Rangeland degradation assessment using remote sensing and vegetation species

Khalid Manssour Yousif Manssour

A thesis submitted to the Faculty of Science and Agriculture, at the University of KwaZulu-Natal, in fulfillment of the requirements for the degree of Doctor of Philosophy in Environmental Sciences

December 2011
Pietermaritzburg
South Africa

Abstract

The degradation of rangeland grass is currently one of the most serious environmental problems in South Africa. Increaser and decreaser grass species have been used as indicators to evaluate rangeland condition. Therefore, classifying these species and monitoring their relative abundance is an important step for sustainable rangelands management. Traditional methods (e.g. wheel point technique) have been used in classifying increaser and decreaser species over small geographic areas. These methods are regarded as being costly and time-consuming, because grasslands usually cover large expanses that are situated in isolated and inaccessible areas. In this regard, remote sensing techniques offer a practical and economical means for quantifying rangeland degradation over large areas. Remote sensing is capable of providing rapid, relatively inexpensive, and near-real-time data that could be used for classifying and monitoring species. This study advocates the development of techniques based on remote sensing to classify four dominant increaser species associated with rangeland degradation namely: *Hyparrhenia hirta*, *Eragrostis curvula*, *Sporobolus africanus* and *Aristida diffusa* in Okhombe communal rangeland, KwaZulu-Natal, South Africa. To our knowledge, no attempt has yet been made to discriminate and characterize the landscape using these species as indicators of the different levels of rangeland degradation using remote sensing.

The first part of the thesis reviewed the problem of rangeland degradation in South Africa, the use of remote sensing (multispectral and hyperspectral) and their challenges and opportunities in mapping rangeland degradation using different indicators. The concept of decreaser and increaser species and how it can be used to map rangeland degradation was discussed.

The second part of this study focused on exploring the relationship between vegetation species (increaser and decreaser species) and different levels of rangeland degradation. Results showed that, there is significant relationship between the abundance and distribution of different vegetation species and rangeland condition.

The third part of the study aimed to investigate the potential use of hyperspectral remote sensing in discriminating between four increaser species using the raw field spectroscopy data and discriminant analysis as a classifier. The results indicate that the spectroscopic approach used in this study has a strong potential to discriminate among increaser species. These positive results

prompted the need to scale up the method to airborne remote sensing data characteristics for the purpose of possible mapping of rangeland species as indicators of degradation. We investigated whether canopy reflectance spectra resampled to AISA Eagle resolution and random forest as a classification algorithm could discriminate between four increaser species. Results showed that hyperspectral data assessed with the random forest algorithm has the potential to accurately discriminate species with best overall accuracy. Knowledge on reduced key wavelength regions and spectral band combinations for successful discrimination of increaser species was obtained. These wavelengths were evaluated using the new WorldView imagery containing unique and strategically positioned band settings. The study demonstrated the potential of WorldView-2 bands in classifying grass at species level with an overall accuracy of 82% which is only 5% less than an overall accuracy achieved by AISA Eagle hyperspectral data.

Overall, the study has demonstrated the potential of remote sensing techniques to classify different increaser species representing levels of rangeland degradation. In this regard, we expect that the results of this study can be used to support up-to-date monitoring system for sustainable rangeland management.

Preface

The research work described in this thesis was carried out in the School of Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, from January 2008 to November 2011, under the supervision of Prof. Onisimo Mutanga (School of Environmental Sciences, University of KwaZulu-Natal; South Africa) and Dr. Terry Everson, (School of Biological and Conservation Sciences, University of KwaZulu-Natal; South Africa).

I would like to declare that the research work reported in this thesis has never been submitted in any form to any other university. It therefore represents my original work except where due acknowledgments are made.

Khalid Manssour Yousif Signed: ________________________ Date:_________________

As the candidate's supervisors, we certify the above statement and have approved this thesis for submission.

1. Prof. Onisimo Mutanga Signed:___________________ Date:_________________
2. Dr. Terry Everson Signed:___________________ Date:_________________

Declaration 1 – Plagiarism

I, Khalid Manssour Yousif, declare that:

1. The research reported in this thesis, except where otherwise indicated, is my original research.
2. This thesis has not been submitted for any degree or examination at any other university.
3. This thesis does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.
4. This thesis does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:
   a. Their words have been re-written but the general information attributed to them has been referenced.
   b. Where their exact words have been used, then their writing has been placed in italics and inside quotation marks, and referenced.
5. This thesis does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source being detailed in the thesis and in the References section.

Signed________________________________

Declaration 2 – Publications and manuscripts

1. **Manssour,** K., Everson, T., and Mutanga, O., (In review). Evaluating rangeland degradation using vegetation species and soil properties as indicators across a gradient of management regimes. *African Journal of Range and Forage Science*.

2. **Manssour,** K., Mutanga, O., and Everson, T., (In review). Remote sensing based indicators of vegetation species for assessing rangeland degradation: Opportunities and challenges. *African Journal of Agricultural Research.*

3. **Manssour,** K., Mutanga, O., and Everson, T., (In review). Spectral discrimination of increaser species as an indicator of rangeland degradation using field spectrometry. *Journal of Spatial Science.*

4. **Manssour,** K., Mutanga, O., Everson, T., and Adam, E., (In revision). Discriminating increaser grass species using hyperspectral data resampled to AISA Eagle resolution to assess rangeland degradation. *ISPRS Journal of Photogrammetry and Remote Sensing*.

5. **Manssour,** K. and Mutanga, O., (In revision). Classifying increaser species as an indicator of different levels of rangeland degradation using Worldview imagery. *Journal of Applied Remote Sensing*.

Signed________________________________

Dedication

To my beloved parents, brothers and sisters

Acknowledgements

I would like to express my sincere thanks and appreciation to all those who have made this work possible. I am particularly indebted to the following individuals and organizations:

Firstly, I would like to thank Allah for the gift of my life, for the desire, the dream and the ability to do this work, and for being my light throughout my life.

Thank you to Prof. Onisimo Mutanga, who was my main supervisor in the field of remote sensing and GIS. I cannot adequately put my appreciation and thanks into words, but let me just say thank you for your expert scientific guidance, the continuous encouragement and support that you gave to me, the patience that you displayed, and the effort you put into helping me complete my study.

I would like to express my deepest gratitude to Dr Terry Everson, who aided me in the field of rehabilitation of degraded rangeland and communal grazing systems. Thank you for accepting the task of being my co-supervisor, even though the study had already begun, and for then proceeding to give so generously of your time and resources.

I would like to thank Dr Denis Rugege, who supervised my study in its early days, up till he resigned from his position at the University of KwaZulu-Natal (UKZN). His friendly and enthusiastic approach made the first stage of this study a thoroughly enjoyable experience.

I am thankful to the Sudan Ministry of Higher Education for affording me this once-in-a-lifetime opportunity. Special thanks are to go to the Elfashir University. This work is based upon research that is supported by the National Research Foundation as well as the UKZN Research Grants, and the efforts of these bodies are also appreciated. I would like to thank the South African National Space Agency (SANSA) as well as DigitalGlobe for making high-quality SPOT5 and WorldView-2 data available to me free of charge.

There are many people who deserve formal recognition for their help and support with regard to this study. My special gratitude goes to Dr Monique Solomon, who helped me select the case study, introduced me to the Okhombe community, made critical comments during the CEAD-PhD forum, and always found time to answer my questions. I wish to extend my gratitude to Dr Elhadi Adam, for his moral support, helpfulness when it came to data collection and the analysis techniques (particularly in the application of machine learning algorithms), and his valuable comments. I am grateful to Dr Elfatih Abdel-Rahman (UKZN) who made helpful suggestions that improved the study. A special thank you to the Okhombe community and, in particular, the Okhombe Monitoring Group (OMG) for the support they gave me during the course of my field work. Special thanks are extended to Themba Khumalo and the Masaka family. I am grateful to Prof. Fethi B. Ahmed (UKZN) and Dr Esam Elzeen (former postdoctoral fellow at UKZN) for their support, encouragement and help during my PhD study. I am also indebted to Prof. Omer Hayati (my Masters supervisor at Khartoum University), who was also supportive and encouraged me to undertake my PhD degree in South Africa.

I wish to acknowledge the help I received from Dr Riyad Ismail, who aided me in terms of atmospheric correction and contributed valuable information concerning the random forest algorithm. My gratitude also goes to Abdallah Ibrahim and Desale Okubamichael for their support during the data collection phase. Thank you to Dane Lee Marx and Craig Morris for their help in the identification of plant species as well as in data collection. Thank you to Irene Bame from her assistance with matters pertaining to soil analysis. I extend my gratitude to the statisticians Ali Satty and Dawit Getnet for their assistance in statistical analysis. I also thank Susan Davies and Megan White for editing my dissertation.

I extend me thanks to the staff and technicians at the Centre for Environment, Agriculture and Development (CEAD) for their encouragement and support. I would also like to thank the Geography Department of UKZN for the same. Special thanks go to Philippa McCosh , Kerry-Ann Jordaan, Shanita Ramroop, Victor Bangamwabo, Ruth Howison, Donavan de Vos and Brice Gijsbertsen for their help in facilitating the field work, for assisting me in ArcMap, for configuring the ASD sensor and GPS, and for organising other logistics related to my work. I am also indebted to my colleagues at UKZN, and as such extend my thanks to Clement Adjorlolo, Amediano Gomes, Simon Rukera Tabaro and Khoboso Seutloali for their advice, support and encouragement.

Thank you to the Sudanese families and my Sudanese colleagues here in KZN for their steadfast support and social interactions. Also, special thanks are given to Dr Ibrahim Elzeen and Dr Saed Kozi at Elfashis University for their support and assistance with my family back home in Sudan.

Finally, there are those who have sowed greatly into my life: my parents, brothers and sisters. I here give very special thanks to all of you.

Table of contents

List of figures

List of tables

CHAPTER ONE

General introduction

1.1Background

Rangeland occupies roughly 51% of the earth's total land area and includes savannas, grasslands, shrublands and desert (Asner et al., 2004). These areas of rangeland are responsible for the employment of more than 38% of the world's population (Nalule, 2010). However, a total of 10 to 20% of rangeland has been identified as being severely degraded (Reynolds et al., 2007).

Rangeland degradation is a reduction in the quantity and quality of the natural vegetation available for grazing and it is a serious problem in arid, semi-arid and sub-humid areas (Passmore and Brown, 1991). Rangeland degradation and the development of rehabilitation techniques, specifically in arid, semi-arid and sub-humid areas, have become pressing concerns in terms of the sustainable management of rangelands (Passmore and Brown, 1991; Snyman and Du Preez, 2005).

South Africa's rangelands are ecological ecosystems that provide an environment for fauna and flora, which include wildlife animals and vegetation species (Sheona, 2003; Tainton, 1999; Wessels et al., 2008). Rangeland occupies more than 70% (1,219,000 km^2) of South Africa's land surface and is used almost exclusively for pastoral production (Snyman, 2003). South African rangelands have been classified into two groups, namely communal rangelands and commercial rangelands, a classification that is based on the tenure system, the quantity and quality of forage production and livestock production techniques (Hoffman et al., 1999; Joubert and Ryan, 1999; Shackleton et al., 2003).

Communal rangeland, which occupies roughly 13% of the total agricultural land in South Africa, has been characterised by the South Africa National Land Care (NLC) Programme as one of the areas most severely affected by soil and vegetation degradation, and it is arguably a situation that is completely out of control (Hoffman and Todd, 2000; Palmer and Ainslie, 2006). These communal rangelands are characterised by high human populations, an increased number of livestock, increased runoff, poor water infiltration, severe soil erosion, the loss of grass cover (particularly palatable grazing species) and poor land use management (Hoffman and Todd, 2000; Moyo et al., 2008; Reid and Vogel, 2006). A total of 4.8% (5.8 million ha) of communal rangeland has been identified as being degraded due to its low vegetation cover when compared with surrounding areas (Thompson, 1996). A number of experimental studies show that communal rangeland degradation can be attributed to land cover modification, which is a continuous process that – alongside human influences such as long-term extensive grazing – is driven by climate, geology, topography and vegetation characteristics (Hoffman et al., 1999; Snyman and Du Preez, 2005; Wessels, 2007).

Okhombe is a communal rangeland situated in the mountainous region of the northern Drakensberg, which lies within the province of KwaZulu-Natal, South Africa. Okhombe is a degraded rangeland, characterised by soil erosion, rills, gullies, shrub and bush encroachment, and the dominance of unpalatable grass species throughout the foot, mid and upper slopes (Everson et al., 2007; Von Maltitz, 1998). The land use interventions and communal land tenure system that have been applied in Okhombe over the past few decades had negative impacts on the condition of the rangeland (Everson et al., 2007) (Figure 1.1). Tau (2005) and Temme et al. (2008) argued that the visual indicators of rangeland degradation in Okhombe - such as the development of bare soil surfaces, gullies and rills and sedimentation in streams - are the result of soil erosion, fuel-wood collection and intensive grazing. Human intervention such as LandCare Project played a significant role in establishing baseline conditions in the Okhombe communal area (Everson et al., 2007). The LandCare project, a program based on a community-based monitoring system was initiated at Okhombe communal rangeland in 1998 (Mulder and Brent, 2006; Peden, 2005). The objectives of this project were: (1) to identify changes that have taken place in the degraded areas; (2) to promote sustainable land-use practices so as to improve land productivity; and (3) to establish effective rehabilitation techniques for land management in communal lands.

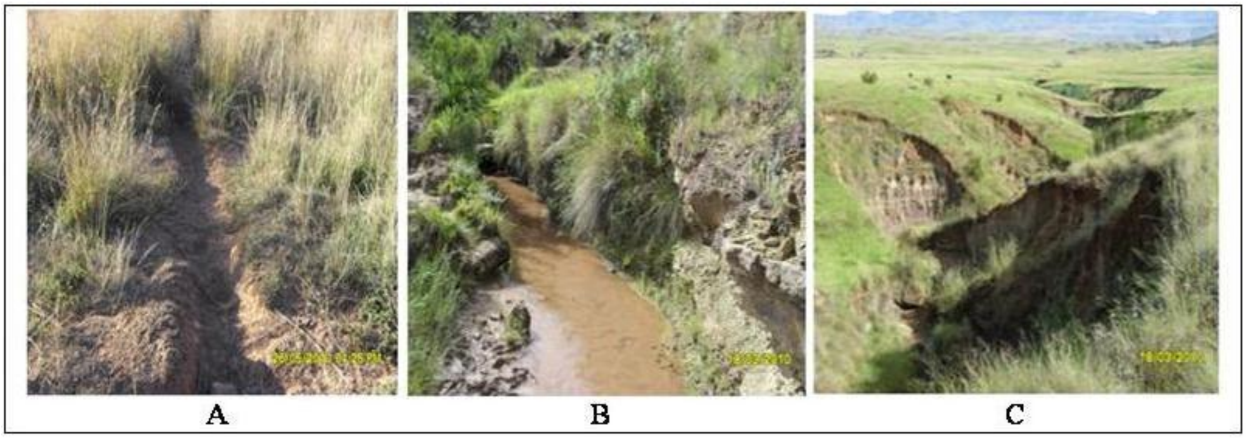

Figure 1.1: Visual indicators of rangeland degradation as observed in Okhombe: (A) cattle access routes, (B) sedimentation in streams, and (C) gullies.

Cathedral Peak is one of the KwaZulu-Natal wildlife conservation areas where several changes in vegetation and soil have taken place over the past couple of decades (Granger, 1976). For example, *Themeda triandra* grassland on the south-facing slopes was gradually replaced by a number of different woody communities of which *Philippia ecansii* and *Leucosidea sericea* are the characteristic species (Bosch, 1979). The soils in this area are highly leached, acidic and structure-less, having high organic content (6 to 10%) and a mean soil depth of 0.8 m (Everson, 2001; Schulze, 1975).

In the past few decades, the mapping and monitoring of rangeland degradation in South Africa has primarily focused on commercial rangeland (Palmer and van Rooyen, 1998; Shackleton et al., 2005), meaning communal rangeland has not as yet enjoyed the same degree of attention (Hoffman and Todd, 2000; Trollope, 2011; Wessels et al., 2004). The continued degradation of communal rangeland is a major threat to livestock production, biodiversity and human livelihoods (Hoffman et al., 1999). Therefore, several agronomic and ecological techniques have been developed over the past two decades to evaluate and monitor rangeland based on the relative abundance and distribution of increaser and decreaser species. The techniques include, for example, weighted palatability composition methods (Barnes et al., 2007), the benchmark method (Foran et al., 1978), the ecological index (Vorster, 1982), the key species method (Mentis, 1981), the weighted key species method (Hurt and Hardy, 1989), and the use of degradation gradients (Bosch and Gauch, 1991). These methods have achieved differing degrees of success for evaluating and monitoring rangelands over small geographic areas. However, these agronomic and ecological techniques require intensive and difficult fieldwork in terms of species identification and this exercise is often too expensive and time-consuming because grasslands often cover large spatial extents and are, moreover, frequently to be found in isolated, inaccessible areas (Tainton et al., 1980; Tainton, 1999; Trollope, 1990). The best method, which includes generating real-time, consistent, repeatable and spatially explicit data, is required for mapping and evaluating rangeland degradation. In this regard, remote sensing techniques offer a practical and economical means for quantifying rangeland degradation over large areas (Wessels, 2007) because they are capable of providing rapid, relatively inexpensive, and near-real-time data that can be used for the sustainable and effective management of rangelands (Kiguli et al., 1999; Tanser and Palmer, 1999; Wessels et al., 2004; Wessels, 2007). The application of remote sensing in rangeland degradation has been explored by various scientists and has been found to be potentially useful for assessing, mapping and monitoring rangeland degradation when using different indicators such as soil properties and vegetation (Paudel and Andersen, 2010; Wessels et al., 2008; Wessels et al., 2004).

Some authors, in their work on rangeland degradation assessment using different indicators of soil properties and vegetation, have mainly focused on identifying degraded and non-degraded areas (Conant and Paustian, 2002; Greenwood and McKenzie, 2001; Hill et al., 2008; Wessels et al., 2008). Although these previous studies were able to draw a line between degraded and non-degraded areas, one of their limitations, however, is that they lack in-depth classification of the different levels of rangeland degradation (i.e. poor, moderate and highly degraded) on large spatial extents. Such classifications require the development of indicators that can be easily and directly detected and monitored. In South Africa, rangeland species have been classified into two groups – increaser and decreaser species – to indicate different conditions of rangeland based on changes in the species' relative abundance in the presence or absence of grazing (Dobarro et al., 2010).

1.2 Increaser and decreaser species

Increaser and decreaser species provide economic and environmental benefits such as: grazing lands for cattle and wildlife, soil protection, medicinal plants and nutrient cycling (Oluwole et al., 2008; Van Oudtshoorn, 1992). Decreaser species are species that dominate in rangeland of good condition but greatly decline when the rangeland deteriorates through over- or underutilisation (Hardy et al., 1999). Increaser species are species that increase their relative abundances through overgrazing and/or underutilisation, and these are therefore indicators of the poor condition of a rangeland (Van Oudtshoorn, 1992). Increaser species have been classified into the following four types: increaser I, increaser IIa, increase IIb, increaser IIc and increaser III (Oluwole and Dube, 2008; Trollope et al., 1990). The relative abundances and distribution of increaser and decreaser species have successfully been used to assess the condition of South Africa's rangeland (Oluwole and Dube, 2008; Trollope, 1990).This is because increaser and decreaser species are well adapted to environmental conditions and their numbers will reduce or increase dramatically if these conditions change (Hurt and Hardy, 1989; Trollope et al., 2008). Increaser I includes species that increase in abundance with underutilisation, while increaser IIa includes species that increase in abundance when the veld is overgrazed. Increaser IIb species are those that increase in abundance when the veld is excessively overgrazed, while increaser IIc species are those that increase in abundance with extremely severe over-utilisation. Increaser III are species that increase their relative abundances in rangeland that is selectively grazed (Hardy et al., 1999; Oluwole and Dube, 2008; Trollope, 1990; Van Oudtshoorn, 1992). In the present study, the increaser species – namely *Hyparrhenia hirta* (HH), *Eragrostis curvula* (EC), *Sporobolus africanus* (SA) and *Aristida diffusa* (AD) – indicate different levels of rangeland degradation (see Table 1.1 and Figure 1.2). Mapping these species allows for the classification of rangeland degradation into different levels based on the relative abundances and distribution of the increaser species.

Table 1.1: Visual indicators of Okhombe rangeland degradation based on different increaser species

Indicator species	Common name	General characteristics	Grazing value*	Visual indicators of rangeland degradation	Degradation stage
Increaser I (HH)	Thatching grass.	A relatively dense, perennial tufted grass. Spikelets are covered with white to grey hairs. Culms 300-1,500 mm tall. Leaf blade 1-4 mm wide. Flowers from September to March.	5	Bare soil on cattle access routes. Accumulations of soil around trees and fences. Dust storms. Muddy water.	Poor
Increaser II (EC, SA)	EC: Weeping lovegrass. SA: Ratstail dropseed.	EC: Densely perennial tufted grass. Inflorescences are mostly an open panicle. Spikelets are dark grey to dark olive green. Culms 300-1,200 mm tall. Leaf blade up to 4 mm wide. Flowers from August to June. SA: Perennial tufted grass. Long panicle with a pointed tip. Culms 280-1,500 mm tall. Leaf blade 1-4 mm wide. Flowers from October to April.	3-5	Barren spot. Sandy layer on soil surface. Vetiver grass. Damaged swales. Sedimentation in streams.	Moderate
Increaser III (AD)	Iron grass.	A tufted perennial grass. Leaves are hard, narrow and rolled. Inflorescences are a spare, expanded and open panicle. Culms 300-800 mm tall. Leaf blade up to 2 mm wide. Flowers from November to April.	0	Bare soil. Eroded slopes. Rills and gullies. Exposed roots. Dongas. Parent material (stones).	High

* Van Oudtshoorn (1992)

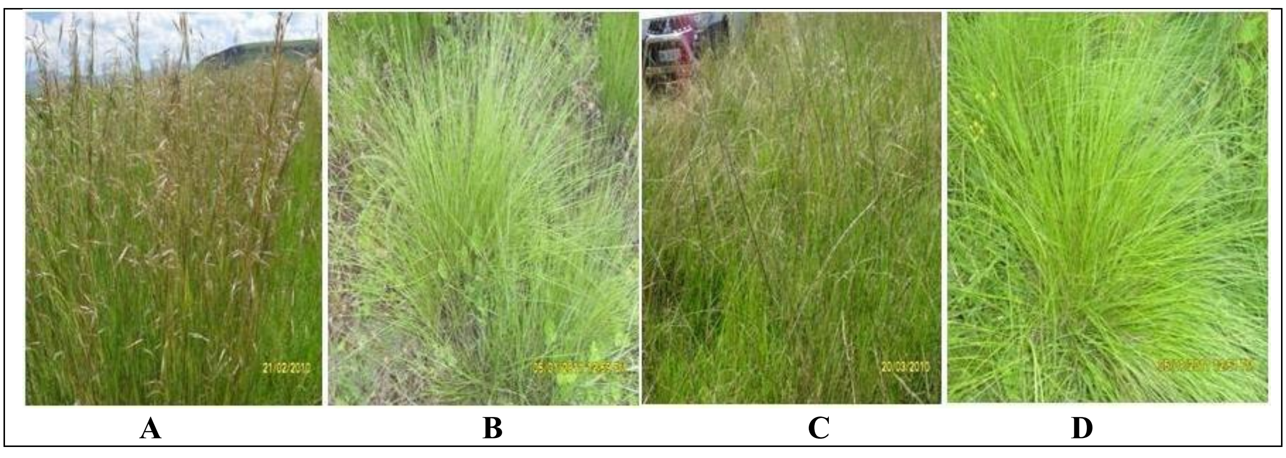

Figure 1.2: The most common grass species associated with rangeland degradation: (A) *Hyparrhenia hirta*, (B) *Eragrostis curvula*, (C) *Sporobolus africanus*, and (D) *Aristida diffusa*.

Generally, traditional techniques for mapping vegetation species are considered to be time-consuming, economically inefficient, and labour intensive (Feng et al., 2009; Peterson et al., 2002; Xie et al., 2008). A complementary remote sensing technique has successfully been used to provide a fairly accurate, repetitive and unbiased means for classifying and monitoring vegetation species. Therefore, techniques that make use of the advantages of remote sensing are needed for classifying increaser and decreaser species in order to determine the condition of rangelands.

1.3 Remote sensing of increaser species: Challenges and opportunities in degraded areas

Acquiring accurate information for the sake of classifying and monitoring increaser species distribution is an important technical task for sustainable rangeland management (Ramoelo et al., 2011). Remote sensing is a powerful tool that can obtain accurate information for mapping and monitoring vegetation species in different ecosystems (Wessels et al., 2008). Multispectral and hyperspectral remote sensing have been used for several decades in discriminating and mapping vegetation cover in disturbed areas (Escadafal and Huete, 1991; Okin et al., 2001; Pinet et al., 2006; Ray, 1995; Sun et al., 2007; Tromp and Epema, 1998; Tueller, 1987). However, remote sensing for the mapping and monitoring of changes in the spatial distribution of vegetation species in degraded environments faces some challenges (Beck et al., 1990; Okin et al., 2001; Tueller, 1987). These challenges are associated with the characteristics of degraded vegetation species as well as with sensor technology.

The challenges facing scientists in terms of the application of remote sensing for discriminating between vegetation species in degraded environments are as follows: vegetation species' phenological changes as a result of climate change, particularly precipitation, which leads to the spectral variability of the same species (Ray, 1995); the likelihood of nonlinear mixing due to the multiple scattering of light rays, which leads to an overestimation of green vegetation species (Ray and Murray, 1996) and vegetation species' adaptations to harsh environmental factors, which make the spectral reflectance of these species different (Ray, 1995). Multispectral imageries (i.e. Landsat and SPOT) are affordable, relatively available, and provide accurate data for discriminating between increaser and decreaser communities in degraded areas (Vogel and

Strohbach, 2009). However, multispectral data have proved ineffective for classifying vegetation at species level due to low spectral and spatial resolution (Harvey and Hill, 2001).

Currently, hyperspectral remote sensing is considered one of the most advanced techniques for species level discrimination due to its detailed features on many, very fine and contiguous spectral wavelengths (Vaiphasa et al., 2007). Imageries from sensors, such as Hyperion, HyMAP and AISA Eagle, are critical for the mapping and classification of small vegetation units (less than 2 m) at species levels (Mutanga and Kumar, 2007). However, in spite of the detailed spectral information of hyperspectral data, processing tends to be more difficult due to the statistical properties associated with high dimensional data, the high cost of images, and the need for an excessive number of field samples (Bajcsy and Groves, 2004; Vaiphasa et al., 2007).
Recent developments in multispectral sensor technology, such as WorldView-2 satellite provides better spectral resolution of eight wavelengths with high spatial resolution data of 0.5 m and 2.0 m on the panchromatic and multispectral wavelengths respectively (Omar, 2010; Sridharan, 2010). Therefore, since there is now the availability of relatively high spectral resolution sensors such as WorldView-2, it might be useful if the specific spectral wavelengths of this sensor for discriminating increaser species were investigated through the visible, red-edge, NIR-1, and NIR-2 of the electromagnetic spectrum and compare them to hyperspectral as well as traditional multispectral image data sets.

1.4 Study objectives

The main aim of this study was to investigate the potential use of remote sensing to discriminate between those increaser vegetation species (namely *Hyparrhenia hirta*, *Eragrostis curvula*, *Sporobolus africanus* and *Aristida diffusa*) that indicate different levels of rangeland degradation in the Okhombe communal grazing lands of South Africa.

The specific objectives in this study were as follows:

1. To evaluate the abundance and distribution of the increaser species and the different levels of rangeland degradation in the Okhombe communal lands and compare it with the Cathedral Peak conservation area using a veld condition assessment technique;
2. To assess the utility of *in situ* spectroscopic data in discriminating between four different increaser species;
3. To investigate whether or not canopy reflectance spectra, resampled to AISA Eagle spectral resolution, could be used to discriminate between the four increaser species; and
4. To investigate the potential use of the new 8-band WorldView-2 imagery in classifying the four increaser species.

1.5 Scope of the study

This study evaluated the condition of rangeland in the Okhombe communal grazing lands as well as in the Cathedral Peak area of KwaZulu-Natal Province by using the factors of species composition, basal cover and soil characteristics. The potential application of remote sensing techniques for classifying different levels of rangeland degradation based on the relative abundances and distribution of increaser species was also examined. Because increaser species are characterised by a low grazing value and because their relative abundances increase through overgrazing or underutilisation, these two factors can be used as indicators of the poor condition of rangeland. The usefulness of hyperspectral data in classifying increaser species was tested through the use of a handheld spectrometer under field conditions. Since the current available hyperspectral image sensors lack the fine spectral resolution of the field spectroscopic (ASD) data, the ASD data were resampled to AISA Eagle resolution. The utility of multispectral datasets for classifying increaser species was also assessed using WorldView-2 satellite imagery.

1.6 General description of the study area

The two different sites of Okhombe communal rangeland (dominated by increaser species) and the KZN wildlife conservation area of Cathedral Peak (dominated by decreaser species) were selected for detailed investigation. The locations of the study sites are shown in Figure 1.3. The reason behind the choice of these two study sites was (1) to evaluate the veld condition based on the relative abundances and distribution of the species (increaser and decreaser) on degraded and conserved sites, and (2) to investigate the potential use of remote sensing to discriminate between those increaser species (namely increaser I, increaser II and increaser III) that indicate different levels of rangeland degradation in the Okhombe communal rangeland.

1.6.1 Okhombe

The study was conducted in the Okhombe communal rangelands (latitude 28^{o} 30' S to 30^{o} 30' S and longitude 28^{o} 30' E to 29^{o} 30' E), which have an area of 200 km^2. Okhombe is a ward that comprises six sub-wards, namely Mpameni, Mahlabathini, Ngubhela, Oqolweni, Sgodiphola and Enhlannokhombe. The selected area lies within the foothills of the northern Drakensberg (a mountain range) in the province of KwaZulu-Natal (KZN). The average altitude for the site is 1,200 m. The average air temperature is 11.5 to 16^{o} C in summer (October to March), while in winter (June and July) the mean monthly temperature reaches only 5^{o} C, with frost and snow occurring almost every winter (Temme et al., 2008). The mean annual rainfall of the area is about 800 to 1,000 mm, and about 82% of this rainfall falls in the summer months (Dollar and Goudy, 1999). Precipitation has resulted in significant leaching of the major soils in the area as well as heavy erosion along the slopes of the foothills. There are occasional cycles of drought during the summer, severe to very severe frost in winter, short growing seasons, and hailstorms (Camp, 1997).

The vegetation is predominantly grassland, but there are also patches of forest and shrubland (Tainton, 1999). Vegetation communities are associated with the following three distinct altitudinal zones (O'Connor and Bredenkamp, 1997): river valleys (1,250 to 1,800 m), the Little Berg (1,800 to 2,500 m), and the summit plateau (2,500 to 3,350 m). The corresponding vegetation belts of these zones are: the Montane Belt, the Subalpine Belt, and the Alpine Belt. The dominant species within these zones are as follows: the *Hyparrhenia* species, the *Eragrostis* species, the *Digitaria* species, the *Diheteropogon* species, the *Panicum* species, *Monocymbium ceresiiforme, Harpochloa falx, Cymbopogon validus,* the *Sporobolus* species, and *Miscanthus capense* (O'Connor and Bredenkamp, 1997). The vegetation is influenced by many factors, which can be divided into natural factors (namely climate, soil properties and altitude) and man-induced factors (such as population increase, overgrazing and deforestation) (Critchley and Netshikovhela, 1998; Everson and Tainton, 1984; Hoffman and Todd, 2000). The absence of effective management strategies with regard to the natural resources of communal rangelands has had negative effects on the land's productivity (Nsuntsha, 2000; Peden, 2005). Therefore, large parts of the study area are severely degraded, which has resulted in the loss of grass cover, increased runoff, poor water infiltration, and severe soil erosion (Everson et al., 2007). The Okhombe LandCare Project was part of the National LandCare Programme that was initiated to rehabilitate the degraded areas in the communal rangelands of Okhombe and it used simple erosion control techniques (Everson et al., 2007). This programme was followed by the implementation of a community-based monitoring project which aimed to determine the effect of rehabilitation on reducing soil erosion and increasing vegetation cover in the degraded areas.

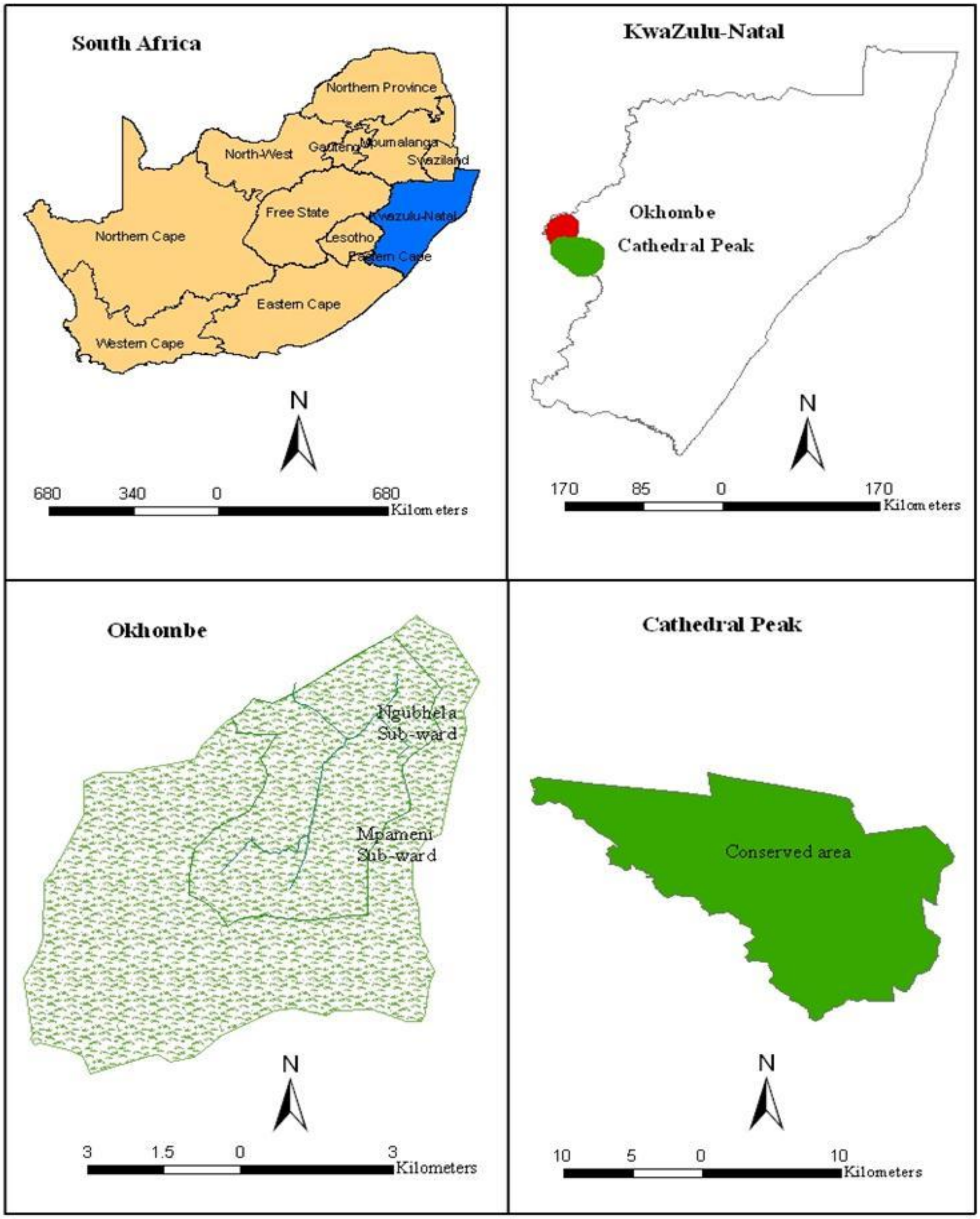

Figure 1. 3: Location of study area in the KwaZulu-Natal (KZN) province of South Africa.

1.6.2 Cathedral Peak

The study was also conducted in the KZN wildlife conservation area of Cathedral Peak (longitude 29° 00' E to 29° 30' E and latitude 28° 45' S to 29° 15' S), which is situated in the northern part of the uKhahlamba-Drakensberg Park. The uKhahlamba-Drakensberg Park has an altitude that varies from about 1,860 to 2,070 m above sea level (Everson, 2001). The climate consists of wet, humid summers and dry, cold winters. The study area receives between 1,300 and 1,400 mm of rain annually. Most of the rain (80%) falls during the summer months, from October to March (Nel and Sumner, 2005; Schulze, 1975). Roughly half the precipitation (45 to 50%) results in stream flow (Bosch, 1979; Scott, 1993). The average maximum monthly temperature varies from 18° to 26° C, and the average minimum monthly temperature ranges from 3° to 14° C (Smith and Scott, 1992). The soil materials are basalt-derived silty clays in the low areas, and shales, sandstone and mudstone on the slopes and plateau (Everson, 2001; Govender and Everson, 2005; Watson, 1984). Soils are classified as lateritic red and yellow earths, grading into heavy black soils (Granger and Schulze, 1977). Characteristically these soils are highly leached, acidic and structure-less, having high organic content (6 to 10%) and a mean soil depth of 0.8 m (Everson, 2001; Schulze, 1975). The study area is extensively covered by grassland and falls into the Montane Belt. The vegetation falls under the Moist Highland Sourveld, KZN Bioresource Group 8 (Mucina and Rutherford, 2006).

1.7 Outline of the thesis

Apart from the first and last chapters (i.e. the introduction and the synthesis), the thesis consist of a set of research papers that address each of the objectives listed in Section 1.4. Most of these papers have been submitted to peer-reviewed international journals: four are currently under review whilst the fifth is still in revision. The thesis consists of seven chapters in total.

Chapter One: This chapter serves as an introduction to the study.

Chapter Two: This chapter covers the problem of rangeland degradation in South Africa and the use of remote sensing (multispectral and hyperspectral) in mapping rangeland degradation by way of different indicators. The concept of decreaser and increaser species and how this concept can be used to map rangeland degradation is discussed. The gap and need for using decreaser and increaser species as indicators for rangeland degradation is also discussed.

Chapter Three: This chapter focuses on exploring the relationship between vegetation species (increaser and decreaser species) in determining rangeland condition by using factors of species composition, basal cover, and soil characteristics, the latter of which includes phosphorus, potassium, calcium, magnesium, pH, zinc, manganese, copper, organic matter and nitrogen.

Chapter Four: The focus of this chapter is the potential use of remote sensing in discriminating among four increaser species by using raw field spectrometry (ASD) data and discriminant analysis as classifiers. The study also determines whether or not there is a significant difference ($P < 0.05$) between the mean reflectance at each measured wavelength (from 350 to 2500 nm) and the four increaser species (*Hyparrhenia hirta, Eragrostis curvula*, *Sporobolus africanus* and *Aristida diffusa*) indicative of different levels of rangeland degradation. The crucial wavelengths that are most sensitive in discriminating these four species are also identified.

Chapter Five: This chapter investigates the potential use of hyperspectral remote sensing in discriminating among increaser species ($n = 4$) by resampling the ASD data to AISA Eagle resolution and using random forest as a classification algorithm. The models developed are linked to the knowledge presented in Chapter 4.

Chapter Six: In this chapter a new WorldView-2 imagery with unique band settings is evaluated in relation to the task of classifying increaser species within a complex rangeland environment. Specifically, the study examined the ability of 8bands, of different vegetation indices derived from WorldView-2 imagery, and of combined bands and vegetation indices to better improve the classification accuracy of increaser species using the random forest algorithm.

Chapter Seven: This chapter highlights the study's main results. Conclusions are also derived based on the findings of the preceding chapters. In this chapter the contribution of the thesis to collective knowledge on the topic is discussed. Finally, the limitations of the study are discussed, and avenues for future studies are recommended.

CHAPTER TWO

Literature review

This chapter is based on:

Manssour, K., Mutanga, O., and Everson, T., (In review). Remote sensing based indicators of vegetation species for assessing rangeland degradation: Opportunities and challenges. *African Journal of Agricultural Research.*

Abstract

Rangeland degradation is a serious hindrance to sustainable development in degraded areas. Mapping and monitoring vegetation species is an increasingly important issue across various fields of rangeland management. Remote sensing technology is a tool for mapping and monitoring vegetation species and it provides timely and relatively accurate information concerning degradation in biological rangeland resources. The objective of this review was to provide precise and essential information relating to the application of both multispectral and hyperspectral sensors as well as to their limitations with regard to mapping and monitoring rangeland degradation based on the abundance and distribution of vegetation species and algorithms used to process remotely sensed data when classifying these species. The abundance and distribution of the different vegetation species can be used to indicate the gradient level of rangeland degradation. It can be concluded that up-to-date spatial information and appropriate processing techniques are essential requirements for extracting increaser and decreaser spectral information that can be used for sustainable rangeland management.

Keywords: Remote sensing; rangeland degradation; indicator; vegetation indices; increaser and decreaser species.

2.1 Introduction

Rangeland is an important natural ecosystem that offers a habitat for wildlife, grazing areas for domestic stock, and goods for local communities (Kawanabe et al., 1998). Rangeland grass degradation has been identified as being one of the most serious global environmental issues that needs to be addressed (Hill et al., 1995; Kassahun et al., 2008).Grassland degradation can be defined as a reduction in grassland productivity at a particular site in moist or dry sub-humid areas as a result of human activities and natural factors (Liu et al., 2004; Ravi et al., 2010). Human causes of grassland degradation are: overstocking, the expansion of cropped areas, increased fires, and poor land use management and planning. Natural causes include changes in climate elements and soil properties (Eswaran et al., 2001; Hoffman and Todd, 2000). Grassland degradation can usefully be considered in terms of types of grass communities and the production characteristics of different grasses, particularly their grazing value (Tainton, 1999). Grassland plant quality and quantity have been successfully used as indicators for mapping, monitoring and classifying rangeland degradation in degraded areas (Van den Berg and Zeng, 2006). This is because some plant species are well adapted to specific growth conditions and their quality and quantity characteristics may change dramatically if these conditions change (Van den Berg and Zeng, 2006; Van Oudtshoorn, 1992).

Grasses are classified into two categories (i.e. increasers and decreasers) based on their grazing value and the changes in their relative abundance in the presence or absence of grazing (Dobarro et al., 2010). Decreaser species are the dominant species in flourishing rangelands, but they diminish when rangeland deteriorates through over- or underutilisation (Hardy et al., 1999). Increaser species, by contrast, flourish in rangelands that are overgrazed or underutilised, and the abundance of these species is therefore an indicator of the poor condition of rangeland (Dobarro et al., 2010; Van Oudtshoorn, 1992). The assessment of rangeland degradation based on the abundance and distribution of decreaser and increaser species has been successfully evaluated and classified (Tainton, 1988; Trollope et al., 2008; Van Oudtshoorn, 1992).

Mapping the extensively degraded grasslands requires the use of conventional survey methods such as local expert knowledge and field observation to provide accurate information on the spatial distribution of grass species. These methods provide significantly better results when it comes to mapping species over small geographic areas. However, these conventional field-based methods require visual estimation of species percentage as well as intensive fieldwork, which includes the identification of species characteristics. Such undertakings are both costly and time-consuming, because grasslands usually cover large expanses that are, moreover, situated in isolated and inaccessible areas (Feng et al., 2009; Tromp and Epema, 1998). On the other hand, the remote sensing techniques to map the spatial distribution of grass species over large geographic areas of degraded rangeland have attracted scientific attention, resulting in the provision of different spatial resolution imageries that are not only feasible and cost-effective but that also provide timely and accurate information (Lees and Ritman, 1991; Shoshany, 2000; Tromp and Epema, 1998; Ustin et al., 2009).

The advancement in remote sensing comes up with high-resolution hyperspectral data that provide a significant enhancement of spectral measurement capabilities for investigating the most powerful contiguous and narrow wavelengths (less than 10 nm) throughout the ultraviolet, visible and infrared portions of the electromagnetic spectrum (Kumar et al., 2001; Thenkabail et al., 2004). These narrow spectral wavelengths allow the identification of characteristic spectral attributes for the mapping and monitoring of vegetation at species levels in different ecosystems (Thenkabail et al., 2004; Zwiggelaar, 1998). In spite of the great capability of remote sensing to provide detailed spectral information, the mapping of vegetation species using hyperspectral remote sensing data is challenging due to data dimensionality, data processing, and the fact that the images are too prohibitively expensive to use (Metternicht et al., 2010; Okin et al., 2001; Pinet et al., 2006; Schmidtlein and Sassin, 2004; Underwood et al., 2003). However, multispectral data is relatively available, at a low cost, and does not require complex preprocessing and processing techniques. Considering these advantages, the use of multispectral data should be operationalised and implemented in order to provide accurate and up-to-date information on mapping vegetation species over large areas. However, mapping vegetation in degraded areas at species level using multispectral data such as Landsat TM and SPOT imagery is challenging because of the low spectral resolution of sensors and spectral overlap between the vegetation species (Harvey and Hill, 2001).

The development in multispectral sensors, such as WorldView containing key spectral bands, has brought about unique opportunities for those wishing to classify vegetation at species level (Dlamini, 2010; Omar, 2010). Multispectral and hyperspectral data have been used for several decades in mapping vegetation communities in degraded ecosystems (Schmidtlein and Sassin, 2004; Tromp and Epema, 1998; Vogel and Strohbach, 2009).

Previous reviews concerning the application of remote sensing techniques in grassland degradation have been done. Lass et al. (2005) investigated the use of hyperspectral remote sensing of invasive species detection. Metternicht et al. (2010) reviewed the potential use of remote sensing for assessing and mapping different indicators of land degradation. Shoshany (2000) reviewed the utility of spectral, temporal and spatial data for identifying Mediterranean grassland regions and the limitations of multispectral applicability. Pinet et al. (2006) reviewed the possibilities of using imaging spectroscopy for monitoring land degradation and desertification. Hill et al. (1995) discussed the potential use of multispectral remote sensing for mapping and monitoring land degradation in Mediterranean environments. Based on the results of the above-mentioned studies, the human and physical factors causing rangeland degradation are thought to be severe overstocking and climate change respectively. The application of multispectral and hyperspectral remote sensing techniques provides accurate and timely information for mapping and monitoring vegetation cover. The shortcomings of the above-mentioned studies are that no specific review has focused on the application of multispectral and hyperspectral remote sensing techniques for mapping and classifying the increaser and decreaser species as indicators of different levels of rangelands condition.

This study reviews the research results concerning the application of both multispectral and hyperspectral remotely sensed data for vegetation species discrimination. The specific objectives of this study were: (1) to review discriminating and mapping vegetation species in degraded rangelands; (2) to highlight the advancement in remote sensing technologies in terms of spectral bands and critical band settings and their capabilities for classifying vegetation species within a complex rangeland environment; and (3) to highlight the major challenges still involved in remote sensing and suggest what further research is needed for the successful application of remote sensing in mapping vegetation species in degraded areas.

2.2 Assessing and monitoring rangeland degradation using different traditional field-based methods and approaches

Rangeland condition is measured to evaluate the rangeland productivity and plan management interventions (Passmore and Brown, 1991; Paudel and Andersen, 2010; Peden, 2005). Numerous efforts have been made to assess and monitor rangeland degradation using various methods and approaches, such as expert opinions, herder knowledge, focus group discussions, land users' opinions, benchmarks, basal cover, Shannon's diversity index, observations and measurement of soil properties, and estimates of productivity changes (Moyo et al., 2008; Oba and Kaitira, 2006; Oluwole and Dube, 2008; Stringer and Reed, 2007). Oba and Kaitira (2006) used the herder knowledge approach to evaluate the communal rangelands in Maasai grazing territory in northern Tanzania. The method was based on the relative abundance of increaser and decreaser species. Their results showed that herder knowledge approach can be used to classify the rangeland into the following different levels: non-degraded, stable and degraded. Moreover, the herder knowledge method provides a quick way of understanding the current status of the rangelands. Unfortunately due to the herders' migratory behaviour, the challenge was how to engage them in participatory research.

In the Eastern Cape of South Africa, Oluwole and Dube (2008) assessed the utility of the benchmark method, the basal cover technique, and soil analysis to evaluate rangeland condition. Their results demonstrated the feasibility of using the benchmark method, the basal cover technique, and soil analysis, as these three methods were able to classify the condition of the rangeland into non-degraded, moderately degraded, poorly degraded, and extremely degraded. Stringer and Reed (2007) used land users' opinions to evaluate soils (erosion, fertility and productivity) in Botswana and Swaziland. They concluded that combining local and scientific knowledge can enhance rangeland degradation assessments at national and regional levels. The expert opinion method (e.g. indicators, questionnaires, interviews and focus groups) was developed by Jones et al. (2003) to assess the causes, degree, extent and impact of rangeland degradation in Europe. The study produced reasonable results for rangeland degradation assessment using the expert opinion method. However, because some respondents did not reply, or the replies of others were incomplete, the results were difficult to use when comparing regions. However, most of the above-mentioned scientists utilised these methods in the assessment of commercial rangeland. The usefulness of such methods for assessing communal rangelands is less well established (Reed and Dougill, 2002). Moreover, such methods tend to be economically inefficient, time consuming and labour intensive, and are sometimes impossible to accomplish due to the fact that rangelands cover a large spatial extent and are difficult to access (Feng et al., 2009; Peterson et al., 2002). The remote sensing technique offers quick and repetitive data (including detailed information on vegetation status) and is accurate and potentially inexpensive, and could thus successfully evaluate rangeland degradation in a large region (Tanser and Palmer, 1999; Wessels et al., 2008). Although the previous studies produced reasonable results with regard to mapping rangeland degradation based on vegetation communities using conventional field-based methods and remote sensing, more attention needs to be given to the issue of how to improve the accuracy of mapping increasers and decreasers at species level in order to identify different levels of rangeland degradation.

2.3 Spectral properties of vegetation species in degraded areas

In degraded environments that are characterized by sparse vegetation species and the spectral effects by soil background, a careful consideration should be given to the spectral properties (Hill et al., 1995). Sunlight is the main source of energy for several biological activities taking place inside the plant cells (Ustin et al., 2009). When light interacts with the vegetation surface, it can be reflected, absorbed, and/or transmitted due to different materials on the earth's surface. An understanding of the spectral behaviour of increaser and decreaser species is essential for interpretation of a remotely sensed image. In general, many efforts have been made to better understand the relationship between light solar radiation and plant leaves. The spectral response of vegetation depends upon the properties of both the incoming radiation (e.g. angle of incidence, conditions of radiation and wavelength) and the vegetation (chlorophyll a and b, α-carotene, b-carotene, xanthophylls, protein, oil, water, starches, lignin, cellulose, sugar and nitrogen) (Asner, 1998; El-Nahry and Hammad, 2009). The spectral reflectance of vegetation species in degraded areas is normally subdivided into three domain regions namely; the visible (400 - 700 nm), the near-infrared (NIR; 700 - 1300 nm), and the mid-infrared (MIR; 1300 - 2500 nm) (Figure 2.1) (El-Nahry and Hammad, 2009; Ustin et al., 2009). Vegetation types have low reflectance and transmittance in the visible region due to strong absorption by chlorophyll a and b, b-carotene, α-carotene, and xanthophyll (El-Nahry and Hammad, 2009; Ustin et al., 2009). They have a high reflectance and transmittance in the NIR region because of their very low absorption of xanthophylls, chlorophyll a and b, b- carotene, and α-carotene. Plant leaves absorb only 4% of the radiation and the remaining 96% is reflected and transmitted (Woolley, 1971). In the NIR, a plant leaf will typically reflect between 40 and 50%, while the rest is transmitted, with only about 5% being absorbed (Govender et al., 2009). The limited absorption in this region is aided by dry leaves, primarily cellulose, lignin, and other structural carbohydrates (Asner, 2000; Cochrane, 2000). Ustin *et al.* (2009) and Cochrane (2000) reported that the internal leaf structure is the dominant factor controlling the spectral response of plants in the NIR region. Also, reflectance in this region is affected by numerous scatterings, including refraction at air-water interfaces and the fraction of air spaces (Ustin et al., 2009). Spectral reflectance is characterised by being much lower in the MIR than in the NIR due to the strong water absorption by the leaves and the minor absorption features of their biochemical content (Hestir et al., 2008). In green leaves reflectance and transmittance in the short wave infrared (SWIR) are influenced by water absorption (Ustin et al., 2009).

As there has been no specific research on how increaser and decreaser grass species interact with light, detailed investigation into these aspects is needed for a better understanding of the spectral response of vegetation species in degraded areas. The results of such studies could help researchers to develop accurate models describing, for example, the discrimination of increaser and decreaser species, estimations of grazing value in the rangelands based on increaser and decreaser species, and increaser and decreaser species' biophysical characteristics. Scientists working in the environmental conservation field could use these models to develop methods for rangeland management.

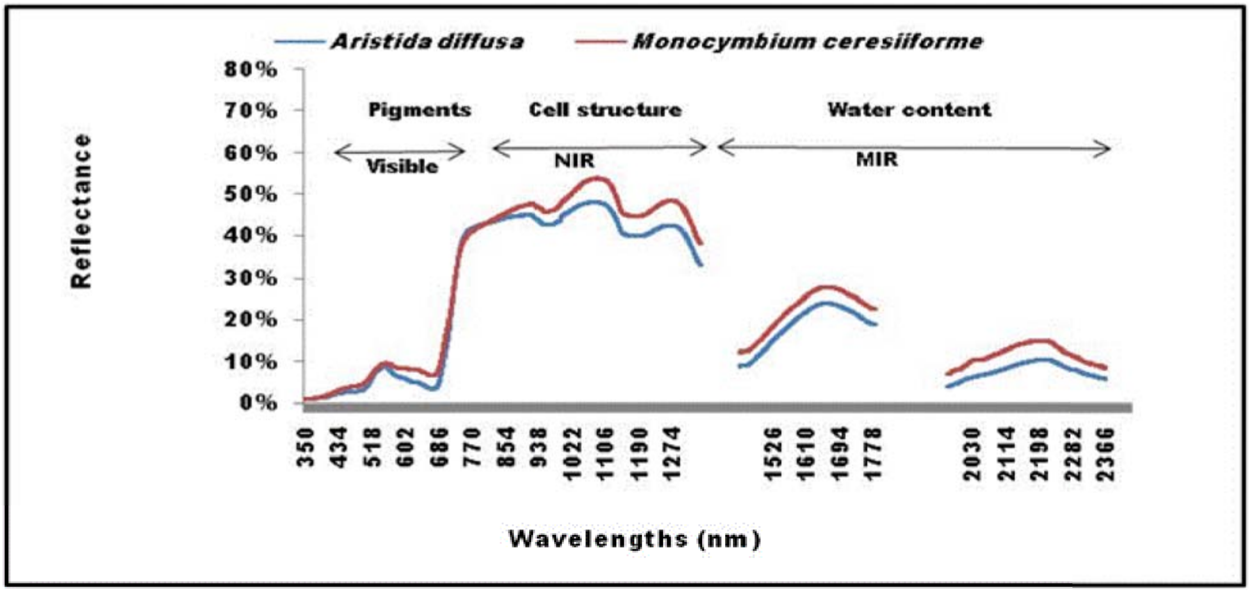

Figure 2. 1: Mean spectral canopy curves for increaser species (*Aristida diffusa*) and decreaser species (*Monocymbium ceresiiforme*) in Drakensberg montane grasslands with the dominant factors controlling reflectance being displayed.

2.4 Application of multispectral remote sensing in mapping vegetation species in degraded areas

Mapping and monitoring vegetation species in disturbed areas require that there be extensive coverage and that quantitative, timely, accurate and regularly collected information be gathered. All these factors have made the use of remote sensing a powerful tool (Ustin et al., 2009). Since the early 1900s, when the first aerial photographs were taken, aerial photography with low spatial resolution has been considered the first remote sensing technique, being used as a source of information for mapping vegetation cover (Lillesand, 1999; Mumby, 1999). It can be concluded that aerial photography has considerable advantages over satellite-based data because of the former's availability, low cost, and because the span of the record covers a longer time period (Wentz et al., 2006). However, aerial photography has not been widely used for mapping and monitoring vegetation cover because of the high costs of colour-infrared film and processing, as well as the coarse spatial and low spectral resolutions, which affect the actual mapping of vegetation (Kakembo, 2001; Laliberte et al., 2004). Recently, multispectral remote sensing with different properties (spatial and spectral resolution) and a variety of sensors (Landsat TM, Landsat ETM+ and SPOT) have been used to discriminate vegetation cover in degraded areas (Liu et al., 2004; Sun et al., 2007; Wu, 2008). Wu et al. (2008) evaluated the potential of multispectral remote sensing by using Landsat images (MSS and TM) to classify vegetation cover in the degraded land of MuUs sandy land in China. The maximum likelihood classifier was used. They concluded that Landsat has great potential when it comes to classifying vegetation cover as there was an overall accuracy of 98.4% (Kappa 0.947) for Landsat MSS, and 99.8% (Kappa 0.995) for Landsat TM.

Savanna rangeland degradation in Namibia was classified by Vogel and Strohbach (2009), who used Landsat TM and ETM+ data. The decision tree classifier was also used. Their results show that savanna degradation can be classified into the following six classes: vegetation densification, vegetation decrease, complete vegetation loss, long-term vegetation patterns, the recovery of vegetation on formerly bare soils, and no change with an overall accuracy of 73.4% with respect to the class pairs' accuracies' which ranged from 80% to 100% for producers' and users' accuracies.

The relative effectiveness of Landsat ™ was tested in terms of mapping the severity of grassland degradation near Lake Qinghai in west China, which was divided into the following four classes: severe, moderate, slight, and intact, with an overall accuracy of 91.7% (Liu et al., 2004).

Feng et al. (2009) attempted to discriminate grassland degradation in Guinan County, China, by using data from Landsat MSS, Landsat 5 and Landsat 7 ETM. Visual interpretation and digitisation were performed. The results showed that grassland degradation can be classified into three classes: high density, medium density, and low density, with an overall accuracy of 91.07%.

The results of the above-mentioned studies produced reasonable results for discriminating between vegetation communities on a regional scale when using multispectral data. However, Landsat and SPOT data have proven insufficient for classifying vegetation at species level because of the low spectral resolution of sensors and the spectral overlap between the vegetation species. Also, most multispectral remote sensing data do not have the red-edge region that is insensitive to atmospheric interference and soil background (Vogel and Strohbach, 2009; Wu, 2008). Therefore, the developments in multispectral data (WorldView) and hyperspectral data can be useful for discriminating rangeland degradation based on the spatial distribution of vegetation species (at species level) because of the detailed spectral information that they can provide. More work is needed to improve the classification accuracy of mapping the spatial distribution of increaser and decreaser species.

2.5 Limitations when applying hyperspectral remote sensing to vegetation species classification in degraded areas

In the field of remote sensing, hyperspectral remote sensing – also known as „imaging spectrometry', „imaging spectroscopy', „ultraspectral imaging', „hyperspectral spectroscopy' and „narrow-band imaging' – is a relatively new technology that is currently being used in vegetation studies (Clark, 1999; Mutanga, 2004). Hyperspectral remote sensing has hundreds of narrow, continuous spectral bands between 400 nm and 2500 nm throughout the visible (0.4 to 0.7 nm), near-infrared (0.7 to 1 nm) and shortwave-infrared (1 to 2.5 nm) portions of the electromagnetic spectrum (Govender et al., 2009). These narrow bands of hyperspectral remote sensing allow for in-depth mapping and discrimination of vegetation species, something that would not be possible with other multispectral sensors (Okin et al., 2001; Pinet et al., 2006; Wang et al., 2010a). Spectral absorptions and reflectance changes in the 400 - 2500 nm range of the reflected electromagnetic radiation provide analytical features that can be used to identify vegetation species (Pinet et al., 2006).

Okin et al. (2001) assessed the utility of AVIRIS satellite imagery for accurately discriminating among vegetation types in the Mojave Desert, USA. Multiple Endmember Spectral Mixture Analysis (MESMA) and Spectral Mixture Analysis (SMA) were performed to estimate the proportion of each ground pixel's area that fits with different cover types. They concluded that AVIRIS show low potential for classifying vegetation types with an overall accuracy of only 30% due to low vegetation cover.

Hestir *et al*. (2008) tested the ability of HyMap data in the visible near-infrared region (VNIR) and in SWIR (0.45 - 2.5 µm) for discriminating and mapping two invasive species in the California Delta, USA, when using a logistic regression. Their results showed that the HyMap data distinguished perennial *pepperweed* from *pseudoabsence* with accuracies of 75.8% and 63.0% respectively.

Discriminating and mapping vegetation degradation at Fowlers Gap Arid Zone Research Station in western New South Wales, Australia, was also done using random forest by Lewis (2000). In this research, perennial vegetation, *chenopod* shrubs and trees were selected for classification using the hyperspectral imaging (CASI). An area of less than 25% was discriminated and mapped. He concluded that high-spectral resolution imagery has potential for the discrimination of vegetation cover in arid regions. However, some authors have successfully used hyperspectral remote sensing for mapping grassland degradation. Wang et al. (2010) assessed the utility of hyperspectral remote sensing for mapping dominant vegetation species (*Leymus chinensis*, *Stipa krylovii* and *Artemisia frigid*) in Hulunbeier, China. They concluded that hyperspectral remote sensing has considerable potential for the discrimination and mapping of these species with an overall accuracy of 95%. Spectral classification of grass quality in African rangeland was also done by Mutanga (2005) using the high-resolution GER spectra, which were resampled to the HYMAP. In this research, Fisher's linear discriminant function was used to discriminate between groups of *Cenchrus ciliaris* grass, which were all grown under different nitrogen treatments. The results showed that it is possible to classify samples to their respective groups with an overall accuracy of 77.1%.

In general there are limitations to using hyperspectral remote sensing for vegetation discrimination at species level. These limitations are due to the following: (1) the effects of a large soil background as a consequence of relatively sparse vegetation (Escadafal and Huete, 1991); (2) plant adaptations to the harsh environment that make the spectral reflectance of the same plants different (Ray, 1995); (3) phenological changes as a result of changes in climatic conditions (in particular, rainfall leads to spectral variability of the same species) (Ray, 1995); (4) the possibility of nonlinear mixing due to multiple scattering of light rays, which leads to an overestimation of green vegetation cover (Ray and Murray, 1996); (5) variations in chlorophyll and carotenoid pigments, leaf structure and succulence (Lewis, 2000); and (6) changes in land use and the relative impact of vascular tissue (Asner et al., 2000). Moreover, there are some limitations related to the hyperspectral data which are extremely large and of high dimensionality (Thenkabail et al., 2004). This problem is termed "curse dimensionality" which leads to the "peaking phenomenon" or "Hughes phenomenon" (Hsu, 2007). Hughes phenomenon means that the field samples are insufficient for the classification requirement which makes the estimation of statistical parameters for the classifier performance inaccurate and unreliable (Hsu, 2007;

Jackson and Landgrebe, 2001). Therefore, the analysis of hyperspectral data is complex and needs to be simplified by way of selecting the optimum number of bands required for mapping and classifying vegetation species.

Different statistical band reduction techniques for classification of hyperspectral data have been developed. These include discriminant analysis, classification trees, principal component analysis, support vector machines, artificial neural network, partial least square regressions and random forest (Adam and Mutanga, 2009; Bajcsy and Groves, 2004; Filippi and Jensen, 2006; Huang et al., 2002; Lawrence et al., 2006; Mutanga, 2005; Thenkabail et al., 2004).

All the above-mentioned studies have shown the potential of hyperspectral data (as opposed to multispectral data) to provide significant improvements in spectral information for discriminating vegetation at species level. More studies for mapping and classifying vegetation species particularly increaser species are needed to build a spectral library for rangeland in degraded areas.

2.6 Improving the classification accuracy of vegetation species using the advanced multispectral sensors

As mentioned above, there is a limitation to traditional multispectral sensors (Landsat and SPOT) when it comes to increaser and decreaser classification at species level since they can only provide limited spectral information. Considerable efforts have been made to improve the multispectral data characteristics to work within the species classification field. These efforts include advances in sensor technology, the development of spectral vegetation indices, the improving of classification techniques and the use of multi-sensor imageries (Cavayas, 2010; Liu et al., 2004; Sun et al., 2007). The WorldView-2 satellite sensor is a new generation sensor that significantly enhances spectral measurements' capabilities over those of traditional multispectral sensors (Dlamini, 2010; Kumar and Roy, 2010; Omar, 2010). The 8-bands multispectral WorldView-2 is a new satellite imaging that was launched in October 2009 by DigitalGlobe. It has a high spatial resolution of 2 m (multispectral) and 0.5 (panchromatic) at nadir. The 8 multispectral bands include four conventional wavelengths located at visible region: blue (450 nm - 510 nm), green (510 nm - 580 nm), red (630 nm - 690 nm), and near-infrared region (770 nm - 895 nm), in addition to four new wavelengths, which are located at the following places:

coastal (400 nm - 450 nm), yellow (585 nm - 625 nm), red-edge (705 nm - 745 nm) and near-infrared 2 region (770 nm - 895 nm).

In Malaysia, Omar (2010) was able to identify ten of the country's tropical vegetation species using WorldView-2 imagery. Classification techniques such as maximum likelihood and linear discriminant analysis were performed. The findings from this research showed that the most potentially useful information can be used to discriminate among tropical vegetation species with an overall accuracy of 90%. Better discrimination was achieved in the 903 nm (NIR 2), 831 nm (NIR 1), and 724 nm (red-edge) bands.

Cavayas et al. (2010) evaluated the effectiveness of WorldView-2 data in classifying vegetation cover in the city of Laval in Quebec, Canada. The authors showed the potential of WorldView-2 data for classifying vegetation cover into Crop 1, Crop 2, Crop 3, Crop 4, Crop 5, Crop 6, grass/herbaceous, grass/terrain golf, woodlands, woodlands (urban trees), and non-vegetation area, using training data and supervised classification (maximum likelihood). They concluded that spectral bands in the blue, green, red and NIR 1 regions have strong potential for vegetation cover separation.

In central Swaziland, the new spectral bands of Worldview-2 satellite were tested by Dlamini (2010), who was able to classify two invasive alien plants, namely *Chromolaena odorata* and *Lantana camara*. These results demonstrated that invasive alien plants can be classified using traditional bands (blue, green, red and NIR 1) with a classification accuracy of 95%; the greatest classification accuracies of 99% were obtained using new bands (Coastal blue, yellow, red-edge and NIR 2). Kumar and Roy (2010) used WorldView-2 data to classify the following six agricultural crops in Muzaffarnagar, India: early wheat, ratoon, berseen (fodder), late wheat, sugarcane, and cauliflower. The results showed that the WorldView-2 data was capable of classifying six agricultural crops with accuracies that varied from 93% to 98%. The researchers also found the following important bands for identifying and mapping crops: existing bands 5 (red) and 7 (NIR 1), and new bands 4 (yellow), 6 (red-edge) and 8 (NIR 2).

Research into the classification of vegetation species by way of WorldView-2 data has achieved promising results. However, more research is still needed in terms of the classification of increaser species in disturbed areas. Increaser species classification has inconsistencies due to different species' responses under different ecosystems, and understanding their ecophysiological mechanisms therefore remains unclear. Investigators need to use the capability of WorldView-2 satellite sensors to look at the biochemical and biophysical parameters that can be used to discriminate and monitor increaser species.

2.7 Improvement of vegetation species' classification using spectral vegetation indices

Early remote sensing measurements of vegetation used data collected by different satellite sensors that measured wavelengths of absorbed light (red portion) and reflected light (near-infrared portion) by way of certain pigments in the plant leaves in degraded areas. These portions of the electromagnetic spectrum (red and near-infrared) are the most important in vegetation indices calculation (Ibrahim, 2008). Spectral vegetation indices (VIs) derived from remotely sensed data have become one of the most important information sources for mapping and monitoring vegetation species in degraded areas (Sun et al., 2007). VIs are useful in the following: (1) reducing variations caused by atmospheric conditions, irradiance, sun view angles, canopy geometry, and shading; (2) minimising the effect of soil background on the canopy reflectance (Elvidge and Chen, 1995); and (3) enhancing the variability of spectral reflectance of vegetation (Liu et al., 2004). VIs are calculated based either on multispectral data or on hyperspectral data. The most widely used VIs are the normalised difference vegetation index (NDVI) (Rouse, 1974), the simple ratio (SR) (Gitelson and Merzlyak, 1993), and the transformed vegetation index (TVI) (Deering et al., 1975), all of which respond to the variation in the red and near-infrared portions. Other VIs were developed in order to minimise the effects of soil background, atmospheric conditions, canopy geometry, and sun view angles. These VIs include the modified chlorophyll absorption in reflectance index (MCARI) (Daughtry et al., 2000), the transformed chlorophyll absorption in reflectance index (TCARI) (Haboudane et al., 2002), the visible atmospherically resistant index (VARI) (Gitelson et al., 2002), the visible green index (VGI) (Gitelson et al., 2002), the plant senescence reflectance index (PSRI) (Merzlyak et al., 1999), the structure-insensitive pigment index (SIPI) (Penuelas et al., 1995), the modified normalised difference (MND) (Sims and Gamon, 2002), and the soil-adjusted vegetation index (SAVI) (Huete, 1988).

Mahboob et al. (2011) assessed the effectiveness of NDVI to classify between coniferous and broadleaved species in Ayubia National Park, Pakistan, using SPOT 5 and ALI imageries. Supervised classification methods were performed. The authors recorded an overall accuracy of 91% and 88% for SPOT 5 and ALI imageries respectively.

Hasmadi et al. (2010) tested seven vegetation indices for mapping five classes of mangrove species – namely *Avicennia*, *Avicennia-Sanneratia*, *Acanthus-Sanneratia*, *Mixed Sanneratia* and *Mixed Acrostichum* – in Kelantan, Malaysia, using Landsat TM data. The results show that SAVI performed the best, followed by MSAVI, NDVI, PVI, IPVI, RVI and DVI with accuracies of 79.17%, 78.89%, 74.44%, 74.44%, 72.22%, 69.17% and 69.17% respectively.

Although the usefulness of using different vegetation indices in improving the classification accuracy has been proved, there are still challenges facing the classification of vegetation species in degraded areas where the reflectance is strongly affected by the background of soil as a result of relatively sparse vegetation and atmospheric conditions. More work is needed to develop different spectral indices that could help reduce the effects of soil background and atmospheric circumstances.

2.8 Overall challenges and opportunities in applying remote sensing in degraded environments

Rangeland degradation in arid, semi-arid and sub-humid areas is one of the problems that lower the land's productivity in terms of it being able to provide local communities with livelihoods through the grazing of domestic stock and planting of crops. Therefore, monitoring the spatial extent of rangeland degradation offers a means of understanding the nature and causes of this phenomenon. Different indicators have been used to map rangeland degradation by using soil properties and vegetation. Vegetation is an important component of ecosystems and it also serves as an excellent indicator of early signs of any physical or chemical degradation of the land.

The mapping and monitoring of vegetation species using traditional field-based methods, which allow only a small area to be covered, is costly and time-consuming; it is also sometimes impossible to undertake field data collection due to the poor accessibility of the area being surveyed (Rocchini et al., 2010). On other hand, remote sensing techniques offer a practical, near-real-time, rapid, relatively inexpensive and accurate data for mapping vegetation species over large areas (Ustin et al., 2009). Although considerable progress has been made with regard to mapping and monitoring rangeland degradation based on vegetation species using remote sensing data such as sensor development and data processing, there are still challenges to be met. There are limitations in using multispectral data (i.e. Landsat and SPOT) to map and monitor rangeland vegetation at species level, especially in degraded environments (where vegetation is sparse and there is spectral influence by soil background), due to the low spectral resolution of sensors and spectral overlap between the vegetation species. In addition to this, the vegetation species in a degraded environment are different from those elsewhere due to their spatial and temporal characteristics. Spatial variables include species diversity, structural attributes, and biomass, and are influenced by environmental factors such as soil properties, climate change, geology, topography, and the past biogeographic distributions of the species. Temporal variables relate to seasonal phenology and growth stage, and are influenced primarily by climate (drought) and hydrology (flood). Therefore, spectral discrimination between vegetation types in degraded environments is a challenging task because commonly different vegetation types show the same spectral reflectance signature.

In contrast to data from broadband satellite images, narrow bands of hyperspectral remote sensing (<10 nm) and contiguous spectral bands between 400 nm and 2500 nm occur throughout the ultraviolet, visible and infrared portions of the spectrum (Govender et al., 2009). These contiguous and many narrow spectral bands allow for in-depth mapping and monitoring of rangeland vegetation at species levels (Asner et al., 2000; Lewis, 2000). However, due to the excessive need for sufficient field samples, availability, and the high cost of images in Africa, only a few studies have investigated the potential of using hyperspectral data (Rocchini et al., 2010; Thenkabail et al., 2004). Yet in spite of these shortcomings, there is no doubt that the improvements in sensor instruments and analytical methods over the past ten years, combined with an increased knowledge of vegetation biophysical and biochemical properties, have provided important advances in terms of mapping the spatial distribution of rangeland vegetation in degraded areas at species level. More research is needed to enhance our ability to discriminate between increaser species for the purpose of identifying rangeland degradation using the development of new multispectral sensors such as WorldView-2 data. WorldView-2 data, with its capability of new wavelengths (including coastal, yellow, red-edge and NIR 2) to resolve lacking spectral features in the traditional sensors (Landsat TM, Landsat ETM+ and SPOT), offers great possibilities with regard to increaser species classification.

In chapter (2) the problem of rangeland degradation in South Africa and the application of traditional methods and remote sensing (multispectral and hyperspectral) in evaluating and mapping rangeland degradation using different indicators were reviewed. The results revealed a dearth in the availability of techniques for quantifying indicators of rangeland degradation. The potential use of decreaser and increaser species as indicators for rangeland degradation were highlighted.

CHAPTER THREE

Evaluating rangeland degradation using vegetation species and soil properties as indicators across a gradient of management regimes

This chapter is based on:

Manssour, K., Everson, T., and Mutanga, O., (In review). Evaluating rangeland degradation using vegetation species and soil properties as indicators across a gradient of management regimes. *African Journal of Range and Forage Science*.

Abstract

An understanding of the response of indicators of rangeland degradation to rehabilitation is essential for the successful implementation of Payment for Environmental Services. We evaluated the following four potential indicators of rangeland degradation: veld condition, basal cover, species diversity and soil fertility. The indicators were measured in a degraded and rehabilitated communal rangeland at Okhombe in northern KwaZulu-Natal, South Africa, and were compared to a conserved area at Cathedral Peak, KwaZulu-Natal. Two transects were established at each site for basal cover and species composition. The species were classified into the following ecological categories based on their responses to defoliation: decreaser, increaser I, increaser II and increaser III. Soil samples were collected and their elements were analysed for each site. The results revealed that the rangeland condition was higher (86.6%) in the conserved site when compared with two rehabilitated (46.7% and 42.4%) and two degraded (35.2% and 36.4%) sites. Species diversity ranged from moderate (2.48 and 2.34) in degraded sites to high (3.16) in the conserved site. The rehabilitated sites had a higher veld condition when compared with the degraded areas.There were highly significant differences in P, K, pH, Mn, Org. C and N compared to Mg, Zn and Cu. Based on these results, we concluded that the LandCare Programmes, which try to promote social, economic and environmental development in rehabilitated areas, are combating the problems of rangeland degradation. The results also indicated the severity of rangeland degradation in communal areas as compared to conserved areas.

Keywords: decreaser and increaser; species diversity; soil fertility; veld condition.

3.1 Introduction

Land degradation remains a topical issue because of its adverse impact on rangelands. It has been defined differently by different agencies and researchers (Eswaran et al., 2001; FAO et al., 1994; Stringer and Reed, 2007; UNCCD, 1995; Young, 1994), but all the definitions describe a reduced biological productivity of the land. These definitions cover the topics of vegetation species composition, soil properties, and the biological productivity of land in arid, semi-arid and sub-humid areas. Rangeland degradation has been identified as being one of the most serious global environmental issues of the present time (Hoffman and Todd, 2000; Wessels et al., 2007). A total of 4.8% (i.e. 5.8 million ha) of South African land has been identified as being degraded due to its low vegetation cover when compared with surrounding areas (Thompson, 1996). The greatest areas of extensively degraded land coincide with the moderately to severely degraded communal rangelands where there is a considerable population of South African livestock (Hoffman and Todd, 2000; Reid and Vogel, 2006).

Several indicators have been suggested for assessing rangeland degradation based on the effects of livestock grazing on the spatial distribution of soil and vegetation quality (Conant and Paustian, 2002; Greenwood and McKenzie, 2001; Reeder and Schuman, 2002; Zhao et al., 2007). Intensive livestock grazing has been reported as increasing the following: soil compaction (da Silva et al., 2003; Greenwood et al., 1997), the erosion of topsoil (Snyman, 1998), shrub and bush encroachment (Roques et al., 2001), and the growth of unpalatable grass species (Hoffman and Todd, 2000; Tainton et al., 1980). Intensive livestock grazing has been reported as decreasing the following: soil organic carbon and nitrogen (Biondini et al., 1998; Manley et al., 1995; Shariff et al., 1994), total sulphur concentration (Steffens et al., 2008), soil infiltration rates (Proffitt et al., 1993), soil water content (Zhao et al., 2007), basal cover (Hardy and Tainton, 2007), the community of soil organisms (which are responsible for nutrient recycling and organic matter decomposition) (Bardgett et al., 2001), and growth of palatable grass species (Kraaij and Milton, 2006; Todd and Hoffman, 1999).

To date, the mapping of rangeland degradation in South Africa based on vegetation species has mainly focused on commercial rangelands (Palmer and van Rooyen, 1998; Shackleton et al., 2005), and communal rangelands have thus not yet received the same level of attention (Hoffman and Todd, 2000; Wessels et al., 2004). Continued land deterioration represents a major threat to the socio-economic well-being and biodiversity of communal rangelands (Hoffman and Todd, 2000). There is therefore a need for planning strategies that use consistent, repeatable and spatially explicit measures to map and monitor land degradation at different scales (Prince et al., 2009; Ravi et al., 2010). These planning strategies for sustainable land management require techniques that can effectively reveal the spatial extent, magnitude and temporal behaviour of the lands (Prince et al., 2009; Ravi et al., 2010; Van Lynden and Mantel, 2001).

Vegetation species have been classified into two categories (i.e. increasers and decreasers) based on their grazing value and the changes in their relative abundances in the presence or absence of grazing (Dobarro et al., 2010). Decreaser and increaser species have been successfully used as indicators for assessing and classifying of rangeland degradation (Tainton, 1988; Trollope et al., 2008; Van Oudtshoorn, 1992). This is because the species are well adapted to specific growth conditions and their numbers will reduce or increase dramatically if these conditions change (Hardy and Hurt, 1989; Trollope et al., 2008; Van Oudtshoorn, 1992). Decreaser species are species that predominate in veld of good condition but greatly decline when the veld deteriorates through over- or under-utilisation (Hardy et al., 1999). Increaser species are species that increase their relative abundances through over-grazing or under-utilisation, and these species therefore indicate that a rangeland is in poor condition (Dobarro et al., 2010; Van Oudtshoorn, 1992). In South Africa, increaser species have been classified into the following four types: increaser I, increaser IIa, increaser IIb and increaser III (Oluwole and Dube, 2008; Trollope, 1990). Increaser I includes species that increase in abundance with under-utilisation, while increaser IIa includes species that increase in abundance when the veld is overgrazed. Increaser IIb species are those that increase in abundance when the veld is excessively overgrazed, while increaser III are species that increase their relative abundances in rangeland that is selectively grazed (Hardy et al., 1999; Oluwole and Dube, 2008; Trollope, 1990; Van Oudtshoorn, 1992).

Over the past two decades, different agronomic and ecological techniques have been developed for assessing the condition of rangeland in South Africa (Barnes et al., 2007; Bosch and Gauch, 1991; Foran et al., 1978; Mentis, 1981; Tainton et al., 1980; Trollope et al., 1990; Van Rooyen et al., 1991; Vorster, 1982; Willis and Trollope, 1987). However, the monitoring of the trend, reliability and validity of these different techniques still needs serious and considerable attention (Friedel, 1991; Hardy and Hurt, 1989; Jordaan et al., 1997; Mentis et al., 1980; Tainton, 1988; Trollope et al., 1990). Nevertheless, the benchmark technique, whereby the species composition of a site is compared to a benchmark site (rangeland in excellent condition), offers an economical and effective solution that produces timely and accurate information for assessing South Africa's rangelands (Foran et al., 1978; Tainton et al., 1980). This technique can also be applied to different ecosystems (Hardy et al., 1999).

There is increasing interest in predicting the key mechanisms governing the dynamics of species. The desire for predictions is being driven by the pressing need to improve vegetation composition in the rangelands, which requires a good understanding of the ecological mechanisms that cause change (Mapiye et al., 2008; Snyman, 1998). Furthermore, knowledge of the major processes operating on natural resources and of their subsequent effects on the rate and direction of the changes is vital if one is to determine whether or not management practices such as rangeland burning, mowing, plant establishment and veld fertilisation are in fact successful tools (Mapiye et al., 2008). The objective of this study was, therefore, to evaluate the condition of the rangelands in both the Okhombe communal rangelands and the Cathedral Peak area by using factors of species composition, basal cover and soil characteristics, the latter of which includes phosphorus, potassium, calcium, magnesium, pH, zinc, manganese, copper, organic matter and nitrogen. These two study areas constitute a gradient of rangeland degradation as subjected to different management regimes. A secondary objective was to evaluate the success of the Landcare project in combating land degradation in the Okhombe communal area. The landcare project was introduced in some parts of Okhombe communal area in 1998. The objective of this project was to promote ecologically sustainable approaches to land management in communal areas (Mulder and Brent, 2006).

3.2 Material and Methods

3.2.1 Data collection

3.2.1.1 Veld condition assessment

During November and December of 2010, the benchmark method developed by Foran *et al.* (1978) and Tainton *et al.* (1980) was used to assess the rangeland condition of five study sites, four of which were in the sub-wards of the Okhombe communal rangelands whilst the fifth site was within the Cathedral Peak conservation area. These five sites included degraded areas (Mpameni and Ngubhela), rehabilitated areas (Mpameni and Ngubhela), and one conserved area (Cathedral Peak). The benchmark method involves measuring the composition of the plant species and then comparing that measurement to a reference benchmark site which is characterised by grassland of excellent condition (Tainton et al., 1980). The benchmark for the present study area was the Moist Highland Sourveld Group 8 (Foran et al., 1978; Tainton et al., 1980). The motivation for using this procedure was to evaluate the rangeland condition based on species count (Oluwole and Dube, 2008). The procedure also shows if the rangeland has been optimally grazed, under-grazed or overgrazed, and it furthermore reveals the degree of degradation (Hardy and Hurt, 1989). The vegetation assessment was conducted on sampling areas of conserved, rehabilitated and degraded land using the point sampling method described by both Tainton et al. (1980) and Trollope et al. (1990). This method was used to determine the composition of grass species to provide a precise measure of relative grass abundances in each site. Two transect lines, each 200 m long, were established at each site. The nearest living plant to the point of a metal spike was identified and recorded for 200 points. This sample size was shown to be sufficient to evaluate the veld (Hardy and Tainton, 2007). At each transect, elevation, slope and GPS coordinates were recorded. The observed grass species were classified into their species categories (i.e. Decreaser, Increaser I, Increaser II and Increaser III). The condition of a sample of veld was calculated by comparing the species composition of the particular site with that of the benchmark (Camp, 1997).

3.2.1.2 Basal cover

Basal cover for each sample site was determined using paired observations of the mean distance and mean basal diameter of the tufts (Hardy and Tainton, 2007; Oluwole and Dube, 2008). All the techniques that have been used to monitor grassland quality and quantity in South Africa require an estimate of basal cover (Hardy and Tainton, 2007). This is because grass basal cover is well adapted to specific growth conditions and will increase or decrease dramatically if these conditions change (O'Connor et al., 2001; Snyman and Fouché, 2007). Basal cover data were collected by using a measuring tape and a metal spike. The distance from the nearest living plant to the point of a metal spike was then measured (D), and the basal diameter of the tuft (d) was identified, measured and recorded for 100 points (Hardy and Tainton, 2007). Basal cover was calculated using the following equation, as developed by Hardy and Tainton (2007):

$$BC = 19.8 + 0.39(D) - 11.87(\log_e D) + 0.64(d) + 2.93(\log_e d) \qquad (1)$$

Where *BC* is basal cover, *D* is the mean distance (cm) from a point to the nearest tuft, and *d* is the mean basal diameter (cm) of the tuft.

3.2.1.3 Species diversity index

Species diversity is the number of different species in a particular place (Beisel and Moreteau, 1997; Borda-de-Água et al., 2002; Magurran, 1988; Shackleton, 2000). It is used as an indicator of rangeland degradation (Metzger et al., 2005; Rutherford and Powrie, 2010). This is because both plant quantity and quality decline with heavy grazing (Metzger et al., 2005; Rutherford and Powrie, 2010). Shannon's diversity index, which was developed by Shannon & Weaver (1963), has been widely used within the ecological field. It is a nonparametric statistical technique for establishing species diversity, which is the proportion of species relative to (qi) the total number of species (Q) (Chao and Shen, 2003; Lande, 1996). The use of Shannon's diversity index was preferred in this study because it is suited to the comparison of different ecosystems. In this study, Shannon's diversity index was applied to degraded, rehabilitated and conserved sites at Okhombe and Cathedral Peak during November and December of 2010. The nearest plant to 200 random points along a transect line was identified and recorded. Species diversity was calculated by considering the number of species per ecological category (decreaser species, increaser I, increaser IIa, increaser IIb, increaser IIc, and increaser III). The equation for computing species diversity is as follows (Shannon and Weaver, 1963):

$$H' = -\sum_{i=1}^{S} \left(\frac{qi}{Q}\right) \log \left(\frac{qi}{Q}\right) \qquad (2)$$

Where H' is the Shannon-Weaver diversity index, *qi* is the fraction of individuals belonging to the *i* species, *Q* is the total number of the individual species in the sample, and *S* is species richness.

Grassland species evenness was measured by Pielou's equation (Pielou, 1966), where evenness (E) is represented as follows:

$$E = H/ \ln S \tag{3}$$

Where H' is the Shannon-Weaver diversity index and S is the number of species within the community.

3.2.1.4 Soil assessment

Soil samples were collected from 56 sites (18 non-degraded, 19 rehabilitated and 19 degraded). Soil samples were collected under dry atmospheric conditions, and care was taken to ensure that these sites were representative of their respective ecosystems. Field borders, ditch banks and burn sites were therefore avoided (Maitima and Olson, 2001). Soil samples were taken using a soil-sampling auger to a depth of 15 cm. A field label was written on each sample bag, which included soil sample plot number, species names, elevation, slope, and GPS coordinates. All the labelled bags were stored in dry conditions until they were transported to the laboratory for analysis. Soil samples were analysed for soil fertility. P was measured using a photometer, while K, Ca, Mg, Zn, Mn and Cu were determined using electrothermal flame atomic absorption spectrometry. The N and organic carbon were both measured by mid-infrared spectroscopy. Soil pH was measured with a pH meter. The soil density was measured using a 10 ml scoop.
The data were analysed statistically using one-way ANOVA in the GenStat (version 12) statistical software package (Payne, 2009) to determine whether or not there were any significant differences between the different soil classes. Least significant differences (LSDs) ($P < 0.05$) were calculated to separate the means of the soil properties.

3.3 Results

3.3.1 Botanical composition

The veld condition (VC) ranged from 35.2% to 86.6% (Table 3.1). The degraded sites in Mpameni and Ngubhela yielded the lowest veld condition of 35.2% and 36.4% respectively. In the rehabilitated areas of Mpameni and Ngubhela, the veld condition indices were slightly higher at 42.4% and 46.7% respectively. The results indicate high relative abundances of increaser II and increaser III species in Mpameni and Ngubhela. A veld condition of 86.6% was recorded in the conserved site at Cathedral Peak. The high veld condition score in this site is largely attributed to the dominance of palatable decreaser grasses (e.g. *Themeda triandra*), which have high grazing values when compared with the degraded and rehabilitated sites.

Table 3. 1: Percentage species composition, ecological category totals, basal cover and veld condition scores for each ecosystem (i.e. conserved, rehabilitated and degraded)

Ecological category	Species	Veld condition assessment					
		Benchmark	Conserved	Rehabilitated		Degraded	
				Mp.	Ng.	Mp.	Ng.
Decreaser	*Themeda triandra*	45	26	0	1	0	0
	Brachiaria serrata	1	1	0	0	0	0
	Diheteropogon amplectens	1	6	0	0	0	0
	Monocymbium ceresiiforme	2	6	0	0	0	0
Sub-total		**49**	**39**	**0**	**1**	**0**	**0**
	Alloteropsis semialata	2	7	4	5	4	6
	Trachypogon spicatus	2	8	3	5	3	4
Increaser I	*Eulalia villosa*	1	1	1	1	0	1
	Tristachya leucothrix	20	9	2	3	2	2
	Koeleria capensis	0	1	0	0	0	0
	Festuca costata	0	4	0	0	0	0
	Digitaria tricholaenoides	0	9	4	4	7	5
	Hyparrhenia hirta	1	1	3	2	2	1
Sub-total		**26**	**40**	**17**	**20**	**18**	**19**
	Eragrostis capensis	1	1	13	9	12	14
Increaser IIa	*Heterpogon contortus*	4	5	9	11	08	9
	Harpochloa falx	3	1	3	3	0	2
Sub-total		**8**	**7**	**25**	**23**	**20**	**25**
	Eragrostis racemosa	1	1	13	12	13	11
	Eragrostis curvula	1	1	6	3	2	3
Increaser IIb	*Eragrostis plana*	1	1	7	7	3	6
	Eragrostis obtusa	0	0	0	0	0	1
	Digitaria mondactyla	0	1	1	2	1	2
	Sporobolus africanus	0	1	1	1	5	1
	Loudetia simplex	0	1	1	0	1	0
Sub-total		**3**	**6**	**29**	**25**	**25**	**24**
	Microchloa caffra	1	1	1	2	1	1
	Melinis repens	0	1	8	5	6	7
Increaser IIc	*Felicia filifolius*	0	0	1	1	0	1
	Paspalum dilatatum	0	2	2	3	1	4
	Paspalum notatum	0	1	3	4	2	2
	Forbs	5	3	1	1	1	0
	Sedges	1	1	1	0	1	0
Sub-total		**7**	**9**	**17**	**17**	**12**	**15**

Continued…

	Diheteropogon filifolius	2	1	2	1	1	1
	Elionurus muticus	5	0	0	1	0	0
Increaser III	*Rendlia altera*	0	1	3	2	2	1
	Aristida diffusa	0	0	11	10	18	13
Sub-total		**7**	**2**	**16**	**14**	**21**	**15**
VCS		714	619	303	334	251	260
VC (%)		100	86.6	42.4	46.7	35.2	36.4
BC (%)			14.83	15.06	16.87	19.65	20.78

VCS = veld condition score; VC = veld condition; BC = basal cover; Mp. = Mpameni; Ng. = Ngubhela.

3.3.2 Changes in basal cover as an indicator of rangeland degradation

The basal cover of the veld in each of the three areas (i.e. conserved, degraded and rehabilitated) ranged from good (14.83%) to excellent (20.78%) (Table 3.1). Unexpectedly, the Mpameni and Ngubhela degraded areas yielded a high basal cover (19.65% and 20.78%). Although they were in poor condition (< 36.4%), there were no large open spaces between the grass tufts (Figure 3.1).The distance between the point of the spike and the nearest grass tuft (D) ranged from 0.5 cm to 8 cm, while the diameter of the tufts (d) ranged from 1.5 cm to 9 cm. In the rehabilitated areas of Mpameni and Ngubhela, the basal cover could be characterised as being reasonable (15.06% and 16.87%) (Figure 3.2). The distance between the point of the spike and the nearest grass tuft ranged from 0.5 cm to 9 cm, while the diameter of the tufts ranged from 3 cm to 12 cm, and the rehabilitated areas were dominated by increaser IIa and increaser IIb species. The grasslands in the Cathedral Peak area were in good condition with an excellent basal cover of 14.83%. The distance between the point of the spike and the nearest grass tuft (D) ranged from 0.5 cm to 4.5 cm, while the diameter of the tufts (d) ranged from 0.5 cm to 11 cm (Figure 3.3).

Figure 3. 1: Good basal cover with no large open spaces (dominated by increaser II and increaser III species), as seen in the Mpameni site.

Figure 3. 2: Reasonable basal cover with sparse vegetation cover, as seen in the Mpameni rehabilitated site.

Figure 3. 3: Excellent basal cover with a high canopy cover (dominated by decreaser species), as seen in the Cathedral Peak site.

The ANOVA with a Tukey's HSD post hoc test was conducted for the plant basal cover parameters (diameter and distance) to find out if the differences in the mean parameters between the rehabilitated and degraded sites were statistically significant. The result showed that the two parameters had highly significant differences ($P < 0.001$) between the different groups (rehabilitated and degraded) (Table 3.2). The results also indicated that there is a significant difference between the Ngubhela degraded and the Mpameni rehabilitated sites and the Ngubhela rehabilitated and the Mpameni degraded sites in terms of diameter. However, there is no significant difference ($P < 0.05$) between the two sites in terms of distance from tuft. On the other hand, there is no significant difference between the Ngubhela rehabilitated and Mpameni rehabilitated sites in terms of both parameters (distance and diameter) (Table 3.3).

Table 3. 2: Statistical analysis using ANOVA for plant basal cover parameters (distance and diameter) and different groups (rehabilitated and degraded sites) with a 95% confidence level ($P < 0.05$)

	df	Mean square	F	Sig
Distance – between groups	4	16.518	6.491	0.000
Diameter – between groups	4	57.097	12.185	0.000

Table 3. 3: Statistical analysis using ANOVA with a Tukey's HSD post hoc test for plant basal cover parameters (distance and diameter) and different locations (rehabilitated and degraded) with a 95% confidence level ($P < 0.05$)

Location	Distance (Sig)	Diameter (Sig)
DNG vs RMP	0.237	0.000
RNG vs DMP	0.119	0.000
RNG vs RMP	0.866	0.416

DNG = Ngubhela degraded; DMP = Mpameni degraded; RNG = Ngubhela rehabilitated; RMP = Mpameni rehabilitated.

3.3.3 Variations in species diversity in response to rangeland degradation

A total of 1,000 points was recorded in the study areas. Twenty-six species were recorded in the rehabilitated and degraded areas and 28 in the conserved site. There were five grass species that were only recorded in the conserved area and seven grass species that were only recorded in the rehabilitated and degraded areas. The results of species diversity using Shannon's index and Evenness for the five sites – i.e. conserved (Cathedral Peak), rehabilitated (Mpameni and Ngubhela) and degraded (Mpameni and Ngubhela) – ranged from moderate 2.34 (0.75) to high 3.16 (0.94) (Table 3.4).

Table 3. 4: Shannon's diversity index (H') and evenness for the following five sites: conserved (Cathedral Peak), rehabilitated (Mpameni and Ngubhela), and degraded (Mpameni and Ngubhela)

	Site	Number of species (S)	Shannon-Weaver diversity index (H')	Evenness
1	Conserved Cathedral Peak	29	3.16	0.94
2	Rehabilitated Ngubhela	26	2.82	0.87
3	Rehabilitated Mpameni	25	2.51	0.78
4	Degraded Ngubhela	23	2.48	0.78
5	Degraded Mpameni	22	2.34	0.75

Species richness was highest in the conserved site (29) and lowest in the degraded sites (<23). This was supported by the higher diversity of the conserved site (3.16) when compared to the degraded sites (<2.48). The degraded and rehabilitated sites were dominated by increaser IIb, increaser IIc and increaser III species. The dominant species that contributed to Shannon's index were *Eragrostis capensis*, *Heterpogon contortus*, *Eragrostis racemosa*, *Eragrostis plana, Paspalum dilatatum*, *Melinis repens* and *Aristida diffusa.* We assessed the Okhombe LandCare Project in the rehabilitated and degraded areas of Mpameni and Ngubhela. The results indicated that there was a significant difference between the Ngubhela rehabilitated and the Ngubhela degraded sites ($t = 9.194$, $P < 0.05$), and between the Mpameni rehabilitated and the Mpameni degraded sites ($t = 9.91$, $P < 0.05$). In the conserved site of Cathedral Peak, a high number (i.e. 29) of different grass species was found. The results indicated high species diversity for Shannon's diversity index and an evenness of 3.16 (0.94). The site was dominated by decreaser and increaser I species. Most of the species characterising the Cathedral Peak site were palatable species.

3.3.4 Changes in soil properties as an indicator of rangeland degradation

The soils of the conserved, rehabilitated and degraded sites were significantly different for P, K, PH, Mn, Org. C and N when a 95% confidence level ($P < 0.05$) was used (Table 3.5). P, pH, Org. C and N were highly significant (< 0.001). High values of P, pH, Org. C and N content were obtained in the conserved site (10.93, 4.18, 6.02 and 0.40 respectively) when compared with the rehabilitated and degraded sites. However, there were no significant differences (P >

0.05) among sites for Ca, Mg, Zn and Cu. The results show that there was a decrease in soil pH in the degraded sites (2.71) when compared with the conserved and rehabilitated sites (4.18 and 4.00).

Table 3. 5: The mean, standard deviation and P values of the soil samples collected from the five study sites, namely the conserved (Cathedral Peak), rehabilitated (Mp. and Ng.) and degraded (Mp. and Ng.) sites

Soil properties	Conserved	Rehabilitated	Degraded	LSD	P value
P mg/kg	10.93 ± 4.32^{b}	4.41 ± 1.63^{a}	3.30 ± 2.21^{a}	2.16	< 0.002 **
	(5.88 - 22.50)	(2.65 - 8.74)	(2.61 - 10.10)		
K cmol/kg	0.50 ± 0.14^{b}	0.30 ± 0.23^{a}	0.37 ± 0.28^{a}	0.15	0.038 *
	(0.30 - 0.71)	(0.05 - 0.91)	(0.15 - 1.05)		
Ca cmol/kg	3.78 ± 1.77^{b}	1.78 ± 1.50^{b}	3.28 ± 2.14^{a}	1.69	0.099 ns
	(1.83 - 7.48)	(0.25 - 5.53)	(0.61 - 8.67)		
Mg cmol/kg	0.83 ± 0.30^{b}	0.67 ± 0.88^{b}	1.55 ± 1.04^{b}	0.72	0.164 ns
	(0.61 - 1.63)	(0.08 - 1.93)	(0.41 - 4.35)		
pH_{KCl}	4.18 ± 0.18^{a}	4.00 ± 0.26^{a}	2.71 ± 2.37^{b}	0.89	< 0.001 **
	(4.03 - 4.61)	(3.80 - 4.84)	(0.20 - 9.30)		
Zn cmol/kg	0.68 ± 0.55^{b}	1.37 ± 3.14^{a}	1.63 ± 2.14^{b}	0.48	0.067 ns
	(0.00 - 1.83)	(0.10 - 12.23)	(0.17 - 8.38)		
Mn cmol/kg	6.87 ± 3.48^{b}	6.24 ± 4.15^{b}	11.50 ± 6.99^{a}	3.39	0.042 *
	(2.35 - 14.08)	(2.02 - 15.00)	(3.54 - 21.21)		
Cu cmol/kg	2.16 ± 0.34^{b}	2.00 ± 2.56^{a}	3.32 ± 4.00^{b}	1.09	0.082 ns
	(1.65 - 2.63)	(0.00 - 10.10)	(0.00 - 14.78)		
Org. C (%)	6.02 ± 0.61^{b}	3.66 ± 0.79^{a}	2.15 ± 1.00^{a}	0.69	< 0.001 **
	(4.90 - 7.00)	(0.80 - 4.20)	(0.80 - 4.50)		
N (%)	0.40 ± 0.05^{b}	0.19 ± 0.06^{a}	0.16 ± 0.08^{a}	0.05	< 0.001 **
	(0.26 - 0.47)	(0.05 - 0.25)	(0.05 - 0.32)		

Mean values of soil properties with different superscript letters (^{a} and ^{b}) in the same row were significantly different ($P < 0.05$); * = significant P value; ** = highly significant P value; ns = non-significant P value; LSD = least significant difference. Values between two brackets are the minimum and maximum values.

3.4 Discussion

The aim of this study was to evaluate rangeland using vegetation species and soil properties as indicators of degradation across a gradient of different management regimes.

3.4.1 Changes in botanical composition and basal cover

The veld condition was low (35.2%, 36.4%) in the degraded sites of Mpameni and Ngubhela and moderate (42.4%, 46.7%) in the rehabilitated sites of Mpameni and Ngubhela when compared to the conserved site (86.6%) (Table 3.1). The veld condition assessment successfully indicated a distinct difference in species composition between these different environments. In the Mpameni and Ngubhela degraded areas, the veld condition can be classified as low (35.2% and 36.4%). This can be explained by the fact that these areas were dominated by species such as *Digitaria tricholaenoides* 7% and 5%, *Alloteropsis semialata* 4% and 6%, *Eragrostis capensis* 12% and 14%, *Eragrostis racemosa* 13% and 11%, *Melinis repens* 8% and 9%, *Aristida diffusa* 18% and 13%, and *Eragrostis plana* 3% and 6%. These grasses are unpalatable and they thus have a low grazing value that ranges from 0 to 6 according to the Moist Highland sourveld benchmark (Camp, 1997; Van der Westhuizen et al., 2005; Van Oudtshoorn, 1992). The dominance of these species indicated poor veld condition which may be attributed to the low soil organic carbon and nitrogen (Table 3.5).

A moderate veld condition (42.4% and 46.7%) was recorded in the rehabilitated areas of Mpameni and Ngubhela. Both sites had their palatable species reduced to 0% and 1% when compared with the degraded sites (0%) and the benchmark of 49%. This indicates their poor grazing quality. The proportional abundance of Increaser I decreased to 17% (18%) in Mpameni rehabilitated and degraded and to 20% (19%) in Ngubhela rehabilitated and degraded when compared with the benchmark of 26%. This decrease in Increaser I is due to over-utilisation (Tainton, 1999). The percentage increase in species such as the undesirable increaser IIa 25% (20%) and 23% (25%), increaser IIb 30% (25%) and 25% (24%), increaser IIc 17% (12%) and 17% (15%) and increaser III 16% (21%) and 14% (15%) in Mpameni and Ngubhela rehabilitated and degraded respectively when compared with the benchmark of 8%, 3%, 7% and 7% indicated poor veld. The high percentage of increaser II values is largely attributed to the dominance of *Eragrostis capensis*, *Heterpogon contortus*, *Eragrostis racemosa* and *Eragrostis plana.* Also, both these sites of Mpameni and Ngubhela rehabilitated and degraded had a high abundance of *Melinis repens* (characteristic of disturbed areas) (8% and 6%) and (5% and 7%) as well as *Aristida diffusa* (11% and 18%) and (10% and 13%) a species associated with shallow soils in overgrazed veld. These species were absent in the benchmark, and their dominance indicates poor veld condition (Camp, 1997). The rehabilitated sites had a higher veld condition when compared with the degraded areas. This may be attributed to the success of the rehabilitation techniques used by the community in a LandCare Project that was established in 1998. The objective of this project was to promote ecologically sustainable approaches to land management in communal areas (Mulder and Brent, 2006). Much success has been achieved through soil erosion prevention techniques such as stone lines, stone packs, strips of Kikuyu and Vetiver grass, and swales (Peden, 2005). These techniques are considered to be important for rehabilitation interventions and rangeland management (Everson et al., 2007; Peden, 2005) because they have several advantages, such as being able to stabilise loose soil, decrease overland flow and runoff and lead to an increase soil organic and phosphorus.

A high veld condition was recorded at the conserved site of Cathedral Peak (86.6%). This can be explained by the fact that this area is dominated by decreaser species. A decrease was found in the proportional abundance of decreaser (39%), increaser IIa (7%) and increaser III (2%) species when compared with the benchmark values of 49%, 8% and 7% respectively. According to the benchmark, the high percentage of decreaser species and the low percentage of increaser IIa and increaser III indicate that the grazing quality in the area is good. The low percentage of increaser species is attributed to the limited wildlife, no domestic livestock and a regular burning regime (Granger, 1976). This is comparable to the results of Camp (1997) and Snyman (1998) who indicate that conserved grasslands are dominated by decreaser species. On the other hand, there was an increase in the proportional abundance of increaser I and increaser IIb to 39% and 5% respectively when compared with the benchmark of 25% and 4%.

The basal cover in each of the five sites – degraded (Mpameni and Ngubhela), rehabilitated (Mpameni and Ngubhela) and conserved (Cathedral Peak) – was 19.65% and 20.78%, 15.06% and 16.87% and 14.83% (Table 3.1) respectively, which ranged from excellent in poor veld condition to reasonable to good respectively. The results of those previous studies that reported that the differences in the basal covers may be attributed to the grazing regime, topography and rainfall, all of which can influence species distribution and increase the rate of runoff and soil loss (Snyman, 2002; Tau, 2005; Vetter et al., 2006). These variations in the basal cover were supported by the ANOVA results, which indicate that there is a significant difference in basal parameters at these sites (Table 3.2). In the low veld condition sites of Mpameni and Ngubhela, the basal cover was excellent, and this is attributed to the high relative abundance of increaser II and increaser III, in addition to the low of soil pH, Org. C and N (Table 3.5). This situation could explain the fact that the basal cover decreased linearly along with a deterioration in the veld condition (Snyman, 2002). Tuft diameter and distance between tufts are the main factors influencing basal cover. Tuft diameter was significantly different ($P < 0.05$, Table 3.3) between the degraded and rehabilitated sites. This indicates that the rehabilitation programmes have been successful in improving basal cover of degraded areas. However, there was no significant difference ($P > 0.05$) between these sites in terms of distance from tuft. This may be due to the stoloniferous nature of some of the species used in rehabilitation.

3.4.2 Variations in species diversity in response to rangeland degradation

There were differences in the Shannon diversity index of the study's five sites, which were: degraded (Mpameni and Ngubhela), rehabilitated (Mpameni and Ngubhela) and conserved (Cathedral Peak). These indices were 2.34, 2.48, 2.51, 2.82 and 3.16 (Table 3.4) respectively, and they ranged from moderate to high respectively. Changes in soil properties may be responsible for the variation in species diversity (Stohlgren et al., 1999). The study's soil analysis, which was done in the rehabilitated and degraded sites show a decline in soil properties such as P, Org. C and N. These soil properties are considered to be important in plant growth and survival (Oluwole and Dube, 2008). In the degraded sites the species diversity index was moderate (2.34 and 2.48) and there was a high evenness index (0.75 and 0.78). These results are similar to those of previous studies in degraded grassland (Anderson and Hoffman, 2007; Frank, 2005; Hoffmann and Zeller, 2005; Stohlgren et al., 1999; Tanser and Palmer, 1999; Todd and Hoffman, 1999), all of which indicate that overgrazing on communal rangeland results in low plant species richness, a decreased proportion of palatable grass species, and an increased proportion of unpalatable grass species. The results of this study indicate that the rehabilitated sites of Mpameni and Ngubhela have a high diversity index and an evenness of 2.51(0.78) and 2.82(0.87). These sites were dominated by different species, such as *Eragrostis racemosa*, *Eragrostis curvula*, *Eragrostis plana*, *Hyparrhenia hirta*, *Sporobolus africanus*, *Paspalum dilatatum* and *Paspalum notatum*. This state of affairs may be due to the planting in the rehabilitated sites of different species such as *Kikuyu*, *Vetiver* and indigenous and exotic grasses

(Everson et al., 2007; Peden, 2005). The results indicate that the conserved site of Cathedral Peak has a slightly higher diversity index than do the other sites; this is supported by the Shannon diversity index and the evenness results 3.16(0.94). These results are supported by a few other studies (Anderson and Hoffman, 2007; Frank, 2005; Hoffmann and Zeller, 2005), all of which indicate that South Africa's conserved areas are characterised by high plant species diversity and high grazing quality. Moreover, there are certain environmental management programmes that are in place, and these are there to ensure that the Cathedral Peak area is protected from harmful human activities and thereby conserved.

3.4.3 Changes in soil properties as an indicator of rangeland degradation

The results from this study indicate that soil properties contribute a considerable amount of information towards our knowledge of grassland status. The results show that levels of P, K, pH, Mn, Org. C and N were significantly lower ($P < 0.05$) in the rehabilitated and degraded sites when compared to the conserved site (Table 3.5). These results are comparable to the results of previous studies (Islam and Weil, 2000; Oluwole and Dube, 2008; Su and Zhao, 2003) which mention that the overgrazing of rangelands has a negative impact on vegetation species and soil properties because of reduced vegetation cover, reduced productivity, and litter accumulation. These factors reduce soil infiltration, enhance soil erosion vulnerability, and lead to a decline in soil fertility. On the other hand, the good veld condition that was measured in the conserved area (86.6%) is an indication of good soil fertility. The relative abundance of Org. C and N for vegetation growth is considered to be the main cause of high vegetation diversity in the conserved site (Du Preez and Snyman, 1993; Oluwole and Dube, 2008). However, the decrease in species diversity in the rehabilitated and degraded sites may be associated with poor soil fertility (low Org. C and N). The low organic carbon and N are due to the leaching of vital nutrients by heavy rainfall, the veld type generally occurs in acid soil that is poor in nutrients (Tainton, 1999).

A considerable variation occurred in the Mn of the soils in the sampled sites; it ranged from 6.24 to 14.05. The Mn was significantly higher (11.5 ± 6.9, $P < 0.05$) in the degraded sites due to low vegetation cover when compared with the conserved and rehabilitated sites. There was a decrease in the soil pH in the degraded sites (2.71) when compared with the conserved and rehabilitated sites (4.18 and 4.00). These results confirm that the pH in degraded areas decreased as a result of overgrazing (Moolenaar et al., 1998).

3.5 Conclusions

The aim of this study was to evaluate potential vegetation species and soil properties as indicators of rangeland degradation across a gradient of management regimes. Our results have shown that:

1. There is a significant variation in rangeland condition across a gradient of management regimes: conserved, rehabilitated and communal areas.
2. Veld condition assessment based on the benchmark method was successfully used to quantify the differences in degraded, rehabilitated and conserved sites at Okhombe and Cathedral Peak.
3. Vegetation indicators based on the relative abundance of decreaser and increaser species have a high potential to evaluate different levels of rangeland degradation.
4. The outcomes of the LandCare Programmes, which try to promote social, economic and environmental development in rehabilitated areas, have been successful in combatting the problems of rangeland degradation.
5. The use of soil properties such as P, pH, Org. C and N as indicators of degradation were highly significant (< 0.001) and can be used to discriminate between conserved and degraded sites.
6. The different indicators (i.e. veld condition, basal cover, species diversity and soil properties) that were used in this study show that the use of a combination of indicators for evaluating rangeland degradation is an effective approach to environmental studies.

Overall, the use of vegetation species (decreaser, increaser I, increaser IIa, increaser IIb, increaser IIc and increaser II) and soil properties (P, K, Ca, Mn, pH, Zn, Mg, Cu, Org. C and N) as indicators is an important step in mapping different levels of rangeland condition.

Acknowledgements

Thanks are due to Dane Lee Marx and Craig Morris for their help in the identification of plant species as well as their help with the data collection. We gratefully acknowledge the financial support that was given to us by the University of KwaZulu-Natal. We extend our gratitude to the statisticians Ali Satty and Dawit Getnet for their statistical analysis of the data. Thanks are also given to Irene Bame for her assistance with matters pertaining to soil science.

Chapter 3 focused on exploring the relationship between vegetation species (increaser and decreaser species) and rangeland condition in the Okhombe communal lands and the Cathedral Peak conservation area using a veld condition assessment technique.
Results showed that Okhombe communal area is subjected to rangeland degradation as indicated by low veld condition. The subsequent chapters (4, 5 and 6) therefore, advocates the development of techniques based on remote sensing to quantify the veld condition.

CHAPTER FOUR

Spectral discrimination of increaser species as an indicator of rangeland degradation using field spectrometry

This chapter is based on:

Manssour, K., Mutanga, O., and Everson, T., (In review). Spectral discrimination of increaser species as an indicator of rangeland degradation using field spectrometry. *Journal of Spatial Science.*

Abstract

Discriminating increaser species (Species indicative of over- and under-utilization) is important for mapping rangeland degradation. The main objectives of this paper were to: (1) determine whether four increaser species could be spectrally discriminated from each other and (2) determine the key wavelengths that have high discriminatory power. Field spectrometry data were taken from *Hyparrhenia hirta; Eragrostis curvula; Sporobolus africanus* and *Aristida diffusa* from Okhombe rangeland, KwaZulu-Natal province, South Africa. A total of 1723 narrow bands in the 350 nm to 2500 nm range were used in the analysis. Three tier hierarchical techniques of one-way ANOVA, stepwise discriminant function analysis and canonical function analysis were used. The results revealed that there were statistically significant differences in spectral reflectance between the four species on 439 wavelengths. The most important wavelengths (n=8) that were selected for spectral discrimination were largely located in the visible, red-edge and near-infrared regions of the spectrum. The three tiers of analysis yielded species discrimination with an overall accuracy of 83.02 % and a KHAT value of 0.77. The use of the spectroscopic approach applied in this study indicated that the increaser species were spectrally different, a promising result for the ultimate mapping of indicators of rangeland degradation.

***Keywords*:** rangeland degradation; vegetation species; indicator; field spectrometry.

4.1 Introduction

Rangeland degradation is defined as a reduction in or temporary loss of the vegetation species and economic productivity of a rangeland (UNCCD, 1995). Rangeland occupies roughly 51% of the earth's total land area (Wilcox, 2007). About 73% of rangelands in arid, semi-arid and sub humid areas is currently degraded (UNCCD, 1995). Because vegetation species in these rangeland areas are well adapted to specific growth circumstances, their quantity and quality will be diminished if these circumstances change. As a result of this sensitivity to specific conditions, vegetation species make good indicators of rangeland degradation (Van Oudtshoorn, 1992).

Previous studies have found that vegetation degradation often appears alongside a decrease in plant species' diversity, an increase in unpalatable grass species, sharp reductions in plant yields, and low grass height and vegetation cover (Foran et al., 1978; Snyman, 2009; Van den Berg and Zeng, 2006). Grassland plant quality and quantity have been reported to change in accordance with the degree of utilization in degraded grasslands (Snyman, 2009). For example, high quality grasses that are preferred by grazing animals tend to disappear or decrease, while unpalatable grasses tend to increase (Kawanabe et al., 1998). Consequently, the disappearance of key forage species and an increase in species less desired by animals are used as indicators of rangeland degradation (Oba and Kaitira, 2006). In South Africa, grassland is a fundamental ecosystem for the rural population because of its agricultural, environmental, and economic importance. Due to recent increases in the degradation of vegetation cover, there is a pressing need for resource conservation (Hoffman and Todd, 2000). Grass species in South Africa are classified into two categories, namely decreasers and increasers, based on their grazing value and changes in their relative abundances in the presence or absence of grazing (Foran et al., 1978; Van Oudtshoorn, 1992). Decreasers refer to grasses that are abundant in good rangeland but decrease in number when the rangeland deteriorates. These grasses are the palatable ones such as *Themeda triandra*. Increaser species are those grasses that increase their relative abundances with grazing and therefore indicate the poor condition of a rangeland (Oluwole and Dube, 2008). In South Africa, increaser species have been classified into three types, namely: increaser I; increaser IIa; increaser IIb; and increaser III (Oluwole and Dube, 2008; Trollope, 1990). Increaser I species such as *Hyparrhenia hirta* increase in abundance with under-utilization and can be found in old cultivated land, while increaser IIa species increase in abundance when the rangeland is overgrazed (e.g. *Eragrostis curvula*). Increaser IIb species, for example *Sporobolus africanus,* are those that increase in abundance when the rangeland is excessively overgrazed, while increaser III, for example *Aristida diffusa,* are species that increase their relative abundance in rangeland that is selectively grazed (Oluwole and Dube, 2008; Trollope, 1990; Van Oudtshoorn, 1992).

The continued growth in increaser species' habitat represents a significant threat to biodiversity conservation in South Africa's rangeland (O'Connor, 2005). Environmental factors, particularly poor adaptation to rainfall variability, vulnerability to poor soils and the adverse changes to traditional patterns of land use, such as the intensified agricultural activities taking place in many parts of South Africa, have threatened the existence of highly desirable grasses and increased the number of unpalatable grass species (Harrison and Shackleton, 1999).

Through intensive fieldwork, in a game reserve in the Eastern Cape, South Africa (Oluwole and Dube, 2008), increaser and decreaser species have been successfully used as indicators to classify the extent of rangeland degradation according to the categories good, moderately degraded, poorly degraded, and extremely degraded. Since different increaser species can indicate or represent a certain level of rangeland degradation, it may be possible by discriminating and ultimately mapping these increaser species, to obtain a spatially explicit gradient of the level of rangeland degradation.

Traditionally, the mapping of vegetation species in small areas requires intensive fieldwork. This includes the identification of species' characteristics and the visual estimation of species' percentage, all of which are costly and time-consuming as grassland can cover large isolated and inaccessible areas (Berry et al., 2003; Muchoney and Haack, 1994). Therefore, complementary techniques are needed that can provide a fairly accurate, repetitive and rapid means for classifying and monitoring change in vegetation species. In this regard, remote sensing is a developed technique that has a wide and extensive coverage, regular data availability, offers near-real-time data, is potentially inexpensive, contains a large archive of historical data, and produces updated maps of inaccessible areas (Tanser and Palmer, 1999; Wessels et al., 2008; Wessels et al., 2007). Multispectral and hyperspectral remote sensing techniques have been used to discriminate and map vegetation species in disturbed areas for several decades (Palmer and van Rooyen, 1998; Tanser and Palmer, 1999; Vogel and Strohbach, 2009; Wessels et al., 2008; Wessels et al., 2007). Although considerable progress has been made in developing the potential use of multispectral remote sensing to discriminate and map vegetation species in degraded areas, there are still challenges to be met. Multispectral sensors generally gather data in three to six spectral channels from the visible to middle infrared region of the electromagnetic spectra. These few spectral bands are the primary limiting factors of multispectral sensor systems. Some researchers (Harvey and Hill, 2001; Liu et al., 2004) were able to identify challenges of multispectral sensors due to their inability to provide sufficient spectral detail, spectral overlap between the vegetation species, and the spatial resolution of the multispectral data. However, recent developments in sensor technology have overcome these limitations of earth observation systems.

Hyperspectral remote sensing (such as MSMI76, HyMap, Hyperion, and AVIRIS, etc.) has been successful in mapping vegetation species, because of its ability to provide many, narrow, and contiguous spectral bands throughout the visible, near-infrared, mid-infrared, and thermal infrared portions of the electromagnetic spectrum and to provide highly accurate images. These properties make it possible and more effective to discriminate and map vegetation species in comparison with multispectral remote sensing (Govender et al., 2009; Martínez and Gilabert, 2009; Mutanga et al., 2009). Multispectral and hyperspectral data have been used for several decades in classifying and mapping vegetation species in disturbed areas (Escadafal and Huete, 1991; Okin et al., 2001; Pinet et al., 2006; Ray, 1995). According to the ecological literature, spectral discrimination of the different levels of increaser species such as *Hyparrhenia hirta, Eragrostis curvula*, *Sporobolus africanus* and *Aristida diffusa* has been largely ignored in the field of scientific research, despite the fact that it has been proven to be a simple and straightforward method of assessing rangeland conditions compared to intensive laboratory analysis of plant biochemical content. To our knowledge, no attempt has yet been made to spectrally discriminate and characterize the landscape using these species as indicators of the different levels of rangeland degradation. In the last few decades, field spectrometry has been playing essential roles in describing the reflectance spectra of grass species *in situ*, and providing a means of scaling up measurement at field and laboratory levels (Kumar et al., 2001). Therefore, hyperspectral remote sensing was investigated at field level using a portable spectrometer data in order to identify indicators of rangeland degradation in communal areas of KwaZulu-Natal. The specific research objectives of this study were as follows: (1) to determine whether there is a significant difference between the mean reflectance at each measured wavelength (from 350 nm to 2500 nm) for four increaser species (*Hyparrhenia hirta, Eragrostis curvula*, *Sporobolus africanus* and *Aristida diffusa*) that indicate different levels of rangeland degradation, and (2) to identify crucial wavelengths that are the most sensitive in discriminating these four species. In order to achieve these objectives, three tier hierarchical techniques were proposed based on three integrated analysis tiers namely, one-way ANOVA, stepwise discriminant analysis, and canonical function analysis to spectrally discriminate among the four increaser species in Okhombe rangeland, South Africa. It would have been ideal to discriminate between all the vegetation indicators of rangeland degradation, from decreaser up to increaser III species. However, as the rangeland in the study area was severely degraded, the relative abundance of decreaser species (which are typically abundant in veld in good condition) was too low to be used in this study. As a result, four different of increaser species (*Hyparrhenia hirta* (HH) representing increaser I level, *Eragrostis curvula* (EC) representing increaser IIa level, *Sporobolus africanus* (SA) representing increaser IIb and *Aristida diffusa* (AD) representing increaser III were studied.

4.2 Material and methods

4.2.1 Field data collection

4.2.1.1 The identification of vegetation species

Four common species associated with rangeland degradation were selected in the Okhombe ward of the Upper Thukela region in the KwaZulu-Natal Drakensberg mountains. The main features of these species are as follows (Oluwole and Dube, 2008; Van Oudtshoorn, 1992): (1) *Hyparrhenia hirta* (Thatching grass), Increaser I: this is a perennial grass that is fairly dense and tufted. Its spikelets are white or grey and each raceme has four to seven brown and hairy awns. Flowers from September to March (2) *Eragrostis curvula* (Weeping love grass), Increaser IIa: this is a perennial grass that is dense and tufted and flowers from August to June. Inflorescences are usually open and spikelets are dark olive or grey (3) *Sporobolus africanus* (Ratstail Dropseed), Increaser IIb: this is a perennial grass that is tufted and has straight culms and flowers from October to April. Inflorescences are dense with pointed tips, and the leaves are strong (4)

Aristida diffusa (Iron grass) is an increaser III perennial grass species that flowers from November to April and it has strong, narrow, and rolled leaves. Inflorescences are usually sparse, expanded, with an open panicle. These four species were identified and then spectral measurements were taken from different plots.

4.2.1.2 Canopy spectral measurements

Field measurements were taken with the Analytical Spectral Devices (ASD) FieldSpec® 3 to measure the spectral reflectance at canopy level from the following four species: *Hyparrhenia hirta* (HH), *Eragrostis curvula* (EC), *Sporobolus africanus* (SA) and *Aristida diffusa* (AD). The ASD spectrometer has a wavelength ranging from 350 nm to 2 500 nm with a sampling interval of 1.4 nm for the spectral region 350 nm to1000 nm, and 2.0 nm for the spectral region 1000 nm to 2 500 nm, and a spectral resolution of 3 nm to 10 nm (ASD. Analytical Spectral Devices, 2005). Random points were generated using Hawth's Analysis Tool (HAT) in ArcGIS 9.3 and an existing land cover map of the study area developed by the research group (Bangamwabo, 2009). A vegetation plot was defined as covering 3 m × 3 m, where the target species (n = 4) were more homogenous and were representative of more than 80% of the target species in each plot. A total of 53 plots were measured for each grass species (HH, EC, SA and AD). A total of 20 to 25 spectral measurements were then taken randomly in each plot at nadir from 1.5 m using a 5º field of view (Table 4.1). This yielded a ground field of view of about 13 cm above the leaves on a clear sunny day on the 21st of November 2010 between 11:00 am and 2:30 pm local time (Greenwich Mean Time: GMT+2). The spectral measurements from each plot (n = 20 to 25) were then averaged to represent the spectral reflectance of the vegetation plot (n = 212). Data in the spectral range of 1351 to 1439 nm, 1791 to 1989 nm, and 2361 to 2500 nm were affected by atmospheric absorption (ASD. Analytical Spectral Devices, 2005; El-Nahry and Hammad, 2009). Hence, the data in these wavelength regions were removed from all analyses. The remaining data were allocated between 350 to 1350 nm, 1440 to 1790 nm, and 1990 and 2360 nm that comprised a total of 1723 wavelengths which were then used in further analyses (Figure 4.1).

Table 4. 1: Species name, number of sample plots and the total number of measurements

Species name	Type code	No. of subplots	Total number of spectral measurements
Hyparrhenia hirta	HH	53	1325
Eragrostis curvula	EC	53	1166
Sporobolus africanus	SA	53	1060
Aristida diffusa	AD	53	1113

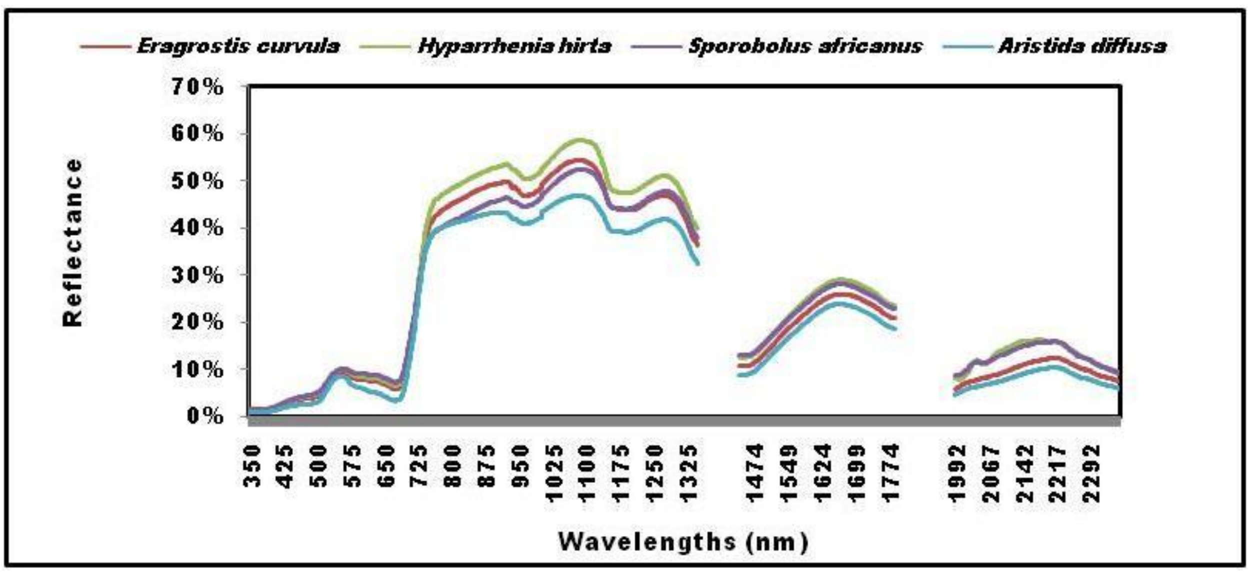

Figure 4. 1: Mean reflectance spectrum data for *Hyparrhenia hirta* (HH), *Eragrostis curvula (EC), Sporobolus africanus* (SA) and *Aristida diffusa* (AD).

4.3 Data analysis

Hyperspectral data require data reduction before applying standard statistical classification techniques (Schmidt and Skidmore, 2003). This study investigated three methods of data reduction and classification. These three methods included: (1) One-way analysis of variance (ANOVA), (2) Stepwise discriminant analysis (SDA), (3) Canonical function analysis (CFA).

4.3.1 One-way ANOVA

One-way ANOVA was used with 95% confidence levels ($P < 0.05$) to test the research hypothesis as to whether there were significant differences in means of reflectance between four increaser species (HH, EC, SA and AD) in communal rangeland among the wavelengths ranging from 350 nm to 2500 nm. We tested the research null hypothesis H0: $\mu1 = \mu2 = \mu3 = \mu4$ versus the alternative hypothesis H1: $\mu1$ # $\mu2$ # $\mu3$ # $\mu4$, where $\mu1$, $\mu2$, $\mu3$ and $\mu4$ are the mean reflectance values for *Hyparrhenia hirta*, *Eragrostis curvula, Sporobolus africanus* and *Aristida diffusa* respectively.

4.3.2 Band selection using discriminant analysis

Discriminant function analysis is a technique used to determine which variables discriminate between two or more groups (Fisher, 1936). The Fisher Discriminant Analysis (FDA) has been extensively used as a technique to reduce dimensionality in pattern recognition. FDA provides an optimal lower dimension for discriminating among classes of data (Zhou et al., 2006). Two approaches of discriminant function analysis have been used in this study:

4.3.2.1 Stepwise discriminant function analysis (SDA)

SDA is the most common technique of discriminant analysis used to determine the variables that discriminate between different groups. To achieve this task, independent variables (wavelengths) are added to the model one by one until it is found that adding extra variables does not significantly improve the discrimination. There are various criteria that can be used for deciding which variables to include in the analysis and which to exclude (Duarte Silva and Stam, 1995; Zhou et al., 2006). In this study three criteria were used: (1) Wilks' Lambda: this is a general test statistic used in multivariate analysis of variance to test whether there are differences between the means of more than two groups. Wilks' Lambda is a ratio of the within-class sum of squares to the total sum of squares, and it varies from 0 to 1. Lower values indicate larger mean differences, thus indicating stronger group separation (Duarte Silva and Stam, 1995); (2) Significance level: this is indicated by the overall *F* of the model. All the variables can be entered if the significance level of the *F* value is 0.05 or less, which means that the result has a 95% chance of being true, and then the model is considered to be significant; (3) *F* to enter and *F* to remove: this determines which variable makes a unique contribution to the prediction of group membership and it depends on the *F* value. The variables with large enough *F* values should be kept in the analysis; the other variables do not significantly contribute to group separation and should be omitted (Duarte Silva and Stam, 1995). The default setting is the optimum values for *F* to enter and *F* to remove and was used in this study as reported in other literature (Duarte Silva and Stam, 1995). The minimum partial *F* to enter was 3.84 and the maximum partial *F* to remove was 2.71.

4.3.2.2 Canonical function analysis (CFA)

Canonical function analysis (CFA) is a multivariate analysis technique to determine functions of the variables that can be used to discriminate among the groups (Manly, 2005). The simplest approach involves taking a linear combination of the X variables.

$$Z = a\,X + e \quad \text{...................} \; (1)$$

Where:
Z= dependent variables
X= independent variables
a= parameters
e= error's term

$$Z = a_1\ X_1 + a_2\ X_2 + \ldots + a_p\ X_p \; \text{...................} (2)$$

The first canonical function implies the maximum possible *F* ratio on a one-way analysis of variance for the variations within and between groups. If there is more than one function, then the second one gives the maximum possible *F* ratio on a one-way analysis of variance subject to the condition that there is no correlation between Z1 and Z2 within groups.

$$Z_1 = a_{11}\ X_{1i} + a_{12}\ X_{2i} + \ldots + a_{1p}\ X_{pi} \; \ldots\ldots\ldots\ldots\ldots\ldots.(3)$$

$$Z_2 = a_{21}\ X_{1i} + a_{22}\ X_{2i} + \ldots + a_{2p}\ X_{pi} \; \ldots\ldots\ldots\ldots\ldots\ldots.(4)$$

From this background, we used stepwise discriminant function analysis and canonical function analysis to achieve the following two objectives: (1) to identify the optimal number of wavelengths to discriminate between four groups of species (HH, EC, SA and AD), or to recognize which wavelengths are most related to the separation of groups and (2) to predict the group membership for samples of undefined origin based on the measured values of the discriminating variables.

4.3 Classification accuracy assessment

To examine the effectiveness of hyperspectral data to discriminate among four increaser species, the optimal wavelengths selected by stepwise discriminant function analysis were used to test the classification accuracy. Two methods of accuracy assessment were adopted. The first method assessed the overall accuracy which was calculated by dividing the total number of correctly classified samples by the total number of sample units in the matrix (Fung et al., 2003). The second method, Kappa analysis, is a discrete multivariate technique used in accuracy assessment that was developed by Cohen (1960). The result of the Kappa analysis is the KHAT statistic, which is calculated in order to determine if one error matrix is significantly different from another (Cohen, 1960). This statistical method helps as an indicator of the extent to which the percentage of correct values of an error matrix are due to the actual agreement in the error matrix and the chance agreement that is indicated by the row and column totals (Mutanga, 2005). If the KHAT coefficients are one, or close to one, then there is perfect agreement.

4.5 Results

4.5.1 One-way ANOVA test

The results of the one-way ANOVA test indicate that there was a statistically significant difference in the spectral reflectance among the four increaser species: *Hyparrhenia hirta*, *Eragrostis curvula, Sporobolus africanus* and *Aristida diffusa*. The significant wavelengths (439) are located in the three different regions of the electromagnetic spectrum, namely the visible (18 wavelengths), red-edge (71 wavelengths) and near-infrared (350 wavelengths). Results of frequency analysis show that in the mid-infrared region (1300 – 2500 nm) there is no wavelength that can be used to discriminate between all the class pairs (n = 4). See Figure 4.2 below.

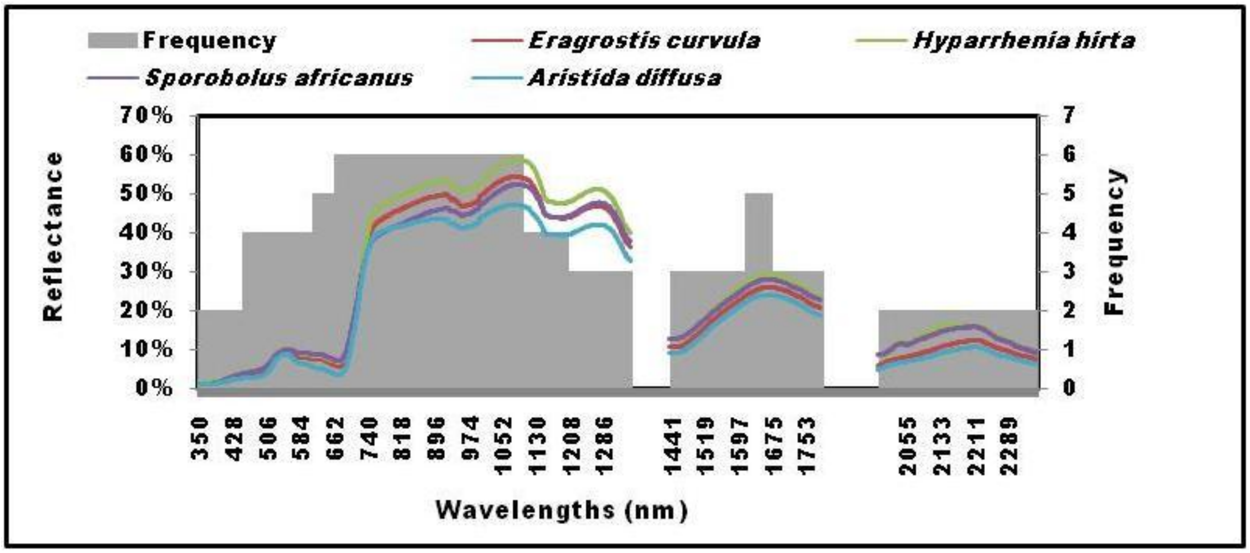

Figure 4. 2: Frequency of statistical differences using ANOVA with 95% confidence level (P< 0.05) between the mean reflectance of four species (*Hyparrhenia hirta, Eragrostis curvula, Sporobolus africanus* and *Aristida diffusa).* The maximum grey shading shows the wavelengths where all four species can be discriminated. Spectral features between 1351nm and 1439 nm, 1791 nm and 1989 nm, and 2361 nm and 2500 nm were removed due to excessive noise.

4.5.2 Stepwise discriminant function analysis results

Table 4.2 below shows the wavelengths selected by the stepwise discriminant function analysis according to Wilks' Lambda value (0.115 to 0.512), *F* statistic (32.556 to 75.119), and significance level (P < 0.001). The wavelengths in the analysis with the highest value *F* to enter are 665 nm, 729 nm, 848 nm, 895 nm, 1039 nm, 998 nm, 681 nm and 972 nm. It revealed that the important wavelengths that can be used to discriminate among the four species (HH, EC, SA and AD) were found in the visible, red-edge and near-infrared regions.

Table 4. 2: Variables entered/ removed using stepwise discriminant function analysis

Step	Variables entered	Lambda	Statistic	Sig.
1	665	0.512	44.849	0.000
2	729	0.302	75.119	0.000
3	848	0.189	66.916	0.000
4	895	0.173	53.205	0.000
5	1039	0.156	48.146	0.000
6	998	0.131	40.974	0.000
7	681	0.123	36.728	0.000
8	972	0.115	32.556	0.000

4.5.3 Canonical function analysis

Discriminant functions are explained by means of standardized coefficients and the factor structure matrix. Table 4.3 shows the function values and standardized canonical discriminant function coefficients that were given to every variable (wavelength). Standardized canonical discriminant function coefficients represent the correlation between the variables and the canonical functions. The larger the standardized coefficient, the greater is the contribution of the variable (wavelength) to the discrimination among the four species. The largest contribution is contained in the first canonical function which includes the wavelengths 895 nm (the coefficient is 0.957), followed by 998 nm, 681 nm, 745 nm, 998 nm and a low standardized coefficient includes 665, the coefficient is (-0.053), followed by 1039 nm, 848 nm and 972 nm. The second canonical function also shows that the largest contribution is contained in the 685nm band with the highest coefficient (18.343), followed by 665 nm, 848 nm, 729 nm and the low coefficient located at 681 nm, 972 nm, 1039 nm and 895 nm. It can be noted that the wavelengths 895 nm and 998 nm have been selected by the first and second canonical functions which reflect the importance of this wavelength in discrimination.

Table 4. 3: Standardized canonical discriminant function coefficients representing the correlation between wavelengths and canonical functions

Wavelengths	Function 1	Function 2
972	-0.238	-0.165
998	0.942	0.512
681	0.745	0.115
848	0.146	0.591
895	0.957	-0.303
1039	0.124	-0.186
729	-0.665	-0.519
665	-0.053	-0.697

Many scientists use the structure matrix correlations because they are considered to be more accurate than the standardized canonical discriminant function coefficients (Mardia et al., 1979). Table 4.4 shows the correlation between the wavelengths and the canonical functions. The highest factor structure coefficients are representing the wavelengths with high discriminatory power (Manly, 2005). The most wavelengths that have a positive correlation with canonical function are located in the visible, red-edge and near-infrared regions. The 665 nm wavelength is the most important in discrimination, followed by the 1039 nm, 729 nm, 848 nm and 895 nm wavelengths.

Table4.4: Factor structure matrix representing the correlation between the significant wavelengths and the canonical functions

Wavelengths	Function 1	Function 2
665	0.372	-0.207
729	0.361	-0.236
848	0.345	-0.209
895	0.339	-0.216
1039	0.371	-0.203
998	0.285	-0.225
681	-0.252	0.093
972	0.212	-0.214

Table 4.5 shows the mean of canonical variables required to determine the nature of the discrimination for each canonical function. The results show that the first canonical function discriminates mostly between HH and other increaser species; followed by AD and SA. The second canonical function seems to distinguish mostly between EC and other increaser species; however, the magnitude of the discrimination is much smaller for the second canonical function than the first canonical function, because of the weak association with the discriminant function.

Table 4. 5: Means of canonical variables to determine the nature of the discrimination for each function and significant wavelengths

Species	Function 1	Function 2
HH	2.981	0.314
EC	-0.725	-1.356
SA	-2.16	0.615
AD	-2.683	0.532

Classification of the four species was applied using the canonical functions. Cross validation was done to assess the classification accuracy (Table 4.6). In cross validation, each variable is classified by the functions derived from all the variables. Of the original grouped species, 83.02% were correctly classified, and 77.36% of the cross-validated grouped species were correctly classified. The results also show that HH can be successfully classified with an accuracy of 89%, with an accuracy of AD 87%, with an accuracy of EC 79% and SA with an accuracy of 77%. We noted that some of the EC (15%) was classified as SA and 13% of the SA was classified as EC. This may be attributed to the similarity in structure between the two species.

Table 4. 6: A confusion matrix to estimate the accuracy of the classification technique

		Predicted group membership					
		species	HH	EC	SA	AD	Total
Original	Count	HH	47	3	2	1	53
		EC	1	42	8	2	53
		SA	1	7	41	4	53
		AD	4	1	2	46	53
	%	HH	89	6	4	2	100
		EC	2	79	15	4	100
		SA	2	13	77	7	100
		AD	7	2	4	87	100
Cross-validation	Count	HH	46	4	2	1	53
		EC	2	39	9	3	53
		SA	3	10	35	5	53
		AD	2	0	7	44	53
	%	HH	87	8	4	2	100
		EC	4	73	17	6	100
		SA	5	19	66	9	100
		AD	4	0	13	83	100

A confusion matrix was constructed for selected wavelengths and it shows the classification error obtained for all the species (HH, EC, SA and AD). The confusion matrix shows that we could classify these species into their respective groups with an overall accuracy of 83.02% and a KHAT value of 0.77. Producers' accuracy and users' accuracy were also calculated (Table 4.7).

Table 4. 7: Confusion matrix for selected wavelengths showing the classification error obtained for the species (HH, EC, SA and AD)

Selected wavelength	Overall accuracy	KHAT	Users' accuracy		Producers' accuracy	
			Presence	absence	Presence	absence
8 wavelengths	83.02	0.77	88.68	79.25	88.68	79.25

4.6 Discussion

The advantages of hyperspectral remote sensing are the abundance of the spectral information that is available and its power in distinguishing objects. This does not mean that the more wavelengths that are used in classification, the higher the precision will be. On the contrary, if all wavelengths are used, precision will decrease (Jusoff and Pathan, 2009). Therefore, different techniques were used: one-way ANOVA, stepwise discriminant analysis (SDA) and canonical function analysis for data reduction and classification.

4.6.1 One-way ANOVA

The results of the one-way ANOVA test indicated that there were significant differences in the mean reflectance among the increaser species *Hyparrhenia hirta, Eragrostis curvula*, *Sporobolus africanus* and *Aristida diffusa* when a 95% confidence level ($p < 0.05$) was used (439 wavelengths). The significant wavelengths ($n = 439$) were located in three different regions of the electromagnetic spectrum: the visible region from 662 nm to 679 nm ($n = 18$); the red-edge region from 680 nm to 750 nm ($n = 71$); and the near-infrared region from 751 nm to 1100 nm ($n = 350$). The results demonstrated that there was no wavelength selected in the mid-infrared region. The significant wavelengths were highlighted using a histogram for four species (Figure 4.2). The grey shaded areas show the wavelengths where the four species can be discriminated. Similar results in previous studies (Ustin et al., 2009), found that high discriminatory power is contained in the visible, red-edge, and near-infrared regions. The differences between the four species in the visible region, specifically in the red (600 nm - 700 nm) region, are due to the absorption of light by photosynthetic pigments which dominate green leaf characteristics such as chlorophyll a, chlorophyll b, xanthophylls, α-carotene, b-carotene, and anthocyanins (El-Nahry and Hammad, 2009; Ustin et al., 2009). The significant wavelengths in the red-edge (680 nm - 750 nm) and near-infrared (700 nm -1300 nm) regions are due to variations among the four species in leaf internal structure and water content (El-Nahry and Hammad, 2009; Ustin et al., 2009). Differences in organic matter, neutral detergent fibre, acid detergent fibre, acid detergent lignin, crude protein and in vitro dry matter digestibility amongst increaser species during the growing season, are responsible for the spectral variations (Majuva-Masafu and Linington, 2006;

Teklu et al., 2010; Theron, 1966). For instance, both EC and SA when observed at the close of the season appeared as green and as moist as they were at the beginning of the season. On the other hand, HH senesced at the close of the season, so that the leaves had completely desiccated by comparison with those of EC and SA (Theron, 1966).

4.6.2 Band selection using stepwise discriminant function analysis (SDA)

The SDA was applied to reduce dimensionality in the significant wavelengths (n = 439) obtained from ANOVA as well as to select the most important wavelengths to discriminate among the four increaser species. The SDA has successfully described and explored the relative importance of each individual wavelength and reduced the wavelengths to 8, located at 665 nm, 729 nm, 848 nm, 895 nm, 1039 nm, 998 nm, 681 nm and 972 nm (Table 4.2). These wavelengths are within $\pm$ 12 nm from the known wavelengths that have been selected for discriminating species in previous studies. These are 689 nm (Martin et al., 1998), 670 nm (Daughtry and Walthall, 1998), 670.37 nm, 695.69 nm, 728.14 nm (Fung et al., 2003), 690 nm, 684 nm, and 740 nm (Bajwa et al., 2004).These significant wavelengths are located in the visible, red-edge and near-infrared regions. These results are comparable to those arising from the studies of others (Curran, 1989; Van Aardt and Wynne, 2001) who have reported that the visible, red-edge, and near-infrared regions have great potential for species discrimination. Wavelengths selected in the visible region are directly related to the physio-chemical characteristics of species, such as different leaf pigments and different sensitivity levels to the visible light source, that help discrimination among species (Elvidge, 1990; Jiang et al., 2004; Thenkabail et al., 2004; Ustin et al., 2009; Vaiphasa et al., 2007). The wavelength in the red-edge region could discriminate among species that contained different morphological and anatomical properties (Elvidge, 1990; Mutanga and Skidmore, 2007; Schmidt and Skidmore, 2003).

4.6.3 Canonical function analysis

Canonical function analysis helped to reduce dimensionality in the hyperspectral data set as well as to describe and explore the relative importance of individual wavelengths in explaining the discrimination among the four species. The technique also provided an insight into the relationships between variables and the potential of hyperspectral remote sensing in discriminating between groups (Mutanga, 2005). The canonical function analysis showed that there were correlations between the wavelengths and the canonical functions. The highest factor structure coefficients representing the wavelengths with high discriminatory power were found in the red-edge and near-infrared regions (Table 4.4). As shown by the first function, the magnitude of canonical discrimination of the wavelengths 895 nm followed by 998 nm, 681 nm, 745 nm and 998 nm were greater compared to those of the second function, thereby indicating the importance of the significant wavelengths in the red-edge and near-infrared regions for discriminating among the three species. This is explained mainly by the difference in pigments and other optical characteristics of the leaves of the different species (Kumar et al., 2001; Ustin et al., 2009; Van Aardt and Wynne, 2001).

This separation has helped to discriminate and characterize the landscape using these species as indicators of the different levels of land degradation. Based on these results, the SDA could select optimal wavelengths for discriminating increaser species, with high and acceptable levels of overall accuracy (83.02%), using spectrometry data.

4.7 Conclusions

The aim of this study was to discriminate between four increaser species namely, *Hyparrhenia hirta, Eragrostis curvula, Sporobolus africanus* and *Aristida diffusa* in degraded rangeland in the Okhombe region using field spectrometry data. Our results have shown that:

1. The analytical spectral devices (ASD) FieldSpec®3 spectrometer measurements at canopy level can be used to discriminate among four species (HH, EC, SA and AD). This indicates that the mean reflectance of each of these species is different.
2. Stepwise discriminant techniques effectively reduced data dimensionality and selected the most important wavelengths for discriminating among the four increaser species with a high accuracy of 83.02%.
3. The use of SDA has revealed that the high discriminatory power for identifying increaser species (HH, EC, SA and AD) is located in the visible, red-edge and near-infrared regions specifically at 665 nm, 729 nm, 848 nm, 895 nm, 1039 nm, 998 nm, 681 nm and 972 nm.

4. Canonical function has explored the relative importance of individual wavelengths in explaining the discrimination among four species. The canonical structure matrix has revealed that greater discriminatory power is contained in the visible, red-edge and near-infrared regions including the 665 nm wavelength which is most important in discrimination, followed by the 1039 nm, 729 nm, 848 nm and 895 nm wavelengths.

In addition, the results demonstrated the possibility of discriminating between increaser species using hyperspectral data. This allows for the upscaling of methods to airborne sensors, such as AISA Eagle, for mapping increaser species in degraded rangelands.

Acknowledgements

I would like to thank Amazizi Traditional Administrative Council, for the permission granted us to conduct this research within the Okhombe ward. My appreciation also extends to El-fashir University (Sudan) and the University of KwaZulu-Natal (South Africa) for giving me the opportunity to read for a PhD. Our gratitude further extends to Elhadi Adam and Monique Salomon for their assistance and valuable comments.

Chapter 4 has shown that increaser species are spectrally distinct using field spectrometry at canopy level. The next step is to use the knowledge of spectral bands and curves identified for discriminating the species to upscale to airborne sensors.

The following chapter (5) therefore, aimed to investigate the potential use of hyperspectral RS in discriminating among increaser species by resampling the field spectrometry data to AISA Eagle resolution and tested the random forest as a classification algorithm.

CHAPTER FIVE

Discriminating indicator grass species for rangeland degradation assessment using hyperspectral data resampled to AISA Eagle resolution

This chapter is based on:

Manssour, K., Mutanga, O., Everson, T., and Adam, E., (In revision). Discriminating indicator grass species for rangeland degradation assessment using hyperspectral data resampled to AISA Eagle resolution. *ISPRS Journal of Photogrammetry and Remote Sensing.*

Abstract

The development of techniques to estimate and map increaser grass species is critical for better understanding the condition of the rangeland and levels of rangeland degradation. This paper investigates whether canopy reflectance spectra, resampled to AISA Eagle resolution can discriminate among four increaser species representing different levels of rangeland degradation. Canopy spectral measurements were taken from the four indicator species: *Hyparrhenia hirta* (HH), *Eragrostis curvula* (EC), *Sporobolus africanus* (SA) *and Aristida diffusa* (AD). The random forest algorithm and a forward variable selection technique were used to identify optimal wavelengths for discriminating the species. The results revealed that the optimal number of wavelengths (n = 10) that yielded the lowest OOB error (13.68%) in discriminating among the four increaser species are located in 966.7 nm, 877.6 nm, 674.1 nm, 854.8 nm, 703 nm, 732 nm, 718.7 nm, 691.9 nm, 741 nm and 902.7 nm. These wavelengths are located in the visible, red-edge and near-infrared regions of the electromagnetic spectrum. The random forest algorithm can accurately discriminate species with an overall accuracy of 87.50 % and a KHAT value of 0.83. The study demonstrated the possibility to upscale the method to airborne sensors such as AISA Eagle for mapping indicator species of rangeland degradation.

Keywords: rangeland degradation; random forest; increaser grass species; field spectrometer measurements.

5.1 Introduction

Rangeland degradation is defined as the reduction or temporary loss of the biological and economic productivity of grasslands (UNCCD, 1995). Currently, rangeland degradation has been identified as one of the most serious global environmental issues (Wessels et al., 2007). Approximately over 250 million people in over 100 countries are directly affected by rangeland degradation (Adger, 2000; Wessels et al., 2007). In South Africa, rangeland degradation is believed to be one of the most severe and widespread environmental problems facing the country (Hoffman and Todd, 2000; Wessels et al., 2004). A total of 4.8% (5.8 million ha) of South African land has been identified as degraded as indicated by its lower vegetation cover when compared with the surrounding areas (Thompson, 1996; Wessels et al., 2004). The greatest areas of extensively degraded land coincide with communal lands and rangelands where a considerable population of South Africa and livestock live (Hoffman and Todd, 2000; Reid and Vogel, 2006). Many South African studies on rangeland degradation have been concentrated on commercial areas (Palmer and van Rooyen, 1998; Shackleton et al., 2005). However, the communal areas have not yet received the same level of attention that has been apparent in the commercial areas (Hoffman and Todd, 2000; Wessels et al., 2004). The continued rangeland degradation represents a significant threat to the livestock and biodiversity (Hoffman et al., 1995).Therefore, there is a need for planning strategies to map and monitor rangeland degradation at different scales through use of consistent, repeatable and spatially explicit measures (Prince et al., 2009; Ravi et al., 2010). These planning strategies for sustainable land management require techniques that can effectively reveal the spatial extent, magnitude, and temporal behaviour of the lands (Prince et al., 2009; Ravi et al., 2010; Van Lynden and Mantel, 2001). Remote sensing techniques provide an efficient cost-effective means for assessing and mapping rangeland degradation (Ustin et al., 2009). However the use of remote sensing techniques in mapping rangeland degradation requires simple indicators that allow combining ground-based methods with remotely sensed data (Pyke et al., 2002). Several indicators have been suggested for mapping rangeland degradation such as soil organic matter (Wang et al., 2010b), vegetation production (Wessels et al., 2008), and natural and semi-natural vegetation communities (Hill et al., 2008). The limitation of these studies is that they have mainly been focused on binary maps that identify the degraded and non-degraded areas. Although these methods can allow drawing the line between the two classes, they do not allow identifying different levels of rangeland degradation using indicators that can easily and directly be detected and monitored. Such indicators could be vegetation species. This is because certain vegetation species are well adapted to specific growth conditions and their quality and quantity reduce or increase according to change in the growth conditions (Nordberg and Allard, 2002; Van Oudtshoorn, 1992).

In South Africa, grassland species have been classified into two groups of increaser and decreaser species based on changes in their relative abundances in the presence or absence of grazing, and these changes indicate the condition of the rangeland (Dobarro et al., 2010). Increaser species are species that increase their relative abundances through grazing or under-utilization, and therefore indicate the poor condition of the rangeland (Dobarro et al., 2010; Van Oudtshoorn, 1992). Increaser species have been classified into three types, namely, increaser I, increaser II, and increaser III (du Toit, 2009; Oluwole and Dube, 2008; Trollope, 1990). Increaser I species such as *Hyparrhenia hirta* increase in abundance with under-utilization and can be found in areas with low grazing capacity (e.g. conserved areas), while increaser II species increase in abundance when the rangeland is over-utilized (e.g. *Eragrostis curvula and Sporobolus africanus),* and increaser III species (e.g. *Aristida diffusa)* increase in relative abundance in rangeland that is selectively grazed (du Toit, 2009; Oluwole and Dube, 2008; Trollope, 1990; Van Oudtshoorn, 1992). A gradient of degradation has been classified to range from severe with a high relative abundance of increaser I, increaser II and increaser III species to non-degraded rangeland with a high abundance of decreaser species. Therefore, the relative abundance and distribution of the different increaser species can be used to classify rangeland condition into moderate (increaser I), poor (increaser II), and highly degraded (increaser III), thereby indicating the gradient of rangeland degradation.

Up-to-date spatial information about increaser species is essential for classifying rangeland condition. To our knowledge, no attempt has yet been made to discriminate increaser species with remote sensing as indicators of the different levels of rangeland degradation.

Traditionally, mapping vegetation species generally requires intensive fieldwork, including the identification of species characteristics and the visual estimation of species percentage all of which are costly and time-consuming and sometimes impossible to accomplish due to the poor accessibility of the areas (Adam et al., 2009; Muchoney and Haack, 1994). On the other hand, remote sensing techniques offer an economic and effective technique, producing timely and accurate information for mapping vegetation species (Ustin et al., 2009).

Hyperspectral remote sensing, in particular, is developing as a more in-depth means of investigating spatial, temporal, and spectral discrimination of vegetation species quantity and quality (Ustin et al., 2009). This is due to its use of many narrow and contiguous spectral bands of less than10 nm. These bands allow the detection of vegetation at species levels which are otherwise masked by broad bands of multispectral satellites such as SPOT (Kumar et al., 2001; Mutanga and Skidmore, 2004; Mutanga et al., 2005). Hyperspectral remote sensing data are acquired using spaceborne, airborne sensors and a hand-held spectrometer (Adam et al., 2009). At the moment, hyperspectral remote sensing has not reached operational level at a wider scale due to the high costs of the images and the small areal extent covered by airborne images. However, research on the behavior of indicator vegetation species using field spectroscopic data is an important step towards understanding the critical bands, absorption features and curves that can be targeted for building operational sensors so as to reveal the behavioral patterns of rangeland degradation. The processing of hyperspectral remote sensing data is challenging due to the high dimensionality, overfitting when applying statistical methods, an excessive demand for sufficient field samples, and high cost (Bajcsy and Groves, 2004; Vaiphasa et al., 2007). Therefore, identifying the optimal and most powerful wavelengths using variable selection methods without losing any important information is a pre-requisite in hyperspectral remote sensing application (Adam and Mutanga, 2009; Bajcsy and Groves, 2004; Vaiphasa et al., 2007). This method is utilised, not only to reduce the number of variables so as to simplify the model, but also to determine which explanatory variables are most suitable in classifying increaser species. Different statistical techniques such as discriminant analysis, canonical variate analysis, classification trees, support vector machines; and principal component analysis have been used to identify the optimal wavelengths (Adam and Mutanga, 2009; Cochrane, 2000; Mutanga and Skidmore, 2004).

Recently, the random forest algorithm which was developed by Breiman (2001), has been successfully used as a variable selection and classification algorithm for hyperspectral data (Adam et al., 2009; Ismail, 2009; Lawrence et al., 2006). Random forest is a tree ensemble algorithm that uses a bagging, i.e., bootstrap aggregation, ensemble procedure to build multiple individual decision trees that are provided to be diverse by the use of random samples derived from the training data set (Breiman, 2001). The training data is sampled to create an in-bag partition to construct the tree (2/3 of the training data), and a smaller out-of-bag partition (1/3 of the training data set) to validate the performance of each constructed tree (Özçift, 2011). The multiple trees then vote by majority on correct classification.

The objectives of this study were to investigate the use of the random forest algorithm to identify the crucial wavelengths that are the most sensitive in discriminating between the four indicator species (*Hyparrhenia hirta, Eragrostis curvula*, *Sporobolus africanus* and *Aristida diffusa*) for different levels of rangeland degradation in the Okhombe communal area, South Africa. We also sought to investigate whether or not, when using random forest algorithm, canopy reflectance spectra resampled to AISA Eagle spectral resolution could be used to discriminate among these four species.

5.2 Material and methods

5.2.1 Field data collection

5.2.1.1The identification of increaser grass species

Intensive field work was conducted to identify the grass species that are associated with rangeland degradation in the study area (Figure 5.1). Four indicator grass species were then selected based on their high relative abundances. These species were *Hyparrhenia hirta* (HH*),* *Eragrostis curvula* (EC), *Sporobolus africanus* (SA) and *Aristida diffusa* (DA*).* These species represent the increaser I, increaser II and increaser III categories.

Figure 5. 1: Visual indicators of rangeland degradation observed in Okhombe: (A) cattle access routes, (B) sedimentation in streams and (C) gullies.

5.2.1.2 Canopy spectral measurements

Spectral measurements at canopy level were taken from the four increaser species (*Hyparrhenia hirta*, *Eragrostis curvula*, *Sporobolus africanus,* and *Aristida diffusa*) using the Analytical Spectral Devices (ASD) FieldSpec® 3(ASD). The spectral range of the ASD is 350 nm to 2 500 nm with a resolution of 1.4 nm in the 350 nm to1000 nm range and 2.0 nm for the spectral region 1000 nm to 2 500 nm (ASD. Analytical Spectral Devices, 2005). Random points were generated using Hawth's Analysis Tool (HAT) in ArcGIS 9.3 (Adam and Mutanga, 2009) and an existing land cover map of the study area developed by the research group (Bangamwabo, 2009). A species plot was defined to cover 3 m × 3 m, where the target species (n = 4) were more homogenous with high relative abundances of more than 80% of the target species in each plot. A total of 75 plots were generated for each grass species (HH, EC, SA and AD). A total of 20 to 25 spectral measurements were then taken randomly in each plot at nadir from 1.5 m using a 5º field of view (Table 5.1). This yielded a ground field of view of about 13 cm above the leaves on a clear sunny day of 21st of November 2010 between 11:00 am and 2:30 pm local time (Greenwich Mean Time: GMT+2). These spectral measurements from each plot (n= 20 to 25) were then averaged so as to represent the spectral reflectance of the vegetation plot (n = 308). The spectral measurements were then resampled to the AISA Eagle spectral resolution using ENVI 4.3 image processing software (Mutanga, 2005) (Figure 5. 2). AISA Eagle data has a 2 m spatial resolution and a spectral range from 393.2 nm to 994.1 nm (272 wavelengths) at 2.04 nm to 2.29 nm spectral resolutions. The resampled AISA Eagle spectra were then used for subsequent analysis. The data set for each target species was then split randomly into 70/30 training data set (n = 53) and test data set (n = 22) respectively (Ismail and Mutanga, 2010).

Table 5. 1: Species name, number of sample plots, and the total number of spectral measurements

Species name	Type code	No. of plots	Spectral measurements
Hyparrhenia hirta	HH	75	1730
Eragrostis curvula	EC	75	1700
Sporobolus africanus	SA	75	1715
Aristida diffusa	AD	75	1780

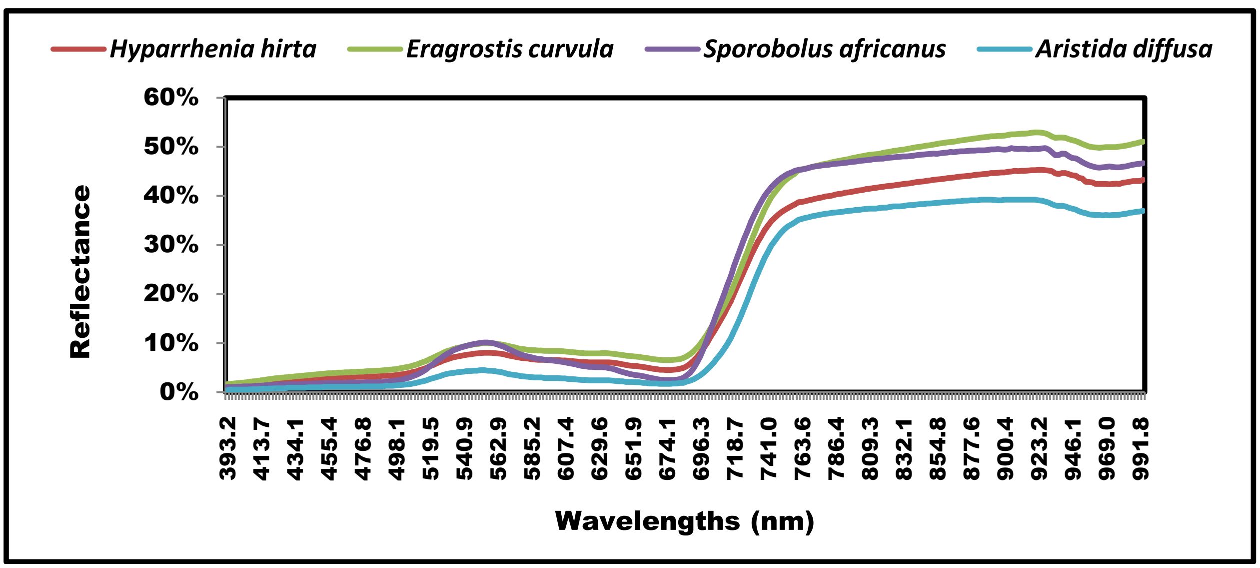

Figure 5. 2: Mean reflectance spectrum data for *Hyparrhenia hirta* (HH), *Eragrostis curvula (EC)*, *Sporobolus africanus* (SA) and *Aristida diffusa* (AD).

5.3 Data analysis

5.3.1 Measuring variable importance using the random forest algorithm (RF)

The random forest algorithm is a forest-based method developed by Breiman (2001) to overcome the instability of traditional tree-based methods. Breiman (2001) defined the random forest algorithm as follows: random forest consists of a collection of multiple decision tree classifiers that are defined as ($h(x, \Theta_k)$, $k = 1,...$).where Θ_k represents identically distributed random vectors and each tree casts a unit vote for the most popular class at input X.

Each decision tree in the forest is constructed by the following steps:

1. The number of trees (T) to be grown is selected.
2. The number of variables (f) to split each node is chosen. If the variables of the input data are denoted by F, then $f < F$ must be satisfied. The subset of features f is kept constant during the formation of the forest.
3. T number of trees (*ntree*) is grown with the following criteria:

a) A bootstrap sample of size n is constructed with a replacement and samples of S_n are selected to grow a tree.

b) To grow a tree at each node, m features are selected randomly and they are used to find the best split.

c) Each tree is grown to maximum size without pruning.

In order to classify a sample X (in our case the increaser species) a majority voting scheme is used to evaluate votes from each tree in the forest.

The RF algorithm provides three independent variable importance measures, specifically, the permutation accuracy importance measure, the Gini importance, and the number of times each variable is selected (Breiman, 2001). The permutation accuracy importance measure, is considered to be the best measure in random forests because of its capability in assessing the variable importance that relies on mean decreases in accuracy as measured using the out-of-bag (OOB) samples (Breiman, 2001). The OOB is referring to the element not included in bootstrap iteration. The OOB error produces a measure of the importance of the variables by comparing how much the OOB error of estimate increases when a variable is permutated, whilst all other variables are left unchanged (Archer and Kimes, 2008; Peters et al., 2007).

In this study, the permutation of variables (mean decrease in accuracy) to measure the importance of AISA Eagle wavelengths in discriminating between the increaser species was used (Breiman, 2001) as a ranking index to measure of the importance of the variable and thereafter identifying the wavelengths with relatively large importance in the classification process (Archer and Kimes, 2008; Díaz-Uriarte and de Andrés, 2006).

In order to obtain the highest accuracy, the RF model was optimized based on OOB estimate of error rate (Adam et al., 2009; Breiman, 2001; Ismail, 2009; Svetnik et al., 2003), using different number of trees (*ntree*) from 500 to 10000 with intervals of 500, while *mtry* was optimized using the values between 1 and 20. The "randomForest" package (Liaw and Wiener, 2002) developed in R environment software (R Development Core Team, 2008) was implemented.

5.3.2 Forward variable selection

The shortcoming of the random forest algorithm in measuring variables importance is that it does not automatically select the optimal number of variables that produce the best classification accuracy (Adam et al., 2009). Therefore, forward variable selection (FVS) was used to determine the optimal number of wavelengths based on the random forest measurement of variables importance (Adam et al., 2009; Ismail and Mutanga, 2010). Forward variable selection iteratively builds multiple random forests (n = 54). At each iteration, five wavelengths are added to the variable selection model, and the error was calculated using the OOB estimate method. Initially, the top five wavelengths were selected for the first iteration, and thereafter the next top five wavelengths were selected. This process was repeated until no more explanatory variables could be included into the final model (Adam et al., 2009).

5.3.3 Classification accuracy assessment

To test the prediction performance of any algorithm, the use of an independent test data set that has not been used in training is recommended (Congalton and Green, 1999). In random forest algorithms, it has been reported that the OOB error is considered to be a type of cross-validation that provides an unbiased estimate of error (Archer and Kimes, 2008; Breiman, 2001; Lawrence et al., 2006; Peters et al., 2007). However, some studies have recommended that the reliability of the OOB estimate of error has to be further tested (Ismail and Mutanga, 2010; Lawrence et al., 2006). In this study the OOB error was used to estimate the classification accuracy. Nevertheless, we further tested the reliability of the OOB error (Lawrence et al., 2006). Two methods were used: an independent test data set (n = 22) and the .632+ Bootstrap error for variables selection and classification. The .632+ Bootstrap error is a statistical approach developed by (Efron, 1979) and (Efron and Tibshirani, 1997), and it has been widely used for obtaining a nonparametric estimate of error. The .632+ bootstrap error was used with a replication of 50 times to estimate the prediction error at each iteration in forward variables selection. The optimal number of wavelengths that yielded the smallest error rate as determined by the three methods (OOB, independent test data set and the .632+ bootstrap) were then used to classify the increaser species. A confusion matrix was constructed so as to compare the true class with the class assigned by the classifier and to calculate the overall accuracy as well as the producer's and user's accuracies. The producer's accuracy is computed by splitting the number of correctly classified trees in each crown condition class by the number of data sets used for that class (column total in the confusion matrix). User's accuracy is calculated by dividing the number of correctly classified trees by the total number of trees that were classified in that crown condition class (row total in the confusion matrix) (Ismail, 2009). In addition, a discrete multivariate technique, called Kappa, was used in accuracy assessment. The result of the Kappa analysis is the KHAT statistic which was calculated in order to determine if one error matrix is significantly different from another (Cohen, 1960). If the Kappa (K) coefficients are one or close to one then there is perfect agreement between the training and test data.

5.4 Results

5.4.1 Optimization of *ntree* and *mtry*

Following the experiment, the optimization of the number of trees (*ntree*) and the number of variables at each split yielded an *mtry* value of 16 (which is the default setting) and an *ntree* of 6500 (Figures 5.3 and 5.4) resulting in the lowest and most stable value of the OOB error rate (14.25%). This optimization result was then used for subsequent analyses.

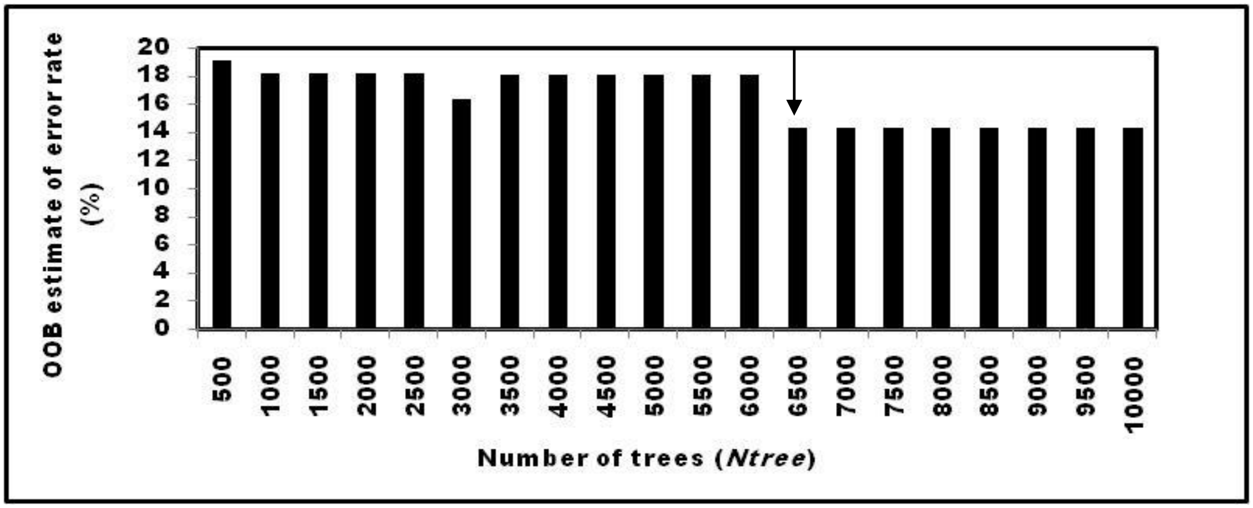

Figure 5. 3: Optimizing the number of trees (*ntree*) based on the default setting of *mtry* (16) using the OOB estimate of error rate. The *ntree* with the lowest and most stable OOB error rate is shown by an arrow.

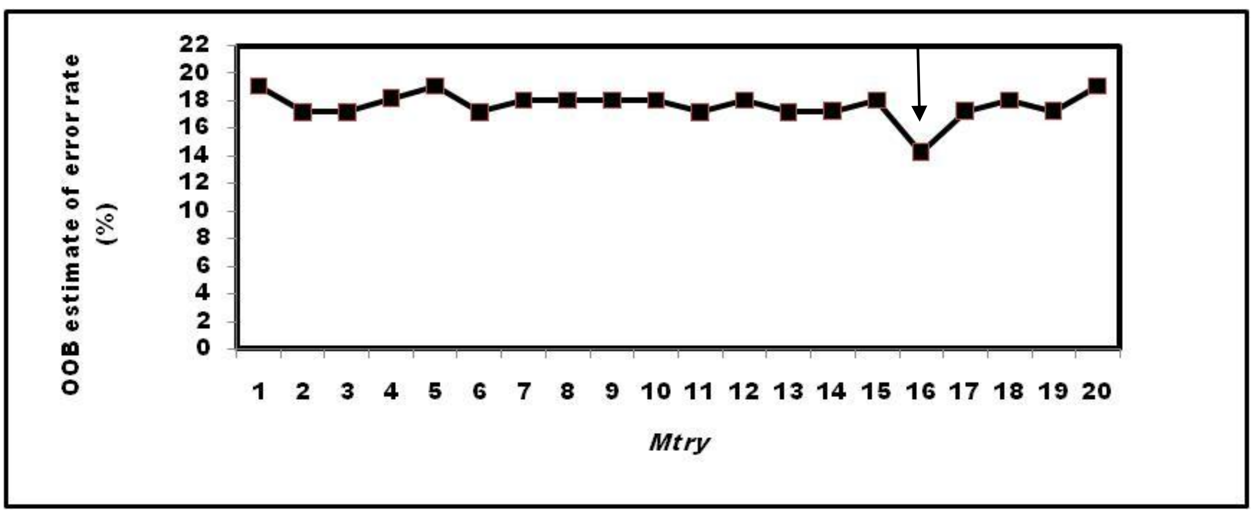

Figure 5. 4: Optimizing the number of variables at each split (*mtry*) based on 6500 *ntree* (optimal *ntree*) using the OOB estimate of error rate. The *mtry* that yielded the lowest OOB error rate (14.25%) is shown by an arrow.

4.5.2 Variables importance using the random forest algorithm

The random forest algorithm effectively explored and described the relative importance of each individual wavelength in discriminating among the increaser species. The most important wavelengths with the highest mean decrease in accuracy when they are permutated are located at 651.9 nm to 691.9 nm, 700.8 nm to 741 nm and 854.8 nm to 966.7 nm (Figure 5.5).

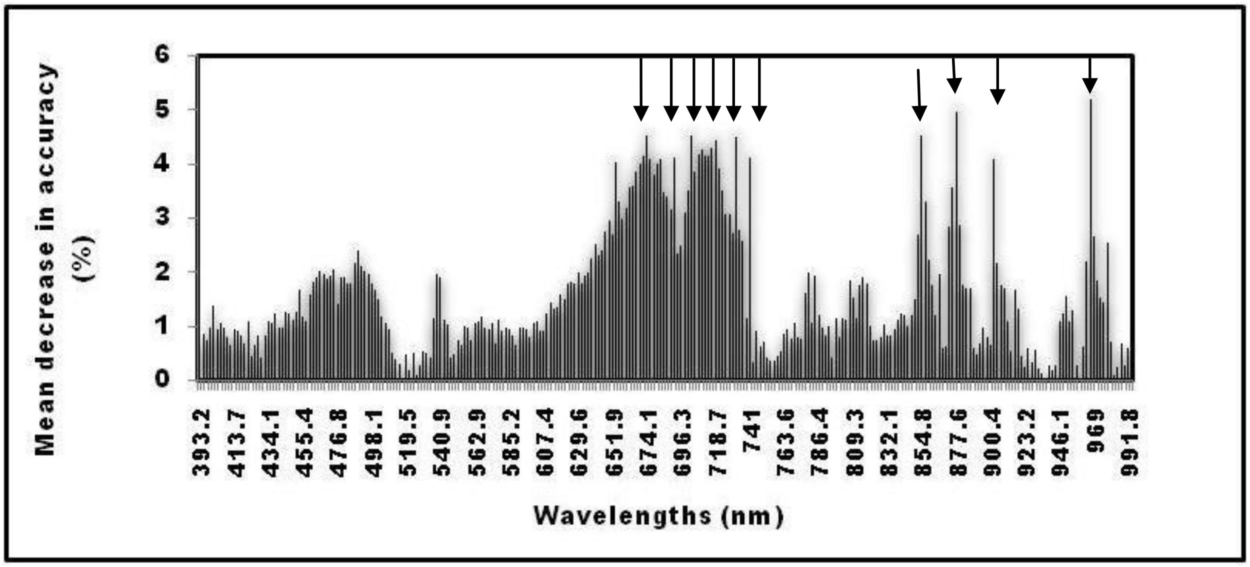

Figure 5. 5: Identifying the variables (wavelengths) importance by the way of random forest algorithm. Wavelengths with the highest mean decrease in accuracy (shown by arrows) represent the most important wavelengths.

5.3.3 Forward variable selection

Based on the random forest ranking, the forward variable selection method for the full resampled AISA Eagle wavelengths (n^{wl} =272) was then used to identify the optimal number of wavelengths required to discriminate among the species (n^{sps} = 4). The top 10 wavelengths yielded the lowest OOB error are using the training dataset (9.65 %), the test dataset (12.53 %), and the .632+ bootstrap error (11.93%) (Figure 5.6), compared with the use of the entire wavelengths (n = 272), which yielded 14.25% (training dataset), 16.05% (test dataset), and 15.95% (.632+ bootstrap error). A t-test was used to test if there was any significant difference among the training data (OOB), test data (OOB) and .632+ bootstrap error. The results show that there is no significant difference between training data (OOB) and test data (OOB) ($t = 2.347$, $P > 0.05$) and between training data (OOB) and .632+ bootstrap error. ($t = 1.581$, $P > 0.14$). The optimal number of wavelengths that yielded the lowest OOB error rate (9.65%) and misclassification error based on the .632+ bootstrap error measure (15.95%) were selected to classify the species. These wavelengths (n = 10) are located at 966.7 nm, 877.6 nm, 674.1 nm, 854.8 nm, 703 nm, 732 nm, 718.7 nm, 691.9 nm, 741 nm and 902.7 nm of the electromagnetic spectrum. These important wavelengths are similar to those wavelengths selected by the test data set except for one wavelength (651.9 nm).

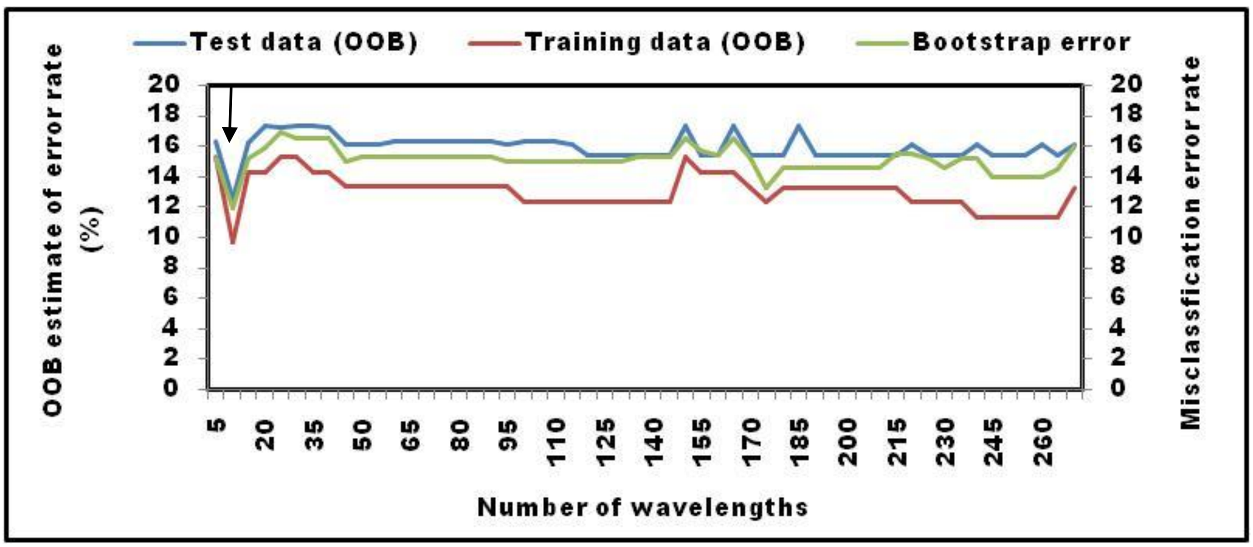

Figure 5. 6: FVS for the test data set, training data set using OOB, and the bootstrap error rate. The optimal number of wavelengths, which yielded the lowest OOB and bootstrap error is shown by an arrow.

5.4.4 Classification accuracy

Selected optimal wavelengths (n = 10) were used to test the classification accuracy using the confusion matrix derived from the OOB error estimation. The confusion matrix includes overall accuracy (ACC), KHAT, user's accuracy (UA), and producer's accuracy (PA) as shown in Table 5.2. The random forest algorithm using resampled AISA Eagle data successfully distinguished among increaser species (HH, EC, SA and AD) with an overall accuracy of

87.50% and a KHAT value of 0.83 for the test data set. An independent test data set was used to test the reliability of the OOB error for the classification accuracy. The difference in overall accuracy between the training data and independent test data was less than 3 %.

Table 5. 2: Confusion matrix for 10 wavelengths from the test data set showing the classification error obtained for the species (HH, EC, SA and AD). The confusion matrix includes overall accuracy, KHAT, user's accuracy, and producer's accuracy for class pair (n = 6) and over all classes

Classes	ACC %	KHAT	PA %		UA %	
			Presence	Absence	Presence	Absence
HH vs EC	97.50	0.95	100.00	95.00	95.24	100.00
HH vs SA	95.00	0.90	95.24	94.74	95.24	94.74
HH vs AD	97.56	0.95	100.00	95.24	95.24	100.00
EC vs SA	92.50	0.85	95.00	90.00	90.48	94.74
EC vs AD	97.50	0.95	95.00	100.00	100.00	95.24
SA vs AD	92.68	0.85	90.00	95.24	94.74	90.91
All classes	87.50	0.83	95.24	86.36	86.96	90.48

5.5 Discussion

This study aimed at discriminating increaser species as indicators of rangeland degradation using field spectrometry. The motivation of the study was to investigate whether there is a possibility to map the different levels of rangeland condition based on the spatial different distribution of increaser species using their reflectance spectra. To achieve this, the utility of spectra resampled to AISA Eagle resolution (272 wavelengths) in discriminating among four increaser species was tested.

5.5.1 Optimization of *ntree* and *mtry*

Previous studies have shown that RF is sensitive to *ntree* and *mtry* parameters (Adam et al., 2009; Ismail, 2009; Lawrence et al., 2006). Our result in this study confirmed that the high *ntree* and default setting of mtry (*mtry* = √variables) yielded the lowest of OOB error rate (14.25%). This result is similar to previous studies (Adam et al., 2009; Breiman, 2001; Ismail, 2009; Menze et al., 2009; Svetnik et al., 2003) and can be explained by the fact that the highest number of trees allows most of the variables (AISA Eagle bands) to be tested in discriminating the species (Breiman, 2001).

5.5.2 Variables importance using the random forest algorithm

The random forest algorithm and forward variable selection have successfully explored and described the relative importance of each individual wavelength and selected the optimal number of wavelengths (n = 10) in discriminating increaser species using the OOB method. This optimal number of wavelengths (n = 10) yielded the lowest OOB error (9.65%) when compared with the entire wavelengths (n = 272), which yielded a 14.25% OOB error rate. This can be explained by the fact that in a model-based analysis, redundancy in data can cause convergence instability of models due to noise in information that has no relation to the increaser species being classified (Adam et al., 2009; Bajcsy and Groves, 2004; Ismail and Mutanga, 2010). These 10 wavelengths are located at 966.7 nm, 877.6 nm, 674.1nm, 854.8 nm, 703 nm, 732 nm, 718.7 nm, 691.9 nm, 741 nm and 902.7 nm and are within + 12 nm from known wavelengths that have been reported in previous studies on species discrimination. These known wavelengths are 695 nm, 711 nm (Chan and Paelinckx, 2008a), 689 nm (Martin et al., 1998), 670 nm (Daughtry and Walthall, 1998), 675 nm (Thenkabail et al., 2004), 676 nm, 713 nm, 723 nm (Warner and Shank, 1997), 668 nm, 682 nm, 696 nm, 720 nm (Thenkabail et al., 2000), 670.37 nm, 695.69 nm, 728.14 nm (Fung et al., 2003), 692 nm (Van Aardt and Wynne, 2007) and 720 nm (Vaiphasa et al., 2005).

It can be noted that, all these wavelengths (n = 10) are located in three different regions of the spectrum which include the visible portion (n= 1), the red-edge portion (n= 5) and near-infrared portion (n = 4) (Figure 5.5). This confirms the results of previous studies that found that green leaves have the greatest variation in the visible, red-edge and near-infrared regions (Asner, 1998; Schmidt and Skidmore, 2003; Thenkabail et al., 2004; Vaiphasa et al., 2005). Although no leaf biochemical characteristics were directly measured in our study, it is likely that the occurrence of selected wavelengths in the visible region (400 nm to 700 nm) could be due to variation among the increaser species in term of their chlorophyll a and b, b-carotene, a-carotene, and xanthophylls (El-Nahry and Hammad, 2009; Ustin et al., 2009). The variations between increaser species in the red-edge region (680 nm to 750 nm) may be due to the chlorophyll concentration, nitrogen concentration and water content (Ustin et al., 2009). The differences among species in the near-infrared region (700 nm to 1300 nm) can be the result of internal leaf structure and water content (El-Nahry and Hammad, 2009; Ustin et al., 2009).

The evaluation of the reliability of the OOB method as an internal estimate of error rate in measuring the importance of the wavelengths using the .632+ bootstrap and test dataset has shown that this method is reliable. The estimate of error rates from the test datasets and .632+ bootstrap is nearly identical with a slight difference of less than 3% to the OOB method. This confirms the findings of previous studies and supports the assertion that, with random forest, it is not necessary to have an independent test data set (Lawrence et al., 2006).

5.5.3 Classification accuracy

The optimal wavelengths (n = 10) yielded an overall accuracy of 90 % and a KHAT value of 0.87 and 92.45 % (90.57) and 92.45% (88.89%) for both the producer and user accuracies, respectively. The results offer the possibility of classifying and mapping rangeland degradation with a high classification accuracy (90%) based on the distribution of the increaser species.

The reliability of the OOB error for the classification accuracy was tested using an independent test data set which yielded an overall accuracy of 87.50% and a KHAT value of 0.83. The difference in overall accuracy between the training data set and the independent test data was less than 3% (Table 5.2), which confirms the stability and reliability of the OOB error (Lawrence et al., 2006). The use of the internal error measure could save field data collection time by reducing the number of the samples to be collected for validating the performance of RF (Lawrence et al., 2006).

In summary, the results presented in this study confirm that the RF algorithm is a robust and accurate method for the combined purposes of variables selection and the classification of hyperspectral data. Overall, this study has demonstrated the possibility of discriminating increaser species using resampled data. This finding allows the upscaling of methods to airborne sensors such as AISA Eagle for mapping rangeland degradation using increaser species as indicators.

5.6 Conclusions

The aim of this study was to discriminate between four increaser species: *Hyparrhenia hirta, Eragrostis curvula, Sporobolus africanus* and *Aristida diffusa* using field spectrometry data, resampled to AISA Eagle resolution. Our results have shown that:

1. These increaser species have a strong potential to be classified accurately when using spectrometry data.
2. The random forest algorithm has several advantages, such as being able to provide better performance, reasonable accuracies, and ease of use.
3. The random forest algorithm, using hyperspectral data, discriminated among four increaser species with a high accuracy of 87.50% (KHAT of 0.83).
4. The random forest algorithm has revealed that greater discrimination power is contained in the visible, red-edge and near-infrared regions of the spectrum. The optimal number of wavelengths that yielded the lowest OOB error rate are at 966.7 nm, 877.6 nm, 674.1 nm, 854.8 nm, 703 nm, 732 nm, 718.7 nm, 691.9 nm, 741 nm and 902.7 nm.

The results demonstrated the possibility of discriminating increaser species using hyperspectral data, resampled to an airborne sensor. This permits the possibility of upscaling the methods to airborne sensors such as AISA Eagle for mapping increaser species areas as an indicator of rangeland condition.

Acknowledgements

Thanks are due to Brice Gijsbertsen, a chief cartographer at the Department of Geography, University of KwaZulu-Natal for assistance in configuring the ASD sensor. My gratitude goes to Abdallah Ibrahim and Dasali for their support during the data collection phase and to Susan Davies for her editing of the paper.

Chapter (5) has shown the possibility of airborne hyperspectral data (AISA Eagle) to discriminate increaser species by identifying specific bands located in the visible, red-edge, and near-infrared region of the electromagnetic spectrum.

However, hyperspectral data comes with difficulties in terms of cost and high dimensionality. Therefore, in chapter 6, we investigated the potential use of advanced multispectral remote sensing such as WorldView data and tested the random forest as a classification algorithm, as an alternative, particularly for low income countries.

CHAPTER SIX

Classifying increaser species as an indicator of different levels of rangeland degradation using WorldView-2 imagery

This chapter is based on:

Manssour, K. and Mutanga, O., (In revision). Classifying increaser species as an indicator of different levels of rangeland degradation using WorldView-2 imagery. *Journal of Applied Remote Sensing.*

Abstract

The development of new multispectral sensors with unique band settings is critical for mapping the spatial distribution of increaser vegetation species in disturbed areas. The objective of this study was to evaluate the potential of WorldView-2 imagery for spectral classification of four increaser species, namely *Hyparrhenia hirta* (HH), *Eragrostis curvula* (EC), *Sporobolus africanus* (SA) and *Aristida diffusa* (AD) in the Okhombe communal rangelands of South Africa. The 8-bands were extracted from the WorldView-2 image and 24 of the most widely used vegetation indices in estimating grassland biophysical parameters were calculated. The random forest algorithm and forward variable method were applied in order to identify the optimal variables (wavelengths and spectral vegetation indices) for classifying the species. Using 6 wavelengths and a sub set of spectral vegetation indices (n = 9), the random forest algorithm could classify species with an overall accuracy of 82% and 90% and a KHAT value of 0.76 and 0.87 respectively. Three wavelengths selected were located at the new WorldView-2 spectral regions of coastal blue, yellow, and the red-edge. There was no significant improvement in increaser species classification by using a combination of the raw WorldView-2 bands and the spectral vegetation indices. Overall, the study demonstrated the potential of the WorldView-2 data for improving increaser separability at species level.

Keywords: WorldView-2, increaser species, rangeland degradation, random forest algorithm.

6.1 Introduction

Rangeland degradation has been identified as one of the most serious global environmental issues (Wessels et al., 2007).Communal rangeland, which occupies roughly 13% of the total agricultural land in South Africa, has been characterised by rangeland scientists as being one of the areas most severely affected by degradation and arguably, one that is completely out of control (Palmer and Ainslie, 2006). This degradation of South African communal rangelands has resulted in poor grassland plant quality and quantity when compared with surrounding areas (Thompson, 1996; Wessels et al., 2004).
From an ecological perspective, grassland species have been classified into two categories (i.e. increasers and decreasers) based on their grazing value and changes in their relative abundance in the presence or absence of grazing (Dobarro et al., 2010). Increaser species are species that increase their relative abundance with grazing and therefore indicating that the condition of the veld is poor (Dobarro et al., 2010; Van Oudtshoorn, 1992). In South Africa, increaser species have been classified into three types, namely Increaser I, Increaser II, and Increaser III (Oluwole et al., 2008; Trollope et al., 1990) based on the level of degradation. The spatial distribution of the different increaser species can be used to indicate the gradient of rangeland degradation and their mapping can direct resource managers to critical areas in need of conservation measures.

Mapping the general spatial distribution of increaser species over large areas using traditional methods is a complex task and requires intensive fieldwork, including the identification of species' characteristics and the visual estimation of species' percentage, all of which are costly and time-consuming and are sometimes impossible to accomplish due to the poor accessibility of the area (Adam et al., 2009; Muchoney and Haack, 1994). On the other hand, remote sensing offers a technologically appropriate technique that is both economic and effective, and is able to produce timely and accurate information for use when mapping the spatial distribution of increaser species (Ustin et al., 2009).

Multispectral images have been used for several decades in classifying and mapping vegetation (Frank, 1984; Hanafi and Jauffret, 2008; Li et al., 2005; May et al., 1997; Turner et al., 1999). However, mapping vegetation in disturbed areas at increaser species level using multispectral data (i.e. Landsat and SPOT) is challenging because of the low spectral resolution of sensors as well as spectral overlap between the vegetation species (Harvey and Hill, 2001). Recently, hyperspectral remote sensing has been considered as one of the most advanced methods for species level classification as it captures subtle variations due to many narrow wavelengths of less than 10 nm (Thenkabail et al., 2000; Vaiphasa et al., 2007; Van Aardt and Wynne, 2007). Imageries from these sensors, such as Hyperion, HyMAP, and AISA Eagle, allow for the mapping of vegetation at species levels (Kumar et al., 2001; Mutanga and Skidmore, 2004). However, in spite of their ability to provide detailed spectral information, processing hyperspectral remote sensing data is challenging due to over fitting when applying statistical methods, the excessive need for sufficient field samples, and the high cost of the images (Bajcsy and Groves, 2004; Vaiphasa et al., 2007). Furthermore, many hyperspectral wavelengths are redundant when it comes to vegetation species studies (Adam et al., 2009; Mutanga and Kumar, 2007; Mutanga and Skidmore, 2004).

The development in multispectral sensors, such as WorldView-2 containing key spectral bands, has brought about unique opportunities for those wishing to classify vegetation at species level. It does this by offering more spectral wavelengths than the traditional broadband satellite images while reducing unnecessary redundancy as contained in hyperspectral data (Omar, 2010). The WorldView-2 satellite provides better spectral resolution of eight wavelengths, with high spatial resolution data of 0.5 m and 2.0 m on the panchromatic and multispectral wavelengths respectively (Omar, 2010; Sridharan, 2010). Recently, different studies assessed the utility of WorldView-2 data (400-1040 nm) in classifying vegetation species. The results demonstrated the feasibility of WorldView-2 data with regard to classifying vegetation species, with overall accuracies of above 85% (Dlamini, 2010; Kumar and Roy, 2010; Omar, 2010; Sridharan, 2010).To our knowledge, no attempt has yet been made to use WorldView-2 images in classifying increaser species as indicators of the different levels of land degradation.

In this study, it is hypothesised that WorldView-2 data offers possibilities with regard to increaser species classification. With its capability of new bands (including coastal, yellow, red edge, and NIR 2) to resolve lacking spectral features in the traditional sensors (Landsat TM, Landsat ETM+ and SPOT), WorldView-2 data can classify increaser species accurately.

Previous studies have shown that different statistical methods such as principal component analysis, discriminant analysis, and the support vector machine have been successfully applied in order to classify plant species (Adam and Mutanga, 2009; Cochrane, 2000; Thenkabail et al., 2004). A random forest algorithm (RF), developed by Breiman (2001) has recently been used to predict or classify features of interest (Adam et al., 2009; Ismail, 2009; Pal, 2005).The random forest algorithm is a bagging operation where multiple classification trees are constructed based on a random subset of the training data set (*ntree*) (Breiman, 2001). Each tree is grown to its maximum size based on a bootstrap sample from the training data set (approximately 70%) without pruning and with a randomised subset of predictors (*mtry*) so as to determine the best split at each node of the tree (Breiman, 2001).The multiple trees then vote by majority on correct classification (Lawrence et al., 2006).The random forest algorithm has several advantages when compared with other conventional classification trees, such as being able to provide better performance, having reasonable accuracies, being relatively easy to implement as well as its capability in ranking important prediction variables (Archer and Kimes, 2008; Díaz-Uriarte and de Andrés, 2006). We hypothesise that, the integration of the random forest algorithm with WorldView-2 data could successfully classify the level of rangeland degradation using increaser species as indicators as well as providing an insight on important classification bands from the WorldView imagery.

The objective of this study was therefore to investigate the potential use of Digital Globe WorldView-2 imagery and the random forest algorithm in distinguishing between four increaser species (*Hyparrhenia hirta*, *Eragrostis curvula*, *Sporobolus africanus* and *Aristida diffusa*) in the Okhombe communal rangeland of South Africa. The specific objectives of this paper were: (1) to determine if four increaser species could be distinguished from each other using the WorldView-2 bands; (2) to investigate whether spectral vegetation indices computed from WorldView-2 imagery can improve classification accuracy; (3) to determine whether a combination of the raw bands and the vegetation indices improve the increaser species classification and, (4) to ascertain and rank the importance of bands and indices extracted from WorldView-2 imagery using the random forest algorithm.

6.2 Material and methods

6.2.1 Image acquisition and pre-processing

In this study, the WorldView-2 high resolution satellite with 8-multispectral bands at 2.0 m resolution, as provided by DigitalGlobe® and covering the Okhombe communal rangeland, was used to classify increaser species (Table 6.1). The image was acquired on 24 February 2011 at 08:20:39 GMT. The image acquisition period was found to be the best acquisition time because the vegetation was green. The WorldView-2 is a sunsynchronous orbital satellite located at 770 km altitude. The image scenes were atmospherically corrected using quick atmospheric correction procedure in ENVI 4.7.

Table 6. 1: Spectral wavelengths' properties for WorldView-2 multispectral imagery

WV-2 Band	Region name	Centre band (nm)
1	Coastal blue (400-450 nm)	427
2	Blue (450-510 nm)	478
3	Green (510-580 nm)	546
4	Yellow (585-625 nm)	608
5	Red (630-690 nm)	659
6	Red-edge (705-745 nm)	724
7	NIR 1(770-895)	831
8	NIR 2 (860-1040 nm)	903

6.2.2 Field data collection

Field data collection was carried out in February 2011 in the Okhombe communal rangeland. This was done so as to collect the ground control points of four increaser species, namely HH, EC, SA and AD. The Leica GS20 sub-meter GPS yielding an accuracy of between 0 m to 0.246 m after the post-processing differential correction was used. A vegetation polygon was defined as covering 10 m × 10 m (Figure 6.1), where the target species (n = 4) were more homogenous and were representative of more than 80% of the target species in each plot. In order to obtain accurate reference data, the central point of each geographic position plot was also recorded. This method resulted in 50 to 56 polygons for each target species (n = 4). The polygons measurements were then used as reference data for generating areas of interest. The polygons were then overlaid on the true colour composite WorldView-2 image to extract the pixels' spectra (2 m × 2 m) using Environment for Visualising Images (ENVI) software (ENVI, 2006). In this study, only pixels that fell completely within the measured polygons were used in the reference dataset so as to minimise variability and exclude mixed pixel effects of other grass species (Adam, 2010; Peckham et al., 2008). The field data for each polygon was thus averaged to represent one sample, and was then used for analysis (Figure 6.2).

Figure 6. 1: Vegetation plot of 10 m × 10 m demarcated using a measuring tape and the centre point recorded using the Leica GS20 sub-meter GPS.

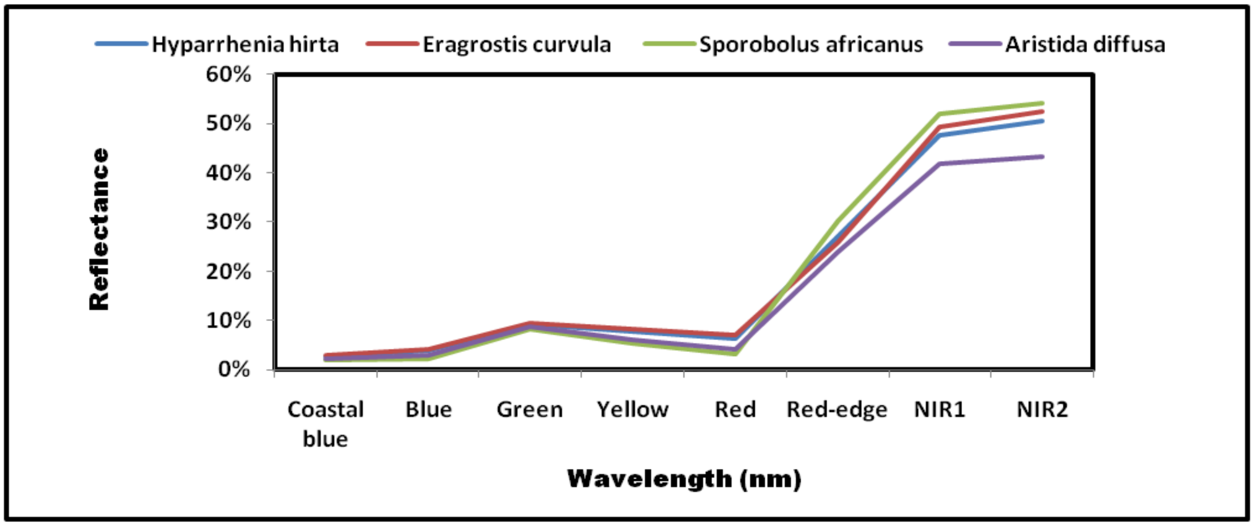

Figure 6. 2: Mean reflectance spectrum data for *Hyparrhenia hirta* (HH), *Eragrostis curvula* (EC), *Sporobolus africanus* (SA) and *Aristida diffusa* (AD) using WorldView-2 imagery.

6.2.3 Spectral vegetation indices

Spectral vegetation indices based on absorbance and reflectance in the visible and NIR regions have been widely used for species classification (Blackburn, 1998; Gitelson et al., 2005).In this study, 24 different vegetation indices were calculated from the spectral values extracted from WorldView-2 imagery for the three different regions (visible, red-edge, and near-infrared) in order to enhance the classification accuracy. These indices were selected because it has been proved that they are sensitive to biophysical parameters such as chlorophyll content, leaf area index, photosynthetic activity, and biomass, all of which vary per species (Blackburn, 1998; Gitelson et al., 2002; Penuelas et al., 1995).Vegetation index names, abbreviations, equations, and the references for each index are listed in Table 6.2 below.

Table 6. 2: Summary of WorldView-2-derived vegetation indices used in this study

No	Vegetation index name	Abbreviation	Equation	Reference
1	Simple Ratio	SR	Rnir1/Rred	(Gitelson and Merzlyak, 1993)
2	Modified Simple Ratio	MSR	(Rnir1 − Rblue)/(Rred − Rblue)	(Sims and Gamon, 2002)
3	Normalised Difference Vegetation Index	NDVI	Rnir – Rred/Rnir + Rred	(Rouse, 1974)
4	Transformed Vegetation Index	TVI	√Rnir1 – Rred/Rnir1+Rred +0.5	(Deering et al., 1975)
5	Normalised Difference Index	NDI	(Rnir1 – Rred)/ (Rnir1 + Rred)	(Sims and Gamon, 2002)
6	Modified Chlorophyll Absorption inReflectance Index	MCARI	[(Rred-edge–Rred)–0.2(Rred-edge–Rgreen)](Rred-edge/Rred)	(Daughtry et al., 2000)
7	Transformed Chlorophyll Absorption inReflectance Index	TCARI	3[(Rred-edge–Rred)–0.2(Rred-edge–Rgreen)(Rred-edge/Rred)]	(Haboudane et al., 2002)
8	Visible Atmospherically Resistant Index	VARI	(Rgreen-red)/(Rgreen+Rred-Rblue)	(Gitelson et al., 2002)
9	Visible Green Index	VGI	(Rgreen-Rred)/(Rgreen+Rred)	(Gitelson et al., 2002)
10	Green Normalised Difference Vegetation Index	GNDVI	(Rnir1-Rgreen)/(Rnir1+Rgreen)	(Gitelson and Merzlyak, 1996)
11	Structure-Insensitive Pigment Index	SIPI	(Rnir1–Rblue)/(Rnir1–Rred-edge)	(Penuelas et al., 1995)
12	Pigment Specific Simple Ratio (Chlorophyll a)	PSSRa	Rnir1/Rred-edge	(Blackburn, 1998)
13	Pigment Specific Simple Ratio(Chlorophyll b)	PSSRb	Rnir1/Rred	(Blackburn, 1998)
14	ModifiedNormalised Difference	MND	(Rnir1–Rblue)/(Rnir1+Rred-edge–2Rblue)	(Sims and Gamon, 2002)
15	Plant Senescence Reflectance Index	PSRI	(Rred-edge–Rblue)/Rnir1	(Merzlyak et al., 1999)
16	Renormalised Difference Index	RDI	(Rnir1-Rred)/(Rnir1+Rred)^{½}	(Roujean and Breon, 1995)
17	Green Index	GI	(Rnir1/Rred) - 1	(Gitelson et al., 2005)
18	Enhanced Vegetation Index	EVI	2.5 *((Rnir1 − Rred)/ (Rnir1+ 6* Rred −7.5* Rblue + 1))	(Huete et al., 1999)
19	Red Index	RI	(Rnir1/Rred) -1	(Gitelson et al., 2005)
20	Modified Simple Ratio*	MSR*	(Rnir1/Rred-1)/((Rnir1/Rred)^{½}+1	(Chen, 1996)
21	Non-Linear Index	NLI	Rnir^2-Rred)/(Rnir^2+Rred)	(Goel and Quin, 1994)
22	Atmospherically Resistant Vegetation Index	ARVI	(Rnir2-(2*Rred-Rblue))/(Rnir2+(2*Rred-Rblue)	(Kaufman and Tanre, 1992)
23	Carotenoid Reflectance Index	CRI	(1/Rblue)-(1/red-edge)	(Gitelson et al., 2002)
24	Ratio Vegetation Index	RVI	Rred/Rnir1	(Richardson and Wiegand, 1977)

R= Reflectance

6.2.4 Statistical analysis

6.2.4.1 The random forest algorithm (RF)

The random forest algorithm was used to measure the importance of every WorldView-2 band and index in classifying the increaser species and also to select the optimal number of bands for better classification accuracy (Adam et al., 2009). Random forest is a machine learning algorithm and forest-based method developed by Breiman (2001) to overcome the instability of traditional tree-based methods. The algorithm generates multiple bootstrap samples from the original training data set with a replacement to create multiple classification trees (*ntree*). Each tree is grown to its maximum size (without being pruned) and uses a randomised subset of predictors (*mtry*) to determine the best split at each node of the tree (Breiman, 2001). The classification trees in the ensemble then vote by plurality on the correct classification. The functional details of the random forest algorithm can be found in (Breiman, 2001; Ismail, 2009; Lawrence et al., 2006; Pal, 2005).

The RF algorithm provides three independent variable importance measures: the permutation accuracy importance measure, the Gini importance measure, and the number of times that each variable is selected (Breiman, 2001). The permutation accuracy importance measure is considered to be the best measure in random forests because of its ability to assess the variable importance, which relies on mean decreases in accuracy as measured using the out-of-bag (OOB) samples (Breiman, 2001). The OOB error produces a measure of the importance of the variables by comparing how much the OOB error of estimate increases when a variable is permutated whilst all other variables are left unchanged (Archer and Kimes, 2008). In this study, the importance of each WorldView-2 band in classifying the increaser species is determined using OOB estimates of classification error. Each tree is built based on a bootstrap sample of reflectance of WorldView-2 band and about 1/3 of the original data are left out of the sample in the tree construction (OOB) (Breiman, 2001). These modified OOB data are then passed down each tree so as to obtain a new estimation of the classification error for that bootstrap sample. The difference between the misclassification rate for the modified and original OOB data over all the trees that are grown in the forest was then averaged to measure the importance of the variables (WorldView-2 bands). The variable importance measurement was then used as a ranking index (mean decrease in accuracy) to identify the bands that are able to better classify the increaser species (Archer and Kimes, 2008; Díaz-Uriarte and de Andrés, 2006).

The R software package was used to carry out the random forest algorithm (R Development Core Team, 2008). The two RF parameters –*mtry* and *ntree*– were optimised based on the OOB estimate of error rate in order to obtain the highest classification accuracy (Breiman, 2001). The *ntree* values were tested from a default setting of 500 to 10,000 trees with intervals of 500 (Adam et al., 2009), while the *mtry* values were optimised by creating random forest ensembles using all possible *mtry* values (2), (3), and (5) for WorldView-2 bands (n = 8), vegetation indices (n = 24) and combined vegetation indices and bands (n = 32) respectively.

6.2.4.2 Forward variable selection

A limitation of the random forest algorithm, when it comes to measuring importance of variables, is that it does not automatically select the optimal number of variables that produce the best classification accuracy (Adam et al., 2009). The technique of forward variable selection (FVS) (Guyon and Elisseeff, 2003) was thus implemented so as to determine the best wavelengths and the least number of vegetation indices based on the random forest measurement of variables' importance (Ismail, 2009). Forward variable selection builds randomly numerous random forests with repetitions on all the ranked bands (n = 8), vegetation indices published in the literature (n = 24), and combined vegetation indices and bands (n = 32). At each iteration, one variable (band and vegetation index) was added, and the error was calculated using the OOB estimate method.

6.2.4.3 Image classification

The bands that yielded the lowest OOB error were used as input variables in the random forest algorithm developed in the R package for classifying increaser species. Studies have indicated that the OOB error is a suitable measure of accuracy since it provides an unbiased estimate of error (Archer and Kimes, 2008; Breiman, 2001; Lawrence et al., 2006; Peters et al., 2007). A confusion matrix was constructed so as to compare the true class with the class assigned by the classifier and to calculate the overall accuracy as well as the producer's and user's accuracies. The producer's accuracy is computed by splitting the number of correctly classified trees in each crown condition class by the number of data sets used for that class (column total in the confusion matrix). User's accuracy is calculated by dividing the number of correctly classified trees by the total number of trees that were classified in that crown condition class (row total in the confusion matrix) (Ismail, 2009). In addition, a discrete multivariate technique, called Kappa, was used in accuracy assessment. The result of the Kappa analysis is the KHAT statistic, which was calculated in order to determine if one error matrix is significantly different from another (Cohen, 1960). If the Kappa (K) coefficients are one or close to one, then there is perfect agreement for the training.

6.3 Results

6.3.1 Model optimisation

The results of optimising random forest parameters (*ntree* and *mtry*) at each split has shown that, the default setting of *mtry* (2, 5, and 5) and a large number of *ntree* (4000, 4500, and 5000) yielded the lowest and most stable OOB error rates (20.53%, 12.06%, 14.89%) for WorldView-2 bands, vegetation indices published in the literature and combined bands and vegetation indices respectively (Table 6.3).The results show that changes in *ntree* and *mtry* parameters influence the OOB error. This optimisation was thus adopted for the classification of the study's four increaser species.

Table 6. 3: Random forest parameter (ntree) optimisation based on the default setting of mtry using the OOB estimate of error rate

	Variables	Number of variables	Model optimisation		OOB estimate of error rate (%)
			ntree	*mtry*	
1	WorldView-2 band	8	4000	2	20.53
2	VIs published in literature	24	4500	5	12.06
3	Combined bands and vegetation indices.	32	5000	5	14.89

6.3.2 Variables importance using the random forest algorithm

The random forest algorithm was applied in order to measure the relative importance of each band (n = 8) as well as the vegetation indices published in the literature (n = 24) for classifying the increaser species. These variables (bands and vegetation indices published in the literature) yielded an OOB error rate of 20.53% and 12.06% respectively. The mean decrease in accuracy was then applied to rank the bands and vegetation indices. The results indicated that the most important bands (n = 6) and vegetation indices (n = 9) were those with the highest mean decrease in accuracy. These bands were located in the coastal blue, blue, green, yellow, red and red-edge portions of the electromagnetic spectrum. In order to obtain better classification accuracy, we combined both vegetation indices and individual bands (n = 32). The combined bands and vegetation indices (n = 32) yielded an OOB error rate of 14.89%.The most important variables (bands, vegetation indices and combined bands and vegetation indices) were those with the highest mean decrease in accuracy (Figure 6.3).

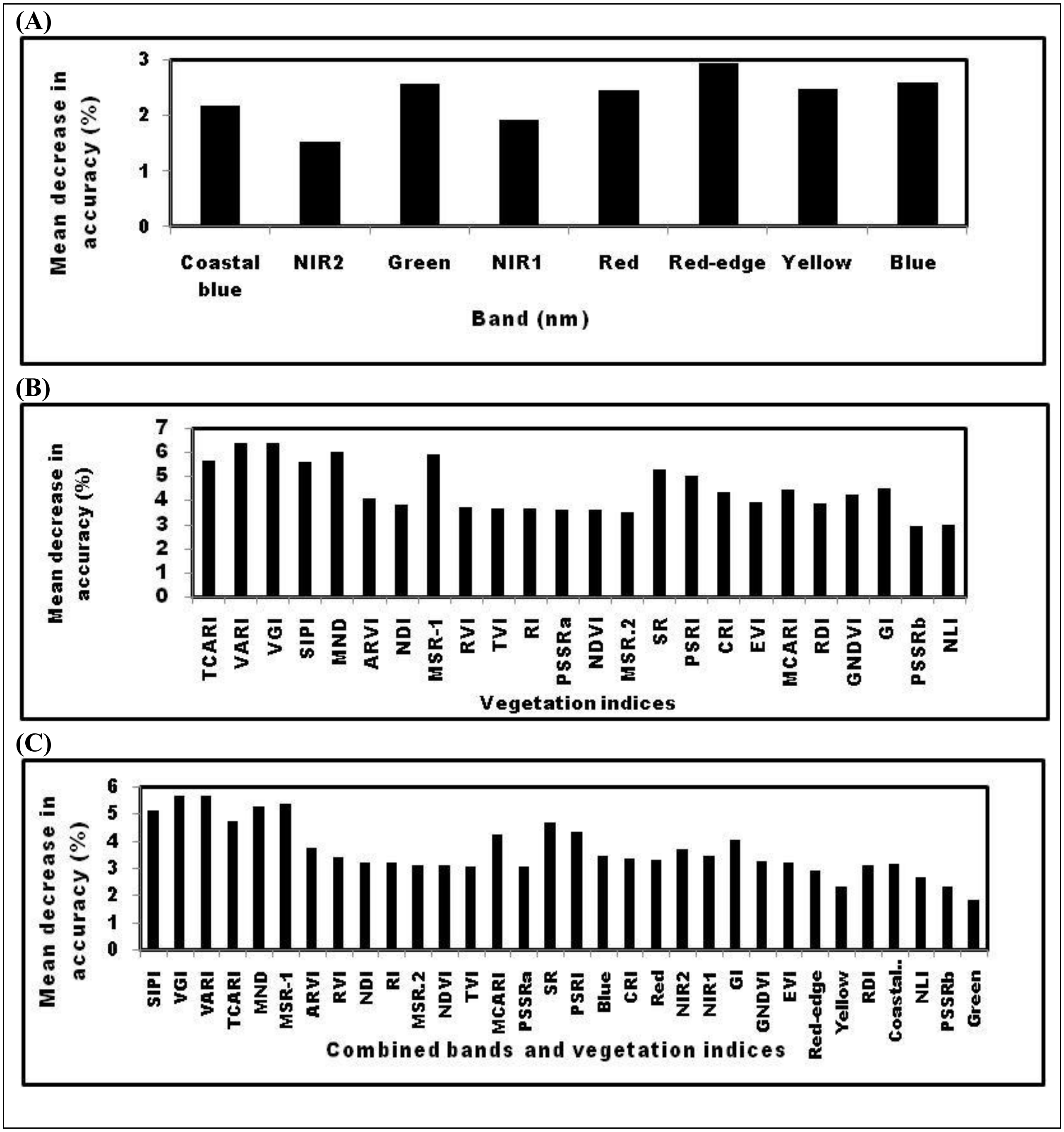

Figure 6. 3: The important variables bands (A), vegetation indices (B), and combined bands and vegetation indices (C) in classifying increaser species as selected by the random forest algorithm. The important variables have the highest mean decrease in accuracy.

6.3.3 Variable selection using the OOB method

Based on the random forest ranking, the FVS method was performed for the full WorldView-2 bands (n = 8), spectral vegetation indices (n = 24) and combined bands and vegetation indices (n = 32) in classifying the four increaser species (HH, EC, SA and AD).The 6 most important bands ranked by the OOB error yielded the lowest OOB error (17.36%) (Figure 6.4-A), as compared to the use of the entire bands (n = 8), which yielded 20.53%. These bands were located in the coastal blue (400 nm to 450 nm), blue (450 nm to 510 nm), green (510 to 580 nm), yellow (585 nm to 625 nm), red (630 nm to 690 nm) and red-edge (705 nm to 745 nm) regions of the electromagnetic spectrum. A subset of 9 spectral vegetation indices published in the literature as shown in Figure 6. 4-B resulted in the lowest OOB error (9.93%), as compared to the use of the entire vegetation indices (n = 24) (12.06%). These indices include VGI, VARI, MSR-1, MND, SIPI, TCARI, SR, PSRI and MCARI. Combined bands and vegetation indices produced an OOB error of 14.89%. Therefore, the FVS method was implemented on these combined bands and vegetation indices (n = 32) to select the optimal subset of indices. Ten vegetation indices were selected with the smallest OOB error (10.64%) as shown in Figure 6.4-C. Nine of these vegetation indices are similar to those vegetation indices published in the literature and selected in the first step (VGI, VARI, MSR-1, MND, SIPI, TCARI, SR, PSRI, MCARI and GI).The results indicated that most of the vegetation indices that could distinguish between increaser species, were calculated from the bands located at the blue, green, red, and red-edge portions. The optimal variables of bands (n = 6), vegetation indices (n = 9) and combined bands and vegetation indices (n = 10) were then used for further classification.

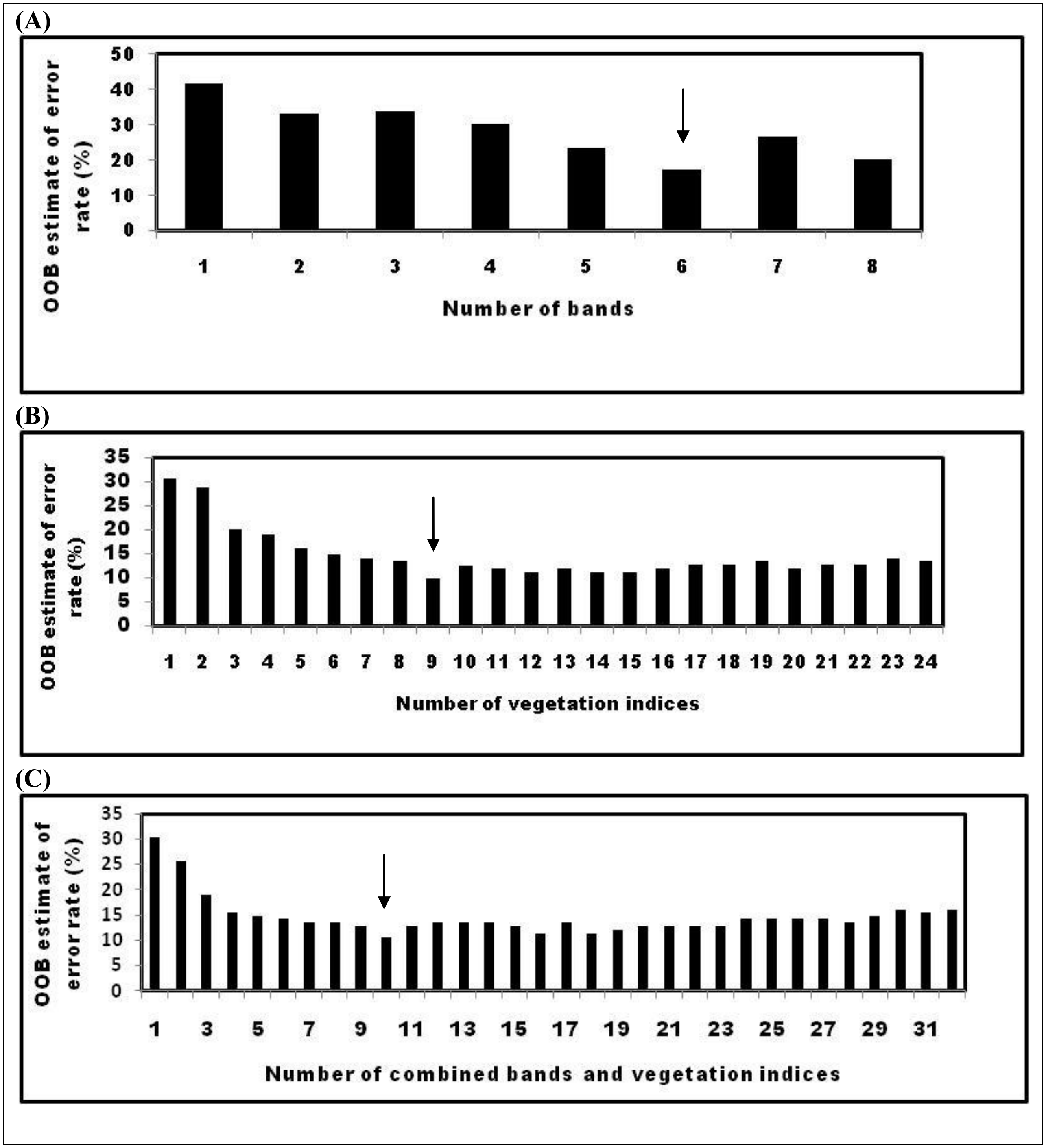

Figure 6. 4: A subset of variables (bands (A), vegetation indices (B), and combined vegetation indices with bands (C)) selected by forward variable selection according to their OOB estimate of error. The black arrows show the most important variables used for classification accuracy.

6.3.4 Classification accuracy

Table 6.4 illustrates the confusion matrix derived from the OOB error estimation for WorldView-2 bands (n = 8), spectral vegetation indices (n = 24) and combined bands and vegetation indices (n = 32).This matrix includes overall accuracy (ACC), KHAT, user's accuracy (UA) and producer's accuracy (PA). When all the generated WorldView-2 bands (n = 8) were used to test the classification accuracy, the random forest algorithm, which used WorldView-2 data, successfully distinguished the four increaser species (HH, EC, SA and AD) with an overall accuracy of 79.50% and a KHAT value of 0.73. On the other hand, when utilising the top 6 wavelengths, the random forest algorithm explained 82% of the overall accuracy and gave a KHAT value of 0.76. Table 6.4 shows results of the random forest algorithm for all vegetation indices (n = 24) and the most important vegetation indices (n = 9). When all generated vegetation indices (n = 24) were used, the random forest algorithm accounted for 87.50% of the overall accuracy and 0.83 of the KHAT value. On the other hand, when utilising the subset of 9 vegetation indices, the random forest algorithm explained 90% of the overall accuracy and 0.87 of the KHAT value. The top 10, derived from the combined bands and vegetation indices, accounted for an accuracy of about 89.36% with the KHAT value of 0.86. Utilizing all the combined bands and vegetation indices (n = 32) produced an overall accuracy of 85.11% with a KHAT value of 0.80 (Table 6.4).

Table 6. 4: Confusion matrix for different variables showing the classification error obtained for the species HH, EC, SA and AD. The confusion matrix includes overall accuracy (ACC), KHAT, producer's accuracy (PA), and user's accuracy (UA)

Accuracy assessment	Band		Published VIs		Combined bands+ VIs	
	Top 6	Full dataset	Top 9	Full dataset	Top 10	Full dataset
ACC (%)	82.00	79.50	90.00	87.50	89.36	85.11
KHAT	0.76	0.73	0.87	0.83	0.86	0.80
PA (%)	92.00	84.00	91.00	88.00	96.00	90.00
UA (%)	92.00	84.00	90.00	87.00	96.00	90.00

6.4 Discussion

This study aimed at classifying four vegetation species associated with rangeland degradation, namely *Hyparrhenia hirta, Eragrostis curvula, Sporobolus africanus* and *Aristida diffusa* in the Okhombe communal grazing lands. The motivation for the study was to investigate the ability of the new 8-band imagery in classifying the four increaser species when using the random forest algorithm.

6.4.1 Variables importance using the random forest algorithm

The importance of the variables (bands and spectral vegetation indices) in increaser species classification as measured by the random forest algorithm was ranked, and forward variable selection was carried out in order to reduce the number of variables that could discriminate increaser species for the sake of better classification. The results show that the random forest and forward variable selection successfully selected the optimal number of bands (n = 6) based on the OOB method. This optimal number of bands (n = 6) yielded a lower OOB error (17.36%) than did all the wavelengths (n = 8), which yielded a 20.53% OOB error rate. These bands (n = 6) are located at the visible portion in the coastal blue, blue, green, yellow, red, and red-edge position. Three bands are located at conventional regions of blue, green and red, while the other three bands are located at the new WorldView-2 regions of coastal blue, yellow and red-edge. Most of the optimal bands (n = 5) are located in the visible portion (450 nm to 690 nm).This is due to variations amongst the increaser species on chlorophyll a and b, b-carotene, a-carotene, and xanthophylls (Ustin et al., 2009). The variation in spectral reflectance of these species in the red-edge portion (705 nm to 745 nm) may be due to significant variations in internal leaf structure and water content (El-Nahry and Hammad, 2009; Ustin et al., 2009). These results are comparable to those of Dlamini (2010) and Omar (2010), who stated that the potential usefulness of the WorldView-2 visible and red-edge portions can distinguish amongst different vegetation species. The results (as shown in Figure 6.4-B and 6.4-C) show a subset of 9 and 10 spectral vegetation indices, which were selected in order to classify the four increaser species with the lowest OOB error (9.93%) and (10.64%), in comparison with the use of all the vegetation indices (n = 24) (12.06%) and all combined bands and vegetation indices (n = 32) (14.89%). These vegetation indices included VGI, VARI, MSR-1, MND, SIPI, TCARI, SR, PSRI, MCARI and GI. These results are comparable to those from previous studies, which showed that the subset of a few variables (bands and vegetation indices) based on random forest selection produced a high degree of accuracy when compared with those based on the full data set (Adam et al., 2009; Ismail, 2009). Most of the significant differences in vegetation indices published in the literature, were computed using a combination of bands located at green, yellow, red-edge and NIR2. These optimal spectral vegetation indices (n = 9) that yielded the highest classification accuracy could be due to the relatively high variance of plant biochemical and biophysical properties such as chlorophyll content and green biomass (Daughtry et al., 2000; Gitelson and Merzlyak, 1993; Gitelson et al., 2002; Green et al., 1997; Merzlyak et al., 1999).

In this study, the random forest algorithm was used as a variable selection method for reducing the number of the WorldView-2 bands that are used for better classification. The successful use of this algorithm for the classification of increaser species with only a few bands confirmed its utility as a variable selection method (Lawrence et al., 2006). As shown in Table 6.4, the increaser species have a greater potential for being distinguished from others (82%, 89.36% and 90% of overall accuracy) when using a random forest classifier. This result confirms the assertions of previous studies (Chan and Paelinckx, 2008b; Lawrence et al., 2006; Pal, 2005) that have reported that the random forest algorithm has been applied in remote sensing image classifications with much better performance.

Specifically, the most important 9 vegetation indices indicate the best classification of increaser species. Therefore, these results are consistent with the previous studies that have found that WorldView-2 imagery, with its high spatial resolution and new bands of coastal, yellow, red edge and NIR 2, has great potential in terms of classifying and mapping vegetation species (Borel, 2010; Dlamini, 2010; Omar, 2010; Wolf, 2010).

6.4.2 Classification assessment

Estimated overall accuracy based on OOB estimate of error rate for the optimal bands (n = 6), optimal vegetation indices reported in the literature (n = 9), and optimal combined bands and vegetation indices (n = 10) yielded overall accuracies of 82% (KHAT= 0.76), 90% (KHAT= 0.87), 89.36% (KHAT= 0.86) and from 84% to 92% for both producer and user accuracies respectively (Table 6.4). These results were particularly remarkable when compared with the use of a full data set of bands (n = 8), vegetation indices (n = 24) and optimal combined bands and vegetation indices (n = 32) which yielded overall accuracies of 79.50% (KHAT = 0.73), 87.50% (KHAT = 0.83), 85.11% (KHAT = 0.80) and from 84% to 90% for both producer and user accuracies respectively (Table 6.4). There was no improvement in increaser species classification by using combined bands and vegetation indices (89.36%). Increasing the number of redundant variables introduces noise to the model and thereby decreases the model's stability and accuracy (Bajcsy and Groves, 2004; Price et al., 2002). The successful use of the random forest algorithm for classifying increaser species, with a subset of only a few wavelengths and vegetation indices, confirmed its utility as a feature selection method (Lawrence et al., 2006).

In summary, the results from the present study demonstrate the possibility of classifying increaser species using WorldView-2 data and also confirm that the random forest algorithm is a robust, effective and accurate method for both variables' selection and classification application.

6.5 Conclusions

In this study a multispectral WorldView-2 satellite image was used to classify the four increaser species in the Okhombe communal rangelands of South Africa. The study indicates the feasibility of using WorldView-2 data since it yielded an accuracy of 82%, 90% and 89.36% for raw bands (n = 8), vegetation indices (n = 24) and combined bands and vegetation indices (n = 32) respectively. The following conclusions can be drawn from this study:

1. The high spatial resolution that is offered by multispectral WorldView-2 satellite imagery can be used to identify the relatively huge variability in plant species, especially in a small area.
2. The new WorldView-2 bands are potentially useful and applicable in increaser species classification.
3. Selected spectral vegetation indices yielded better classification accuracy when compared with individual WorldView-2 bands and the combined dataset.

Overall, the classification of increaser species represents different levels of rangeland degradation. In this regard, we expect that the results of this study can be used to support precision rangeland analysis with regard to, for example, the separability of increaser species, the estimation of grazing value, and the measuring of biophysical characteristics. These applications can be further enhanced by developing methods to map the spatial distribution of rangeland degradation in disturbed areas.

Acknowledgements

The authors would like to thank DigitalGlobe for making high-quality WorldView-2 data available free of charge for this research. This work is based upon research supported by the National Research Foundation and the University of KwaZulu-Natal research grants. The authors also wish to acknowledge the help they received from Dr Riyad Ismail in terms of atmospheric correction. We extended our thanks to Dr Elhadi Adam and Brice Gijsbertsen of the University of KwaZulu-Natal for their help and support, which contributed greatly towards this study. Their assistance is much appreciated.

In this chapter (6), new worldview imagery, with unique band settings was evaluated to discriminate increaser species. The results showed that the optimal bands (n = 6) for discriminating increaser species are located in the visible portion, and red-edge portion of the electromagnetic spectrum. Three of these bands are located at the new WorldView-2 regions of coastal blue, yellow and red-edge. The results also showed the reliability and robustness of the random forest algorithm as a variable selection and classification algorithm in discriminating increaser species.

CHAPTER SEVEN

The application of earth observation techniques for identifying different levels of rangeland degradation based on increaser species: A synthesis

7.1 Introduction

South Africa's rangelands are an ecological ecosystem which provides habitats for wildlife animals and grazing ground for domestic livestock (Sheona, 2003; Tainton, 1999; Wessels et al., 2008). Communal rangelands, which occupy roughly 13% of the total agricultural land in South Africa, have been characterised by rangeland scientists as one of the areas most severely affected by degradation and arguably as being completely out of control (Palmer and Ainslie, 2006). A total of 4.8% of South African land (i.e. 5.8 million ha) has been identified as being degraded due to its low vegetation cover when compared with surrounding areas (Thompson, 1996). The greatest areas of extensively degraded land coincide with the moderately to severely degraded communal rangelands where there is a considerable population of South African livestock (Hoffman and Todd, 2000; Reid and Vogel, 2006).

Several South African studies have focused on rangeland degradation assessment using different indicators such as soil properties and vegetation quality (Conant and Paustian, 2002; Greenwood and McKenzie, 2001; Reeder and Schuman, 2002; Zhao et al., 2007). Although these studies achieved differing degrees of success for rangeland degradation assessment, one of the drawbacks and limitations of these studies is that they mainly focused on identifying degraded and non-degraded areas (Hill et al., 2008; Wang et al., 2010b; Wessels et al., 2008). Although these studies were able to draw the line between the two classes, they do not allow the classification of different levels of rangeland degradation using indicators that can easily and directly be detected and monitored. Such a classifying and monitoring system allows rapid assessment and also proactively adopts the most appropriate course of intervention where necessary. Vegetation species are sensitive and well adapted to specific growth conditions, and their quality and quantity reduce or increase according to changes in the growth conditions, therefore it can be used as an indicator of an ecosystem's functions and characteristics (Nordberg and Allard, 2002; Van Oudtshoorn, 1992). Recently, the development of earth observation techniques allows for the detection of small vegetation units (less than 2 m). These techniques have the potential for identifying different levels of degradation based on vegetation species that are indicators of rangeland degradation (e.g. increaser species).

.

In South Africa, grassland species have been classified into two categories – increasers and decreasers – so as to assess rangeland degradation based on the grazing value and relative abundance of the species in the presence or absence of grazing (Dobarro et al., 2010). Rangeland increaser species increase their relative abundance with overgrazing and therefore their dominance indicates that the rangeland is in poor condition (Dobarro et al., 2010; Van Oudtshoorn, 1992). Increaser species have been classified into three types, namely increaser I, increaser II, and increaser III (Oluwole et al., 2008; Trollope, 1990). The relative abundance and distribution of the different increaser species can be used to indicate the gradient of rangeland degradation (Oluwole et al., 2008; Trollope, 1990; Van Oudtshoorn, 1992) (Table 7.1).

It can therefore be seen that up-to-date spatial information about increaser species is essential for classifying rangeland condition into the categories of poor, moderate and high degradation. To our knowledge, no attempt has yet been made to use remote sensing to map increaser species as indicators of the different levels of rangeland degradation.

Mapping the general spatial distribution of vegetation species over large areas using traditional methods is costly and time-consuming and is also sometimes impossible to accomplish due to the inaccessibility of certain areas (Adam et al., 2009; Muchoney and Haack, 1994). On the other hand, remote sensing offers a technologically appropriate technique that is both economical and effective and is moreover able to produce timely and accurate information for use when mapping the spatial distribution of vegetation species (Ustin et al., 2009). The aim of this study was to investigate the potential use of remote sensing for mapping those increaser species – namely *Hyparrhenia hirta*, *Eragrostis curvula*, *Sporobolus africanus* and *Aristida diffusa* – that indicate different levels of rangeland degradation in the communal rangelands of South Africa.

Table 7. 1: Visual indicators of Okhombe rangeland degradation based on different increaser species

Indicator species	Common name	General characteristics	Grazing value*	Visual indicators of rangeland degradation	Degradation stage
Increaser I (HH)	Thatching grass	A relatively dense, perennial tufted grass. Spikelets are covered with white to grey hairs. Culms 300-1,500 mm tall. Leaf blade 1-4 mm wide. Flowers from September to March.	5	Bare soil on cattle access routes, accumulations of soil around trees and fences, dust storm, and muddy waters.	Poor
Increaser II (EC, SA)	EC: Weeping lovegrass SA: Ratstail Dropseed	EC: Densely perennial tufted grass. Inflorescences are mostly an open panicle. Spikelets are dark grey to dark olive green. Culms 300-1,200 mm tall. Leaf blade up to 4 mm wide. Flowers from August to June. SA: Perennial tufted grass. Long panicle with a pointed tip. Culms 280-1,500 mm tall. Leaf blade 1-4 mm wide. Flowers from October to April.	3-5	Barren spot, sandy layer on soil surface, Vetiver grass, damaged swales, and sedimentation in streams.	Moderate
Increaser III (AD)	Iron grass	A tufted perennial grass. Leaves are hard, narrow and rolled. Inflorescences are a spare, expanded and open panicle. Culms 300-800 mm tall. Leaf blade up to 2 mm wide. Flowers from November to April.	0	Bare soil, eroded slope, rills, gullies, exposed roots, Dongas, and parent material (stones).	High

* Van Oudtshoorn (1992)

The specific objectives in this study were as follows:

1. To evaluate the abundance and distribution of the increaser species and different levels of rangeland degradation in the Okhombe communal lands and compare it with the Cathedral Peak conservation area using a veld condition assessment technique;
2. To assess the utility of *in situ* spectroscopic data in discriminating between four different increaser species;
3. To investigate whether or not canopy reflectance spectra, resampled to AISA Eagle spectral resolution, could be used to discriminate between the four increaser species; and

4. To investigate the potential use of the new 8-band WorldView-2 imagery in classifying the four increaser species.

7.2 Rangeland condition assessment using vegetation abundance and composition

An improved understanding of the indicators of rangeland degradation as well as the best response to disturbance is essential for the creation of effective management plans and conservation policies. We evaluated rangeland condition using indicators of vegetation species (decreaser, increaser I, increaser IIa, increaser IIb, increaser IIc and increaser III) and soil properties (phosphorus, potassium, calcium, magnesium, pH, zinc, manganese, copper, organic matter and nitrogen) to discriminate between degraded and non-degraded rangeland within the Okhombe rangeland (dominated by increaser species) and the conserved area of Cathedral Peak (dominated by decreaser species) (Chapter 3). Four indicators of rangeland condition were tested: veld condition, basal cover, species diversity, and soil properties. The results revealed that the condition of the rangeland was good (86.6%) in the conserved site and poor (35.2% and 36.4%) in the degraded sites. The basal cover scores indicated that the degraded sites of the Mpameni and Ngubhela yielded a high basal cover (19.65% and 20.78%) but they were in poor condition (< 36.4%) and the conserved site was well covered (14.83%). Species diversity ranged from high in conserved sites (3.16) to slightly moderate in degraded sites (2.48 and 2.34) (Table 7.2).

Table 7. 2: Veld condition score, veld condition, basal cover, Shannon's diversity index (H') and Evenness (E) for each ecosystem (i.e. conserved, rehabilitated and degraded)

Technique	Conserved	Rehabilitated		Degraded	
	Cathedral Peak	Mpameni	Ngubhela	Mpameni	Ngubhela
Veld condition (%)	86.6	42.4	46.7	35.2	36.4
Basal cover (%)	14.83	15.06	16.87	19.65	20.78
Shannon's index (H')	3.16	2.82	2.51	2.48	2.34
Evenness (E)	0.94	0.87	0.78	0.78	0.75

The results of the soil analysis showed that there was a significant difference ($P < 0.05$) between degraded and non-degraded rangeland in terms of the soil properties of P, K, pH, Mn, Org. C and

N. However, there were no significant differences in Mg, Zn and Cu between the degraded, rehabilitated and conserved sites. We therefore concluded, making use of our knowledge of species composition, that a veld condition assessment based on the relative abundance of decreaser and increaser (I, II and III) grass species may be useful in terms of mapping different levels of rangeland degradation. However, the use of the benchmark technique to evaluate veld condition is considered to be time consuming. We therefore investigated the potential usefulness of remote sensing data to classify different types of increaser species in order to identify different levels of rangeland degradation.

7. 3 Are increaser species spectrally different?

To answer this question, reflectance measurements were collected from four increaser species – namely *Hyparrhenia hirta*, *Eragrostis curvula*, *Sporobolus africanus* and *Aristida diffusa* – at canopy level using the Analytical Spectral Devices (ASD) FieldSpec® 3 wavelength ranging from 350 nm to 2500 nm (Chapter 4). Conventional statistical techniques such as one-way ANOVA, stepwise discriminant function analysis and canonical function analysis were implemented to discriminate between the various species. The results of one-way ANOVA showed that there was a significant difference ($P < 0.05$) in the spectral reflectance between the four increaser species ($n = 439$). The significant wavelengths (439) are located in the three different regions of the electromagnetic spectrum, namely the visible (18 wavelengths), red-edge (71 wavelengths) and near-infrared (350 wavelengths) regions (Figure 7.1).

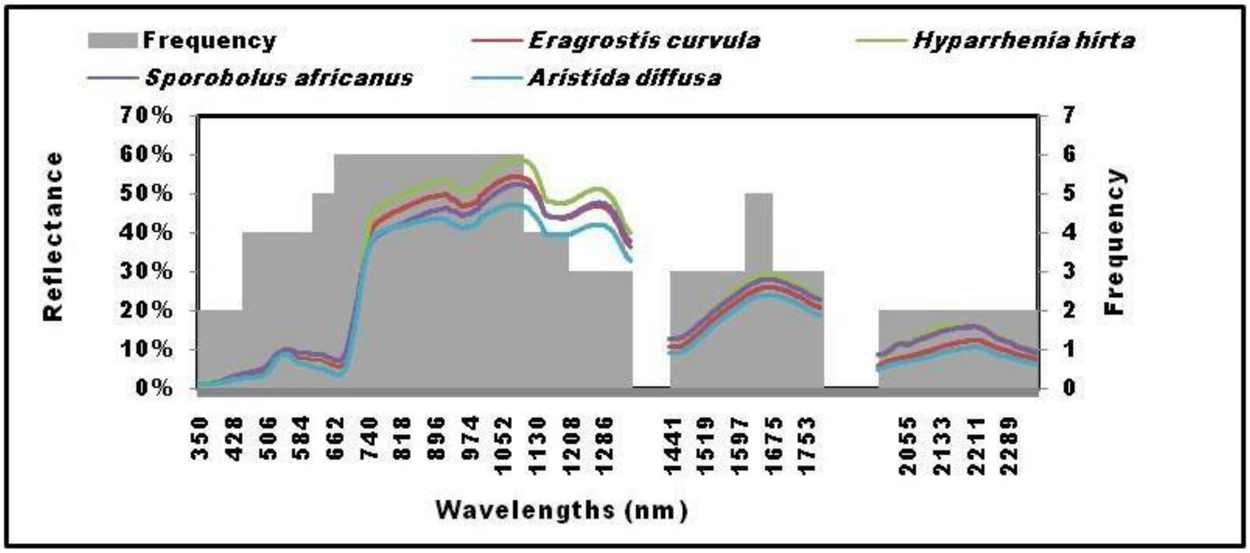

Figure 7. 1: Frequency of statistical differences using ANOVA with a 95% confidence level (P < 0.05) between the mean reflectance of four species (*Hyparrhenia hirta, Eragrostis curvula, Sporobolus africanus* and *Aristida diffusa*). The maximum grey shading shows the wavelengths where all four species can be discriminated. Spectral features between 1351 nm and 1439 nm, 1791 nm and 1989 nm, and 2361 nm and 2500 nm were removed due to excessive noise.

The results of the frequency analysis of statistical differences showed that in the mid-infrared region, there was no wavelength that could be used to discriminate between all the class pairs (n = 4) (Figure 7. 1). The significant wavelengths (n = 439) were used in a subsequent analysis to select the optimal wavelengths in increaser species discrimination using stepwise discriminant function analysis. In accordance with Wilks's lambda value, the *F* statistic and a significance level (P < 0.000), and 8 wavelengths were selected (Table 7.3).

Table 7. 3: Variables entered/removed using stepwise discriminant function analysis

Step	Variables entered	Lambda	Statistic	Sig.
1	665	0.512	44.849	0.000
2	729	0.302	75.119	0.000
3	848	0.189	66.916	0.000
4	895	0.173	53.205	0.000
5	1039	0.156	48.146	0.000
6	998	0.131	40.974	0.000
7	681	0.123	36.728	0.000
8	972	0.115	32.556	0.000

These wavelengths were located in the visible, red-edge and near-infrared regions. Canonical function analysis was used to determine the functions of the variables (wavelengths) that could be used to discriminate among the species. Standardised canonical discriminant function coefficients represent the contribution of the variable (wavelength) to the discrimination among the four species. The largest contribution was contained in the first canonical function, which includes the wavelengths 895 nm (the coefficient is 0.957), followed by 998 nm, 681 nm, 745 nm, and 998 nm, and a low standardised coefficient which includes 665 (the coefficient is -0.053) followed by 1039 nm, 848 nm and 972 nm. The three tiers of analysis yielded increaser species discrimination with an overall accuracy of 83.02% and a KHAT value of 0.77 (Table 7.4). The use of the spectroscopic approach applied in this study indicated that the increaser species were spectrally different, and as such these results encouraged us to further investigate the possibility of mapping increaser species as indicators of different levels of rangeland degradation using different types of remotely sensed data (hyperspectral and multispectral).

Table 7. 4: Confusion matrix for selected wavelengths showing the classification error obtained for the species (HH, EC, SA and AD)

Selected wavelength	Overall accuracy	KHAT	Users' accuracy		Producers' accuracy	
			Presence	absence	Presence	absence
8 wavelengths	83.02	0.77	88.68	79.25	88.68	79.25

7.4 The potential use of hyperspectral remote sensing for increaser species

Hyperspectral remote sensing data were acquired using a hand-held spectrometer as a means of spectrally discriminating the four increaser species. However, current operational airborne sensors such as AISA Eagle do not reach a fine spectral resolution of spectrometers such as Analytical Spectral Devices (ASD) FieldSpec® 3, which has a spectral range of 350 nm to 2500 nm (Mutanga, 2005). The hand-held spectrometer spectral measurements were therefore resampled to AISA Eagle spectral resolution using ENVI 4.3 image processing software (Mutanga, 2005). AISA Eagle data were collected with a 2 m spatial resolution, a spectral range of 393.2 nm to 994.1 nm (272 wavelengths), and 2.04 nm to 2.29 nm spectral resolutions. Hyperspectral AISA Eagle was evaluated to discriminate between four increaser species (*Hyparrhenia hirta, Eragrostis curvula*, *Sporobolus africanus* and *Aristida diffusa*) and thereby identify the different levels of rangeland degradation (Chapter 5). The random forest algorithm and a forward variable selection technique were used to identify optimal wavelengths for discriminating the species. The results showed that the optimal number of wavelengths (n = 10) that yielded the lowest OOB error (12.53%) in discriminating among the four increaser species are located at 966.7 nm, 877.6 nm, 674.1 nm, 854.8 nm, 703 nm, 732 nm, 718.7 nm, 691.9 nm, 741 nm and 902.7 nm (Figure 7.2).

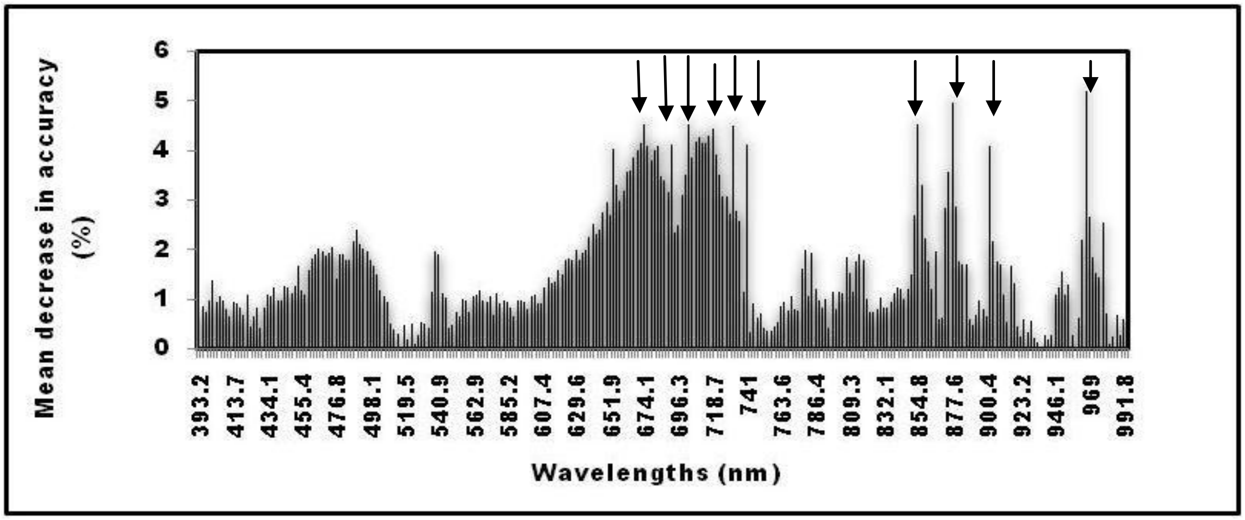

Figure 7. 2: Identifying the variables (wavelengths) importance by way of the random forest algorithm. Wavelengths with the highest mean decrease in accuracy (as shown by arrows) represent the most important wavelengths.

These wavelengths were located in the visible, red-edge and near-infrared regions of the electromagnetic spectrum. The random forest algorithm could accurately discriminate species with an overall accuracy of 87.50 % and a KHAT value of 0.83 (Table 7.5). The results demonstrated the potential of hyperspectral data to discriminate between increaser species. This makes it possible to upscale the methods to airborne sensors such as AISA Eagle for mapping increaser species areas as an indicator of rangeland degradation. However, the use of hyperspectral data comes with its own difficulties in terms of cost, availability, processing and high dimensionality. Therefore, we investigated the potential use of advanced multispectral remote sensing such as WorldView data.

Table 7. 5: Confusion matrix for 10 wavelengths from the test data set showing the classification error obtained for the species (HH, EC, SA and AD). The confusion matrix includes overall accuracy, KHAT, user's accuracy, and producer's accuracy for class pair (n = 6) and over all classes

Classes	ACC %	KHAT	PA %		UA %	
			Presence	Absence	Presence	Absence
HH vs EC	97.50	0.95	100.00	95.00	95.24	100.00
HH vs SA	95.00	0.90	95.24	94.74	95.24	94.74
HH vs AD	97.56	0.95	100.00	95.24	95.24	100.00
EC vs SA	92.50	0.85	95.00	90.00	90.48	94.74
EC vs AD	97.50	0.95	95.00	100.00	100.00	95.24
SA vs AD	92.68	0.85	90.00	95.24	94.74	90.91
All classes	87.50	0.83	95.24	86.36	86.96	90.48

7.5 Evaluating the capability of WorldView-2 high resolution data in classifying the increaser species

Mapping vegetation species using multispectral data such as SPOT and Landsat TM is challenging in general because of their lack of spectral and spatial resolution, which causes the problem of spectral overlap and mixed pixels between the different vegetation species (Harvey and Hill, 2001). However, the development in multispectral sensors, such as WorldView-2 containing key spectral bands such as red-edge make mapping vegetation at species level possible (Dlamini, 2010; Omar, 2010). In this study WorldView-2 was tested in mapping the increaser species (Chapter 6). The random forest algorithm and forward variable technique were able to identify the optimal wavelengths (coastal blue, yellow, red-edge, blue, green and red) for classifying the four increaser species with an overall accuracy of 82% and a KHAT value of 0.76 (Table 7.6). In order to improve the classification accuracy, the vegetation indices derived from WorldView-2 were tested. From the results, both classification accuracy and the KHAT value improved by 8% and 0.11 respectively (Table 7.6).

Table 7. 6: Confusion matrix for different variables showing the classification error obtained for the species HH, EC, SA and AD. The confusion matrix includes overall accuracy (ACC), KHAT, producer's accuracy (PA) and user's accuracy (UA)

Accuracy assessment	Band		Published VIs		Combined bands+ VIs	
	Top 6	Full dataset	Top 9	Full dataset	Top 10	Full dataset
ACC (%)	82.00	79.50	90.00	87.50	89.36	85.11
KHAT	0.76	0.73	0.87	0.83	0.86	0.80
PA (%)	92.00	84.00	91.00	88.00	96.00	90.00
UA (%)	92.00	84.00	90.00	87.00	96.00	90.00

Overall, the relatively high classification accuracy that was achieved by the raw bands and vegetation indices in the study demonstrated the potential of WorldView-2 data for increaser species separability. The results demonstrated the potential of WorldView-2 bands in classifying increaser grass at species level with an overall accuracy of 82%, which is only 5% less than the overall accuracy achieved by AISA Eagle. The use of WorldView-2 data was better than AISA Eagle data in terms of cost, data accessibility and processing.

7.6 Conclusions

The main aim of this study was to examine the potential use of remote sensing to discriminate between increaser vegetation species – namely *Hyparrhenia hirta*, *Eragrostis curvula*, *Sporobolus africanus* and *Aristida diffusa* – to help identify different levels of rangeland degradation in the Okhombe area of South Africa. The research carried out in this study showed that there is potential for using hyperspectral and multispectral data to discriminate between the four increaser species. However, the use of multispectral data (WorldView-2) was better than that of hyperspectral data (ASIA Eagle) in terms of the cost and availability.

The final concluding remarks were based on the following results from the different objectives addressed in this study:

1. The use of soil properties such as P, pH, Org. C and N as indicators of degradation were highly significant ($P < 0.001$) and can be used to discriminate between conserved and degraded sites.

2. The outcomes of the LandCare Programmes, which try to promote social, economic and environmental development in rehabilitated areas, have been successful in combatting the problems of rangeland degradation.
3. The application of remote sensing techniques has a high potential for identifying different levels of degradation based on Increaser species.
4. The field spectrometry measurements and the statistical analysis showed that the increaser species (n = 4) were spectrally different in the visible (400 nm - 700 nm), the red-edge (680 nm -750 nm) and the near-infrared (700 nm - 1300 nm) regions.
5. There is potential to use hyperspectral and multispectral data to discriminate increaser species. However, the use of the multispectral data (WorldView-2) was better than that of the hyperspectral data (ASIA Eagle) in terms of the cost and accessibility.
6. The use of selected spectral vegetation indices as calculated from the multispectral WorldView-2 satellite imagery improved the overall classification accuracy from 82% (raw bands) to 90% (of vegetation indices) of rangeland vegetation at increaser species level.
7. The results presented in this study confirm that the random forest algorithm is a robust and accurate method for both variables selection and the classification of hyperspectral and multispectral data.

7.7 Recommendations

The classification of increaser species represents different levels of rangeland degradation. There is a need for accurate, precise, and up-to-date spatial information on the current status of rangeland degradation vegetation as a prerequisite for the sustainable management of rangeland systems. In this regard, we expect that the results of this study could be used to support precision rangeland analysis and develop effective and sustainable rangeland management. In this vein, we make the following recommendations for future research work:

1. This study concentrated on determining the possibility of the spectral discrimination of increaser species (n = 4) in serving as an indicator of different levels of rangeland degradation. In order for remote sensing methods to become operational for mapping these different levels, future research is needed to investigate the optimal spatial resolution and pixel size that could better map the different levels of rangeland degradation when using increaser species as indicators.
2. Further research should investigate and measure the biophysical and biochemical characteristics of increaser species in relation to the degradation stages of rangeland.
3. Multispectral data do not require complex processing techniques and are available and relatively inexpensive. In this regard, the capability of multispectral sensors other than WorldView (e.g. Sumbandilasat, QuickBird, RapidEye and IKONOS) in classifying increaser species should be tested.

References

Adam, E., and Mutanga, O. , 2010. Hyperspectral remote sensing of papyrus swamps, The 8th Conference of the African Association of Remote Sensing for the Environment (AARSE 2010), Addis-Ababa, Ethiopia pp. 256-259.

Adam, E., Mutanga, O., 2009. Spectral discrimination of papyrus vegetation (Cyperus papyrus L.) in swamp wetlands using field spectrometry. ISPRS Journal of Photogrammetry and Remote Sensing 64(6), 612-620.

Adam, E., Mutanga, O., Rugege, D., Ismail, R., 2009. Field spectrometry of papyrus vegetation (Cyperus papyrus L.) in swamp wetlands of St Lucia, South Africa. In, Geoscience and Remote Sensing Symposium,2009 IEEE International,IGARSS 2009 (pp.V-260-IV-263).

Adger, W.N., Benjaminsen, T.A., Brown, K., Svarstad, H., 2000. Managing Fragile Ecosystems: Combating Desertification and Drought. Centre of Social and Economic Research on the Global Environment, University of East Anglia, London.

Anderson, P., Hoffman, M., 2007. The impacts of sustained heavy grazing on plant diversity and composition in lowland and upland habitats across the Kamiesberg mountain range in the Succulent Karoo, South Africa. Journal of Arid Environments 70(4), 686-700.

Archer, K., Kimes, R., 2008. Empirical characterization of random forest variable importance measures. Computational Statistics & Data Analysis 52(4), 2249-2260.

ASD. Analytical Spectral Devices, I., 2005. Analytical Spectral Devices, Inc., Handheld Spectroradiometer: User's Guide, Version 4.05, Boulder, USA.

Asner, G., 1998. Biophysical and biochemical sources of variability in canopy reflectance. Remote Sensing of Environment 64(3), 234-253.

Asner, G.P., 2000. Contributions of multi-view angle remote sensing to land-surface and biogeochemical research. Remote Sensing Reviews 18(22), 137-162.

Asner, G.P., Elmore, A.J., Olander, L.P., Martin, R.E., Harris, A.T., 2004. Grazing systems, ecosystem responses, and global change. Annu. Rev. Environ. Resour. 29(1), 261-299.

Asner, G.P., Wessman, C.A., Bateson, C., Privette, J.L., 2000. Impact of tissue, canopy, and landscape factors on the hyperspectral reflectance variability of arid ecosystems. Remote Sensing of Environment 74(1), 69-84.

Bajcsy, P., Groves, P., 2004. Methodology for hyperspectral band selection. Photogrammetric Engineering and Remote Sensing 70(7), 793-802.

Bajwa, S., Bajcsy, P., Groves, P., Tian, L., 2004. Hyperspectral image data mining for band selection in agricultural applications. Transactions American Society of Agricultural Engineers 47(3), 895-908.

Bangamwabo, V.M., 2009. Spatial and temporal extents of land degradation in a communal landscape of KwaZulu-Natal, In, *School of Environmental Sciences*. Pietermaritzburg, South Africa: University of KwaZulu-Natal.

Bardgett, R.D., Jones, A.C., Jones, D.L., Kemmitt, S.J., Cook, R., Hobbs, P.J., 2001. Soil microbial community patterns related to the history and intensity of grazing in sub-montane ecosystems. Soil Biology and Biochemistry 33(12-13), 1653-1664.

Barnes, D., Rethman, N., Beukes, B., Kotze, G., 2007. Veld composition in relation to grazing capacity. African Journal of Range and Forage Science 1(1), 16-19.

Beck, L.R., Hutchinson, C.F., Zauderer, J., 1990. A comparison of greenness measures in two semi-arid grasslands. Climatic change 17(2), 287-303.

Beisel, J.N., Moreteau, J.C., 1997. A simple formula for calculating the lower limit of Shannon's diversity index. Ecological Modelling 99(2-3), 289-292.

Berry, L., Olson, J., Campbell, D., 2003. Assessing the extent, cost and impact of land degradation at the national level: findings and lessons learned from seven pilot case studies, Report commissioned by the Global Mechanism with the support of the World Bank, available online at: http://global-mechanism.org/dynamic/documents/document_file/cost-of-land-degradation-case-studies.pdf (accessed 11 October 2011).

Biondini, M.E., Patton, B.D., Nyren, P.E., 1998. Grazing intensity and ecosystem processes in a northern mixed-grass prairie, USA. Ecological Applications 8(2), 469-479.

Blackburn, G.A., 1998. Spectral indices for estimating photosynthetic pigment concentrations: a test using senescent tree leaves. International Journal of Remote Sensing 19(4), 657-675.

Borda-de-Água, L., Hubbell, S.P., McAllister, M., 2002. Species-area curves, diversity indices, and species abundance distributions: a multifractal analysis. American Naturalist 159(2), 138-155.

Borel, C.C., 2010. Vegetative canopy parameter retrieval using 8-band data, DigitalGlobe 8-Band Research Challenge.

Bosch, J., 1979. Treatment effects on annual and dry period streamflow at Cathedral Peak. South African Forestry Journal 108(1), 29-38.

Bosch, O., Gauch, H., 1991. The use of degradation gradients for the assessment and ecological interpretation of range condition. Journal of the Grassland Society of southern Africa 8(4), 138-146.

Breiman, L., 2001. Random forests. Machine learning 45(1), 5-32.

Camp, K., 1997. The bioresource groups of KwaZulu-Natal. Cedara Report.

Cavayas, F., Ramos, Y., Boyer, A., 2010. Urban Vegetation Cover Inventory Update and Monitoring from Space using WorldView 2 Imagery: the Case of the Montreal Metropolitan Community Territory, Digital Globe® 8Bands Research Challenge.

Chan, J., Paelinckx, D., 2008a. Evaluation of Random Forest and Adaboost tree-based ensemble classification and spectral band selection for ecotope mapping using airborne hyperspectral imagery. Remote Sensing of Environment 112(6), 2999-3011.

Chan, J.C.W., Paelinckx, D., 2008b. Evaluation of random forest and adaboost tree-based ensemble classification and spectral band selection for ecotope mapping using airborne hyperspectral imagery. Remote Sensing of Environment 112(6), 2999-3011.

Chao, A., Shen, T.J., 2003. Nonparametric estimation of Shannon's index of diversity when there are unseen species in sample. Environmental and Ecological Statistics 10(4), 429-443.

Chen, J.M., 1996. Evaluation of vegetation indices and a modified simple ratio for boreal applications. Canadian Journal of Remote Sensing 22(3), 229-242.

Clark, R.N., 1999. Spectroscopy of rocks and minerals, and principles of spectroscopy, in: Rencz, A.N. (Ed.), Remote Sensing for the Earth Sciences. John Wiley and Sons, New York, pp. 3–57.

Cochrane, M.A., 2000. Using vegetation reflectance variability for species level classification of hyperspectral data. International Journal of Remote Sensing 21(10), 2075-2087.

Cohen, J., 1960. A coefficient of agreement for nominal scales. Educational and psychological measurement 20(1), 37-46.

Conant, R.T., Paustian, K., 2002. Potential soil carbon sequestration in overgrazed grassland ecosystems. Global Biogeochemical Cycles 16(4), 1143.

Congalton, R., Green, K., 1999. Assessing the Accuracy of Remotely Sensed Data: Principles and Practices (Boca Raton, FL: Lewis).
Critchley, W., Netshikovhela, E., 1998. Land degradation in South Africa: conventional views, changing paradigms and a tradition of soil conservation. Development Southern Africa 15(3), 449-469.
Curran, P., 1989. Remote sensing of foliar chemistry. Remote Sensing of Environment 30(3), 271-278.
da Silva, A.P., Imhoff, S., Corsi, M., 2003. Evaluation of soil compaction in an irrigated short-duration grazing system. Soil and Tillage Research 70(1), 83-90.
Daughtry, C., Walthall, C., 1998. Spectral discrimination of Cannabis sativa L. leaves and canopies. Remote Sensing of Environment 64(2), 192-201.
Daughtry, C., Walthall, C., Kim, M., De Colstoun, E.B., McMurtreyIII, J., 2000. Estimating corn leaf chlorophyll concentration from leaf and canopy reflectance. Remote Sensing of Environment 74(2), 229-239.
Deering, D.W., Rouse, J.W., Haas, R.H., Schell, J.A., 1975. Measuring `forage production' of grazing units from Landsat MSS data, Proceedings of the 10th International Symposium on Remote Sensing of Environment 11, pp. 1169-1178.
Díaz-Uriarte, R., de Andrés, A., 2006. Gene selection and classification of microarray data using random forest. BMC bioinformatics 7(1), 3.
Dlamini, W.M., 2010. Multispectral detection of invasive alien plants from very high resolution 8-band satellite imagery using probabilistic graphical models, Digital Globe® 8Bands Research Challenge.
Dobarro, I., Valladares, F., Peco, B., 2010. Light quality and not quantity segregates germination of grazing increasers from decreasers in Mediterranean grasslands. Acta Oecologica 36(1), 74-79.
Dollar, E., Goudy, A., 1999. Environmental change, in: Fox, R., Rowntree, K. (Eds.), The geography of South Africa in a changing world. Oxford University Press, Oxford, p. 477.
Du Preez, C., Snyman, H., 1993. Research note: Organic matter content of a soil in a semi-arid climate with three long-standing veld conditions. African Journal of Range & Forage Science 10(2), 108-110.
du Toit, J.C.O., 2009. Early survival and growth of vegetatively propagated indigenous grasses in a clear-felled timber plantation in KwaZulu-Natal, South Africa. African Journal of Range & Forage Science 26(2), 97-101.
Duarte Silva, A.P., Stam, A., 1995. Discriminant analysis, in: Grimm, L.G. (Ed.), Reading and understanding multivariate statistics. DC: American Psychological Association, Washington, pp. 277–318.
Efron, B., 1979. Bootstrap methods: another look at the jackknife. The annals of Statistics 7(1), 1-26.
Efron, B., Tibshirani, R., 1997. Improvements on cross-validation: The. 632+ bootstrap method. Journal of the American Statistical Association 92(438), 548-560.
El-Nahry, A., Hammad, A., 2009. Assessment of Salinity Effects and Vegetation Stress, West of Suez Canal, Egypt Using Remote Sensing Techniques. Journal of Applied Sciences Research 5(3), 316-322.
Elvidge, C., 1990. Visible and near infrared reflectance characteristics of dry plant materials. International Journal of Remote Sensing 11(10), 1775-1795.

Elvidge, C.D., Chen, Z., 1995. Comparison of broad-band and narrow-band red and near-infrared vegetation indices. Remote Sensing of Environment 54(1), 38-48.

ENVI, 2006. Environment for Visualising Images. USA: ITT industries, Inc.

Escadafal, R., Huete, A., 1991. Improvement in remote sensing of low vegetation cover in arid regions by correcting vegetation indices for soil" noise", C. R. ACAD. SCI.(PARIS),(II). pp. 1385-1391.

Eswaran, H., Lal, R., Reich, P.F., 2001. Land degradation: an overview, in: E. M. Bridges, I.D.H., L. R. Oldeman, F. W. T. Penning de Vries, S. J. Scherr and S. Sompatpanit (Ed.), Responses to Land Degradation. Proceedings 2nd International Conference on Land Degradation and Desertification. Oxford Press, New Delhi, India, Khon Kaen, Thailand, pp. 20-35.

Everson, C., 2001. The water balance of a first order catchment in the montane grasslands of South Africa. Journal of Hydrology 241(1-2), 110-123.

Everson, C., Tainton, N., 1984. The effect of thirty years of burning on the Highland Sourveld of Natal. African Journal of Range and Forage Science 1(3), 15–20.

Everson, T.M., Everson, C.S., Zuma, K.D., 2007. Community based research on the influence of rehabilitation techniques on the management of degraded catchments. WRC Report No. 1316/1/07 97pp., pp. 1-97.

FAO, UNDP, UNEP, a., 1994. Land Degradation in South Asia: Its Severity, Causes and Effects upon the People. World Soil Resources Report 78.

Feng, Y., Lu, Q., Tokola, T., Liu, H., Wang, X., 2009. Assessment of grassland degradation in Guinan county, Qinghai Province, China, in the past 30 years. Land Degradation & Development 20(1), 55-68.

Filippi, A.M., Jensen, J.R., 2006. Fuzzy learning vector quantization for hyperspectral coastal vegetation classification. Remote Sensing of Environment 100(4), 512-530.

Fisher, R.A., 1936. The use of multivariate measurements in taxonomic problems. Annals of Eugenics 7(part 2), 179 -188.

Foran, B., Tainton, N., Booysen, P., 1978. The development of a method for assessing veld condition in three grassveld types in Natal. Proceedings of the Annual Congresses of the Grassland Society of Southern Africa 13(1), 27-33.

Frank, D.A., 2005. The interactive effects of grazing ungulates and aboveground production on grassland diversity. Oecologia 143(4), 629-634.

Frank, T., 1984. The effect of change in vegetation cover and erosion patterns on albedo and texture of Landsat images in a semiarid environment. Annals of the Association of American Geographers 74(3), 393-407.

Friedel, M., 1991. Range condition assessment and the concept of thresholds: a viewpoint. Journal of Range Management 44(5), 422-426.

Fung, T., Yan, H., Siu, W., 2003. Band selection using hyperspectral data of subtropical tree species. Geocarto International 18(4), 3-11.

Gitelson, A., Merzlyak, M.N., 1993. Spectral reflectance changes associated with autumn senescence of Aesculus hippocastanum L. and Acer platanoides L. leaves. Spectral features and relation to chlorophyll estimation. Journal of Plant Physiology 143(3), 286-292.

Gitelson, A.A., Kaufman, Y.J., Stark, R., Rundquist, D., 2002. Novel algorithms for remote estimation of vegetation fraction. Remote Sensing of Environment 80(1), 76-87.

Gitelson, A.A., Merzlyak, M.N., 1996. Signature analysis of leaf reflectance spectra: algorithm development for remote sensing of chlorophyll. Journal of Plant Physiology 148(3), 494-500.
Gitelson, A.A., Vina, A., Ciganda, V., Rundquist, D.C., Arkebauer, T.J., 2005. Remote estimation of canopy chlorophyll content in crops. Geophysical Research Letters 32, L08403, doi:08410.01029/02005GL022688.
Goel, N.S., Quin, W., 1994. Influences of canopy architecture on relationships between various vegetation indexes and LAI and FPAR: a computer simulation. Remote Sensing of Environment 10(4), 309–347.
Govender, M., Chetty, K., Bulcock, H., 2009. A review of hyperspectral remote sensing and its application in vegetation and water resource studies. Water SA 33(2), 145-151.
Govender, M., Everson, C.S., 2005. Modelling streamflow from two small South African experimental catchments using the SWAT model. Hydrological Processes 19(3), 683-692.
Granger, J., Schulze, R., 1977. Incoming solar radiation patterns and vegetation response: examples from the Natal Drakensberg. Plant Ecology 35(1), 47-54.
Granger, J.E., 1976. The vegetation changes, some related factors and changes in the water balance following 20 years of fire exclusion in catchment IX, Cathedral Peak Forestry Research Station. University of Natal, Pietermaritzburg, p. 604.
Green, E.P., Mumby, P.J., Edwards, A.J., Clark, C.D., Ellis, A.C., 1997. Estimating leaf area index of mangroves from satellite data. Aquatic Botany 58(1), 11-19.
Greenwood, K., MacLeod, D., Hutchinson, K., 1997. Long-term stocking rate effects on soil physical properties. Australian Journal of Experimental Agriculture 37(4), 413-419.
Greenwood, K., McKenzie, B., 2001. Grazing effects on soil physical properties and the consequences for pastures: a review. Australian Journal of Experimental Agriculture 41(8), 1231-1250.
Guyon, I., Elisseeff, A., 2003. An introduction to variable and feature selection. The Journal of Machine Learning Research 3(7-8), 1157-1182.
Haboudane, D., Miller, J.R., Tremblay, N., Zarco-Tejada, P.J., Dextraze, L., 2002. Integrated narrow-band vegetation indices for prediction of crop chlorophyll content for application to precision agriculture. Remote Sensing of Environment 81(2-3), 416-426.
Hanafi, A., Jauffret, S., 2008. Are long-term vegetation dynamics useful in monitoring and assessing desertification processes in the arid steppe, southern Tunisia. Journal of Arid environments 72(4), 557-572.
Hardy, M., Hurt, C., 1989. An evaluation of veld condition assessment techniques in Highland Sourveld. Journal of the Grassland Society of Southern Africa 6(2), 51-58.
Hardy, M., Tainton, N., 2007. Towards a technique for determining basal cover in tufted grasslands. African Journal of Range and Forage Science 10(2), 77-81.
Hardy, M.B., Hurt, C.R., Bosch, O.J.H., 1999. Grassveld, in: N.M.Tainton (Ed.), Veld management in South Africa. University of Natal Press, Pietermaritzburg, pp. 195-206.
Harrison, Y., Shackleton, C., 1999. Resilience of South African communal grazing lands after the removal of high grazing pressure. Land Degradation & Development 10(3), 225-239.
Harvey, K., Hill, G., 2001. Vegetation mapping of a tropical freshwater swamp in the Northern Territory, Australia: a comparison of aerial photography, Landsat TM and SPOT satellite imagery. International Journal of Remote Sensing 22(15), 2911-2925.

Hestir, E.L., Khanna, S., Andrew, M.E., Santos, M.J., Viers, J.H., Greenberg, J.A., Rajapakse, S.S., Ustin, S.L., 2008. Identification of invasive vegetation using hyperspectral remote sensing in the California Delta ecosystem. Remote Sensing of Environment 112(11), 4034-4047.

Hill, J., Mégier, J., Mehl, W., 1995. Land degradation, soil erosion and desertification monitoring in Mediterranean ecosystems. Remote Sensing Reviews 12(1), 107-130.

Hill, J., Stellmes, M., Udelhoven, T., Röder, A., Sommer, S., 2008. Mediterranean desertification and land degradation: Mapping related land use change syndromes based on satellite observations. Global and Planetary Change 64(3-4), 146-157.

Hoffman, M., Bond, W., Stock, W., 1995. Desertification of the eastern Karoo, South Africa: conflicting paleoecological, historical, and soil isotopic evidence. Environmental Monitoring and Assessment 37(1), 159-177.

Hoffman, M., Todd, S., 2000. A national review of land degradation in South Africa: the influence of biophysical and socio-economic factors. Journal of Southern African Studies 26(4), 743-758.

Hoffman, M., Todd, S., Ntshona, Z., Turner, S., 1999. Land degradation in South Africa Department of Environment Affairs and Tourism. Pretoria.

Hoffmann, A., Zeller, U., 2005. Influence of variations in land use intensity on species diversity and abundance of small mammals in the Nama Karoo, Namibia. Belg. J. Zool 135(supplement), 91–96.

Hsu, P.H., 2007. Feature extraction of hyperspectral images using wavelet and matching pursuit. ISPRS journal of photogrammetry and remote sensing 62(2), 78-92.

Huang, C., Davis, L., Townshend, J., 2002. An assessment of support vector machines for land cover classification. International Journal of Remote Sensing 23(4), 725-749.

Huete, A., Justice, C., van Leeuwen, W., 1999. MODIS vegetation index (MOD13) algorithm theoretical basis document. Link: http://modis. gsfc. nasa. gov/data/atbd/atbd_mod13. pdf.

Huete, A.R., 1988. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment 25(3), 295-309.

Hurt, C.R., Hardy, M.B., 1989. A weighted key species method for monitoring changes in species composition of Highland Sourveld. African Journal of Range and Forage Science 6(3), 109-113.

Ibrahim, A.A., 2008. Using remote sensing technique (NDVI) for monitoring vegetation degradation in semi-arid lands and its relationship to precipitation: Case study from Libya, The 3rd International Conference on Water Resources and Arid Environments 16-19 November, Riyadh, Saudi Arabia.

Islam, K., Weil, R., 2000. Land use effects on soil quality in a tropical forest ecosystem of Bangladesh. Agriculture, Ecosystems & Environment 79(1), 9-16.

Ismail, R., 2009. Remote sensing of forest health: the detection and mapping of Pinus patula trees infested by Sirex noctilio. In, School of Environmental Sciences. Pietermaritzburg, South Africa: University of KwaZulu-Natal.

Ismail, R., Mutanga, O., 2010. A comparison of regression tree ensembles: Predicting Sirex noctilio induced water stress in Pinus patula forests of KwaZulu-Natal, South Africa. International Journal of Applied Earth Observation and Geoinformation 12(1), S45-S51.

Jackson, Q., Landgrebe, D.A., 2001. An adaptive classifier design for high-dimensional data analysis with a limited training data set. Geoscience and Remote Sensing, IEEE Transactions on 39(12), 2664-2679.
Jiang, X., Tang, L., Wang, C., 2004. Spectral characteristics and feature selection of hyperspectral remote sensing data. International Journal of Remote Sensing 25(1), 51-59.
Jordaan, F., Biel, L., Du Plessis, P., 1997. A comparison of five range condition assessment techniques used in the semi-arid western grassland biome of southern Africa* 1. Journal of Arid Environments 35(4), 665-671.
Joubert, D., Ryan, P., 1999. Differences in mammal and bird assemblages between commercial and communal rangelands in the Succulent Karoo, South Africa. Journal of Arid Environments 43(3), 287-299.
Jusoff, K., Pathan, M., 2009. Mapping of individual oil palm trees using airborne hyperspectral sensing: An overview. Applied Physics Research 1(1), 15-30.
Kakembo, V., 2001. Trends in vegetation degradation in relation to land tenure, rainfall, and population changes in Peddie District, Eastern Cape, South Africa. Environmental Management 28(1), 39-46.
Kassahun, A., Snyman, H.A., Smit, G.N., 2008. Impact of rangeland degradation on the pastoral production systems, livelihoods and perceptions of the Somali pastoralists in Eastern Ethiopia. Journal of Arid Environments 72(7), 1265-1281.
Kaufman, Y.J., Tanre, D., 1992. Atmospherically resistant vegetation index (ARVI) for EOS-MODIS. Geoscience and Remote Sensing, IEEE Transactions on 30(2), 261-270.
Kawanabe, S., Nan, T., Oshida, Z., Kou, D., Jiang, N., Takada-Oikawa, S., Mukaiyama, S., 1998. Degradation of grassland in Keerqin Sandland, Inner Mongolia, China. Journal of Japanese Society of Grassland Science 44(2), 109-114.
Kiguli, L., Palmer, A., Avis, A., 1999. A description of rangeland on commercial and communal land, Peddie district, South Africa. African Journal of Range and Forage Science, 16 2(3), 89-95.
Kraaij, T., Milton, S.J., 2006. Vegetation changes (1995-2004) in semi-arid Karoo shrubland, South Africa: Effects of rainfall, wild herbivores and change in land use. Journal of Arid Environments 64(1), 174-192.
Kumar, A., Roy, P.S., 2010. Effect on specific crop mapping using WorldView-2 multispectral add-on bands- A soft classification approach, Digital Globe® 8Bands Research Challenge.
Kumar, L., Schmidt, K.S., Dury, S., Skidmore, A.K., 2001. Review of hyperspectral remote sensing and vegetation science, in: F. D.Van Der Meer, S.M., De Jong (Ed.), Imaging Spectrometry: Basic Principles and Prospective Applications. Kluwer Academic Press, Dordrecht, pp. 111-155.
Laliberte, A.S., Rango, A., Havstad, K.M., Paris, J.F., Beck, R.F., McNeely, R., Gonzalez, A.L., 2004. Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. Remote Sensing of Environment 93(1-2), 198-210.
Lande, R., 1996. Statistics and partitioning of species diversity, and similarity among multiple communities. Oikos 76(1), 5-13.
Lawrence, R.L., Wood, S.D., Sheley, R.L., 2006. Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (RandomForest). Remote Sensing of Environment 100(3), 356-362.

Lees, B.G., Ritman, K., 1991. Decision-tree and rule-induction approach to integration of remotely sensed and GIS data in mapping vegetation in disturbed or hilly environments. Environmental Management 15(6), 823-831.

Lewis, M., 2000. Discrimination of arid vegetation composition with high resolution CASI imagery. The Rangeland Journal 22(1), 141-167.

Li, L., Ustin, S., Lay, M., 2005. Application of multiple endmember spectral mixture analysis (MESMA) to AVIRIS imagery for coastal salt marsh mapping: a case study in China Camp, CA, USA. International Journal of Remote Sensing 26(23), 5193-5207.

Liaw, A., Wiener, M., 2002. Classification and Regression by randomForest. R news 2(3), 18–22.

Lillesand, T.M., Kiefer, R. W. , 1999. Remote sensing and image interpretation. John Wiley and Sons, New York, USA.

Liu, Y., Zha, Y., Gao, J., Ni, S., 2004. Assessment of grassland degradation near Lake Qinghai, West China, using Landsat TM and in situ reflectance spectra data. International Journal of Remote Sensing 25(20), 4177-4189.

Magurran, A.E., 1988. Ecological diversity and its measurement. Taylor & Francis.

Maitima, J., Olson, J.M., 2001. Guide to field methods for comparative site analysis for the land use change, impacts and dynamics projects The Land Use Change, Impacts and Dynamics (LUCID) Projects Working Paper Number: 15. Nairobi, Kenya. international Livestock Research.

Majuva-Masafu, M., Linington, M., 2006. The effect of feeding varying levels of Leucaena leucocephala on intake and digestibility of low-quality forages in the Highveld of South Africa. African Journal of Range & Forage Science 23(3), 177-183.

Manley, J., Schuman, G., Reeder, J., Hart, R., 1995. Rangeland soil carbon and nitrogen responses to grazing. Journal of Soil and Water Conservation 50(3), 294.

Manly, B., 2005. Multivariate statistical methods: a primer. Chapman & Hall/CRC.

Mapiye, C., Mwale, M., Chikumba, N., Chimonyo, M., 2008. Fire as a rangeland management tool in the savannas of Southern Africa: A review. Tropical and Subtropical Agroecosystems 8(2), 115-124.

Mardia, K., Kent, J., Bibby, J., 1979. Multivariate analysis Academic Press. Inc., San Diego.

Martin, M., Newman, S., Aber, J., Congalton, R., 1998. Determining forest species composition using high spectral resolution remote sensing data. Remote Sensing of Environment 65(3), 249-254.

Martínez, B., Gilabert, M., 2009. Vegetation dynamics from NDVI time series analysis using the wavelet transform. Remote Sensing of Environment 113(9), 1823-1842.

May, A., Pinder, J., Kroh, G., 1997. A comparison of Landsat Thematic Mapper and SPOT multi-spectral imagery for the classification of shrub and meadow vegetation in northern California, USA. International Journal of Remote Sensing 18(18), 3719-3728.

Mentis, M., 1981. Evaluation of the wheel-point and step-point methods of veld condition assessment. African Journal of Range & Forage Science 16(1), 89-94.

Mentis, M., Collinson, R., Wright, M., 1980. The precision of assessing components of the condition of moist tall grassveld. African Journal of Range & Forage Science 15(1), 43-46.

Menze, B., Kelm, B., Masuch, R., Himmelreich, U., Bachert, P., Petrich, W., Hamprecht, F., 2009. A comparison of random forest and its Gini importance with standard chemometric methods for the feature selection and classification of spectral data. BMC bioinformatics 10(1), 213.

Merzlyak, M.N., Gitelson, A.A., Chivkunova, O.B., Rakitin, V.Y.U., 1999. Non destructive optical detection of pigment changes during leaf senescence and fruit ripening. Physiologia plantarum 106(1), 135-141.
Metternicht, G.Z., Blanco, J.A., del Valle, P.D., 2010. Remote sensing of land degradation: Experiences from Latin America and the Caribbean. Journal of environmental quality 39(1), 42-61.
Metzger, K., Coughenour, M., Reich, R., Boone, R., 2005. Effects of seasonal grazing on plant species diversity and vegetation structure in a semi-arid ecosystem. Journal of Arid Environments 61(1), 147-160.
Moolenaar, S., Temminghoff, E., De Haan, F., 1998. Modeling dynamic copper balances for a contaminated sandy soil following land use change from agriculture to forestry. Environmental Pollution 103(1), 117-125.
Moyo, B., Dube, S., Lesoli, M., Masika, P.J., 2008. Communal area grazing strategies: institutions and traditional practices. African Journal of Range & Forage Science 52(2), 47-54.
Muchoney, D., Haack, B., 1994. Change detection for monitoring forest defoliation. Photogrammetric Engineering and Remote Sensing 60(10), 1243-1251.
Mucina, L., Rutherford, M.C., 2006. The vegetation of South Africa, Lesotho and Swaziland. Strelitzia 191–807.
Mulder, J., Brent, A.C., 2006. Selection of sustainable rural agriculture projects in South Africa: Case studies in the LandCare programme. Journal of Sustainable Agriculture 28(2), 55-84.
Mumby, P.J., Green, E. P., Edwards, A. J., Clark, C. D., 1999. The cost-effectiveness of remote sensing for tropical coastal resources assessment and management. Journal of Environmental Management 55(3), 157–166.
Mutanga, O., 2004. Hyperspectral remote sensing of tropical grass quality and quantity, ITC. University of Wageningen, Enschede, The Netherlands.
Mutanga, O., 2005. Discriminating tropical grass canopies grown under different nitrogen treatments using spectra resampled to HYMAP. International Journal of Geoinformatics 1(2), 21-32.
Mutanga, O., Kumar, L., 2007. Estimating and mapping grass phosphorus concentration in an African savanna using hyperspectral image data. International Journal of Remote Sensing 28(21), 4897-4911.
Mutanga, O., Skidmore, A., 2004. Hyperspectral band depth analysis for a better estimation of grass biomass (Cenchrus ciliaris) measured under controlled laboratory conditions. International Journal of Applied Earth Observation and Geoinformation 5(2), 87-96.
Mutanga, O., Skidmore, A., 2007. Red edge shift and biochemical content in grass canopies. ISPRS Journal of Photogrammetry and Remote Sensing 62(1), 34-42.
Mutanga, O., Skidmore, A., Kumar, L., Ferwerda, J., 2005. Estimating tropical pasture quality at canopy level using band depth analysis with continuum removal in the visible domain. International Journal of Remote Sensing 26(6), 1093-1108.
Mutanga, O., van Aardt, J., Kumar, L., 2009. Imaging spectroscopy (hyperspectral remote sensing) in southern Africa: an overview. South African Journal of Science 105(5-6), 193-198.
Nalule, A.S., 2010. Social Management of Rangelands and Settlement in Karamoja Subregion. Food and Agriculture Organization (FAO)

Nel, W., Sumner, P.D., 2005. First rainfall data from the KZN Drakensberg escarpment edge (2002 and 2003). Water S. A. 31(3), 399-402.
Nordberg, M., Allard, A., 2002. A remote sensing methodology for monitoring lichen cover. Canadian journal of remote sensing 28(2), 262-274.
Nsuntsha, A.N.M., 2000. Change and continuity in government institutional arrangements: implications for environmental management in the Upper Tugela area of KwaZulu-Natal.
O'Connor, T., Haines, L., Snyman, H., 2001. Influence of precipitation and species composition on phytomass of a semi arid African grassland. Journal of Ecology 89(5), 850-860.
O'Connor, T.G., 2005. Influence of land use on plant community composition and diversity in Highland Sourveld grassland in the southern Drakensberg, South Africa. Journal of Applied Ecology 42(5), 975-988.
O'Connor, T.G., Bredenkamp, G.J., 1997. Grassland, in: R.M. Cowling, R., D.M., Pierce, S.M. (Ed.), Vegetation of Southern Africa. Cambridge University Press, Cambridge, pp. 215–257.
Oba, G., Kaitira, L., 2006. Herder knowledge of landscape assessments in arid rangelands in northern Tanzania. Journal of Arid environments 66(1), 168-186.
Okin, G.S., Roberts, D.A., Murray, B., Okin, W.J., 2001. Practical limits on hyperspectral vegetation discrimination in arid and semiarid environments. Remote Sensing of Environment 77(2), 212-225.
Oluwole, F., Sambo, J., Sikhalazo, D., 2008. Long-term effects of different burning frequencies on the dry savannah grassland in South Africa. African Journal of Agricultural Research 3(2), 147-153.
Oluwole, F.A., Dube, S., 2008. Land degradation evaluation in a game reserve in Eastern Cape of South Africa: soil properties and vegetation cover. Scientific Research and Essays 3(3), 111-119.
Omar, H., 2010. Commercial Timber Tree Species Identification Using Multispectral Worldview2 Data, Digital Globe® 8Bands Research Challenge, 2-13.
Özçift, A., 2011. Random forests ensemble classifier trained with data resampling strategy to improve cardiac arrhythmia diagnosis. Computers in Biology and Medicine 41(5), 265-271.
Pal, M., 2005. Random forest classifier for remote sensing classification. International Journal of Remote Sensing 26(1), 217-222.
Palmer, A., van Rooyen, A., 1998. Detecting vegetation change in the southern Kalahari using Landsat TM data* 1. Journal of Arid Environments 39(2), 143-153.
Palmer, A.R., Ainslie, A., 2006. Arid rangeland production systems of Southern Africa. Science et changements planétaires/Sécheresse 17(1), 98-104.
Passmore, G., Brown, C.G., 1991. Analysis of rangeland degradation using stochastic dynamic programming. Australian Journal of Agricultural Economics 35(2), 131-157.
Paudel, K.P., Andersen, P., 2010. Assessing rangeland degradation using multi temporal satellite images and grazing pressure surface model in Upper Mustang, Trans Himalaya, Nepal. Remote Sensing of Environment 114(8), 1845-1855.
Payne, R.W., Harding, S.A., Murray, D.A. Soutar, D.M., Baird, D.B., Glaser, A.I. , Channing, I.C. , Welham, S.J., Gilmour, A.R., Thompson, R., Webster. R., 2009. The Guide to GenStat, 12 ed. VSN International, Oxford, United Kingdom.

Peckham, S.D., Ahl, D.E., Serbin, S.P., Gower, S.T., 2008. Fire-induced changes in green-up and leaf maturity of the Canadian boreal forest. Remote Sensing of Environment 112(9), 3594-3603.
Peden, M., 2005. Tackling'the most avoided issue': communal rangeland management in KwaZulu-Natal, South Africa. African Journal of Range & Forage Science 22(3), 167-175.
Penuelas, J., Baret, F., Filella, I., 1995. Semi-empirical indices to assess carotenoids/chlorophyll a ratio from leaf spectral reflectance. Photosynthetica 31(2), 221-230.
Peters, J., De Baets, B., Samson, R., Verhoest, N., 2007. Modelling groundwater-dependent vegetation patterns using ensemble learning. Hydrology and Earth System Sciences Discussions 4(5), 3687-3717.
Peterson, D., Price, K., Martinko, E., 2002. Discriminating between cool season and warm season grassland cover types in northeastern Kansas. International Journal of Remote Sensing 23(23), 5015-5030.
Pielou, E., 1966. The measurement of diversity in different types of biological collections. Journal of theoretical biology 13, 131-144.
Pinet, P.C., Kaufmann, C., Hill, J., 2006. Imaging spectroscopy of changing Earth's surface: a major step toward the quantitative monitoring of land degradation and desertification. Comptes Rendus Geosciences 338(14-15), 1042-1048.
Price, K.P., Guo, X., Stiles, J.M., 2002. Optimal Landsat TM band combinations and vegetation indices for discrimination of six grassland types in eastern Kansas. International Journal of Remote Sensing 23(23), 5031-5042.
Prince, S., Becker-Reshef, I., Rishmawi, K., 2009. Detection and mapping of long-term land degradation using local net production scaling: Application to Zimbabwe. Remote Sensing of Environment 113(5), 1046-1057.
Proffitt, A., Bendotti, S., Howell, M., Eastham, J., 1993. The effect of sheep trampling and grazing on soil physical properties and pasture growth for a red-brown earth. Australian journal of agricultural research 44(2), 317-331.
Pyke, D., Herrick, J., Shaver, P., Pellant, M., 2002. Rangeland health attributes and indicators for qualitative assessment. Journal of Range Management 55(6), 584-597.
R Development Core Team, 2008. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, available online at: http://www.R-project.org. (Accessed 21 January, 2011).
Ramoelo, A., Cho, M., Mathieu, R., Skidmore, A., Schlerf, M., Heitkonig, I., Prins, H., 2011. Integrating environmental and in situ hyperspectral remote sensing variables for grass nitrogen estimation in savannah ecosystems, The International Symposium on Remote Sensing of Environment (ISRSE), Sydney, Australia, pp. 10-15
Ravi, S., Breshears, D., Huxman, T., D'Odorico, P., 2010. Land degradation in drylands: Interactions among hydrologic-aeolian erosion and vegetation dynamics. Geomorphology 116(3-4), 236-245.
Ray, T.W., 1995. Remote monitoring of land degradation in arid/semiarid regions. California Institute of Technology, Pasadena, CA.
Ray, T.W., Murray, B.C., 1996. Nonlinear spectral mixing in desert vegetation. Remote Sensing of Environment 55(1), 59-64.
Reed, M.S., Dougill, A.J., 2002. Participatory selection process for indicators of rangeland condition in the Kalahari. Geographical Journal 168(3), 224-234.

Reeder, J., Schuman, G., 2002. Influence of livestock grazing on C sequestration in semi-arid mixed-grass and short-grass rangelands. Environmental Pollution 116(3), 457-463.
Reid, P., Vogel, C., 2006. Living and responding to multiple stressors in South Africa--Glimpses from KwaZulu-Natal. Global Environmental Change 16(2), 195-206.
Reynolds, J.F., Smith, D., Lambin, E.F., Turner, B., Mortimore, M., Batterbury, S.P.J., Downing, T.E., Dowlatabadi, H., Fernández, R.J., Herrick, J.E., 2007. Global desertification: building a science for dryland development. science 316(5826), 847-851.
Richardson, A.J., Wiegand, C.L., 1977. Distinguishing vegetation from soil background information. Photogrammetric Engineering and Remote Sensing 43(12), 1541-1552.
Rocchini, D., He, K.S., Oldeland, J., Wesuls, D., Neteler, M., 2010. Spectral variation versus species b-diversity at different spatial scales: a test in African highland savannas. Journal of Environmental Monitoring 12(4), 825-831.
Roques, K., O'connor, T., Watkinson, A., 2001. Dynamics of shrub encroachment in an African savanna: relative influences of fire, herbivory, rainfall and density dependence. Journal of Applied Ecology 38(2), 268-280.
Roujean, J.L., Breon, F.M., 1995. Estimating PAR absorbed by vegetation from bidirectional reflectance measurements. Remote Sensing of Environment 51(3), 375-384.
Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D.W. , 1974. Monitoring vegetation systems in the Great Plains with ERTS. In: Proceedings of the third Earth Resources Technology Satellite-1 Symposium, NASA, , Washington, DC. , pp. 309 - 317.
Rutherford, M., Powrie, L., 2010. Severely degraded rangeland: Implications for plant diversity from a case study in Succulent Karoo, South Africa. Journal of Arid Environments 74(6), 692-701.
Schmidt, K., Skidmore, A., 2003. Spectral discrimination of vegetation types in a coastal wetland. Remote Sensing of Environment 85(1), 92-108.
Schmidtlein, S., Sassin, J., 2004. Mapping of continuous floristic gradients in grasslands using hyperspectral imagery. Remote Sensing of Environment 92(1), 126-138.
Schulze, R.E., 1975. Catchment Evapotranspiration in the Natal Drakensberg. Unpublished Ph.D. Thesis. University of Natal, Pietermaritzburg, p. 244
Scott, D., 1993. The hydrological effects of fire in South African mountain catchments. Journal of Hydrology 150(2-4), 409-432.
Shackleton, C., Guthrie, G., Main, R., 2005. Estimating the potential role of commercial over harvesting in resource viability: a case study of five useful tree species in South Africa. Land Degradation & Development 16(3), 273-286.
Shackleton, C.M., 2000. Comparison of plant diversity in protected and communal lands in the Bushbuckridge lowveld savanna, South Africa. Biological Conservation 94(3), 273-285.
Shannon, C.E., Weaver, W., 1963. The mathematical theory of communication. University of Illinois Press, Urbana.
Shariff, A.R., Biondini, M.E., Grygiel, C.E., 1994. Grazing intensity effects on litter decomposition and soil nitrogen mineralization. Journal of Range Management 47(6), 444-449.
Shackleton, S., Shackleton, C., Myles, M., Rachel, W., Caroline, S., Roger, L., 2003. Diversifying communal rangeland use and benefits: the case of Marula (Sclerocarya birrea) in Bushbuckridge, South Africa, Proceedings of VII International Rangeland Congress In: International Rangeland Congress, Durban, South Africa. 26 July - 1 August 2003. Rhodes University. South Africa.

Shoshany, M., 2000. Satellite remote sensing of natural Mediterranean vegetation: a review within an ecological context. Progress in Physical Geography 24(2), 153–178.
Sims, D.A., Gamon, J.A., 2002. Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages. Remote Sensing of Environment 81(2-3), 337-354.
Smith, R., Scott, D., 1992. The effects of afforestation on low flows in various regions of South Africa. Water S. A. 18(3), 185-194.
Snyman, H., 1998. Dynamics and sustainable utilization of rangeland ecosystems in arid and semi-arid climates of southern Africa* 1. Journal of Arid Environments 39(4), 645-666.
Snyman, H., 2002. Short-term response of rangeland botanical composition and productivity to fertilization (N and P) in a semi-arid climate of South Africa. Journal of Arid Environments 50(1), 167-183.
Snyman, H., 2003. Revegetation of bare patches in a semi-arid rangeland of South Africa: an evaluation of various techniques. Journal of Arid Environments 55(3), 417-432.
Snyman, H., Du Preez, C., 2005. Rangeland degradation in a semi-arid South Africa--II: influence on soil quality. Journal of Arid Environments 60(3), 483-507.
Snyman, H.A., 2009. Root studies on grass species in a semi-arid South Africa along a degradation gradient. Agriculture, Ecosystems & Environment 130(3-4), 100-108.
Snyman, H.A., Fouché, H.J., 2007. Estimating seasonal herbage production of a semi-arid grassland based on veld condition, rainfall and evapotranspiration. African Journal of Range and Forage Science 10(1), 21-24.
Sridharan, H., 2010. Multi-level urban forest classification using the WorldView-2 8-band hyperspatial imagery, Digital Globe® 8Bands Research Challenge.
Steffens, M., Kölbl, A., Totsche, K.U., Kögel-Knabner, I., 2008. Grazing effects on soil chemical and physical properties in a semiarid steppe of Inner Mongolia (PR China). Geoderma 143(1-2), 63-72.
Stohlgren, T.J., Schell, L.D., Vanden Heuvel, B., 1999. How grazing and soil quality affect native and exotic plant diversity in Rocky Mountain grasslands. Ecological Applications 9(1), 45-64.
Stringer, L., Reed, M., 2007. Land degradation assessment in southern Africa: integrating local and scientific knowledge bases. Land Degradation & Development 18(1), 99-116.
Su, Y.Z., Zhao, H., 2003. Soil properties and plant species in an age sequence of Caragana microphylla plantations in the Horqin Sandy Land, north China. Ecological Engineering 20(3), 223-235.
Sun, J., Ai, T., Zhao, C., Yan, H., 2007. Assessing vegetation degradation in loess plateau by using potential vegetation index. IEEE, pp. 1794-1797.
Svetnik, V., Liaw, A., Tong, C., Culberson, J., Sheridan, R., Feuston, B., 2003. Random forest: a classification and regression tool for compound classification and QSAR modeling. J. Chem. Inf. Comput. Sci 43(6), 1947-1958.
Tainton, N., 1988. A consideration of veld condition assessment techniques for commercial livestock production in South Africa. Journal of the Grassland Society of Southern Africa 5(2), 76-79.
Tainton, N., Edwards, P., Mentis, M., 1980. A revised method for assessing veld condition. Proceedings of the Annual Congresses of the Grassland Society of Southern Africa 15(1), 37-42.

Tainton, N.M., 1999. The grassland biome, in: Tainton, N.M. (Ed.), Veld management in South Africa. University of Natal Press, Pietermaritzburg, pp. 25-33.
Tanser, F.C., Palmer, A.R., 1999. The application of a remotely-sensed diversity index to monitor degradation patterns in a semi-arid, heterogeneous, South African landscape. Journal of Arid Environments 43(4), 477-484.
Tau, M.S., 2005. Grazing management in the communal rangelands of the upper Thukela, KwaZulu-Natal. In, School of Environmental Sciences. Pietermaritzburg, South Africa: University of KwaZulu-Natal.
Teklu, B., Negesse, T., Angassa, A., 2010. Effects of farming systems on species composition, nutrient content and digestibility of forages of the natural pasture of Assosa zone (Western Ethiopia). Tropical and Subtropical Agroecosystems 12 (3), 583 -592.
Temme, A.J.A.M., Baartman, J.E.M., Botha, G.A., Veldkamp, A., Jongmans, A.G., Wallinga, J., 2008. Climate controls on late Pleistocene landscape evolution of the Okhombe valley, KwaZulu-Natal, South Africa. Geomorphology 99(1-4), 280 - 295.
Thenkabail, P., Enclona, E., Ashton, M., Van Der Meer, B., 2004. Accuracy assessments of hyperspectral waveband performance for vegetation analysis applications. Remote Sensing of Environment 91(3-4), 354-376.
Thenkabail, P., Smith, R., De Pauw, E., 2000. Hyperspectral vegetation indices and their relationships with agricultural crop characteristics. Remote Sensing of Environment 71(2), 158-182.
Theron, E., 1966. A study of certain chemical and physical properties of ten indigenous grasses and their relationship to animal preference. PhD thesis, University of Natal, Pietermaritzburg.
Thompson, M., 1996. Standard land-cover classification scheme for remote-sensing applications in South Africa. South African Journal of Science 92(1), 34-42.
Todd, S., Hoffman, M., 1999. A fence-line contrast reveals effects of heavy grazing on plant diversity and community composition in Namaqualand, South Africa. Plant Ecology 142(1), 169-178.
Trollope, W., 1990. Development of a technique for assessing veld condition in the Kruger National Park using key grass species. Journal of the Grassland Society of Southern Africa 7(1), 46-51.
Trollope, W., 2011. Personal perspectives on commercial versus communal Afri-can fire paradigms when using fire to manage rangelands for domestic livestock and wildlife in southern and east African ecosystems. Fire Ecology 7(1), 57-73.
Trollope, W., Trollope, L., Bosch, O., 1990. Veld and pasture management terminology in southern Africa. Journal of the Grassland society of Southern Africa 7(1), 52-61.
Trollope, W.S.W., Potgieter, A.L.F., Zambatis, N., 2008. Assessing veld condition in the Kruger National Park using key grass species. Koedoe-African Protected Area Conservation and Science 32(1), 67-93.
Tromp, M., Epema, G.F., 1998. Spectral mixture analysis for mapping land degradation in semi-arid areas. Geologie en Mijnbouw 77(2), 153-160.
Tueller, P.T., 1987. Remote sensing science applications in arid environments. Remote Sensing of Environment 23(2), 143-154.
Turner, D.P., Cohen, W.B., Kennedy, R.E., Fassnacht, K.S., Briggs, J.M., 1999. Relationships between leaf area index and Landsat TM spectral vegetation indices across three temperate zone sites. Remote Sensing of Environment 70(1), 52-68.

UNCCD, 1995. United Nations Convention to Combat Desertification in Countries Experiencing Serious Drought and/or Desertification, Particularly in Africa, text with Annexes. UNEP, Geneva.

Underwood, E., Ustin, S., DiPietro, D., 2003. Mapping nonnative plants using hyperspectral imagery. Remote Sensing of Environment 86(2), 150-161.

Ustin, S.L., Jacquemoud, S., Palacios-Orueta, A., Li, L., Whiting, M.L., 2009. Remote sensing based assessment of biophysical indicators for land degradation and desertification, in: A., R., J., Hill (Ed.), Recent advances in remote sensing and geoinformation processing for land degradation assessment. CRC Press pp. 15–44.

Vaiphasa, C., Ongsomwang, S., Vaiphasa, T., Skidmore, A., 2005. Tropical mangrove species discrimination using hyperspectral data: A laboratory study. Estuarine, Coastal and Shelf Science 65(1-2), 371-379.

Vaiphasa, C., Skidmore, A., de Boer, W., Vaiphasa, T., 2007. A hyperspectral band selector for plant species discrimination. ISPRS Journal of Photogrammetry and Remote Sensing 62(3), 225-235.

Van Aardt, J., Wynne, R., 2001. Spectral separability among six southern tree species. Photogrammetric Engineering and Remote Sensing 67(12), 1367-1376.

Van Aardt, J., Wynne, R., 2007. Examining pine spectral separability using hyperspectral data from an airborne sensor: An extension of field-based results. International Journal of Remote Sensing 28(2), 431-436.

Van den Berg, L., Zeng, Y., 2006. Response of South African indigenous grass species to drought stress induced by polyethylene glycol (PEG) 6000. South African Journal of Botany 72(2), 284-286.

Van der Westhuizen, H., Snyman, H., Fouché, H., 2005. A degradation gradient for the assessment of rangeland condition of a semi-arid sourveld in southern Africa. African Journal of Range & Forage Science 22(1), 47-58.

Van Lynden, G., Mantel, S., 2001. The role of GIS and remote sensing in land degradation assessment and conservation mapping: some user experiences and expectations. International Journal of Applied Earth Observation and Geoinformation 3(1), 61-68.

Van Oudtshoorn, F.P., 1992. Guide to grasses of South Africa. Briza, Pretoria.

Van Rooyen, N., Bredenkamp, G., Theron, G., 1991. Kalahari vegetation: veld condition trends and ecological status of species. Koedoe-African Protected Area Conservation and Science 34(1), 61-71.

Vetter, S., Goqwana, W., Bond, W., Trollope, W., 2006. Effects of land tenure, geology and topography on vegetation and soils of two grassland types in South Africa. African Journal of Range & Forage Science 23(1), 13-27.

Vogel, M., Strohbach, M., 2009. Monitoring of savanna degradation in Namibia using Landsat TM/ETM+ data, International Geosciences and Remote Sensing (IGARSS) IEEE, Cape Town, South Africa, pp. III-931-III-934.

Von Maltitz, G.P., 1998. Communal rangeland management options for the Okhombe community in: de Bruyn, T.D., Scogings, P.F. (Eds.), Communal rangelands in southern Africa: a synthesis of knowledge, Proceedings of a symposium on policy-making for the sustainable use of southern Africa communal rangelands, University of Fort Hare, South Africa, p. 68.

Vorster, M., 1982. The development of the ecological index method for assessing veld condition in the Karoo. Proceedings of the Annual Congresses of the Grassland Society of Southern Africa 17(1), 84-89.

Wang, H.J., Fan, W.J., Cui, Y.K., Zhou, L., Yan, B.Y., Wu, D.H., Xu, X.R., 2010a. Hyperspectral remote sensing monitoring of grassland degradation. Guang pu xue yu guang pu fen xi 30(10), 2734-2738.

Wang, J., He, T., Lv, C., Chen, Y., Jian, W., 2010b. Mapping soil organic matter based on land degradation spectral response units using Hyperion images. International Journal of Applied Earth Observation and Geoinformation 12(2), S171-S180.

Warner, T., Shank, M., 1997. Spatial autocorrelation analysis of hyperspectral imagery for feature selection* 1. Remote Sensing of Environment 60(1), 58-70.

Watson, H.K., 1984. Veld burning and sediment yield from small drainage basins, in: Walling, D.E., Forster, S.S.D., Wurzel, P. (Eds.), Challenges in African Hydrology and Water Resources. International Association of Hydrological Sciences Publication 144, pp. 323-333.

Wentz, E.A., Stefanov, W.L., Gries, C., Hope, D., 2006. Land use and land cover mapping from diverse data sources for an arid urban environments. Computers, Environment and Urban Systems 30(3), 320-346.

Wessels, K., Pretorius, D., Prince, S., 2008. Reality of rangeland degradation mapping with remote sensing: the South African experience. Ecological Applications 17(3), 815–827.

Wessels, K., Prince, S., Frost, P., Van Zyl, D., 2004. Assessing the effects of human-induced land degradation in the former homelands of northern South Africa with a 1 km AVHRR NDVI time-series. Remote Sensing of Environment 91(1), 47-67.

Wessels, K.J., Prince, S., Malherbe, J., Small, J., Frost, P., VanZyl, D., 2007. Can human-induced land degradation be distinguished from the effects of rainfall variability? A case study in South Africa. Journal of Arid Environments 68(2), 271-297.

Wessels, K.J., Prince, S. D., Carro, M., and Malherbe, J., 2007. Relevance of rangeland degradation in semi-arid northeastern South Africa to the nonequilibrium theory. Ecological Applications 17 (3), 815–827.

Wilcox, B.P., 2007. Does rangeland degradation have implications for global streamflow? Hydrological Processes 21(21), 2961-2964.

Willis, M., Trollope, W., 1987. Use of key grass species for assessing veld condition in the eastern Cape. Journal of the Grassland Society of Southern Africa 4(3), 113-115.

Wolf, A., 2010. Using WorldView 2 Vis-NIR MSI Imagery to Support Land Mapping and Feature Extraction Using Normalized Difference Index Ratios., DigitalGlobe 8-Band Research Challenge.

Woolley, J.T., 1971. Reflectance and transmittance of light by leaves. Plant Physiology 47(5), 656-662.

Wu, W., De Pauw, E., Zucca, C., 2008. Land degradation monitoring in the west Muus, China. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVII. Part B8847-858.

Xie, Y., Sha, Z., Yu, M., 2008. Remote sensing imagery in vegetation mapping: a review. Journal of Plant Ecology 1(1), 9-23.

Young, A., 1994. Land degradation in South Asia: its severity, causes, and effects upon the people.–World Soil Resources Report 78. UNDP/UNEP/FAO, Rome.

Zhao, Y., Peth, S., Krümmelbein, J., Horn, R., Wang, Z., Steffens, M., Hoffmann, C., Peng, X., 2007. Spatial variability of soil properties affected by grazing intensity in Inner Mongolia grassland. Ecological Modelling 205(1-2), 241-254.
Zhou, Y., Hahn, J., Mannan, M.S., 2006. Process monitoring based on classification tree and discriminant analysis. Reliability Engineering & System Safety 91(5), 546-555.
Zwiggelaar, R., 1998. A review of spectral properties of plants and their potential use for crop/weed discrimination in row-crops. Crop Protection 17(3), 189-206.