Characterizing selected invasive plants in the Klipriviersberg Nature Reserve using field based spectroradiometer data

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Abstract

The Klipriviersberg Nature Reserve has proportionally large number of invasive plant species (Morné Britz, personal communication). Management of these species currently focuses on conspicuous woody species and less attention is placed on smaller plant species that are likely to threaten biodiversity. This can potentially result in more costly and labour intensive management programmes if imminent environmental threats are not timeously identified. The use of timely spatial distribution maps aids in improving invasive plant management strategies. Invasive plant distribution maps have been developed using traditional mapping methods; but these are costly and time consuming. Remote sensing techniques on the other hand have shown the potential in characterizing invasive plants species in different studies. This study aimed to extend this potential by discriminating selected invasive plant species, namely, *Artemisia afra*, *Asparagus laricinus* and *Seriphium plumosum* from adjacent land cover types using continuum spectra of a field spectrometer data. In addition, the study aimed to investigate the use of spectra simulated according to bands of SPOT and Landsat images in an effort to explore the potential of extending field based analysis to airborne or spaceborne remote sensing systems. Data were analysed at individual, plot and group levels, respectively. Results showed *A. afra* and *A. laricinus* to be best discriminated from adjacent land cover types using the near infrared (NIR) region from analysis using both original and simulated spectra. None of the regions that were assessed for *S. plumosum*, however, did show the potential of discriminating the species from grass using both the original and simulated spectra. Successful discrimination of *A. afra* and *A. laricinus* from adjacent land cover types using simulated bands shows the potential of upscaling field based techniques, particularly the NIR region, to spaceborne and airborne remote sensing technologies such as SPOT and Landsat. Further studies are, however, recommended to improve the reliability of the findings obtained in this study. Such studies would need to address the shortcomings encountered in this study by (1) using more samples, (2) categorising data analysis according to plant phonological stages to help determine best timing for discrimination of the species, and (3) taking of spectral measurements under ideal environmental conditions. Studies on biochemical composition of the species are also encouraged to inform on reflectance behaviours of the species as plant compounds or pigments influence electromagnetic reflectance differently.

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List of abbreviations

AISA	Airborne Imaging System for different Applications
ANOVA	Analysis of Variance
BT	Bhattacharya
CART)	Classification and Regression Tree
CCA	Canopy Area
CVA	Change Vector Analysis
Df	Degrees of freedom
ETM+	Enhanced Thematic Mapper Plus
F	F variable
Fcrit	F critical value
GLMs	Generalised Linear Models
GPS	Global Positioning System
IAPs	Invasive alien plants
InSAR	Interferometric Synthetic Aperture Radar
iSDM	Invasive Species Distribution Models
JM	Jeffries–Matusita
KNR	Klipriviersberg Nature Reserve
LDA	Linear Discriminant Analysis
LSD	Least Significant Difference
MaxEnt	Maximum Entropy
MDA	Multiclass Discriminant Analysis
MESMA	Multiple Endmember Spectral Mixture Analysis
Mix.ground& herb	Mixture of herbaceous and bare ground
MS	Mean of squares
MTMF	Mixture Tuned Matched Filtering
NGIS	Next Generation Imaging Spectrometer
NIR	Near Infrared
PALSAR	Phased Array type L-band Synthetic Aperture Radar
PCA	Principal Component Analysis
PCA-LDA	Principal Component Analysis-Linear Discriminant Analysis
PLS	Partial Least of Squares

PolInSAR	Polarimetric Synthetic Aperture Radar
RAC	Regenerated After Cutting
RF	Random Forest
RFDI	Radar Forest Degradation Index
SANBI	South African National Biodiversity Institute
SAPIA	Southern African Plant Invaders Atlas
SS	Sum of squares
SVM	Support Vector Machines
SWIR	Shortwave Infrared
UAV	Unmanned Aerial Vehicle
WBC	Weed Biological Control Agents
WfW	Working for Water Programme
WTA	Winner-Takes-All

CHAPTER 1

INTRODUCTION

1.1. Background

South Africa is ranked third highest in terms of biodiversity, and hosts 10% of world's plants and 7% of reptiles, birds, and mammals (Environmental Affairs, 2010; Le Maitre et al., 2007). It has a well-known plant diversity and high plant endemism distributed in different ecological biomes, namely, Fynbos, Succulent Karoo, Desert, Nama-Karoo, Grassland, Savanna, Albany Thicket, Indian Ocean Coastal Belt and Forest biomes (Khavhagali, 2010; SANBI, 2006; Schmiedel and Jürgens, 2010). Biodiversity is essentially ecological infrastructure or natural capital that provides ecosystem services such as primary production, soil conservation, provision of water and improvement of water quality (Driver et al., 2012; Le Maitre et al., 2007). Accordingly, the rich plant diversity of South Africa provides a range of benefits such as food products together with those that meet basic human needs and those that enhance human well-being (socio-cultural services)(Le Maitre et al., 2007; Van Wilgen et al., 2008). They also have renowned medicinal use both within the traditional and commercial sectors (Khavhagali, 2010; Mahwasane et al., 2013; Shackleton et al., 2007; Williams et al., 2013). The services provided by indigenous plants are, however, threatened by increased invasive plant encroachment.

Invasive plants are plants that do not occur naturally in an area, and are introduced either intentionally or unintentionally (Chenje and Mohamed-Katerere, 2006; Enright, 2000; Rouget et al., 2015). These plants have adverse environmental effects, when they are poorly managed. They may spread to other areas and successfully replace indigenous vegetation particularly in the absence of natural competitors or enemies. The dire consequences of invasive plant infestations encompass alteration of ecosystem functioning through changing disturbance frequency or intensity, alteration of trophic structure and change in resource availability which jeopardise delivery of ecosystem services (Chamier et al., 2012; Roura-Pascual et al., 2009a, 2009b; Sharma and Raghubanshi, 2009; Van Wilgen et al., 2012b).

Efforts to control invasive plant species in South Africa date back to 1970s when sweet prickly pear (*Opuntia ficus-indica*) was introduced for the first time which inspired use of weed biological control agents (Moran et al., 2013). Such initiatives were followed by a various control programmes that include, among others, the Working for Water programme (WfW) which is still operational (Richardson and Van Wilgen, 2004; Rouget et al., 2004). The mandates of this programme include controlling invasive plants, restoring pristine ecosystem service levels and economic empowerment of rural populations (Turpie et al., 2008; Van Wilgen and de Lange, 2011).Government departments support this and other programmes considerably (Turpie, 2004; Turpie et al., 2008; Van Wilgen and de Lange, 2011). These programmes need, however, to develop better management strategies that would be replicated in larger spatial areas, as current management strategies focus on rather small spatial areas. This could be achieved through the use of mapping techniques that would provide timely information on the spatio-temporal distribution of invasive species. Map-based monitoring approaches offer opportunity for prioritising control of newly infested areas and keeping track of successes made on control of invasive plants (Caffrey et al., 2014; Meier et al., 2014). Remote sensing techniques are a promising tool in providing such maps.

1.2. Research problem statement

The ecosystem services in South Africa are affected by an increasing magnitude and spread of invasive plants (De Lange et al., 2012). These invasions have resulted in considerable ecosystem service reductions, thereby negatively influencing water resources, grazing resources, biodiversity, fire intensity, soil productivity and human and animal health (Van Wilgen and de Lange, 2011). The impacts invasive plants have on ecosystem services in South Africa are expressed in terms of monitory value by De Lange and Wilgen (2010). The problems of invasive plants came into recognition around the 1880s to South African botanists. There have been growing research on invasive plants since then, and a number of control efforts were initiated since the 1970s, with notable application of biological weed control measures (Moran et al., 2013; Van Wilgen, 2012). Although the country invests considerably on WfW, the programme needs to improve in prioritising actions and at enhancing efficiency of the control efforts (Turpie, 2004). These control efforts include combination of mechanical, chemical and biological control, including habitat management which are applied at small spatial scales (De Lange et al., 2012).

Spatial and temporal distribution maps of invasive plants can help land managers in developing appropriate management strategies. The maps provide the basis for monitoring existing invasions, assisting in prediction of potential spread of invasive plants, and providing comprehensive information on invasive plant behaviours and their effects on the environment (Gavier-pizarro et al., 2012b; Rodgers et al., 2014). Such maps can be developed using traditional methods which rely mostly of field surveys. Although these methods are able to detect plant species with high level of accuracy, they are limited by rough terrains, large spatial areas, and manpower resources available to undertake the survey (Dewey et al., 1991; Rodgers et al., 2014). On the other hand, high spatial resolution sensors such as aerial photography are commonly used to map invasive plants, but their data acquisition is made only on request and require that the target species studied is clearly different from its background and neighbouring areas (Huang and Asner, 2009).

Remote sensing is a promising tool for mapping invasive plants (Gavier-pizarro et al., 2012b). The technique offers cost effective and practical means of vegetation monitoring over large areas, monitors vegetation dynamics in a repeated data acquisition mode and provides reliable and objective means of data acquisition and analysis (Cuneo et al., 2009; Dronova et al., 2015). As a result, multispectral and hyperspectral remote sensing applications have been used in a number of studies to discriminate and map spatial distribution of plant species, including invasive plants. Applications using multispectral remote sensing techniques include, for example, studies by Azong et al. (2015), Dronova et al. (2015), Dubovyk et al. (2015) Forsyth et al. (2014). The level of success of such applications is influenced mainly by the relatively coarse spectral resolution of such remote sensing systems. Hyperspectral remote sensing systems overcome this shortcoming by providing detailed spectral information of earth features. As such, hyperspectral remote sensing has been applied successfully to discriminate and map invasive and non-invasive plant species in several studies (e.g. Amaral et al., 2015; Bue et al., 2015; Fernandes et al., 2014).

Hyperspectral data analysis techniques that are applied in most vegetation studies often seek to identify specific narrow bands that can discriminate between plant species efficiently. Such capability cannot be extended into multispectral remote sensing techniques because these individual hyperspectral bands are not clumped to create broad-bands in multispectral remote sensing systems. This property limits testing the suitability of multispectral remote sensing techniques to discriminate plant species successfully. Although hyperspectral remote sensing techniques offer superior capability of discriminating even subtle differences that are present in plants, they are still limited mainly to research efforts. Despite the fast growth in terms of data acquisition and analysis of hyperspectral data, translating their utilities to practical applications that are required for land management purposes is not as encouraging mainly due to the cost of data acquisition. Multispectral remote sensing techniques on the other hand remain the most widely used sources of information for vegetation mapping purposes, since they are available freely or at relatively low cost. Therefore, hyperspectral data analysis needs to close this gap and encourage extending of hyperspectral information into multispectral remote sensing techniques as well.

The Klipriviersberg Nature Reserve has a number of invasive plants whose degree of infestation remains unquantified and their effects to the natural vegetation have not been documented (Morné Britz, personal communication). Such a lack of knowledge hampers control of invasive plant species in the reserve as imminent threats are not timely identified. The current control of invasive plants focuses on easily recognized and accessible infestations. Spatial mapping could, however, assist managers of the reserve in developing more efficient control methods. The maps could provide timely information on infestations and would offer opportunity for identifying new infestations at early stages of development, and thus opportunity for early response and eradication. There are few or no remote sensing based studies done to characterize invasive plants occurring in the reserve. Currently, identification of these species relies on field inventories. Although such methods give accurate information about the species, they are limited to small spatial areas. This study focuses on three invasive species, namely, *Artemisia afra*, *Asparagus laricinus*, and *Seriphium plumosum*. There are no studies that assessed the selected species using remote sensing.

1.3. Research question

In light of the aforementioned problem, the following question is then formulated as follows to guide the study presented in this dissertation:

> Does remote sensing based analysis have the potential to discriminate *Artemisia afra*, *Asparagus laricinus* and *Seriphium plumosum* from coexisting plant species in the Klipriviersberg Nature Reserve?

1.4. Aim and objectives

The general aim of the study is to investigate the ability of field collected hyperspectral data in discriminating *A. afra*, *A. laricinus* and *S. plumosum* from adjacent land cover types that co-exist with each of these species. It focusses on each species separately, and thus is presented in manuscript format. Each manuscript forms a chapter of this dissertation. Thus, specific objectives related to each species are presented in the respective chapters while generic objectives of the study are to:

- Determine whether or not *A. afra*, *A. laricinus* and *S. plumosum* can be discriminated from adjacent land cover types using spectroradiometer data.
- Assess the performance of spectral data simulated based on of Landsat and SPOT image bands in discriminating *A. afra*, *A. laricinus* and *S. plumosum* from adjacent land cover types.

1.5. Significance of the study

This study intends to provide useful information on the efficacy of multispectral and hyperspectral remote sensing techniques in mapping the plant species. A positive outcome will be of great value to land managers. Such information will help land managers develop better control methods of the species as the maps will provide timely information on the spatial distribution of the species.

Hyperspectral remote sensing techniques may be ideal for developing spatial distribution maps of these invasive species because of the hyperspectral bands they possess which allow detection of subtle differences between vegetation types. However, most hyperspectral remote sensing research efforts however focus on identifying suitable, individual bands for plant discrimination, which cannot be extracted from broad-bands of multispectral remote sensing systems (Amaral*et al.* 2015, Landmann *et al.* 2015). This study will contribute by translating hyperspectral capabilities into multispectral remote sensing systems that are widely used worldwide. It is anticipated that this study will encourage others to follow suit in exploring the full capabilities of multispectral remote sensing.

1.6. Structure of the dissertation

Findings of this research are compiled in this dissertation as stand-alone manuscripts. Accordingly, all efforts have been made to incorporate the necessary information in the chapter presenting the findings for each species of interest. It was also deemed appropriate to include literature review chapter. The second chapter therefore presents reviews of relevant studies and facts, including background information on South African biodiversity and the importance of the country's indigenous plant species. It also includes drivers and threats posed by invasive plants on ecosystem services, control efforts on managing and eradication of invasive plant species, and reviews usefulness of remote sensing techniques in studying invasive plants, both multispectral and hyperspectral. The results on efficacy of hyperspectral remote sensing data in discriminating each of the selected species, namely, *A. afra*, *A. laricinus* and *S. plumosum* are from co-existing land cover types are presented in chapters three, four and five respectively. Analysis and presentation of the findings are presented per each of the three species, instead of combining all species in a single analysis. This is because these three species were not observed co-existing in any of the sample plots that were surveyed. Finally, chapter six provides concluding remarks and recommendations based on all five chapters.

CHAPTER 2

Literature Review

2.1. Introduction

Invasive plants are becoming a problem throughout the world. These plants pose a threat to biodiversity because of the special physiological characters that give them at a competitive advantage over natural vegetation in areas they invade, successfully replacing them and cause change in ecosystem functioning. It is therefore critical to develop efficient management strategies to mitigate the problem. An important source of information to designing such strategies is knowledge of the characteristics of the target plant. Remote sensing is one approach that is capable of differentiating earth's features and has shown great potential to characterise invasive plants spatially and temporally. In this chapter, a literature survey related to invasive plants is presented. A brief description regarding South African biodiversity is given first. This is followed by description of invasive plants, their dynamics as well as the threats they pose to ecosystems. Next, the need for monitoring invasive plants is presented. Finally various techniques of mapping invasive species are reviewed, with emphasis placed on remote sensing approaches.

2.2. An overview of South Africa's biodiversity

South Africa is ranked the third-highest in terms of biodiversity richness in the world (Environmental Affairs, 2010). The country is home to 10% of world's plants and 7% of reptiles, birds and mammals (Environmental Affairs, 2010; Le Maitre et al., 2007). It is also known for its floristic diversity and high plant endemism (SANBI, 2006; Schmiedel and Jürgens, 2010). SANBI (2006) declared 21721 plant taxa to have been reported as indigenous to South Africa, with more than half (13192 taxa) considered endemic to South Africa and not found anywhere else in the world. The number of South African plant taxa continues to increase as new discoveries and taxonomic/systematic research add new records. SANBI (2006) reported that more than 268 new species were recorded between 1994 and 2004. Such biodiversity can be likely influenced by a wide range of climatic conditions and topography present in the country (Khavhagali, 2010).

The diverse flora of South Africa is distributed in different ecological biomes, namely, Fynbos, Succulent Karoo, Desert, Nama-Karoo, Grassland, Savanna, Albany Thicket, Indian Ocean Coastal Belt and Forest biomes (Khavhagali, 2010). These biomes support specific collections of plant and animal species (Khavhagali, 2010; Rutherford et al., 1999). The Fynbos biome in the Cape Floristic Region, Succulent Karoo biome and Albany Thicket biome in the Maputoland-Pondoland region are internationally recognised biodiversity hot spots (Environmental Affairs, 2010). The Cape Floristic Region represents one of the world's six floral kingdoms, entirely located within South Africa (Rutherford et al., 2006). The Succulent Karoo is also the richest arid flora on earth, containing half of the world's known succulent species (Environmental Affairs, 2010; Rutherford et al., 2006).

2.3. Indigenous plants of South Africa and their benefits

Biodiversity constitutes ecological infrastructure or natural capital that provides ecosystem services to society and maintains various ecosystem functions such as primary production, soil conservation, provision of water and improvement of water quality (Driver et al., 2012; Le Maitre et al., 2007). Ecosystem services are nature's goods and services that are fundamental for human life (Driver et al., 2012). The biodiversity of South Africa harbours various indigenous plants that provide such services. These range from food products to activities that enrich human lives such as recreational and spiritual benefits (Le Maitre et al., 2007). For example, economically marginalised people residing close to forested areas rely heavily on the subsistence use of forest products for food, fuelwood, wooden utensils, grass hand-brushes and twig hand-brushes (Shackleton and Shackleton, 2004; Shackleton et al., 2007). Some of these products are regularly used in the savannas of the northern provinces of South Africa (Northern Cape, Northwest and Limpopo provinces) where approximately 200–300 different plant species are used for such purposes, while fewer plant species are reported to have been exploited in the Eastern Cape Province for similar purposes (Shackleton and Shackleton, 2004).

A number of other indigenous plant species are used for commercial and non-commercial medicinal purposes (Khavhagali, 2010). These are used mostly as traditional medicine by an estimated 72% of black South Africans, and an estimated 200 000 traditional healers are known to rely on approximately 3000 plant species (Mahwasane et al., 2013; Williams et al., 2013). These estimates are approximately equivalent to 70 000 tonnes of plant material per year, with a potential minimum generation of 134 000 income-earning opportunities through trade in medicinal plants and related products (Williams et al., 2013). The various services provided by the indigenous plant species are, however, threatened and compromised by increased encroachment of invasive plants.

2.4. Drivers and behaviours of invasive plants and threats posed on indigenous vegetation

Invasive plants are plants that do not occur naturally in an area (Enright, 2000). These are described by Rouget et al., (2015) and Semenya et al., (2012) as plants that survive more than one life cycle without human intervention and freely produce offspring just near adult plants. Invasive plants dominate vegetation in many parts of the world and are a major biodiversity threat (Rouget et al., 2015; Schor et al., 2015; Vicente et al., 2013).

In documenting invasive plants, it is important that their behavioural and physiological characters are determined to help develop better control measures. Some elements that could help document the distribution and abundance of invasive include, assessment of life history traits and interactions with natural vegetation of invaded areas and the likelihood of exposure to ecosystems that favour their spread (Rouget et al., 2015). Accordingly, their spread is becoming documented throughout the world (Moran et al., 2005). Richardson & Rejmánek (2011) gave a global overview of non-native invasive trees and shrubs by compiling a list of clear invasive trees and shrubs. The list was compiled for fifteen biological regions of known invasion for invasive plants of different populations. A total of 622 invasive plant species (357 tree species and 265 shrub species) were documented. According to the list, 52% of known invasive trees and shrubs occur in one region, 20% in two regions and 6% are widespread. Henderson (2007) provided an overview of species identity, invasion status, geographical extent and abundance of invasive alien plants (IAPs) in South Africa, Swaziland and Lesotho using field records from 1979 to 2000. This involved compilation of 548 naturalised and casual alien plant species and recording of invasions in the study area. Most invasions were recorded in the Fynbos and Forest biomes including eastern parts of the Grassland and Savanna biomes. All the infestations in the region were documented in the Southern African Plant Invaders Atlas (SAPIA) database. The database is, however, not fully operational but phase II of SAPIA project aims at improving its functionality and access to data (Henderson, 2015).

Invasive plants are introduced intentionally or unintentionally in an area and many establish themselves in foreign ecosystems (Rouget et al., 2015). Intentional introductions include for such purposes as erosion control, provision of shade, animal forage and as ornamentals (Belnap et al., 2012). The main means of unintentional introduction of IAPs is through human mobility that facilitates species migration and colonisation (Vicente et al., 2013). This mobility is mostly influenced by economic and human population growth which are main urbanisation drivers, mostly in developing countries. These movements induce changes in anthropogenic activities (Roura-Pascual et al., 2009b). For example, McConnachie et al. (2008) conducted a study on the extent of green spaces and prevalence of alien woody plant in 10 small towns in the Eastern Cape. The study found towns which had less green space as a result of vegetation clearance to have lower percentage of indigenous spaces and higher percentage of alien invasive species.

Invasive plants can also be introduced unintentionally by natural processes such as cyclones, water currents and changes in climatic conditions (Chenje and Mohamed-Katerere, 2006). Effects of climate on invasive plant distribution were studied by Taylor et al. (2012) who developed a model of the climate response of *Lantana camara* based on its native distribution and invasive distribution outside Australia. The results showed the potential distribution to exceed current distribution in other parts of the world (e.g. Africa and Asia) while results suggested some areas (North Africa, Europe and Australia) to become climatically suitable for its distribution under future climate scenarios. In South Africa and China, distributions were predicted to go inland.

Poorly controlled invasive plants have the potential to spread to other areas and cause serious problems, and may ultimately replace indigenous plants particularly if there is lack of enemies or competitors. These plants result in alteration of ecosystem functioning by changing disturbance frequency or intensity, alteration of trophic structure and change in resource availability (Chamier et al., 2012; Roura-Pascual et al., 2009a, 2009b; Sharma and Raghubanshi, 2009; Van Wilgen et al., 2012b). Changes in ecosystem functioning jeopardise the delivery of ecosystem goods and services such as water discharge, maintenance of soil stability in water prone catchments, replenishment of sand in beaches, provision of timber, grazing of livestock and wildlife, recreation and fishing (Chamier et al., 2012; Richardson and Van Wilgen, 2004; Van Wilgen et al., 2008).The effects not only affect indigenous species and ecosystems, but human health and well-being as well (Poona, 2008).

2.5. Efforts to control invasive plants in South Africa

South Africa has a long history of invasive plants that dates back to the 1750s when sweet prickly pear (*Opuntia ficus-indica*) was introduced for the first time (Moran et al., 2013). A lot of research on invasive plants in South Africa has been conducted since and it has provided managers with guidance to manage the problem. As a result, the country is able to confront challenges of invasive plants with a great deal of confidence (Van Wilgen, 2006). An initial attempt to deal with the problem included the first meeting that was held to discuss on the control of sweet prickly pear infestations in 1906. The meeting led to approval of the use of weed biological control agents (WBC) in 1913 (Moran et al., 2013). Such control agents are believed to offer the opportunity of halting or even reversing the effects of IAPs (Van Wilgen et al., 2013). Although the effectiveness of WBC is not guaranteed, their use in South Africa has a proven success record, which includes, among others, successful release of a cochineal insect (*Dactylopius ceylonicus*) on alien cactus (*Opuntia monacantha*) in 1913 (Moran et al., 2013; Van Wilgen et al., 2013).

Besides WBCs, a number of invasive plant control programmes were initiated in South Africa. These include Biological Control of Invasive Alien Plants (1930 and ongoing), Catchment Conservation Research Programme (1973–1990), South African National Programme for Ecosystem Research (1977–1985), Scientific Committee on Problems of the Environment (SCOPE), Programme on Biological Invasions (1982-1986), South African Plant Invaders Atlas (1975 and ongoing); Invasive Plant Ecology Programme (1994 and ongoing); and Working for Water programme (WfW) (1995 and ongoing) (Richardson and Van Wilgen, 2004; Rouget et al., 2004).

The WfW was launched by the Department of Environmental Affairs and Forestry in 1995 with the aim of conducting and coordinating alien plant management strategies and creating employment opportunities for rural communities (Chamier et al., 2012; Görgens and Wilgen, 2004; Marais et al., 2004; Morris et al., 2008; Richardson and Van Wilgen, 2004; Roura-Pascual et al., 2009b). The costs of containing the invasive plant problem were once estimated at approximately R600 million per year in a period of 20 years, assuming that invasive alien plants spread at a rate of 5% per year (Van Wilgen et al., 1998, 2012a). Ecosystem services in South African are estimated at a value of approximately R152 billion per annum, in which R6.5 million of this is lost yearly due to plant invasions (Van Wilgen et al., 2012a). This loss is estimated to have spiralled to R41 billion per year, had no control measures taken place (Van Wilgen et al., 2012a, 2012b). Despite the efforts made by the WfW, it is still uncertain whether or not: (1) correct, top priority species are being targeted; (2) progress has been made in reducing the extant of invasion, since there is no evaluation system in place to monitor progress that has been made by the programme (Van Wilgen et al., 2012b).

2.6. Remote sensing of invasive plant species

Spatial and temporal mapping are important tools in the fight against invasive plant infestations. Distribution maps serve as the basis for monitoring existing and potential spread of invasive plants and thus improve efficiency of mitigation and prevention measures (Asner et al., 2008; Gavier-pizarro et al., 2012b; Rodgers et al., 2014). In addition to providing information on spread of invasive plant species, maps give a good understanding of invasive plant behaviours and their effects (Crimmins et al., 2008). Such information is essential for developing improved management strategies. Furthermore, spatial and temporal distribution maps detect early infestations and offer opportunity for rapid response to new infestations when populations have relatively small spatial coverage, which is a preferred effective control measure of invasive plants (Bradley, 2014; Caffrey et al., 2014; Meier et al., 2014).

Traditional mapping methods involve the use of field survey techniques which employ various sampling strategies (Huebner, 2007). These methods can offer reliable information with high degree of locational accuracy and species detection capability (Rodgers et al., 2014). Nonetheless, traditional mapping methods can be limited by factors such as rough terrains, large spatial areas and limited manpower resources (Dewey et al., 1991; Rodgers et al., 2014). As such, better mapping techniques need to be explored, as traditional methods cannot be practical for operational monitoring purposes.

High spatial resolution sensors such as aerial photography are commonly used to map invasive plants. For example, Lishawa et al. (2013) determined the spatial-temporal spread of invasive cattail (*Typha*) in Great Lakes coastal wetlands, United

States of America by linking historical aerial photos to a paleo-botanical analysis of pollen cores. Peña et al. (2013) generated a weed map in an experimental maize field in Spain using images acquired by an Unmanned Aerial Vehicle (UAV). Rodgers et al. (2014) mapped invasive plant distributions in the Florida Everglades of the United States of America using digital aerial sketch mapping technique. Similarly, Barrell and Grant (2015) successfully characterised eelgrass (*Zostera marina* L.) and blue mussel (*Mytilus edulis* L.) using landscape mosaic observed using low-altitude aerial photography from a balloon mounted digital camera platform in McCormacks Beach near Eastern Passage, Canada. Although they provide better and quicker mapping capabilities than field survey techniques, aerial photograph interpretation has limitations. Most notable limitations are; data acquisition using this method is made only on request and it requires for the target species to be distinct from its background and neighbouring areas (Huang and Asner, 2009).

Remote sensing is a promising tool for mapping invasive plants (Gavier-pizarro et al., 2012b). Remote sensing is the science of obtaining information from an object without being in direct contact with it, typically from airborne and spaceborne platforms (Ajmi, 2009; Asner et al., 2008; Huang and Asner, 2009; Lillesand et al., 2015). The technique makes use of the varying interaction properties of ground objects and electromagnetic radiation. This principle allows for building relationships between electromagnetic radiation and features on the ground such as vegetation types. As such, remotely sensed data can be used to discriminate between different vegetation species (Ajmi, 2009; Manevski et al., 2011; Pu et al., 2012; Schmidt and Skidmore, 2003). This capability can be translated into discriminating various invasive plants.

Applying remote sensing in vegetation mapping has a number of advantages. Firstly, it offers cost effective and practical means of monitoring vegetation cover over large spatial areas. Secondly, it allows for monitoring vegetation dynamics in a repeated data acquisition mode (Pasqualini *et al.* 2005, Xie *et al.* 2008, Cuneo *et al.*2009, Dronova *et al.* 2015). Furthermore, remote sensing techniques provide reliable and objective means of data acquisition and analysis. Such advantages make remote sensing an attractive tool in the field of biological invasion (Joshi et al., 2004). Numerous studies applied remote sensing for mapping invasive plants. This literature review categorises the applications into two tyres, according to spectral resolution of remotely-sensed data. These include applications using multispectral and hyperspectral remote sensing. Selected applications of multispectral and hyperspectral sensors are summarised in Table 1 and Table 2, respectively, while few applications have been detailed in the next section.

2.6.1. Multispectral remote sensing for characterizing invasive plant species

Remote sensors in this category have low spectral resolution and collect data usually in less than 20 bands of relatively broad electromagnetic widths (Huang and Asner, 2009). One example is Landsat imagery which has bands of 70 to 350 nm band width (Schmidt and Skidmore, 2003). Such a resolution makes it inefficient in separating subtle differences among plants. Adam & Mutanga (2009) reported that the use of multispectral data for discriminating and mapping plants is challenging due to spectral overlap as a result of low spectral resolution. Their data is mostly preferred due to affordability (Somodi et al., 2012). Multispectral sensors have proved useful in discriminating between feature groups such as vegetation communities, vegetation types, or land use classes (Manevski et al., 2011). A variety of studies have employed these sensors for discriminating and mapping vegetation types, including invasive plants.

For example, Martín et al. (2011) explored the possibility of using very high spatial resolution commercial sensors to discriminate and map patches of a weed sterile oat (*Avena sterilis L.*) existing in winter barley crops using QuickBird at two winter months (March and June) at Poveda Research Farm, Spain. The images underwent standard pre-processing that included radiometric corrections and geometric corrections using ground control points. Logistical regression of vegetation indices was used to estimate different densities of sterile oat. Sterile oat was best discriminated in high densities with accuracies of 86% and 94% in June and March images, respectively, while accuracies in low densities were 72% and 75% in June and March images, respectively. The QuickBird images showed the capacity for mapping patches of sterile oat in barley crops when weed density is relatively high. The study also provided valuable information on best spectral regions and/or vegetation indices for discriminating between sterile oat and cereal crops and the most suitable period for discrimination.

On the other hand, Somodi et al. (2012) tested low cost data sources, including Landsat Enhanced Thematic Mapper Plus (ETM+) and airborne orthophotos from summer and spring) to identify *Robinia pseudacacia* at large spatial extent and relatively fine resolution using simple and automated method in the Prekmurje region, Slovenia. The study involved delineation of a training site to provide training data for models derived from generalised linear models (GLMs). *R. pseudacacia* was sampled in the field using a geographic base map and digital orthophotos. The information from the field was combined with visual interpretation of aerial photographs. Spectral signatures were collected from areas with presence of *R. pseudacacia*. The predictive ability of different models developed for all data sources using generalised linear model (GLMs) was tested. The spring orthophoto gave best recognition of the species, and thus it was concluded that less detailed spectral data sources can successfully be used to monitor *R. pseudacacia* when its phenology is also considered.

Forsyth et al. (2014) assessed the suitability of a SPOT 6 image for mapping invasive adult *Pinus* trees in Klein Swartberg, South Africa. The multispectral bands of the images with a 6 m resolution were pan-sharpened to a 1.5 m resolution. Classification was done on a small site where trees survived and some recovered following a veld fire that occurred in 2012. Supervised classification based on decision rules was used to map the trees. Because field validation data was not available due to time constraints, expert knowledge from previous studies was used for verification of the results. Accuracy assessment for each of the sites using confusion matrix returned an overall accuracy of 84% with a kappa coefficient of 0.68.

Azong et al. (2015) assessed the utility of WorldView-2 (0.5–2 m spatial resolution) for mapping tree species and canopy gaps in a protected subtropical coastal lowland forest in South Africa. Information from stakeholders on the importance of maps for conservation of subtropical lowland forest patches in South Africa was gathered. Object-based Support Vector Machines (SVM) were used for tree species classification. Patterns of dominant species distribution were determined using descriptive statistics from computed percentages of each species per grid square. Two stakeholder workshops were conducted to present the map products and to assess the utility of the maps for forest management and as well as raising awareness on the potential role of remote sensing in indigenous forest inventorying in South Africa. Forest disturbances were revealed in the maps, and the participants of the two stakeholder meetings agreed that very high resolution maps provided valuable information that can be used for implementing and monitoring the effects of rehabilitation measures. Consequently, such imagery was recommended for timely inventorying and monitoring of the small and fragile patches of subtropical forests in

Southern Africa. Table 1 summarises the applications of multispectral remote sensing in characterising invasive plants.

Table 1: Applications of multispectral sensors

Sensor	Application	Study area	Species	Methodology	Accuracy	Author
SPOT	Mapping seagrass	Laganas Bay, Greece	*Posidonia oceanica*	Supervised classification	Overall accuracy for 2.5 m resolution =73% Overall accuracy for 10 m =96%	(Pasqualini et al., 2005)
Landsat	Determining the spatial extent of African Olive	Cumberland Plain region west of Sydney, Australia	African Olive (*Olea europaea* L.ssp. *cuspidate* Wall ex G. Don Ciferri)	Supervised classification	Overall accuracy=85%	(Cuneo et al., 2009)
SPOT and coarse-resolution (GLC2000) and high-resolution imagery (Africover)	Mapping and characterization of vegetation types	Democratic Republic of Congo	18 vegetation classes	Data stratification, classification (unsupervised classifications) and evaluation of SPOT VGT and GLC2000 images	Global accuracy=81%	(Vancutsem et al., 2009)
Landsat	Assessment of potential distribution of Japanese honeysuckle	Cumberland Plateau and Mountain Region in the southeast of USA	Japanese honeysuckle (*Lonicera japonica* Thunb.)	Logistic regression and Maximum Entropy (MaxEnt) models including ensemble models	Kappa=41%+ Cohen's Kappa and Area under the ROC (AUC) =75%+	(Lemke et al., 2011)
Landsat	Feasibility assessment for identification of *Pennisetum ciliare* in desert scrub habitats	Santa Catalina Mountains in Southern Arizona, USA	*Pennisetum ciliare*	Classification using combined Classification and Regression Tree (CART) and logistic regression	Best overall accuracy 76% Cohen's Kappa and Area under the ROC (AUC) <85%	(Olsson et al., 2011)
QuickBird	Discrimination of sterile oat (*Avena sterilis*) in winter barley (*Hordeum vulgare*)	La Poveda Research Farm, Arganda del Rey, Madrid	Sterile oat (*Avena sterilis* L.)	Classification using binary logistic regressions	High density (predicted=86% and observed densities=94%) Low density (predicted=72% and observed densities=75%)	(Martín et al., 2011)

Sensor	Application	Study area	Species	Methodology	Accuracy	Author
Landsat	Improving pasture mapping of buffelgrass	Sonoran Desert of Mexico	buffelgrass (*Pennisetum ciliare*)	Binary classification tree algorithm	Segmented (Kappa Index of Agreement=95%) and Non-segmented (Kappa Index of Agreement=85%)	(Brenner et al., 2012)
SPOT	Assessment of the suitability of the image for mapping adult *Pinus* trees	Klein Swartberg, Western Cape, South Africa	*Pinus* trees	Supervised classification	Overall accuracy=84% (kappa coefficient of 0.68)	(Forsyth et al., 2014)
WorldView-2	Assessing utility of the image for tree species mapping	Dukuduku indigenous coastal forest in KwaZulu-Natal, South Africa	*Albizia adianthifolia*, *Strchynos spp*. and *Acacia spp.*	Support Vector Machines Classifier	Overall accuracy=89±2%	(Azong et al., 2015)
QuickBird-2/WorldView-2	Demonstrating potential of compressed Canopy Area (CCA) of invasive species in conjunction with Invasive Species Distribution Models (iSDM) for assessing species success by computing a 'range filling'	Tropical islands of the Society archipelago (Tahiti, Moorea and Raiatea), South Pacific ocean	African tulip tree *Spathodea campanulata* (Bignoniaceae)	Calculation of CCA of *Spathodea* and Creation of potential distribution maps	Tahiti (Kappa=87%) Moorea (Kappa=87%) Raiatea (Kappa=(88%)	(Pouteau et al., 2015)

2.6.2. Hyperspectral remote sensing for characterizing invasive plant species

Hyperspectral remote sensing techniques offer high spectral resolution, since such sensors take measurements over the visible, near infrared and middle infrared regions at narrow wavelength intervals (Alparone et al. 2015; Carroll et al. 2008; Huang & Asner 2009; Jensen 2014). The method is therefore advantageous since it allows identifying subtle differences between features (Campbell and Wynne, 2011; Galvão et al., 2011; Lillesand et al., 2015). Customarily, hyperspectral data contain hundreds of contiguous bands of 10 nm or less spectral width that offer successful spectral discrimination capability between vegetation species (Ahmad et al., 2012; Thenkabail, 2014). Nevertheless, the high spectral data provided by hyperspectral remote sensors increase image dimensionality and data redundancy, with certain bands contributing little in the discrimination of vegetation species (Ahmad et al., 2012; Bioucas-dias et al., 2013; Demarchi et al., 2014; Ren et al., 2014). It is therefore important to select suitable bands for discriminating among vegetation species without losing important information (Adam and Mutanga, 2009). A variety of parametric and non-parametric statistical techniques are used to achieve this (Adam and Mutanga, 2009; Manevski et al., 2011; Pu et al., 2012; Rudolf et al., 2015). A combination of such techniques and hyperspectral data acquired using spacebourne, airborne and field spectroscopy have been used to map invasive and/or invasive plants successfully.

For example, Abdel-Rahman et al. (2014) examined the utility of Random Forest (RF) and Support Vector Machines (SVM), and Airborne Imaging System for different Applications (AISA) Eagle hyperspectral data to discriminate between healthy, *Sirex noctilio* grey-attacked, and lightning-damaged pine trees in Hodgsons Sappi plantation area, KwaZulu-Natal. Capabilities of RF and SVM classifiers to discriminate *S. noctilio* grey-stage and lightning damaged pine trees were established. AISA Eagle wavebands were ranked according to their ability to discriminate among healthy, *Sirex noctilio* grey- and lightning-damaged pine trees and other classes. Accuracies of each classifier were assessed using a 30% holdout sample. Discrimination was achieved with accuracy of 75% using RF and 74% using SVM. RF classifier returned an accuracy of 78% while SVM classifier had an accuracy of 77% when most useful bands were used. However, no significant differences were observed between the two classifiers; thus it was concluded that AISA Eagle data classified using both algorithms would provide relatively accurate information important to forest industry for making informed decision regarding pine plantations health protocols.

Ghulam et al. (2014) combined satellite observations including GeoEye-1 stereo imagery, IKONOS-2, ETM+, Hyperion, Radarsat-2 and the Phased Array type L-band Synthetic Aperture Radar (PALSAR) datasets with field sampling to detect sub-canopy native and non-native habitat-altering plant species (guava, Madagascar cardamom and Molucca raspberry) in Betampona Nature Reserve, Madagascar. The spatial extent and spectral features of the species were characterised using a decision tree algorithm. This algorithm uses a number of input variables that include Mixture Tuned Matched Filtering (MTMF), land-cover maps, tree height information derived from high resolution stereo imagery, polarimetric feature images, Radar Forest Degradation Index (RFDI), Polarimetric (PolInSAR) and Interferometric SAR (InSAR) coherence and phase difference images. Plant species were mapped using a pixel-based Winner-Takes-All (WTA) algorithm, object oriented feature extraction and spectral unmixing. The maps were subsequently compared with the developed decision tree approach. The results showed the InSAR phase difference and PolInSAR HH–VV coherence images of L-band PALSAR data as the most important variables of the MTMF outputs for mapping sub-canopy invasive plant species in the study area.

Field hyperspectral sensors are well received in remote sensing discipline and are proving to be of significance in discriminating between plants at a species level (Manevski et al., 2011). This could be attributed to their ability of directly collecting vegetation spectra of living vegetation in the field comparable to laboratory measurements. Field hyperspectral data have been used to identify invasive plants. For example, Fernandes et al. (2013) evaluated spectral separability of a giant reed (*Arundo donax* L.) alien invasive riparian species from surrounding vegetation in different phenological periods using field spectrometry in River Aveiras and River Alcabrichel, western Portugal. Spectral data were taken during vegetative and senescent periods of the species using a field spectrometer. Wavelengths with significant spectral differences between vegetation types (giant reed versus herbaceous vegetation; giant reed versus woody vegetation; giant reed versus common reed) were determined using Kruskal-Wallis test and classification accuracy was determined using Classification and Regression Trees (CART). Wave regions with optimal classification ability were identified. Finally, Jeffries–Matusita (JM) and the Bhattacharya (BT) distances were calculated to determine spectral separability between giant reed and other vegetation types from data simulated according to bands of IKONOS, Landsat and SPOT imagers to explore future applications. The results showed the giant reed to be spectrally separable from adjacent vegetation, both during vegetative and senescent periods, but were not separable from common reed (*Phragmites australis* (Cav.) Trin. ex Steud) at the vegetative period. Although red edge (located in the near infrared region) region was repeatedly selected for discriminating the species, the visible region was also important in separating giant reed from the herbaceous vegetation. The mid infrared region enabled discrimination of giant reed from woody vegetation. The highest separability was obtained for the giant reed Regenerated After Cutting (RAC) stands, due to its highly homogeneous, dense and dark-green stands.

Rudolf et al. (2015) used a field spectrometer to identify spectral features corresponding to leaf tannin content of the invasive *Acacia longfolia* (non-native) and six other abundant and common native and non-native shrub and tree species (*Acacia cyanophylla* Lindl. (non-native), *Corema album* (L.) D. Don ex Steud., *Halimium halimifolium* Willk., *Juniperus phoenicea* subsp. *turbinata* (Guss.) Parl., *Pistacia lentiscus* L. and *Pinus pinea* L) in the Atlantic coast, southwest of Portugal. They differentiated between species based on leaf spectral reflectance related to variation in tannin content. Leaf reflectance of selected plant species using a field spectroscopy and tannin concentration of measured samples was determined in a laboratory. The Kruskal-Wallis test was used to compare tannin concentration between sites. Wilcox rank sum test pairwise comparison was used to test differences in tannin concentrations of all tested species. Tannin-related wavelengths of *A. longifolia* were determined using the Partial Least of Squares (PLS) regression model. Finally, a combination of Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) was used to test the classification ability of the tannin-related wavelength regions. The spectra-based classification in the regions that were correlated with tannin content achieved had higher user accuracy of accuracy of 99% in both 1360–1450 nm and 1630–1740 nm regions, with producer's accuracies of 85% in the 1360–1450 nm region and 77% in the 1630–1740 nm region. Table 2 summarises applications of hyperspresctral remote sensing on invasive plants.

Table 2Applications of hyperspectral sensors

Sensor	**Application**	**Study area**	**Species**	**Methodology**	**Accuracy**	**Author**
Field spectrometer	Evaluation of spectral separability of the giant reed from surrounding vegetation, in different phenological periods	River Aveiras and River Alcabrichel, Western Portugal	Giant reed or cane (*Arundo donax L.*)	Classification and Regression Trees (CART) classifier	Giant reed versus herbaceous=96% Giant reed versus Woody vegetation=99% Giant reed versus Common reed=97%	(Fernandes et al., 2013)
High-resolution aerial digital photographs and QuickBird	Mapping of tropical forest trees	Barro Colorado Island, Panam	*Attalea butyracea*, *Astrocaryum standleyanum*, *Jacaranda copaia*, *Dipteryx panamensis*	Manual digitizing of crowns	*Attalea butyracea* (65%) *Astrocaryu*m *standleyanum* (19%) *Jacaranda copaia* (76%) *Dipteryx panamensis* (65%)	(Garzon-Lopez et al., 2013)
AISA (Airborne Imaging System for different Applications)	Detection of *Sirex noctilio* grey-attacked and lightning-struck pine trees	Hodgsons Sappi plantation area, KwaZulu-Natal, South Africa	*Sirex noctilio*	Random Forest (RF) and Support Vector Machines(SVM) classifiers	All usable AISA Eagle spectra and subsets of 51 bands (RF: 75%; 78%) (SVM: 74%; 77%)	(Abdel-Rahman et al., 2014)
LIDAR and AVIRIS	Mapping of urban tree species	Santa Barbara, California	Broadleaf, Coniferous and Palm trees	Canonical discriminant analysis	Species-level (83%) and leaf-type level (94%)	(Alonzo et al., 2014)
GeoEye-1 Stereo imagery, IKONOS-2, Landsat Enhanced Thematic Mapper Plus (ETM+), Hyperion, Radarsat-2 and the Phased Array type L-band Synthetic Aperture Radar (PALSAR)	Detection of subcanopy invasive plant species in tropical rainforest	Betampona Nature Reserve, Madagascar	Guava and Molucca raspberry (invasive); and Madagascar cardamom (indigenous)	Decision tree algorithm	Accuracy=83% and kappa coefficient of 0.75	(Ghulam et al., 2014)
AISA/Eagle hyperspectral data	Testing the suitability and accuracy of hyperspectral data to produce the first African flowering and short-term floral cycle map	Mwingi Central Sub County, Kenya	Melliferous plants	Linear spectral unmixing and Change Vector Analysis (CVA)	Overall accuracy=83%	(Landmann et al., 2015)

Sensor	Application	Study area	Species	Methodology	Accuracy	Author
AVIRIS-C spectrometer and Next Generation Imaging Spectrometer (NGIS)	Vegetation species discrimination	University of California Riverside Citrus Research Center Agricultural Experiment Station (CRC-AES)	Citrus plants	Multiclass Discriminant Analysis (MDA) transformations	Overall accuracy=75%	(Bue et al., 2015)
Field spectrometer	Discrimination of Mediterranean native plants from exotic-invasive shrubs based on leaf tannin content	Lagoa da Sancha (LDS), Melides (MEL) and Pinheiro da Cruz (PDC), Atlantic coast, Portugal	Invasive *Acacia longifolia* and six other abundant and common native and non-native shrub and tree species	Classification using Principal Component Analysis-Linear Discriminant Analysis (PCA-LDA)	Best user's accuracies=99% and 87% Best producer's accuracies of 85% and 77%	(Rudolf et al., 2015)
Infrared camera (Thermal imaging) and pushbroom system designed by Specim (hypespectral data)	Use of hyperspectral image and thermal data from Norway spruce seeds to identify viable seeds, empty seeds and seeds infested by *Megastigmus* sp. larvae.	Suhola seed orchard, Central Finland	Norway spruce (*Picea abies*)	Support Vector Machines and logistic regression based feature selection	Best overall accuracy=94%	(Dumont et al., 2015)
MODIS-EVI	Monitoring temporal changes of vegetation characteristics	Southern African countries (South Africa, Lesotho, Mozambique, Swaziland, Zimbabwe and Botswana)	Vegetation dynamics	Calculation of vegetation trends from MODIS data using a robust trend analysis method	Temporal trends of vegetation characteristics could be identified using MODIS	(Dubovyk et al., 2015)
ProSpecTIR-VS hyperspectral data	Mapping of invasive species and spectral mixture relationships with neotropical woody formations	Mogi-Guaçu Ecological Park (MGEP), south-eastern Brazil	*Dendrocalamus* sp. (bamboo) and *Pinus elliottii* L. (slash pine)	Multiple Endmember Spectral Mixture Analysis (MESMA)	Bamboo=72% Slash pine=62%	(Amaral et al., 2015)

2.7. Summary

The studies above show the utility of remote sensing techniques for detecting and mapping the distribution of invasive plants. Multispectral remote sensing methods have been used extensively with certain degrees of success. But the level of information acquired using these methods needs to be enhanced to improve results. Hyperspectral remote sensing methods offer better discriminability potential because of the higher spectral resolution data of such systems, compared to multispectral remote sensing. Knowledge learned from these studies will be applied in this study which will focus on the spectral characterization of three types of invasive species that have not been studied previously.

CHAPTER 3

Discrimination of *Artemisia afra* from surrounding land cover types using field spectrometer

Abstract

This chapter investigated the utility of remote sensing to discriminate invasive *A. afra* from adjacent land cover types using continuum reflectance spectra acquired using a field spectrometer. Reflectance comparisons between *A. afra* and adjacent land cover types were made using original spectra as well as spectra simulated based on Landsat and SPOT 5 bands. Regions perceived to be noise free and capable of discriminating *A. afra* from adjacent land cover types were visually identified and extracted for further analysis. Comparisons between *A. afra* and adjacent land cover types for original spectral analysis were subsequently done at individual pair of plants and plot levels. Comparisons for spectra simulated per Landsat and SPOT 5 bands were done at individual and group levels. All comparisons were made using analysis of variance (ANOVA) or t-test. Results from all levels of analysis showed the near infrared region to be best in discriminating *A. afra* from adjacent land cover types. A number of factors attributed to inconsistent results in other bands, such as inconsistency in measurement times, difference in phenology between individuals of the species, and impurity of samples including *A. afra* and adjacent land cover types. Nonetheless, the results of analysis using simulated Landsat and SPOT 5 images showed the potential of extending the technique to actual remotely-sensed images with more emphasis in the near infrared band. Further studies are encouraged to address some shortcomings of the study such as sampling homogenous land cover types, creating ideal electromagnetic illumination scenarios and increasing sample size to improve the reliability of results for up scaling the technique to remotely sensed data.

3.1. Introduction

Artemisia afra (African wormwood) is a perennial woody shrub growing to about two meters in height, with dark green and light green leaves respectively that grow to eight centimetres length and four centimetres width, and with a leafy and hairy stem (Jide et al., 2011; Liu et al., 2009).It occurs in different parts of the world including South Africa (Jide et al., 2011; Liu et al., 2009; Mukinda and Syce, 2007; Patil et al., 2011). The plant grows mainly in highland areas at altitudes between 1500 m to 3000 m above sea level, along forest margins and streams (Patil et al., 2011; Scott and Springfield, 2004).

A. afra has various medicinal, economic and cultural values. Medicinal values, both traditional and commercial, are reported in the works of Burits et al. (2001), Otang et al. (2015), and Patil et al., (2011). Van Wyk (2008) found the plant to possess antimicrobial, antioxidant, antimalarial, anti-nematodal, cardiovascular (hypotensive), cytotoxic as well as sedative effects. Ethnomedicinally, this plant is used to treat a variety of ailments from simple headaches to neurological disorders such as epilepsy in various parts of Africa (Jide et al., 2011; Liu et al., 2009; Mukinda and Syce, 2007; Patil et al., 2011). Likewise, *A. afra* is used cormmeciallly to produce a number of commercial products such as Healer's Choice (tincture) and Phyto Nova (tablets) that were first commercialised in South Africa during 1996 and 2002, respectively, including anti-malaria capsules produced by Nordman Superior Food supplements (Van der Kooy et al., 2008; Van Wyk, 2011).

Despite such benefits, the plant can become invasive if the edaphic conditions of a given area are conducive to its growth. It is likely that like other invasive plants possesses highly specialised physiological characteristics that give it a competitive advantage over native plants (Richardson and Van Wilgen, 2004). Two of these characteristics include the capacity to use high amounts of water and nutrients, thereby depriving other native plants of these resources. Adverse effects of invasive plants in general on ecosystems is well studied (Chamier et al., 2012; Enright, 2000; Eviner et al., 2012; Hejda et al., 2009; Henderson, 2007; Le Maitre et al., 2014, 2000; Marais et al., 2004; Peh et al., 2015). Le Maitre et al. (2002) summarised invasive alien tree management plans developed for four catchments in South Africa. They compared composition, extent and impacts of invasive alien trees in the four catchments and provided estimates of the costs and benefits of control measures. Both impacts and costs were found to be significant, and infestations were estimated to spread and cause reduced stream flows, if not controlled. Also, introducing control measures after infestations had fully established was estimated to incur more control costs. Le Maitre et al. (2014) showed the potential of increased risk of flood damages as a result of pines and acacias invading the Fynbos biome in South Africa. A global assessment of invasive plant impacts on species, communities and ecosystems by Pyšek et al. (2012) reveals significant impacts of invasive plants on ecosystem services such as survival of biota, activity of animals, community productivity, mineral and nutrient content in plant tissues, fire frequency and intensity, species richness and diversity, and soil resources.

Identifying and preventing invasions before they spread into new areas is a major environmental conservation challenge for land managers (Bradley and Marvin, 2011). Therefore, reliable spatial and temporal information on new infestations is needed in order to control infestations at early stages (Lawrence et al., 2006). Traditional mapping methods such as field surveys can be used for mapping invasive plants (Dewey et al., 1991; Xie et al., 2008). Although these methods are considered accurate for small areas, they require considerable logistical inputs and thus are often impractical for large spatial areas (Lawrence et al., 2006; Rodgers et al., 2014). In contrast, remote sensing methods have proven effective in mapping invasive plants (Asner et al., 2008; Bradley and Marvin, 2011; T L Hawthorne et al., 2015; Laba et al., 2008; Lawrence et al., 2006; Lu and Zhang, 2013). Remote sensing is the science of obtaining information from a distant object without being in direct contact with the object, typically from an aircraft or satellite (Ajmi, 2009; Asner et al., 2008; Huang and Asner, 2009). The technique exploits varied characteristics of interaction between electromagnetic radiations and objects on the earth's surface (Lillesand et al., 2015). Remote sensing is advantageous over traditional mapping methods in a number of ways such as wide area coverage, timely data acquisition, cost effectiveness, and multitemporality that allow continuous monitoring (Lillesand et al., 2015; Mansour, 2013; Rodgers et al., 2014; Xie et al., 2008). These advantages render the technique applicable for assessing biological invasion (Joshi et al., 2004).

Field spectroscopy is one form of remote sensing that can contribute significantly in discriminating between plant species (Manevski et al., 2011), because field spectrometers have a large number of contiguous spectral bands that help acquire detailed spectral properties from target objects (Garfagnoli et al., 2013). A number of studies have employed this capability to characterize invasive plant species. Ouyang et al. (2013) for example discriminated an invasive plant (*Spartina alterniflora*) from native plant species (*Phragmites australis* and *Scirpus mariqueter*) at multiple phenological stages in a saltmarsh wetland at eastern Chongming Island, China. The study found phenology to have affected separability between plant communities. Vegetation indices showed a great potential for differentiating *S. alterniflora* from other vegetation types at withering stage. Rudolf et al. (2015) discriminated invasive *Acacia longfolia* and six other commonly occurring native and non-native shrub and tree species in the Atlantic coast of southwest Portugal by identifying spectral features corresponding to leaf tannin content. They further differentiated between the species based on leaf spectral reflectance related to variation in tannin content. Principal Component Analysis-Linear Discriminant Analysis (PCA-LDA) was used to calculate a spectra based classification model of the plant species. The results determined wavelength regions (675–710 nm, 1060–1170 nm, 1360–1450 nm and 1630–1740 nm) to be highly correlated with tannin concentration. *A. longfolia* was best predicted in the 1360–1450 nm and 1630–1740 nm wavelength regions with an accuracy of 99% when using the entire wavelength. Other applications of field spectroscopy in invasive species characterization include spectral discrimination of papyrus vegetation (*Cyperus papyrus L.*) (Adam and Mutanga, 2009), assessment of changes in spatial distribution of intertidal *Zostera noltii* seagrass beds (Barillé et al., 2010), discrimination of common Mediterranean plant species (Manevski et al., 2011), and discrimination of seagrass and cover classes (Pu et al., 2012).

Currently used hyperspectral data analysis methods mainly search for specific narrow bands that best discriminate between plant species. These bands usually occur in isolation and cannot be joined together to represent broad-bands available from multispectral remote sensing sensors. Therefore such methods remain limited to hyperspectral remote sensing techniques, and do not offer the opportunity of extending the techniques to multispectral remote sensing systems. This is compounded by the fact that hyperspectral remote sensing techniques are predominantly in the domain of research communities, although it is hoped to be translated into practical applications that can be implemented for various ecological monitoring efforts. This is attributed chiefly to the cost of data acquisition and the relatively infant stage of management of large volume of data provided by the system. In contrast, multispectral remote sensing systems are widely used for vegetation mapping purposes, including for routine monitoring and management programmes.

Therefore analysis involving hyperspectral data should take into consideration the extension of findings to multispectral remote sensing systems. This study aims to contribute to such a cause by investigating the utility of remote sensing technique to discriminate *A. afra* from adjacent land cover types (grass, herbaceous and bare ground) using a continuum of field spectrometer bands. As such, the use of a continuum spectral regions rather than identifying specific individual bands will be explored. Specific objectives of the study are to (1) determine whether or not *A. afra* can be discriminated from adjacent land cover types using a field spectrometer data, and (2) assess the performance of spectra simulated according to Landsat and SPOT 5 bands in discriminating *A. afra* from adjacent land cover types.

3.2. Methods

3.2.1. Study Area

The study was conducted in the Klipriviersberg Nature Reserve, in Johannesburg, South Africa (Figure 1). The reserve has the largest spatial coverage of approximately 680 hectares and is managed by the City of Johannesburg Metropolitan Municipality. Klipriviersberg Nature Reserve lies in the Klipriviersberg area that is in the transition zone between the grassland and the savanna biome in the northern edge of the Highveld (Faiola and Vermaak, 2014). The Highveld climate is characterised by warm to hot summer and cool to cold nights in winter with temperatures ranging between 17–26 ºC in summer and 5–7 ºC in winter (Kotze, 2002). Three geology types contribute to the floristic composition of the reserve and these include volcanic rock (basalt and andesite) that underlay the reserve, quartzites and conglomerates of the upper Witwatersrand system underneath the lavas in the north of the reserve and dolomites of the Transvaal system in the south of the reserve (Kotze, 2002). Vegetation types in the reserve are classified as Andesite Mountain Bushveld and a section of Tsakane Clay Grassland at its flatter southern end (Faiola and Vermaak, 2014). The biodiversity of the reserve is relatively rich with approximately 650 indigenous plant species, 215 bird species, 16 reptile species and 32 butterfly species. Mammals that occur in the reserve include lesser spotted genet, African civet, zebra, red hartebeest, blesbok, springbok, duiker, black wildebeest, porcupines, meerkats and otters.

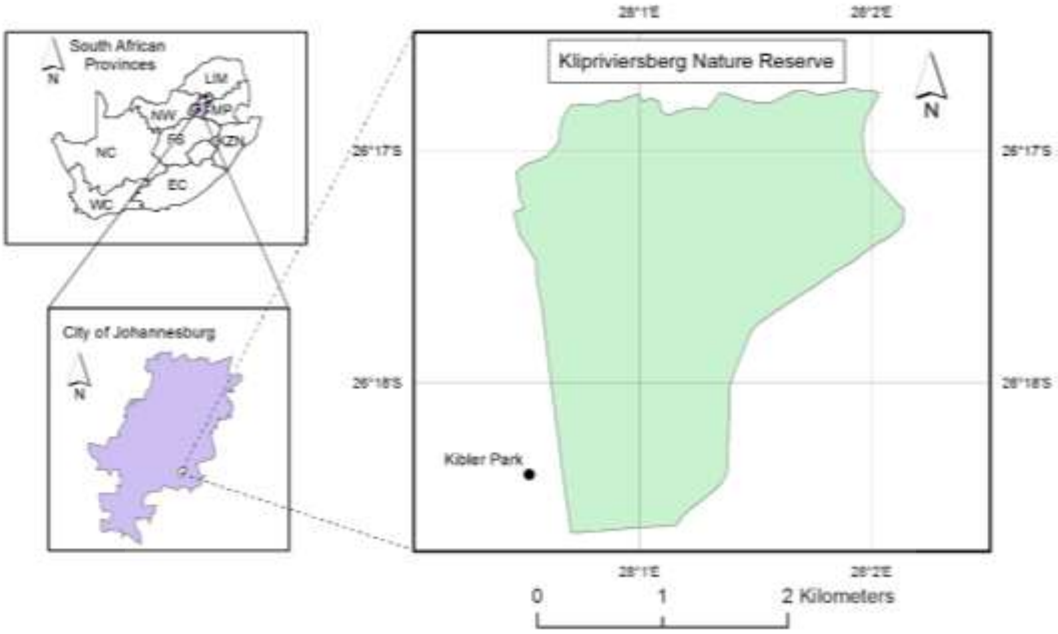


Figure 1: Map showing the Klipriviersberg Nature Reserve.

3.2.2. Field data

A field survey was conducted between the 2nd and 14th of December 2014 during summer when vegetation was green, which is the most preferred time for remote sensing applications on vegetation(Lillesand*et al.* 2015). *A. afra* was found in a scattered pattern within the reserve, and this limited the number of areas with substantial concentration of the species. As a result, twelve sample plots, each measuring 15 m radius, were delineated. This size takes into consideration the potential extension of the analysis to space-borne remote sensing techniques. The plot therefore accommodates at least one pixel of Landsat imagery (30 m resolution) and a number of SPOT 5 imagery pixels (2.5–10 m resolutions). The centre of each plot was recorded using a GPS (global positioning system) with 3 m accuracy. A line transect was laid between the centre and the periphery of the plot in each of the north, south, east and west directions. Individual plants of *A. afra* were taken at five metre intervals along each transect (Figure 2). The nearest *A. afra* was sampled, where there was no individual plant of the species lying along the transect line.

A field spectrometer, namely Spectral Evolution®, was used to collect spectral data during the field survey. The spectrometer has a 1.6 nm spectral resolution ranging between 340 nm and 2503 nm. A white reference measurement was used to convert target radiance in energy unit into percent reflectance (Prospere et al., 2014). Three spectral measurements were taken at 4 cm above the leaf canopy from different positions of each *A. afra* plant. All these positions were viewed from the top of canopy in an attempt to mimic a remotely sensed data (airborne and space-borne) viewpoint. Similarly, three spectrometer measurements were taken from an adjacent land cover type (plant or bare ground) at each sample location. This resulted in a total of 13 measurement pairs (each pair consisting of *A. afra* and an adjacent land cover type) per plot. Spectral measurements were at most taken at nadir under sunny conditions. The ideal time period when this can be achieved for a given area is between 10:00 am and 2:00 pm. Such a measurement protocol is important to acquire optimal electromagnetic radiation and to mimic the scanning mechanism of the remotely sensed data (Cho et al., 2008; Fernandes et al., 2013; Mansour, 2013; Olsson et al., 2011; Rudolf et al., 2015). It should however be noted that this protocol was not applied for all measurements due to time which forced data acquisition outside of the ideal time.

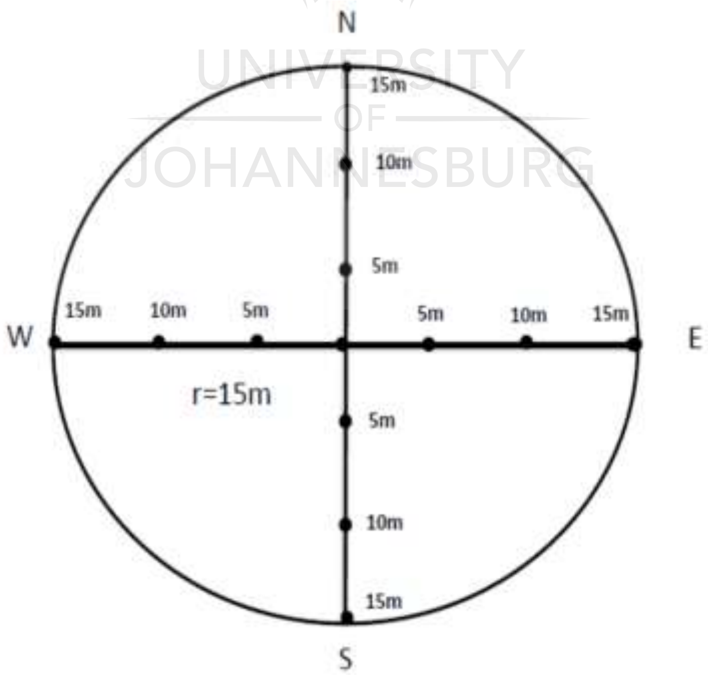


Figure 2: A layout of sampling design for spectral measurements of individual target plant.

3.2.3. Analysis of spectral reflectance per region

The study sought to identify spectral regions that show consistent differences in spectral properties between *A. afra* and adjacent land cover types. In order to achieve this, average spectra were firstly computed from the three spectral measurements that were taken for individual *A. afra* plants and adjacent land cover types. Subsequently, spectral reflectance of all *A. afra* plants were pooled together and averaged. Spectra of all adjacent land cover types were averaged in the same manner. These computations resulted in separate 'global' spectral curves representing *A. afra* as well as adjacent land cover types (Figure 3). The global spectra of adjacent land cover types were computed to determine if *A. afra* could be differentiated from them. Comparing the global pair of spectral curves is preferred since it offers results that are more representative of the study area. In contrast, comparison of each pair separately would yield a plethora of results that would complicate the choice of a result that would represent all individuals.

A visual assessment of the global spectra (*A. afra* vs adjacent land cover types) was used to reduce dimensionality of data by excluding wavelength regions that are not useful for discriminating between land cover types. A full global reflectance comparison curve of *A. afra* and grass is illustrated in Figure 4. Comparisons of other global spectra against *A. afra* are not presented here for the sake of brevity. Two criteria were used for the exclusion of unnecessary regions. The first one targeted wavelength regions that returned random reflectance properties commonly referred to as noise (*A. afra* vs Grass: 1859-1967 and 2318-2503 nm; *A. afra* vs Herbaceous: 1838-1945 nm and 2301-2503 nm; *A. afra* vs bare ground: 1861-1967 nm and 2349-2503 nm). The second exclusion targeted wavelength regions that did not show spectral reflectance differences between *A. afra* and adjacent land cover types (*A. afra* vs Grass: 340-343, 684-757 nm and 1335-1459 nm; *A. afra* vs Herbaceous: 651-737 nm and 1350-1452 nm; *A. afra* vs bare ground: 684-741 nm and 1331-1455 nm). This process resulted in four discontinuous regions (Figure 5) that were used as reference in further analysis (Table 3).

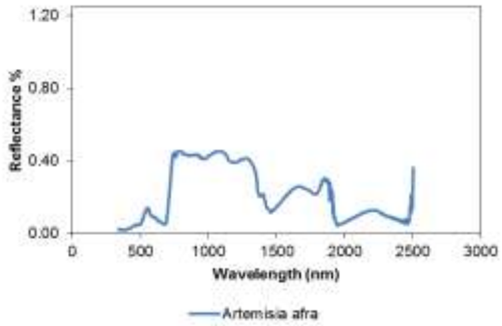
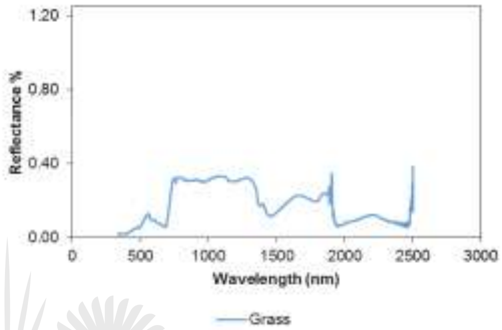
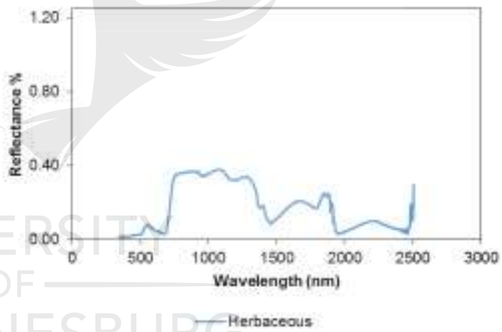
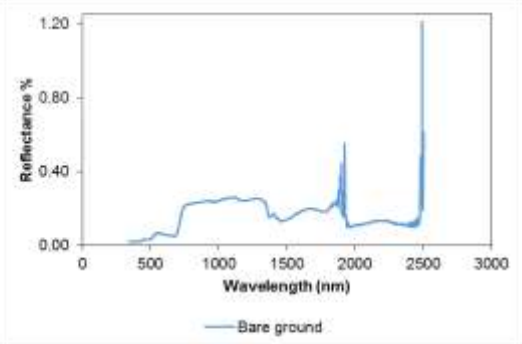
Pictures	Global reflectance
 *Artemisia afra*	
 Grass	
 Herbaceous	
 Ground	

Figure 3: Global spectra of *A. afra* and adjacent land cover types

Table 3: Wavelength regions used in the analysis

Comparison pairs	*Wavelength regions*			
	Region 1 (Ultraviolet and Visible), nm	*Region 2 (NIR), nm*	*Region 3 (NIR and SWIR), nm*	*Region 4 (SWIR), nm*
A. afra vs Grass	345-683	758-1331	1463-1855	1970-2315
A. afra vs Herbaceous	340-650	739-1346	1455-1835	1948-2299
A. afra vs bare ground	340-683	743-1327	1459-1859	1970-2346

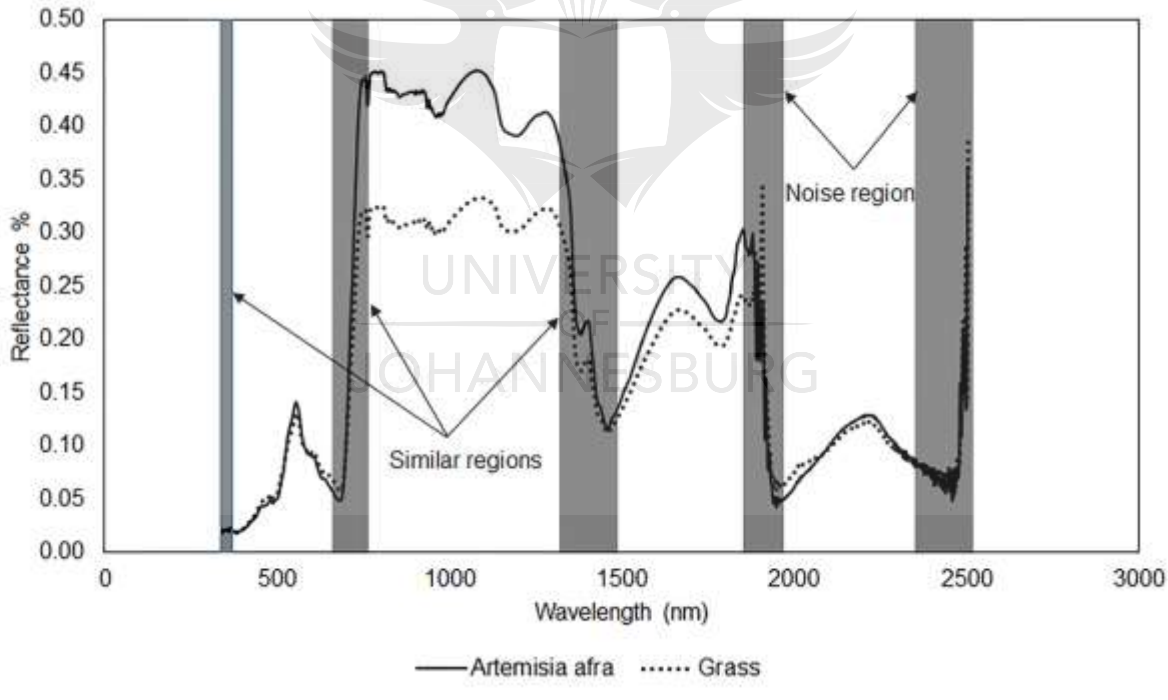


Figure 4: An example of global reflectance of *A. afra* and grass showing comparison of full spectrum.

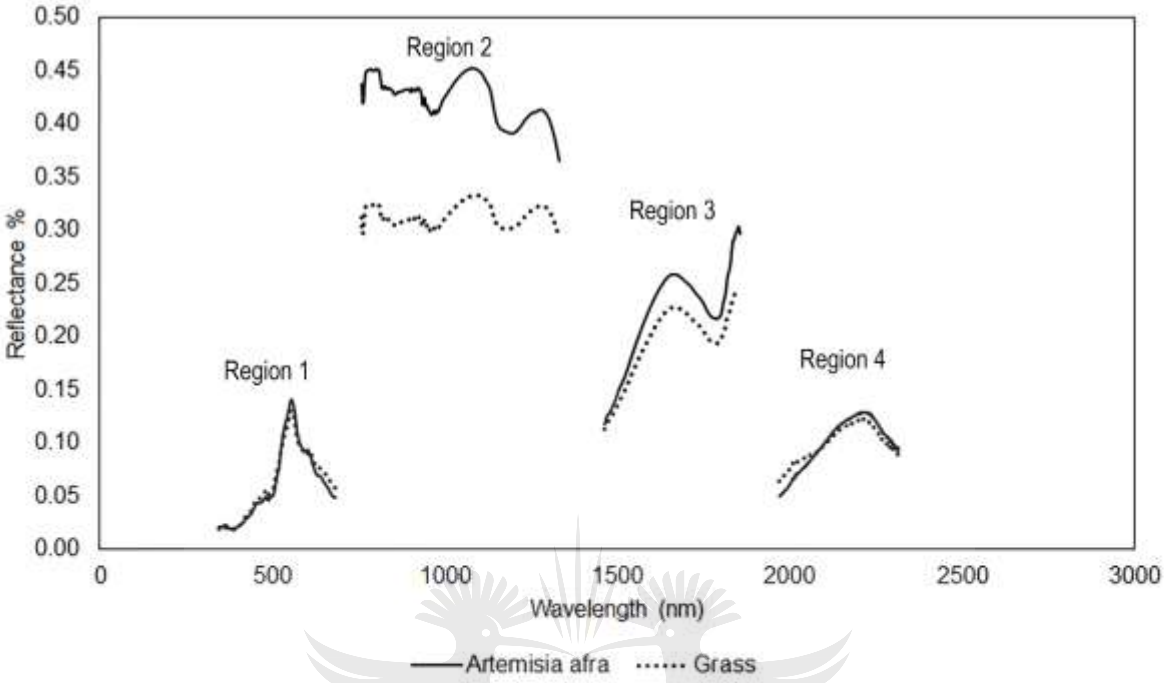


Figure 5: An example of global reflectance of *A. afra* and grass, representing wavelength regions used for further analysis.

Comparison of reflectance between *A. afra* and adjacent land cover types was done both at individual and plot levels. The individual level of analysis involved comparison of *A. afra* and adjacent land cover types encountered at each 5m interval in all plots. Plot level analysis compared plot level mean reflectance of *A. afra* against plot level mean reflectance of dominant the adjacent land cover type. These comparisons focussed on the four regions that were determined based on the global mean wavelength ranges (Table 1). Thus, spectra of the four regions were extracted for *A. afra* and adjacent land cover types for the individual level analysis. Likewise, spectra of the regions defined by the global spectra were extracted from the plot level mean spectra for analysis at the plot level. Graphical methods and statistical significance tests such as Analysis of Variance (ANOVA) and t-test were used to compare spectra of *A. afra* and adjacent land cover types. Least Significant Difference (LSD) test was used in the ANOVA analysis.

3.2.4. Simulation of Landsat and SPOT 5 imagery bands

Reflectance data acquired by the field spectrometer were extracted for wavelength regions corresponding to Landsat and SPOT 5 imagery bands. This simulation is a preliminary attempt to investigate the potential of upscaling field-based remote sensing to airborne or satellite based imaging remote sensing. Although Landsat 5 and later missions have seven or more bands, only blue, green, red and near-infrared bands were simulated while three spectral bands including green, red and near-infrared bands of SPOT 5 imagery were simulated (Table 4). Emphasis was placed on these bands, since they are widely used in the assessment of photosynthesis.

Table 4: Simulated data for Landsat and SPOT 5 remote sensing technologies

Simulated bands	*Wavelength range (nm)*	
	Landsat	*SPOT 5*
Blue band	450.4- 520.8	N/A
Green band	520.8- 600.7	500-590.7
Red band	630.5- 689.9	610.7-680.3
NIR band	759.9- 900.1	790.4-890.1

The simulation was done for all individual plants of *A. afra* and adjacent land cover types. Thus, four separate pools of simulated bands were created, representing *A. afra*, grass, herbaceous plants and bare ground. Subsequently, comparisons were made at both individual level and at the group-level. While the individual level analysis compared the four pools, the group level compared comparison simply compared *A. afra*, against all other land cover types combined together. All comparisons were made using ANOVA or t-test.

3.3. Results

3.3.1. Reflectance properties per region

Grasses represented the majority of adjacent land cover types scanned by the spectrometer with eight plots while herbaceous and bare ground were the dominant covers in two plots each. Comparison of all individuals for each spectral region resulted in overall significant differences among all land cover types including *A. afra* and adjacent land cover types, based on ANOVA in all plots (Table 5). However, separate reflectance comparisons of each of the individuals per plot did not consistently show significant difference between *A. afra* and an adjacent land cover types. This can be seen in Figure 6. The graphs in Figure 6 show no distinct separation between *A. afra* and adjacent land cover types in the ultraviolet to visible spectral region (region 1). Similar results were observed for the NIR to SWIR (region 3) and the SWIR (region 4). In contrast, NIR (region 2) showed a more distinct separation between *A. afra* and adjacent land cover types whereby reflectance by individual plants of *A. afra* had higher values compared to adjacent land cover types in most cases. The separability tests using Least Significant Difference (LSD) further showed within species significance differences.

Table 5: ANOVA results showing spectral separability between *A. afra* and adjacent land cover typesof a typical plot

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	0.912683	25	0.036507	110.7938	0	1.509822
Within Groups	0.976658	2964	0.00033			
Total	1.889341	2989				

*SS=Sum of squares; df=Degrees of freedom; MS=Mean of squares; F=F variable; Fcrit=F critical value

Plot level comparisons using the t-test showed significant differences between *A. afra* and dominant adjacent land cover types in all plots (Figure 7). *A. afra* had higher reflectance than adjacent land cover types for 7 of 12 plots and 8 of 12 plots in the ultraviolet to visible region (region 1) and NIR region (region 2), respectively. Similarly, *A. afra* had higher reflectance than adjacent land cover types for 6 of 12 plots in the NIR to SWIR region (region 3) and SWIR region (region 4). The plant's spectral reflectance was notably higher in NIR region (region 2) than other regions.

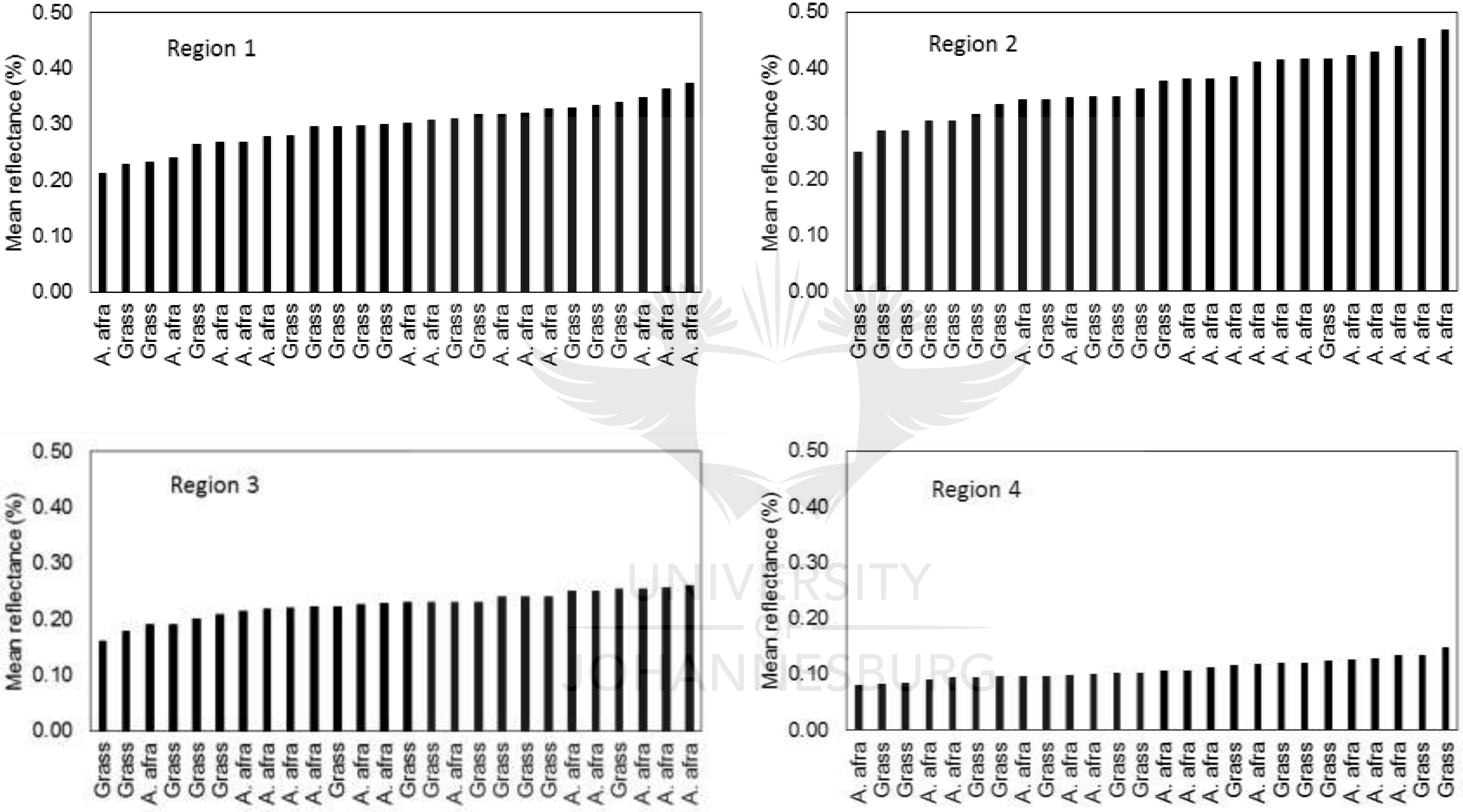


Figure 6: Reflectance of the regions used for analysis at individual plant level for a typical plot.

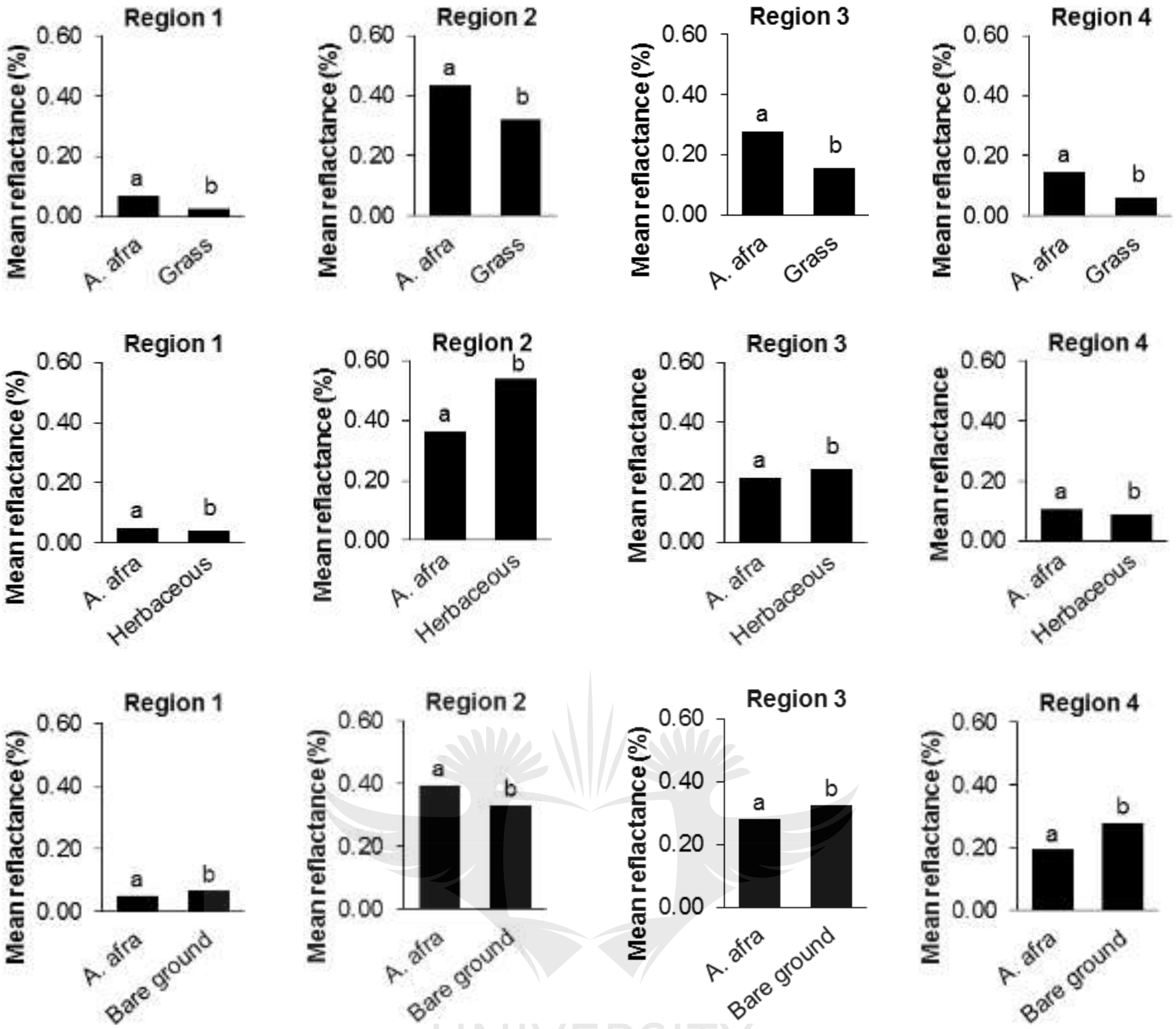


Figure 7: Plot level mean reflectance of *A. afra* and adjacent land cover types. Different letters represent spectral significant differences at α=0.05. Note that the comparisons are per region and per plot.

3.3.2. Landsat simulation

Individual level analysis using ANOVA showed an overall significant difference among all land cover types, including *A. afra* and adjacent land cover types (i.e. grass, herbaceous and bare ground grouped separately) in the landsat simulated red and NIR bands. There were however no significant differences in the blue and green bands. Pairwise comparisons between *A. afra* and individual adjacent land cover types showed significant differences in all bands, based on LSD (Figure 8). Grass had higher reflectance than *A. afra* in all bands, except for the NIR band (Figure 8). All plants had relatively higher reflectance in the NIR band compared to other bands.

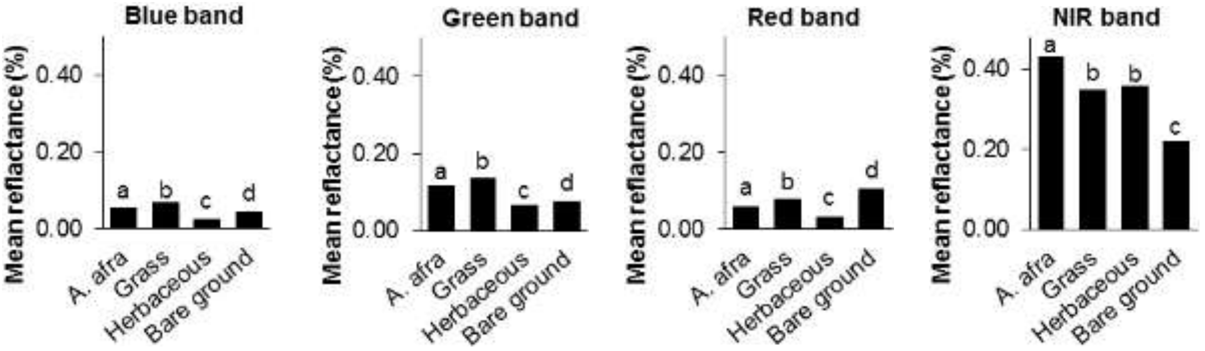


Figure 8: Mean reflectance of simulated Landsat bands per land cover type (individual level). Different letters represent spectral significant differences at α=0.05. Note that the comparison are per spectral band.

Group level analysis using t-test showed significant difference between *A. afra* and combined adjacent land cover types in the red and NIR bands, whilst there were no significant differences in the blue and green bands. Combined adjacent land cover types had higher reflectance than *A. afra* in the blue, green, and red bands, while the opposite was observed in the NIR band (Figure 9). Spectral reflectance of *A. afra* and combined adjacent land cover types was relatively higher in the NIR band than other bands.

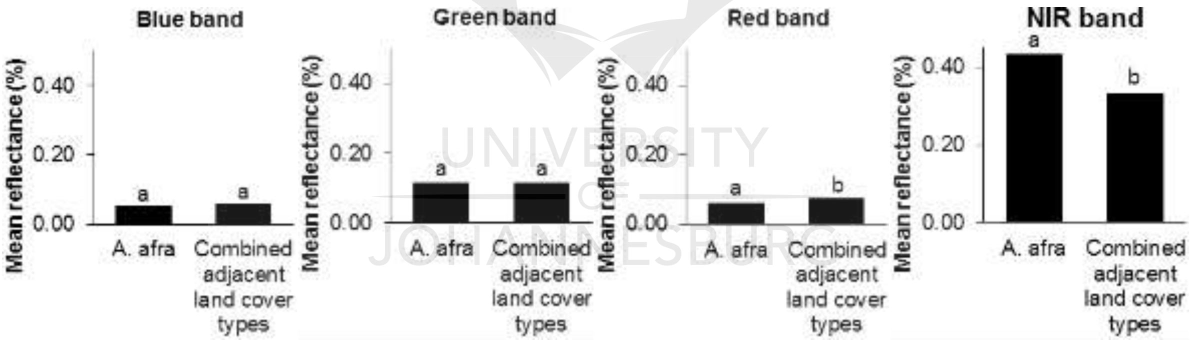


Figure 9: Mean reflectance of simulated Landsat bands of *A. afra* vs. grouped land cover types (group level). Different letters represent spectral significant differences at α=0.05. Note that the comparison are per spectral band.

3.3.3. SPOT 5 simulation

Individual level analysis using ANOVA showed an overall significant difference among all cover types, including *A. afra* and adjacent land cover types (i.e. grass, herbaceous and bare ground grouped separately) in the red and NIR SPOT simulated bands. There were no significant differences in the green band. Pairwise comparison between *A. afra* and adjacent land cover types showed significant differences in all bands, based on LSD (Figure 10). Grass had higher reflectance than *A. afra* in all bands, except for the NIR band (Figure 10).Spectral refectances of all plants turned high in the NIR band compared to other bands.

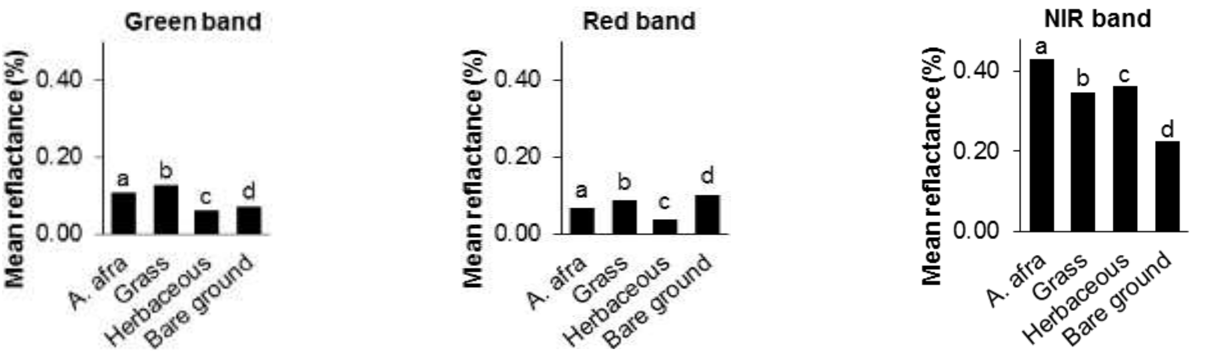


Figure 10: Mean reflectance of simulated SPOT 5 bands per land cover type (individual level). Different letters represent spectral significant differences at α=0.05. Note that the comparisons are per spectral band.

Group level analysis using t-test showed significant between *A. afra* and combined adjacent land cover types in the NIR band, while there was no significant difference in the green and red bands (Figure 11). Combined adjacent land cover types had higher reflectance than *A. afra* in the blue, green, and red bands, while the opposite was observed in the NIR band (Figure 11). *A. afra* and combined adjacent land cover types had higher reflectance in the NIR band compared to other bands.

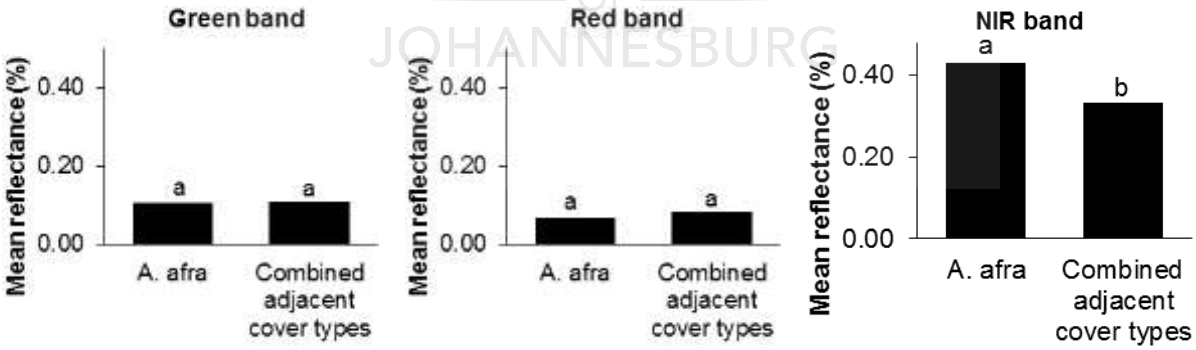


Figure 11: Mean reflectance of simulated SPOT 5 bands of *A. afra* vs. grouped land cover types (group level). Different letters represent spectral significant differences at α=0.05. Note that the comparisons are per spectral band.

3.4. Discussion

This study intended to investigate the utility of field spectroscopy to discriminate *A. afra* from adjacent land cover types. Comparisons of reflectance between *A. afra* and adjacent land cover types were made using original spectra as well as spectra simulated based on Landsat and SPOT 5 bands. Graphs using regions selected from the global spectra showed no clear reflectance differences in ultraviolet to visible wavelength region, SWIR region, with some differences in NIR to SWIR region (Figure 5). There was however, a remarkable difference between *A. afra* and adjacent land cover types in the NIR region (Figure 5).

ANOVA results showed overall significant difference between *A. afra* and adjacent land cover types in all plots for all the regions at individual level analysis. But it was not clear which individual pairs influenced such differences, because significant differences occurred even between individuals of *A. afra* when compared using LSD. This can also be seen from graphical observation of mean reflectance values of all individual land cover types as illustrated by a typical plot containing *A. afra* and grass in Figure 6. For example, there was no distinct reflectance pattern for *A. afra* and adjacent land cover types in ultraviolet to visible region (region 1). This can be explained by the fact that there were strong similarities in reflectance in the wavelength region between 350–680 nm between *A. afra* and adjacent land cover types (Figure 5). Similarly, the inability to differentiate *A. afra* and adjacent land cover types in the NIR to SWIR region (region 3) (Figure 6) can be attributed to the spectral comparability between *A. afra* and adjacent land cover types between 1463 and 1600 nm, while the difference is greater between 1600 and 1855 nm (Figure 5). SWIR region (region 4) did not allow differentiating *A. afra* from adjacent land cover types at the individual-level analysis (Figure 6). This region reflectance pattern of *A. afra* and adjacent land cover types showed association with slight overlaps, which could have contributed to the observed results (Figure 5).

Comparisons using t-test at plot levels showed significant differences in all spectral regions used for analysis in all plots (Figure 7). It should, however, be noted that all plants had higher reflectance in the NIR region compared to other regions. But *A. afra* returned a relatively high reflectance in this region. Generally, plants with high chlorophyll content absorb electromagnetic radiation in ultraviolet and visible wavelengths, and reflect more in the NIR (Manevski et al., 2011; Mirik et al., 2013). Vegetation reflectance and bare ground reflectance on the other hand differ in the

SWIR region because of electromagnetic radiation absorption in plants due to presence of cellulose which is absent in bare ground (Daughtry et al., 2006; Guerschman et al., 2009; Nagler et al., 2000; Serbin et al., 2009). Higher reflectance by *A. afra* in the NIR region could be an indication of higher chlorophyll content than adjacent land cover types. Certain factors that were encountered during sampling could have played a role as well. Firstly, not all plants were in the same phenological stages, and thus might have possessed different physiological structures that induced differences in spectral reflectance. Secondly, there were instances where spectral measurements were taken in overcast conditions or when there were slight cloud covers. Thirdly, nearly all samples had a certain degree of impurity in terms of land cover types (vegetal cover or bare ground), making the comparisons among land cover types imperfect.

Results comparing *A. afra* and adjacent land cover types using Landsat and SPOT 5 simulated spectra are encouraging (Figure 8, 9, 10 and 11). The ability to differentiate the species from another relatively homogenous co-existing plant (Figure 8 and 10) may not be surprising; however, it is not common to observe such homogeneity in a natural environment such as the area of interest of this study. On the other hand, the results comparing the species against all co-existing plants combined (Figure 9 and 11) are promising, as it indicates the potential of using remotely sensed image to differentiate the species from adjacent land cover types. There was, however, difference in significance level between SPOT 5 and Landsat simulated red bands when differentiating the species from adjacent land cover types. This is related to variation in the width of the band, whereby SPOT 5 had a wider range that approaches the green region of Landsat (Table 3). It should be noted that the green region in both simulations returned insignificant difference of all the simulated bands, the NIR returned higher (and significantly different) reflectance than adjacent land cover types indicating the importance of placing more emphasis on this band for further studies.

Our results compare favourably with other studies. For example, Manevski et al. (2011), Ouyang et al. (2013), and Schmidt and Skidmore (2003) found the NIR region to be the best for discriminating between different plant species. A more similar species to our study was done by Dammer et al. (2013) who reported the discrimination ability of plant species (*Ambrosia artemisiifolia* and *Artemisia vulgaris*) belonging to the Asteraceae family (same family as *A. afra*) using 550 and 650 nm wavelengths (visible region). On the other hand Mirik et al. (2013) used hyperspectral imagery and successfully discriminated a species in the Asteraceae family against other land cover types. This particular study also reported significantly higher reflectance for the species than other plants including grass and bare ground in the NIR region.

3.5. Conclusion

This chapter aimed at determining whether or not *A. afra* could be differentiated from adjacent land cover types in the Klipriviersberg Nature Reserve using a field spectrometer. Separability was tested using spectral reflectance of *A. afra* and adjacent land cover types, wherein analysis was done at individual and plot level. Reflectance was simulated for the bands of Landsat and SPOT 5 to see the potential of the two sensors for mapping *A. afra*. *A. afra* and adjacent land cover types were best discriminated in the NIR waveband region for comparisons at both individual and plot level analysis. The inability of differentiating the species from adjacent plants at the individual level in visible, NIR to SWIR and shortwave infrared regions (Figure 6) is noteworthy. This can in part be solved by changing the arbitrarily and visually decided regions. This could however be an iterative process that may involve trial and error analyses. It is important to take other factors of the study into consideration, too. The comparisons between the species and adjacent land cover types were not necessarily made in ideal scenarios. Further studies therefore need to be conducted by creating scenarios such as using homogenous land cover types similar to a laboratory set-up and making spectral measurements during ideal time-frames when there is optimal electromagnetic illumination. It is also important to undertake laboratory analysis to make conclusive remarks regarding spectral responses to variations in biochemical properties.

Results from the simulated reflectance spectra of both Landsat and SPOT 5 showed the NIR region as best in discriminating *A. afra* from adjacent land cover types. This paves the way for further studies to investigate the ability of remotely sensed data (e.g. SPOT 5 and Landsat) images to map the species. It is however critical to increase the sample size for such analysis. This can be achieved by using imagery with high spectral resolutions such as SPOT 6 and 7 that have a 2.5 m spatial resolution.

CHAPTER 4

Assessing the potential of remote sensing to discriminate invasive *Asparagus laricinus* from adjacent land cover types

Abstract

The utility of remote sensing technique to discriminate *Asparagus laricinus* from adjacent land cover types using a field spectrometer data was explored in this chapter. Analysis was carried out using original spectra and spectra simulated based on Landsat and SPOT 5 bands. Regions that showed spectral differences between *A. laricinus* and adjacent land cover types were identified from global reflectance pair comparisons and used in further analyses. Analysis of variance (ANOVA) and t-test were used to compare reflectance differences at individual and plot level using original spectra, and at individual and group level using simulated spectra. The near infrared region showed strong reflectance differences between *A. laricinus* and adjacent land cover types at the individual level analysis. Landsat and SPOT 5 simulated spectra showed significant differences in only the NIR band, with insignificant differences in the green and red bands, including the blue band for Landsat simulation. Both original and simulated spectra showed the NIR region as best in differentiating *A. laricinus* from adjacent land cover types. Global reflectance pair comparison of the plant and each adjacent land cover showed substantial reflectance differences in this region. This result is in agreement with several other studies that successfully used the region to discriminate plant species. These findings suggest the potential of upscaling field-based data into airborne or spaceborne remote sensing techniques with more emphasis on the NIR band. However, more studies need to be undertaken that will make up for the shortcomings encountered in this study. In this regard, improvements can be made by using large number of samples, stratifying target plants according to phenologies and taking spectral measurements at ideal times as much as possible. Furthermore, laboratory measurements would help in drawing up conclusive statements on the discriminability of the species or even draw up the spectral library of the species for further related studies. Profiling of biochemical contents of plants is suggested because they strongly influence on reflectance patterns.

4.1. Introduction

Invasive plants are a growing global concern (Richardson and Van Wilgen, 2004; Rouget et al., 2015; Schor et al., 2015; Vicente et al., 2013). These plants hold special characters that make them outcompete and replace indigenous vegetation, and have a potential of spreading to other areas (Bradley and Marvin, 2011; Mgidi et al., 2007; Van Wilgen, 2006). As a result, they compromise ecosystem stability, delivery of ecosystem goods and services, and threaten biodiversity and economic productivity (Van Wilgen, 2006; Van Wilgen et al., 2008, 2012b). Mitigating such effects is costly; South Africa, for example, spends considerable amounts of money in programs such as the Working for Water (WfW) which is mandated to control invasive plants.

Most invasive plant control measures focus primarily on established invasions and less attention is given to new infestations (Mgidi et al., 2007). The success of this practice is unsatisfactory, as effective management of invasive plants depends on early detection and eradication (Mgidi et al., 2007). One method of achieving early detection of plant invasions is through the use of spatial and temporal distribution maps (Dorigo et al., 2012). Traditional mapping methods can provide these maps, but the methods rely often on field inventories which are limited in spatial coverage, are time consuming and relatively expensive (Dewey et al., 1991; Dorigo et al., 2012; Rodgers et al., 2014).

Remote sensing methods make up for most inefficiencies of the traditional mapping methods and are used to characterise the spatial and temporal distribution of plants(Alparone et al., 2015; Campbell and Wynne, 2011; Galvão et al., 2011; Jensen, 2014; Lillesand et al., 2015). Remote sensing is the science of deriving information from electromagnetic energy reflected from objects on the ground (Alparone et al., 2015; Campbell and Wynne, 2011; Jensen, 2014). The method differentiates earth features using varying sensitivity of ground objects to electromagnetic radiation, often acquired within the visible, infrared and microwave regions of the electromagnetic spectrum (Campbell and Wynne, 2011; Lillesand et al., 2015). Several studies have used a variety of remote sensing techniques to study invasive plants (e.g. Adam and Mutanga 2009; Narumalani et al. 2009; Manevski et al. 2011; Martín et al. 2011; Bentivegna et al. 2012; Berg and Africa 2013; Abdel-Rahman et al. 2014; Adelabu et al. 2014; Mirik et al. 2014; Prasad and Gnanappazham 2014).

Plants have been mapped using multispectral remote sensing techniques in a number of studies (e.g. Laba et al. 2008; Vancutsem et al. 2009; Johansen et al. 2010; Lemke et al. 2011; Dronova et al. 2015). This method is good particularly for large spatial area mapping purposes (Azong et al., 2015; Cuneo et al., 2009; Dronova et al., 2015; Vancutsem et al., 2009). In comparison, hyperspectral remote sensing offers better accuracy levels of vegetation characterisation due to high spectral resolution and hyperspectral bands (Alparone et al., 2015; Carroll et al., 2008; Gavier-pizarro et al., 2012b; Huang and Asner, 2009; Jensen, 2014). For example, Bentivegna et al. (2012) detected invasive cutleaf teasel (*Dipsacus laciniatus* L.) in Missouri, United States of America using high spatial resolution (1 m) hyperspectral images (63 bands in visible to near-infrared spectral region). Mirik et al. (2013) explored the ability of hyperspectral imagery for mapping infestation of musk thistle (*Carduus nutans*) on a native grassland during the pre-and peak flowering stages using support vector machine classifier in Friona in Parmer County, United States of America. Ouyang et al. (2013) used a field spectrometer data to find most appropriate period for mapping invasive *Spartina alterniflora* by measuring its community and major victims at different phonological stages in Chongming Island, China. Similarly, Rudolf et al. (2015) developed a classification model to spectrally discriminate between invasive shrub *Acacia longifolia* from other non-native and native species using field-based spectra and condensed leaf tannin content in Portugues dune ecosystems, Portugal.

However, discrimination of plant species using hyperspectral data often places emphasis on identification of best specific bands for discrimination. These bands are narrow and cannot be separated in broad-bands of multispectral data. Hyperspectral remote sensing has grown significantly in the past few decades. However, its application in operational characterization is rather limited. Although there is a promise to translate research efforts of hyperspectral remote sensing into operational tools, current advances in data availability show that multispectral remote sensing remains the most important source of information in vegetation monitoring. Therefore, research efforts involving hyperspectral remote sensing analysis need to consider extending the technique into multispectral remote sensing techniques.

This study uses a continuum of hyperspectral bands to identify best wavelength regions for discriminating *Asparagus laricinus* from adjacent land cover types (Grass, Acacia, Herbaceous, and Mixture of herbaceous and bareground). As such, it focusses on spectral regions rather than identifying individual bands, in an attempt to simulate multispectral remote sensing systems. Specific objectives of the study are (1) to determine whether or not *A. laricinus* can be differentiated from adjacent land cover types using a field spectrometer data and (2) to investigate the performance of spectra simulated according to Landsat and SPOT 5 images in discriminating *A. laricinus* from adjacent land cover types. There is little or no studies that focussed on discriminating *A. laricinus* from other vegetation and land cover types. *A. laricinus* is a plant belonging to the Asparagaceae family and occurs in different parts of South Africa. However, the plant is not indigenous to South Africa and has a status of "list concern" in the South African National Biodiversity Institute (SANBI) national Red List of South African plants (Foden and Potter, 2005). Knowledge on the spectral and spatial characteristics of the species aids for developing better management strategies in areas where it invades. Such maps can also help traditional health practitioners and pharmaceutical industries to locate stands of the plant for medicinal purposes, as it also has medicinal uses (Fuku et al., 2013; Mashele and Kolesnikova, 2010; Ntsoelinyane and Mashele, 2014).

4.2. Methods

4.2.1. Study Area

The study was conducted in the Klipriviersberg Nature Reserve, in Johannesburg, South Africa (Figure 12). It covers an area of approximately 680 hectares in extent and is managed by the City of Johannesburg. The reserve lies in the Klipriviersberg area, a transition zone between the grassland and the savannah biome in the northern edge of the Highveld (Faiola and Vermaak, 2014). Climatic conditions experienced in the reserve vary from warm to hot summer (17–26 ºC) and cool to cold winter (5–7 ºC) (Kotze, 2002). Three geology types occur in the reserve, namely, basalt and andesite volcanic rocks that underlay the reserve; quartzites and conglomerates of the upper Witwatersrand system underneath the lavas in north of the reserve; and dolomites of the Transvaal system south of the reserve (Kotze 2002). The flora of the reserve is categorized into two broad vegetation types, the Andesite Mountain Bushveld and a section of Tsakane Clay Grassland at its flatter southern end (Faiola& Vermaak, 2014). There is relatively rich biodiversity with approximately 650 indigenous plant species, 215 bird species, 16 reptile species and 32 butterfly species. Mammals that occur in the reserve include Lesser potted Genet, African Civet, zebra, Red Hartebeest, Blesbok, Springbok, Duiker, Black Wildebeest, porcupines, meerkats and otters.

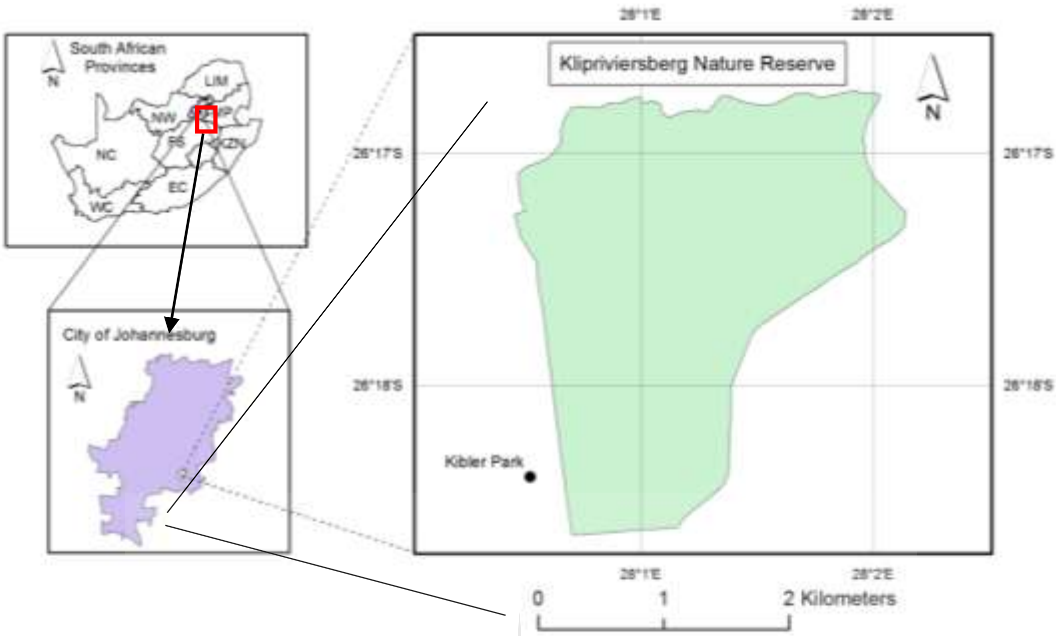


Figure 12: Map showing the Klipriviersberg Nature Reserve.

4.2.2. Field data

Field surveys were conducted between the 2nd and 14th of December 2014 during summer season of the area with the aim of characterising the vegetation in relatively high vigour condition (Lillesand*et al.* 2015). *A. laricinus* is found extensively in one part of the reserve while other occurrences are scattered in small spatial extents. Such a rather limited distribution resulted in delineation of 10 plots of 15 m radius each (Figure 13). The plot size was chosen with the anticipation of extending the investigation to space-borne remote sensing techniques. Each plot therefore accommodates at least one pixel of Landsat imagery (30 m resolution) and a number of SPOT 5 imagery pixels (2.5–10 m resolutions). The centre of each plot was recorded using GPS (Global Positioning System) with 3 m accuracy. A total of thirteen samples were taken randomly of which *A. laricinus* individuals varied between six to eight plants per plot. This sampling method was preferred as it was difficult walking through the thorny and dense stands of *A. laricinus*.

Spectral data were collected using Spectral Evolution®SR-3500 Remote Sensing Portable Spectroradiometer (Spectral Evolution Inc., Lawrence, MA, USA). The spectrometer has 1.6 nm spectral resolution that ranges between 340 nm and 2503 nm. Target radiance in energy unit was converted into percent reflectance using a white reference measurement (Prospere et al., 2014). Three spectral measurements were taken for each *A. laricinus* plant from different canopy parts at 4 cm above the canopy. All the measurements were taken at nadir to mimic a remotely sensed data (airborne and space-borne) viewpoint. Spectral measurements from adjacent land cover types were taken in a similar manner. These measurements should ideally be taken between 10:00 am and 2:00 pm when the sun is overheard to acquire electromagnetic radiation reflectance optimally (Cho et al., 2008; Fernandes et al., 2013; Mansour, 2013; Olssonet al, 2011; Rudolfet al, 2015). However, time constraints did not necessarily allow the application of this protocol and thus not all measurements were taken using this protocol.

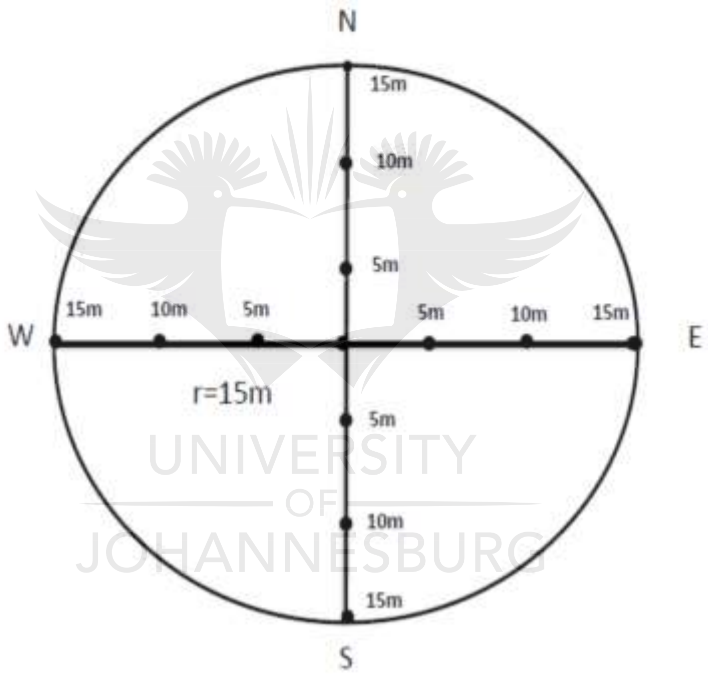


Figure 13: A layout of sampling design for spectral measurements of individual target plant.

4.2.3. Analysis of spectral reflectance per region

Analysis was limited to the regions that showed consistent spectral differences between *A. laricinus* and adjacent land cover types. In order to identify these regions an average spectrum was computed from the three spectral measurements taken from each target (*A. laricinus* and adjacent land cover type, respectively). The resultant average values were pooled per land cover type and averaged to generate 'global' spectral curves representing *A. laricinus* and each adjacent land cover type in the study area as illustrated (Figure 14). The global spectrum of *A. laricinus* was compared against each adjacent land cover types as illustrated for *A. laricinus* and grass in Figure 15. Please note not all global comparisons are presented in here for the sake of brevity. The global spectra of adjacent land cover types were computed to determine the potential discrimination of *A. laricinus* from them, since the species can co-exist with a mixture of land cover types in a natural environment. Comparison using global pairs is deemed a better representation of the study area than comparison of individual pairs that most likely yields results that are unable to converge to a compromise generic conclusion.

A visual assessment of the global spectra was used to determine regions that were considered unnecessary for differentiating *A. laricinus* and adjacent land cover types. Two rules were used to determine these regions. The first rule included regions that returned random reflectance properties commonly known as noise (*A. laricinus* vs Grass: 1873-1954 and 2351-2503 nm; *A. laricinus* vs Acacia: 1821-1956 nm and 2282-2503 nm; *A. laricinus* vs Herbaceous: 1838-1942 nm and 2272-2503 nm; *A. laricinus* vs Mixture of herbaceous and bare ground: 1831-1970 nm and 2351-2503 nm). The second rule included regions that did not show spectral reflectance difference between *A. laricinus* and adjacent land cover types (*A. laricinus* vs Grass: 340-343, 684-750 nm and 1350-1824 nm; *A. laricinus* vs Acacia: 650-749 and 1331-1448 nm: *A. laricinu*s vs Herbaceous: 340-387, 641-748 nm and 1316-1448 nm; *A. laricinus* vs Mixture of herbaceous and bare ground: 340-467, 685-745 nm and 1357-1455 nm). These exclusions resulted in four discontinuous regions (Table 6, Figure 16) based on which spectra of individual targets (individuals of *A. laricinus* and adjacent land cover types) were used in further analyses.

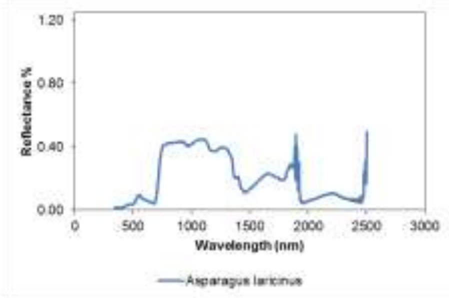
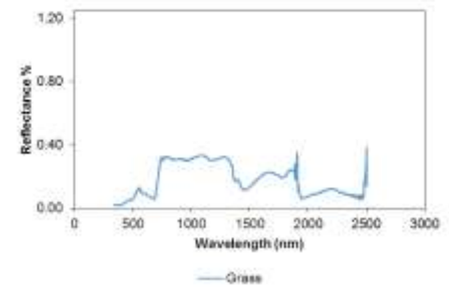
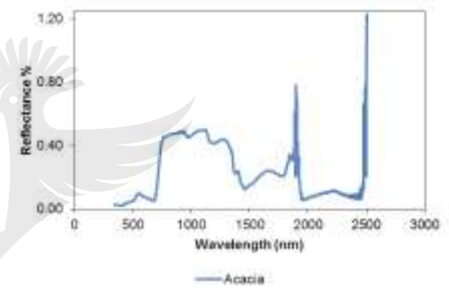
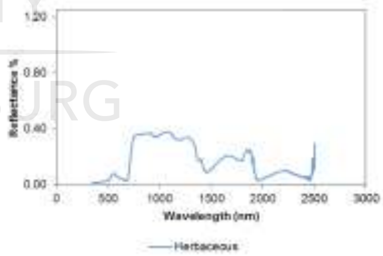
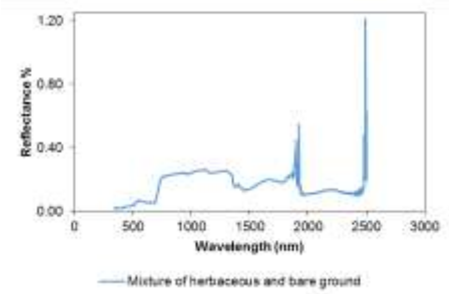
Pictures	Global reflectance
 *Asparagus laricinus*	
 Grass	
 Acacia	
 Herbaceous	
 Mixture of herbaceous and bare ground	

Figure 14: Global spectra of *A. laricinus* and adjacent land cover types

Table 6: Wavelength regions used in the analysis

Comparison pairs	*Wavelength regions*			
	Region 1 (Ultraviolet & Visible), nm	*Region 2 (NIR), nm*	*Region 3 (NIR & SWIR), nm*	*Region 4 (SWIR), nm*
A. laricinus vs Grass	345-683	752-1346	1828-1872	1956-2349
A. laricinus vs Acacia	340-648	750-1327	1452-1817	1959-2279
A. laricinus vs Herbaceous	389-640	749-1312	1452-1835	1945-2269
A. laricinus vs Mixture of herbaceous and bare ground	468-684	747-1354	1459-1828	1973-2349

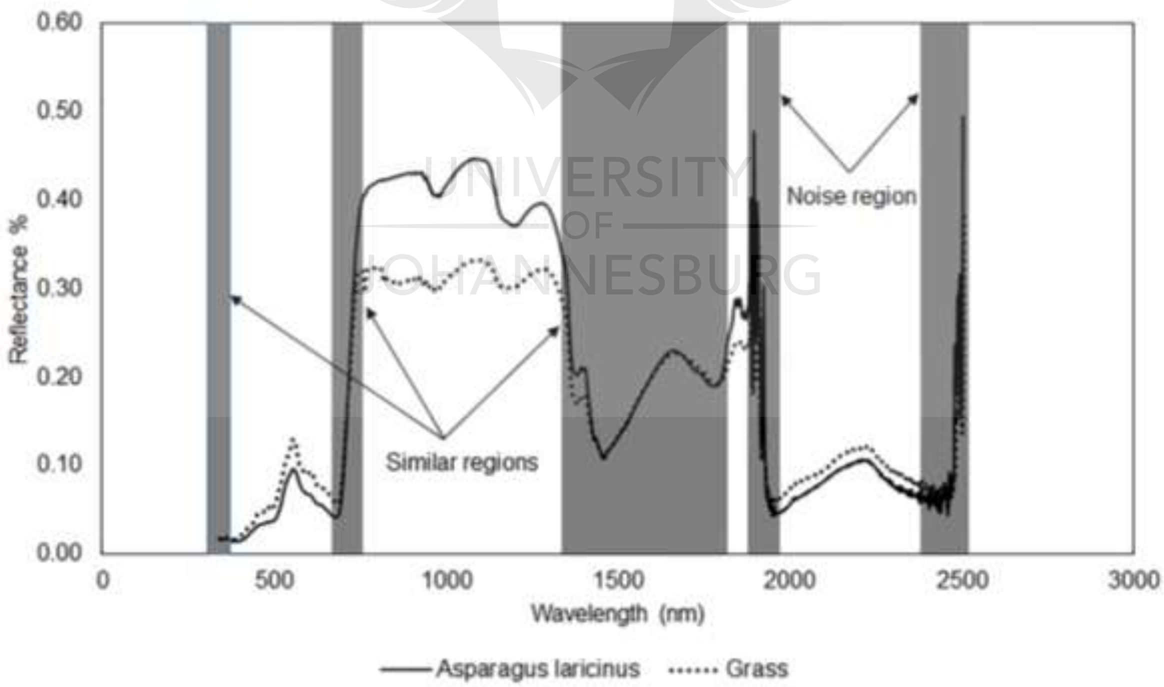


Figure 15: Global reflectance of *A. laricinus* and grass across the full spectrum. Highlighted regions show spectral parts excluded from further analysis.

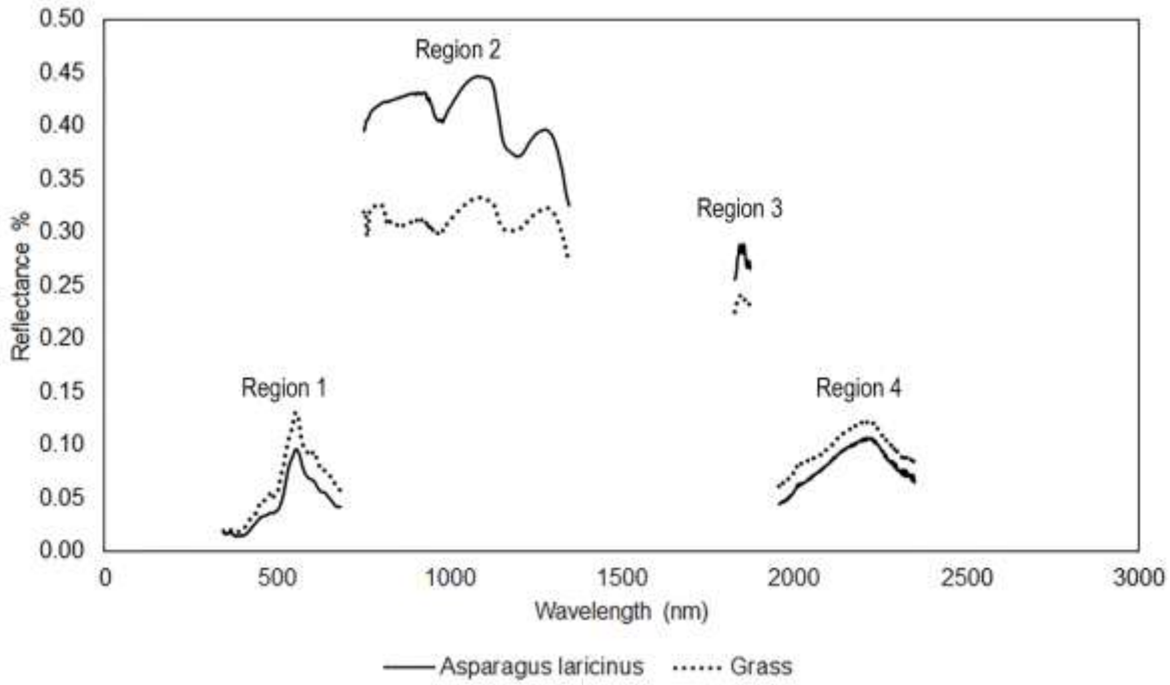


Figure 16: An example of global reflectance of *A. laricinus* and grass, representing wavelength regions used in further analysis.

Analysis involved comparison of reflectance between *A. laricinus* and adjacent land cover types at two levels, namely, individual and plot levels. Individual level comparison was made between *A. laricinus* and adjacent land cover type at each sampling point within each plot. On the other hand, plot level comparison was made between plot level mean reflectance of *A. laricinus* against plot level mean reflectance of dominant adjacent land cover type. Differences at both levels were assessed graphically and using statistical tests such as the analysis of variance (ANOVA) and t-test. The ANOVA analysis included use of Least Significant Difference (LSD).

4.2.4. Simulation of Landsat and SPOT 5 imagery bands

Wavelength regions corresponding to Landsat and SPOT 5 bands were extracted from the original reflectance spectra for all *A. laricinus* and adjacent land cover types. This was an initial step to testing the potential of upscaling field-based remote sensing information to airborne or satellite based remote sensing. Only blue, green, red, and NIR bands were simulated for Landsat while green, red, and NIR spectral bands were simulated for SPOT 5 imagery. The selected bands are widely used in the assessment of vegetation characteristics (e.g. Manevski et al. 2011; Mirik et al. 2013; Mirik et al. 2014). Five separate pools representing *A. laricinus*, grass, acacia, herbaceous, and mixture of herbaceous and bare ground were created. Reflectance comparisons were done at individual and group level. Individual level compared the pool of *A. laricinus* against separate pools of grass, acacia, herbaceous, and mixture of herbaceous and bare ground. The group level compared *A. laricinus* pool against combined pool of adjacent land cover types. Spectral differences were assessed using ANOVA and t-test.

4.3. Results

Individual level comparisons between *A. laricinus* and adjacent land cover types resulted in an overall significant difference in all plots for each spectral region, based on ANOVA results. However, separate reflectance comparisons of each of the individuals per plot showed inconsistent significant differences. Distinct spectral separability between *A. laricinus* and adjacent land cover types was observed mostly in the NIR region (region 2), with seven of 10 plots. In contrast, only two in the ultraviolet to visible (region 1), three in the NIR to SWIR (region 3) and five in the SWIR (region 4) regions showed clear separation. These differences are illustrated in Figure 17 which shows spectral reflectance differences between *A. laricinus* and grass for one plot. The distinct separation between *A. laricinus* and adjacent land cover types in the NIR region (region 2) is shown by higher reflectance of *A. laricinus* than other land cover types (Figure 17).However, individual comparison using the Least Significance Difference (LSD) showed significant differences even between individuals of same species differences per plot.

Grasses represented majority of land cover types at plot level analysis (seven of 10 plots) while Herbaceous, Acacia and Mixture of ground and herbaceous were dominant in each of the remaining plots. Comparison at this level resulted in significant differences in all plots based on t-test results as illustrated in Figure 18. In most cases, *A. laricinus* had higher reflectance than adjacent land cover types in the NIR region (region 2) in eight of 10 plots. The species had higher reflectance in five plots in the ultraviolet to visible (region 1), six plots in the NIR to SWIR (region 3) and five plots in the SWIR region (region 4). All plants further returned high significant difference in the NIR region (region 2), particularly *A. laricinus*.

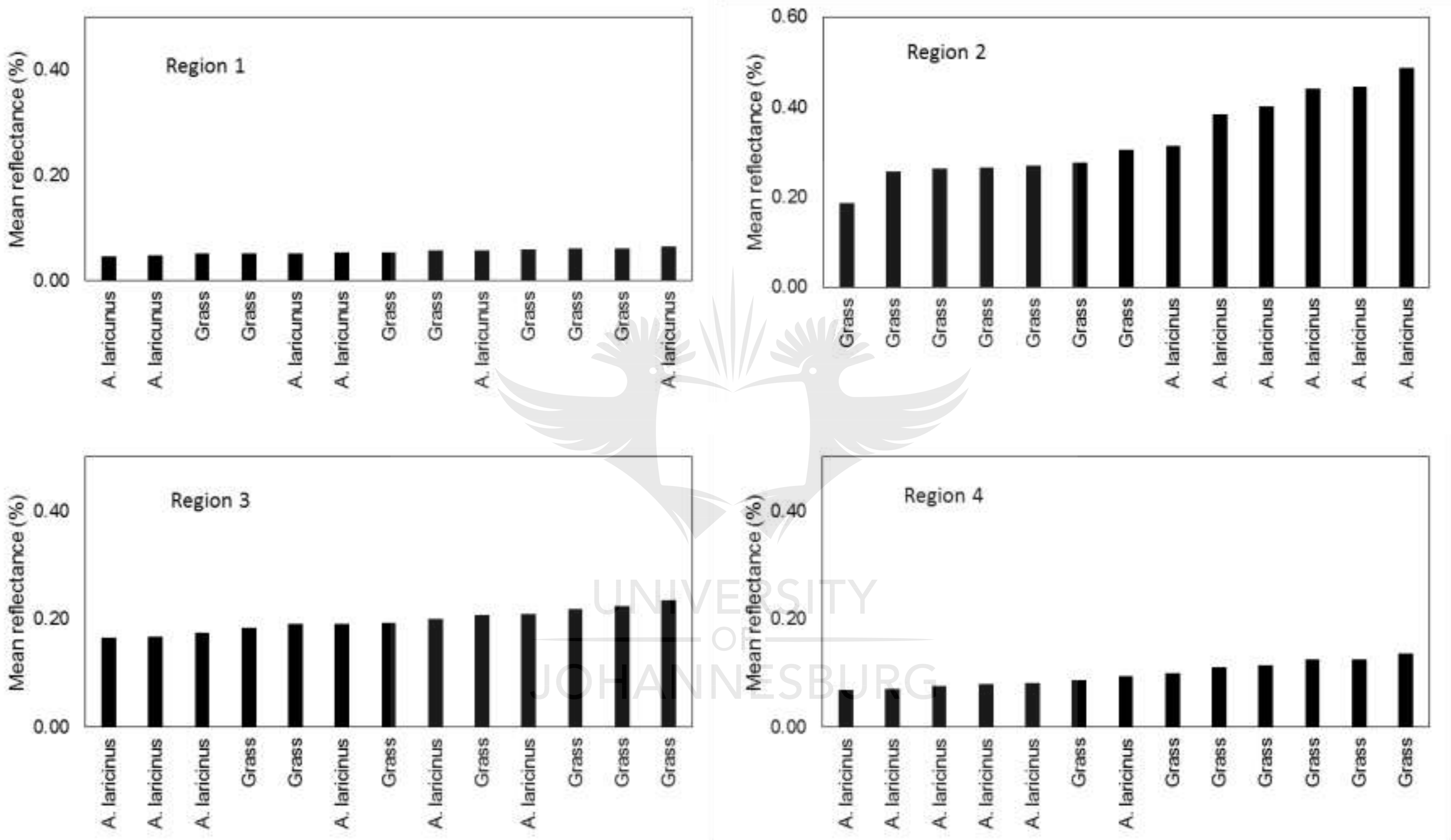


Figure 17: Reflectance of the regions used for analysis at individual plant level for a typical plot at α=0.05.

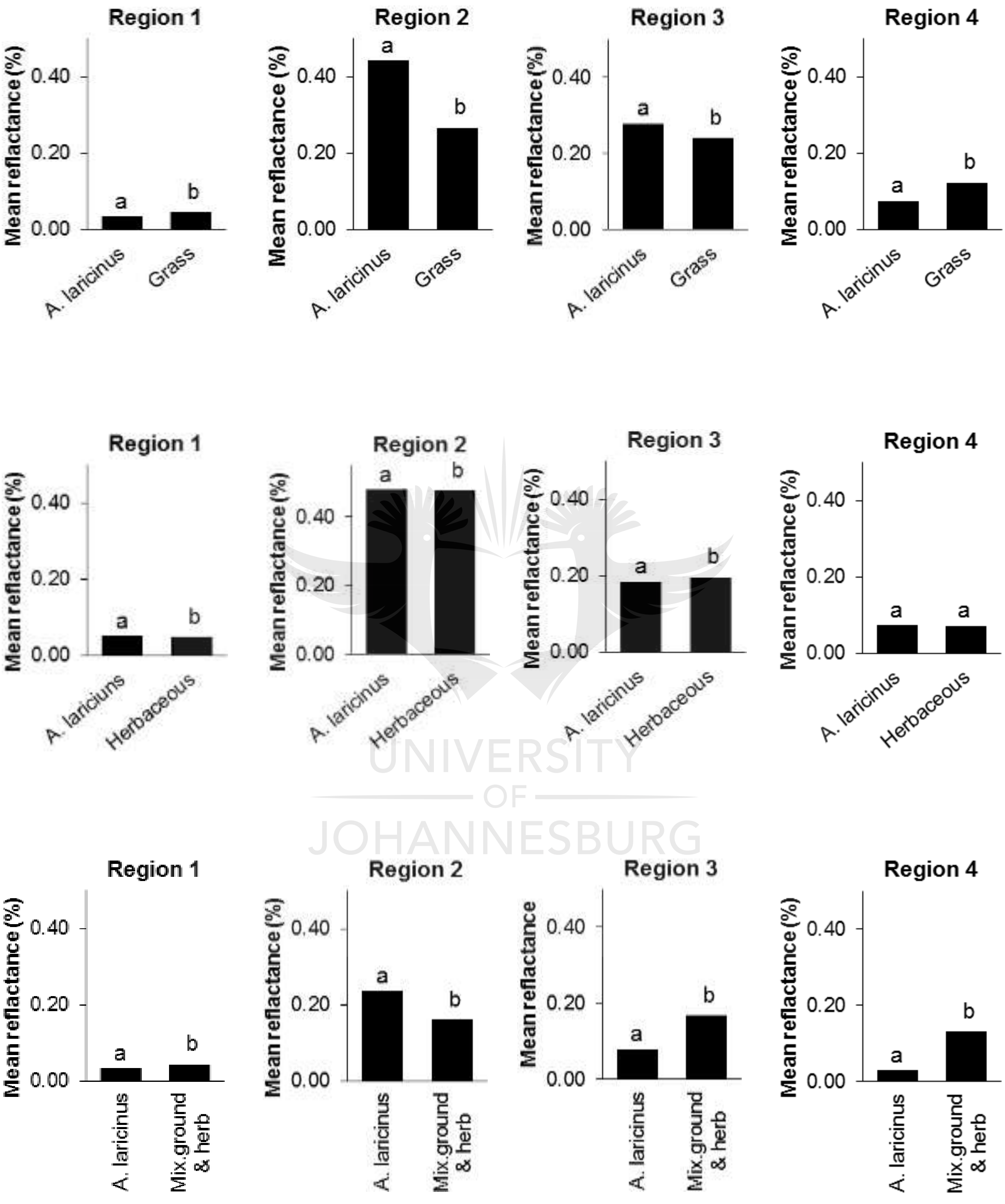


Figure 18: Plot level mean reflectance of *A. laricinus* and adjacent land cover types. Different letters indicate spectral significant differences at α=0.05. Note that the comparisons are per region and per plot. (Mix. ground & herb= Mixture of herbaceous and bare ground).

4.3.1. Landsat simulation

Comparisons between *A. laricinus* and adjacent land cover types at the individual level resulted in an overall significant difference in all Landsat simulated bands (blue, green, red, and NIR), based on the ANOVA results. Individual pair comparsions using LSD resulted in significant difference between *A. laricinus* and all land cover types in most cases (Figure 19). Similarities were however observed between *A. laricinus* and grass in the blue and red bands, and between *A. laricinus* and herbaceous vegetation in the green band (Figure 19). *A. laricinus* had higher reflectance than other adjacent land cover types with exception of Acacia in the blue band, Acacia and herbaceous in the green and NIR bands, and Acacia and grass in the red band. But, there was a notably high reflectance of plants in the NIR band compared to other bands.

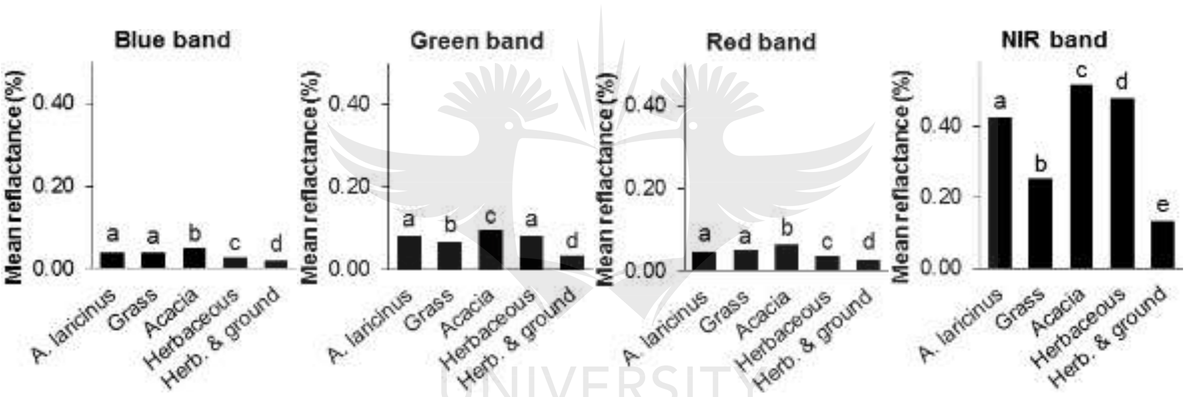


Figure 19: Mean reflectance of simulated Landsat bands per land cover type (individual level). Different letters indicate spectral significant differences at α=0.05. Note that the comparison are per spectral band. (Herb. & ground=Mixture of herbaceous and bare ground).

Comparison of reflectance at the group level between *A. laricinus* and combined adjacent land cover types resulted ininsignificant difference in the blue, green, and red bands while the difference was significant in the NIR (Figure 20). *A. laricuns* had higher reflectance than combined adjacent land cover types in the green and NIR band, while it had lower reflectance in the blue and red bands (Figure 20). All plants had high reflectance in the NIR band in relation to other bands.

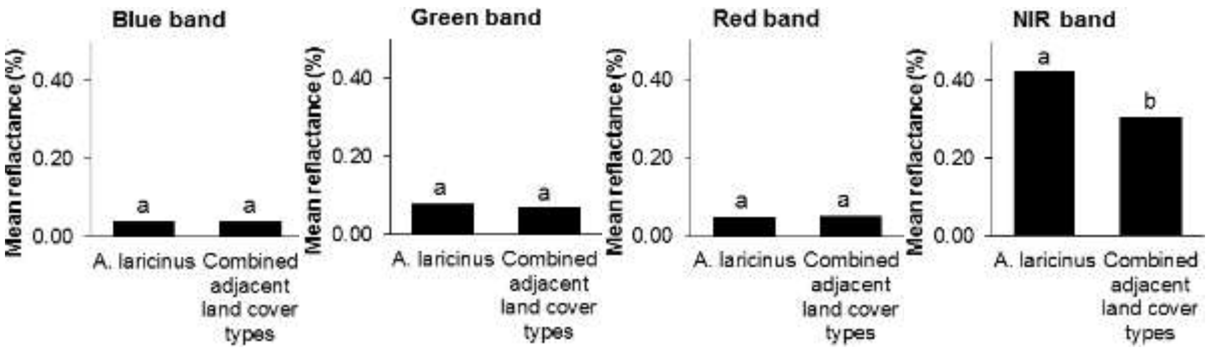


Figure 20: Mean reflectance of simulated Landsat bands per land cover type (Group level). Different letters indicate spectral significant differences at α=0.05. Note that the comparison are per spectral band.

4.3.2. SPOT 5 simulation

Reflectance comparisons of SPOT 5 simulated bands resulted in overall significant differences in all bands, based on ANOVA. Individual pair camparison using LSD showed significant differences between *A. laricinus* and adjacent land cover types in all bands, except for comparison between *A. laricinus* and herbaceous vegetation in the green band as well as between *A. laricinus* and grass in the red band (Figure 21). *A. laricinus* had a relatively high reflectance in all bands. However, it had lower reflectance than Acacia plants in all bands and herbaceous vegetation in the green and NIR bands, and grass in the red band (Figure 21). But, in the NIR band all plants had high reflectance compared to other bands.

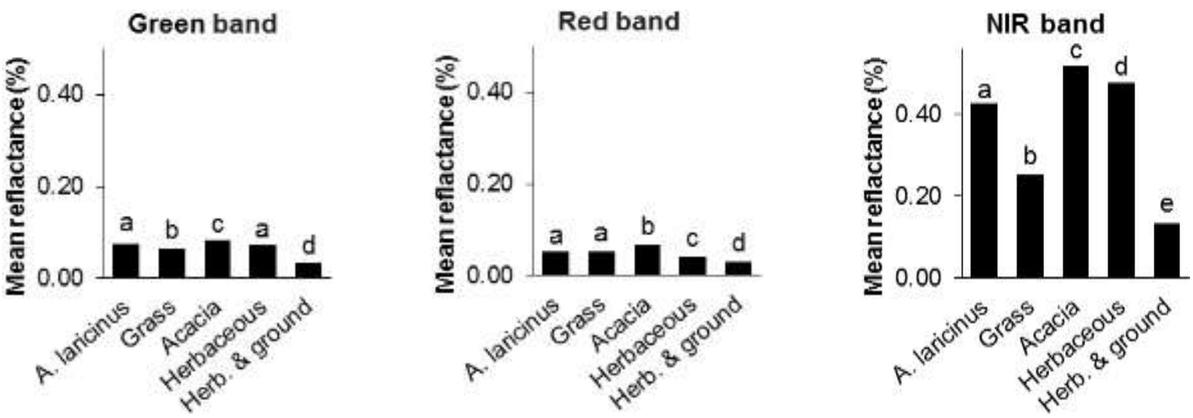


Figure 21: Mean reflectance of simulated Landsat bands per land cover type (individual level). Different letters indicate spectral significant differences at α=0.05. Note that the comparison are per spectral band. (Herb. & ground= Mixture of herbaceous and bare ground)

Group level compararions between *A. laricinus* and combined adjacent land cover types showed significant difference in only the NIR band (Figure 22). *A. laricinus* had higher reflectance than combined adjacent land cover types in the green and NIR bands while it had lower reflectance in the red band (Figure 22). Both *A. laricinus* and grass had high reflectance in the NIR red compared to other regions.

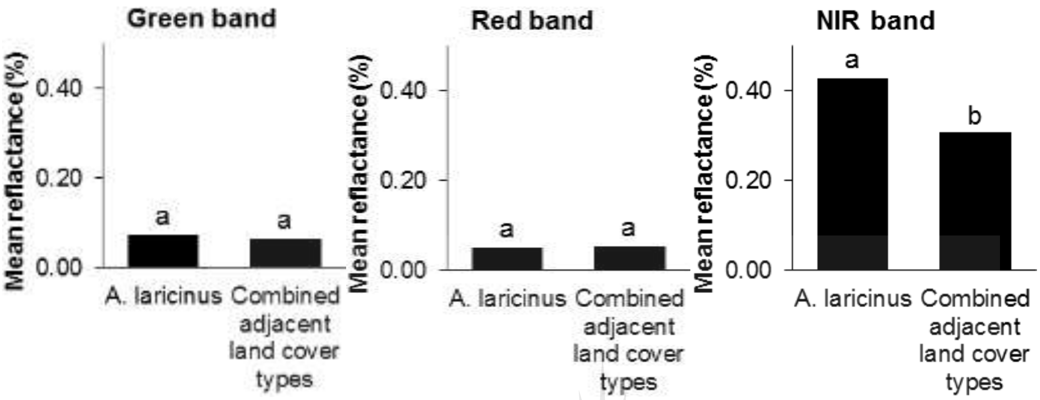


Figure 22: Mean reflectance of simulated Landsat bands per land cover type (Group level). Different letters indicate spectral significant differences at α=0.05. Note that the comparison are per spectral band.

4.4. Discussion

The utility of a field-based spectral data to discriminate *A. laricinus* from adjacent land cover types was investigated in this study. Investigations were made using original spectra and spectra simulated based on bands of Landsat and SPOT 5 images. These simulations were intended to assess the potential of upscaling the technique to spaceborne remote sensing techniques. Analyses were done at individual and plot levels using original spectra, and individual and group level for the simulated spectra. Visual comparisons using global pair reflectance of *A. laricinus* and each adjacent land cover type showed differentiation in the ultraviolet to visible (region 1), NIR (region 2), NIR to SWIR (region 3) and SWIR (region 4) spectral regons, but the difference was considerable in the NIR region (e.g.Figure 16). *A. laricinus* had high reflectance in NIR (region 2) and NIR to SWIR (region 3) and low reflectance in ultraviolet to visible region (region 1) and SWIR region (region 4) when compared with grass. *A. laricinus* reflectance was high in all regions when compared with herbaceous, while it was high in ultraviolet to visible (region 1), NIR (region 2) and NIR to SWIR (region 3) when compared with mixture of bare ground and herbaceous plants, but it was low in all regions when compared with Acacia. All these wavelength regions are considered best at characterising vegetation types (e.g. Cho et al., 2008; Ouyang et al., 2013; Pu et al., 2012; Schmidt and Skidmore, 2003). The far SWIR region on the other hand is considered best at discriminating between photosynthetic, non-photosynthetic vegetation and ground due to spectral absoption attributable to presence of cellulose in healthy vegetation (Daughtry et al., 2006; Guerschman et al., 2009; Nagler et al., 2000; Serbin et al., 2009).

The overall significanct differences observed for individual level comparsions per plot are not attributable to reflectance difference between *A. laricinus* and adjacent land cover types. This is because significant differences were observed even within individuals of same land cover types, based on pairwise comparison using LSD. There were further inconsitent singnificant differences when comparing individuals per plot seperately. As such, distinct seperation between *A. laricinus* and adjacent land cover types was mostly achieved in the NIR region, for 7 of 10 plots, while ony few plots showed clear speration in the ultraviolet to visible region, NIR to SWIR, and SWIR regions (Figure 17). Consistent significance difference observed in the NIR region was somewhat expected, given the distinct reflectance differences between *A. laricinus* and adjacent land cover types from the global spectra comparisons (e.g. Figure 16).

The plot level differences between *A. laricinus* and dominant adjacent land cover types were considerable particularly between *A. laricinus* and grass as well as *A. laricinus* and mixture of herbaceous vegetation and bare ground (e.g. Figure 18). The differences were some what expected given different global reflectance patterns of *A. laricinus*, grass and mixture of herbaceous vegetation and bare ground (Figure 14). In contrast, the differences between *A. laricinus* and herbaceous were lower, although they were significant in the visible, NIR and lower end of SWIR regions. This can as well be explained by the global reflectance resemblance of *A. laricinus* and herbaceous (Figure 14). Another noteworthy observation at the plot level was the fact that the magnitude of reflectance of *A. laricinus* was greater than for herbaceous vegetation in the ultraviolet to visible (regions 1), NIR region (region 2) and SWIR (region 4), and smaller in NIR to SWIR (region 3). This is the opposite of what were observed in comparisons between *A. laricinus* and grass as well as *A. laricinus* and a mixture of herbaceous vegetation and bare ground. This dissimilarity can be attributed to the relatively heterogenous species composition of herbaceous plants within a plot. In contrast, grass and bare grounds can be comparatively considered homogenous land cover types, respectively, having marked spectral difference with *A. laricinus*.

The significant difference between *A. laricinus* and adjacent land cover types using the Landsat and SPOT 5 simulated bands achieved at the individual level analysis (Figure 19 to 22) was anticipated, given the distinct homogeneous set-up of *A. laricinus* and adjacent landcover types. This setting does, however, occur rarely in an ideal natural environment where plant of different species co-exist. Unlike individual level analysis which showed significant differences in all bands (Figure 19 and 21), only the NIR band showed significant difference at group level (Figure 20 and 22). These results showed the potential of discriminating *A. laricinus* from adjacent land cover types using this band which is available in most remotely sensed data. This agrees with a study that classified *Asparagus officinalis* (a species that belongs to the same family as *A. laricinus*) successfully using Landsat imagery (Tatsumi et al., 2015).

The NIR band was most useful in discriminating between *A. laricinus* and adjacent land cover types. This is not suprising as the band has been widely used in discriminating between plant species in a number of studies. For example, *A. officinalis* was succesfully identified using NIR reflectance spectroscopy by Perez and Sanchez (2001). This region was used in studies on plants not related to *A. laricinus*, too, such as by Xu et al. (2009) who successfully discriminated between two tomato varieties in China using visible-near infrared reflectance spectroscopy. Thenkabail et al. (2013) on the other hand identified individual bands that included the visible to NIR bands as well as vegetation indices that best characterise, classify, model, and map the world's main agricultural crops.Bentivegna et al. (2012) detected cutleaf teasel (*Dipsacus laciniatus*) with hyperspectral imagery using visible to NIR spectral region along Missouri Highway, USA. Calvini et al. (2015) tested sparse methods for classifying Arabica and Robusta coffee species using near infrared hyperspectral images.

4.5. Conclusion

This chapter aimed at determining the potential of discriminating between *A. laricinus* and adjacent land cover types in the Klipriviersberg Nature Reserve using a field spectrometer data. Analysis of spectral reflectance was done at individual and plot levels using the original spectra. Although different spectral wavelength regions showed the ability to differentiate the species from other land cover types, the NIR region was found to be the most consistent of all. This finding is in line with other vegetation studies, although such studies on asparagus are rare.

A comparative similarity between *A. laricinus* and herbaceous plants was noteworthy. This similarity can make identification of the plant challenging in such co-existence. In contrast, the species can be discriminated from grass and mixed land cover (ground and herbaceous vegetation) at relative ease. The separability from grass is particularly important if the species favours to co-exist more with grass than with other species (7 of 10 plots were dominated by *A. laricinus* and grass in this study). The ability to discriminate the species from mixed land cover types that includes bareground, among others, is useful since it enables early detection in sparsely vegetated areas. Further studies are however needed to determine the relative contribution of different land cover types in the mixture to spectral reflectance.

Analysis of spectra simulated based on Landsat and SPOT 5 imagery bands showed the NIR to be consistent in discriminating *A. laricinus* from other land cover types. This finding is encouraging in that it shows the potential of upscaling the application to airborne and spaceborne remote sensing that mostly include the NIR region of electromagnetic energy. This study however used limited number of samples and thus should rather be considered a preliminary indicator that needs further studies. Future studies should attempt to utilize large number of samples. Such sample size can be achieved with the use of small sampling units and high spatial resolution imagery (e.g. SPOT 5 6/7), particualrly in areas where the spatial extent of invasion is small relative to imagery with small spatial resolution (e.g. Landsat). In addition, limiting spectral measurements in ideal time frames when there is enough illumination would need to be considered. Furthermore, it is vital to profile the biochemical contents of the species so that relationships can be built between the inherent contents of the plant and their effects on spectral signatures. In connection to this, it is important to take into consideration spectral properties at different phnological stages of the species.

CHAPTER 5

Assessing the potential of remote sensing to discriminate invasive *Seriphium plumosum* from grass

Abstract

The usefulness of remote sensing to discriminate *Seriphium plumosum* from grass using a field spectrometer data was investigated in this chapter. Wavelength regions that showed potential of discriminating *S. plumosum* and grass were visually determined from global spectra comparison. The identified regions were used as reference base on which spectra of individual plants were extracted for further analysis. Comparisons between spectra of *S. plumosum* and grass were done at individual and plot levels using original spectra and spectra simulated based on bands of Landsat and SPOT 5 images. Simulations were done to investigate the possibility of extending field based information into airborne and spaceborne remote sensing techniques. The global reflectance spectra of *S. plumosum* and grass were relatively comparable. Comparisons at all levels of analysis using original spectra did not show noteworthy reflectance difference in all regions (ultraviolet to visible, near infrared (NIR), NIR to shortwave infrared (SWIR), and SWIR). Similarly, simulated spectra of *S. plumosum* and grass did not show significant spectral differences. The spectral similarities between the two were somewhat expected, given the similarity of their global spectra. The results therefore did not encourage upscaling of the application to airborne and spaceborne remote sensing techniques. There were, however, some shortcomings that complicate making conclusive remarks on whether the plant can be differentiated from grass. These include, firstly, that not all species were in the same phenology. Secondly, that spectral measurements were not necessarily taken in an ideal scenario of optimal sunny conditions. It is therefore advised that a similar study be carried out that will address the shortcomings of this study. Furthermore, studies on the biochemical composition of both *S. plumosum* and grass species are encouraged, since they explain spectral properties of plants.

5.1. Introduction

Seriphium plumosum is an aggressive grass encroacher formerly known as *Stoebe vulgaris* (Snyman, 2012a, 2010). Although the plant is indigenous to South Africa, it has become naturalised in some parts of Africa (Angola, Madagascar Mozambique, Namibia, and Zimbabwe) and the USA (Snyman, 2012b). The species encroaches Fynbos and Grassland Biomes of South Africa in localities of the Eastern Cape, Free State, Mpumalanga, North West and Gauteng provinces (Snyman, 2012b). Generally, the species encroaches and proliferates in disturbed or overgrazed areas including grasslands in good condition, with reported rapid spread in farms (Eldridge et al., 2013; Snyman, 2012a, 2012b, 2010). Infestation by the species results in reduced grass productivity, altered habitat value, altered availability of soil nutrients and soil water, including alteration of functions carried out by soil such as respiration, decomposition and infiltration (Eldridge et al., 2013; Snyman, 2010). For example, in the *Themeda/Cymbopogon* veld which is generally infested by *Seriphium* plants, grass production decreases by approximately 75% as a resultof10 000 or more infestations per hectare (Jordaan, 2009). Such and other effects of the species have caused it to be proclaimed as encroacher in the Conservation of Agricultural Resources Act (CARA) legislation in South Africa (Snyman, 2012a, 2012b).

S. plumosum is a multi-stemmed woody shrub growing to a height of 60 cm and width of 60 cm (Jordaan, 2009). The plant grows best in areas with average rainfall of 620-750 mm and low soil fertility, preferably lighter soils on foot slopes and mid slope terrains (Jordaan, 2009; Snyman, 2012a, 2010). It prefers sandy soils with low pH although soils with 24%clay content can also be encroached, including wet areas (Snyman, 2012a). The plant flowers in autumn (March to May) and its fruits mature in winter (Snyman, 2010). It produces thousands of seeds that are wind blown over long distances, although its seeds take time to germinate (Snyman, 2010). Because of the adversaries that the plant has once it invades, development of best control strategies to curb its effects is essential. Currently, control measures depend mainly on mechanical and chemical methods (Jordaan, 2009; Snyman, 2012b). These control methods have certain limitations which include, amongst others, inaccessibility of infested areas as a result of rough terrain and absence of temporal and spatial distribution maps of the species for development of efficient management strategies (Jordaan, 2009). Such limitations necessitate establishment of inexpensive and effective control methods for this species. Spatio-temporal distribution maps showing dynamics of infestations by the species can help improve efficiency of the currently used control measures.

Mapping is a useful tool for providing information on spatial and temporal distribution of plants including invasive plant species. Maps are essential in decision making since they allow of spotting of new infestations that have not fully established, therefore offering opportunity for early response and eradication (Bradley, 2014; Caffrey et al., 2014; Meier et al., 2014). Traditional mapping methods that involve use of field inventories do provide spatial distribution maps of plant species, but such maps may only cover a limited spatial area due to inaccessible landscapes and often limited spatial coverage capabilities. In addition, the methods can be expensive and consume considerable amount of time (Dewey et al., 1991; Rodgers et al., 2014; Tsai et al., 2007). Remote sensing techniques make up for these limitations because they are cost effective, time efficient and capable of covering large spatial areas (Asner et al., 2008; Bradley and Marvin, 2011; T.L. Hawthorne et al., 2015; Laba et al., 2008; Lawrence et al., 2006; Lu and Zhang, 2013; Rodgers et al., 2014). Remote sensing is the science of acquiring information about an object without being in direct contact with it by interpreting different responses of objects to electromagnetic radiation illumination (Alparone et al., 2015; Campbell and Wynne, 2011; Jensen, 2014). As a result, plants have been mapped and discriminated with mixed levels of success using both multispectral and hyperspectral remote sensing techniques (e.g. Abdel-Rahman et al., 2014; Azong et al., 2015; Dronova et al., 2015; Gavier-pizarro et al., 2012; Ghulam et al., 2014; Jia et al., 2014; Somers et al., 2015).

Specifically, the ability of hyperspectral remote sensing to record electromagnetic radiations continuously and at narrow wavelength intervals allows for differentiation of vegetation types that appear similar on multispectral data (Carroll et al., 2008). These sensors often have over 100 nm continuous bands of 10 nm or less bandwidth (Adam and Mutanga, 2009; Cho et al., 2008; Manevski et al., 2011; Pu et al., 2012; Rudolf et al., 2015). Because of a large volume of spectral information provided by hyperspectral remote sensors, plants can be discriminated even to a species level (Tsai et al., 2007). For these reasons, hyperspectral sensors have been applied successfully in a number of studies to characterise plants.

For example, Xu et al. (2009)discriminated two tomato plant varieties in China making use of visible to near infrared (NIR) spectroscopy. Thenkabail et al. (2013) selected hyperspectral bands and composed hyperspectral vegetation indices from field-based reflectance and Hyperion/EO-1 data to biophysically characterise and discriminate crop types. Neill and Costa (2013) mapped eelgrass (*Zostera marina*) in the Gulf Islands National Park Reserve of Canada using high spatial resolution satellite (known as IKONOS)and airborne imagery(known as Airborne Imaging System for different Applications-AISA).Jia et al. (2014) also used hyperspectral data to map spatial distribution of mangrove species in the Core Zone of Mai Po Marshes Nature Reserve, Hong Kong. On the other hand Fernandes et al. (2013)discriminated giant reed (*Arundo donax L.*) from surrounding vegetation at different phonological stages using field spectrometer. Similarly, Abdel-Rahman et al. (2014) detected *Sirex noctilio* grey-attacked and lightning-struck pine trees using airborne hyperspectral data, Random Forest and Support Vector Machines classifiers.

Although hyperspectral remote sensing techniques are able of identify subtle differences between vegetation species, they make use of specific bands identified using different classifiers. These bands are narrow and often cannot be isolated from within broad-bands of multispectral images. As a result, it is difficult to translate the findings of hyperspectral data analysis into multispectral remote sensing systems. This is critical due to the fact that current applications of hyperspectral remote sensing are predominantly limited to research efforts, despite the significant growth of the system over the past few decades. Multispectral remote sensing on the other hand remains the main source of earth observation applications. As much as possible, research efforts involving analysis of hyperspectral data must therefore factor in the potential of extending findings to multispectral remote sensing. This study seeks to identify spectral bands suitable for discriminating *S. plumosum* from grass using a field spectrometer data over a long spectrum. Unlike numerous studies that aimed at identifying suitable individual bands, this study uses spectral regions containing contiguous bands as the basic unit of information source. The main objectives of the study are (1) to determine whether or not *S. plumosum* can be discriminated from grass and (2) to investigate the performance of spectra simulated according to Landsat and SPOT 5 images in discriminating *S. plumosum* from grass species. The second objective is intended as a preliminary indicator on whether or not spaceborne or airborne sensors could be used in developing spatial distribution map of the species.

5.2. Methods

5.2.1. Study Area

The study was conducted in the Klipriviersberg Nature Reserve, in Johannesburg, South Africa (Figure23). The reserve covers an area of approximately 680 hectares, making it the largest reserve in the City of Johannesburg. It is located in the Klipriviersberg area which is in transition between grassland and savanna biomes in the northern edge of the Highveld (Faiola and Vermaak, 2014). The Highveld climate characterised by temperatures ranging between 17–26 ºC in summer and 5–7 ºC in winter in winter (Kotze, 2002). Three geology types occur in the reserve: volcanic rock (basalt and andesite), quartzites and conglomerates, and dolomites (Faiola and Vermaak, 2014). Vegetation types of the reserve are classified as Andesite Mountain Bushveld and a section of Tsakane Clay Grassland at the flatter southern end (Faiola and Vermaak, 2014). The reserve holds a relatively rich biodiversity of approximately 650 indigenous plant species, 215 bird species, 16 reptile species and 32 butterfly species. Mammals that occur in the reserve include lesser spotted genet, African civet, zebra, red hartebeest, blesbok, springbok, duiker, black wildebeest, porcupines, meerkats and otters.

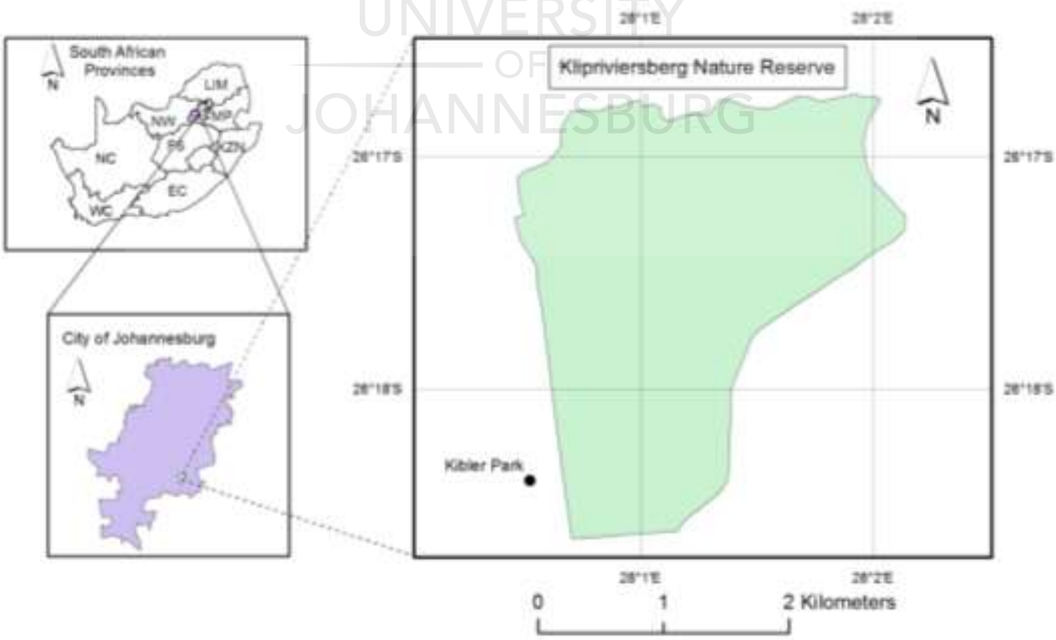


Figure 23: Map showing the Klipriviersberg Nature Reserve.

5.2.2. Field data

Field surveys were conducted within the summer season between the 2nd and 14th of December 2014. This is the time when vegetation is green and it is the most preferred time for remote sensing applications on vegetation (Lillesand*et al.* 2015). *S. plumosum* infestations occur in scattered patterns which limited the number and size of samples and only fifteen stands that had the species were identified. This led to fifteen plots of a radius of 2 m circle with fairly considerable concentration of S*. plumosum* being delineated. The size of the circle was adequate to accommodate imagery with high spatial resolution such as SPOT imagery that has 2.5 m spatial resolution. A Global Positioning System (GPS) was used to record the position of each plot. Subsequently, line transects were laid between the centre and the periphery of the plot in each of the north, south, east and west directions. Spectral measurements of individual plants of *S. plumosum* and adjacent grass were taken at the centre and at 2 m distance along each transect (Figure 24). In cases where no individual *S. plumosum* was not encountered along the transect line, one closest to the transect was sampled.

Spectra were collected using a field spectrometer, namely, Spectral Evolution®SR-3500 Remote Sensing Portable Spectroradiometer (Spectral Evolution Inc., Lawrence, MA, USA). The spectrometerhas1.6 nm spectral resolution that ranges between 340 nm to 2503 nm. Target radiance in energy units was converted into percent reflectance using a white reference measurement (Prospere et al., 2014). Three spectral measurements were taken from individual *S. plumosum* plant and grass in close proximity. These measurements were taken from different canopy parts of the plant at nadir, under sunny conditions. Such conditions are best achieved between 10:00 am and 2:00 pm. This position permits attaining most of the reflected electromagnetic radiation (Cho et al. 2008; Fernandes et al. 2013; Mansour 2013; Olsson et al. 2011; Rudolf et al. 2015). However, not all measurements were taken using this protocol due to time constraint of the study that forced data acquisition outside of the ideal time.

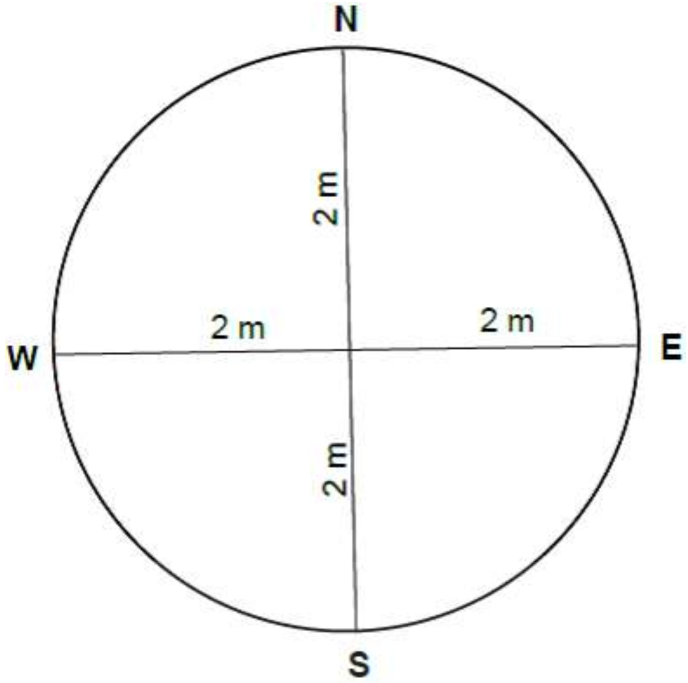


Figure 24: A layout of sampling design for spectral measurements of individual target plant.

5.2.3. Analysis of spectral reflectance per region

Wavelength regions better at differentiating *S. plumosum* from grass were identified. To accomplish this, an average reflectance spectrum was computed from the three spectral measurements taken for each plant. Subsequently, an average reflectance was computed from all individual plants of *S. plumosum* and grass plants to create two 'global' spectral curves, respectively (Figure 25). The separate pools were mainly made to determine if *S. plumosum* could be differentiated from grass using reflectance spectra. Comparing the pairs using global spectral curves offers results that are more representative of the study area. In contrast, comparing each pair separately would yield a plethora of results and complicate choice of a result that would represent all individuals.

Wavelength regions that were not useful in discriminating between the *S. plumosum* and grass were excluded from further analysis following visual observations of global spectra pair comparisons (Figure26). Two criteria were used for the exclusions; these are, regions that returned random reflectance properties commonly referred to as noise (1824-2016 nm and 2282-2503 nm) and those which did not show noticeable spectral reflectance differences between *S. plumosum* and grass (580-758 nm and 1095-1422.2 nm). This resulted in four discontinuous regions (Figure27) to be used as reference in further analysis. Region 1 included wavelengths in the ultraviolet to visible (340-579 nm); region 2 included wavelengths in the Near Infrared (NIR) (759-1091 nm); region 3 included wavelengths in the NIR to Shortwave Infrared (SWIR) (1425.9-1821 nm); and region 4 included wavelengths in the SWIR (2019-2279 nm).

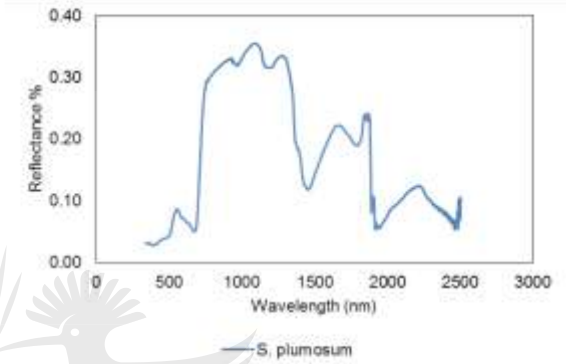
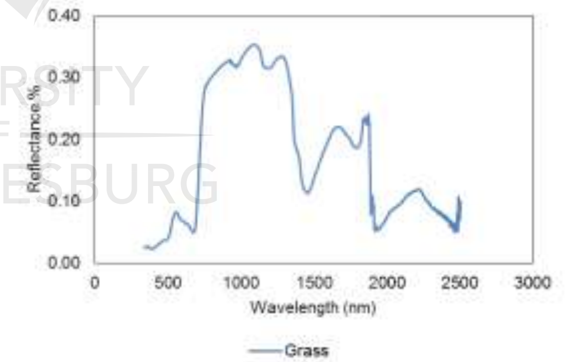
Pictures	Global reflectance
 *Seriphium plumosum*	
 Grass	

Figure 25: Table 1 Global spectra of *S. plumosum* and grass

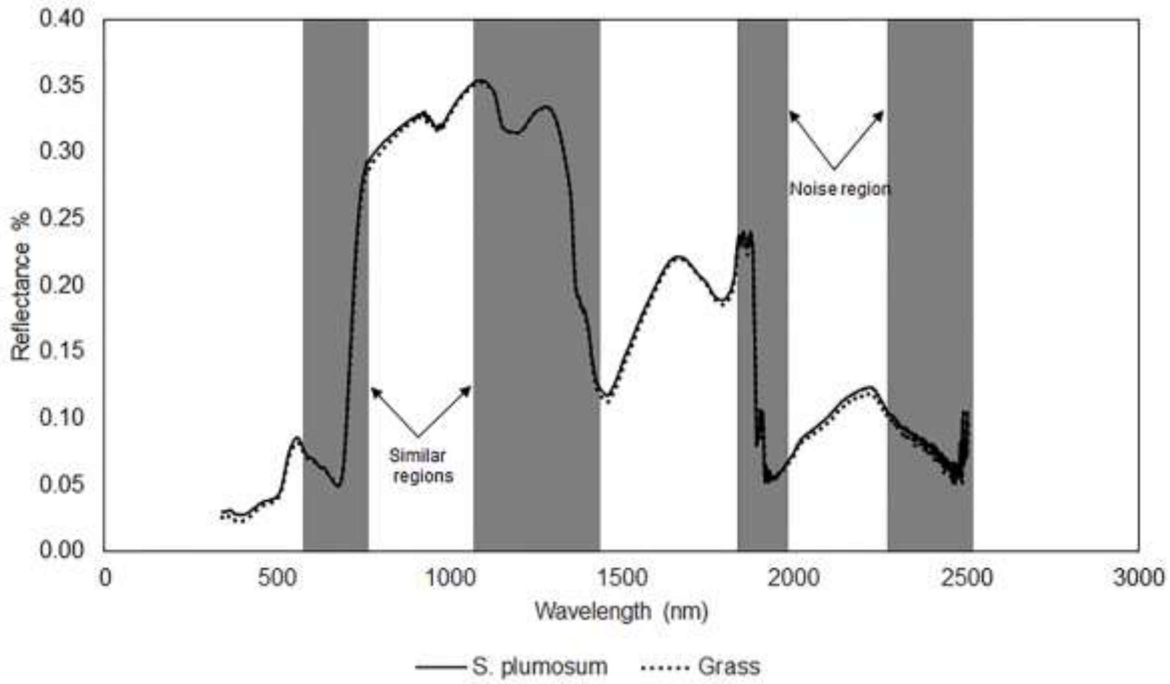


Figure 26: Global reflectance of *S. plumosum* and grass across the full spectrum. Shaded regions show spectral regions that were excluded from further analysis.

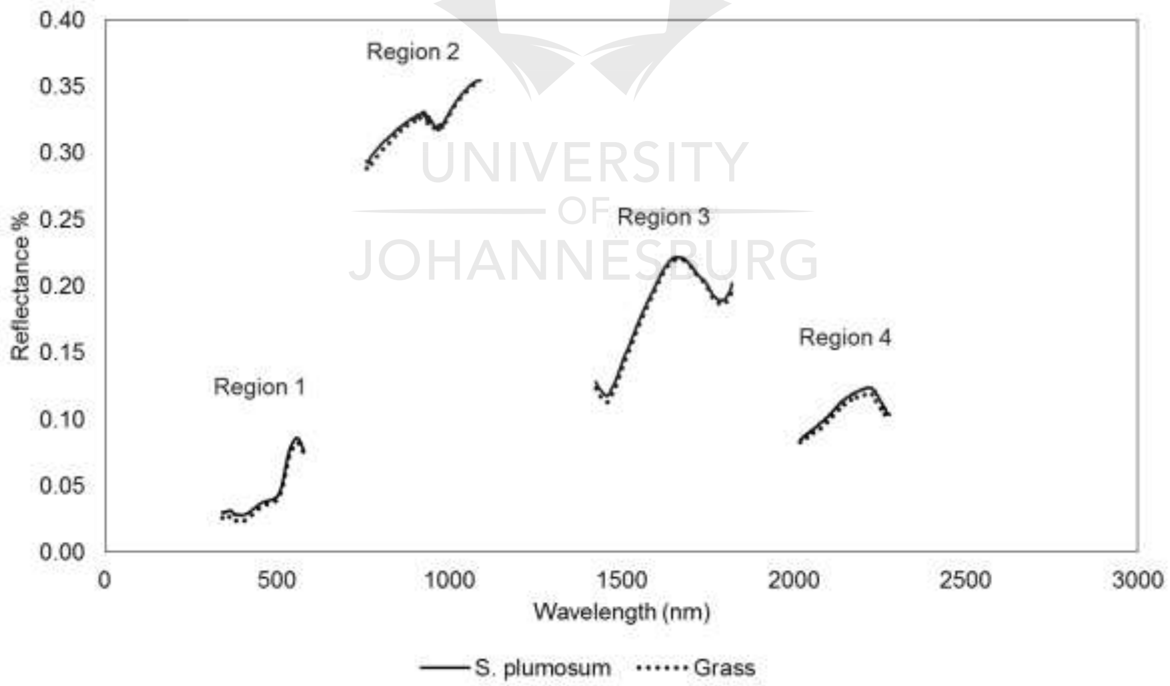


Figure 27: An example of global reflectance of *S. plumosum* and grass, representing wavelength regions used in further analysis.

Analysis involved comparisons of *S. plumosum* and grass reflectance spectra at individual and plot levels. The individual level analysis compared all individual pairs of *S. plumosum* and grass encountered in each of the plots, while plot level analysis involved comparisons of plot level mean reflectance of *S. plumosum* against plot level mean reflectance of grass in all plots. At both levels, analysis was done per region determined from the global reflectance pair comparison (Figure 27). Reflectance spectra were extracted according to these regions. Comparisons were made using graphical and statistical methods. The graphs made use of mean reflectance of all individual plants encountered per plot. Statistical tests involved the use of the analysis of variance (ANOVA) and t-test.

5.2.4. Simulation of Landsat and SPOT 5 imagery bands

Although the size of sample plots was not enough to accommodate spatial resolution of Landsat (30 m), the competence of its bands to discriminate the species was tested. Accordingly, reflectance data acquired from the field spectrometer were extracted according to bands of Landsat and SPOT 5 images. This was done to investigate the potential of upscaling the technique to airborne or satellite based remote sensing. Although Landsat 5 and later missions have seven or more wavebands, only the blue, green, red and NIR bands were simulated, while on the other hand the green, red and NIR bands of SPOT 5 imagery were simulated (Table 7). These bands have been widely used in studies focussing on remote sensing of vegetation characteristics (e.g. Calvini et al., 2015; Dale et al., 2011; Glenn et al., 2008; Manevski et al., 2011; Pflugmacher, 2007; Tuxen et al., 2008; Xu et al., 2009). Simulations were done for all individuals of *S. plumosum* and grass, resulting in two separate pools per spectral band. Comparisons were made using these pools, and the significance of differences between *S. plumosum* and grass were tested using t-test.

Table 7: Simulated data for Landsat and SPOT 5 remote sensing technologies

Simulated bands	*Wavelength range (nm)*	
	Landsat	*SPOT 5*
Blue band	450-520	N/A
Green band	520-600	500-590
Red band	630-689	610-680
NIR band	759-900	790-890

5.3. Results

Comparisons at the individual level showed an overall significant difference between *S. plumosum* and grass in all plots, based on ANOVA results for all individuals per plot. There were, however, within species differences from individual pair comparison per plot using the Least Significant Difference (LSD).Graphical presentation of individual reflectance difference of *S. plumosum* and grass within each plot did not exhibit strong distinction the two. *S. plumosum* was fairly discriminated in the NIR to SWIR region (region 3) with eight plots at most showing similarity amongst individuals of *S. plumosum*. Only six plots in NIR (region 2) and SWIR (region 4) regions exhibited similarity amongst individuals of the species, while only three plots showed clear separation in the ultraviolet to visible region (region 1). Figure 28 illustrates a typical plot that shows similarity among individuals of *S. plumosum* and grass, respectively, in the NIR region (region 2) and NIR to SWIR region (region 3). The NIR region (region 2) returned high reflectance differences than region 1 (ultraviolet to visible), region 3 (NIR to SWIR) and region 4 (SWIR).

Plot level results of reflectance comparisons between *S. plumosum* and grass showed significant difference in all plots. Figure 29 illustrates such a result for a typical plot. Note that results for other plots are not presented here. It is important to note that the differences were not considerable (Figure 29). *S. plumosum* had slightly high reflectance than grass in 11 plots in the ultraviolet to visible region (region 1), 10 plots in the NIR region (region 2) and SWIR region (region 4), with eight plots in the NIR to SWIR region (region 3). Spectral reflectance of both was reflectively high in the NIR region (region 2) in comparison with other regions.

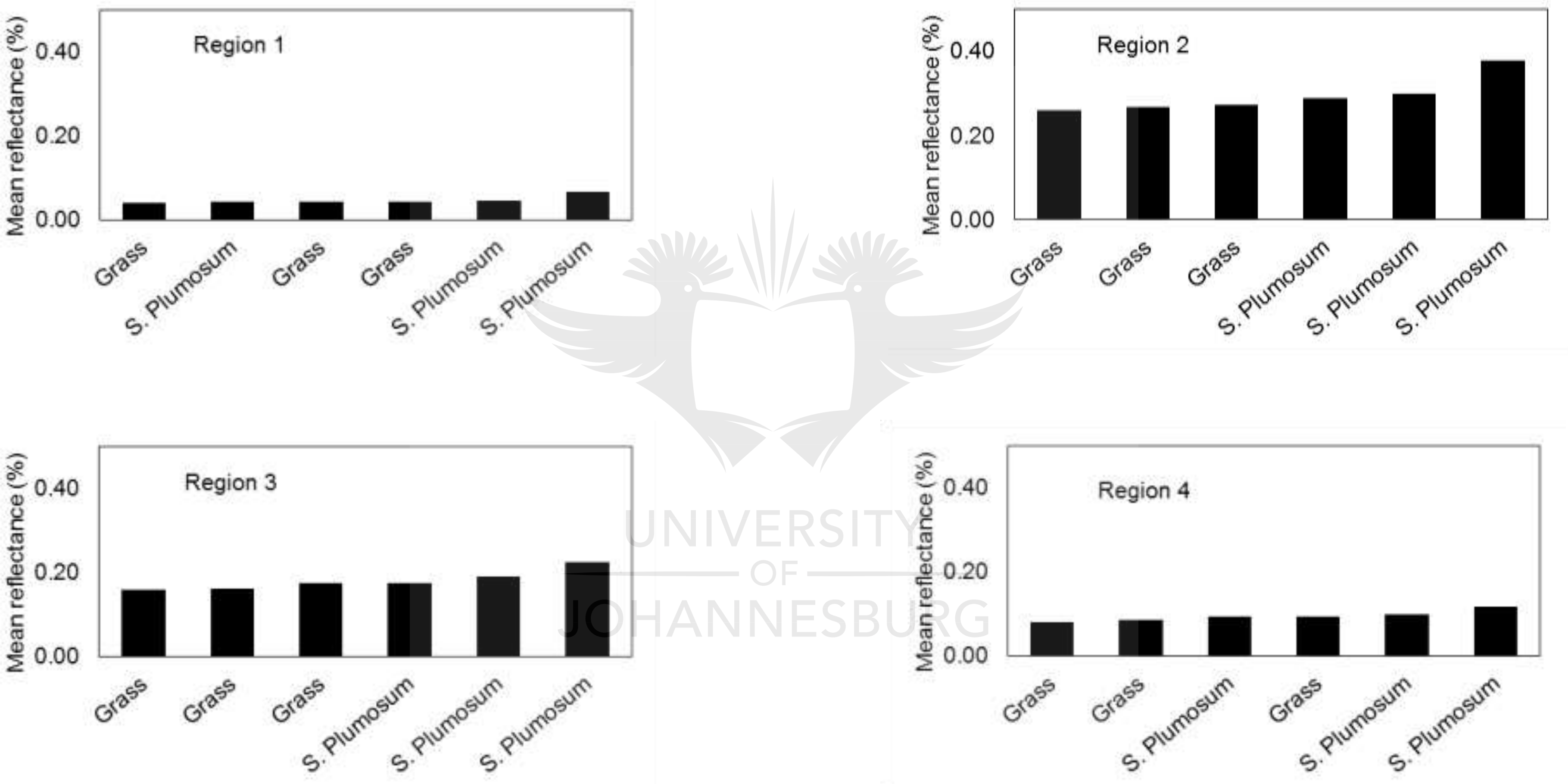


Figure 28: Reflectance of the regions used for analysis at individual plant level for a typical plot at α=0.05.Region 1(Ultraviolet to visible region), region 2 (NIR region), region 3 (NIR to SWIR region), region 4 (SWIR region).

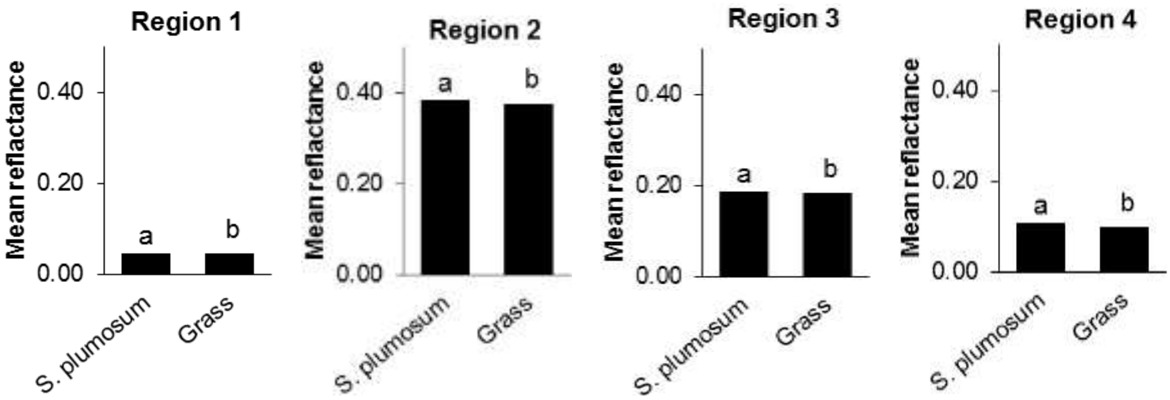


Figure 29: An illustration ofplot level mean reflectance of *S. plumosum* and grass. Different letters indicate spectral significant differences at α=0.05.

5.3.1. Landsat and SPOT 5 simulations

The statistical results for reflectance comparisons using Landsat simulated spectra showed significant difference in only the blue band while the differences were insiginificant in the other bands (Figure 30). The mean reflectance of all band comparisons between *S. plumosum* and grass were comparable as illustrated in Figure 30.All the plants had a notable high reflectance in the NIR band than other bands. Comparison between *S. plumosum* and grass using SPOT 5 simulated spectra showed no significant differences in all the bands, as illustrated in Figure 31.

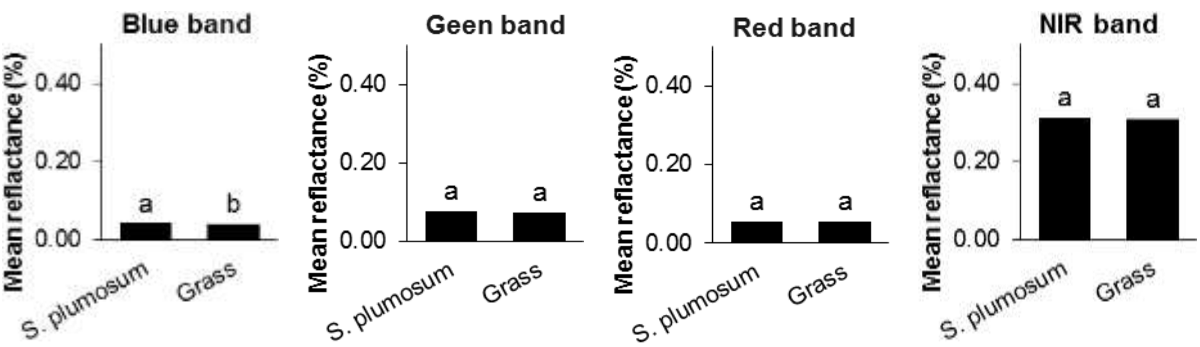


Figure 30: Mean reflectance comparisons of simulated Landsat bands between all *S. plumosum* and grass individuals. Different letters represent spectral significant differences at α=0.05. Note that the comparison are per spectral band.

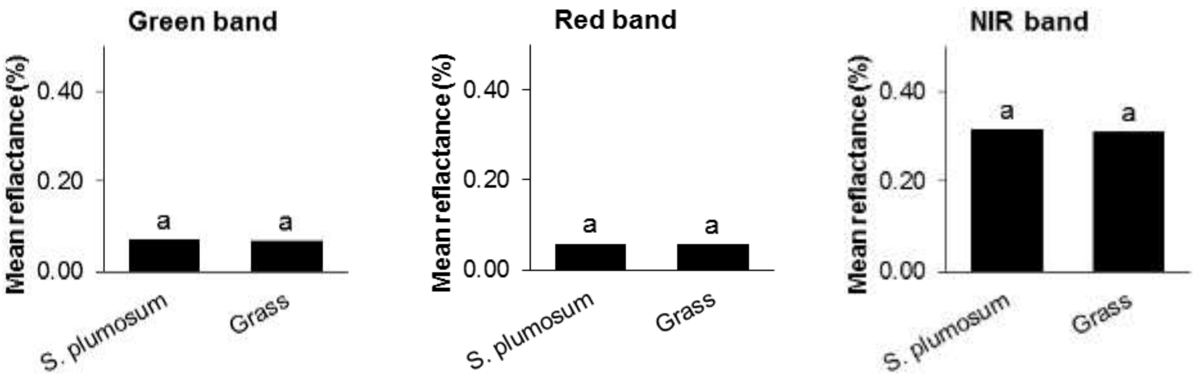


Figure 31: Mean reflectance comparisons of simulated SPOT 5 bands between all *S. plumosum* and grass individuals. Different letters represent spectral significant differences at α=0.05. Note that the comparison are per spectral band.

5.4. Discussion

In this study, the efficiency of data acquired using a field spectrometer to discriminate *S. plumosum* from grass was investigated. Reflectance spectra comparisons were made using original spectra and spectra simulated according to bands of Landsat and SPOT sensors. The simulation was to determine the possibility of upscaling field based data into spaceborne or airborne remote sensing techniques. Global spectra of *S. plumosum* and grass were highly comparable when visually compared, with no distinct spectral separation between the two (Figure 26).

Even though the individual level analysis using ANOVA showed overall significant differences in all plots, these differences were not necessarily the result of reflectance differences between *S. plumosum* and grass individuals per plot. This is because there were within species differences when comparing individual pairs using Least Significance Difference (LSD). Graphical presentation of reflectance differences for all individuals per plot further showed poor separability between *S. plumosum* and grass. The outcome was not surprising given comparable spectral reflectance patterns of both *S. plumosum* and grass (Figure 25). As such, only eight plots at most in the NIR to SWIR region (region 3) showed best separability between *S. plumosum* and grass, while a few plots showed distinction in reflectance differences between *S. plumosum* and grass, with three plots in the ultraviolet to visible (region 1) and six plots in the NIR (region 2) (e.g. Figure 28). The clear spectral separability that is observed in the SWIR (region 4) from global pair comparisons was not evident when comparing individuals of *S. plumosum* and grass (Figure 27), only six plots showed clear differences in this region (e.g. Figure 28). Reflectance differences that appear in the first part of ultraviolet to visible reference region (region 1) and NIR reference region (region 2) were not observed in the analysis (Figure 27). Had the analysis not focused on the entire wavelength region of the ultraviolet to visible region (region 1) and the NIR region (region 2) and instead focused on regions that showed distinction (340-335 nm and 759-829 nm), the species could have been clearly differentiated.

Significant differences that were observed at the plot level may not be considered large as illustrated by Figure 29. The slight differences are supportive of poor separability that is observed in visual comparison of global spectra (Figure 26). These slight differences could have resulted from a number of factors. These include limited number of samples per plot, different phonological stages of *S. plumosum* and grass, as well as taking of spectral measurements under overcast conditions or when there were slight cloud covers. Such factors complicate a choice of making decisive remarks on whether *S. plumosum* and grass are spectrally similar or not the same.

The simulation results do not suggest possibility of upscaling of field data into spaceborne and airborne remote sensors such as Landsat and SPOT. Reflectance comparisons using bands simulated according to Landsat showed significant difference only in the blue band, with no significant difference in the green, red and NIR bands (Figure 30). Likewise, reflectance comparisons using simulated bands of SPOT imagery showed no significance difference in the green, red and NIR bands (Figure 31). This was not surprising, given the similarity of global spectra of *S. plumosum* and grass (Figure 26).

Different classifiers have been used to identify best bands for discriminating between plant species in a number of studies using hyperspectral data. For example, Fernandes et al. (2013) found the visible and the mid infra-red region best at discriminating giant reed (*Arundo donax* L.) from adjacent vegetation. Abdel-Rahman et al. (2014) found 50 bands located in the red edge (670–780 nm), blue (400–500 nm) and green edge (500–600 nm) of the electromagnetic spectrum of the AISA Eagle image best at detecting *Sirex noctilio* grey-attacked and lightning-struck pine trees. Dumont et al. (2015) identified 1310 nm, 1710 nm and 1985 nm bands located in the SWIR region as best at identifying viable seeds, empty seeds and seeds infested by *Megastigmus sp*. Larvae using hyperspectral image and thermal data. Information provided using the technique of selecting specific bands and cannot be extended to broadbands of multispectral remote sensing techniques.

However, the method of analysing continuum spectra in this study made up for the ineffectiveness of selecting specific hyperspectral bands best at differentiating between vegetation species. Because hyperspectral data is not freely available, multispectral remote sensing techniques would have been given preference in providing spatio-temporal distribution maps of *S. plumosum*. These are in main realm of earth observation due to the fact that their data are available in public domain. Unfortunately, the species could not be differentiated from grass in this study, most likely as a result of shortcomings that were encountered. As such, the results did not show the potential of extending field based data into airborne or spaceborne remote sensing techniques. Therefore, a same study discriminating *S. plumosum* from grass needs to be undertaken, using more samples and take all measurements using a standard method (at nadir under sunny conditions) to draw a more conclusive remarks on this basis. Because biochemical composition of plants strongly affects reflectance pattern (Campbell et al., 2008; Jensen, 2014; Zhang, 2011), a study profiling biochemical constituents of *S. plumosum* and of any adjacent land cover type (such as grass) in coexistence is recommended.

5.5. Conclusion

The potential of field spectral data to discriminate *S. plumosum* from grass was investigated in this study. The study specifically aimed to determine whether or not *S. plumosum* can be discriminated from grass using reflectance spectra. It also sought to test the potential of upscaling field based spectra into airborne and spaceborne remote sensors. Analysis was done using the original spectral and spectra simulated according to bands of Landsat and SPOT imagers, at individual and plot levels. However, spectral discrimination between *S. plumosum* and grass was achieved with limited success. Only a maximum of eight plots showed statistical difference (ANOVA at α=0.05) at individual level of analysis. Although statistically significant differences (t-test at α=0.05) were observed at the plot level, they were not large (e.g. Figure28). Only the blue band of the Landsat simulated spectra proved significant, while there was no significant difference for other bands, including SPOT simulated bands. As such, the results do not suggest a possibility of upscaling field based information into remote sensing technologies such as airborne or spaceborne sensing technologies. A study with enough number of samples is, however, suggested as a follow up study. Such a study would need to consider taking spectral measurements during ideal time frames when there is enough illumination. Other factors that need to be considered are the possibility of stratifying samples based on phenological stages and assessment of biochemical compostion of *S. plumosum* and grass to draw conclusive remarks on whether they truly share same reflectance pattern.

CHAPTER 6

Conclusion and recommendations

6.1. Conclusion

The potential of remote sensing techniques to discriminate and map invasive *A.afra*, *A.laricinus* and *S. plumosum* from adjacent land cover types were investigated in this study, making use of a field spectrometer data. The study is rather a preliminary effort towards developing the spatial distribution maps of these species. Unlike specific narrow band selection methods used in most hyperspectral remote sensing analysis studies, a continuum of wavelength regions were targeted by the study. This was in an attempt to accommodate broad-bands of multispectral remotely sensed data which are widely used in vegetation studies due to easy accessibility of data. Wavelength regions that showed discriminability potential between target species and adjacent land cover types were visually identified from global spectra comparisons of the species and the adjacent land cover types. These included wavelength regions in the (1) ultraviolet to visible, (2) near infrared, (3) near infrared to shortwave infrared and (4) shortwave infrared regions. Subsequent analyses were performed based on these regions using original spectra and spectra simulated based on bands of Landsat and SPOT 5 at individual, plot level and group level. The simulations in particular were done to explore the possibility of upscaling field spectrometer data into spaceborne and airborne remote sensing techniques. Statistical methods, namely, analysis of variance (ANOVA) and t-test were used to determine reflectance differences between test species and adjacent land cover types.

The near infrared region (NIR) returned best at discriminating *A. afra* from adjacent land cover types at individual and plot level analysis. Group level analyses of the simulated bands of Landsat showed significance difference between *A. afra* and adjacent land cover types in the red and NIR bands, while only the NIR band proved significant for SPOT 5 simulated data. *A. laricinus* was also best discriminated using the NIR bands at both individual and plot level analysis using original spectra. The simulated spectra showed the NIR as best in discriminating *A. laricinus* from adjacent land cover types at group level analysis. But *S. plumosum* could not be clearly discriminated from grass at all levels of analysis. The results relating to *A. afra* and *A. laricinus* therefore suggest the potential of extending field based data into airborne or spaceborne remote sensing with more emphasis on the NIR band, while this was not confimed for *S. plumosum* which was not successfully differentiated from grass.

There were however some shortcomings that were encountered in the study. These include, (1) use of a few number of samples, (2) not all plants were in the same phenological stages, (2) not all spectral measurements were taken under ideal scenario of optimal sunny conditions due to time constraints. In addition, almost all samples had a certain degree of impurity in terms of land cover types (vegetal cover or bare ground), making the comparisons among land cover types imperfect.

6.2. Recommendations

It is believed that the results reported in this study can be improved by applying the recommendations given here. One recommendation is use of more number of samples. Second recommendation is categorising data analysis according to plant phonological stages to help determine best timing for discrimination of the species. A third recommendation is taking of spectral measurements under ideal environmental sunny conditions. Additionally, studies on biochemical composition plant species are encouraged to inform on reflectance behaviours of the species because different plant compounds or pigments strongly influence electromagnetic reflectance responses (Cho et al., 2008; Daughtry et al., 2006; Guerschman et al., 2009; Ouyang et al., 2013; Pu et al., 2012; Schmidt and Skidmore, 2003; Serbin et al., 2009). Such studies would help draw up more conclusive remarks on whether *A. afra*, *A. laricinus* and *S. plumosum* can be differentiated from adjacent land cover types.

The suggested follow up studies would need to be consistent with the method of using a continuum of hyperspectral bands so to factor on extending the information into multispectral remote sensing techniques. Multispectral remote sensing are at present most practical for vegetation applications than hyperspectral due to their free data. As such, need to be given preference on mapping plant species to avoid excessive spending on hyperspectral remote sensing techniques. Therefore, once conclusive remarks on whether *A. afra*, *A. laricinus* and *S. plumosum* can be discriminated from adjacent land cover types are drawn, remote sensing techniques deemed suitable at discriminating the plant species would need to be expended in developing species spatio-temporal distribution maps. Land managers would need to use these maps for planning mitigation and control methods of infestations by these plants and therefore develop and enhance currently used control techniques.

References

Abdel-Rahman, E.M., Mutanga, O., Adam, E., Ismail, R., 2014. Detecting Sirex noctilio grey-attacked and lightning-struck pine trees using airborne hyperspectral data, random forest and support vector machines classifiers. ISPRS J. Photogramm. Remote Sens. 88, 48–59.

Adam, E., Mutanga, O., 2009. Spectral discrimination of papyrus vegetation (Cyperus papyrus L .) in swamp wetlands using field spectrometry. ISPRS J. Photogramm. Remote Sens. 64, 612–620.

Adelabu, S., Mutanga, O., Adam, E., Sebego, R., 2014. Spectral discrimination of insect defoliation levels in mopane woodland using hyperspectral data. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 7, 177–186.

Ahmad, M., Lee, S., Haq, I.U., Mushtaq, Q., 2012. Hyperspectral remote sensing: Dimensional reduction and end member extraction. Int. J. Soft Comput. Eng. 2, 170–175.

Ajmi, D. Al, 2009. Remote sensing: Fundamentals, types and monitoring applications of environmental consequences of war. Handb. Environ. Chem. 41–123.

Alonzo, M., Bookhagen, B., Roberts, D.A., 2014. Urban tree species mapping using hyperspectral and lidar data fusion. Remote Sens. Environ. 148, 70–83.

Alparone, L., Aiazzi, B., Baronti, S., Andrea Garzelli, 2015. Remote Sensing Image Fusion, Signal and Image Processing of Earth Observations. CRC Press.

Amaral, C.H., Roberts, D.A., Almeida, T.I.R., Souza, C.R., 2015. Mapping invasive species and spectral mixture relationships with neotropical woody formations in southeastern Brazil. ISPRS J. Photogramm. Remote Sens. 108, 80–93.

Asner, G.P., Knapp, D.E., Kennedy-bowdoin, T., Jones, M.O., Martin, R.E., Boardman, J., Hughes, R.F., 2008. Invasive species detection in Hawaiian rainforests using airborne imaging spectroscopy and LiDAR. Remote Sens. Environ. 112, 1942–1955.

Azong, M., Malahlela, O., Ramoelo, A., 2015. Assessing the utility WorldView-2 imagery for tree species mapping in South African subtropical humid forest and the conservation implications : Dukuduku forest patch as case study. Int. J. Appl. Earth Obs. Geoinf. 38, 349–357.

Barillé, L., Robin, M., Harin, N., Bargain, A., Launeau, P., 2010. Increase in seagrass distribution at Bourgneuf Bay (France) detected by spatial remote sensing. Aquat. Bot. 92, 185–194.

Barrell, J., Grant, J., 2015. High resolution, low-altitude aerial photography in physical geography: A case study characterizing eelgrass (Zostera marina L .) and blue mussel (Mytilus edulis L.) landscape mosaic structure. Prog. Phys. Geogr. 39, 440–459.

Belnap, J., Ludwig, J. a., Wilcox, B.P., Betancourt, J.L., Dean, W.R.J., Hoffmann, B.D., Milton, S.J., 2012. Introduced and invasive species in novel rangeland ecosystems: Friends or Foes? Rangel. Ecol. Manag. 65, 569–578.

Bentivegna, D.J., Smeda, R.J., Wang, C., Bentivegna, D.J., Smeda, R.J., Wang, C., 2012. Detecting Cutleaf Teasel (Dipsacus laciniatus) along a Missouri Highway with Hyperspectral Imagery. Invasive Plant Sci. Manag. 5, 155–163.

Berg, V. Den, Kotze, I., Beukes, H., 2013. Detection , Quantification and Monitoring of Prosopis in the Northern Cape Province of South Africa using Remote Sensing and GIS. South African J. Geomatics 2, 68–81.

Bioucas-dias, J.M., Plaza, A., Camps-valls, G., Scheunders, P., Nasrabadi, N.M., Chanussot, J., 2013. Hyperspectral remote sensing data analysis and future challenges. IEEE Geosci. Remote Sens. Mag. 6–36.

Bradley, B.A., 2014. Remote detection of invasive plants: A review of spectral, textural and phenological approaches. Biol. Invasions 16, 1411–1425.

Bradley, B.A., Marvin, D.C., 2011. Using Expert Knowledge to Satisfy Data Needs: Mapping Invasive Plant Distributions in the Western United States. West. North Am. Nat. 71, 302–315.

Brenner, J.C., Christman, Z., Rogan, J., 2012. Segmentation of Landsat Thematic Mapper imagery improves buffelgrass (Pennisetum ciliare) pasture mapping in the Sonoran Desert of Mexico. Appl. Geogr. 34, 569–575.

Bue, B.D., Thompson, D.R., Sellar, R.G., Podest, E. V, Eastwood, M.L., Helmlinger, M.C., Mccubbin, I.B., Morgan, J.D., 2015. Leveraging in-scene spectra for vegetation species discrimination with MESMA-MDA. ISPRS J. Photogramm. Remote Sens. 108, 33–48.

Burits, M., Asres, K., Bucar, F., 2001. The Antioxidant Activity of the Essential Oils of Artemisia afra , Artemisia abyssinica and Juniperus procera. Phyther. Res. 15, 103–108.

Caffrey, J.M., Baars, J., Barbour, J.H., Boets, P., Boon, P., Davenport, K., Dick, J.T. a, Early, J., Edsman, L., Gallagher, C., Gross, J., Heinimaa, P., Horrill, C., Hudin, S., Hulme, P.E., Hynes, S., Macisaac, H.J., Mcloone, P., Millane, M., Moen, T.L., Moore, N., Newman, J., Conchuir, R.O., Farrell, M.O., Flynn, C.O., Oidtmann, B., Renals, T., Ricciardi, A., Roy, H., Shaw, R., Valkenburg, J.L.C.H. Van, Weyl, O., Williams, F., Lucy, F.E., 2014. Tackling invasive alien species in Europe : the top 20 Issues. Manag. Biol. Invasions 5, 1–20.

Calvini, R., Ulrici, A., Manuel, J., 2015. Chemometrics and Intelligent Laboratory Systems Practical comparison of sparse methods for classi fi cation of Arabica and Robusta coffee species using near infrared hyperspectral imaging. Chemom. Intell. Lab. Syst. 146, 503–511.

Campbell, J.B., Wynne, R.H., 2011. Introduction to remote sensing, 5th ed. The Guilford Press, New York, United States of America.

Campbell, P.K.E., Middleton, E.M., Corp, L.A., Kim, M.S., 2008. Contribution of chlorophyll fluorescence to the apparent vegetation reflectance. Sci. Total Environ. 404, 433–439.

Carroll, M.W., Glaser, J.A., Hunt, T.E., Sappington, T.W., 2008. Use of spectral vegetation indices derived from airborne hyperspectral imagery for detection of European Corn Borer infestation in Iowa Corn Plots. J. Econ. Entomol. 101.

Chamier, J., Schachtschneider, K., Maitre, D.C., Ashton, P.J., Wilgen, B.W. Van, 2012. Impacts of invasive alien plants on water quality, with particular emphasis on South Africa. Water SA 38, 345–356.

Chenje, M., Mohamed-Katerere, J., 2006. Invasive alien species. In: Africa Environment Outlook 2: Our Enviornment, Our Wealth. Progress Press Ltd, Malta.

Cho, M.., Sobhan, I., Skidmore, A.., de Leeuw, J., 2008. Discriminating species using hyperspectral indices at leaf and canopy scales. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 37.

Crimmins, T.M., Mauzy, M.S., Studd, S.E., 2008. Assessing exotic plant distribution, abundance, and impact at Montezuma Castle and Tuzigoot National Monuments in Arizona. Ecol. Restor. 26, 44–50.

Cuneo, P., Jacobson, C.., Leishman, M.., 2009. Landscape-scale detection and mapping of invasive African olive (Olea europaea L . ssp . cuspidata Wall ex G . Don Ciferri) in SW Sydney , Australia using satellite remote sensing. Appl. Veg. Sci. 12, 145–154.

Dale, L.M., Rotar, I., Bogdan, A., Pacurar, F., Thewis, A., Pierna, J.F., Mukendi, N.K., Beaten, V., 2011. Pure species of grass discrimination with the help of Hyperspectral Imaging NIR. Lucr. ştiinţifice 54, 23–27.

Dammer, K.H., Intress, J., Beuche, H., Selbeck, J., Dworak, V., 2013. Discrimination of Ambrosia artemisiifolia and Artemisia vulgaris by hyperspectral image analysis during the growing season. Weed Res. 53, 146–156.

Daughtry, C.S.T., Doraiswamy, P.C., Hunt, E.R., Stern, a. J., McMurtrey, J.E., Prueger, J.H., 2006. Remote sensing of crop residue cover and soil tillage intensity. Soil Tillage Res. 91, 101–108.

De Lange, W.J., Stafford, W.H.L., Forsyth, G.G., Le Maitre, D.C., 2012. Incorporating stakeholder preferences in the selection of technologies for using invasive alien plants as a bio-energy feedstock: applying the analytical hierarchy process. J. Environ. Manage. 99, 76–83.

De Lange, W.J., Wilgen, B.W. Van, 2010. An economic assessment of the contribution of biological control to the management of invasive alien plants and to the protection of ecosystem services in South Africa. Biol. Invasions.

Demarchi, L., Canters, F., Cariou, C., Licciardi, G., Chan, J.C.W., 2014. Assessing the performance of two unsupervised dimensionality reduction techniques on hyperspectral APEX data for high resolution urban land-cover mapping. ISPRS J. Photogramm. Remote Sens. 87, 166–179.

Dewey, S.A., Price, K.P., Ramsey, D., 1991. Satellite remote sensing to predict potential distribution of Dyers woad (Isatis tinctoria). Weed Technol. 5, 479–484.

Dorigo, W., Lucieer, A., Podobnikar, T., Čarni, A., 2012. Mapping invasive Fallopia japonica by combined spectral, spatial, and temporal analysis of digital orthophotos. Int. J. Appl. Earth Obs. Geoinf. 19, 185–195.

Driver, A., Sink, K.J., Nel, J.L., Holness, S., Niekerk, L. van, Daniels, F., Jonas1, Z., Majiedt, P.A., Harris, L., Maze, & K., 2012. National Biodiversity Assessment: An assessment of South Africa's biodiversity and ecosystems. Synthesis Report. South African National Biodiversity Institute, Pretoria.

Dronova, I., Gong, P., Wang, L., Zhong, L., 2015. Mapping dynamic cover types in a large seasonally flooded wetland using extended principal component analysis and object-based classification. Remote Sens. Environ. 158, 193–206.

Dubovyk, O., Landmann, T., Erasmus, B.F.N., Tewes, A., Schellberg, J., 2015. Monitoring vegetation dynamics with medium resolution MODIS-EVI time series at sub-regional scale in southern Africa. Int. J. Appl. Earth Obs. Geoinf. 38, 175–183.

Dumont, J., Hirvonen, T., Heikkinen, V., Mistretta, M., Granlund, L., Himanen, K., Fauch, L., Porali, I., Hiltunen, J., Keski-saari, S., Nygren, M., Oksanen, E., Hauta-kasari, M., Keinänen, M., 2015. Thermal and hyperspectral imaging for Norway spruce (Picea abies) seeds screening. Comput. Electron. Agric. 116, 118–124.

Eldridge, D.J., Soliveres, S., Bowker, M. a., Val, J., 2013. Grazing dampens the positive effects of shrub encroachment on ecosystem functions in a semi-arid woodland. J. Appl. Ecol. 50, 1028–1038.

Enright, W.., 2000. The effect of terrestrial invasive alien plants on water scarcity in South Africa. Phys. Chem. Earth, Part B Hydrol. Ocean. Atmos. 25, 237–242.

Environmental Affairs, 2010. South Affrica year book 2010/11. Environmental Affairs.

Eviner, V.T., Garbach, K., Baty, J.H., Hoskinson, S.A., 2012. Measuring the Effects of Invasive Plants on Ecosystem Services: Challenges and Prospects. Invasive Plant Sci. Manag. 5, 125–136.

Faiola, J., Vermaak, V., 2014. Klipriviersberg. Veld Flora 68–71.

Fernandes, M.R., Aguiar, F.C., Silva, J.M.N., Ferreira, M.T., Pereira, J.M.C., 2013. Spectral discrimination of giant reed (Arundo donax L.): A seasonal study in riparian areas. ISPRS J. Photogramm. Remote Sens. 80, 80–90.

Fernandes, M.R., Aguiar, F.C., Silva, J.M.N., Ferreira, M.T., Pereira, J.M.C., 2014. Optimal attributes for the object based detection of giant reed in riparian habitats: A comparative study between airborne high spatial resolution and WorldView-2 imagery. Int. J. Appl. Earth Obs. Geoinf. 32, 79–91.

Foden, W., Potter, L., 2005. Asparagus laricinus Burch. National Assessment: Red List of South African Plants version 2015.1 [WWW Document]. URL http://redlist.sanbi.org/species.php?species=728-59 (accessed 9.18.15).

Forsyth, A.T., Gibson, L.A., Turner, A.A., 2014. Assessment of SPOT 6 imagery for mapping the invasive alien plant species Pinus spp . in a mountainous area of the Western Cape 1–12.

Fuku, S., Al-Azzawi, A., Madamombe-Manduna, I., Mashele, S., 2013. Phytochemistry and free radical scavenging activity of Asparagus laricinus. Int. J. Pharmacol. 9, 312–317.

Galvão, L., Epiphanio, J., Breunig, F., Formaggio, A., 2011. Crop Type Discrimination Using Hyperspectral Data. In: Hyperspectral Remote Sensing of Vegetation. CRC Press, pp. 397–422.

Garfagnoli, F., Martelloni, G., Ciampalini, A., Innocenti, L., Moretti, S., 2013. Two GUIs-based analysis tool for spectroradiometer data pre-processing. Earth Sci. Informatics 6, 227–240.

Garzon-Lopez, C.X., Bohlman, S. a., Olff, H., Jansen, P. a., 2013. Mapping tropical forest trees using high-resolution aerial digital photographs. Biotropica 45, 308–316.

Gavier-pizarro, G.I., Kuemmerle, T., Hoyos, L.E., Stewart, S.I., Huebner, C.D., Keuler, N.S., Radeloff, V.C., 2012a. Monitoring the invasion of an exotic tree (Ligustrum lucidum) from 1983 to 2006 with Landsat TM / ETM + satellite data and Support Vector Machines in Córdoba , Argentina. Remote Sens. Environ. 122, 134–145.

Gavier-pizarro, G.I., Kuemmerle, T., Stewart, S.I., 2012b. Monitoring the invasion of an exotic tree (Ligustrum lucidum) from 1983 to 2006 with Landsat TM / ETM + satellite data and Support Vector Machines in Córdoba , Argentina. Remote Sens. Environ.

Ghulam, A., Porton, I., Freeman, K., 2014. Detecting subcanopy invasive plant species in tropical rainforest by integrating optical and microwave (InSAR/PolInSAR) remote sensing data, and a decision tree algorithm. ISPRS J. Photogramm. Remote Sens. 88, 174–192.

Glenn, E.P., Huete, A.R., Nagler, P.L., Nelson, S.G., 2008. Relationship between remotely-sensed vegetation indices, canopy attributes and plant physiological processes: What vegetation indices can and cannot tell us about the landscape. Sensors 8, 2136–2160.

Görgens, A.H.M., Wilgen, B.W. Van, 2004. Invasive alien plants and water resources in South Africa: Current understanding, predictive ability and research challenges. S. Afr. J. Sci. 100, 27–33.

Guerschman, J.P., Hill, M.J., Renzullo, L.J., Barrett, D.J., Marks, A.S., Botha, E.J., 2009. Estimating fractional cover of photosynthetic vegetation, non-photosynthetic vegetation and bare soil in the Australian tropical savanna region upscaling the EO-1 Hyperion and MODIS sensors. Remote Sens. Environ. 113, 928–945.

Hawthorne, T.L., Elmore, V., Strong, A., Bennett-martin, P., Finnie, J., Parkman, J., Harris, T., Singh, J., Edwards, L., Reed, J., 2015. Mapping non-native invasive species and accessibility in an urban forest : A case study of participatory mapping and citizen science in Atlanta, Georgia. Appl. Geogr. 56, 187–198.

Hawthorne, T.L., Elmore, V., Strong, A., Bennett-Martin, P., Finnie, J., Parkman, J., Harris, T., Singh, J., Edwards, L., Reed, J., 2015. Mapping non-native invasive species and accessibility in an urban forest: A case study of participatory mapping and citizen science in Atlanta, Georgia. Appl. Geogr. 56, 187–198.

Hejda, M., Pyšek, P., Jarošík, V., 2009. Impact of invasive plants on the species richness, diversity and composition of invaded communities. J. Ecol. 97, 393–403.

Henderson, L., 2007. Invasive, naturalized and casual alien plants in southern Africa : a sum- mary based on the Southern African Plant Invaders Atlas (SAPIA). Bothalia 37, 215–248.

Henderson, L., 2015. Geographical Distribution of IAPs in Southern Africa (SAPIA) [WWW Document]. Agric. Res. Counc. URL http://www.arc.agric.za/arc-ppri/Pages/Weeds Research/Geographical-distribution-of-IAPs-in-southern-Africa-%28SAPIA%29-.aspx (accessed 9.7.15).

Huang, C., Asner, G.P., 2009. Applications of remote sensing to alien invasive plant ptudies. Sensors 9, 4869–4889.

Huebner, C.D., 2007. Detection and monitoring of invasive exotic plants: A comparison of four sampling methods. Northeast. Nat. 14, 183–206.

Jensen, J.R., 2014. Remote sensing of the environment: an earth resource perspectivee, 2nd ed. Harlow, Essex: Pearson.

Jia, M., Zhang, Y., Wang, Z., Song, K., Ren, C., 2014. Mapping the distribution of mangrove species in the Core Zone of Mai Po Marshes Nature Reserve, Hong Kong, using hyperspectral data andhigh-resolution data. Int. J. Appl. Earth Obs. Geoinf. 33, 226–231.

Jide, A., Folayan, A., Unmonu, T.O.S., 2011. Artemisia afra Jacq . Ameliorates Oxidative Stress in the Pancreas of Streptozotocin-Induced Diabetic Wistar Rats. Biosci. Biotechnol. Biochem. 75, 2083–2086.

Johansen, K., Phinn, S., Witte, C., 2010. Mapping of riparian zone attributes using discrete return LiDAR , QuickBird and SPOT-5 imagery : Assessing accuracy and costs. Remote Sens. Environ. 114, 2679–2691.

Jordaan, D., 2009. Bankruptbush (Slangbos) – A silent threat to grasslands? Grassroots Newsl. Grassl. Soc. South. Africa 9, 40–42.

Joshi, C., Leeuw, J. De, Duren, I.C. Van, 2004. Remote sensing and GIS applications for mapping and spatial modelling of invasive species 669–677.

Khavhagali, V.P., 2010. Importance , threats , status and conservation challenges of biodiversity in Northern Cape . Gressl. Soc. South. Africa 10, 14–17.

Kotze, P.., 2002. The ecological integrity of the Klip River and the development of a sensitivity weighted fish index of biotic integrity (SIBI). ujdigispace. University of Johannesburg.

Laba, M., Downs, R., Smith, S., Welsh, S., Neider, C., White, S., Richmond, M., Philpot, W., Baveye, P., 2008. Mapping invasive wetland plants in the Hudson River National Estuarine Research Reserve using quickbird satellite imagery. Remote Sens. Environ. 112, 286–300.

Landmann, T., Piiroinen, R., Makori, D.M., Abdel-rahman, E.M., Makau, S., Pellikka, P., Raina, S.K., 2015. Remote sensing of environment application of hyperspectral remote sensing for flower mapping in African savannas. Remote Sens. Environ. 166, 50–60.

Lawrence, R.L., Wood, S.D., Sheley, R.L., 2006. Mapping invasive plants using hyperspectral imagery and Breiman Cutler classifications (RandomForest). Remote Sens. Environ. 100, 356–362.

Le Maitre, D.., van Wilgen, B.., Gelderblom, C.., Bailey, C., Chapman, R.., Nel, J.., 2002. Invasive alien trees and water resources in South Africa: case studies of the costs and benefits of management. For. Ecol. Manage. 160, 143–159.

Le Maitre, D.C., Kotzee, I.M., O'Farrell, P.J., 2014. Impacts of land-cover change on the water flow regulation ecosystem service: Invasive alien plants, fire and their policy implications. Land use policy 36, 171–181.

Le Maitre, D.C., O 'farrell, P.J., Reyers, B., 2007. Ecosystems services in South Africa: A research theme that can engage environmental, economic and social scientists in the development of sustainability science? S. Afr. J. Sci. 103.

Le Maitre, D.C., Versefeld, D.B., Chapman, R.A., 2000. The impact of invading alien plants on surface water resources in South Africa: A preliminary assessment. Water SA Vol. 26, 397–408.

Lemke, D., Hulme, P.E., Brown, J.A., Tadesse, W., 2011. Distribution modelling of Japanese honeysuckle (Lonicera japonica) invasion in the Cumberland Plateau and Mountain Region , USA. For. Ecol. Manage. 262, 139–149.

Lillesand, T., Kiefer, R., Chipman, J. (Eds.), 2015. Remote sensing and image interpretation, 7th ed. John Wiley & Sons Ltd, United States of America.

Lishawa, S.C., Treering, D.J., Vail, L.M., Mckenna, O., Grimm, E.C., Tuchman, N.C., 2013. Reconstructing plant invasions using historical aerial imagery and pollen core analysis: Typha in the Laurentian Great Lakes. Divers. Distrib. 19, 14–28.

Liu, N.Q., Kooy, F. Van Der, Verpoorte, R., 2009. Artemisia afra: A potential flagship for African medicinal plants ? South African J. Bot. 75, 185–195.

Lu, J., Zhang, Y., 2013. Spatial distribution of an invasive plant Spartina alterniflora and its potential as biofuels in China. Ecol. Eng. 52, 175–181.

Mahwasane, S.T., Middleton, L., Boaduo, N., 2013. An ethnobotanical survey of indigenous knowledge on medicinal plants used by the traditional healers of the Lwamondo area , Limpopo province , South Africa. South African J. Bot. 88, 69–75.

Manevski, K., Manakos, I., Petropoulos, G.P., Kalaitzidis, C., 2011. Discrimination of common Mediterranean plant species using field spectroradiometry. Int. J. Appl. Earth Obs. Geoinf. 13, 922–933.

Mansour, K., 2013. Comparing the new generation world view-2 to hyperspectral image data for species discrimination. Int. J. Dev. Res. 3, 8–13.

Marais, C., Wilgen, B.W. Van, Stevens, D., 2004. The clearing of invasive alien plants in South Africa: A preliminary assessment of costs and progress. S. Afr. J. Sci. 100, 97–103.

Martín, M., Barreto, L., Fernández-Quintanilla, C., 2011. Discrimination of sterile oat (Avena sterilis) in winter barley (Hordeum vulgare) using QuickBird satellite images. Crop Prot. 30, 1363–1369.

Mashele, S., Kolesnikova, N., 2010. In vitro anticancer screening of Asparagus laricinus extracts. Pharmacologyonline 2, 246–252.

McConnachie, M.M., Shackleton, C.M., McGregor, G.K., 2008. The extent of public green space and alien plant species in 10 small towns of the Sub-Tropical Thicket Biome, South Africa. Urban For. Urban Green. 7, 1–13.

Meier, E.S., Dullinger, S., Zimmermann, N.E., Baumgartner, D., Gattringer, A., Hülber, K., 2014. Space matters when defining effective management for invasive plants. Divers. Distrib. 20, 1029–1043.

Mgidi, T.N., Le, D.C., Schonegevel, L., Nel, J.L., Rouget, M., Richardson, D.M., 2007. Alien plant invasions — incorporating emerging invaders in regional prioritization : A pragmatic approach for Southern Africa. J. Environ. Manage. 84, 173–187.

Mirik, M., Ansley, R.J., Steddom, K., Jones, D.C., Rush, C.M., Michels, G.J., Elliott, N.C., 2013. Remote distinction of a noxious weed (Musk Thistle: Carduus Nutans) using airborne hyperspectral imagery and the support vector machine classifier. Remote Sens. 5, 612–630.

Mirik, M., Emendack, Y., Attia, A., Chaudhuri, S., Roy, M., Backoulou, G.F., Cui, S., 2014. Detecting Musk Thistle (Carduus nutans) infestation using a Target Recognition Algorithm. Adv. Remote Sens. 95–105.

Moran, V.C., Hoffmann, J.H., Zimmermann, H.G., 2005. Biological control of invasive alien plants in South Africa: Necessity, circumspection, and success. Front. Ecol. Environ. 3, 77–83.

Moran, V.C., Hoffmann, J.H., Zimmermann, H.G., 2013. 100 years of biological control of invasive alien plants in South Africa: History, practice and achievements. S. Afr. J. Sci. 109, 1–6.

Morris, T.L., Witkowski, E.T.F., Coetzee, J.A., 2008. Initial response of riparian plant community structure to clearing of invasive alien plants in Kruger National Park, South Africa. South African J. Bot. 74, 485–494.

Mukinda, J.T., Syce, J.A., 2007. Acute and chronic toxicity of the aqueous extract of Artemisia afra in rodents. J. Ethnopharmacol. 112, 138–144.

Nagler, P.L., Daughtry, C.S.T., Goward, S.N., 2000. Plant Litter and Soil Reflectance. Remote Sens. Environ. 71, 207–215.

Narumalani, S., Mishra, D.R., Wilson, R., Reece, P., Kohler, A., 2009. Detecting and Mapping Four Invasive Species Along The Floodplain of North Platte River, Nebraska. Weed Technol. 23, 99–107.

Neill, J.D.O., Costa, M., 2013. Mapping eelgrass (Zostera marina) in the Gulf Islands National Park Reserve of Canada using high spatial resolution satellite and airborne imagery. Remote Sens. Environ. 133, 152–167.

Ntsoelinyane, P.H., Mashele, S., 2014. Phytochemical screening , antibacterial and antioxidant activities of asparagus laricinus leaf and stem extracts. Bangladesh J. Pharmacol. 9, 10–14.

Olsson, A.D., van Leeuwen, W.J.D., Marsh, S.E., 2011. Feasibility of invasive grass detection in a desertscrub community using hyperspectral field measurements and Landsat TM imagery. Remote Sens. 3, 2283–2304.

Otang, W.M., Grierson, D.S., Afolayan, A.J., 2015. South African Journal of Botany A survey of plants responsible for causing allergic contact dermatitis in the Amathole District , Eastern Cape , South Africa. South African J. Bot. 97, 32–39.

Ouyang, Z.-T., Gao, Y., Xie, X., Guo, H.-Q., Zhang, T.-T., Zhao, B., 2013. Spectral Discrimination of the Invasive Plant Spartina alterniflora at Multiple Phenological Stages in a Saltmarsh Wetland. PLoS One 8, e67315.

Pasqualini, V., Pergent-Martini, C., Pergent, G., Agreil, M., Skoufas, G., Sourbes, L., Tsirika, A., 2005. Use of SPOT 5 for mapping seagrasses: An application to Posidonia oceanica. Remote Sens. Environ. 94, 39–45.

Patil, G. V, Dass, S.K., Chandra, R., 2011. Artemisia afra and Modern Diseases. Pharmacogenomics & Pharmacoproteomics 2.

Peh, K., Balmford, A., Birch, J., Brown, C., Butchart, S., Daley, J., Dawson, J., Gray, G., Hughes, F., Mendes, S., Millet, J., Stattersfield, A., Thomas, D., Walpole, M., Bradbury, R., 2015. Potential impact of invasive alien species on ecosystem services provided by a tropical forested ecosystem: a case study from Montserrat. Biol. Invasions 17, 461–475.

Peña, J.M., Torres-Sánchez, J., de Castro, A.I., Kelly, M., López-Granados, F., 2013. Weed mapping in early-season maize fields using object-based analysis of Unmanned Aerial Vehicle (UAV) images. PLoS One 8, 1–11.

Perez, D., Sanchez, M., 2001. Authentication of Green Asparagus Varieties by Near • Infrared Reflectance Spectroscopy. J. Food Sci. 66, 323–327.

Pflugmacher, D., 2007. Moderate resolution remote sensing alternatives: a review of Landsat-like sensors and their applications. J. Appl. Remote Sens. 1, 012506.

Poona, N., 2008. Invasive alien plant species in South Africa: Impacts and management options. Alternation 15, 160–179.

Pouteau, R., Meyer, J., Larrue, S., 2015. Using range filling rather than prevalence of invasive plant species for management prioritisation: The case of Spathodea campanulata in the Society Islands (South Pacific). Ecol. Indic. 54, 87–95.

Prasad, K., Gnanappazham, L., 2014. Discrimination of mangrove species of Rhizophoraceae using laboratory spectral signatures. In: IEEE Geoscience and Remote Sensing Sympsium.

Prospere, K., Mclaren, K., Wilson, B., 2014. Plant species discrimination in a Tropical Wetland using in situ hyperspectral data. Remote Sens. 6, 8494–8523.

Pu, R., Bell, S., Baggett, L., Meyer, C., Zhao, Y., Pu, R., Bell, S., Baggett, L., Meyer, C., Zhao, Y., 2012. Discrimination of seagrass species and cover classes with in situ hyperspectral data. J. Coast. Res. 28, 1330–1344.

Pyšek, P., Jarošík, V., Hulme, P.E., Pergl, J., Hejda, M., Schaffner, U., Vilà, M., 2012. A global assessment of invasive plant impacts on resident species, communities and ecosystems: The interaction of impact measures, invading species' traits and environment. Glob. Chang. Biol. 18, 1725–1737.

Ren, J., Zabalza, J., Marshall, S., 2014. Effective feature extraction and data reduction in remote sensing using hyperspectral imaging. IEEE Signal Process. Mag. 149–154.

Richardson, D.M., Rejmánek, M., 2011. Trees and shrubs as invasive alien species-a global review. Divers. Distrib. 17, 788–809.

Richardson, D.M., Van Wilgen, B.W., 2004. Invasive alien plants in South Africa: How well do we understand the ecological impacts? S. Afr. J. Sci. 100, 45–52.

Rodgers, L., Pernas, T., Hill, S.D., 2014. Mapping invasive plant distributions in the Florida Everglades using the digital aerial sketch mapping technique. Invasive Plant Sci. Manag. 7, 360–374.

Rouget, M., Hui, C., Renteria, J., Richardson, D.M., Wilson, J.R.U., 2015. Plant invasions as a biogeographical assay: Vegetation biomes constrain the distribution of invasive alien species assemblages. South African J. Bot.

Rouget, M., Richardson, D.M., Nel, J.L., Le Maitre, D.C., Egoh, B., Mgidi, T., 2004. Mapping the potential ranges of major plant invaders in South Africa, Lesotho and Swaziland using climatic suitability. Divers. Distrib. 10, 475–484.

Roura-Pascual, N., Krug, R., Richardson, D., 2009a. Identifying priority areas for the management of invasive alien plants in the Cape Floristic Region. South African J. Bot. 75, 439.

Roura-Pascual, N., Richardson, D., Krug, R., Brown, A., Chapman, R., Forsyth, G., Le Maitre, D., Robertson, M., Stafford, L., Van Wilgen, B., 2009b. Ecology and management of alien plant invasions in South African fynbos: Accommodating key complexities in objective decision making. Biol. Conserv. 142, 1595–1604.

Rudolf, J., Lehmann, K., Große-stoltenberg, A., Römer, M., Oldeland, J., 2015. Field spectroscopy in the VNIR-SWIR region to discriminate between Mediterranean native plants and exotic-invasive shrubs based on leaf tannin content. Remote Sens. 7, 1225–1241.

Rutherford, M., Midgley, G., Bond, W., Powrie, L., Roberts, R., Allsopp, J., 1999. Plant Biodiversity In: Kiker, G. Climate change impacts in southern Africa, Report to the National Climate Change Committee. Pretoria.

Rutherford, M.C., Mucina, L., Powrie, L.W., 2006. Biomes and Bioregions of Southern Africa. In: Strelitzia 19: Vegetation of South Africa, Lesotho & Swaziland.

SANBI, 2006. Conserving South Africa’s plants: A South African response to the Global Strategy for Plant Conservation, Biodiverst. ed. South African National Biodiversity Institute. Obtainable, Pretoria.

Schmidt, K.S., Skidmore, A.K., 2003. Spectral discrimination of vegetation types in a coastal wetland. Remote Sens. Environ. 85, 92–108.

Schmiedel, U., Jürgens, N. (Eds.), 2010. Biodiversity in Southern Africa 2: Patterns and Processes at Regional Scale, 2nd ed. Klaus Hess Publishers, Germany.

Schor, J., Farwig, N., Berens, D.G., 2015. Intensive land-use and high native fruit availability reduce fruit removal of the invasive Solanum mauritianum in South Africa. South African J. Bot. 96, 6–12.

Scott, G., Springfield, E., 2004. Artemisia afra Herba. In: Pharmaceutical Monographs on CD-ROM for 60 South African plant species used as traditional medicines. Pretoria.

Semenya, S., Potgieter, M., Tshisikhawe, M., Shava, S., Maroyi, A., 2012. Medicinal utilization of exotic plants by Bapedi traditional healers to treat human ailments in Limpopo province, South Africa. J. Ethnopharmacol. 144, 646–55.

Serbin, G., Daughtry, C.S.T., Hunt, E.R., Reeves, J.B., Brown, D.J., 2009. Effects of soil composition and mineralogy on remote sensing of crop residue cover. Remote Sens. Environ. 113, 224–238.

Shackleton, C., Shackleton, S., 2004. The importance of non-timber forest products in rural livelihood security and as safety nets : a review of evidence from South Africa. S. Afr. J. Sci. 100, 658–664.

Shackleton, C.M., Shackleton, S.E., Buiten, E., Bird, N., 2007. The importance of dry woodlands and forests in rural livelihoods and poverty alleviation in South Africa. For. Policy Econ. 9, 558–577.

Sharma, G.P., Raghubanshi, A.S., 2009. Lantana invasion alters soil nitrogen pools and processes in the tropical dry deciduous forest of India. Appl. Soil Ecol. 42, 134–140.

Snyman, H., 2010. Allelopathic potential , seed ecology and germination of the encroacher shrub Seriphium plumosum Allelopathic potential , seed ecology and germination of the encroacher. African J. Range Forage Sci. 27, 29–37.

Snyman, H., 2012a. Habitat preferences of the encroacher shrub, Seriphium plumosum. South African J. Bot. 81, 34–39.

Snyman, H., 2012b. Control measures for the encroacher shrub Seriphium plumosum. South African J. Plant Soil 29, 157–163.

Somers, B., Asner, G.P., Martin, R.E., Anderson, C.B., Knapp, D.E., Wright, S.J., Van De Kerchove, R., 2015. Mesoscale assessment of changes in tropical tree species richness across a bioclimatic gradient in Panama using airborne imaging spectroscopy. Remote Sens. Environ.

Somodi, I., Čarni, A., Ribeiro, D., Podobnikar, T., 2012. Recognition of the invasive species Robinia pseudacacia from combined remote sensing and GIS sources. Biol. Conserv. 150, 59–67.

Tatsumi, K., Yamashiki, Y., Canales Torres, M.A., Taipe, C.L.R., 2015. Crop classification of upland fields using Random forest of time-series Landsat 7 ETM+ data. Comput. Electron. Agric. 115, 171–179.

Taylor, S., Kumar, L., Reid, N., Kriticos, D.J., 2012. Climate change and the potential distribution of an invasive shrub, Lantana camara L. PLoS One 7, e35565.

Thenkabail, P., 2014. Research advances in hyperspectral remote sensing. Photogramm. Eng. Remote Sensing 80, 721–723.

Thenkabail, P.S., Mariotto, I., Gumma, M.K., Middleton, E.M., Landis, D.R., Huemmrich, K.F., 2013. Selection of Hyperspectral Narrowbands (HNBs) and Composition of Hyperspectral Twoband Vegetation Indices (HVIs) for Biophysical Characterization and Discrimination of Crop Types Using Field Re fl ectance and Hyperion / EO-1 Data. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens. 6, 427–439.

Tsai, F., Lin, E.K., Yoshino, K., 2007. Spectrally segmented principal component analysis of hyperspectral imagery for mapping invasive plant species. Int. J. Remote 28, 1023–1039.

Turpie, J., 2004. The role of resource economics in the control of invasive alien plants in South Africa. S. Afr. J. Sci. 100, 87–93.

Turpie, J.K., Marais, C., Blignaut, J.N., 2008. The working for water programme: Evolution of a payments for ecosystem services mechanism that addresses both poverty and ecosystem service delivery in South Africa. Ecol. Econ. 65, 788–798.

Tuxen, K.A., Schile, L.M., Kelly, M., Siegel, S.W., 2008. Vegetation Colonization in a

Restoring Tidal Marsh : A Remote Sensing Approach. Restor. Ecol. 16, 313–323.

Van der Kooy, F., Verpoorte, R., Meyer, M.J.J., 2008. Metabolomic quality control of claimed anti-malarial Artemisia afra herbal remedy and A. afra and A. annua plant extracts. South African J. Bot. 74, 186–189.

Van Wilgen, B., 2006. Invasive alien species – an important aspect of global change. CSIR Sci. Scope 1, 8–11.

Van Wilgen, B., 2012. Ecology and Society: Evidence, Perceptions, and Trade-offs Associated with Invasive Alien Plant Control in the Table Mountain National Park, South Africa 17.

Van Wilgen, B., de Lange, W., 2011. The Costs and Benefits of Biological Control of Invasive Alien Plants in South Africa. African Entomol. 19, 504–514.

Van Wilgen, B., Le Maitre, D., Cowling, R., 1998. Ecosystem services, efficiency, sustainability and equity: South Africa's Working for Water programme. Trends Ecol. Evol. 13, 378.

Van Wilgen, B., Reyers, B., Le Maitre, D., Richardson, D., Schonegevel, L., 2008. A biome-scale assessment of the impact of invasive alien plants on ecosystem services in South Africa. J. Environ. Manage. 89, 336–49.

Van Wilgen, B.W., Cowling, R.M., Marais, C., Esler, K.J., McConnachie, M.M., Sharp, D., 2012a. Challenges in invasive alien plant control in South Africa. S. Afr. J. Sci. 108, 11–13.

Van Wilgen, B.W., Forsyth, G.G., Le Maitre, D.C., Wannenburgh, A., Kotzé, J.D.F., van den Berg, E., Henderson, L., 2012b. An assessment of the effectiveness of a large, national-scale invasive alien plant control strategy in South Africa. Biol. Conserv. 148, 28–38.

Van Wilgen, B.W., Moran, V.C., Hoffmann, J.H., 2013. Some perspectives on the risks and benefits of biological control of invasive alien plants in the management of natural ecosystems. Environ. Manage. 52, 531–40.

Van Wyk, B.E., 2008. A broad review of commercially important southern African medicinal plants. J. Ethnopharmacol. 119, 342–355.

Van Wyk, B.E., 2011. The potential of South African plants in the development of new medicinal products. South African J. Bot. 77, 812–829.

Vancutsem, C., Pekel, J.F., Evrard, C., Malaisse, F., Defourny, P., 2009. Mapping and characterizing the vegetation types of the Democratic Republic of Congo using SPOT VEGETATION time series. Int. J. Appl. Earth Obs. Geoinf. 11, 62–76.

Vicente, J.R., Fernandes, R.F., Randin, C.F., Broennimann, O., Gonçalves, J., Marcos, B., Pôças, I., Alves, P., Guisan, A., Honrado, J.P., 2013. Will climate change drive alien invasive plants into areas of high protection value? An improved model-based regional assessment to prioritise the management of invasions. J. Environ. Manage. 131, 185–95.

Williams, V.L., Victor, J.E., Crouch, N.R., 2013. Red Listed medicinal plants of South Africa : Status , trends , and assessment challenges. South African J. Bot. 86, 23–35.

Xie, Y., Sha, Z., Yu, M., 2008. Remote sensing imagery in vegetation mapping: A review. J. Plant Ecol. 1, 9–23.

Xu, H., Yu, P., Fu, X., Ying, Y., 2009. On-site variety discrimination of tomato plant using visible-near infrared reflectance spectroscopy *. J. Zhejiang Univ. Sci. B 10, 126–132.

Zhang, Y., 2011. Forest Leaf Chlorophyll Study Using Hyperspectral Remote Sensing. In: Hyperspectral Remote Sensing of Vegetation. CRC Press, pp. 167–186.