists of 9 bands. The results showed that Hyperion outperformed all of the above mentioned sensors as it has a shortwave infrared band which has been proven to be useful in habitat mapping, and also in detecting the influence of drought on plants (Boyd et al. 2002). The above mentioned case studies by Thenkabail et al. (2004) and Oldeland et al. (2010) showed that a high spectral resolution has more value than a high spatial resolution in vegetation mapping. A trade-off between the two should rather be that of a high spatial resolution.

2.4.3 Temporal resolution

A high temporal resolution is beneficial when doing a change detection study. This is mainly because an increasing temporal resolution can enable researchers in correctly mapping degradation in habitats with seasonal environmental variations (Nagendra 2001). Furthermore, the use of multi-temporal imagery in plant species identification studies has indicated improved classification accuracies (Nagendra 2001).

By using multi-date Landsat ETM+ imagery, De Colstoun et al. (2003) successfully classified eleven different land cover types in a recreational park in the USA. An increase in classification accuracy when multi-date imagery was used, proved that a high temporal resolution is beneficial in land cover studies. A study done by Lucas et al. (2007) also achieved higher classification accuracies when multi-date Landsat TM imagery was used to discriminate natural habitats and agricultural areas. Using a time series classification of Landsat imagery, Prates-Clark et al. (2009) were able to rebuild a fire and land-use history within an Amazonian topical forests from which they could measure the recovery rate of lost biodiversity within these forests. All of the above mentioned studies clearly show that a high temporal resolution is vital when studying change over time.

Sensors with a high spatial resolution such as Landsat and SPOT date as far back as 1972 and 1986 respectively. Due to the long periods that Landsat and SPOT have been acquiring data, they have a higher temporal resolution in comparison with VHR sensors which were recently launched. This characteristic makes Landsat and SPOT more suitable for studies were ecological change over time is mapped at a regional scale. A disadvantage with using multi- seasonal or temporal imagery is that they are acquired at different phonological seasons. Therefore, cloud cover in some areas may pose a few challenges in habitat mapping studies.

2.5 DIFFERENT SENSORS USED FOR SELECTING APPROPRIATE SATELLITE IMAGERY

2.5.1 Very high resolution sensors (IKONOS)

VHR sensors such as IKONOS can be used to identify fine scale changes such as human settlements, expanding urbanisation and mapping tree falls (Fuller 2007). Allard (2003) studied and mapped the impacts of erosion caused by grazing in a dry dwarf shrub heath in Sweden by utilising IKONOS imagery. The results showed that it is possible to detect changes in the distribution of erosion patches with great accuracy by visual interpretation of IKONOS imagery. Asner et al. (2002) compared a 0.8 m IKONOS panchromatic image to field based laser measurements in mapping tree crown diameters in the Amazonian forest. IKONOS obtained results 78% greater than field based derived laser measurements.

In contrast to Landsat, VHR datasets are unsuccessful in plant diversity studies as they tend to be considerably less sensitive to species diversity (Nagendra et al. 2010). Instead, VHR sensors are more sensitive to the number of plant species. IKONOS in particular shows a much lesser power of correlation and also a decrease in statistical significance as compared to most sensors with a lowered spatial resolution such as Landsat (Nagendra 2001). This is because their mean values of greenness are negatively correlated with plant diversity. Shadowing effects caused by VHR sensors are responsible for this negative correlation because the shaded vegetation results in an artefact, which the sensor picks up as a reduction in the amount of greenness in abundant vegetation regions (Nagendra 2001).

VHR sensors are recent and thus have not been used to a greater extent (Nagendra et al. 2012). Difficulties in acquiring and extracting information from VHR sensors has made their use limited (Yichun, Zongyao & Mei 2008). VHR sensors are also limited because of their technically challenging issues such as atmospheric corrections calibration, geometric corrections and spatial enhancement (Nagendra 2001). Therefore, their applicability in ecological studies is limited (Nagendra 2001). An additional limitation with using VHR sensors in vegetation mapping studies is their lack of a short-wave infrared band. Moreover, they provide too much detail than is required such as shadows within and from landscape objects (Nagendra et al. 2012). Nonetheless, they have become popular in other applications such as urban mapping. VHR sensors are said to be ideal for mapping fine scale habitats with a high spatial heterogeneity (Lucas et al. 2011), however, when aiming to map habitats in larger regions, sensors with a high spatial resolution such as Landsat and SPOT are satisfactory.

2.5.2 Medium resolution sensors (Landsat and SPOT)

A major problem that has been recognized with using Landsat and SPOT datasets in ecological studies is that their high spatial resolution is not sufficient for certain studies (Nagendra et al. 2010). This is because an individual pixel in these datasets can be a couple of tens of meters in size. In vegetation mapping studies, this implies that a variation of plant species can be covered in a single pixel, and thus increasing heterogeneity within the pixel (Nagendra 2001). As a result, each pixel matches a mixed field signature averaged across various plant species and thus causing lowered species identification competency (Nagendra 2001). Landsat 7 data sets consist of a panchromatic band with a 15 m spatial resolution, and seven multispectral bands with a 30 m spatial resolution. However, the panchromatic band even with half the multispectral bands resolution is not any more sensitive to change than the multispectral bands (Nagendra 2001). Landsat and SPOT datasets achieved moderate accuracies when used in plant diversity estimation studies, however, they are much more effective in habitat mapping studies (Nagendra 2001).

Landsat datasets have been widely used in many applications, especially in land cover and habitat monitoring studies. Landsat imagery collects data on habitat change and disintegrated spatial patterns over large regions (Nagendra et al. 2012), unlike most VHR sensors. Problems identified with using Landsat data is that it fails to provide suitable data on changes in habitat quality, species distribution and fine-scale disturbances (Nagendra et al. 2012). In a study done by Foody & Cutler (2006), Landsat TM imagery was used to successfully estimate the distribution of plant species richness in a very diverse tropical forest. A study done in the Hyrcanian forest of Iran by Mohammadi & Shataee (2010) used remote sensing indices derived from Landsat ETM+ with the purpose of modelling tree species vegetation within the forest.

2.5.3 Hyperspectral sensors

Hyperspectral sensors are extremely spectrally advanced as they cover the visible, near-infrared, and shortwave-infrared in many narrowly defined spectral channels of the electromagnetic spectrum (Curran 1994; Campbell 2006; Oldeland et al. 2010). Most multispectral sensors provide at least 3 to 7 spectral channels. Hyperspectral sensors provide 200 or more spectral channels, with each band 10nm wide (Campbell 2007). There is solid evidence published suggesting that only hyperspectral bands are powerful enough to distinguish subtle spectral properties of leaf and photosynthetic pigments not simply resolved by other sensors (Mutanga et al. 2004). The visible near infrared region (VNIR) portion of hyperspectral datasets is useful for detecting leaf pigments and vegetation structure. The SWIR portion provides improved information on vegetation description, especially in dry regions (Oldeland et al. 2010).

A number of studies have validated the ability of hyperspectral datasets to classify tree species (Dennison & Roberts 2003; Andrew & Ustin, 2008; Cho et al. 2010). Nonetheless, using these datasets during a classification is a challenging task as one has to select training spectra equivalent to or more than the number of spectral bands, which is time consuming (Cho et al. 2012). This is due to their extremely high data dimensionality (Landgrebe 1997). Consequently, they tend to be subjected to band duplication (Cho et al. 2012). The duplicated bands are prone to be correlated with bands from different sections of the EMS, and therefore contain similar information (Cho et al. 2012). Data reduction techniques such as principal component analysis (PCA) and wavelet energy feature vectors have been employed in several studies to reduce band redundancy (Kakacska et al. 2007).

Hyperspectral datasets are problematic as they are difficult to acquire, in addition to being computationally challenging to analyse (Campbell 2007). Moreover, they collect large amounts of data, leading to an increase in storage requirements. Therefore, Landsat and SPOT datasets are much more suited for habitat studies, as they are available on a regular basis. Nonetheless, hyperspectral sensors have the potential to provide a better understanding of spatial patterns and improved information for ecological monitoring studies in the future (Campbell 2007).

Hyperspectral datasets collect surface radiation from a large number of narrow bands (Nagendra et al. 2012). This is advantageous in assessing habitat degradation and in habitat mapping studies, as they have increased the level of accuracy of measurement of vegetation functionality such as leaf area index (LAI) (Boyd & Danson 2005). Spanhove et al. (2012) compared hyperspectral imagery alongside field assessments to gain information on the conservations status in two Natura 2000 heathland areas. The results of their study showed that field measurements could describe up to 43% of the differences in fine-scale indicators on the state of the habitat. On the other hand, hyperspectral information could only account for 39% of the dissimilarity. The hyperspectral estimates were able to account for variations where field data was subjected to high inter-observer bias. This portrays the potential of hyperspectral sensors in monitoring changes in habitat quality. Hyperspectral datasets can also be used to identify tree canopies at species level in regions which have a few dominant tree species such as temperate forests or mangroves (Wang et al. 2004; Duro et al. 2007; Everitt et. al. 2008). The challenge became greater as the number of tree species increased to tens and hundreds. All of the above mentioned studies prove that hyperspectral imagery can be used successfully to monitor habitats.

2.5.4 Lidar and synthetic aperture radar

Light Detection and Ranging (LiDAR) is an active remote sensing technology which is capable of measuring vegetation structure, specifically vegetation height (Lefsky et al. 2005; Levick et al. 2009; Fisher 2013). LiDAR does so by illuminating a target with a LASER (light amplification by stimulated emission of radiation), which in return, the receiver measures the reflected light (Lefsky et al. 2005) and calculates distance to the object (Cho et al. 2012). LiDAR provides the opportunity to monitor landscapes with much more targeted assessments as it is capable of acquiring above ground biomass (Nagendra et al. 2012). This can be associated with disturbances caused to the landscape, especially in forested areas (Nagendra et al. 2012). However, Boyd & Danson (2005) point out that the use of LiDAR has been somewhat limited in habitat monitoring studies. This is due to the difficulty experienced with acquiring LiDAR datasets, and the technical complexities associated with their use and interpretation.

Synthetic Aperture Radar (SAR) is part of the active remote sensing group. Like most active sensors, SAR is not affected by atmospheric conditions such as cloud cover and haze (Nagendra et al. 2012). As a result, SAR data is increasingly being used in landscape monitoring studies such as wetlands and seasonally inundated forests (Nagendra et al. 2012). This data can be used to delineate between different habitat types, using their three-dimensional (3D) structure and biomass, thus information on species age and species composition can be acquired (Koch 2010). By combining SAR data and optical data such as Landsat or SPOT, different land cover types can be delineated even those which are structurally and spectrally alike (Treuhaft et al. 2004). For example, Kuplich (2006) used SAR data to discriminate Amazonian forest fragments in multiple stages of regrowth. However, SAR fell short in discriminating forest fragments at an acceptable level. When SAR data was jointly used with Landsat TM data, the accuracy increased substantially, showing the potential of using SAR data in combination with optical sensors. Hyde et al. (2006) used SAR data in combination with Landsat ETM+, LiDAR, and Quickird to map the quality of wildlife habitat in the Sierra National Forest. The results showed that combining Landsat data with LiDAR gives the best results, whereas QuickBird and SAR data resulted in borderline improvements. Furthermore, LiDAR and SAR are capable of penetrating below the top vegetation canopy, thus providing better information on habitat degradation (Nagendra et al. 2012). LiDAR in particular is more capable of measuring canopy height and biomass, which are two important indicators of habitat suitability (Nagendra et al. 2012).

2.6 REMOTE SENSING VEGETATION ANALYTICAL METHODS

The most frequently used vegetation mapping methods are digital image classification methods (Oldeland et al. 2010). They make use of the spectral information contained within spectral bands by grouping pixels into different classes (Campbell 2007). Pixel based and object based classification methods exist. They both consist of supervised and unsupervised classification techniques, with supervised classifying data using prior knowledge of land cover. Commonly used supervised classifying algorithms are Maximum likelihood and spectral angle mapper classifiers used in multispectral and hyperspectral data sets respectively (Oldeland et al. 2010).

Remote sensing vegetation indices (VI's) measure the degree of photosynthetic activity occurring in areas covered by vegetation (Lück et al. 2010). A number of spectral bands are selectively added to create a spectral vegetation index (VI). The VI is designed in such a way that spectral features associated with certain environmental variables such as vegetation reflectance are enhanced (Dorigo et al. 2007). Variables which are not of interest such as soil reflectance, sun and view geometry, atmospheric composition (Oldeland et al. 2010), moisture and different levels of band saturation are reduced (Lück et al. 2010).

A number of remote sensing vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), EVI2 and the Soil-Adjusted Vegetation Index (SAVI) have been developed. Vegetation indices are not inherent physical measurers of vegetation presence. They are used as proxies that assess biophysical and biochemical characteristic of vegetation (Jiang et al. 2008).

2.6.1 Normalized difference vegetation index (NDVI)

The NDVI has become the most widely used VI in ecological studies (Pettorelli et al. 2005; Lück et al. 2010). NDVI highlights areas where there is photosynthetic activity, which shows that vegetation is actively growing. It can measure vegetation greenness/ cover on the earth's surface over large areas (Lück et al. 2010). NDVI has been shown to be a reliable correlative measure for vegetation vigour and functions in a range of diverse ecosystems (Running 1990, Myneni et al. 1995). In other studies, NDVI was shown to be a good assessor at forecasting disruptions to land cover such as fire disturbance (Maselli et al. 2003), drought (Singh, Roy & Kogan 2003) and floods (Wang et al. 2003). NDVI's use is based on the principle that vegetation absorbs strongly in the RED wavelength region of the EMS whereas mesophyll leaf structure reflect in the near infrared (NIR) range of the EMS (Pettorelli et al. 2005). Most commercial satellites are able to measure the intensity of reflection in these two regions. NDVI is extracted by measuring the difference in reflectance of the NIR and RED as shown in the formula below:

$$NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED} \text{(Campbell 2002)}$$

Where: ρ NIR covers the reflectance value in the near-infra-red part of the EMS; and ρ RED is the reflectance value in the red region (Lück et al. 2010).

NDVI values range between -1 to 1, and increase with increasing biomass. Values from 0.5 suggest that vegetation density is increasing, whereas values below zero indicate vegetation absence, and much lower values indicate water/ inundated areas (Guerschman et al. 2009). In ecological studies, NDVI has been widely used in delineating and interpreting mapped vegetation units (Hong et al. 2004), and in studies measuring the magnitude of habitat degradation and transformation (Pettorreli et al. 2005).

Despite the usefulness of NDVI in ecological studies, it does present a few limitations. NDVI saturates at high biomass, especially in temperate and tropical forests (Huete et al. 2006). NDVI also introduces problems related to soil background effects (Bausch 1993), and is weakened by highly variable gases in the atmosphere (Ben-Ze'ev et al. 2006) thus EVI was developed as a result.

2.6.2 Enhanced vegetation index

Similar to NDVI, EVI uses the RED and NIR regions in addition to the blue band. EVI is great for enhancing vegetation reflectance to distinguish between slight changes in vegetation response in areas with high biomass as it is more sensitive to canopy structural variations (Lück et al. 2010). Furthermore, EVI incorporates the blue band which is beneficial in reducing the influence of atmospheric conditions on vegetation index values more especially in areas that have been affected by extensive fires such as the Amazon (Miura, Huete & van Leeuwen 1998). Other benefits of EVI include its ability to decouple canopy background signals (Huete et al. 1997; Lück et al. 2010). The many benefits of EVI have prompted researchers such as Chen et al. (2004) to estimate vegetation biophysical parameters, biodiversity Waring et al. (2006) and phenology Xiao et al. (2006) using EVI a proxy. EVI is calculated using the following formula:

$$EVI = G\frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + C_1\rho_{RED} - C_2\rho_{BLUE} + L} \text{ (Jiang et al. 2008)}$$

Where: *ρ BLUE, ρ RED* and *ρ NIR* is atmospherically corrected surface reflectance

G is a gain factor

L is the canopy background adjustment that addresses non-linear, differential NIR and red radiant transfer through a canopy

C_1, C_2 are the coefficients of the aerosol resistance term, which uses the blue band to correct for aerosol influences in the red band (Jiang et al. 2008).

2.7 CONCLUSION

Field surveys are traditional methods which ecologists and biodiversity monitors use to collect valuable information in important ecological regions such as protected areas. However, these methods of collecting data are both time consuming and labour intensive. This review of the literature demonstrated the potential of remote sensing as a valuable tool to provide significant spectral, spatial and temporal information on biodiversity and habitat conditions. Therefore, remote sensing can be used as an essential tool by biodiversity monitors to map habitats and monitor significant changes that occur within protected areas. A review of a number of case studies showed that remote sensing is capable of providing monitoring experts with information on changes in habitats, habitat degradation, and changes in the spatial distribution and diversity of species at both local and regional levels. In addition, persistent trends, pressures and threats to biodiversity such as anthropogenic activities can be monitored rapidly. The vast majority of the case studies that were reviewed showed that high spatial resolution sensors such as Landsat and SPOT are efficient in assessing changes within protected areas, which emphasises their continued use as data providers in ecological studies. Their continued utility is because they are easy to acquire, and they have an invaluable historical record that dates back to a few decades, which further allows change detection studies to be implemented effectively. Case studies showed that remote sensing is becoming widely integrated into conservation planning processes. However, researchers such as Nagendra et al. (2012) point out that remote sensing can only be used to its full potential once remote sensing analysts work with biodiversity monitors to develop effective operational tools for mapping and monitoring habitat quality.

CHAPTER 3 RESEARCH METHODS

This chapter gives an outline of the methods employed in this research. A detailed description of the study area is given, followed by the data products obtained and the process of sourcing the data. The data went through a serious of data preparation methods, followed by the data analysis stage, whereby intactness indices were derived from the data. Thereafter, an accuracy assessment of the indices derived was processed.

3.1 STUDY AREA

3.1.1 Motivation for selecting the study location

The Bushbuckridge region was selected for this study as it shows various degrees of transition from areas that are pristine in the KNP, over natural landscapes moderately impacted by livestock, to fully transformed urban and plantation areas. Considering the rise in threats imposed on biodiversity, the study area serves as a good example for testing whether earth observation can pick up various degrees of degradation in semi/natural environments. A subset of a SPOT and Landsat image was used, as it shortens the processing time, and the selected area is sufficient to answer the research question as it represents all relevant land use types and degradation forms representative for that area.

3.1.2 Description of the study area

The Bushbuckridge region is located in the northernmost part of the Mpumalanga province and lies on the border of the Limpopo province in South Africa (Figure 3.2). The geographic coordinates are situated roughly at 31.181 degrees East and 24.731 degrees South. It includes the south-western parts of the Kruger National Park, the Sabie-Sand Game reserve in the eastern section, and the Sabie River in its southern most section (Dovie, Witkowski & Shackleton 2004).

Bushbuckridge covers an area of approximately 2600 km^2 dominated by a semi-arid savanna landscape with a range of trees, shrubs and grasses. The region is characterised by three major vegetation types: granite lowveld (dominant), gabbro grassy bushveld and legote sour bushveld (Rutherford et al. 2006). The topography and climate of the area are described as a west to east gradient (Shackleton 2000). The underlying geology is characterized by potassic granites and grandiorite's Shackleton (2000), with Timbavati gabbro intrusions (Fisher et al. 2011), whereas the dominant soil type is shallow sandy lithosols (Shackleton 2000).

The terrain in this region is relatively flat to shallowly undulating with an altitude between 600 meters above sea level (Shackleton 2000; Giannecchini, Twine & Vogel 2007; Madubansi & Shackleton 2007). The annual rainfall ranges from 1200mm in the west to ±500mm in the east and has an average annual temperature of 22°C (Shackleton 2000; Fisher et al. 2011). The seasons can be described as hot humid rainy (tropical monsoon-influenced) summers from October to April and warm and dry winters from May to September. Figure 3.1 shows monthly average temperature and rainfalls of the KNP area.

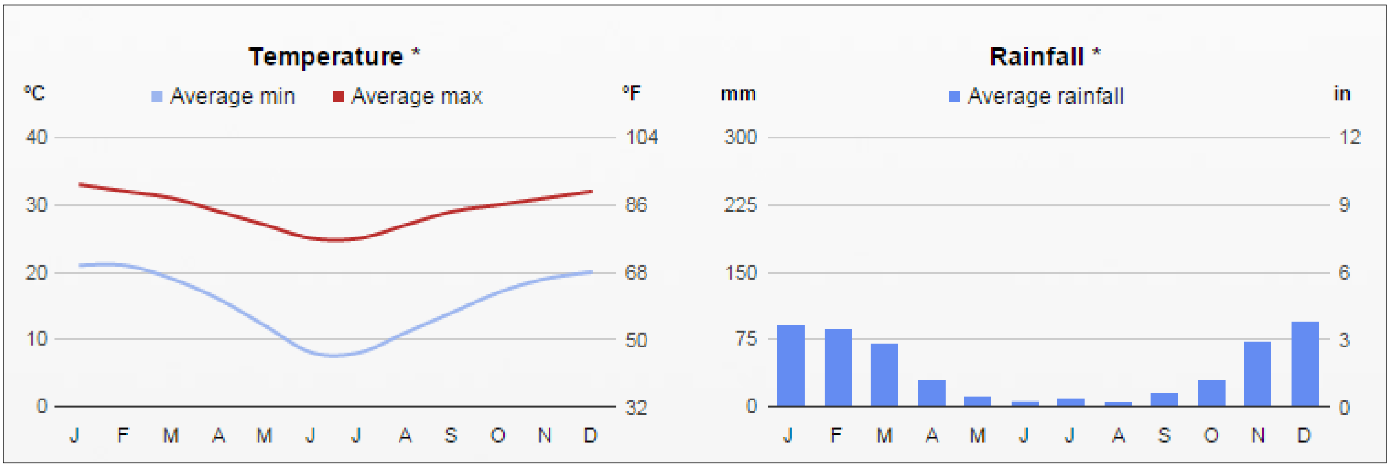


Figure 3.1 Monthly average temperature and rainfall chart of the Kruger National Park from January to December

3.1.3 Kruger to Canons Biosphere Reserve (K2C)

The Bushbuckridge region forms part of the great Kruger to Canons Biosphere Reserve (K2C), which covers an area of approximately 2.6 million hectares (Coetzer et al. 2013). According to

Coetzer et al. (2010), only about half of the K2C region is intended for biodiversity conservation purposes, whereas land use practices in the other half range from agriculture, mining, forestry, plantation, communal grazing and human settlements. The K2C is of significant importance as it is the largest Biosphere reserve in South Africa and the third largest globally. K2C was officially registered in September 2001 with the United Nations Educational, Scientific and Cultural Organization's (UNESCO) Man and the Biosphere (MAB) programme (Coetzer et al. 2010). Three distinct biomes are found within the K2C region, namely: Grassland, savanna, and Forest (Coetzer et al. 2013).

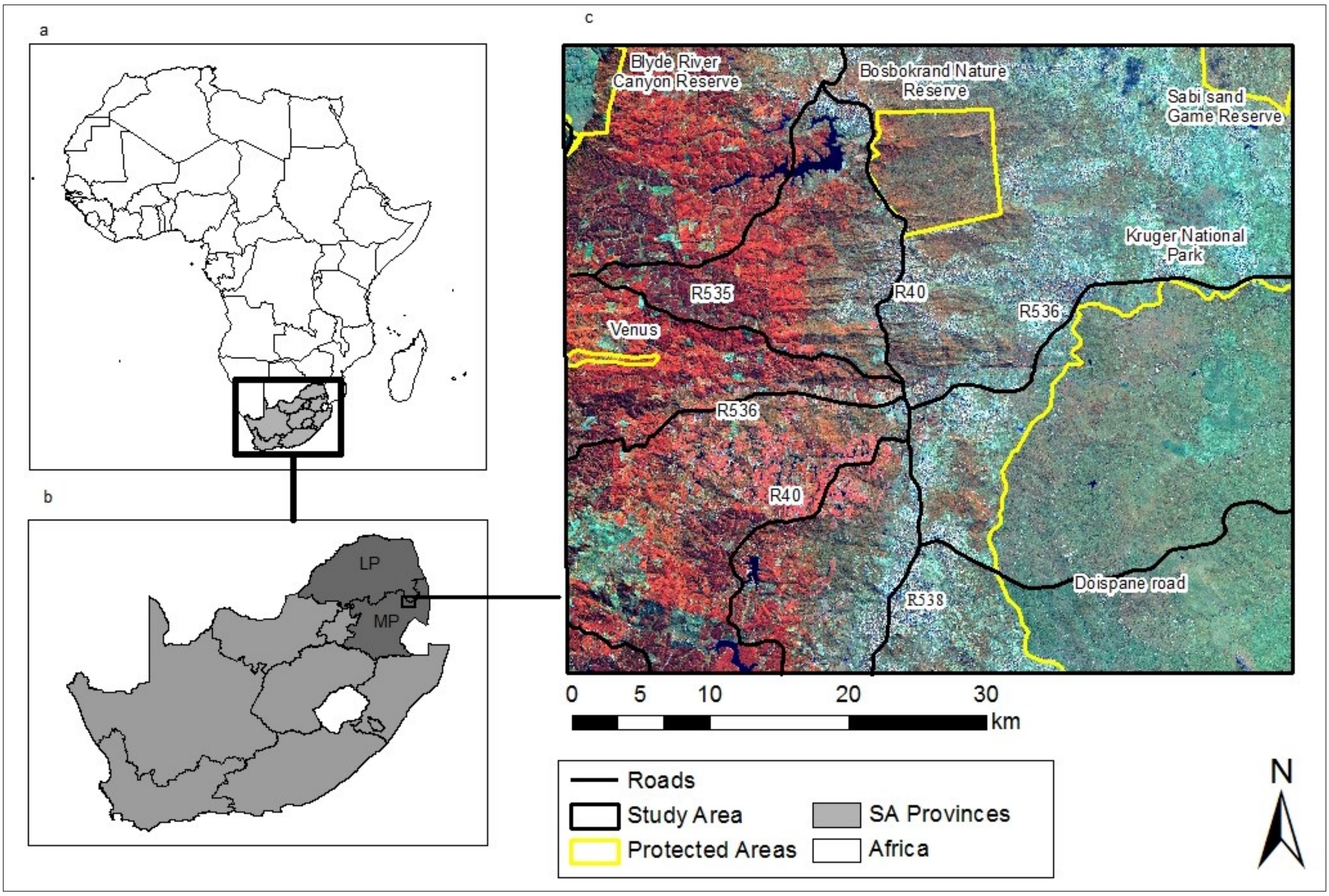


Figure 3.2 a) Placement of South Africa on the African Continent b) Bushbuckridge region within the Limpopo province (LP) and Mpumalanga province (MP) c) Study area subset of a SPOT 5 image used as background showing band combination (NIR-SWIR-red)

3.2 DATA ACQUISITION

The test site selected in the Buschbuckridge region covers an area of 2384 km^2. The study is based on modelling habitat intactness on a landscape level and not on mapping species composition and vegetation structure. Accordingly, moderate spatial resolution images can be used to effectively model habitat intactness at this scale. Medium resolution multispectral Landsat and SPOT have been shown to be successful in studies that measure the diversity of plants rather than the number of plant species (Nagendra et al. 2010a). As explained in the literature review, the use of VHR sensors such IKONOS and Quickbird for environmental management purposes is frequently not possible as data from these sensors are expensive and difficult to acquire. Furthermore, they tend to provide more detail than is necessary, often even introducing additional challenges such as shadows within landscape objects (Nagendra et al. 2012). VHR sensors also offer smaller image footprints than medium resolution imagery like Landsat and SPOT meaning that more images are required to cover the same area. Medium resolution images are easier to acquire as they are available cost-free from the internet. In South Africa, SPOT 4 and SPOT 5 images are made freely available by the government for academic purposes. Consequently, VHR sensors were deemed unsuitable for this study, multispectral Landsat and SPOT 5 imagery were selected accordingly as the main data sources for this study.

SPOT 5 level 1A multispectral and panchromatic images were acquired from the South African National Space Agency (SANSA). The panchromatic images have a 2.5 m spatial resolution, while the multispectral images have a 10 m spatial resolution. Level 1A SPOT data are almost in raw form, thus they are not radiometrically and geometrically corrected. Radiometric and geometric corrections were done on the SPOT image. The most recently available image from (May 2010) was acquired although it had 3% cloud cover.

Two Landsat 8 level 1T processed image scenes were obtained from USGS Earth Explorer. These scenes are (path 168 – row 77, from May 2014 and October 2014). These images are corrected for geometric distortions caused by sensor geometry and terrain (USGS 2013). Orthorectification has already been applied and the projection for orthorectification is set to Universal Transverse Mercator (UTM) zone 36S. Landsat level 1T images are however not radiometrically corrected. Radiometric correction of remotely sensed data reduces errors caused by atmospheric influences and sun geometry and sensor effects. The most suitable Landsat images were identified by inspecting the Earth Explorer catalogue for the study area. The most cloud free images for May and October 2014 were selected. The May image matches with the acquisition date of the SPOT image from May 2010, while the October 2014 image coincides with the date field data was collected.

Table 3.1 lists the images used in this study. Additional data acquired for the study include land cover maps, shapefiles of vegetation, soil and geology types in the study area. These data were acquired from the Centre for Geographical Analysis at the University of Stellenbosch. Orthophotos were acquired from the National Geospatial Institute (NGI). Table 3.2 shows the characteristics of Landsat and SPOT 5 data.

Table 3.1 Image ID's and acquisition date of each acquired image

Sensor	**Product ID**	**Source**	**Acquisition date**	**Spatial resolution (metres)**
Panchromatic SPOT5 Multispectral SPOT5	S100913081100749 (pan) S100913081121557 (multi)	SANSA	2010-05-22 2010-05-22	2.5 10
Landsat	LC81680772014146LGN00 LC81680772014274LGN00	USGS	2014-05-26 2014-10-01	15 (Pan), 30m (multi)
Aerial photographs		NGI	2014-08-10	

Table 3.2 SPOT 5 and Landsat characteristics

Data	**SPOT 5 HRG**		**Landsat 8**	
	Band	µm	Band	µm
Bandwidth interval (micrometers)			1 (Coastal aerosol)	0.43-0.45
			2 (Blue)	0.45-0.51
	1 (Green)	0.50-0.59	3 (Green)	0.53-0.59
	2 (Red)	0.61-0.68	4 (Red)	0.64-0.67
	3 (NIR)	0.78-0.89	5 (NIR)	0.85-0.88
	4 (SWIR)	1.58-1.75	6 (SWIR 1)	1.57-1.65
			7 (SWIR 2)	2.11-2.29
	P (Pan)	0.48-0.71	8 (Pan)	0.50-0.68
			9 Cirrus	1.36-1.38
			10 TIRS 1	10.60-11.19
			11 TIRS 2	11.50-12.51
Spatial resolution (metres)	P = 2.5 m 1-3 = 10 m 4 = 20 m		1–7 and 9 = 30 m 8 =15 m 10-11 = 100 m	
Radiometric resolution (bits)	8 bit		16 bit	
Temporal resolution (days)	4-5 days		16 days	
Swath width (kilometres)	60 Km x 60 Km		185 km	

3.3 SATELLITE DATA PRE-PROCESSING

Satellite images acquired contain radiometric and geometric distortions, which substantially decrease their applicability in environmental studies if uncorrected (Kerr & Ostrovsky 2003). Various data pre-processing steps have to be undertaken to improve the quality of the images. This section describes the pre-processing steps required to prepare the data for further image analysis which were undertaken in various software.

3.3.1 Orthorectification

The aim of geometric corrections is to assign map coordinates to the remotely sensed data, so that it contains a map projection and can accurately be overlaid with other geospatial data. Geometric corrections are also done to correct for distortions resulting from terrain relief; this process is known as orthorectification. The PCI Orthoengine module was used to orthorectify the SPOT images. The Landsat images were not corrected for terrain distortions as they are already geometrically corrected. Aerial photographs from the National Geospatial Information (NGI) and elevation data (SRTM DEM from the National Aeronautics and Space Administration with a spatial resolution of 90 m) were used to correct for terrain distortions in the orthorectification process.

The process of orthorectification involved collecting ground control points (GCPs) from reference data throughout the SPOT 5 scene. Orthorectified orthophotos with a spatial resolution of 0.5 m were used as reference data. Toutins model was selected as the orbital model, as it takes into account the platform, sensor and earth distortions and cartographic projection caused during image acquisition (Toutin & Cheng 2002). The projection of the orthorectification output was set to UTM 36 S, which is the same projection system used on the orthophotos and the Landsat images. GCP points were first collected from the panchromatic SPOT 5 image, which was then used to orthorectify the multispectral SPOT 5 image. The resulting orthorectified images were visually compared to the orthophotos to check for offsets. The root mean square error (RMSE) was 0.4 m, which is quite accurate considering the respective pixel sizes of the multispectral and panchromatic image of 10 m and 2.5 m respectively.

3.3.2 Radiometric corrections

Radiometric corrections are performed on satellite imagery to correct the brightness values of the image, distorted by atmospheric effects and sensor errors, and to convert digital numbers (DN) to reflectance (Campbell 2007). Atmospheric effects occur as a result of the passing of electromagnetic radiation through the atmosphere, whereby scattering, absorption and refraction of the radiation takes place (Campbell 2007). Therefore the digital number values recorded by the satellite receiver are not a true representation of ground conditions. By performing an atmospheric, correction of the images, Top of Canopy (TOC) reflectance is converted to physical values such as true radiance. Radiance is defined as the actual energy measured at the sensor.

Some of the most common algorithms used to atmospherically correct images include the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH), Second simulation of the satellite signal in the solar spectrum (6S) and Quick atmospheric correction (QUAC). ATCOR is a software based on MODTRAN 5 that corrects remotely sensed imagery covering the solar (0.4 to 2.5 µm) and the thermal (8 to 14 µm) regions (Richter 2014).

PCI Geomatica's ATCOR 2 (PCI Geomatica 2013) was used to correct atmospheric distortions on the SPOT 5 image, and ATCOR 2 in ENVI was used to correct distortions on the Landsat images. ATCOR 2 which does not require the input of an elevation model was used as the topography of the study area is rather gently undulating and effects of topography were not expected to have a huge impact in the study area (e.g. through shadows).

3.3.3 Pan-sharpening

Pan-sharpening is the process of combining a high spatial resolution panchromatic image (2.5 m for SPOT image and 15 m Landsat image) to a lower spatial resolution multispectral image (10 m SPOT image and 30 m Landsat image). The resulting output is an image that contains the high spatial resolution of the panchromatic image, and the spectral resolution of the multispectral image. PCI Geomatica's PANSHARP module was used for this step. Initially SPOT 5 images were pan-sharpened to 2.5 m, but due to their large size which painfully increased subsequent processing time, it was decided to discard the pan-sharpened images and to continue with the original 10 m multispectral images for further processing. Further, the 2.5 m pan-sharpened image introduced too much noise such as tree shadows, speckle and noise, which were expected to negatively impact the results. However, May and October 2014 pan-sharpened Landsat 8 images were used for further processing. The original 30 m multispectral Landsat 8 image was also used to test which spatial resolution is needed to effectively assess habitat intactness.

3.3.4 Image subsetting

The pre-processed images were subsetted in Arcmap (ESRI 2010) using the extract by mask algorithm (ESRI 2010). A shapefile of the study area extent was used to mask out the images to the same extent. Subsettting is done to shorten processing time, and also sets the goals of the study area into context. The pre-processed Landsat 8 and SPOT 5 images were processed using subsets for all images. Additionally, large water bodies were masked out as they were of no concern for this study.

3.4 SATELLITE DATA PROCESSING

The image analysis begins with the segmentation of the SPOT 5 image and Landsat 8 images as described in section 3.4.1. The generation of the SPOT 5 and Landsat 8 degradation index is explained in Section 3.4.2. The final step is the derivation of a field based index using field assessment methods, details are given in section 3.4.3. Details on deriving an accuracy assessment are described in Section 3.4.5. Results of the segmentation and indices are described in chapter 4 along with the discussion of the results.

3.4.1 Segmentation

Image segmentation is a method used to subdivide an image into meaningful smaller image objects (Blaschke 2004, Navulur 2007). This process is usually the initial data processing step in object based image analysis (OBIA). Segmentation procedures are applied to the automation of image analysis, thus replacing the task of visual digitizing. The object-based paradigm makes use of the images attributes such as shape, colour, size, texture and morphology during image analysis (Navulur 2007). Most importantly for this study, OBIA methods allow the user to extract not only image attributes but also spatial, contextual and textual information (Navulur 2007).

A range of segmentation algorithms exist such as the multi-resolution segmentation which are highly sophisticated, and much simpler algorithms such as chessboard and quad tree segmentation (eCognition Developer 8.0 Training 2010). For this study, the multi-resolution segmentation algorithm was applied as it minimizes the average heterogeneity within image objects and maximizes their respective homogeneity (eCognition Developer 8.0 Training 2010). The segmentation procedure is affected by the respective input parameters, which rely on the analyst's needs. The most important factor to consider when executing a segmentation process is the scale parameter as it controls how homogenous image objects will turn out (Drăguţ, Tiede & Levick 2010). By selecting an appropriate scale parameter, the average heterogeneity of pixels within image objects is reduced (eCognition Developer 8.0 Training 2010). As a general rule, 'good' image objects should be as large as possible, but small enough to show contours of interest and to serve as building blocks for objects of interest not yet identified (Gronemeyer 2012).

In this study, eCognition Developer software was used to execute the segmentation. The optimum scale parameter for discriminating homogenous image objects varied widely, and was determined for each image on a trial and error basis. Values ranging from 5 to 50 were tested for SPOT 5 and 100 to 200 for all three Landsat 8 images, in order to facilitate comparison. Other important parameters that influenced the segmentation results are the shape and compactness criteria. A shape weighting of 0 means the image objects will be delineated purely based on colour criteria, a shape weighting of 1 implies the opposite. A compactness weighting of 0 gives a high perimeter: area ratio, while a weighting of 1 means the opposite. Compactness weightings apply only if the shape weighting selected is greater than 0.0. Therefore, as in this study, shape was set to 0.0, both shape and compactness were irrelevant (and set to 0).

The multi-resolution segmentation algorithm also allows for different weightings for the individual bands depending on how significant they considered for the data analysis. The greater the values the more information of that band will be employed in the segmentation results (eCognition Developer 8.0 Training 2010). A variety of vegetation indices are founded on the spectral information in the RED and NIR spectral bands, for example the NDVI= (NIR-RED)/ (NIR+RED) and the Ratio Vegetation Index (RVI) = NIR/Red (Major, Baret & Guyot 1990). Therefore red and NIR bands were given more weight (1.0) in the segmentation as they are considered important for discriminating of vegetation types and condition. This is of relevance for this study as vegetation it is used as a proxy for habitat intactness. The remaining layers were assigned 0.5 in both sensors.

3.4.2 Generation of image derivatives

The applied method for deriving a habit intactness index is based on (Luck-Vogel, O'Farrell & Roberts 2013). The aim of the method really is to assess habitat degradation/intactness from satellite imagery. These are based on spectral, structural, spatial and textual characteristics of the image. In addition to Luck-Vogel, O'Farrell & Roberts (2013) original work, NDVI and Area were also added for this thesis project as it is a commonly used measure of vegetation presence.

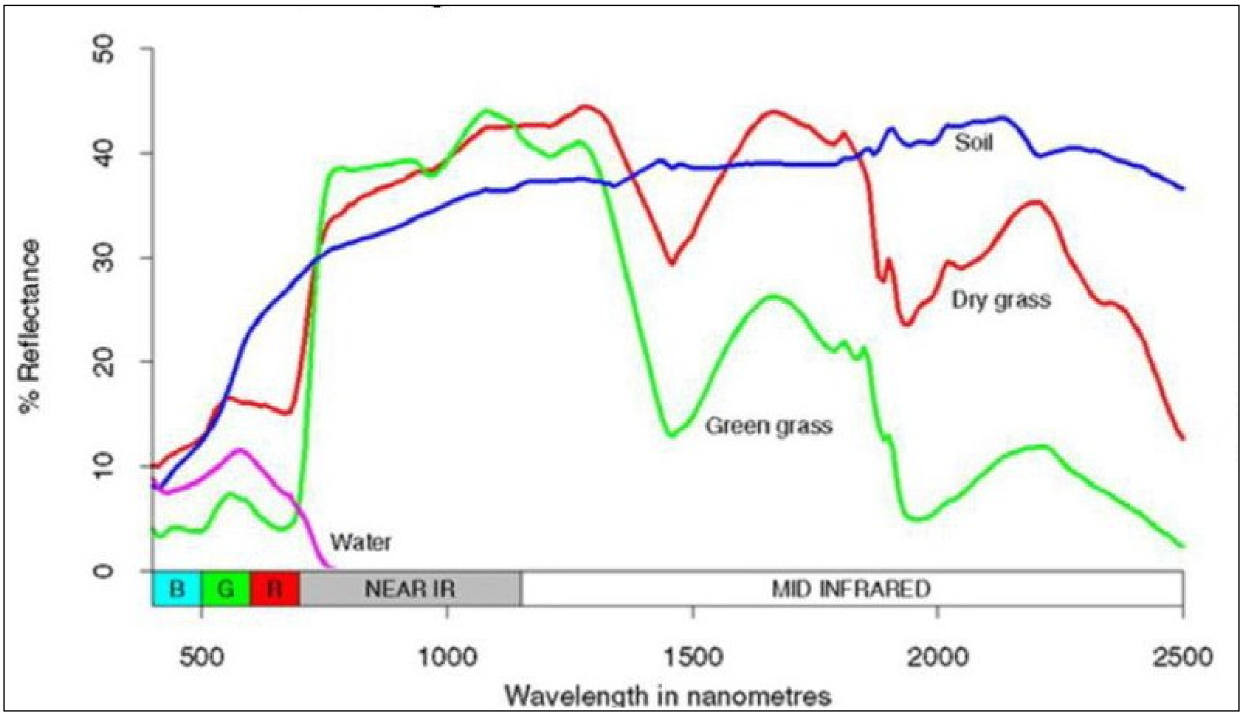
The intactness index was derived firstly by generating derivatives that can distinguish between degraded and non-degraded natural vegetation from satellite imagery. These are based on spectral, structural properties of an image. Further processing was done using Arcmap (ESRI 2010) and ERDAS imagine software (ERDAS 2013).

3.4.2.1 Spectral derivative

The spectral reflectance of a surface is measured as a function of wavelength. Thus, different objects will have distinctive spectral reflectivities. For example, the spectral characteristics of vegetation differ depending on the chlorophyll content contained within the leaves of a plant. This compound tends to reflect radiation in the green region of the EMS and strongly absorbs in the red wavelength. The mesophyll structure of a healthy leave will reflect the NIR region. Therefore, many researchers have explored the NIR region to measure the health of plant species. The spectral derivative can be computed by using brightness values of a satellite image (Luck-Vogel, O'Farrell & Roberts 2013). Brightness in this instance can be defined as the mean of the spectral bands contained in a satellite image (Definiens 2007).

Figure 3.3 below shows typical spectral reflectance curves of soil, vegetation and water. Bare soil tends to appear bright on satellite images, thus has a higher spectral reflectance than vegetation except in the NIR region where vegetation reflects highly (Xiaoa & Moody 2005; Nagendra 2001; Ashraf, Maah & Yusoff 2011). The spectral reflectance of soil can change depending on the moisture content, texture, structure and iron-oxide content (Mujumdar & Nagesh Kumar 2012). Therefore the higher moisture content contained in a soil, the lower the reflectance values will be

(Mujumdar & Nagesh Kumar 2012). However, spectral reflectance can be misleading as a general measure of intact vegetation as some pristine vegetation species types have dispersed vegetation (Luck-Vogel, O'Farrell & Roberts 2013) especially in arid regions. Crops and vegetation alien species are degraded areas with similar brightness values as natural vegetation. As a result, the spectral derivative needs to be accompanied by other derivatives to compensate for where it's limited.



Source: Ashraf, Maah & Yusoff 2011

Figure 3.3 Spectral profile showing reflectance spectra of different materials

3.4.2.2 Structural derivative

The structural derivative is based on structural characteristics of landscapes (Luck-Vogel, O'Farrell & Roberts 2013). Man-made features such as houses and agricultural fields can be identified from satellite imagery as having different organizational patterns such as squares and circular arrangements (Definiens 2007). Contrariwise, natural sceneries like rivers and naturally vegetated areas have irregular and non-geometric shapes (Definiens 2007). Compactness is the relation between a polygon's area and perimeter. It can be used to determine the structural criterion of boundary shape. An increase in compactness will indicate a decrease in habitat intactness. In

Definiens (2007), compactness is calculated as the ratio of the area of a polygon to the area of a circle with the same perimeter using the formula:

$$Compactness = \frac{4\pi \times Area}{Perimeter^2} \text{ (Definiens 2007)}$$

Its feature value range is [0,1], with 0 being the least compact polygon, and 1 the most compact polygon (1 is the compactness value of a perfectly round circle).

Therefore, image object compactness can be used as a proxy to measure vegetation habitat structure (Luck-Vogel, O'Farrell & Roberts 2013). This is founded on the principle that anthropogenic structures such as plantations tend to be more compact and uniform in shape whereas natural habitat appears less compact and irregular. Highly disturbed areas are more likely to have high compactness values closer to 1 and natural areas low compactness values and thus equates to habitat intactness. Circular structures have the highest form of compactness (Definiens 2007).

3.4.2.3 Textural derivative

Texture in this context refers to spectral heterogeneity within a polygon per spectral bands of an image (Definiens 2007). Texture is an important feature that can be used to identify degraded areas from pristine vegetation as it shows how tones very on a satellite image (St-louis et al. 2009). Shadowing is an important function of texture as tress with varying heights exhibit a great deal of shadowing, thus creating a heterogeneous pattern. Young trees for example generally have a smooth texture; whereas older trees tend to have a coarse texture (St-louis et al. 2009).

Texture is a spectral variable and can be measured using different spectral properties of features. The textural derivative is based on the assumption that natural landscapes consist of mosaics of different species with different heights, ages and life form structures which result in a high spectral heterogeneity per polygon, whereas anthropogenically influenced landscapes tend to lose life form and age variety resulting in texturally more homogenous polygons (Luck-Vogel, O'Farrell & Roberts 2013. Extreme examples for these cases are crop fields or forest plantations. An increase in texture will indicate an increase in ecosystem intactness. The standard deviation of NIR range can be used as a proxy for vegetation texture (Luck-Vogel, O'Farrell & Roberts 2013). The spectral resolution of an image needs to be taken into account when texture is being used as a form of vegetation analysis as most landscapes will appear smooth textured and eventually be undistinguishable at a very coarse spatial resolution.

3.4.2.4 Area derivative

Area (excluding inner polygons) is based on the geometry shape attributes of a polygon. The assumption made for area is that, natural areas have large polygons, whereas degraded areas such as settlements and plantations have smaller polygons. The formula for calculating area is:

$$Area = \frac{1}{2}\sum_{i=0}^{x-1} a_i \text{ (Definiens 2007)}$$

Where:

$$a_i = X_i Y_{i+1} - X_{i+1} Y_i$$

3.4.2.5 Normalized difference vegetation index

NDVI was used to distinguish between vegetated areas and non-vegetated areas. NDVI is the most common and widely used vegetation index. NDVI is based on the observation that chlorophyll absorbs Red whereas mesophyll leaf structure scatters near infrared (NIR) (Pettorelli et al. 2005). NDVI is calculated using the formula:

$$NDVI = \frac{(NIR - red)}{(NIR + red)}$$

Dry vegetation will thus result in a low NDVI value and green vegetation will result in high NDVI values (Guerschman et al. 2009). The value range of NDVI is from -1 to 1, and a negative NDVI value implies that water is present (Pettorelli et al. 2005). Furthermore, important information regarding the spatial and temporal distribution of vegetation can be acquired from NDVI when multi-temporal images are used (Pettorelli et al. 2005). The assumption made is that naturally vegetated areas will have high brightness values than degraded areas. NDVI alone is not a good measure of habitat degradation as crop fields and plantations generally have higher NDVI values than savanna vegetation, while they are considered to be degraded landscapes. EVI and SAVI are also important indices that are used to map vegetation vigour (Nagler, Glenn & Huete 2001)

3.4.3 Generation of image index

Image derivatives generated in eCognition (brightness, compactness, NIR standard deviation, area and NDVI) were exported as smoothed polygons using the export vector layers algorithm in eCognition. Polygon outputs were rasterised in ArcGIS (ESRI 2010) using a pixel size of 10m for SPOT and 15m for Landsat. All five derivatives (brightness, compactness, standard deviation NIR, area and NDVI) pixel values were re-scaled to values from 0-1. This rescaling was done manually in MS excel by identifying the upper and lower bounds (min and max 0.5%) and excluding them from the brightness values which tend to be skewed. Thereafter, a transformation was applied to complete the full data range.

The rescaled brightness, standard deviation NIR and compactness layers increase with decreasing habitat intactness. They were inverted so that they increase with increasing habitat intactness using ERDAS (ERDAS 2013) model builder and the formula (1-pixel value was applied). Conversely, area and NDVI, increase with increasing habitat intactness as discussed in sections 2.6.1-2.6.5. The final data analysis step was to create the intactness index by totalling all five derivatives. The output was further rescaled to values between 0 and 10, with 0 representing transformed areas, and 10 intact areas. The data range of 0 to 10 was selected to match field value ranges which are discussed in section 3.4.4.

3.4.4 Collecting reference data

Remote sensing derived products such as classification maps need some form of field of observation data to validate and analyse them (Campbell 2006). It is important for the analyst to collect data that is tailored for the specific purpose for which it will serve as validation data (Congalton & Green 2009). In the context of this study, existing land cover data cannot be used as validation data as the primary aim of the approach followed is to test whether satellite images have the capability to map general patterns of habitat degradation, and not to categorise land cover. Field data also establishes a confidence relationship between the ground conditions and the remote sensing results (Congalton & Green 2009). Campbell (2006) mentions that the three objectives of field data are to verify, to evaluate or to assess the remote sensing results. Proper planning is a crucial step in any field mapping survey as it needs to be as time and cost effective as possible. For this study, field data was collected in order to assess the accuracy of the remote sensing derived ecosystem intactness index.

Field data needs to coincide with the remotely sensed data used to design maps as landscapes are forever changing (Congalton & Green 2009). Changes can occur between the image acquisition date and the date reference data is collected. As a result, some errors in the error matrix are caused by changes in the landscape for example crops harvested, new infrastructure developments or burned areas that might have happened during the different times (Campbell 2006). Congalton and Green (2009) suggest that reference data should be collected as close as possible to the imaging date. However in this study, trade-offs were made between field data collection dates and availability of satellite data. Firstly, the study area was only decided upon in August 2014; secondly, SPOT images for the selected study area were only available for May 2010. Although Landsat data was available during the time the field data was collected, images from May 2013 were used to account for seasonality differences between the two images. Additionally, Landsat 8 from a date as close as possible to field survey were used to test how well or poorly the results will turn out as they displayed the current situation during the field survey. Since this Landsat 8 image from October 2014 is close to the date field data was collected, it was used as reference image to link the May SPOT 5 and Landsat 8 data sets.

A field survey was conducted in the study area over the course of three days, from the 13 to15 October 2014. Taking in to consideration the pixel size of the SPOT (10 m) and Landsat (15 m and 30 m) imagery, estimated homogenous plots of 50 x 50 m were surveyed across the study area which are 0.5 ha in size. Prior to field visits, a range of landscape types were targeted for sampling, with care placed on accessibility (near roads), evidently transformed areas, and areas which have not experienced a great amount of change, as revealed by the remote sensing index derived. Furthermore, outlier's produced by the remote sensing index were targeted in the field. Altogether 155 locations were sampled (Figure 3.4) and geo-referenced with a GPS. GPS locations were recorded using a Garmin etrex 10 handheld GPS for accurate geographic coordinates. Photos were taken at every site sampled. Qualitative descriptions with regards to land use/ land cover type, vegetation structure, and confirmation of degradation were recorded. Table 3.3 below shows the field survey sheet used during data collection.

Table 3.3 Field survey sheet

FIELD ASSESSMENT	**Point No.**

Name of assessor		**Date of Assessment**	

Place		***Position: (decimal degrees)***	**East:**	**EPE (in mts**	
Details on place			**South:**		

Dominating vegetation type		**General condition, type of disturbance?**	

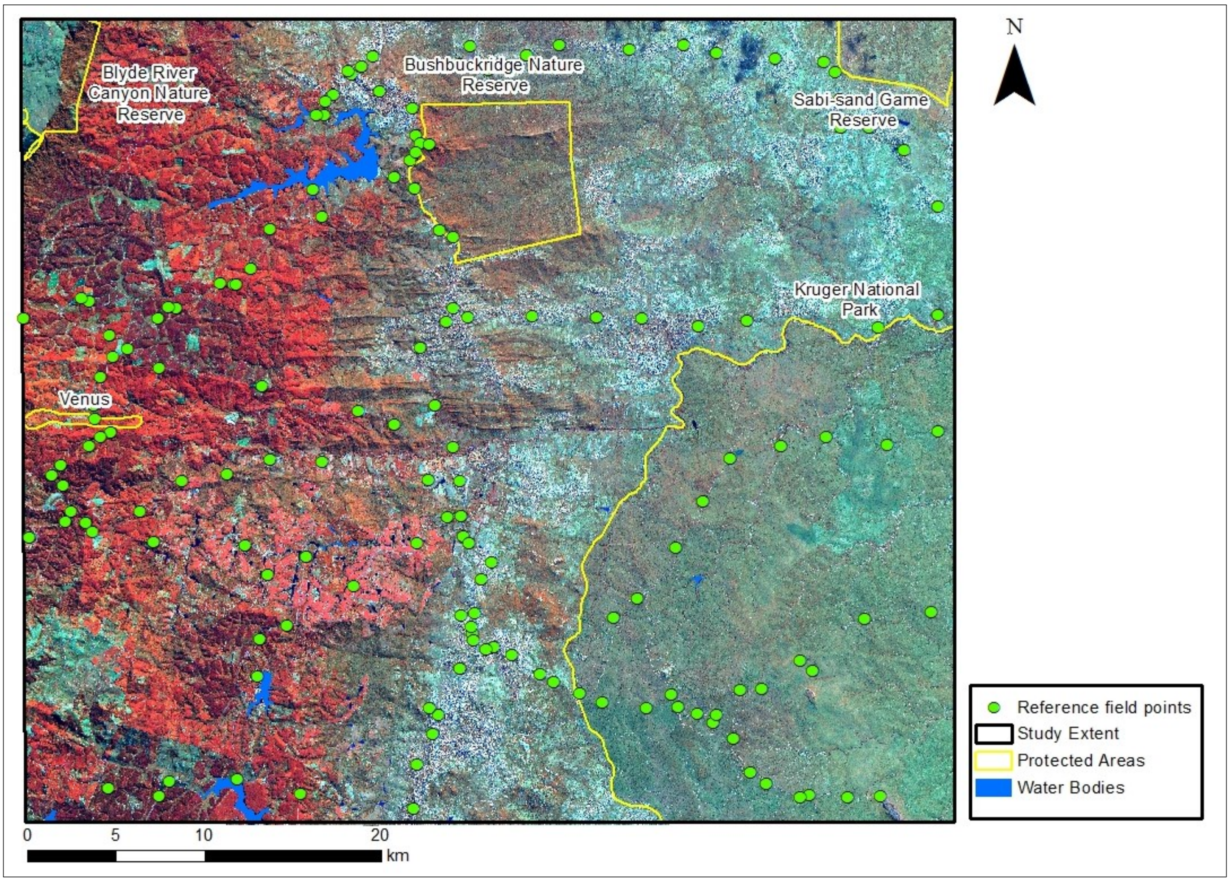


Figure 3.4 Ground reference points collected

The field data collected was used as reference data and were assumed to be accurate. They served as validation data for remote sensing derived maps, and thus needed to coincide temporally with the image acquisition dates. If not, the remote sensing results might differ from the reference data (Campbell 2006), consequently producing false errors. For this study, SPOT 5 images from coinciding dates with field work were not available, so care was taken during the field survey not to sample areas where clearly a change had occurred between May and October. For example, areas were the natural vegetation was not cleared on the SPOT 5 image but had been cleared during the field survey were not sampled. For Landsat an image from the same season as the SPOT 5 image was used, in order to analyse the differences in spectral reflectance's caused by different sensors. In addition a Landsat 8 image from October 2014 was used to maximise correlation with field work. Table 3.4 below shows the beginning of the wet and dry season in relation with when satellite and field data were collected.

Table 3.4 Data collection seasons

	May 2010/ 2014	Oct 2014
	Beginning of dry season	Beginning of wet season
Field survey		X
Landsat 8 image	X	X
SPOT 5 image	X	

For this thesis, a field validation questionnaire based on visual observations was designed. Questions used in this study were primarily adapted from (Luck-Vogel, O'Farrell & Roberts 2013). Though slight modifications where necessary, it was important to adapt a similar questionnaire in order to test whether their method can principally be applied to other landscapes too. Whilst the authors tested the method in the Cape Fynbos region, the study area for this research was in the savanna biome. The questionnaire was kept simple, and designed in such a way that even non-ecologists can apply. A total of 10 questions were designed prior to the field survey (Table 3.5).

Table 3.5 Field based validation questionnaire

No.	Questions	Yes/no	score
1.	Evidence of transformation- Signs of cultivation, urbanisation	Y	0
2.	Is the area used for livestock?- Signs of trampling, hoof action, manure, grazing system	Y	0
3.	Are there any signs of browsing by wild life	Y	0
4.	Signs of soil erosion?- evidence of bare ground, bare roots, damaged soil, soil crust	Y	0
5.	Presence of plant litter/mulch	N	1
6.	Does the variety of natural vegetation life forms appear to have been reduced? – Natural vegetation elimination	Y	0
7.	Is there presence of living crusts, fertile patches, mulch and animal diggings?- Positive signs of soil and habitat health (highest score)	N	0
8.	Are there any signs of selective logging?	Y	0
9.	Is this close to a water point?	N	1
10.	Is the field heterogeneous and does it have a patchy effect?	N	0
	Total score		2

The assessment questions are designed in a way that they can be answered using yes/no answers. These questions are assessing the condition of the natural environment using pointers such as soil condition, urbanisation, agricultural practices and the cutting of live trees. To convert the yes/no answers into a field based index that can be linked to the remote sensing index, the yes/no questions were assigned values of either 0 or 1, with 0 being a negative answer and 1 positive. For example, if the question on a reduction in the vegetation cover is answered yes, which would be negative in terms of intactness, a score of 0 is assigned. In contrast, intact vegetation cover would get assigned a value of 1 as it's a positive answer with regards to habitat intactness. Areas sampled in the field were forest plantations, fruit tree plantations, old abandoned fields, rural and urban areas, pristine savanna vegetation in protected areas, semi degraded savanna vegetation. An example of a completed field survey sampled in the KNP near Numbi gate is found in Table A in Appendix A (sample number 23).

When answering the questions in the field, the following factors were taken into consideration so that the field values are logical and meaningful: 1) areas that are 100% transformed such as urban areas were automatically assigned a value of 0, which is the lowest possible habitat intactness score, 2) areas such as forest plantations are regarded as 100% transformed areas, they were set to 0 although they are vegetated areas, and have similar reflectance properties to natural vegetation, 3) some natural pristine vegetation types are naturally sparse, but not degraded, more especially in the savanna ecology, these were assigned high values, 4) areas that seem to have reduced tree height classes are likely degraded and are therefore assigned lower values.

The field questions with their respective GPS co-ordinates and field scores were converted into a digital database in excel, and further imported into ArcGIS software, then converted into a shapefile for further analysis. The field derived index was lastly compared with the remote sensing index by computing an error matrix in MS excel.

3.4.5 Accuracy assessment

According to Congalton & Green (2009), an accuracy assessment is the most widely used method to assess accuracy of remote sensing derived products. Accuracy assessments are conducted to measure the quality of the remote sensing derived product, and also to identify and improve errors generated in the remote sensing results (Congalton & Green 2009). A thematic accuracy assessment approach was used in this study to check the validity of the remote sensing derived indices using the field survey points as reference data. This type of accuracy method tells the map producer or user if the results produced by earth observation data match ground features.

An error matrix along with the overall accuracy and kappa statistic were computed in MS excel (see Appendix B.2 to B.5). An error matrix is a comparison of a map derived from earth observation methods and one derived from other data sources such as field data and higher resolution imagery. This form of checking accuracy not only produces the overall accuracy for each class but also identifies misclassified classes. Overall accuracy is the most common manner of reporting accuracy, however, not an adequate accuracy measure on its own. Kappa (k), measures to what degree do two data sets correlate with each other. A kappa value of 1 indicates a perfect agreement between field data and classified data, 0 indicates a chance agreement (Table B.1 in Appendix B explains the interpretation of kappa values). Additionally, the error matrix measures the errors of omission and commission, and also the producers and users accuracies. Omission errors (false negatives) measure points excluded from the correct category, while commission errors (false positives) measure points included in the wrong category. Producers and users accuracy, measure the individual accuracy of categories (Congalton & Green 2009).

To compile an error matrix, the reference values and the class values are compared on a location to location basis, to evaluate how each field class is represented in the intactness index. These points are registered to each other, and have the same coordinate system as the index maps, and they are both derived at levels of detail which are comparable (Campbell 2006). Reference data needs to be categorized according to the class values used to create the map (Congalton & Green 2009). This means that the field derived index was based on a compilation of 10 questions, and the remote sensing index was rescaled to a data range between 0 and 10 to effectively establish a comparable relationship between the two data sets.

CHAPTER 4 RESULTS AND DISCUSSION

This chapter provides details on the results of the segmentation outputs and the rule sets designed to extract the brightness, compactness, NIR standard deviation, area and NDVI derivatives for habitat intactness from the SPOT 5 and Landsat 8 sensors used. The SPOT 5 and Landsat 8 habitat intactness indices were generated by summing the five derivatives. The results are discussed in Section 4.3. Subsequently, the intactness index results are compared to field validation by means of an error matrix. The chapter further describes how different techniques can be used to improve the accuracy of the habitat intactness index. Finally, comparisons between SPOT 5 and Landsat 8 are made, in order to establish the transferability of the method to different types of sensors. To illustrate the results, subsets are used to show areas of interest in the discussion.

4.1 SPOT AND LANDSAT BASED SEGMENTATION RESULTS

The following section provides results from the segmentation factors considered in deriving the SPOT 5 and Landsat 8 derivatives. The results acquired from different segmentation parameters are presented using subsets. For each sensor, the segmentation parameter that offered the best results was further used to extract the image derivatives.

The SPOT 5 image scale parameter was tested on a variety of values ranging from 5 to 50. A thorough visual examination of how accurate image objects represent real-world objects was observed on the image. The spatial heterogeneity of objects were examined in various landscapes such as bare areas, forest plantation compartments, degraded rural landscapes and natural vegetation, whole fields, and water bodies and patches not covered by vegetation. Figure 4.1 to Figure 4.4 illustrate subsets of the output results of the tested scale parameters. As can be seen from these figures, the higher the chosen scale parameter, the larger the image objects.

A moderately low scale parameter of 10 (Figure 4.2) was considered to be the most suitable as it separated most features into individual objects well, without either grouping too many unnecessary objects into contiguous units, or unnecessarily subdividing discrete features such as forest plantations. A scale of 5 was too fine (Figure 4.1), and because of the small segment size, ground objects are not clearly identifiable. The higher scales, 20 (Figure 4.3) and 50 (Figure 4.4) showed to be too course for this study as the homogeneity within the image objects was lost. This scale tends to generalise features which are different into one single image object. Additionally, it delineated most cultivated parcels into single objects, but not well in cultivated parcels with boundaries which are not perfectly smoothed. Linear features such as gravel roads were grouped with surrounding land classes when 50 was used.

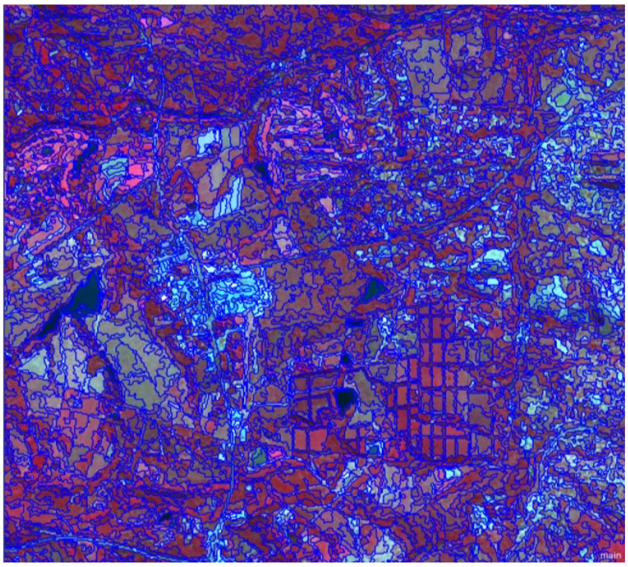


Figure 4.1 SPOT 5 scale parameter 5

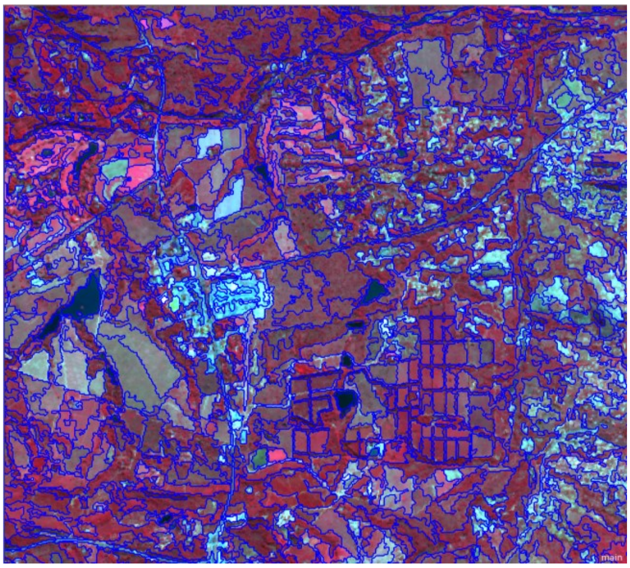


Figure 4.2 SPOT 5 scale parameter 10

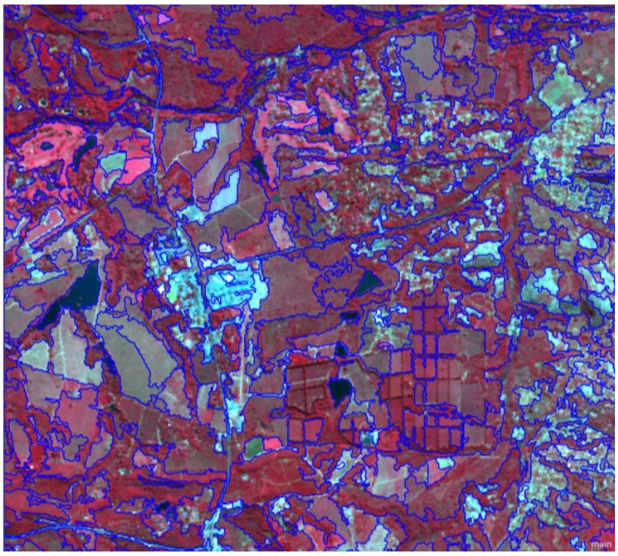


Figure 4.3 SPOT 5 scale parameter 20

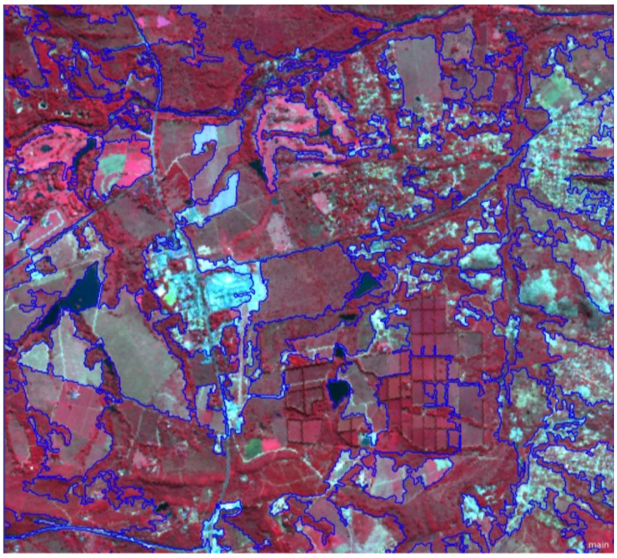


Figure 4.4 SPOT 5 scale parameter 50

The scale parameters tested for Landsat 8 (15 m) ranged from 50 to 200 as illustrated in Figure 4.5 to Figure 4.8. A scale of 120 (Figure 4.6) was selected as it separated objects similar to the scale parameter of 10 selected for the SPOT 5 image (Figure 4.2). Any values higher than 120 were too course for this study. Luck-Vogel, O'Farrell & Roberts (2013) found a scale parameter of 50 to be appropriate for Landsat 7 images (15 m). However, Landsat 8 was used in this study and has a higher data range, 16 bit than Landsat 7 (8 bit), thus the higher scale parameter.

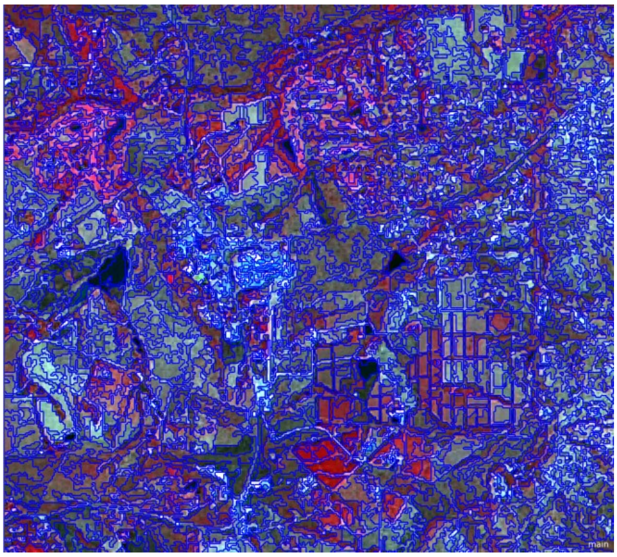


Figure 4.5 Landsat scale parameter 50

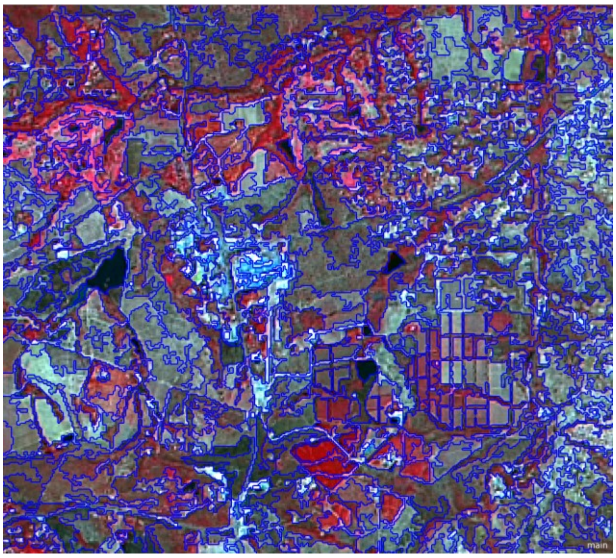


Figure 4.6 Landsat scale parameter 120

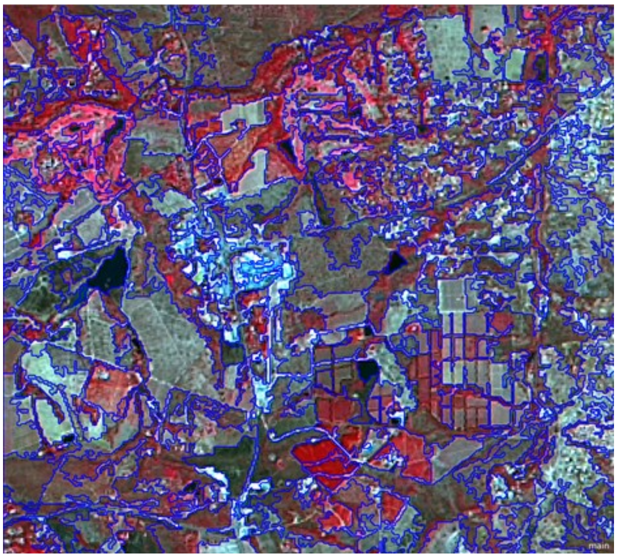


Figure 4.7 Landsat scale parameter 180

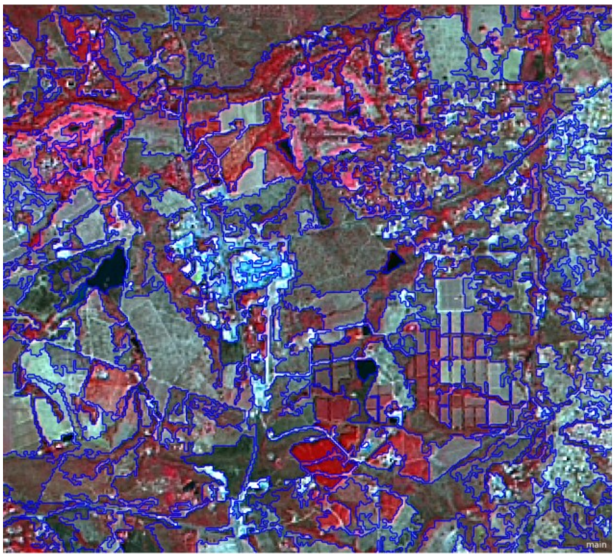


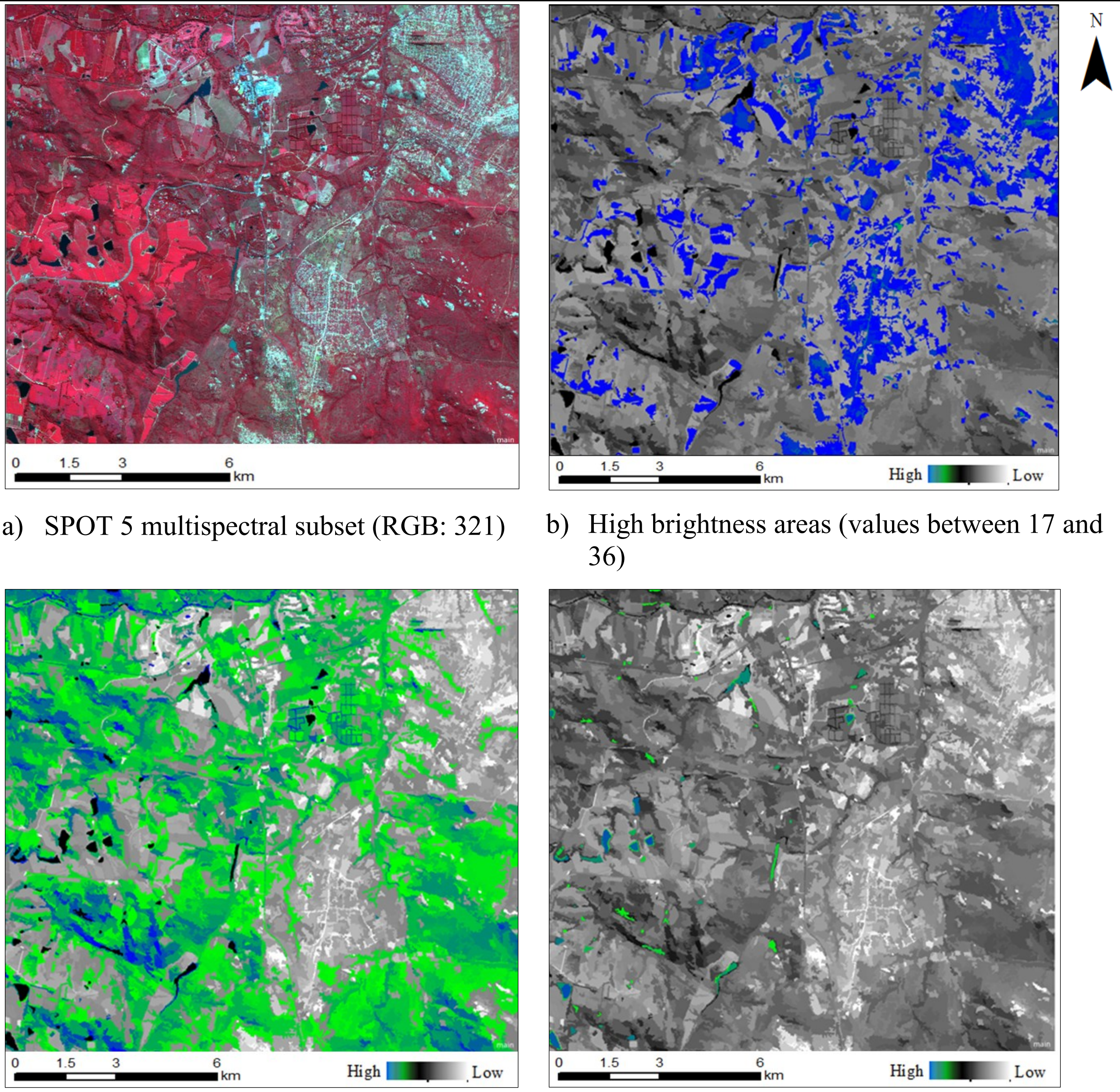
Figure 4.8 Landsat scale parameter 200

4.2 GENERATION OF INDICES

Here the results of the image derivatives and indices calculated from SPOT 5 and Landsat images are presented. The derivatives are a measure of habitat intactness and are extracted from the segmented image objects described above. Brightness was computed, followed by compactness, NIR standard deviation, area and NDVI respectively using SPOT 5 imagery. The results are described in that order. This process was then repeated on the Landsat 8 images from May (both pan-sharpened 15 m and 30 m) and October 2014 (pan-sharpened 15 m). Only SPOT 5 image subsets from eCognition software are used in this section to illustrate examples of the variation in image object values of different land cover types.

4.2.1 Brightness

The spectral derivative was defined by the image objects' mean brightness. Ground features such as roof tops and bare soil reflect highly and thus have high brightness values. Image objects representing brightness were visually inspected, Figure 4.9-a shows a subset of the SPOT 5 image. As expected (Turner et al. 2003), areas with little or no vegetation such as settlements, bare areas, gravel roads, harvested fields showed very high brightness, values above 17 (highlighted blue areas in Figure 4.9-b). Image objects with intermediate brightness values appeared to be dense vegetation with values ranging from 8-15, (highlighted blue and green areas in Figure 4.9-c). Water bodies, burned areas and shadows appear dark on satellite images. Water bodies absorb most solar radiation (Lillesand et al. 1983), hence they have extremely low brightness values below 8 (highlighted blue and green areas Figure 4.9-d).



a) SPOT 5 multispectral subset (RGB: 321)

b) High brightness areas (values between 17 and 36)

c) Intermediate brightness areas (values between 8 and 15)

d) Low brightness areas (values between 1 and 8)

Figure 4.9 Brightness values for SPOT 5

Figure 4.10 to Figure 4.11 shows the final SPOT 5 and Landsat 8 brightness output layers. The western part of the study area is predominantly forest plantation; brightness is relatively low (green areas) in that section. The centre and north-east section of the area is dominated by human settlements, where brightness values are very high (red areas) from the reflection of rooftops, concrete and bare soil. These areas are regarded as degraded. The south-eastern part of the study area is dominated by a portion of the KNP. Vegetation in this area is mostly pristine undisturbed natural vegetation. This region showed medium to low brightness values (yellow to green areas).

Moderate brightness values in the KNP can be explained by seasonal effects, as the images were captured during the dry season when vegetation greenness is lower in the savanna region. Generally, savanna vegetation is less dense than forest plantations. SPOT 5 brightness values in May 2010 were similar to Landsat brightness values from May 2010, as both images are from the same season. The natural vegetation type in the KNP is sparse and has a combination of shrubs, trees and grasses (Fisher et al. 2014), which also lowered brightness values. Brightness values in the KNP were very low during October 2014 (Figure 4.13) as most of the KNP was burned in that month, leaving a layer of black sooty ash. This led to very low brightness values, depicted by dark green patches in Figure 4.13. The red patches in the KNP are intact vegetation not affected by the fire (Figure 4.13).

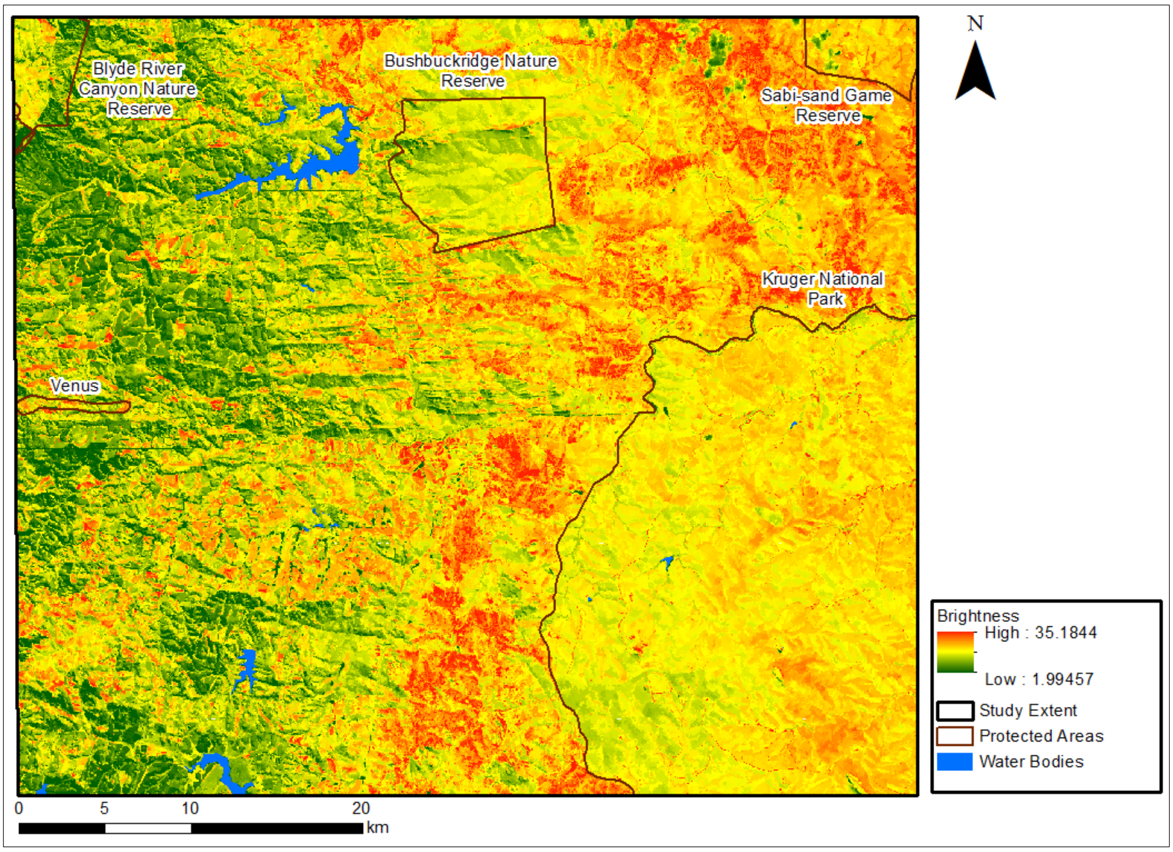


Figure 4.10 SPOT 5 derived brightness from May 2010 (10 m image from the beginning of the dry season)

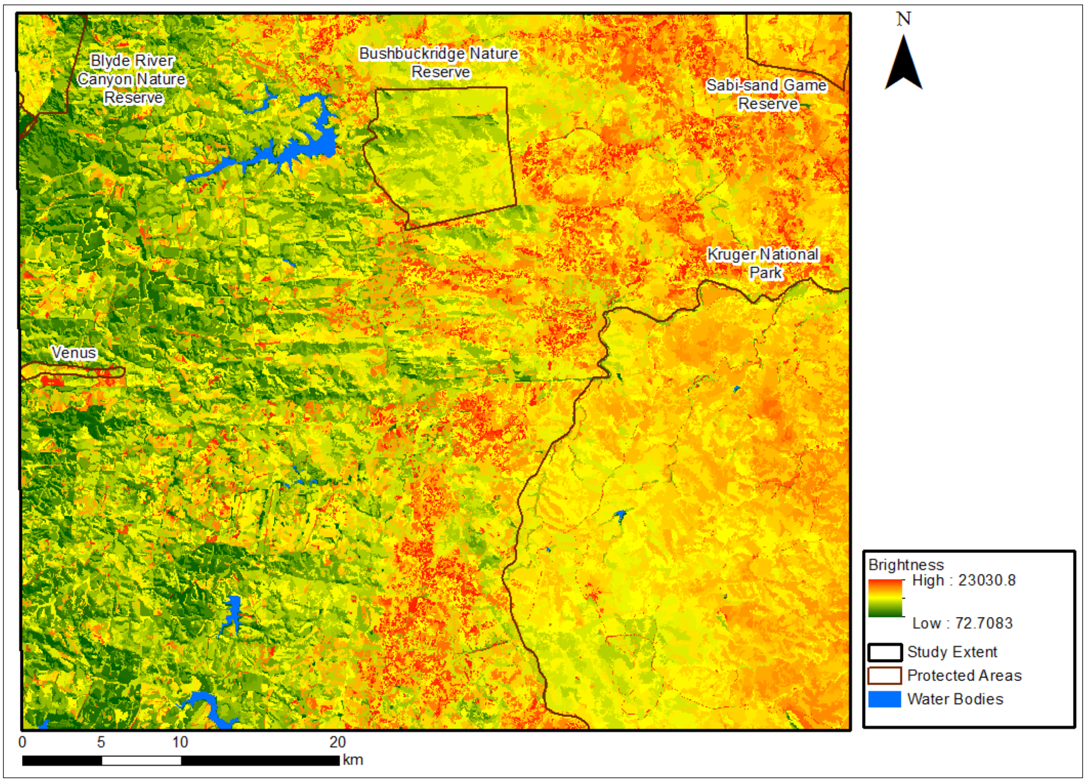


Figure 4.11 Landsat 8 derived brightness from May 2014 (15 m image from the beginning of the dry season)

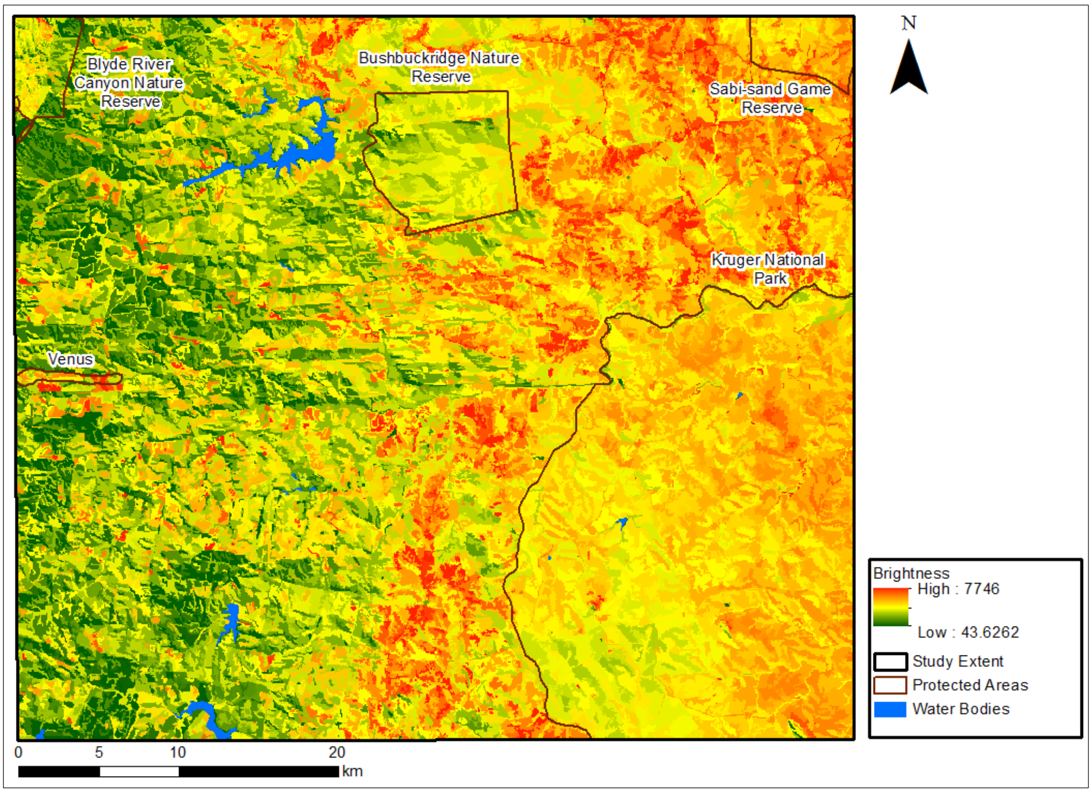


Figure 4.12 Landsat 8 derived brightness from May 2014 (30 m image from the beginning of the dry season)

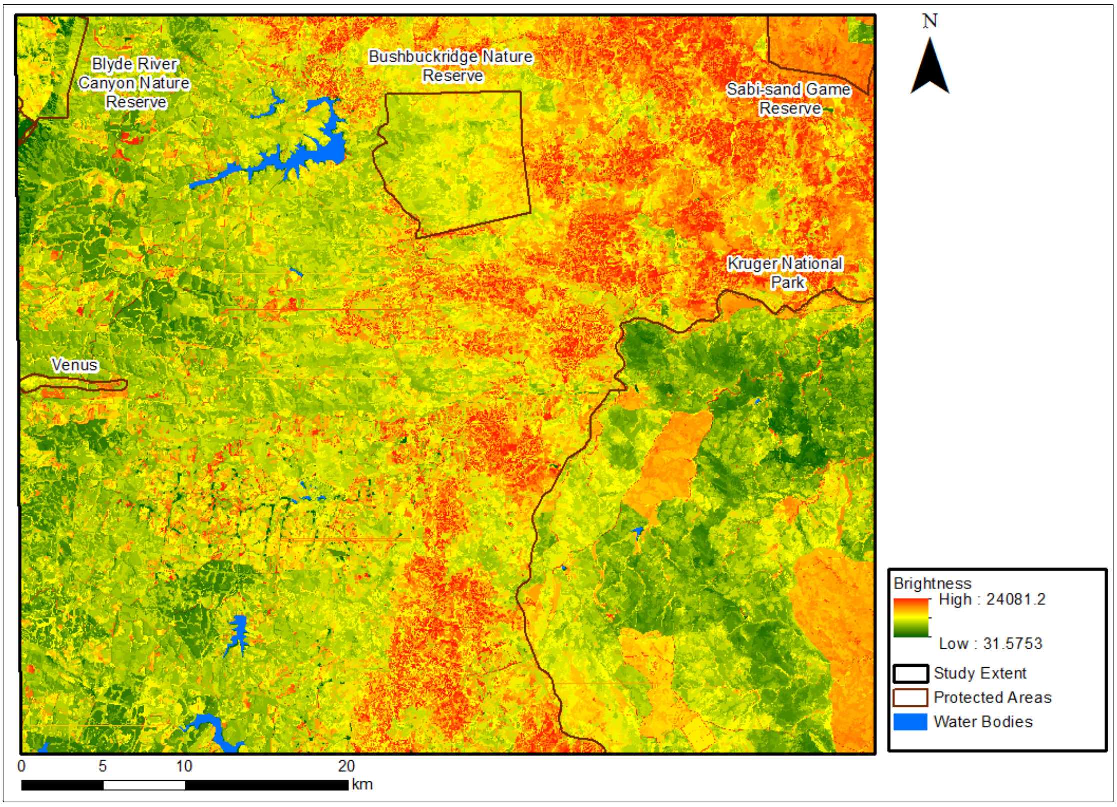


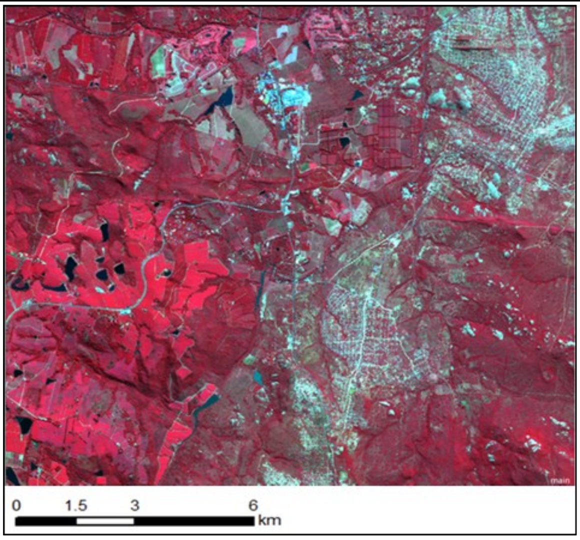
Figure 4.13 Landsat 8 derived brightness from October 2014 (15 m image from the beginning of the wet season)

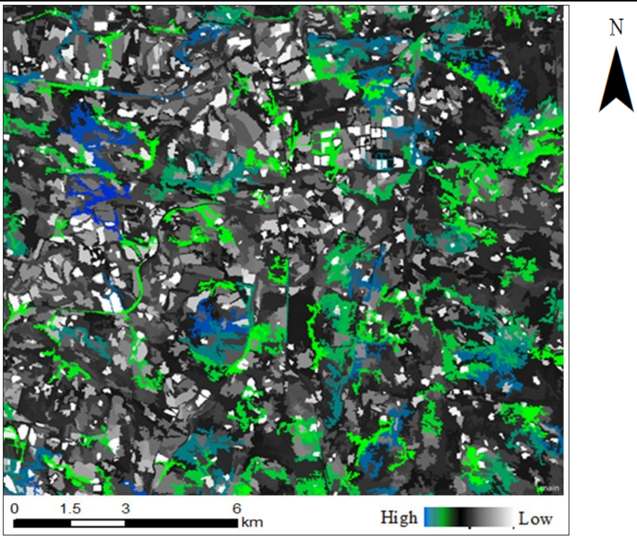
Based on the brightness layers derived, it can then be said that brightness is a good indicator for showing areas which are severely degraded, but is not a good measure for natural pristine vegetation, as those areas sometimes have the same values as moderately disturbed landscapes (medium-low brightness values), which is not always the case in the study area, more especially in protected areas such as the KNP, where human influences are very minimal.

4.2.2 Compactness

The compactness of segments was used to measure the structural criteria of image objects. A compactness value close to 0 shows shapes with highly irregular boundaries as is typical of undisturbed landscapes, while 1 represents perfectly circular structures such as irrigation pivots (Definiens 2007). The higher the compactness values of image objects, the more likely that they represent man-made features and therefore a departure from the natural state, thus degraded. Therefore, compactness is an important parameter in differentiating between natural vegetation from agricultural vegetation.

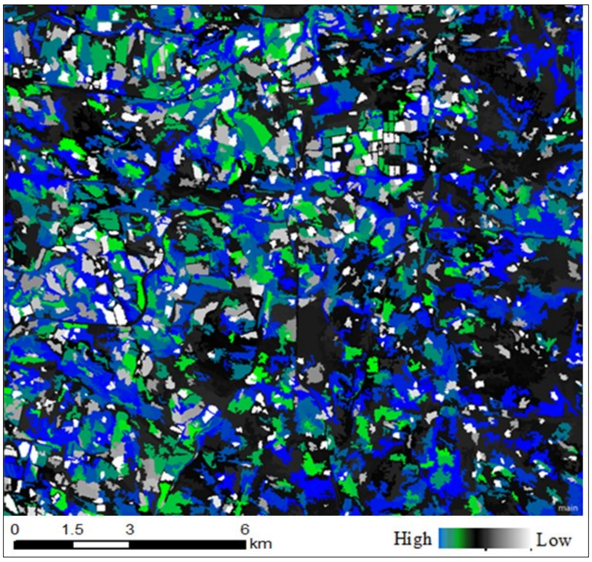
The SPOT 5 compactness values of different object features were analysed. As expected, natural areas gave very low compactness values (values between 0.009-0.06 which are represented by the blue and green highlighted areas in Figure 4.14-b) as they are non-geometric in shape. Intermediate values are mostly plantation compartments with boundaries not clearly defined (values between 0.1-0.3) (blue and green highlighted areas in Figure 4.14-c). Plantations are not planted in blocks, but planted along natural contours on mountain slopes, resulting in semi-irregular objects which produce low compactness values. Agricultural fields showed the highest degree of compactness with values between 0.3-0.8 as crops are cultivated in rectangular shapes in the study area (blue and green highlighted areas in Figure 4.14-d). Linear features such as roads gave relatively low compactness values, because of the elongated boundaries (long edge: area), which lowers the compactness values. Compactness is defined as the ratio of the area of a polygon to the area of a circle with the same perimeter (Definiens 2007). Compactness is derived from the formula $(4\pi \times \text{area})/(\text{perimeter}^2)$. Based on the formula, elongated structures such as roads should provide very low compactness values between.

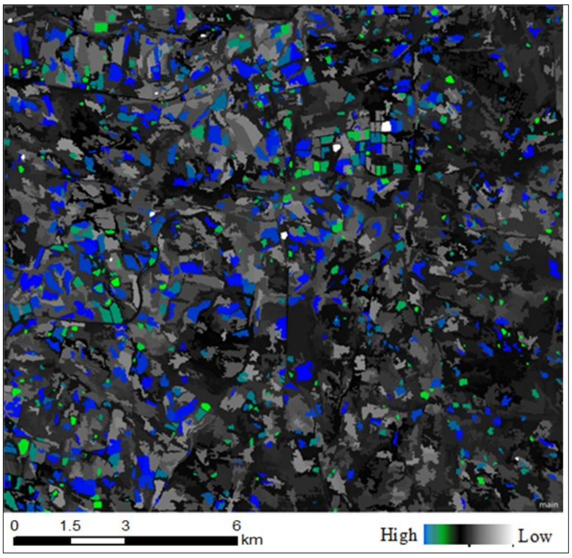




a) SPOT 5 multispectral subset (RGB: 321)

b) Low compactness areas (values between 0.009 and 0.06)





c) Intermediate compactness areas (values between 0.1 and 0.3)

d) High compactness areas (values between 0.009 and 0.06)

Figure 4.14 Compactness values for SPOT 5

Figure 4.15 to Figure 4.18 show the compactness output results for SPOT 5 and Landsat 8. The western sections of the images are dominated by forest plantations. Compactness values came out very high (bright red areas) in these regions while the KNP and other similar nature reserves such as the Bushbuckridge nature reserve gave very low compactness values (bright green areas). Human settlements gave moderate compactness values. Although compactness should be high in human settlements, moderate compactness values were archived because houses are too small to be grouped into single image objects based on the selected scale parameter of 10. Consequently, houses are aggregated into larger image objects which do not have well defined boundaries.

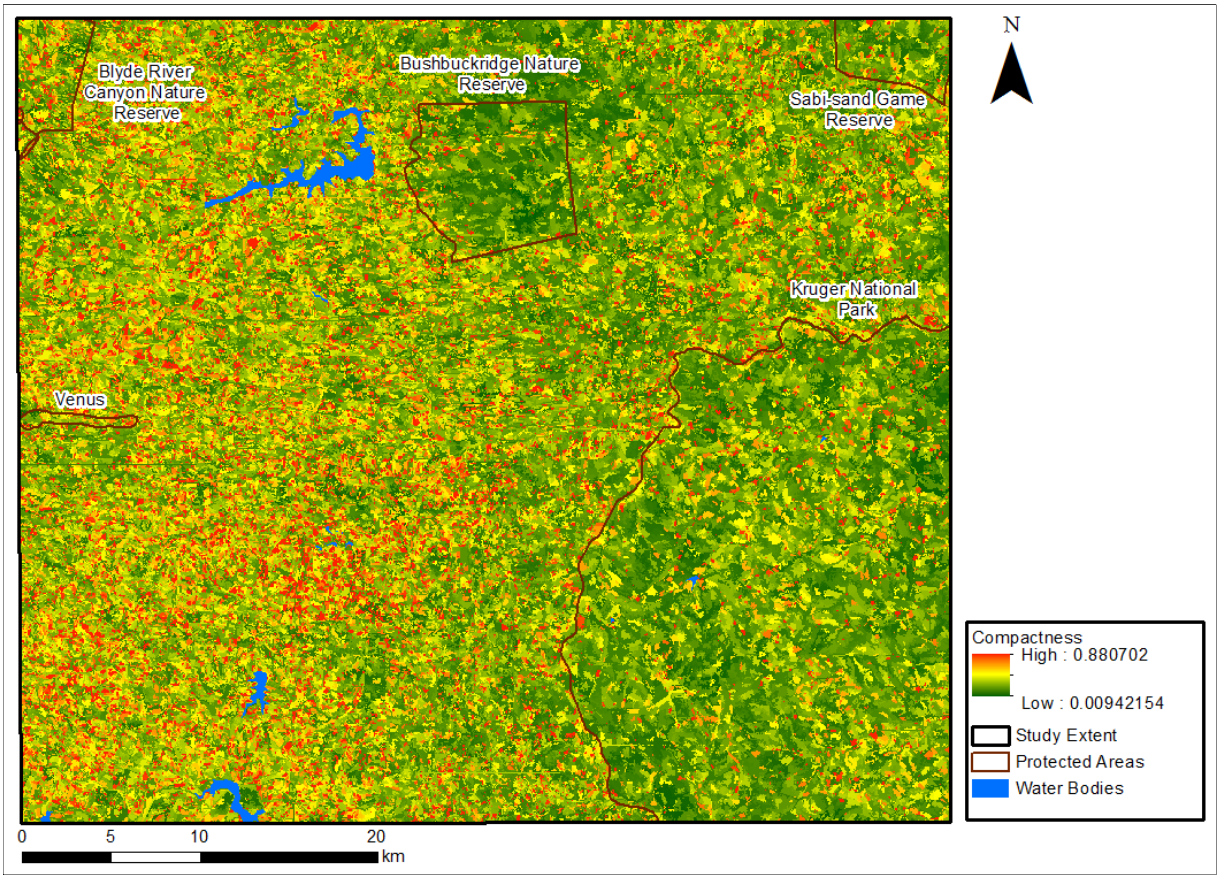


Figure 4.15 SPOT 5 derived compactness from May 2010 (10 m image from the beginning of the dry season)

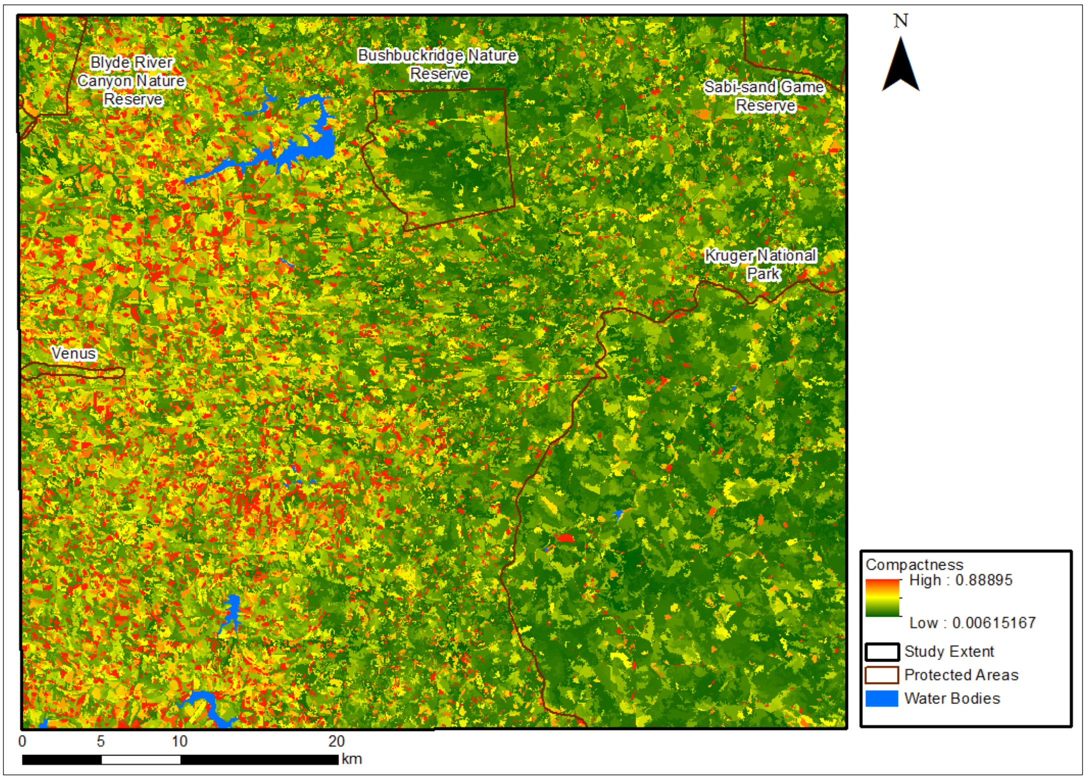


Figure 4.16 Landsat 8 derived compactness from May 2014 (15 m image from the beginning of the dry season)

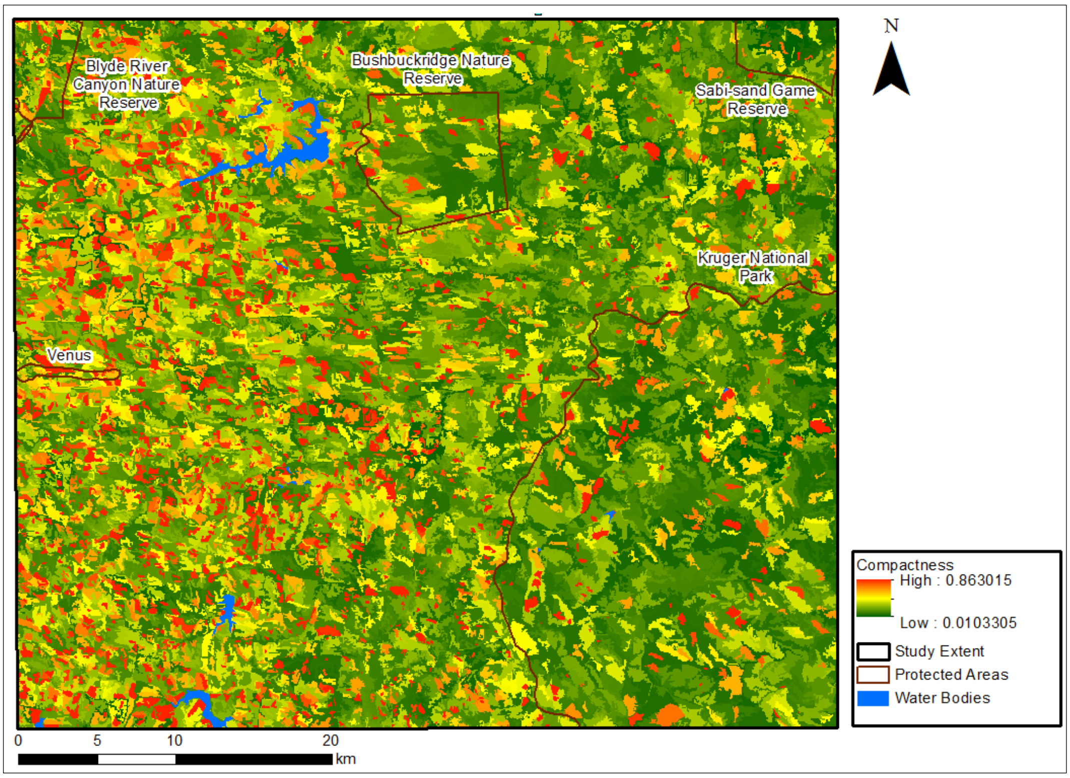


Figure 4.17 Landsat 8 derived compactness from May 2014 (30 m image from the beginning of the dry season)

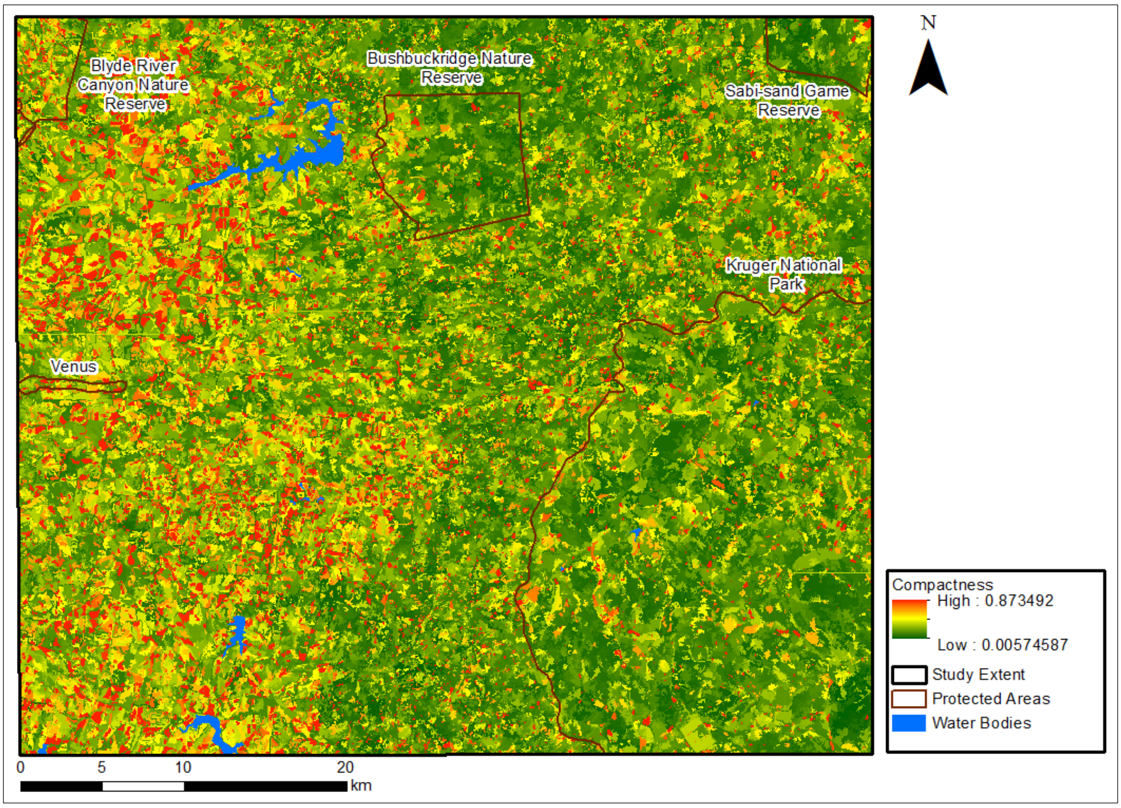
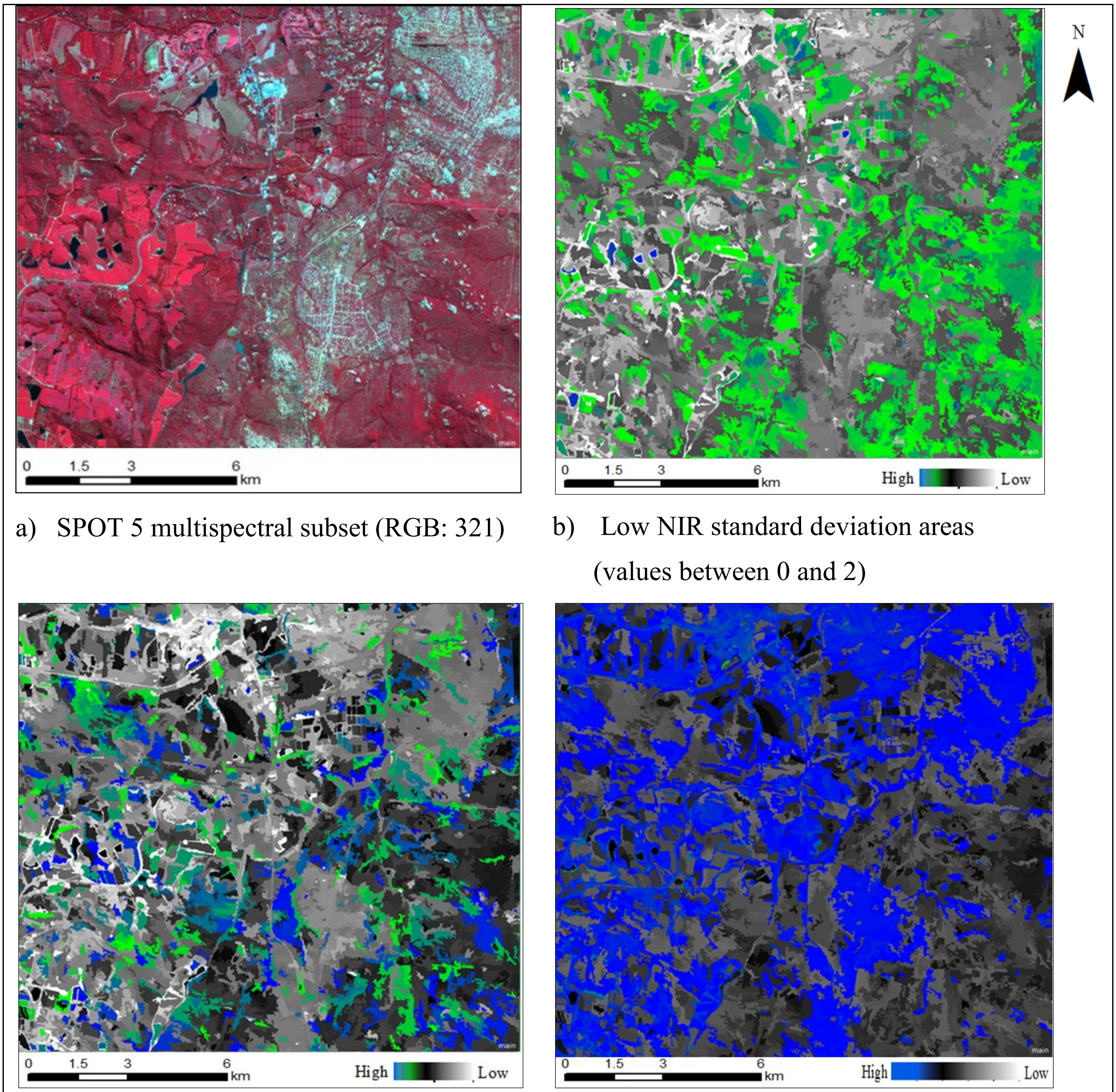


Figure 4.18 Landsat 8 derived compactness from October 2014 (15 m image from the beginning of the wet season)

The compactness results were a good indicator for distinguishing natural vegetation from agricultural vegetation, and are in agreement with Luck-Vogel, O'Farrell & Roberts (2013). The bright red areas (high compactness values) within the KNP are mostly outliers. Manmade watering holes and rocky outcrops also gave high compactness values in the KNP. Although the same scale parameter was used, differences were observed between the May and October Landsat 8 15 m compactness layers. High compactness values in the KNP dominate more on the October image than on the May image, mainly due to burned patches appearing as having shapes in October.

4.2.3 Standard deviation NIR

As a measure for texture, the standard deviation of NIR was calculated. NIR bands are a good measure of green biomass as reflectance is high in this region of the electromagnetic spectrum (Nagendra 2001). Texture is an important feature that can be used to identify degraded areas from pristine vegetation. The NIR standard deviation of objects was studied. Naturally vegetated areas had the lowest NIR standard deviation values between 0 and 2 (Figure 4.19-b). Bare and degraded areas had intermediate values ranging between 2 and 2.5 (Figure 4.19-c). NIR standard deviation is at its peak highest in human settlements, with values ranging from 2.6 to 12, as illustrated in Figure 4.19-d, followed by forest plantations. The spectral resolution of an image needs to be taken into account when texture is being used as a form of vegetation analysis as most landscapes will appear smooth textured and eventually be undistinguishable at a very coarse spatial resolution.



a) SPOT 5 multispectral subset (RGB: 321)

b) Low NIR standard deviation areas (values between 0 and 2)

c) Intermediate NIR standard deviation areas (values between 2 and 2.5)

d) High NIR standard deviation areas (values between 2.6 and 12)

Figure 4.19 NIR standard deviation values for SPOT 5

Figure 4.20 to Figure 4.23 illustrates subsets of the standard deviation NIR output layers of SPOT 5 and Landsat 8. On the SPOT 5 image, forest plantations gave the highest variation in texture, followed by the central part of the image which is dominated by human settlements (orange to red areas). Nature reserves showed the lowest values (bright green values). This contradicts the study's expectation that texture values would rise with increasing intactness similar to what Luck-Vogel, O'Farrell & Roberts (2013) discovered in the Sandveld region for intact Fynbos relative to crops.

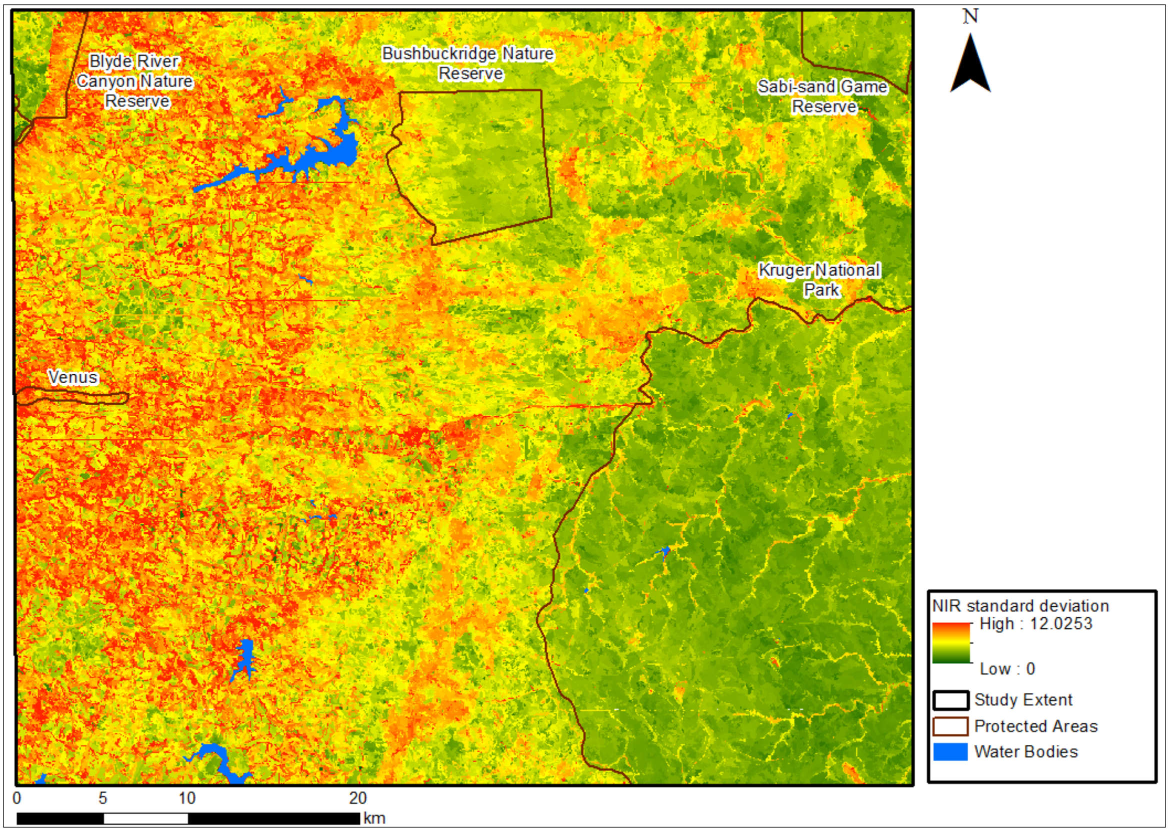


Figure 4.20 SPOT 5 derived NIR standard deviation from May 2010 (10 m image from the beginning of the dry season)

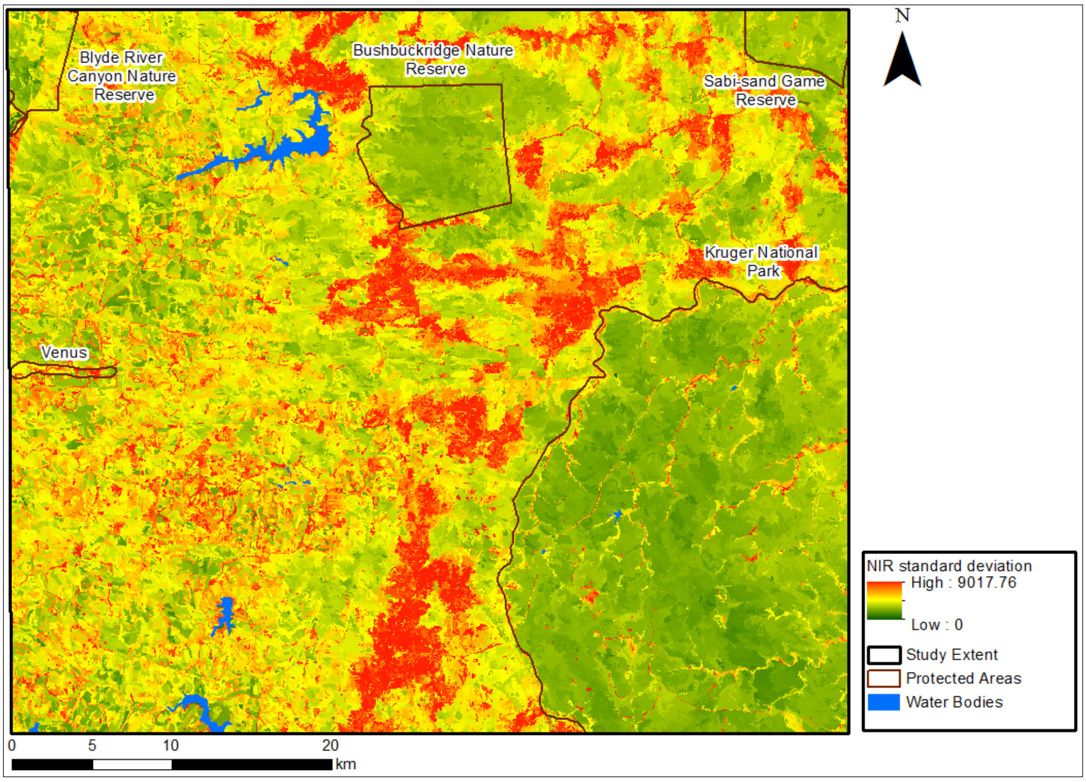


Figure 4.21 Landsat 8 derived NIR standard deviation from May 2014 (15 m image from the beginning of the dry season)

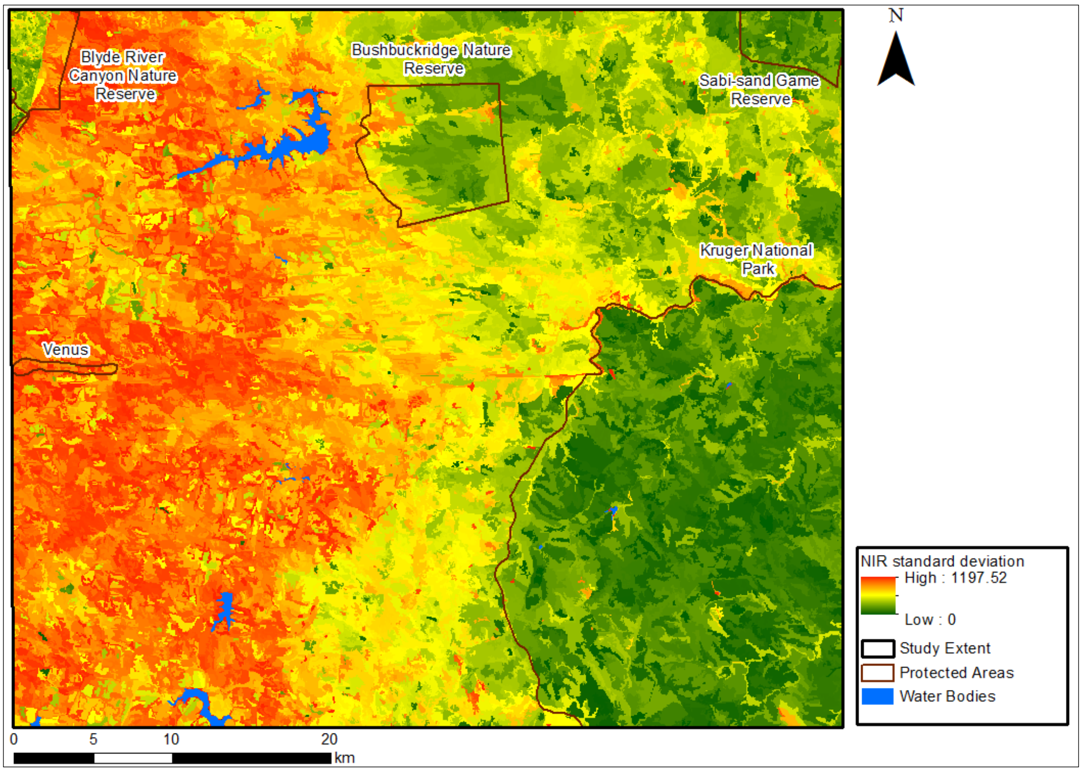


Figure 4.22 Landsat 8 derived NIR standard deviation from May 2014 (30 m image from the beginning of the dry season)

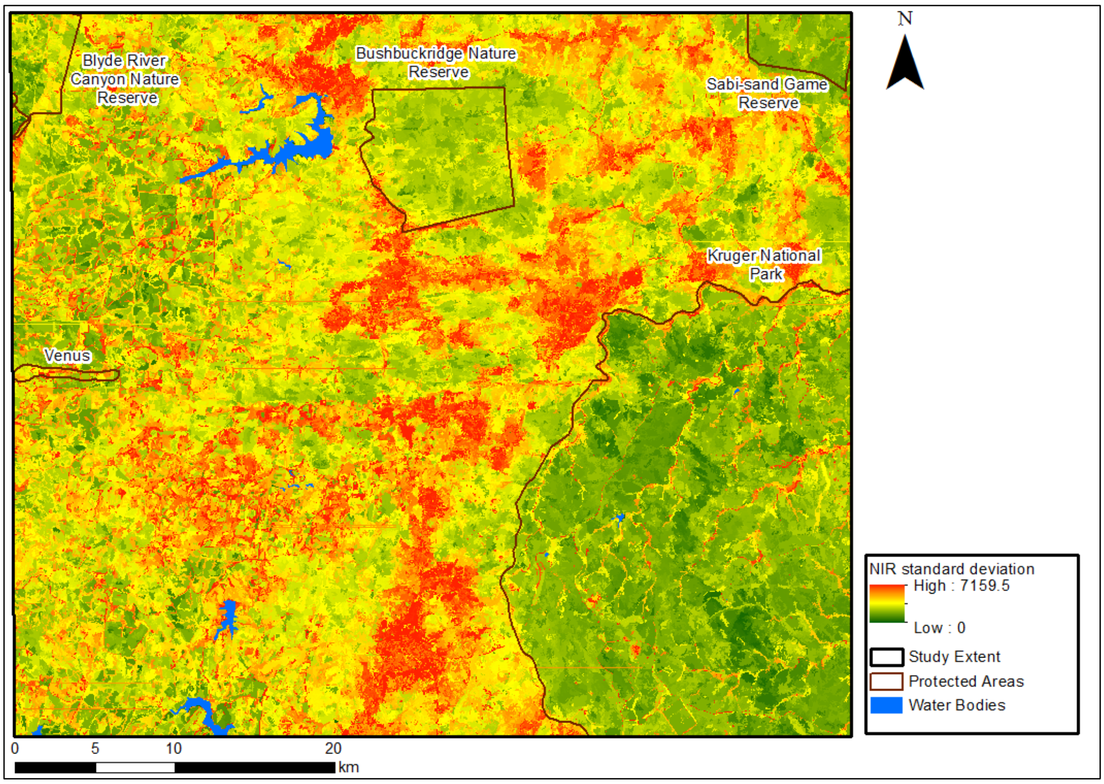


Figure 4.23 Landsat 8 derived NIR standard deviation from October 2014 (15 m image from the beginning of the wet season)

In this study, texture varied because pine and blue gum trees were planted in separate compartments, in different years, such that compartments planted first had taller and older trees. This is demonstrated in Figure 4.24 which shows a SPOT subset of a heterogeneous landscape in a forest plantation. Figure 4.25 shows the variation in texture for this subset. This suggests that spectral characteristics noted in the Sandveld can occasionally be similar to those in forest plantations due to varying canopy heights in natural landscapes which result in a heterogeneous patterns caused by species height, age and type (Luck-Vogel, O'Farrell & Roberts 2013). Secondly, shadows caused by tall trees and various features such as roads, cleared veld, tree species health, can alter the textural properties of forest plantation. Forest plantations are the dominant land cover type in the study area, and all these variations mentioned result in very high texture values, which overwhelm the scale of NIR standard deviation due to tall plantation trees contrasted with smaller savanna woodlands in this study area (Figure 3.2). Consequently, this significantly reduced the importance of texture in sparse, natural savanna vegetation.

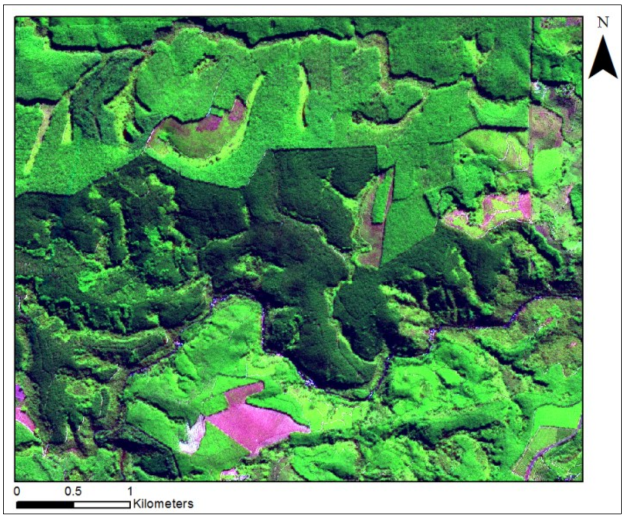


Figure 4.24 SPOT 5 image subset of a heterogenous landscape in a forest plantation (RGB: 4,3,2)

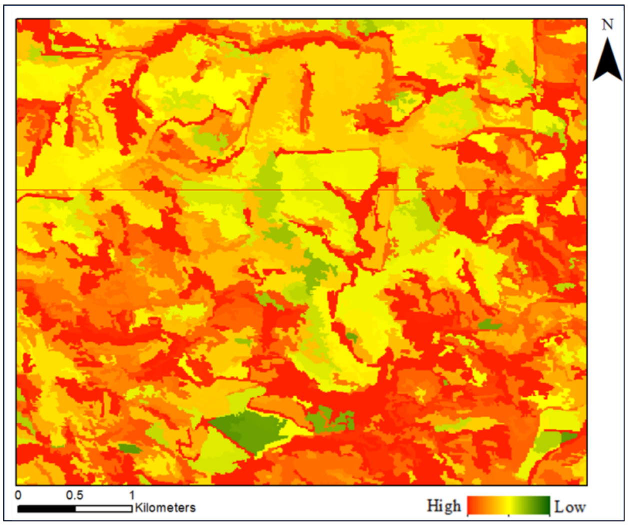


Figure 4.25 SPOT 5 NIR standard deviation of the same area as in Figure 4.29

SPOT NIR standard deviation showed medium values on human settlements and lower values in protected areas in this study area, contrary to expectations. High texture values in the KNP (see Figure 4.26 as reference) are found in river beds and valleys as illustrated in Figure 4.27, also on rocky outcrops with high brightness values. SPOT NIR standard deviation results showed medium values in rural settlements, and lower NIR standard deviation values in protected areas in this study area. In contrast, Landsat gave higher NIR standard deviation values in rural settlements, but lower in KNP, and similar areas (Figures 4.21 to 4.23). Comparisons for NIR standard deviation in plantations and settlements could not be made with reference to NIR standard deviation values in the Sandveld region (Luck-Vogel, O'Farrell & Roberts 2013) where NIR standard deviation was tested on intensely irrigated crops such as circular pivots and intense strip cropping farming practices, while in this study, plantation and settlements added a huge contrast to the outcome of texture. This suggests the need to calibrate this approach in each study area.

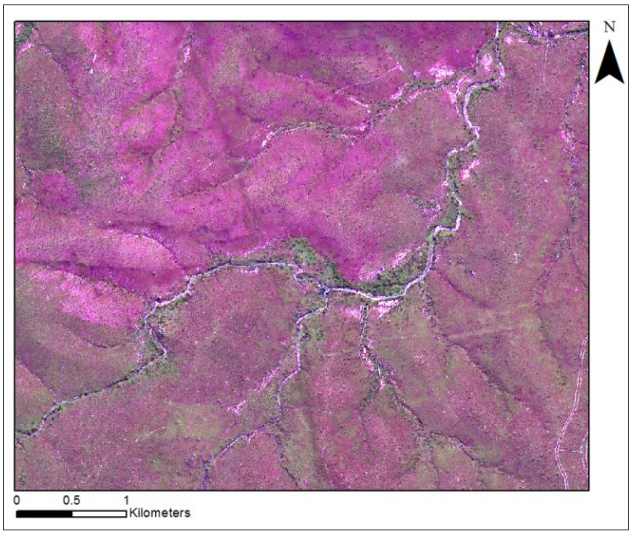


Figure 4.26 SPOT 5 image subset showing high texture around river bed and valleys in the KNP (RGB: 4,3,2)

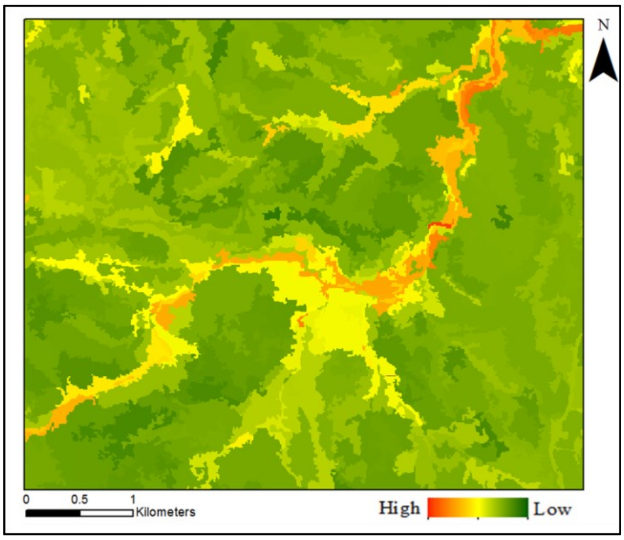
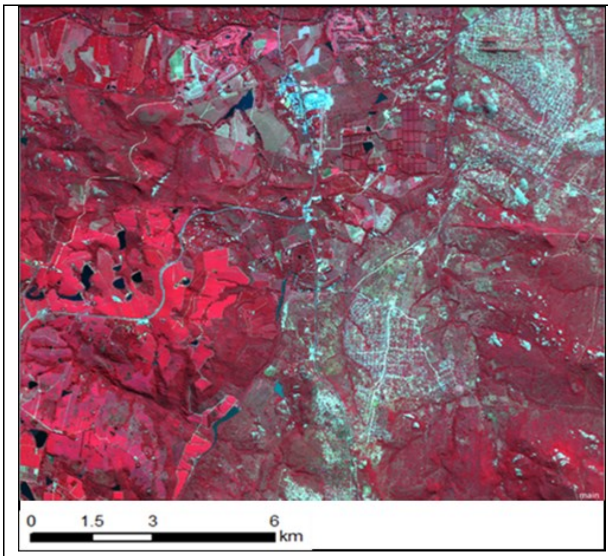


Figure 4.27 SPOT 5 image showing high NIR standard deviation around river beds and valleys in the KNP

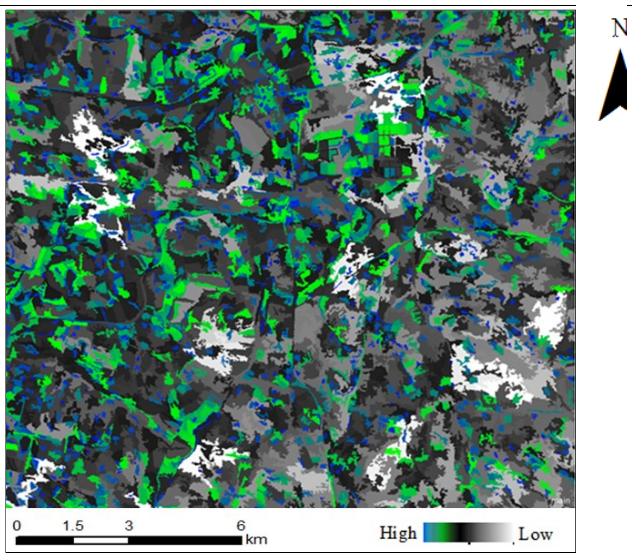
NIR standard deviation can still be considered a good discriminator between degraded (human settlements and forest plantations) and non-degraded (vegetation in the KNP) areas, as it highlighted the differences between different land use types well.

4.2.4 Area

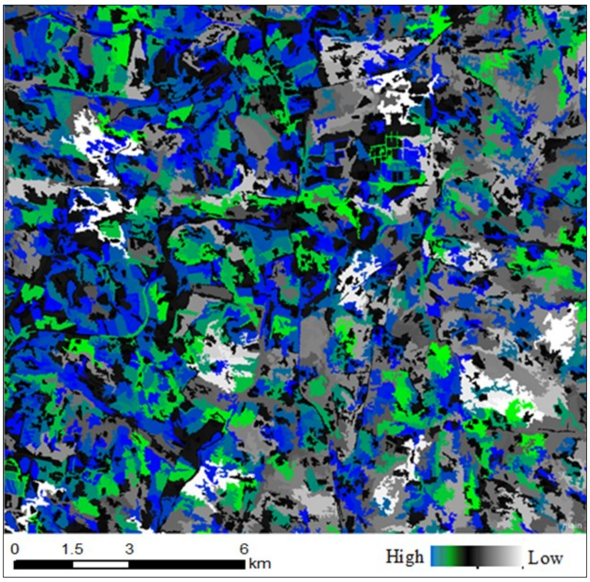
Forest plantations and human settlements image objects were analysed for area and found to have very low values ranging between 2 and 310 (Figure 4.28-b), which was expected for transformed/manmade landscapes. Intermediate values were mostly agricultural fields that do not have clearly defined borders and human settlements (Figure 4.28-c). As expected, natural landscapes such as the KNP and the Bushbuckridge nature reserve presented high area values ranging from 1000-18000 (blue regions in Figure 4.28-d). These new findings are specific to this study area, and thus were not compared to other study areas.



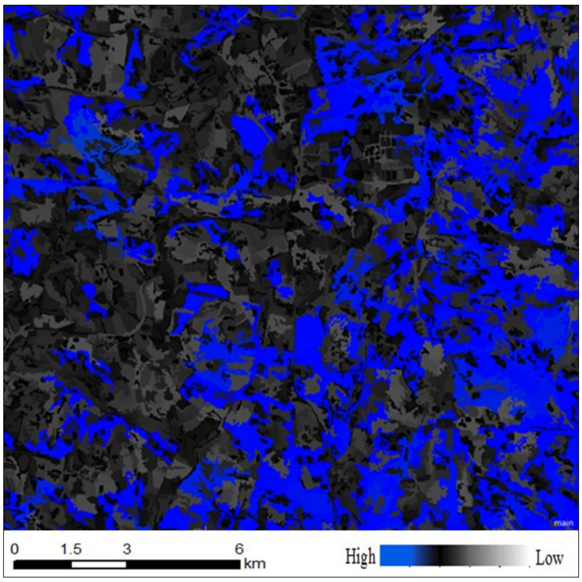
a) SPOT 5 multispectral subset (RGB: 321)



b) Low Area areas (values between 2 and 310)



c) Intermediate Area areas (values between 310 and 1000)



d) High Area areas (values between 1000 and 1800)

Figure 4.28 Area values for SPOT 5

The images below (Figure 4.29 to Figure 4.32) show the computed area derivative output for SPOT 5 and Landsat 8. Bright red areas are regions were area is significantly high, which are mostly natural vegetation as they are mainly found in protected areas. Bright green areas are regions were area had significantly big segments (large area), the area is small, which are mostly areas modified through anthropogenic factors. Area was a good indicator aimed at distinguishing between degraded versus intact regions.

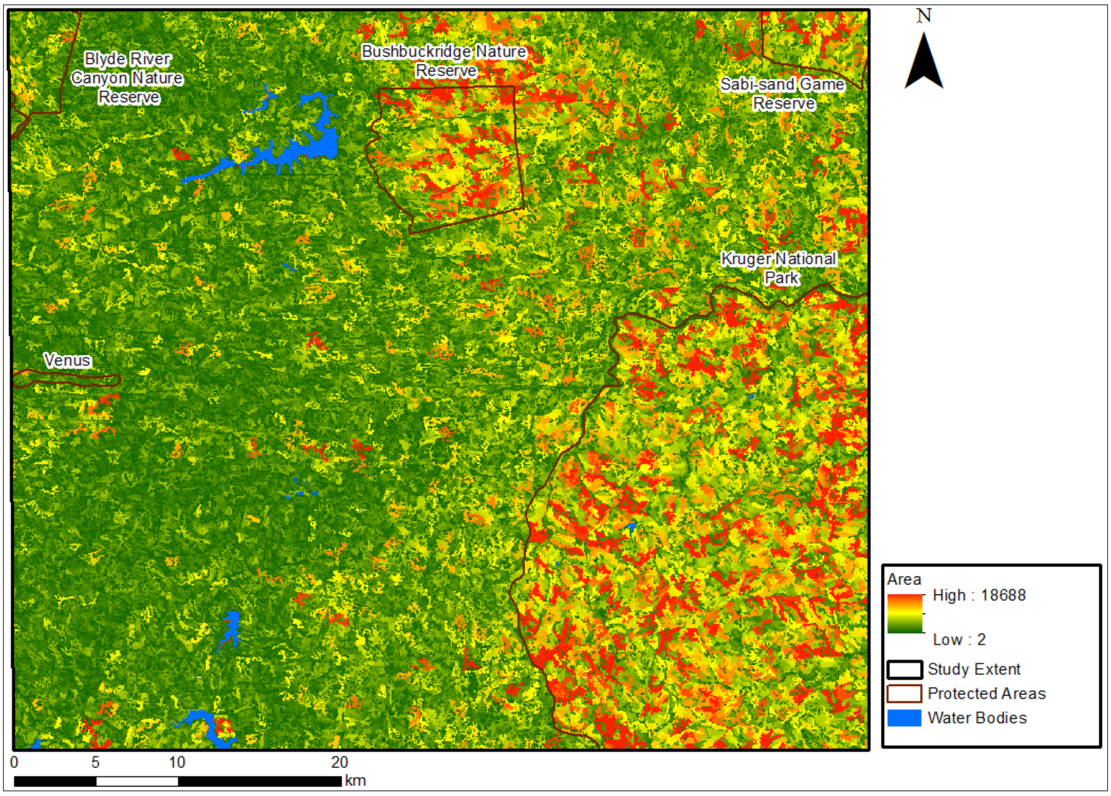


Figure 4.29 SPOT 5 derived Area from May 2010 (10 m image from the beginning of the dry season)

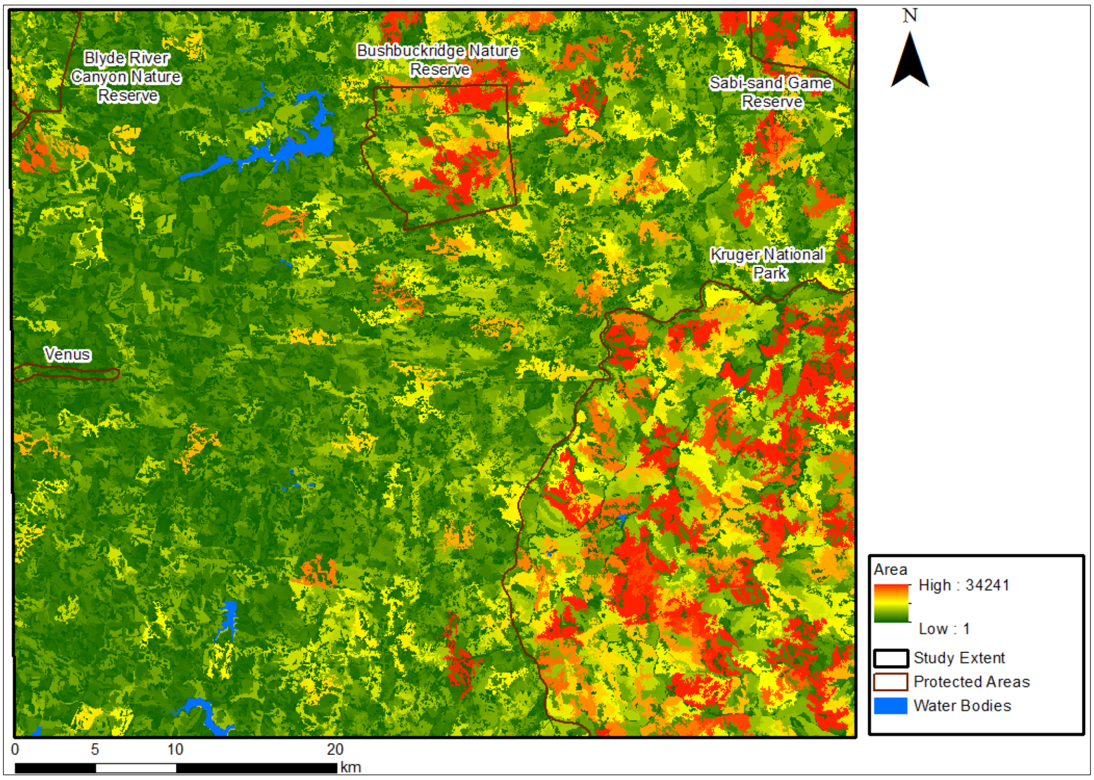


Figure 4.30 Landsat 8 derived area from May 2014 (15 m image from the beginning of the dry season)

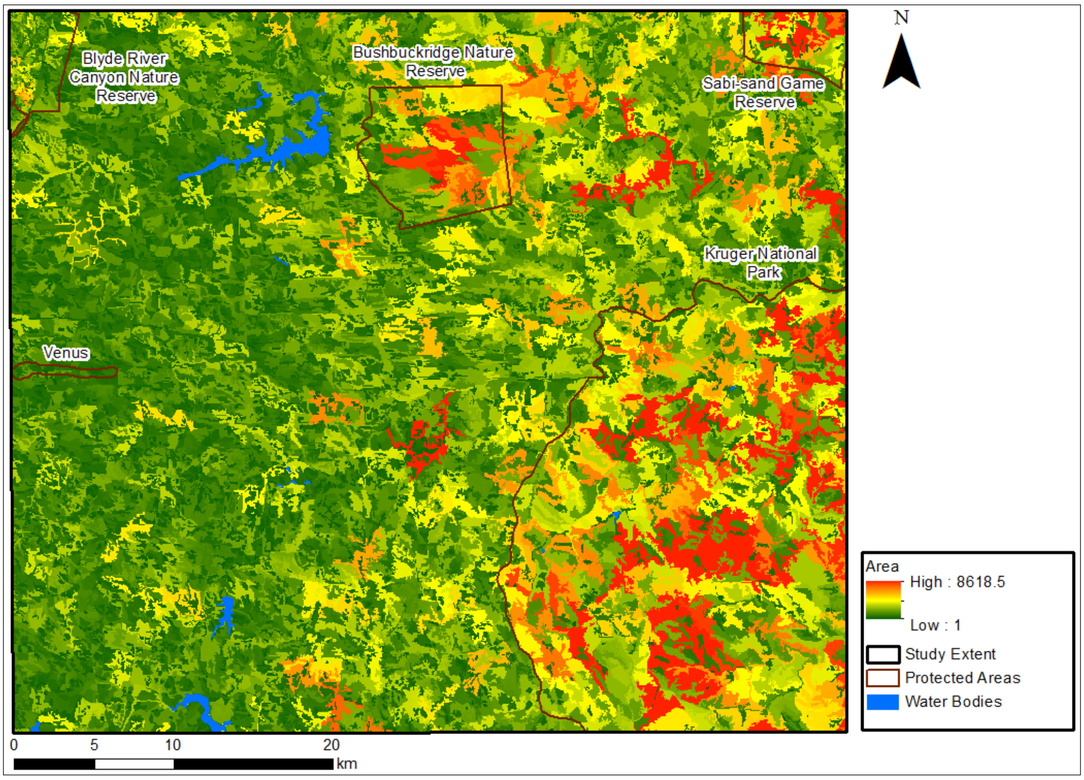


Figure 4.31 Landsat 8 derived area from May 2014 (30 m image from the beginning of the dry season)

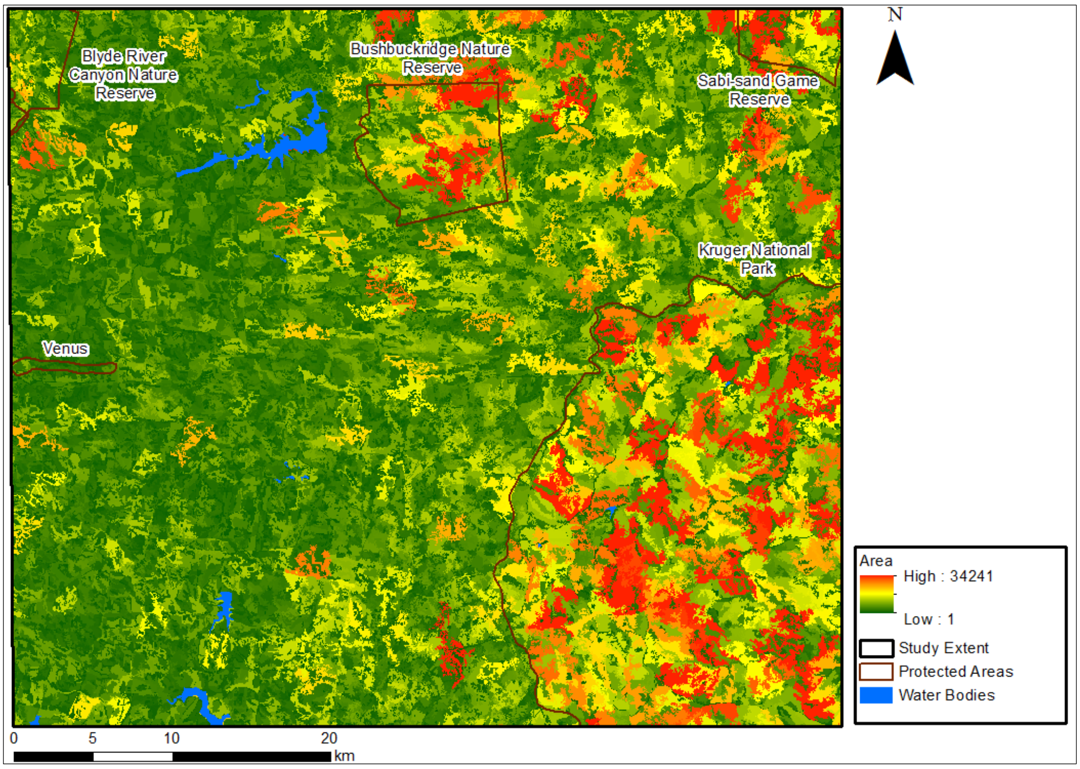
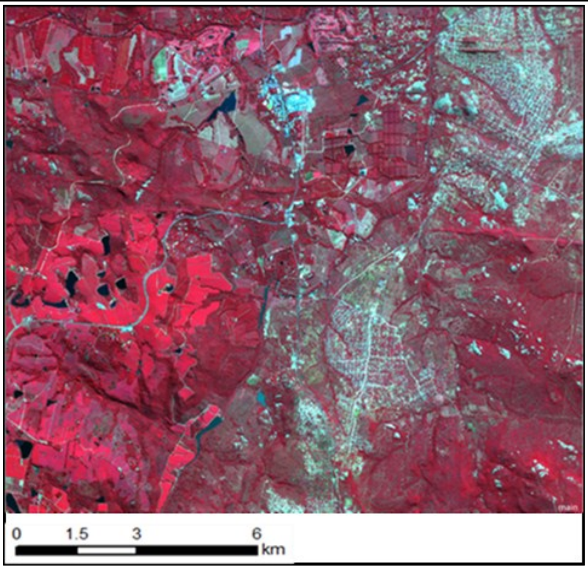


Figure 4.32 Landsat 8 derived area from October 2014 (15 m image from the

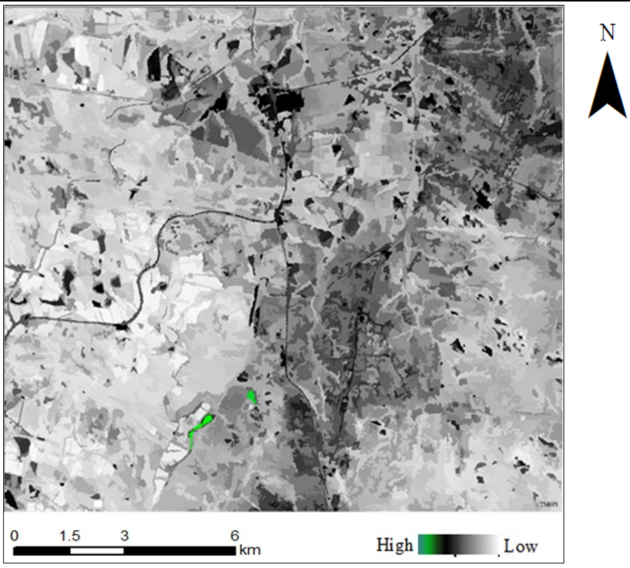
Beginning of the wet season)

4.2.5 NDVI

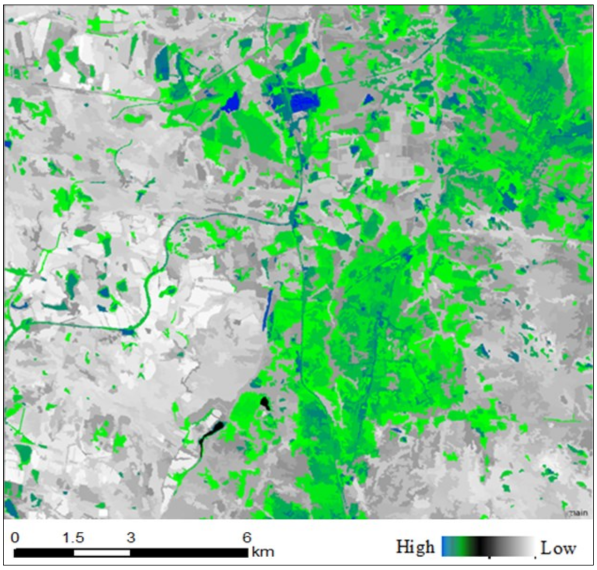
The normalised difference vegetation index (NDVI) was used to measure vegetation vigour. NDVI values range between -1 to 1, and increase with increasing biomass. By analysing the image objects, NDVI values below 0 indicated water or inundated areas although some water bodies produced values higher than 0 (Figure 4.33-b). Bare areas and human settlements had values lower than 0.3 (Figure 4.33-c). NDVI values greater than 0.61 were areas were dense vegetation is present (Figure 4.33-d). Forest plantations showed values greater than 0.8, while intact natural vegetation in protected areas was below 0.8.



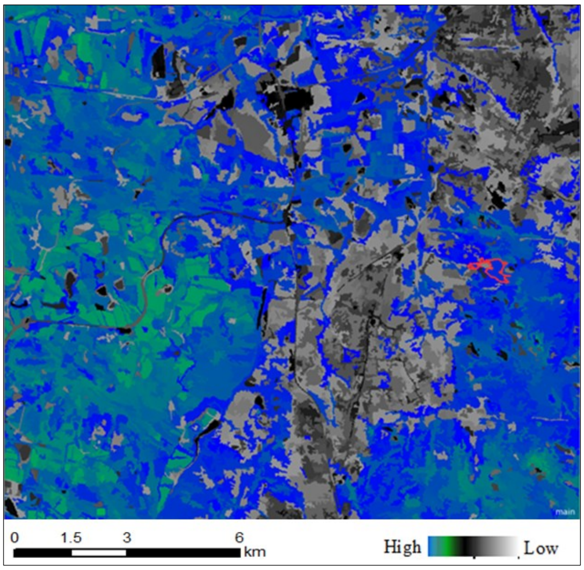
a) SPOT 5 multispectral subset (RGB: 321)



b) Low NDVI areas (values between -1 and 0)



c) Intermediate NDVI areas (values between 0 and 0.6)



d) Low NDVI areas (values between 0.61 And 1)

Figure 4.33 NDVI values for SPOT 5

NDVI is an inverse measure of brightness and has been shown to correlate with vegetation biomass (Myneni et al. 1995) and productivity (Reed et al. 1994). Figure 4.34 to Figure 4.37 illustrate NDVI output layers for SPOT 5 and Landsat 8 images. Forest plantations on the western section of the study area showed the highest NDVI values (bright green areas). The intact natural vegetation in the KNP and similar protected landscapes show intermediate to low NDVI values (yellow areas), except the Bushbuckridge Nature Reserve which shows significantly higher NDVI values than KNP.

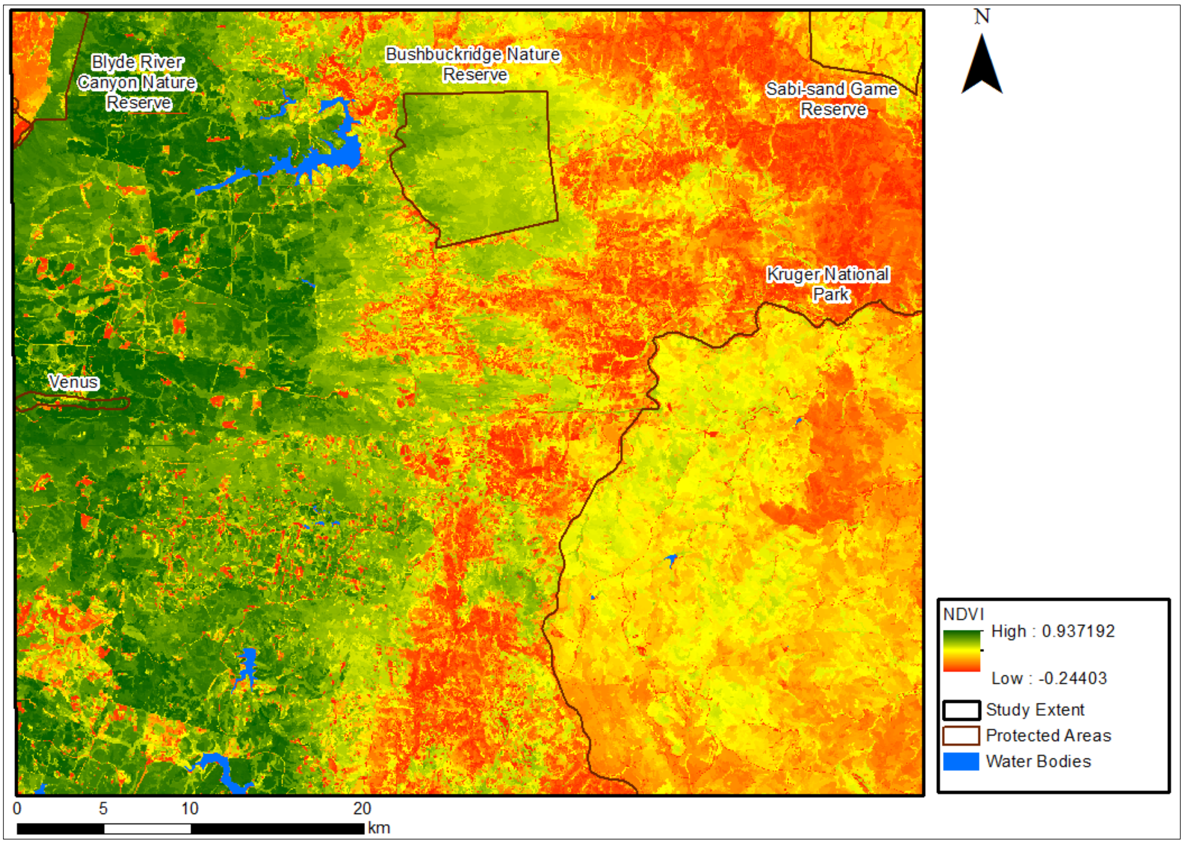


Figure 4.34 SPOT 5 derived NDVI from May 2010 (10 m image from the beginning of the dry season)

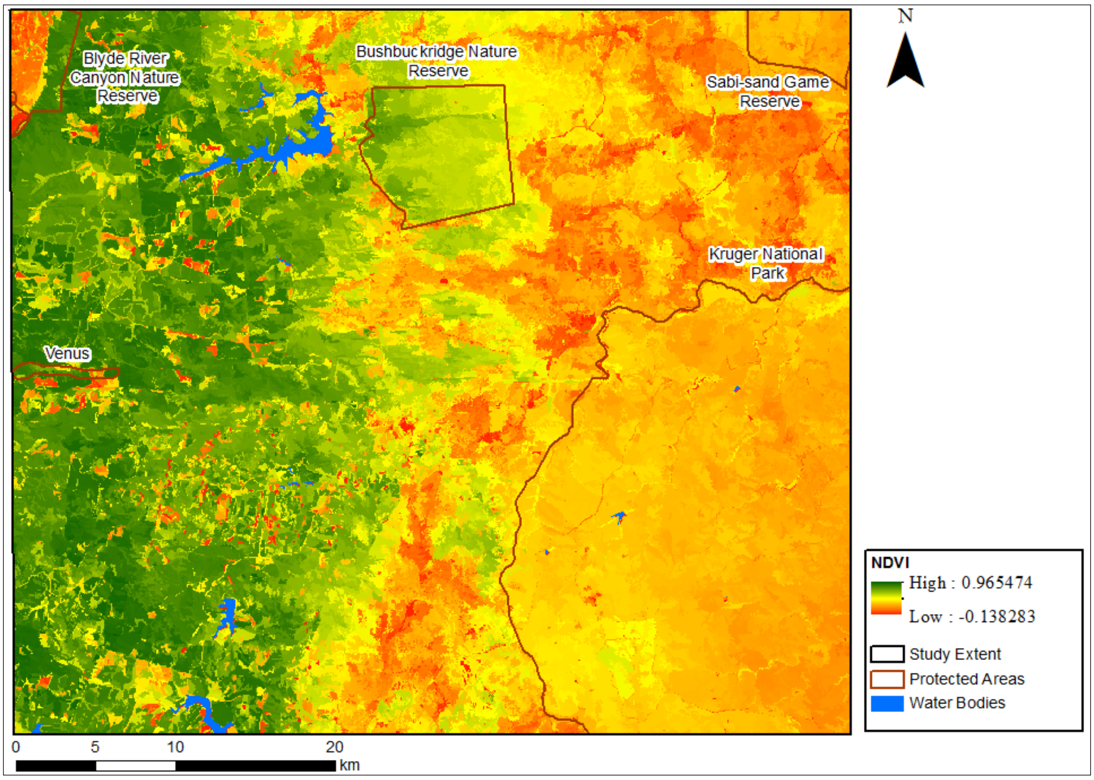


Figure 4.35 Landsat 8 derived NDVI from May 2014 (15 m image from the beginning of the dry season)

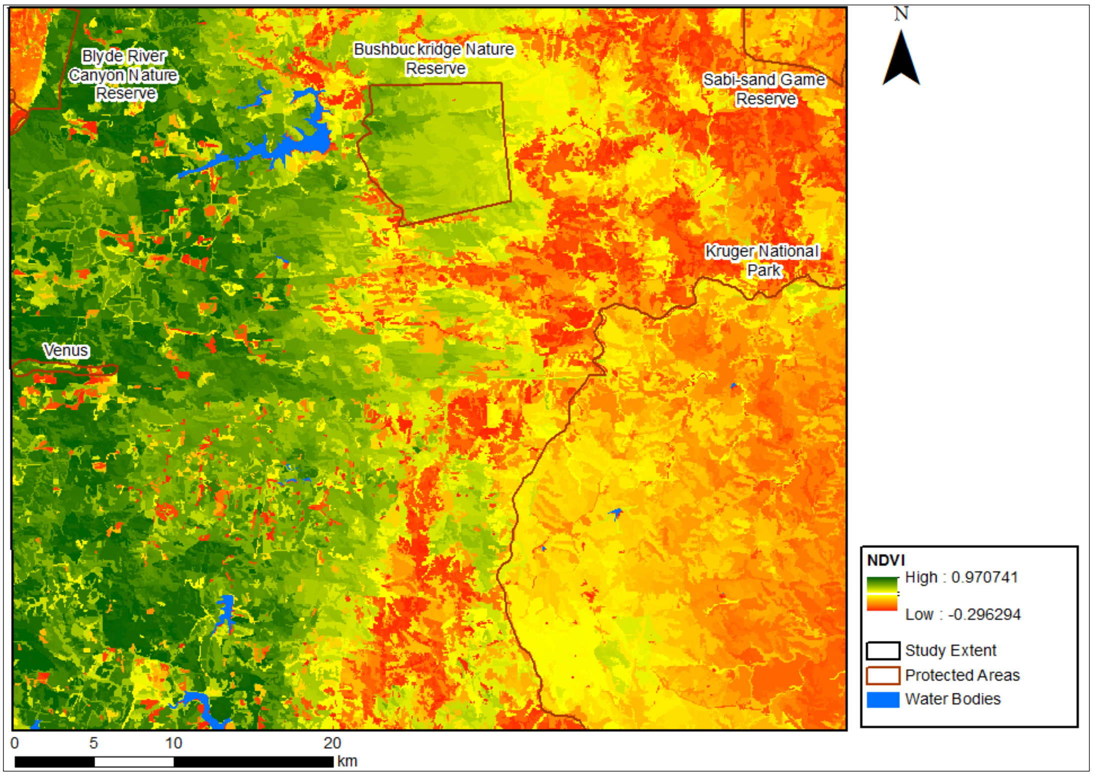


Figure 4.36 Landsat 8 derived NDVI from May 2014 (30 m image from the beginning of the dry season)

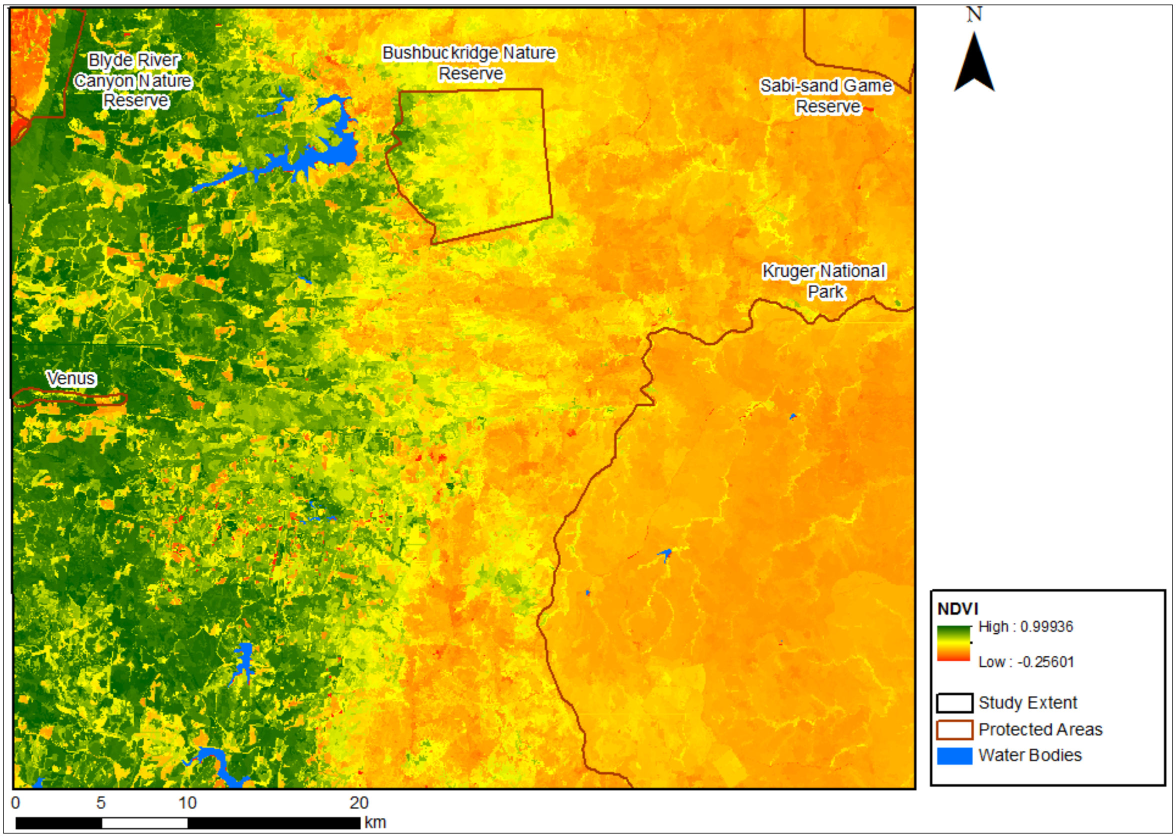


Figure 4.37 Landsat 8 derived NDVI from October 2014 (15 m image from the beginning of the wet season)

The KNP was once a cattle ranch which was converted into a protected area in 1926. Since then it has been fenced and safe guarded from anthropological influences. The reasons for low NDVI values in the KNP are as follows: firstly, precipitation and temperature are the main environmental drivers of NDVI. During a dry cold season (May-September), NDVI values in savanna semi-arid landscapes such as the KNP and similar areas will be relatively low (Wessels et al. 2006). Secondly, these landscapes contain an open vegetation cover due to the climatic conditions they are situated in, in addition to their heterogeneity/patchiness caused by varying vegetation life forms such as trees, grasses and shrubs (Scholes & Archer 1997). Thirdly, Fisher (2013) studied the structure of woody vegetation in the KNP and noted that the abundance of tall trees in the KNP can be reduced due to heavy browsing by increasing elephant populations. Levick & Asner (2013) state that the rate in which tall trees are reduced by elephants in savanna can be averaged to 2.6 trees ha^{-1} $year^{-1}$, which is six times more than in areas not occupied by elephants. Consequently, intensive browsing by elephants can profoundly contribute to low NDVI values observed in the KNP in this study. Fourthly, the same study by Fisher (2013) showed that the percentage of woody vegetation cover is only 19.6% in the KNP. Fisher (2013) used image segments to categorise woody vegetation height into 4 classes namely: plants 1-3 m in height were shrubs, 3-6 m were low trees, 6-10 m were high trees, and >10 m were categorised as tall trees. Using LIDAR data, the results showed that the KNP is dominated by small canopies which can be categorised as shrubs (1-3 m). Fewer tall trees, spaced far apart, subsequently suggests low NDVI values for the KNP, especially when comparing the NDVI values in the KNP to NDVI values in forest plantations dominated by very dense tall trees (greater than 10m in height). Finally, fire is a natural phenomenon which happens frequently in semi-arid savanna regions. However, natural vegetation is sometimes strategically cleared by inducing fires by the park's management in order to improve game viewing for tourism purposes. This results in a reduction of natural vegetation cover and lower abundance of tall trees (Fisher 2013). Although the natural vegetation will recover over time, NDVI values can significantly be reduced during this recovery process to the natural state the vegetation was in, as woody biomass mostly recovers into shorter tree height classes (Levick et al. 2009).

An area similar to the KNP, the Bushbuckridge Nature Reserve showed NDVI values significantly higher than KNP. Landsat images from October 2014 in the KNP gave the lowest NDVI values as most of the natural vegetation was burned down during that time (Figure 4.37). Human settlements, dominating the centre and north eastern part of the study area showed very low NDVI values as expected (bright red areas), for both SPOT 5 and Landsat 8. Bushbuckridge is a communal rangeland which is densely populated by human settlements. Fuel wood is the main source of energy in most households, consequently very low NDVI values are to be expected in these areas.

4.3 ACCURACY ASSESSMENT USING FIELD DATA

Before we can come to any conclusions about the maps produced using remote sensing data, a reliable validation method should be performed to assess the reliability of the map (Lillesand, Kiefer & Chipman 2004; Congalton & Green 2009). A validation method is crucial for this study since the main aim was to test whether remote sensing can effectively model habitat intactness. Additionally, to test whether the method is robust enough to be transferred to different types of satellite sensors. The following section gives an account of the error matrices and related accuracy measures for the SPOT 5 and Landsat 8 derived intactness indices using field collected data as reference. The remote sensing index values were compared to the field index values on a point to point basis.

A summary of the SPOT 5 and Landsat 8 image results computed from the error matrix are presented in Table 4.1 to Table 4.4, (see Table B.2 to B.5 in Appendix B for a more detailed error matrix). The remote sensing index scores are represented by class values while the field index scores are represented by reference values (see Appendix B). Table B.1 in Appendix B explains the interpretation of kappa values. The performances of the results are discussed.

4.3.1 Error matrix results for SPOT 5

The final intactness index map generated from SPOT 5 was compiled by summing the five image derivatives (brightness, compactness, area, texture and NDVI) (illustrated in Figure 4.38). A value of 10 (bright green areas) on the map represents a high degree of intactness, while 0 represents areas which are completely transformed (bright red areas). Areas with a high intactness index are found mostly within protected areas such as the KNP and the Bushbuckridge nature reserve. Low values are mostly found around human settlements, agricultural fields and forest plantations. Water bodies were masked out from the results.

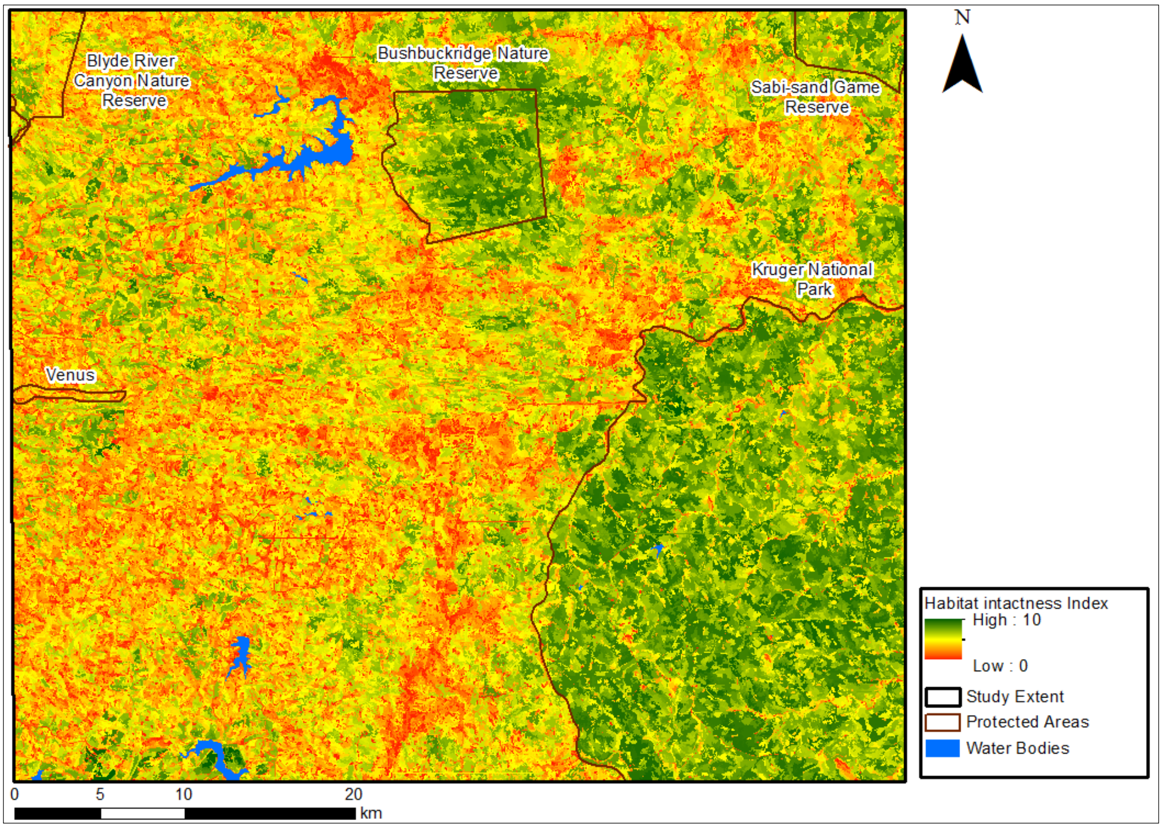


Figure 4.38 Habitat intactness index derived from SPOT 5 from May 2010

In order to present the accuracy results in a clearer manner, the scoring system was divided into class 1 to class 10. Class 1 is the lowest possible intactness score, class 10 is the highest score. Table 4.1 shows a summary of the SPOT 5 error matrix. While the map in Figure 4.38 looks decent, the May 2010 SPOT 5 derived index achieved a poor overall accuracy of 18.7%. The producer's accuracies were higher for class 4 (75%) and class 6 (75%) although 25% of class 4 is actually class 5 on the ground (user's accuracy), indicating high commission errors (93.3%). Class 6 was confused with class 4. The high producer's accuracy for class 4 is mainly because class 4 appears frequently on the intactness index map. Class 1 and 10 were completely omitted (100%) indicating high false negatives. Class 1 and class 10 were omitted out of the error matrix as they were not detected by the satellite image, although they exist in the real world. Class 1 areas are mostly forest plantations and parking lots, which are insignificant as these areas are completely transformed. Only three class 10 values were recorded in the field, and none were detected on the image, thus they were also omitted from the accuracy assessment. The other remaining classes also gave unacceptable accuracies. The kappa index as well is poor (0.07) and indicates a less than chance agreement between the index map and field data.

Table 4.1 Summary of accuracy measures for SPOT 5 from May 2010

Classes	Producer's accuracy (%)	User's accuracy (%)	Omission errors (%)	Commission errors (%)
Class 1	0.0	0.0	100.0	100.0
Class 2	15.4	60.0	84.6	40.0
Class 3	14.3	4.5	85.7	95.5
Class 4	75.0	6.7	25.0	93.3
Class 5	16.7	4.5	83.3	95.5
Class 6	75.0	15.0	25.0	85.0
Class 7	33.3	17.6	66.7	82.4
Class 8	47.8	68.8	52.2	31.3
Class 9	12.5	50.0	87.5	50.0
Class 10	0.0		100.0	

Kappa index	**0.07**
Overall accuracy (%)	**18.7**

4.3.2 Error matrix for Landsat 8

The results for all three Landsat 8 images are grouped under this section. Figure 4.39 to Figure 4.41 illustrate the final intactness indices for Landsat images from May and October 2014. The images are from different seasons, hence there are several differences observed, in particular more especially in the Bushbuckridge nature reserve where intactness is very high in May. General patterns in all three Landsat 8 intactness maps are similar to that of the SPOT 5 intactness map.

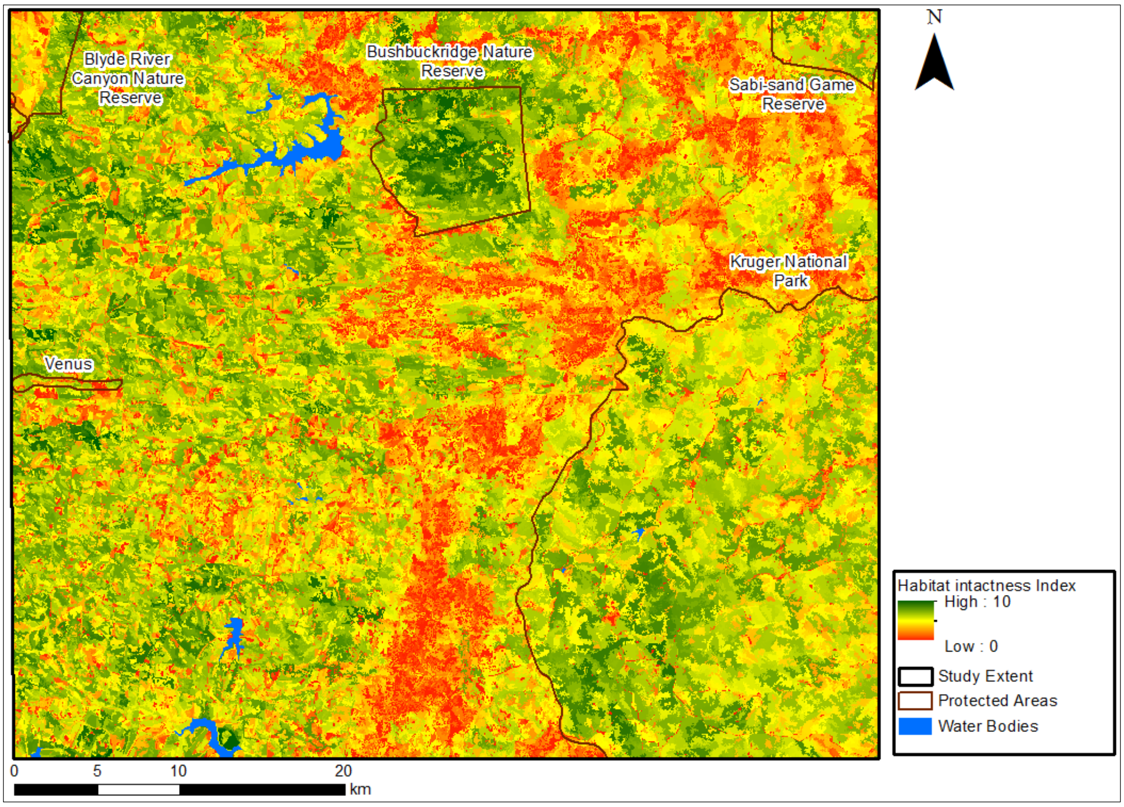


Figure 4.39 Habitat intactness index derived from Landsat 8 from May 2014

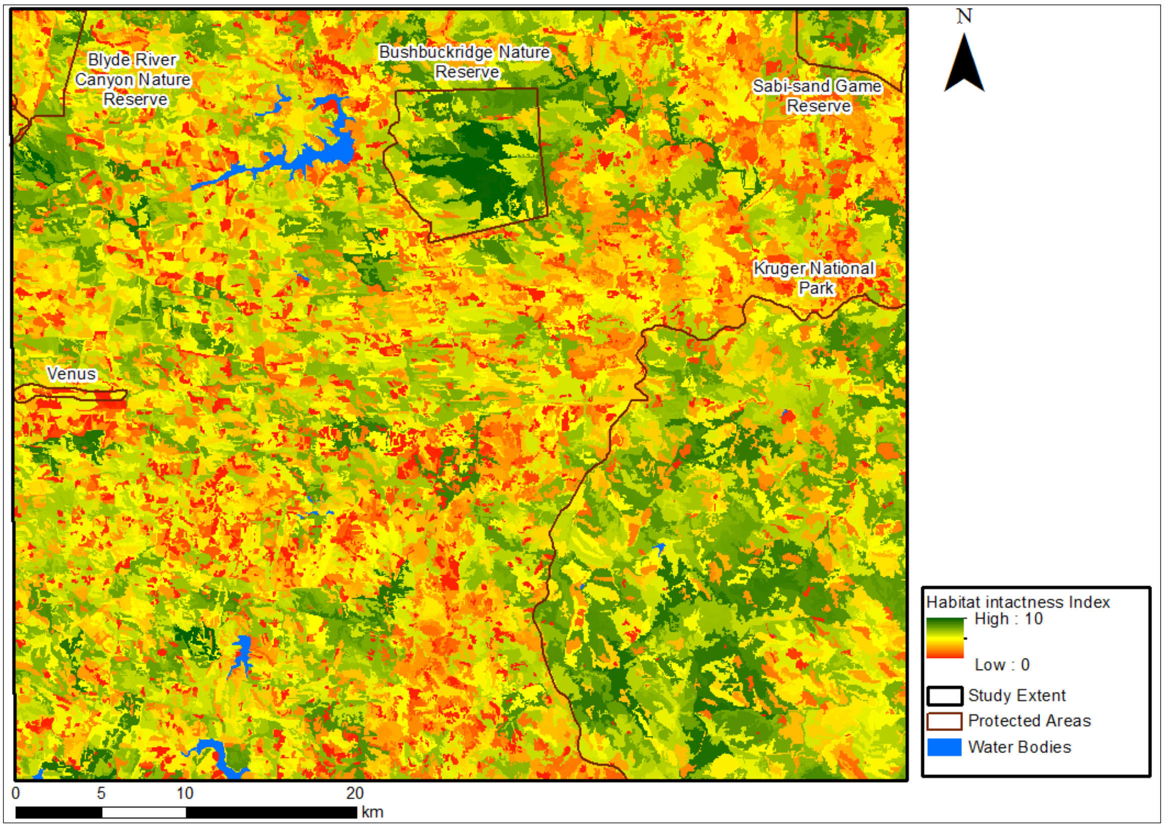


Figure 4.40 Habitat intactness index derived from Landsat 8 from May 2014 (30 m)

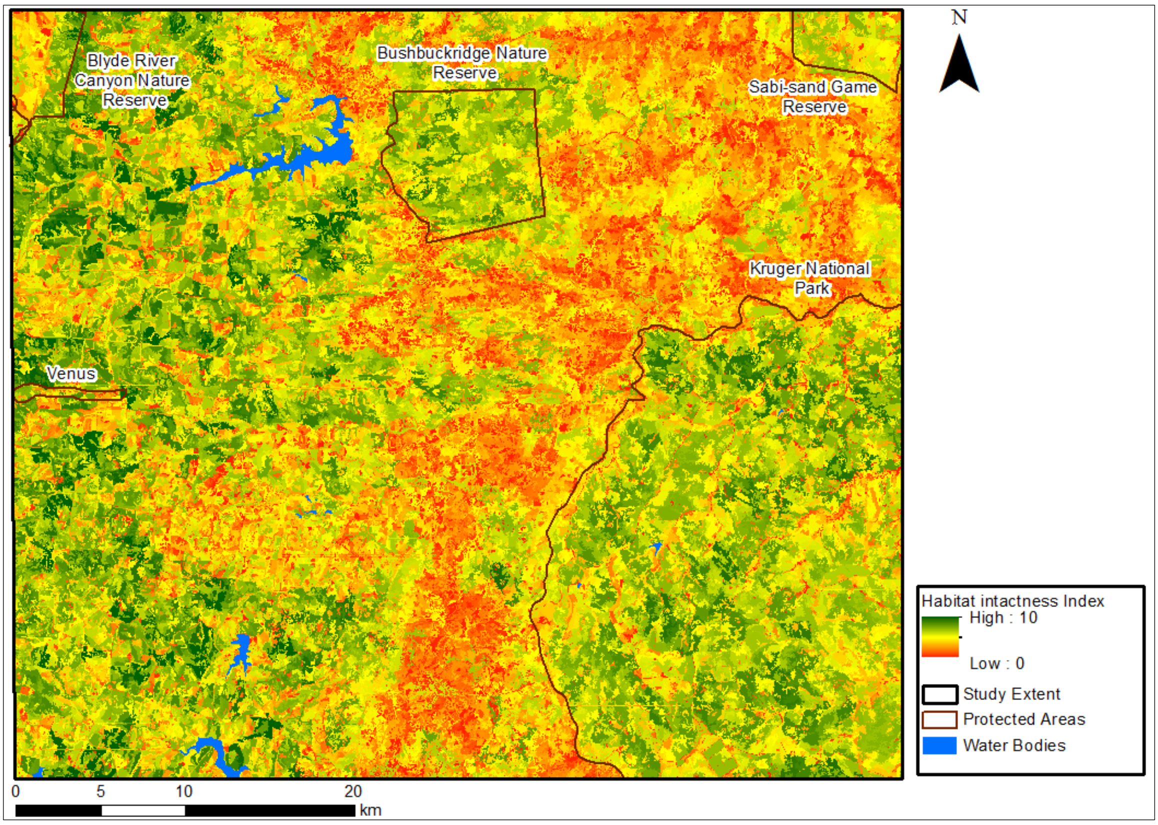


Figure 4.41 Habitat intactness index derived from Landsat 8 from October 2014

The May 2014 Landsat (15 m) and (30 m) results returned an overall accuracy of 19.4% and 13.5% respectively (Table 4.2 and Table 4.3). October 2014 Landsat 8 results returned an overall accuracy of 14.8% showed by Table 4.4. All three images returned very low accuracies. Landsat 8 (15 m) results from May indicated high (100%) false positives for class 4 and 8. Class 10 showed substantial omission errors (100%) in all three Landsat 8 images. Similar to SPOT, the kappa index values were also unacceptably poor for May 15 m (0.02), May 30m (0.04) and October 15 m (-0.09) Landsat 8 images respectively.

Table 4.2 Summary of accuracy measures for Landsat 8 from May 2014 (15 m)

Classes	Producer's accuracy (%)	User's accuracy (%)	Omission errors (%)	Commission errors (%)
Class 1	7.7	36.4	92.3	63.6
Class 2	46.2	85.7	53.8	14.3
Class 3	57.1	19.0	42.9	81.0
Class 4	0.0	0.0	100.0	100.0
Class 5	16.7	4.3	83.3	95.7
Class 6	25.0	3.0	75.0	97.0
Class 7	22.2	10.5	77.8	89.5
Class 8	0.0	0.0	100.0	100.0
Class 9	0.0		100.0	
Class 10	0.0		100.0	

Kappa index	**0.02**
Overall accuracy (%)	**19.4**

Table 4.3 Summary of accuracy measures for Landsat 8 from May 2014 (30m)

Classes	Producer's accuracy (%)	User's accuracy (%)	Omission errors (%)	Commission errors (%)
Class 1	7.69	80.00	92.31	20.00
Class 2	12.82	71.43	87.18	28.57
Class 3	14.29	7.14	85.71	92.86
Class 4	25.00	4.00	75.00	96.00
Class 5	16.67	3.85	83.33	96.15
Class 6	25.00	3.23	75.00	96.77
Class 7	44.44	12.50	55.56	87.50
Class 8	13.04	37.50	86.96	62.50
Class 9	12.50	14.29	87.50	85.71
Class 10	0.00		100.00	

Kappa index	**0.04**
Overall accuracy (%)	**13.5**

Table 4.4 Summary of accuracy measures for Landsat 8 from October 2014 (15 m)

Classes	Producer's accuracy (%)	User's accuracy (%)	Omission errors (%)	Commission errors (%)
Class 1	5.8	21.4	94.2	78.6
Class 2	33.3	56.5	66.7	43.5
Class 3	14.3	4.8	85.7	95.2
Class 4	25.0	3.4	75.0	96.6
Class 5	33.3	6.9	66.7	93.1
Class 6	25.0	3.8	75.0	96.2
Class 7	11.1	9.1	88.9	90.9
Class 8	4.3	100.0	95.7	0.0
Class 9	0.0	0.0	100.0	100.0
Class 10	0.0		100.0	

Kappa index	**-0.09**
Overall accuracy (%)	**14.8**

This concludes the reporting of the SPOT 5 and Landsat 8 accuracy results. The following section discusses the results and several methods which were tested to improve the low accuracies. To better clarify the intactness maps, areas of interest were selected covering a selection of land cover types as examples, discussed in Section 4.3.

4.4 DISCUSSION OF ACCURACY RESULTS

According to the error matrix accuracies reported for both Spot 5 and Landsat 8 images, the results were unacceptably low. For both sensors, the remote sensing scores were mostly either too high, or too low, when compared to field scores. Specifically, class 1, 9 and 10 as they reported very high omission errors. Class 1 is the lowest possible score and is related to areas which are completely transformed such as built up areas and forest plantations, whereas class 9 and 10 refer to pristine areas, as the highest intactness score. The remote sensing index failed to detect these values.

In most instances, low intactness scores were found in the KNP on Landsat 8 image from October, which is the month field data were collected. This was expected as most of the savanna natural vegetation in the study area was burned during the field survey. Fire is a natural phenomenon in savanna ecology, therefore burned areas were assigned values equivalent to that of pristine vegetation as it represents non-degraded area. Burned areas lead to a significant decrease in NDVI and brightness values, resulting in considerably low intactness accuracies for October Landsat 8 image. A total of 50 reference points were collected for natural vegetation, only 20 were correctly assigned as intact vegetation on the SPOT 5 image, 3 and 5 on May Landsat 8 15 m and 30 m images respectively, 7 on October Landsat (15m) image.

In the KNP, there was no significant difference between intactness values in May Landsat (15 m and 30 m) and October Landsat 8 as NDVI values in May were also considerably very low due to the dry period, which resulted in higher brightness and lower NDVI values. Additionally, the naturally lower vegetation canopy (Fisher et al. 2014) in the KNP also contributed to low NDVI and high brightness results, which in the end resulted in a reduced intactness index. For SPOT 5, a higher spatial resolution (10m) lead to natural vegetation being more accurately detected than Landsat (15m), which was unexpected since Landsat 8 from May (15 m) showed a slightly lower predictability of intact vegetation than the lower spatial resolution (30m) Landsat 8 May image.

Regardless of this, Landsat 8 from May (15 m) surprisingly showed the highest overall accuracy of all intactness images.

Forest plantations are characterised by a very dense vegetation canopy, which results in very high NDVI values (>0.8) and low brightness values. As well, NIR values for forest plantations were extremely high on the SPOT 5 image (Figure 4.20), but moderately high on the Landsat 8 images (Figure 4.21 to Figure 4.23). Subsequently, forest plantations showed low intactness for SPOT 5, but inaccurately higher intactness for Landsat 8 images when the results were visually compared. Congalton and Green (2009) mention that reference data is by no means 100% accurate, experience and knowledge of the area should be used to make a more informed interpretation of the results. Statistically, forest plantations were the most inaccurately detected class mainly because, forest plantations were given very low scores of 1, since they are regarded as totally transformed areas, but due to their vegetated nature, their intactness scores came out very high.

Rural settlements were more inaccurately detected by the SPOT 5 and Landsat 8 May (30 m) images. A total of 49 points were sampled in rural settlements. Of these, the SPOT 5 and Landsat 8 May (30 m) images detected 7 reference points accurately. The low score detected on the SPOT 5 image was expected as the image was from 2010, and as Congalton & Green (2009) stated, field data needs to coincide with the remote sensing data, as landscapes are constantly changing, especially since human populations are on the rise in this area. Consequently introducing significant errors into the results. To avoid such errors, field data collection needs to be relative to the imaging date as close as possible.

Additionally, high NIR standard deviation values detected in the forest plantations, but lower in rural settlements, resulted in reduced accuracies for rural settlements in the SPOT 5 and Landsat 8 May (30 m) image (Figure 4.20 and Figure 4.22), in contrast to the Landsat 8 images which showed high textures in rural settlements but lower in forest plantations (Figure 4.21 and Figure 4.23). For Landsat 8 May (15 m) texture was higher in crops, than it was in Forest plantations. Landsat 8 images from May (15 m) and October correctly identified 20 and 14 points respectively. The Landsat 8 image from October was expected to correctly identify more points than older images since coinciding with field data, but that was not the case.

4.5 IMPROVING THE ACCURACY

The results from the accuracy assessment showed that satisfactory index results are not attainable by simply computing an error matrix. Human interpretation is vital when using the methods employed in this study. Due to the low overall accuracies acquired from the error matrix, it was deemed necessary to improve the accuracy results. Two different approaches were used.

Firstly, different combinations of derivatives (brightness, compactness, area, NIR standard deviation and NDVI) were tested to understand which combinations will have more significance in improving the accuracies of the results. Some of the derivatives were re-scaled to 2 instead of 1, in order to give them more weight, in order to test which derivative relates better with the real world. A value of 1 in Table 4.5 represents a re-scale factor of 1, whereas 2, means the derivative was re-scaled to 2. Multiple combinations, were tested, however only three of the best results are presented in this study as tabulated in Table 4.5. October Landsat 8 results showed an insignificant increase of 0.64% in overall accuracies when combination 1 was tested, even though its relative kappa index decreased from 0.04 to 0.01. This may be due to the effects of the fires experienced in the KNP during October. A general decrease observed in the overall accuracies and kappa values after combining different derivatives together, indicates that all five derivatives have a significant role in improving the overall accuracy of the index, as they all measure different environmental factors.

Table 4.5 Accuracy results for different derivative combinations tested

Image type	**Layers used and their weightings (rescaled values)**						**Overall accuracy (%)**	**Kappa index**
	Combinat-ion	**Brightnes-s**	**Compact-ness**	**NIR standard deviation**	**Area**	**NDVI**		
SPOT image (May 2010) 10 m	1.	1	1	2	-	-	14.2%	0.04
	2.	1	2	2	2	1	15.5%	0.02
	3.	1	1	1	1	-	18.7%	0.02
Landsat (May 2014) 15 m	1.	1	1	2	-	-	8.4%	0.00
	2.	1	2	2	2	1	65.2%	0.57
	3.	1	1	1	1	-	7.1%	-0.10
Landsat (October 2014) 15 m	1.	1	1	2	-	-	21.3%	0.00
	2.	1	2	2	2	1	18.1%	-0.4
	3.	1	1	1	1	-	17.4%	-0.05

The results obtained from combining different derivatives did not improve the results to a level that is considered satisfactory. Only Landsat 8 from May (15 m) obtained moderately acceptable results when combination 2 was used (brightness 1, NDVI 1, NIR standard deviation 2, area 2 and compactness 2). Consequently, a second approach was tested.

The second approach involved manual comparison of the reference field scores to the remotely sensed intactness scores, in order to identify which land use type was the most incorrectly assigned or underestimated. By so doing, it was clear that almost all land cover types were inaccurately assigned. A total of 155 points were collected in the field. Forest plantations showed the highest inaccuracy as the remote sensing scores were higher than the field scores. The SPOT 5 derived intactness showed the highest accuracy for natural vegetation than all the other images, but the lowest accuracy for rural settlements and urban areas. This was expected as the image is of an older date than the other images. Rural settlements were mostly accurately detected by Landsat 8 from May 2014 (15 m). Table 4.6 below shows how each land use type scored in the field, three categories were selected.

Table 4.6 Summary of image scores by land use type

Habitats Intactness index	**Land use type**	**Correct points**	**Incorrect points**	**Total points per class (out of 155)**
SPOT May 2010 (10m)	Natural intact vegetation	18	37	55
	Forest plantations/ crops	0	48	48
	Rural settlements/ urban areas	7	45	52
Landsat May 2014 (15 m)	Natural intact vegetation	4	51	55
	Forest plantations/ crops	1	47	48
	Rural settlements/ urban areas	23	29	52
Landsat May 2014 (30 m)	Natural intact vegetation	8	47	55
	Forest plantations/ crops	2	46	48
	Rural settlements/ urban areas	11	41	52
Landsat October 2014 (15 m)	Natural intact vegetation	5	50	55
	Forest plantations/ crops	0	48	48
	Rural settlements/ urban areas	17	35	52

To implement this approach, reference values with a difference of ±1 as compared to the class value, were assigned a correct value (same value as the class value). For example, if the reference value is 4, and the class value was between 3 and 5, then the reference value would get assigned the correct score (see Appendix C)

The accuracy results obtained from using this approach are tabulated in Table 4.7. By implementing this approach, the overall classification accuracies only slightly improved as they were still too low (Table 4.7). Out of the 155 reference points collected, 60 were correctly matched by the SPOT 5 and Landsat 8 from May (15m) remote sensing score. Landsat 8 from May (30 m) categorised a total of 44 points accurately, while the Landsat 8 from October correctly assigned 59 points accurately, when a score difference of ±1 was implemented. The overall accuracy for Landsat 8 from May (15m) showed the highest improvement, however natural vegetation (untransformed areas) did not improve as well as expected. In contrast, SPOT 5 showed the highest accuracy for natural vegetation. Forest plantations were the least improved land use type in all four images as the remote sensing scores were higher than the field scores. Rural settlements and forest plantations showed the highest improvement over pristine vegetation in all three Landsat 8 images.

Table 4.7 Accuracy results improved by a difference of ≤ ±1

Sensors	Overall accuracy	Kappa index
SPOT-May 2010 (10 m)	39.4	0.2
Landsat-May 2014 (15 m)	40	0.2
Landsat-October 2014 (15 m)	38.1	0.1
Landsat-May 2014 (30 m)	29.0	0.2

Values with differences of up to ±2 (most incorrectly assigned) were also tested and resulted in accuracies up to a level which is deemed moderately satisfactory. The SPOT derived index achieved the highest improved overall accuracy of 62.6 %, with 103 of the 155 points being accurately detected, which were mostly natural vegetation. Forestry was still the least improved land use type as the field scores were assigned 1, while the remote sensing scores were mostly greater than 3. The Landsat from May (15 m) also showed a higher accuracy of 60.6%, which is not sufficient. However, rural settlements were the most improved land use type. Landsat from May (30 m) and Landsat from October, showed even lower results (both less than 55%). Forest plantations were also the most inaccurately detected land use type, thus reducing the overall accuracies significantly. The results are displayed in Table 4.8. The kappa results were all between 0.41 and 0.60, which signified that the intactness index only moderately agrees with the field reference scores.

Table 4.8 Error matrix accuracies improved by a difference of ≤ ±2

Sensors	Overall accuracy	Kappa index
SPOT-May 2010	62.6	0.4
Landsat-May 2014	60.6	0.4
Landsat-October 2014	52.9	0.3
Landsat-May 2014 (30 m)	54.8	0.4

4.6 CONCLUSION

The results obtained from the accuracy assessment demonstrated that deriving an accurate intactness index using the field methods implemented in this study can be quite challenging. This research demonstrated that although the intactness index maps look accurate at face value, discrepancies can be detected by implementing an error matrix, which evaluated the standard of accuracy. Similar to the Sandveld study by Luck-Vogel, O'Farrell & Roberts (2013), this study found that acceptable accuracies can only be obtained by extending the methods further. Assigning correct scores to class values ±2 will only provide moderately satisfying results. In addition, combining different derivatives proved to decrease the overall accuracies generally, thus showing that all five derivatives each add value to deriving a successful intactness index for conservation planning. Based on knowledge of the study area, in addition to visually analysing the various landscapes and land use types that exist in the study area from aerial photography (0.5m).

Field methods are somewhat subjective as they are based on the knowledge and understanding of the evaluator and can vary if generated by different persons. Therefore, certain standards of evaluating each land cover/ use type should be implemented, to enforce robustness of the method. As well, the methods implemented in the study need to be tailored for each specific study area as they can impact the outcome of the final results. For example, combinations of brightness, compactness, and texture rescaled to 2, used by Luck-Vogel, O'Farrell & Roberts (2013), only gave very low accuracies in this study. The aim of implementing this method was to demonstrate that earth observation can be used to map patterns of habitat intactness rapidly and effectively.

Six sets of subsets were selected to quantitatively assess how each sensor detects different land use types in the habitat intactness index. Each map shows how the five derivatives (NDVI, brightness, compactness, NIR standard deviation and area) respond to a particular land use types. SPOT 5 (10 m) and Landsat 8 images from May (15 m and 30 m) were used to demonstrate this and to highlight the differences in spatial resolution.

Figure 4.42 to Figure 4.44 below shows a subset for crops derived from SPOT 5 and Landsat 8 from May (15 m and 30 m) respectively. All five indices are represented in each map to facilitate comparison. Water bodies were masked out. Given the brightness subsets below, it is clear that cultivated fields show a lower brightness, whereas fields that are cleared show higher brightness values, irrespective of the images spatial resolution. Shadows appear darker (dark green) on the brightness image, however the higher the spatial resolution, the more pronounced shadows appear on the brightness layer (shadows more pronounced on SPOT 5 image than on Landsat 8).

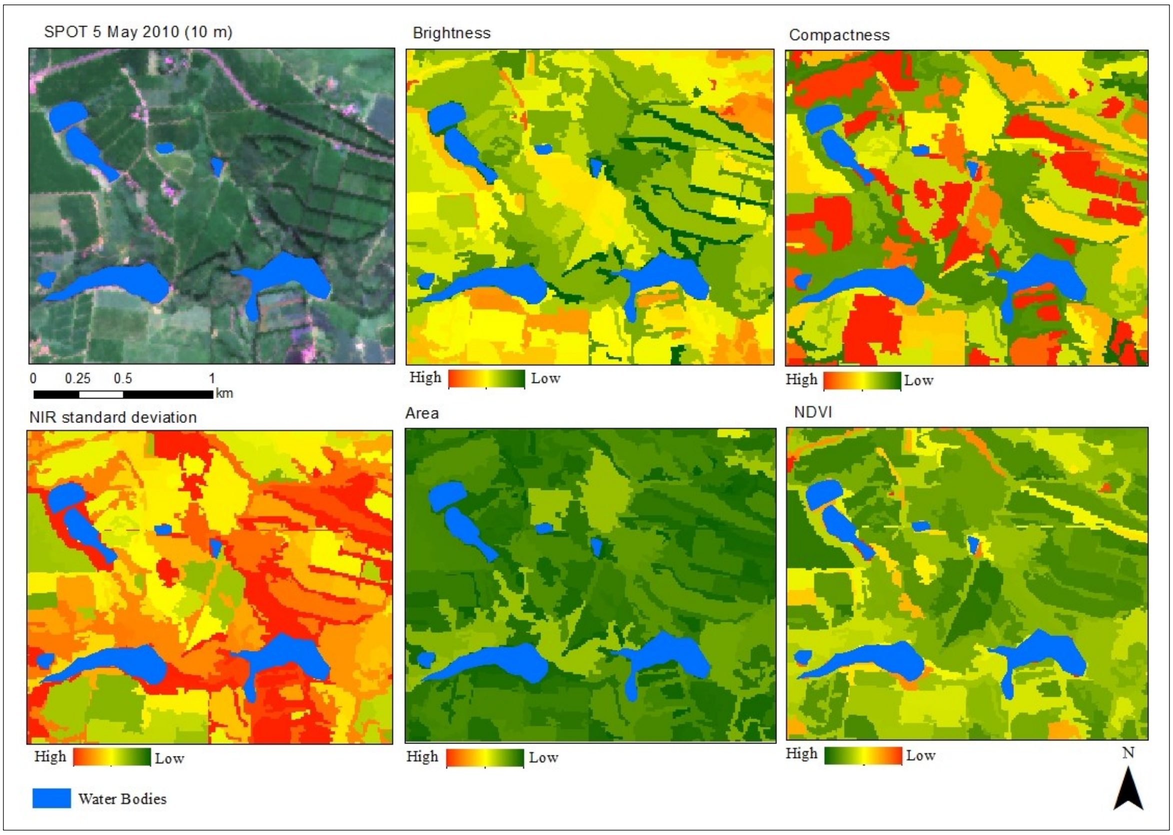


Figure 4.42 Image derivatives showing crops on SPOT 5 (10 m) image

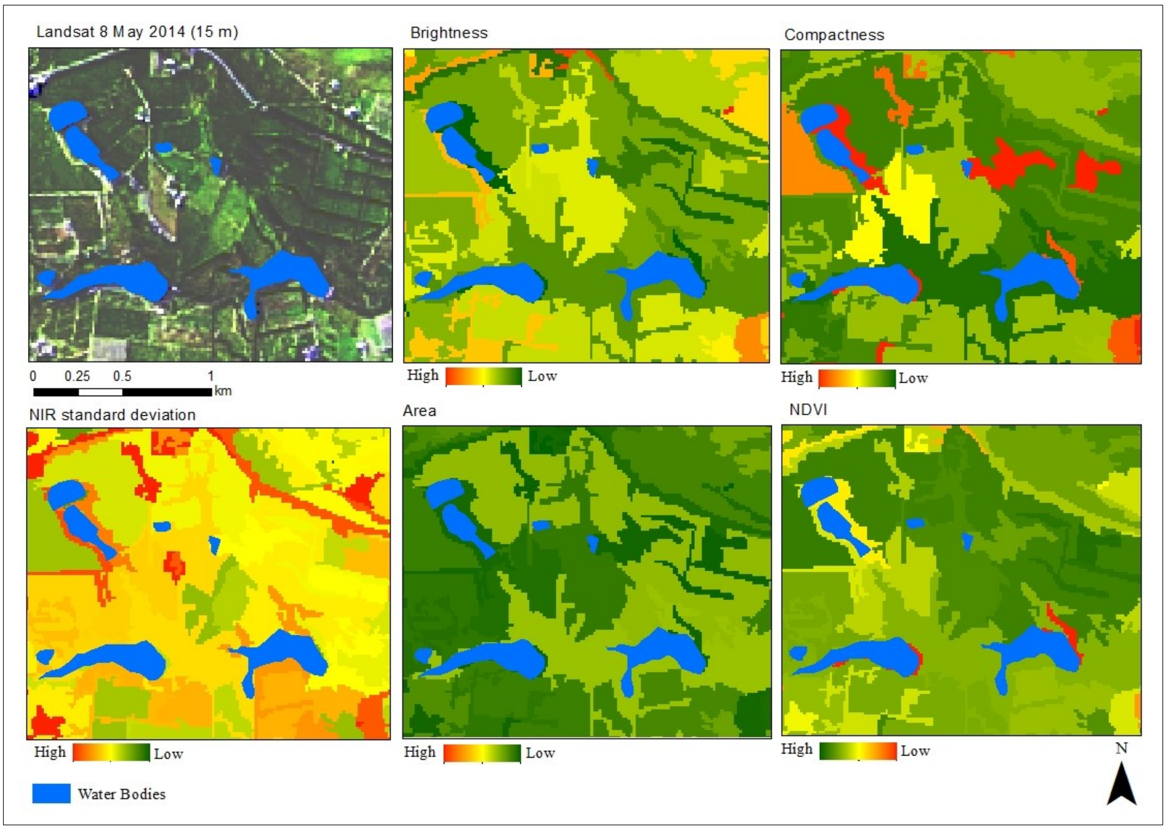


Figure 4.43 Image derivatives showing crops on Landsat 8 from May (15 m) image

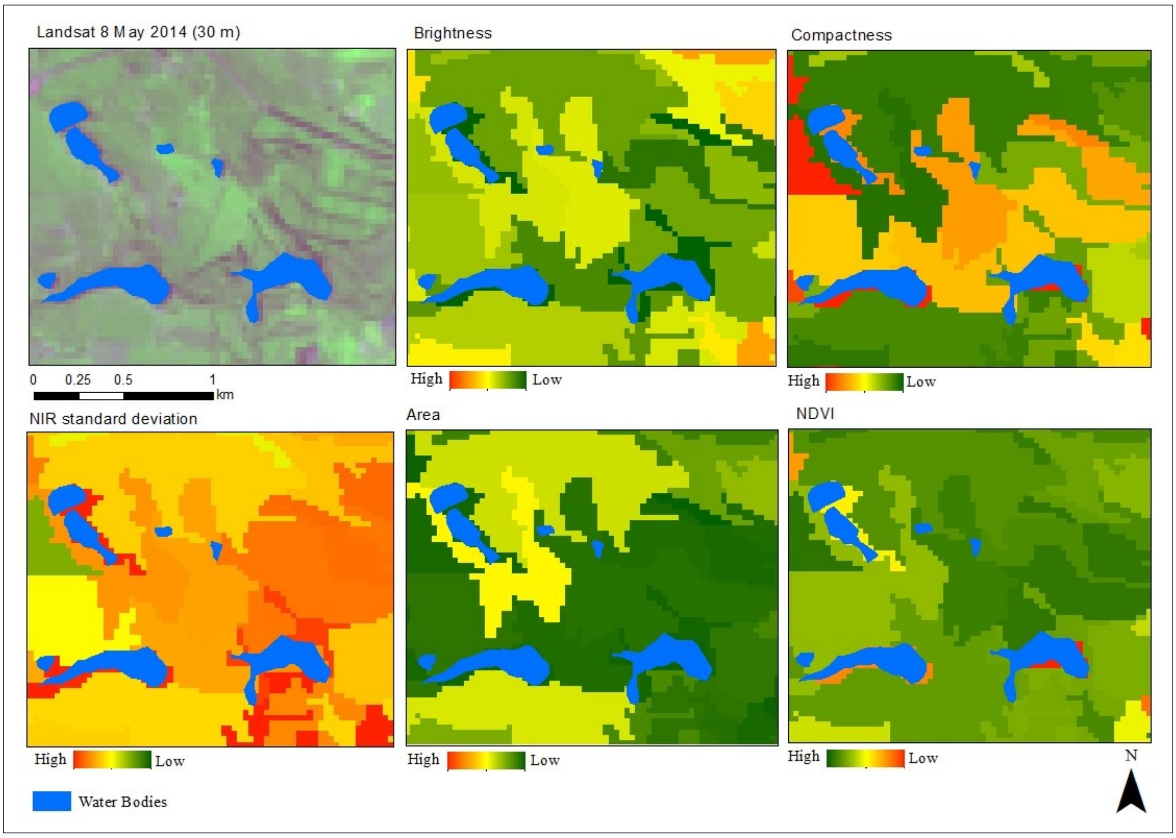


Figure 4.44 Image derivatives showing crops on Landsat from May (30 m) image

CHAPTER 5 CONCLUSIONS AND RECOMMENDATIONS

5.1 SUMMARY OF THESIS

Increasing degradation of savanna's due to fuel wood harvesting and increasing human settlements are a cause for concern in rural savanna ecosystems. Although most communal rangelands in the Bushbuckridge study area are still intact (Dovie, Witkowski & Shackleton 2004), it is important to evaluate and monitor them frequently. This should be done in order to minimise and avoid long term consequences of natural vegetation degradation, especially given the increasing human populations and poverty in Bushbuckridge. Assessing and quantifying the extent of degradation over a regional scale is often not feasible. This is because, monitoring and maintaining habitat intactness in most third world countries in particular is hindered by a lack of financial resources and human skills, to collect degradation data.

Most studies done in the Bushbuckridge region are focused on establishing associations between the livelihoods of people in the rural communities of Bushbuckridge and degradation to woodlands as a result of the socio-economic status of village residents (Kirkland, Hunter & Twine 2007; Higgins et al. 2007; Dovie, Witkowski & Shackleton 2004; Giannecchini, Twine, Vogel 2007; Dovie, Shackleton & Witkowski 2002). Other studies in the Bushbuckridge area focused on classifying Savanna woody vegetation using Lidar data (Fisher et al. 2014). This current study sets out to establish whether existing and recently developed remote sensing image derivatives can be used as an alternative and cost effective way of modelling habitat intactness in the Bushbuckridge and KNP areas, using high spatial resolution multispectral imagery.

The aim of developing such a method is to deliver key information on biodiversity at a rapid pace, using habitat intactness as a proxy for conservationists to effectively assess degradation in terms of cost-effectiveness, reliability, and applicability of the method across a range of landscapes and ecologies. In this study, the method was tested in savanna ecology, and compared with a similar study completed in the fynbos ecology (Luck-Vogel, O'Farrell & Roberts 2013). The study also sought to establish whether the tested method is robust enough to be used on an array of images with different spatial resolutions.

5.2 REVISITING THE OBJECTIVES

The first objective was to derive habitat intactness indices using a series of SPOT 5 and Landsat 8 satellite imagery. In order to effectively map intactness, a relatively suitable segmentation parameter was determined for each satellite image through trial and error experiments, and further used to extract image derivatives. Brightness (spectral derivative), compactness (structural derivative), near infrared (NIR) standard deviation, (textural derivative), area derivative and normalised difference vegetation index (NDVI) (additional spectral derivative) were each set out to test their strength in the final intactness index. These derivatives were assessed individually, and compared to other derivatives provided by the different sensors used. Although the derivatives based on brightness, compactness and NDVI did not show significant variations between the different sensors, those based on NIR standard deviation showed variations, which can affect the outcome of the index.

The second objective was to validate the results using field data. Field data were collected and analysed using a field validation questionnaire which was derived based on measurements of environmental conditions. Prior to the field survey, the intactness maps were derived. Outliers on the intactness maps were surveyed in the field. Using a field derived intactness index as reference data, an accuracy assessment was carried out in the form of an error matrix for both SPOT 5 and Landsat 8 habitat intactness maps. The reference data in this study did not agree with the remote sensing intactness index, as the remote sensing scores were often too high (less than 30% overall accuracy), particularly in completely transformed land use types. An improvement of the accuracy was done by adjusting field scores by a factor ±2. This established a moderate accuracy for both SPOT 5 and Landsat 8 intactness results. A second method was implemented to improve accuracy using a set of three combinations of various derivatives, however the accuracies were lower than expected. This showed that using all five image derivatives equally, can produce slightly higher accuracies as each derivative measures certain environmental attributes.

The final objective was to evaluate the use of SPOT 5 and Landsat 8 data for effective habitat transformation mapping. The results showed that the method can be applied effectively on inexpensive medium resolution imagery (SPOT and Landsat) as the accuracy results between SPOT 5 from May 2010 (10 m) and Landsat 8 from May 2014 (15 m) were only slightly different. The difference was only 0.6% when field scores were adjusted by a factor ±1 and only 2% when a factor of ±2 was used. Therefore, the requirement for a method that is transferable across different sensors was established, in addition to cost-effectiveness. Improving the results by implementing a score difference of ±2 to reference data, moderate accuracies were observed, with the SPOT 5 image for May 2010 detecting 62.6% overall accuracies, while Landsat 8 images for May 2014 (15 m and 30 m), and Landsat 8 for October 2014 showed slightly lower overall accuracies of 60.6%, 54.9% and 54.8% respectively. Although similar overall accuracies were obtained for SPOT 5 and Landsat 8 for May 2014 (15 m), irregularities in the omission errors of certain classes (1 and 10) revealed that the intactness maps detected these classes differently.

Generally, SPOT 5 was found to provide a more reliable habitat intactness map, as lower omission errors for natural vegetation were observed. This suggests that Landsat 8 failed to detect natural tree cover with higher accuracy. On the contrary, Landsat 8 showed more consistency in detecting rural settlements than SPOT 5. Further studies should investigate the influence lower spatial resolution imagery has on detecting natural tree cover in areas such as the Kruger National Park (KNP). The reasons that are observed in this study were pin pointed to the higher detectability of settlements by NIR standard deviation of Landsat 8 images. However, this was not established as a definite reason. Additionally, since the SPOT 5 image was captured four years earlier than the Landsat 8 images, the expansion of settlements over the years could possibly be the reason why lower omission errors were found within this class when using Landsat 8 images. Therefore, further research should emulate the method using imagery from the same year as field data in order to establish a definite consensus.

The study further established that a low spatial resolution can have a significant impact on the outcome of the intactness index, as low accuracies were obtained on the Landsat 8 image for May 2014 (30 m). This suggests the need for high spatial resolution imagery. By comparing the 15 m Landsat 8 image to the 30 m Landsat 8 images, both for May 2014, tests revealed that the lower spatial (30 m) resolution imagery is too course to detect linear ground elements such as roads, as it tends to produce very heterogeneous image objects. This resulted in lower accuracies for the courser Landsat image (13.5%) as compared to the 20% accuracy archived from the 15 m Landsat image.

5.3 LIMITATIONS OF THE STUDY

The shortfalls experienced during the field survey were collecting data in areas which are not easily accessible, in particular in the Bushbuckridge nature reserve, which showed a high habitat intactness from the intactness maps produced. Some areas in forest plantations were not easily accessible during the field work, as they were in mountainous terrains. These areas add no significant value to conservation, and thus should not be extensively surveyed, unless the goal is to categorise land clover. SPOT 5 imagery were only available for May 2010, therefore, this data set could not coincide with the field data collected in October 2014. Landsat 8 images for October 2014 were the only data set that matched the field data collected. Landsat 8 for May 2014 was also used for better comparisons with the 2010 SPOT 5 data set, as they are both from the dry season. Finally, a pan-sharpened SPOT 5 image (2.5 m) could not be used as part of the results, due to the speckled nature of their derived outputs, which was due to the panchromatic band not properly overlaying with the multispectral bands, even after several georeferencing attempts. This image would have provided a definite answer to whether a finer spatial resolution will result in higher accuracies, or whether medium resolution imagery is adequate to effectively map habitat intactness.

5.4 RECOMMENDATIONS

Factors that were established without doubt as the main cause of low accuracies were areas that are completely transformed such as forest plantations and dense urban settlements. These areas were assigned the lowest field score value of one in the field. However, they were assigned a higher remote sensing score, resulting in an underestimation of the method used to evaluate intactness. Therefore, it is important to take into consideration the land cover types in each study area. It is recommended that the method be adapted for each study area. For example, in this study, forest plantations significantly reduced the accuracy values of the intactness maps and similar areas that showed a high considerable degree of transformation. Therefore these areas can either be masked out of the study area, or the field scores would have to be manipulated (for example by assigning a score difference of ±3 or more only for this class, depending on how high the remote sensing scores assigned are) to improve accuracy, as they do not add much value when deriving conservation policies (Luck-Vogel, O'Farrell & Roberts 2013).

The difficulty in obtaining sufficient results for the Landsat 8 image for October 2014 (15 m) suggests that burned areas should be masked out when the method is applied to map intactness, as they reduce the value of the derivatives (for example, low NDVI values in burned areas). Field data should also be treated with caution as it contains anomalies, which are a result of the observers/ assessor's judgement of ecological factors. Establishing standards of answering field questions is therefore recommended for future research in order to avoid operator biasness. A further recommendation to improving the validity of the methods implemented in this research is to combine LIDAR data with multispectral imagery. LiDAR data is capable of penetrating below the top vegetation canopy, thus providing better information on habitat degradation (Nagendra et al. 2012). LiDAR is capable of measuring canopy height and biomass, which are two important indicators of habitat suitability (Nagendra et al. 2012). Hyde et al. (2006) archived high accuracies by using Landsat ETM+ data in combination with LiDAR data to map the quality of wildlife habitat in the Sierra National Forest.

5.5 CONCLUSIONS

This study highlighted the potential of remote sensing methods as an alternative to mapping patterns of degradation. This was archived by developing an intactness index based on various image derivatives that measure pristine and degraded vegetation from satellite imagery. Although moderate accuracies were obtained even after adjusting the reference field scores by a factor ±2, the habitat intactness maps nonetheless form a good basis for visual interpretation. The habitat intactness index results revealed to be adequate in providing a general indication of the degradation patterns found in the Bushbuckridge area, irrespective of the satellite sensor used. However, a level of caution must be adhered to when using visual interpretation of the maps.

(24157 words)

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PERSONAL COMMUNICATION

Fisher JT (Jolene.Fisher@wits.ac.za) 2014. RE: Collecting field reference data in Bushbuckridge. Email to Mp Motswaledi (mokhinemotswaledi@gmail.com) (2 October 2014).

APPENDICES

APPENDIX A: FIELD ASSESSMENT SHEET

Table A Example of a completed assessment form

FIELD ASSESSMENT		Point No.	23		
Name of assessor	MOKHINE MOTSWALEDI	Date of Assessment			
Place	KRUGER National Park	Position: (decimal degrees)	East: 31 21 16.0	EPE (in mts	513
Details on place	H1-1 Road KNP		South: 25 07 008		
Dominating vegetation type	Natural (savcha) intact vegetation	General condition, type of disturbance?	Burned Savanna Vegetation		

No.	Questions	Yes/no
1.	Evidence of transformation- signs of cultivation, urbanisation	N
2.	Is the area used for livestock?- signs of trampling, hoof action, manure, grazing system, vegetation loss elimination	N
3.	Are there any signs of browsing, selective logging	Y
4.	Signs of soil erosion?- evidence of bare ground, bare roots, damaged soil, soil crust	N
5.	Presence of plant litter/mulch	Y
6.	Does the variety of natural vegetation life forms appear to have been reduced?	N
7.	Is there presence of living crusts, fertile patches, mulch and animal diggings? If yes, these are all positive signs of soil and habitat health (highest score)	Y
8.	Is there an abundance of capping, pedestals, exposed roots, saline puffiness and rills? If so then this indicates water loss, soil erosion, salt accumulation and harsh habitat conditions (lowest score).	N
9.	Is this close to a water point?	N
10.	Is the field heterogeneous and does it have a patchy effect?	Y
11.	Is the any mining activities in the area	N

APPENDIX B: ERROR MATRIX

Table B.1 Interpretation of kappa values

	Poor	Slight	Fair	Moderate	Substantial	Almost perfect
Kappa	0.0	0.20	0.40	0.60	0.80	1.0

Kappa	Agreement
< 0	Less than chance agreement
0.01–0.20	Slight agreement
0.21– 0.40	Fair agreement
0.41–0.60	Moderate agreement
0.61–0.80	Substantial agreement
0.81–0.99	Almost perfect agreement

Source: Congalton & Green 2009

Table B.2 Error matrix for habitat intactness index from SPOT May 2010 (15 m) data

		Class data										
		Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**	**Class 6**	**Class 7**	**Class 8**	**Class 9**	**Class 10**	**Total**
Reference data	**Class 1**	4	8	18	9	5	5	2	1			**1**
	Class 2	6	12	14	5	1						**39**
	Class 3		1	4	1	1						**7**
	Class 4			3	1							**5**
	Class 5		1	1	1	3						**49**
	Class 6			1		3						**6**
	Class 7			2	1	2	3	1				**10**
	Class 8			2	2	4	4	11				**23**
	Class 9				1	1	3	2	1			**11**
	Class 10				1		2					**1**
	Total	**1**	**10**	**22**	**45**	**22**	**20**	**17**	**16**	**2**	**0**	**155**
	Overall accuracy 18.7											
	Kappa 0.07											

Table B.3 Error matrix for habitat intactness index from Landsat May 2014 (15 m) data

		Class data										
		Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**	**Class 6**	**Class 7**	**Class 8**	**Class 9**	**Class 10**	**Total**
Reference data	**Class 1**	4	1	8	1	12	13	7	2			**48**
	Class 2	7	18	6	6	2						**39**
	Class 3			4	2	1						**7**
	Class 4		1	1			2					**4**
	Class 5				3	1	2		1			**7**
	Class 6			1	1	1	2	1				**6**
	Class 7			1	2		4	2				**9**
	Class 8				6	5	9	3				**23**
	Class 9		1		1	1	1	6	1			**11**
	Class 10				1							**1**
	Total	**11**	**21**	**21**	**23**	**23**	**33**	**19**	**4**	**0**	**0**	**155**
	Overall accuracy 19.4											
	Kappa 0.02											

Table B.4 Error matrix for habitat intactness index from May 2014 (30 m) data

		Class data										
		Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**	**Class 6**	**Class 7**	**Class 8**	**Class 9**	**Class 10**	**Total**
Reference data	**Class 1**	4	2	6	5	6	15	10	2	2		**52**
	Class 2	1	5	5	15	7	4	2				**39**
	Class 3			1	1	4		1				**7**
	Class 4				1	1	2					**4**
	Class 5			1		1		3	1			**6**
	Class 6				1		1	2				**4**
	Class 7			1	2	1	1	4				**9**
	Class 8					4	7	5	3	4		**23**
	Class 9					2	1	2	2	1		**8**
	Class 10							3				**3**
	Total	**5**	**7**	**14**	**25**	**26**	**31**	**32**	**8**	**7**	**0**	**155**
	Overall accuracy 13.5											
	Kappa 0.04											

Table B.5 Error matrix for habitat intactness index from Landsat October 2014 (15 m) data

		Class data										
		Class 1	**Class 2**	**Class 3**	**Class 4**	**Class 5**	**Class 6**	**Class 7**	**Class 8**	**Class 9**	**Class 10**	**Total**
Reference data	**Class 1**	3	5	5	10	10	13	5		1		**52**
	Class 2	9	13	9	6	2						**39**
	Class 3		3	1	1	2						**7**
	Class 4			1	1		2					**4**
	Class 5	1		1	1	2	1					**6**
	Class 6		1		1	1	1					**4**
	Class 7	1		1	3	2	1	1				**9**
	Class 8			2	4	8	4	4	1			**23**
	Class 9		1	1	2	2	2					**8**
	Class 10						2	1				**3**
	Total	**14**	**23**	**21**	**29**	**29**	**26**	**11**	**1**	**1**	**0**	**155**
	Overall accuracy 14.8											
	Kappa -0.09											

APPENDIX C: REFERENCE POINTS

Table D.1 Summary of reference points with adjusted field scores for May 2010 and SPOT and May 2014 Landsat

		field scores for SPOT for May 2010				field scores for Landsat for May 2014			
Nr.	**Explanation**	**index score**	**Field score**	**Score difference ±1**	**Score difference ±2**	**index score**	**Field score**	**Score difference ±1**	**Score difference ±2**
1	parking lot at shopping mall in urban area in Hazyview near R40 road	2	1	1	2	1	1	1	1
2	rural settlements in Hazyview, on the way to Numbi gate	2	2	2	2	3	2	3	3
3	rural settlements in Hazyview, on the way to Numbi gate	1	2	1	1	2	2	2	2
4	entrance at Numbi gate, natural intact but sparse savannah vegetation	7	7	7	7	7	7	7	7
5	natural intact but dry savannah vegetation inside KNP, near Numbi gate	8	8	8	8	6	8	7	6
6	burned but regrowing natural vegetaion vegetation inside KNP	8	8	8	8	6	8	7	6
7	natural intact but dry savannah vegetation inside KNP	9	9	9	9	8	9	8	8
8	natural intact but dry, sparse vegetation inside KNP	8	9	8	8	4	9	8	7
9	planted grass, few natural natural vegetation (mostly trees) pavement and petrol station, shaleighs, camping site inside KNP at Pretoriuskop	4	4	4	4	6	4	5	6
10	natural intact vegetation inside KNP	5	9	8	7	2	9	8	7
11	burned natural vegetation road H2-2 inside KNP	8	8	8	8	5	8	7	6
12	burned natural vegetation road H2-2 inside KNP	7	8	7	7	5	8	7	6
13	green natural vegetation, fallen trees, and burned patches inside KNP	6	8	7	6	7	8	7	6
14	burned natural vegetation road H2-2 inside KNP, granite outcrop near where point was taken	7	8	7	7	6	8	7	6
15	severly burned natural vegetation road H2-2 inside KNP, mountains near where point was taken	8	8	8	8	4	8	7	6
16	natural intact vegetation inside KNP	8	8	8	8	6	8	7	6
17	natural intact vegetation inside KNP	4	8	7	6	7	8	7	7
18	burned but regrowing natural vegetaion vegetation inside	8	8	8	8	5	8	7	6

	KNP road H1-1								
19	burned natural vegetaion vegetation inside KNP road H1-1	8	9	8	8	5	9	8	7
20	burned natural vegetaion vegetation, trees present but grass burned out inside KNP road H1-1	8	8	8	8	6	8	7	6
21	burned natural vegetaion vegetation inside KNP road H1-1, close to a waterpoint	6	7	6	6	6	7	6	6
22	burned natural vegetaion vegetation inside KNP road H1-1, close to a waterpoint	7	7	7	7	4	7	6	5
23	natural intact dry but dense savannah vegetation inside KNP road H1-1	7	9	8	7	7	9	8	7
24	natural intact dry but dense savannah vegetation inside KNP road H1-1	7	9	8	7	6	9	8	7
25	burned natural vegetation inside KNP road S1	8	8	8	8	6	8	7	6
26	burned natural vegetaion vegetation inside KNP road S1	7	8	7	7	6	8	7	6
27	burned natural vegetaion vegetation inside KNP road S1, close to a waterpoint	6	7	6	6	6	7	6	6
28	burned natural vegetaion vegetation inside KNP road S1	7	8	7	7	4	8	7	6
29	natural sparse vegetation, dominated by dry grass inside KNP road S3	8	8	8	8	4	8	7	6
30	natural vegetation, dominsated by dry grass, fallen and bent trees and signs of tramping on grass inside KNP road S3	8	8	8	8	4	8	7	6
31	burned natural vegetation, bent trees inside KNP road S3	8	8	8	8	6	8	7	6
32	burned natural vegetation inside KNP road S3	7	7	7	7	4	7	4	5
33	burned natural vegetaion vegetation inside KNP road S3, close to a waterpoint	4	7	6	5	7	7	7	7
34	burned but regroing natural vegetation inside KNP road S3, close to waterpoint	6	5	6	6	5	5	5	5
35	rural settlements combined with natural vegetation, outside KNP Numbi gate	3	2	3	3	1	2	1	1
36	rural settlements in Bhekiswayo	4	2	3	4	2	2	2	2
37	rural settlements near R538	3	3	3	3	3	3	3	3
38	burned natural vegetation, trampled grass, brick manufacturing site in Hazyview R538	4	3	4	4	4	3	4	4
39	dumping side, burned natural vegetation, cut down trees near a river in Hazyview	4	3	4	4	3	3	3	3

40	rural settlement, reduced natural vegetation, and a few big trees	5	4	5	5	3	4	3	3
41	rural settlements in Hazyview,point taken near school, no natural vegetation	2	1	2	2	2	1	2	2
42	rural settlements in Hazyview, completely degraded vegetation near R538	4	2	3	4	2	2	2	2
43	rural settlements in Hazyview near R538, point taken on bare soccer field	4	2	3	4	2	2	2	2
44	rural settlements in Hazyview near R538	4	2	3	4	3	2	3	3
45	rural settlements in Hazyview R569	2	2	2	2	1	2	1	1
46	rural settlements in Hazyview near R538, shopping complex near where point was taken	3	2	3	3	4	2	3	4
47	rural settlements in Hazyview point taken near Masayi court	3	2	3	3	2	2	2	2
48	rural settlements in Hazyview	4	2	3	4	3	2	3	3
49	rural settlements in Hazyview R538	3	2	3	3	2	2	2	2
50	rural settlements in Hazyview	3	2	3	3	2	2	2	2
51	rural settlements in Hazyview R538 slight natural vegetation	4	4	4	4	2	4	3	2
52	forest plantation (blue gum trees) R40	6	1	2	3	5	1	2	3
53	forest plantation (Pine trees) R72925 near Klipkoppie dam	4	1	2	3	8	1	6	7
54	natural vegetation, point taken near Swartfontein treatment centre	4	7	6	5	6	7	6	6
55	forest plantation (Pine trees) near Swartfontein	3	1	2	3	3	1	2	3
56	forest plantation (Pine trees) R537	9	1	2	3	8	1	2	3
57	forest plantation (Pine trees) R536	4	1	2	3	5	1	2	3
58	forest plantation (blue gum trees) R536	4	1	2	3	7	1	2	3
59	banana plantations at Mount grace farm	5	1	2	3	3	1	2	3
60	macademia nuts tree plantations	7	1	2	3	6	1	2	3
61	banana plantations	5	1	2	3	5	1	2	3
62	macademia nuts tree plantations at Langspruit	5	1	2	3	5	1	2	3
63	forest plantation R40	4	1	2	3	6	1	2	3
64	macademia nuts tree plantations at Langspruit near Da Gama dam	3	1	2	3	6	1	2	3
65	forest plantation (Pine trees) R40	3	1	2	3	5	1	2	3
66	banana plantations R40	4	1	2	3	7	1	2	3

67	banana plantations R40	6	1	2	3	5	1	2	3
68	natural vegetation, point taken near Umbhaba lodge on R40 near R538	5	5	5	5	6	5	6	6
69	Petrol station on R40 in Hazyview	2	1	1	2	1	1	1	1
70	natural vegetation, patches of burned vegetation on R40	6	8	7	6	5	8	7	6
71	intact natural vegetation R535	4	8	7	6	5	8	7	6
72	banana plantations R535 BBR municipality	4	1	2	3	3	1	2	3
73	forest plantation (blue gum trees) R535	4	1	2	3	7	1	2	3
74	forest plantation (Pine trees) R535	4	1	2	3	6	1	2	3
75	forest plantation (blue gum trees) R535	6	1	2	3	5	1	2	3
76	forest plantation R533	4	1	2	3	6	1	2	3
77	forest plantation (blue gum trees) R533	4	1	2	3	5	1	2	3
78	forest plantation (blue gum trees) R533	5	1	2	3	6	1	2	3
79	forest plantation R533	6	1	2	3	5	1	2	3
80	forest plantation gravel road	4	1	2	3	7	1	2	3
81	forest plantation gravel road near R535	4	1	2	3	5	1	2	3
82	forest plantation (blue gum trees) R535	5	1	2	3	3	1	2	3
83	forest plantation (blue gum trees) gravel road near R538	5	1	2	3	6	1	2	3
84	forest plantation point taken near sunlight river	3	1	2	3	5	1	2	3
85	forest plantation point taken near Mac mac river	4	1	2	3	6	1	2	3
86	forest plantation gravel road	3	1	2	3	1	1	1	1
87	forest plantation gravel road cleared forest plantation	5	1	2	3	4	1	2	3
88	forest plantation	7	1	2	3	6	1	2	3
89	forest plantation	7	1	2	3	3	1	2	3
90	forest plantation	7	1	2	3	6	1	2	3
91	forest plantation	7	1	2	3	8	1	2	3
92	forest plantation (Pine trees) near R536	4	1	2	3	3	1	2	3
93	forest plantation point taken near Sabie river	6	1	2	3	6	1	2	3
94	forest plantation (blue gum trees) R536	4	1	2	3	7	1	2	3
95	forest plantation (blue gum trees) R536	5	1	2	3	3	1	2	3

96	banana plantations R536	4	1	2	3	5	1	2	3
97	natural intact vegetation combined R536	5	8	7	6	7	8	7	7
98	natural intact vegetation combined with forestry, cleared land, bare soil near Sabana river	4	4	4	4	6	4	5	6
99	forest plantation recently planted near R536	4	1	2	3	3	1	2	3
100	natural vegetation combined with few rural settlements R536	4	6	5	4	3	6	5	4
101	natural intact vegetation R40	6	9	8	7	7	9	8	7
102	rural settlements near R40	4	3	4	4	3	3	3	3
103	rural settlements near R40 in Alexandria	5	2	3	4	4	2	3	4
104	rural settlements combined with few natural vegetation R536	3	2	3	3	5	2	3	4
105	natural intact vegetation near Bosbokrand nature reserve R40	6	6	6	6	6	6	6	6
106	rural settlements	4	2	3	4	4	2	3	4
107	rural settlements and BBR shopping complex near R40	2	2	2	2	2	2	2	2
108	rural settlements in Marijane R533	2	2	2	2	3	2	3	3
109	rural settlements in Mapulaneng R533	4	2	3	4	2	2	2	2
110	natural intact vegetation near Forest lodge	6	6	6	6	5	6	5	5
111	natural vegetation combined with forest plantations crossing Ngwaritsi river R533 near Injaka dam	4	5	4	4	7	5	6	7
112	forest plantation (blue gum trees) R533 crossing Ngwaritsana river	3	1	2	3	6	1	2	3
113	forest plantation (blue gum trees) R533	3	1	2	3	4	1	2	3
114	cleared forest plantation R533	8	1	2	3	4	1	2	3
115	natural vegetation combined with forest plantations R533 near Injaka dam	3	5	4	3	6	5	6	6
116	natural degraded vegetation R40 close to Injaka dam	5	7	6	5	3	7	6	5
117	natural burned vegetation R40 near Bosbokrand nature reserve	5	8	7	6	6	8	7	6
118	rural settlements R40	5	2	3	4	2	2	2	2
119	rural settlements R40	4	2	3	4	2	2	2	2
120	rural settlements	4	2	3	4	1	2	1	1
121	rural settlements in Alexandria	4	2	3	4	1	2	1	1
122	rural settlements near Tekamahala RD3978	5	2	3	4	3	2	3	3

123	rural settlements in Oakely	5	2	3	4	5	2	3	4
124	rural settlements and cultivated land	3	2	3	3	4	2	3	4
125	natural vegetation near Belfast R536	8	7	8	8	6	7	6	6
126	natural vegetation near Belfast R536 near KNP fence	6	8	7	6	4	8	7	6
127	natural intact vegetation near KNP R536	6	8	7	6	4	8	7	6
128	rural settlements in Marabhule	3	2	3	3	2	2	2	2
129	rural settlements in Lilydale	6	2	3	4	2	2	2	2
130	rural settlements in Lilydale	4	2	3	4	1	2	1	1
131	natural vegetation	6	6	6	6	4	6	5	4
132	rural settlements combined with few natural vegetation	4	2	3	4	1	2	1	1
133	rural settlement near Sabie sands nature reserve	6	5	6	6	4	5	4	4
134	rural settlements combined with few natural vegetation RD3492	5	3	4	5	5	3	4	5
135	rural settlements RD3492	2	2	2	2	4	2	3	4
136	rural settlements combined with few natural vegetation near Agincourt	4	3	4	4	3	3	3	3
137	rural settlement in Agincourt	3	2	3	3	2	2	2	2
138	rural settlement in Agincourt	5	2	3	4	4	2	3	4
139	natural vegetation	6	3	4	5	4	3	4	4
140	rural settlements	3	2	3	3	2	2	2	2
141	rural settlements	3	2	3	3	3	2	3	3
142	rural settlements in Xanthia	4	2	3	4	2	2	2	2
143	rural settlements in Xanthia	3	2	3	3	2	2	2	2
144	rural settlements R40	4	2	3	4	2	2	2	2
145	rural settlements combined with few natural vegetation R40 near BBR Twincity mall	6	5	6	6	4	5	4	4
146	urban area BBR Twincity mall	2	1	1	2	1	1	1	1
147	rural settlements	2	2	2	2	1	2	1	1
148	natural reduced vegetation R40 entrance to BBR nature reserve	7	9	8	7	7	9	8	7
149	natural intact vegetation inside BBR nature reserve	7	10	8	9	7	10	8	9
150	natural intact vegetation inside BBR nature reserve	7	10	8	9	7	10	8	9

151	natural intact vegetation near BBR nature reserve R40	5	10	8	9	7	10	8	9
152	forest plantation (blue gum trees) R533	5	1	2	3	6	1	2	3
153	forest plantation (blue gum and pine trees) R533	8	1	2	3	7	1	2	3
154	forest plantation (blue gum trees) R533	4	1	2	3	7	1	2	3
155	forest plantation (blue gum trees) R533	3	1	2	3	6	1	2	3