A MULTISCALE REMOTE SENSING ASSESSMENT OF SUBTROPICAL INDIGENOUS FORESTS ALONG THE WILD COAST, SOUTH AFRICA

Sithole Vhusomuzi Blessing

Thesis submitted in fulfilment of the Requirements for the Degree of

PHILOSOPHIAE DOCTOR

in the Faculty of Science at the Nelson Mandela Metropolitan University

January 2015

Promoter: Professor Vincent Kakembo

ABSTRACT

The subtropical forests located along South Africa's Wild Coast region, declared as one of the biodiversity hotspots, provide benefits to the local and national economy. However, there is evidence of increased pressure exerted on the forests by growing population and reduced income from activities not related to forest products. The ability of remote sensing to quantify subtropical forest changes over time, perform species discrimination (using field spectroscopy) and integrating field spectral and multispectral data were all assessed in this study. Investigations were conducted at pixel, leaf and sub-pixel levels. Both per-pixel and sub-pixel classification methods were used for improved forest characterisation. Using SPOT 6 imagery for 2013, the study determined the best classification algorithm for mapping sub-tropical forest and other land cover types to be the maximum likelihood classifier. Maximum likelihood outperformed minimum distance, spectral angle mapper and spectral information divergence algorithms, based on overall accuracy and Kappa coefficient values. Forest change analysis was made based on spectral measurements made at top of the atmosphere (TOC) level. When applied to the 2005 and 2009 SPOT 5 images, subtropical forest changes between 2005-2009 and 2009-2013 were quantified. A temporal analysis of forest cover trends in the periods 2005-2009 and 2009-2013 identified a decreasing trend of -3648.42 and -946.98 ha respectively, which translated to 7.81% and 2.20% decrease. Although there is evidence of a trend towards decreased rates of forest loss, more conservation efforts are required to protect the Wild Coast ecosystem.

Using field spectral measurements data, the hierarchical method (comprising One-way ANOVA with Bonferroni correction, Classification and Regression Trees (CART) and Jeffries Matusita method) successfully selected optimal wavelengths for species discrimination at leaf level. Only 17 out of 2150 wavelengths were identified, thereby reducing the complexities related to data dimensionality. The optimal 17 wavelength bands were noted in the visible (438, 442, 512 and 695 nm), near infrared (724, 729, 750, 758, 856, 936, 1179, 1507 and 1673 nm) and mid-infrared (2220, 2465, 2469 and 2482 nm) portions of the electromagnetic spectrum. The Jeffries-Matusita (JM) distance method confirmed the separability of the selected wavelength bands. Using these 17 wavelengths, linear discriminant analysis (LDA) classified subtropical species at leaf level more accurately than partial least squares discriminant analysis (PLSDA) and random forest (RF).

In addition, the study integrated field-collected canopy spectral and multispectral data to discriminate proportions of semi-deciduous and evergreen subtropical forests at sub-pixel level. By using the 2013 land cover (using MLC) to mask non-forested portions before sub-pixel classification (using MTMF), the proportional maps were a product of two classifiers. The proportional maps show higher proportions of evergreen forests along the coast while semi-deciduous subtropical forest species were mainly on inland parts of the Wild Coast. These maps had high accuracy, thereby proving the ability of an integration of field spectral and multispectral data in mapping semi-deciduous and evergreen forest species.

Overall, the study has demonstrated the importance of the MLC and LDA and served to integrate field spectral and multispectral data in subtropical forest characterisation at both leaf and top-of-atmosphere levels. The success of both the MLC and LDA further highlighted how essential parametric classifiers are in remote sensing forestry applications. Main subtropical characteristics highlighted in this study were species discrimination at leaf level, quantifying forest change at pixel level and discriminating semi-deciduous and evergreen forests at sub-pixel level.

DECLARATION

I, SITHOLE VHUSOMUZI BLESSING solemnly declare that this thesis was composed and written by me. It has never been presented anywhere for an academic award or otherwise. All materials used from other sources are duly appreciated and properly acknowledged.

…………………………………………………….

SITHOLE VHUSOMUZI BLESSING

ACKNOWLEDGEMENTS

I would like to thank my promoter, Prof V. Kakembo for all the feedback, discussions and support throughout the duration of my studies. This study would have been impossible had it not been for the financial resources provided by the National Research Foundation (NRF), NMMU Postgraduate Research Scholarship and DAAD‘s Clim-A-Net programme. I was hosted at the University of Oldenburg in Germany, under the DAAD Clim-A-Net exchange programme, and that is where learnt a lot about R statistical computing. I received assistance from Prof M. Kleyer, Maximilian Pertzold and Godfrey Mmbando. Valuable input was also received from Prof B. Siebenhüner, M. von Möllendorff and Kilian Koebrich, particularly on the underlying environmental problems in forested areas.

I also wish to acknowledge the support received from colleagues, especially Lucky, Mathabo, Nelson and staff members at the DAFF Mthatha office. My sincere gratitude also goes to my immediate family (my father, mother, Douglas, Paul and Stella) for their support and encouragement, which kept me going. Lastly, I would like thank the language editor, Heather Cousins, as well as Tawanda and Kath for editing my work.

Table of Contents

Abbreviations

DAFF	Department of Agriculture, Forestry and Fisheries
GIS	Geographical Information Systems
LDA	Linear Discriminant Analysis
MIN	Minimum-distance
MLE	Maximum likelihood estimation
MTMF	Mixture Tuned Matched Filtering
PLS-DA	Partial Least Squares Discriminant Analysis
RF	Random Forest
SAM	Spectral angle mapper
SANSA	South African National Space Agency
SID	Spectral information divergence

List of Figures

List of Pictures

List of Tables

General Introduction

1.1: Introduction

Forests are of vital importance to the natural ecosystem including humans and biodiversity. There are a number of benefits derived from forests. In Southern Africa, the subtropical biome covers less than 0.25% of the total area (Low and Rebelo, 1996) and supports about 14% of its terrestrial birds and animals (Geldenhuys and MacDevette, 1989). South Africa has seven biomes and the forest biome is the smallest, occupying only 0.1-0.2% of the total land area (Castley and Kerly, 1996). In the Wild Coast region, these forests cover about 50 000 hectares (ha) altogether with each forest patch being generally less than 100 ha (Berliner, 2011). Most of indigenous forests in this area belong to the subtropical forests type, hence for the purpose of this study the subtropical indigenous forest are referred to as subtropical forests. The management of these forests are managed by the Department of Agriculture, Forestry and Fisheries (DAFF), municipalities and conservation non-governmental organisations (NGOs) (Castley and Kerly, 1996). Management is complicated by the forests' proximity to local communities resulting in uncontrolled use. While indigenous forests are of paramount importance and their degradation an issue of major concern, the conservation of South Africa's coastal subtropical forests is often a challenging task.

In South Africa, forests and other woody biomes are essential for their economic contribution at national and local levels. The South African national and local government statutes allow for sustainable use of forest resources by nearby communities. The economic benefits include: supplying fuel (wood), timber, medicines (Brigham et al., 1996); ecotourism (Grossman and Gandar, 1989); regional carbon sequestration (Scholes and Hall, 1996); as well as habitats for biological diversity (Cowling et al., 1997). Besides immediate forest benefits such as food, medicine and raw materials, forest resources are also essential for carbon sequestration. Emissions from forest degradation are a major contributor of carbon emissions into the atmosphere and addressing forest degradation is part of the United Nations programme for Reducing Emissions from Deforestation and forest Degradation (UN-REDD+) initiatives for combating climate change (Mertz et al., 2012). Related to the issue of carbon emission is that the conservation of forests and thickets provides an essential terrestrial carbon store (Mills and Cowling, 2006). If forest use by humans is not managed, there is a big risk of exploitation.

Anthropogenic use of forests often leads to their overexploitation, which in turn may result in deforestation and degradation. The consequence of this unsustainable exploitation is usually a negative knock-on effect for both the environment and those communities reliant on the forest resources.

The coastal subtropical forests of South Africa are under threat from firewood collection, agricultural land expansion, holiday resort expansion and dune mining (Trimble and van Aarde, 2011). A study by Obiri et al. (2002) has shown that in Pondoland nine out of the widely used twenty high-value forest species were overexploited. The negative effects emanating from the overexploitation have prompted to efforts to reduce use as enshrined in the national statutes.

The main drivers of increased forest use by humans in the Wild Coast are the declining agricultural production and lack of alternative economic activities (Shackleton et al., 2013). Migrant labour remittances, livestock, subsistence farming, non-timber forest products and social grants are among the main sources of cash income for many households (Shackleton et al., 2007b). The exploitation of forests is high in forests near local villages compared to those owned by the state. There are therefore conflicts in forest resource use between local communities who live close to forests and the national government department (DAFF) that promotes sustainable forest management.

Forestry monitoring, which is one of the management tools, has been applied using remote sensing. Remote sensing imagery, both from satellites and aircrafts, have been used in assessing forests, processes that would have been difficult using ground research methods (Zwiggelaar, 1998). Past forestry applications of remote sensing in Southern Africa include land-cover mapping in the Southern African savannah (Griscom et al., 2010, Hüttich et al., 2011), monitoring savannah rangeland deterioration (Munyati et al., 2011), as well as analysing vegetation patchiness and its implications (Kakembo, 2009). Remote sensing applications allow early and late season, spatial and spectral analysis for forest monitoring (Shapira et al., 2013). Another reason for forest change monitoring is the need to keep track of changes due to wildfires, which in some instances cause extensive damage constituting a national disaster. Like many of the areas dominated by indigenous forests, the Wild Coast region urgently requires sustainable forest management tools like remote sensing-based forest monitoring. This study uses a combination of the hyperspectral and multispectral data sources with the aim of aiding forest management.

Despite the promotion of sustainable forest utilisation the previous section highlighted the threats presented by human activities especially along the dense indigenous forests along the coast. In South Africa indigenous forests are managed under two different tenure systems with links to the tribal trust land annexure (Johnson, 1983), state and communal management. The regulations used in forest management are enshrined in the environment-related Acts (Africa, 1998, National Environmental Management: Biodiversity Act, 2004, South Africa, 1998) in line with national conservation objectives. Reduced forest cover is due to the two processes of deforestation and forest degradation. Deforestation is defined as the removal of trees leading to earth surface changing from forest to other land cover types (FAO, 2000, Mon et al., 2012). Forest degradation on the other hand refers to the reduction in capacity to provide goods and services (FAO, 2000). Asner et al. (2004) highlighted that the two process are closely related because in a number of cases degradation precedes deforestation and hence it is challenging to analyse the two separately using remote sensing. Remote sensing based monitoring of forests is on the increase mainly due to the need to reduce degradation and deforestation as well as evaluating intervention mechanisms. Forest change is used in this study to account for forest loss due to deforestation and change due to degradation. The next sub-sections constitute an outline of the components of the problem investigated in the present study.

Multispectral monitoring of forest changes

Internationally, multispectral and hyperspectral remote sensing approaches are often used in forest modelling. The majority of forest monitoring programmes are based on multispectral imagery, such as Landsat (Hansen et al., 2013), Advanced Very High

Resolution Radiometer (AVHRR) (Sivanpillai et al., 2007) and Moderate Resolution Imaging Spectroradiometer (MODIS). The two latest satellites (SPOT 6 and 7) from the SPOT series have spatial resolutions of 6m (Airbus Defence and Space, 2014), which can support forest monitoring. At the same time, the South African government is in the process of developing and launching its own high resolution multispectral satellite (EO-SAT 1) (SANSA, 2014). The conditions and changes in forests give more reason for forest monitoring using remote sensing. Multispectral imagery has a number of advantages compared to the hyperspectral ones and these mainly involve both data availability and cost.

1.2: Problem Statement

A comprehensive national forest monitoring programme that utilises remote sensing methods is lacking in South Africa. This is despite the country having a “good” ranking in forest change monitoring capacity (Romijn et al., 2012) by the United Nations Collaborative Programme on Reducing Emissions from Deforestation (UN-REDD) programme. According to study by Rahlao et al. (2012) on the potential contribution of forestry to South Africa’s climate change mitigation, it has lower rates of forest cover and national deforestation compared to other countries, hence its reluctance to participate in UN-REDD+. The reluctance to participate in programmes like this one may have been the reason for not prioritising a monitoring programme.

Field spectroscopy, dimension reduction and species discrimination challenges

Hyperspectral remote sensing has been used in the past for forest conservation related studies at all platform levels, that is, satellite, airborne and ground-based. Airborne based applications in vegetation species discrimination include characterisation for grasslands (Mutanga and Skidmore, 2004), predicting plant water in *Eucalyptus grandis* (Oumar and Mutanga, 2010), discriminating pest attacks (Ismail et al., 2008), papyrus swamps discrimination (Mutanga et al., 2009), and also commercial tree species discrimination (Peerbhay et al., 2013). There has been some work focussing on ground level hyperspectral remote sensing (using a spectrometer/spectroradiometer) to discriminate *Eucalyptus globulus, Eucalyptus nitens* and their F1 hybrid (Humphreys et al., 2008) and also, conifer species recognition (Gong and Yu, 2001). Most of these examples have been applied to different environments dominated by a variety of land cover surfaces such as mangroves, forest plantations and grasslands. There are some undertaken in tropical and subtropical environments. There is a need for up-to-date information on forest species to allow for decisions that seek to achieve sustainable management (Schmidt and Skidmore, 2003). Among those that focussed tropical forests are the discrimination of lianas from tree species (Castro-Esau et al., 2004). A few studies have been applied to the discrimination of subtropical forest species at leaf scale (Fung et al., 2003).

Field spectroscopy, a ground-based form of hyperspectral remote sensing, provides many of the advantages of spaceborne and airborne hyperspectral sensors. Species discrimination using field spectroscopy uses a set of statistical learning algorithms, which identify patterns in the training data and create models using these patterns. The classifiers used in species discrimination include support vector machines (Melgani and Bruzzone, 2004), neural networks, random forests, linear discriminate analysis (LDA), partial-least discriminant analysis (PLS-DA) and Naive Bayes (Bickel and Levina, 2004). Generally, there is no single classifier that outperforms the others as choice depends on prevailing constraints such as accuracy, time for development as well as the nature of the classification problem (Li et al., 2006). Against this background, it would be essential to determine the best classifier method for identifying subtropical forest species on the Wild Coast region of South Africa.

There are challenges in using hyperspectral remote sensing (airborne and satellite-based) in large-scale projects, including costs, data availability and the logistics involved in acquiring the imagery. The practicality of using hyperspectral remote sensing imagery is less for developing countries compared to the developed ones due to these reasons. However, monitoring programmes that characterise forest species on a large-scale using a combination of field spectroscopy and multispectral remote sensing are still few.

Integrating multispectral and hyperspectral remote sensing

Combining the two data sources has the potential to provide more information on surface features, such as forests. Methods that integrate multispectral and hyperspectral data sources are encouraged, as they consolidate their respective advantages. The integration of these two provide information over a wider area therefore answering one of the modern day science challenges – that of upscaling, since most models and algorithms are derived from scale studies (Wu and Li, 2009).

Integrating the two data sources has another challenge in the form of different scales. The proximity of the spectroradiometers and other instruments used in field spectroscopy, to the surfaces of interest gives it a finer scale and spatial resolution. In summary, hyperspectral data has a large spectral coverage with small spatial coverage while multispectral data has large spatial coverage but is spectrally under sampled (Kruse and Perry, 2009). Integrating the two data sources, therefore, seems ideal for forest mapping and modelling. Furthermore, it determines the humans' observation ability (Marceau and Hay, 1999). Essentially, an integration of multispectral and hyperspectral data has the potential to supply accurate and consistent information on the state of forests, especially South Africa's threatened indigenous forests.

In summary, the main opportunities exploited by the study are examining the best methods for land cover classification for forest change analysis (multispectral data), dimension reduction for subtropical species discrimination (field spectroscopy data), species discrimination method (field spectroscopy data), and the integration of multispectral and field spectroscopy to discriminate semi-deciduous and evergreen forest species. Understanding these methods would make it easier for monitoring programmes to translate into management decisions (Christensen and Ringvall, 2013). This research involved data collection to enable monitoring subtropical forests changes in the Wild Coast region of South Africa. The region is located around the town of Port St John's. The main aim and objectives of the study are presented in the next sections.

1.3: Aim

The overall aim of this study was to conduct a multiscale assessment of the subtropical forests along the Wild Coast of South Africa using remote sensing as a way of quantifying forest change, discriminating species and semi-deciduous and evergreen forests.

1.4: Study Objectives

The main objectives of this study were to:

- Determine a supervised classification algorithm with highest accuracy and then quantify changes in subtropical forests from 2005 to 2013 using multispectral remote sensing data in the Wild Coast area of South Africa;
- Determine the optimal wavelengths for the discrimination of the subtropical forest species and evaluate their separability using field spectroscopy at leaf scale;
- Identify the best classifier for the discrimination of subtropical forest species at leaf level based on measured accuracy; and
- Discriminate proportions of semi-deciduous and evergreen forest species using an integration of multispectral and field spectral data.

1.5: Thesis Outline

The organisation of this study is outlined here as starting with the General Introduction (Chapter 1), then Characterisation of the study area (Chapter 2), Remote Sensing Use in Subtropical Forest Change Analysis: A Literature Review (Chapter 3), Methodology (Chapter 4), Multi-temporal Analysis of Subtropical Forest between 2005 and 2013 (Chapter 5), Selection of Optimal Wavelengths for Subtropical Forest Species Discrimination (Chapter 6), Subtropical Forest Species Discrimination using Field Spectroscopy (Chapter 7), Discriminating Semi-deciduous and Evergreen Subtropical Forests Species Using Integrated Multispectral and Field Spectroscopy (Chapter 8), before presenting a Synthesis and Conclusion (Chapter 9). There are four results based chapters (Chapters 5 to 8), from which the major research highlights were generated.

Chapter 1: General Introduction

This section outlines the research aims, objectives and research problem. Moreover, previous studies in forest mapping and species discrimination are critically examined to provide the context of the study. In this way, research gaps are highlighted and it provides reasons supporting a study of this nature in forest management.

Chapter 2: Characterisation of the study area

The main aim of this chapter is to identify the current physical and socio-economic conditions in the study area as these important issues are integral to sustainable indigenous forest management. An explanation of these conditions also highlight the pressures (both natural and manmade) on the subtropical forests along the Wild Coast.

Chapter 3: A review of literature on subtropical forests and remote sensing applications

Forestry conservation in South Africa links to global trends that are driven by scientific information. This chapter evaluates the current national, regional and international statutes and examines the remote sensing methods used in forest monitoring. The chapter has the comprehensive literature to cover all the results-based chapters indicated.

Chapter 4: Methodology

This chapter explains all the data collection and analysis methods. The methods were linked to the set objectives of the study and they include procedures for data collection, analysis, validation and visualisation of the results. Consequently, methods sections are not presented in the respective results-based chapters. The methods selected should be replicable in other forests with environmental conditions similar to the Wild Coast region.

Chapter 5: Multi-temporal analysis of subtropical forest changes between 2005 and 2013

The fifth chapter determined the best method for supervised land cover classification of 2013 SPOT 6 multispectral imagery among the four: maximum likelihood estimation (MLE), minimum-distance (MIN), spectral angle mapper (SAM) and spectral information divergence (SID). The best method in terms of accuracy (MLE) was then applied to the other two years of 2005 and 2009. A comparison of the classification results for the three years (2005, 2009 and 2013) and the changes between the two periods of 2005-2009 and 2009-2013 are discussed. Conclusions were then made on the changes in subtropical forest over the two periods. The 2013 classified map and SPOT 6 image were to be later used in Chapter 8.

Chapter 6: Selection of optimal wavelengths for subtropical forest species discrimination

The selection of significant and optimal wavelength bands for the discrimination of the subtropical indigenous forest species using dimension reduction in field spectroscopy is explored in this chapter. A set of results from the dimension reduction and validation exercise using One Way Analysis of Variance (ANOVA) with Bonferroni correction, Classification and Regression Tree Analysis (CART) and the Jeffries Matusita (JM) distance method is presented. A discussion and conclusion summarised these results in relation to accuracy levels and other studies.

Chapter 7: Subtropical forest species discrimination using field spectroscopy

Chapter 7 deals with the application and evaluation of three classifiers. Three classifier algorithms (linear discriminant analysis, partial least squares discriminant analysis and random forest) were tried on the training data set and later evaluated for accuracy using an independent validation dataset. The most suitable classifier for the subtropical forest species was then identified by comparing the overall accuracy and Cohen's Kappa coefficient results.

Chapter 8: Discriminating semi-deciduous and evergreen subtropical forests species using integrated multispectral and field spectroscopy

The last results-based chapter analyses proportions of semi-deciduous and evergreen forest species after integrating multispectral and field spectroscopy data. The chapter also discusses the results, their accuracy levels as well as effectiveness of the techniques and data used.

Chapter 9: Synthesis and Conclusion

The final chapter merges the different strands of this study and integrates conclusions made in Chapters 5-8. It examines how the new information as well as proposed methodology would assist in subtropical forest management. The chapter further examines how the results have answered all the initial research questions, met set objectives and suggests further research directions.

Characterisation of the Study Area

2.1: Introduction

The focus of this chapter is to characterise the Wild Coast's physical and socio-economic setup to contextualise subtropical forests changes in the study area. The Wild Coast area of the Eastern Cape experiences subtropical weather conditions and the landscape consists of state forests and communal households. The relationship between the forests and neighbouring communities has attracted researchers' attention for many years. The fragile coastal ecosystem, lucrative tourism ventures and an increase in population of the surrounding communities create an environment where grass-roots issues meet nature conservation. The detailed information on the physical and socio-economic setup of the area is necessary in a study like this one, where the emphasis is on characterising forest changes and their spectral properties.

2.2: Location

The study area comprises of coastal indigenous forests, savannah grasslands, woodlands and human settlements around Port St Johns in the Eastern Cape. The boundaries of the study area are the town of Port St Johns (north-eastern tip end), the Indian Ocean, Mthatha Mouth (on the southern end), Mthatha river (the western end), and the Mthatha-Port St Johns road to the north (refer to Figure 2.1 below). The central part of the study area is approximately 90 km from the town of Mthatha. Parts of the study area lie in both Nyandeni and Port St Johns Local Municipalities. The main urban centres in the study area are Libode, Ngqeleni and Port St Johns.

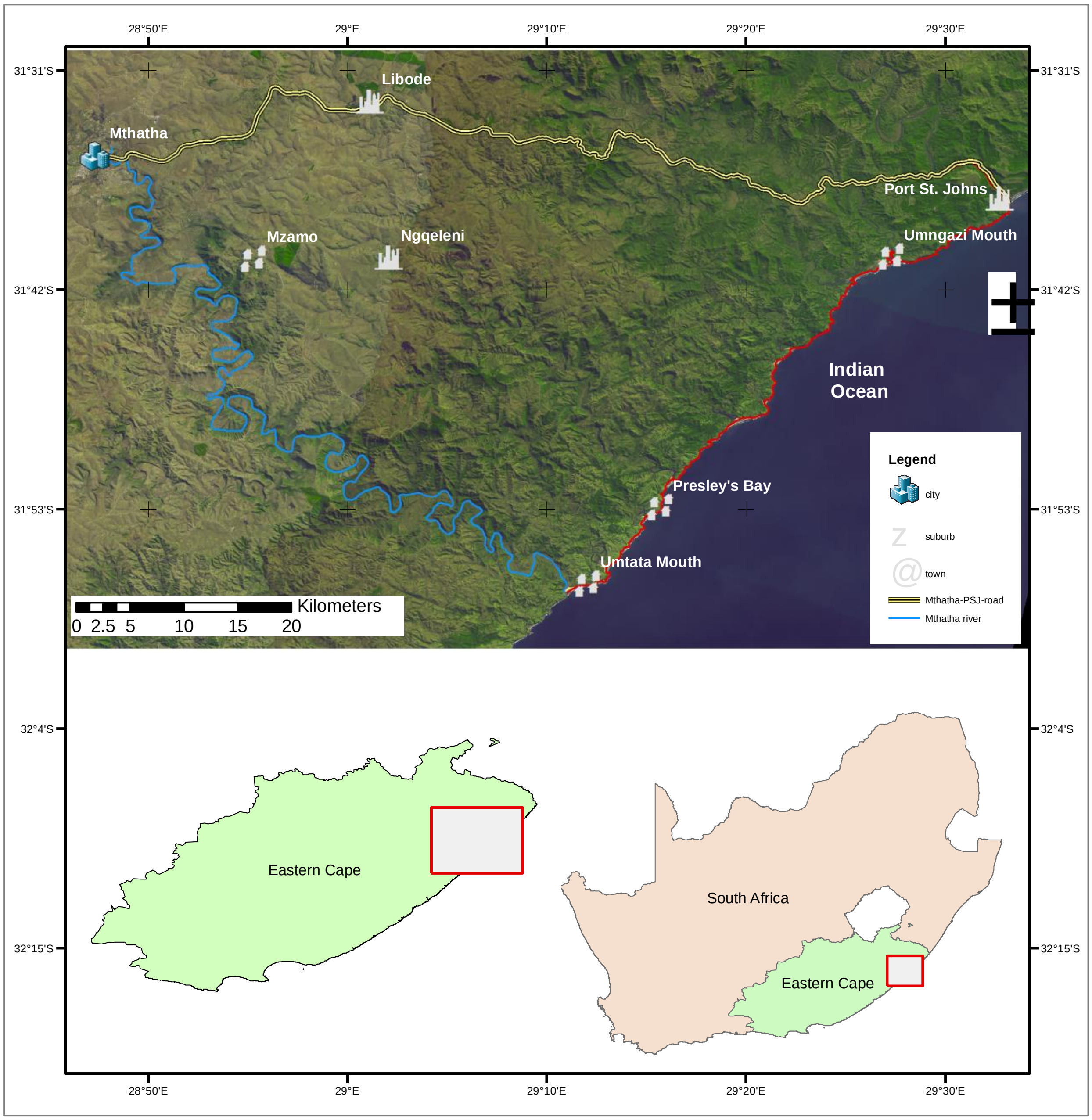

Figure 2.1: Map showing the study area

2.3: Climatic Conditions

Vegetation is influenced by climatic conditions hence a clear understanding of the prevailing conditions is necessary since this study covers phenological classification. The area, which is part of the Wild Coast region of the East coast of South Africa has a warm and humid climate with an annual average rainfall range of 650mm to 1000mm that falls mainly in summer (Port St John's Local Municipality, 2010) and is predominantly in the form of light showers. Daily average temperature ranges between 21°C and 28°C in January and July respectively (Port St John's Local Municipality, 2010). Much of the fieldwork was done between May and mid July 2013, coinciding with the winter and mid-winter seasons in South Africa. Spectral variability between semi-deciduous and evergreen forests species was expected to be high during this time of the year. The seasonal calendar of South Africa is summarised in Table 2.1 below:

Table 2.0: The seasons of South Africa (WeatherSA, 2014)

Season	**Calendar dates**
Autumn	1 March to 31 May
Winter	1 June to 31 August
Spring	1 September to 30 November
Summer	1 December to 28/29 February

2.4: Terrain Characteristics

The topography of the study area comprises of high-lying areas around the northern portion (along the Mthatha-Port St Johns road) which descends towards the Indian Ocean on the southern boundary. The altitude ranges from zero to approximately 600 metres above sea level. The landscape is dominated by the fragmented forests, woodlands, grassland and densely populated hilltop settlements (Obiri et al., 2002). Access to some portions is difficult due to the steeply undulating topography and lack of roads. Mthatha, Umzimvubu, Mneno and Umngazi are the major rivers that drain the area.

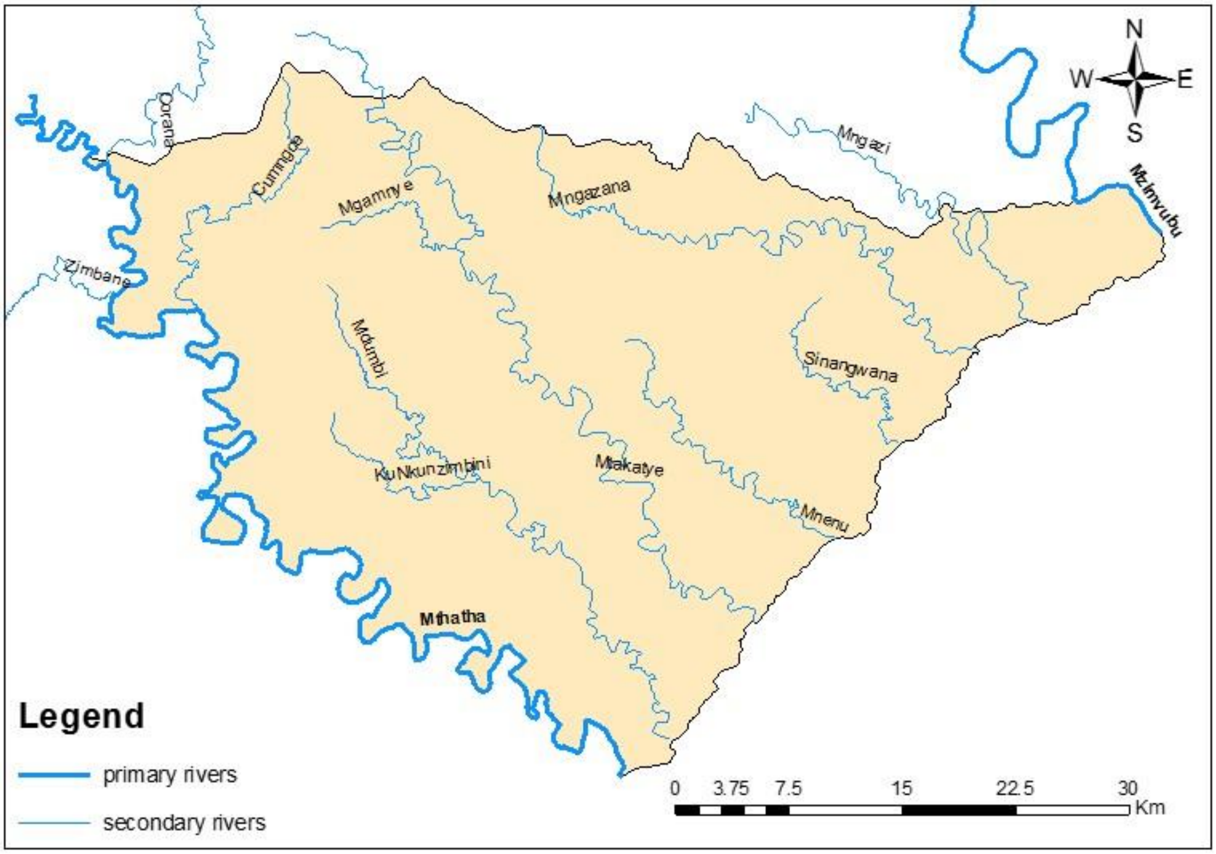

Figure 2.2: Drainage of the study areas (adapted from the National river database (Department of Water Affairs and Forestry, 2006).

Geological formations present in the area are Ecca (most dominant), Balfour, Middleton, Dwyaka, Tillite and Natal groups (Port St John's Local Municipality, 2010). These groups occur together with the following associated soil types: sandstones, siltstone, quartzitic mudstone, diamictite and shale.

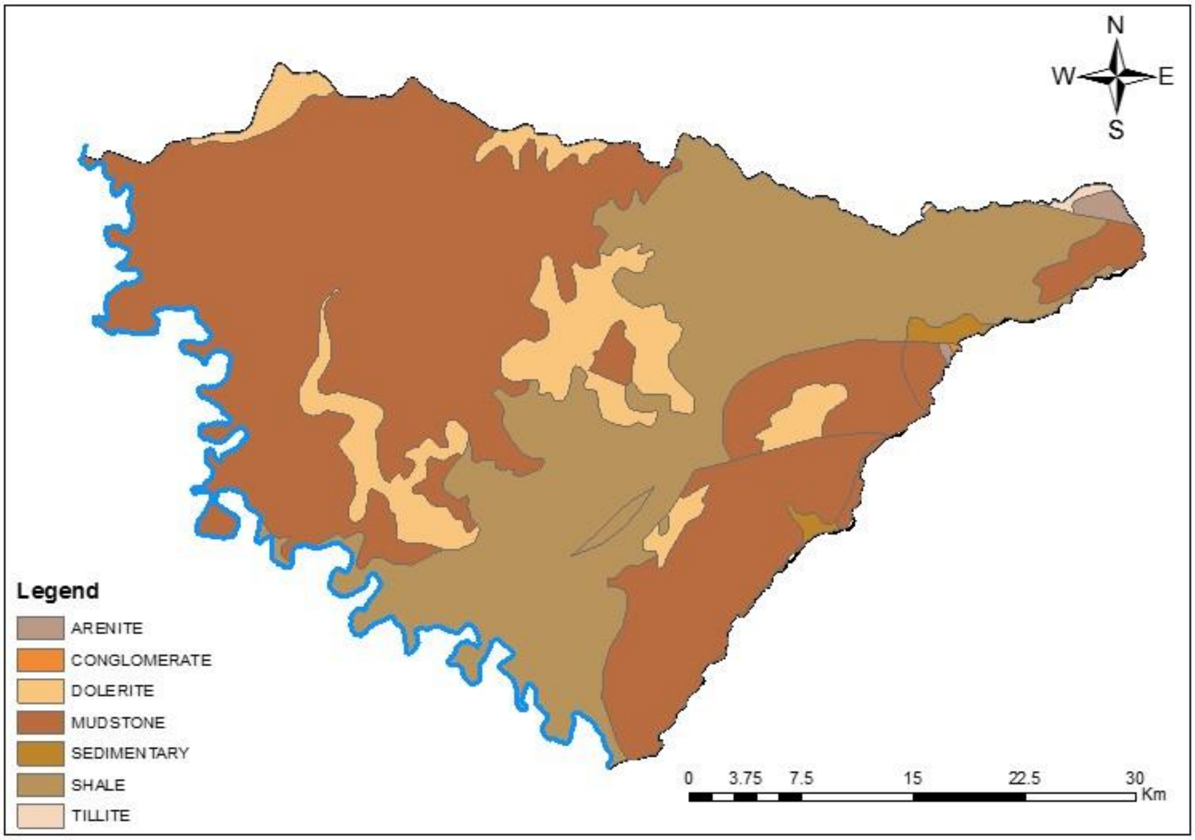

Figure 2.3: Geological Map (Adapted from geological map series)

2.5: Vegetation

The area is partly composed of the coastal subtropical vegetation region, grassland and thicket. The national floristic classification system for indigenous forests classified forests in the Wild Coast as Transkei Coastal Platform Forests (Von Maltitz et al., 2013). The area falls under the Eastern Cape belt ecoregion (Kleynhans et al., 2005). Woodlands and indigenous forest species cover most parts of the area. The indigenous forests are mainly of the subtropical type whose distribution in South Africa is attributed to climate change during the Quartenary period (Griffiths and Lawes, 2006). Common species in woodlands include *Acacia karoo and Lantana camara*. Indigenous natural forests have species such as *Millettia grandis, Heywoodia lucens, Englerophytum natalense* (Obiri et al., 2002), *Ficus natalensis* and *Celtis africana.* The area has been noted to have exceptional endemic plant species leading to the region gaining a "biodiversity hotspot", one of only 230 such sites in the world (Bennie, 2011).

2.6: Population and socio-economic setup

The main land use patterns in the study area include communal grazing land, natural forests, commercial forests, subsistence agriculture and horticulture farms (Obiri et al., 2002). According to the last Census of 2011, the two local municipalities of Nyandeni and Port St Johns have a population of 290 390 and 156 136 respectively (Statistics SA, 2011a, Statistics SA, 2011b). These population figures translate to population growth rates of 0.57% and 0.61%, respectively since the 2001 Census. There is a mixture of land tenure forms but a big portion of land is demarcated communal land thereby being held under Community Trusts. The local traditional leaders have jurisdiction to communal trusts land. The rest is state and freehold land with the latter dominating in the major urban settlements of Port St Johns (Port St John's Local Municipality, 2010), Ngqeleni and Libode. It is worth noting that the majority of indigenous forest belongs to the state, managed on its behalf by DAFF.

The economic activities in the study area include tourism, fishing and subsistence agriculture. Statistics from the 2011 Census give the unemployment rate at 44.8% and 50.3% for Nyandeni and Port St Johns local municipalities respectively (Statistics SA, 2011a, Statistics SA, 2011b). Agriculture practised is mainly subsistence rain-fed crop production with maize being the widely grown crop (Port St John's Local Municipality, 2010). However, subsistence agriculture fails to meet the most families' overall needs and little is sold (Aliber and Hart, 2009). There are a number of tourism projects in the area taking advantage of the rugged terrain and pristine environmental condition earning the region its nickname, the Wild Coast. Main tourism activities are horse and hiking trails, fishing, river cruising and nature-based activities such as game viewing and enjoying the magnificent natural beaches. Household income in the area is between US$32-US$160 per month with pensions and migrant worker remittances (Obiri et al., 2002). Forests and other natural resources, therefore, provide supplementary income to the rural populace.

2.7: Summary

The uniqueness, ecological fragility and potential threats to the Wild Coast's subtropical forests have been highlighted in this chapter. The characterisation of the study area successfully noted that the Wild Coast of South Africa is rich in biodiversity and the subtropical forests are part of this unique feature. Among one of the conclusions of this chapter is the fact that the increasing population could be detrimental to the subtropical forests. Human use of forest resources remains one of the main managerial problems for forest managers and the local leadership. The climatic conditions provide enough rainfall; sunshine and temperatures for the forests to thrive but the local socio-economic conditions within the local communities seem to be a major threat to the health of the subtropical forests along the Wild Coast.

Remote Sensing Use in Subtropical Forests Change Analysis: A Literature Review

3.1: Introduction

The indigenous forests of South African face natural and man-made threats and remote sensing has potential of providing a monitoring framework. There have been some studies for floristic classification of indigenous forests nationally and other parts of the country (Cawe, 1996, Lötter et al., 2014, Von Maltitz et al., 2013), which were mainly one-off exercises. Remote sensing on the other hand, provides the ability to quantify forest changes over time because of repetitive data. Remote sensing makes use of the concept of imaging spectroscopy, which acquires imagery of an object through measuring energy arriving at the sensor (Meer et al., 2002). The image spectra in turn provide useful information about the objects of interest. The main advantage of remote sensing in forestry is that it provides useful information for forest conservation, formulate policy and provide insights into future forest condition and health (Franklin, 2001). In areas with rugged terrain and limited accessibility, terrestrial mapping is difficult and expensive; hence the use of remote sensing in vegetation classification (Salovaara et al., 2005). Remote sensing images provide synoptic and repetitive biophysical and biochemical vegetation data for large areas over long periods of time (Franklin, 2001).

A detailed analysis of the status of indigenous forests, legal framework and remote sensing approaches are presented in this chapter. The chapter discusses these aspects, starting from indigenous forests narrowing down the review to subtropical type of forests, which are dominant in the study area. This chapter essentially provides the theoretical background to cater for the respective results-based chapters.

3.2: The state of subtropical forests in South Africa

3.2.1 Benefits of subtropical forests

South Africa has a variety of climatic regions, which in turn affect the structure and characteristics of vegetation zones. Subtropical forest species are part of the country's indigenous forests; the areal extent and benefits from indigenous forests make their sustainable utilisation an important consideration. By definition, indigenous forests are vegetation formations dominated by mainly trees, which are firstly indigenous to South Africa and which reach a minimum height of 10m when at maturity stage. There are common forest management goals for both society and landowners. The benefits of forests are broadly divided into two: direct and indirect benefits.

The direct forest benefits are either timber-related or non-timber forest products (NFTPS). The timber uses by local communities are mainly for construction poles and firewood. The non-timber products include medicines, food (Scholes, 2004), habitat for wildlife (Cowling et al., 1989) and useable water resources. A study in the Pondoland part of the Wild Coast revealed that much of the tree utilisation was for construction poles, especially for poles with circumference sizes ranging between 10 and 20cm (Obiri et al., 2002). Generally, NFTPS bring direct benefits to rural South Africa through consumption and trade. Cash income from NFTPs is used to complement the generally low income of the local communities. Shackleton and Shackleton (2004) found the annual average ranging from R1000-R12000 per household. According to the same study, the reliance on NFTPS on the Wild Coast is mainly due to a decline in cash revenue from subsistence farming, fishing, tourism and migrant labour remittances. Forest use is not only restricted communities living near the forests, but ecotourism and markets for products also benefit the urban population (Cocks and Wiersum, 2003). However, rural communities rely more on the forests compared to those in urban areas (Shackleton et al. (2007a).

The indirect benefits include ecological services such as carbon sequestration, less carbon emissions from burning and water regulation (Shackleton et al., 2007a). Forests have the potential to regulate atmospheric carbon dioxide through carbo sequestration (Scholes, 2004). With all these benefits, it becomes important to manage forest resources sustainably for both conservation and developmental reasons (Shackleton, 2001).

In summary, indigenous forests have a wide usage in South Africa. Geldenhuys (1999) found that 94% of canopy tree species and 77% of subtropical forest species have either traditional or commercial use. The threats currently confronting these forests are summarised in the next section.

3.2.2 Threats to subtropical forest at national level and global level

With all the benefits that indigenous forests bring to the national and local economies, it is clear that conservation and the sustainable forest use is the main goal of many government departments, local municipalities and traditional leadership structures. The benefits and use are the main drivers of the threats, especially if these uses are not regulated. South Africa's forest policies changed especially since the 1994 democratic dispensation, to include controlled use even in state-controlled indigenous forests. Some studies have summarised this problem as being caused by underdevelopment, poverty and limited opportunities of the areas near the forest patches, particularly by communities with direct dependence on forest resources (Sunderlin et al., 2005). Although poverty can be a driver of forest overexploitation, high standards of living also negatively affects forests (Sunderlin et al., 2005). With few economic alternatives, communities living near forests often expand agricultural land into forested lands (Sunderlin et al., 2005).

Besides the threat of forest overutilization to sustainability, there is a cumulative negative effect to livelihoods of communities dependent on forest products in the wake of forest depletion (Brosius, 1997). The motivation for all the monitoring and identification of threats is driven by the need to maintain a sustainable supply of resources over time and minimise conflicting economic, ecological or social demands on resource use (Guldin and Guldin, 2003).

3.2.3 The legal framework for indigenous forest conservation

There are international initiatives aimed at reducing deforestation through policies that advocate for sustainable use of the forest resources. The main driving forces for the two process of deforestation and degradation have been summarised as the growing world population and increases in technological ability to extract forest resources (Franklin, 2001). The international legal framework for forest conservation is motivated by the need to combat deforestation, reduce carbon emissions and promote biodiversity. The Kyoto Protocol also promotes vegetation observation and characterisation through advocating for mitigating human activities such as afforestation and promoting reforestation (Schulze et al., 2002). There is an international framework for monitoring carbon sinks through the UNREDD+. UNREDD+ has a framework of policies on a carbon stock mapping approach to indigenous forests. The Plan of Implementation of the World Summit on Sustainable Development, held in Johannesburg in 2002 called for integrated indigenous disaster management (UN 2002). Forest monitoring is significantly important in this context, since vegetation acts as fuel for wildfires (Carlson and Burgan, 2003). In summary, international agreements and environmental degradation concerns have increased pressure on accountability in forest use and sustainable management practices, thus leading to more forestry monitoring programmes (Kangas, 2006).

The national government of South Africa has the mandate for conserving woodlands and forest resources. South African conservation laws allow for the sustainable utilisation of forest and woodland resources. South African forests are divided into three broad groups, namely; woodlands, indigenous forests and plantation forests (DAFF, 2012). The mandate is envisioned in the department's main goal, which is to ensure renewed growth, transformation and sustainable use of forestry resources (DAFF, 2012). The National Forestry Act of 1981 gives DAFF the mandate to guide decisions affecting forests, research, monitoring of forests, dissemination of information and reporting (South Africa, 1998). The National Forestry Act of 1998 also sets out provisions for the community management of forests that are in specially designated community forests. The chiefs do the management and enforcement of conservation goals in these forests on behalf of the communities. Community forest management has had its fair share of success stories and failures (Porter-Bolland et al., 2012, Rasolofoson et al., 2015).

According to the National Forest Act of 1998, the Minister is empowered to declare a list of protected forest species and all the listed trees are protected against cutting, damage, destruction, collection, removal, transportation, export, purchase and donation except when one is furnished with a license from DAFF (DAFF, 2014). These regulations also apply to the forest products derived from such trees with perpetrators liable for prosecution in courts of law. The latest list published on the 29th of August 2014 has 47 indigenous trees species (DAFF, 2014) and it includes *Mimusops caffra,* one of the dominant species identified in this study. This makes this study particularly relevant, since it leads to improved mapping of indigenous forests containing protected tree species. It is worth noting that this study only observed dominant species; therefore, there are significant chances of the presence of more protected species within the Wild Coast's subtropical forests.

3.3: Multispectral remote sensing use in forest management

Forest monitoring programmes have gained popularity due to a number of reasons, which include the need to develop long-term plans aimed at conserving, planting, thinning, harvesting and other treatments in the forests (Erk et al., 2003). An assessment of the effectiveness of forest use and compliance to legal and best practice frameworks is made possible through monitoring. Satellite remote sensing provides the most practical, feasible and effective method of monitoring forest ecosystems (Schull et al., 2011). Traditional forest field research is often costly, time-consuming and affected by issues of accessibility, hence remote sensing is the best option (Kent and Coker, 1992). Remote sensing modelling of forest change is an option but is only made possible if rigorous accuracy assessment and validation are conducted (Goetz et al., 2009).

Monitoring programs are important components of integrated environmental research. Monitoring programmes are vital because they provide scientific objectives focusing on learning and understanding the monitored system, information for management decisions (Yoccoz et al., 2001), and databases to support decision makers and assisting the decision making processes (Lovett et al., 2007). The techniques used include using the vegetation indices, spectral mixture analysis and multiple regression (Liu et al., 2009). The Normalised Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) have been widely used as surrogate indicators of vegetation condition and have been extended to reflect degradation, climate change, soil erosion and biological conservation (Xu et al., 2012).

There are a number of remote sensing-based forest monitoring programmes, including the US Forest Inventory and Analysis (Olsen et al., 1999), the Swedish National Forest

Inventory (Axelsson et al., 2010), National Inventory of Landscapes in Sweden (Stahl et al., 2011) and the Earth Observation for Sustainable Development of Forests (EOSD) in Canada (Wulder et al., 2007). Other environment-related monitoring programmes are, the Ecological Monitoring and Assessment Network (Tegler et al., 2001), the UK Butterfly Monitoring Scheme and the Great Britain Countryside Survey (Petit, 2009), the Norwegian Monitoring Program for Agricultural Landscapes in Norway (Dramstad et al., 2002, Fjellstad et al., 2001); Spatial Indices for Land Use Sustainability in Austria (Peterseil et al., 2004). Some of the forests monitoring endeavours have been conducted through land cover mapping, with results interpreted with special focus on the changes in forested areas. On a smaller scale, land cover change analysis provides a way of monitoring forest coverage and change to other classes. It is these ways of assessing forest change that make use of per-pixel (each pixel is allocated one class) as opposed to sub-pixel (each pixel allocated to different classes with varying proportions) classification. Much of these forest monitoring programmes have been developed in developed countries with little effort made in developing countries such as South Africa

The majority of these monitoring programmes make use of supervised classification methods to map forest-covered lands. Past forestry applications of remote sensing in Southern Africa include land-cover mapping in southern African savannah (Griscom et al., 2010, Hüttich et al., 2011), monitoring savannah rangeland deterioration (Munyati et al., 2011), analysing vegetation patchiness and its implications (Kakembo, 2009). The classification algorithms used in forest management are presented in the next section.

3.3.1 Classification algorithms applied to forest management

The classification algorithms used in mapping forests and other land cover analyses are many; varying in terms of how they estimate classes for unknown pixels. The classification methods used in forest analysis are divided into two broad groups, namely object-based and pixel-based. Notwithstanding the use of two pixel-based classification methods in the present study, the following sub-sections examine object-based methods in forest characterisation.

a) *Object-based classification algorithm*

Object based methods use spectral information, shape, texture and contextual relationship to allocate classes to raw images (Ke et al., 2010). The use of all these factors, which are related to vegetation, achieved improved vegetation classification (Mallinis et al., 2008, Yu et al., 2006). Basic units in object-based classification are called segments. In forestry, the methods merge pixels into segments that correspond to different forest stands (Woodcock and Harward, 1992). Examples of specific algorithms that fall under object-based used in forest classification are point-based (Heyman et al., 2003) and rule-based segmentation. Mixed results have come out of the comparison studies between object and pixel-based methods. While in some studies the object-based approach achieved better accuracy (Dorren et al., 2003), there are also cases when pixel-based outperformed the object-based using Quickbird imagery (Wang et al., 2004). This study restricted itself to pixel-based methods, since the study area had other land cover classes such as grass and water requiring more spectral discrimination than adding other characteristics like texture and shape.

b) *Pixel-based classification algorithms*

Pixel-based classification refers to those methods, which only delineate classes based on spectral measurements. Per-pixel methods are further split into two: per-pixel and sub-pixel, based on how each pixel is allocated to class membership. While per-pixel methods allocate a pixel to one class, sub-pixel methods allow unknown pixels to have proportions of all classes under consideration. Per-pixel classification results from assigning each pixel to a cover type that has the most similar signature, while sub-pixel classification evaluates the degree of membership of each pixel in all classes, including unspecified and unknown classes.

Per pixel classification

Per-pixel classification algorithms lead to the assignment of each pixel to a single class thereby making assumptions of pure (Foody, 2002a), discrete and mutually exclusive pixels (Congalton and Green, 2008). These algorithms are grouped into two broad groups of parametric and non-parametric classifiers. Parametric classifiers are based on linear relationships between independent and dependent variables while the non-parametric ones assume the opposite. The parametric ones include the maximum likelihood classifier (MLC), nearest distance, minimum distance (MD) and parallelepiped (PPD) (Shafri et al., 2007, Wang and Jia, 2009). Where the data are not normally distributed, the non-parametric methods have higher chances of success. These include spectral angle mapper (SAM), k-nearest neighbours (KNN), neural network (NN), spectral vector machines (SVM), decision trees, spectral information divergence (SID) (Knorn et al., 2009, Petropoulos et al., 2010, Tan et al., 2011, Wang and Jia, 2009, Yagoub et al., 2014). Past studies have used algorithms, which include MLC (Erbek et al., 2004), MD (Dwivedi et al., 2004), SAM (Kruse et al., 1993), SVM, SID (Chang, 1999) and PPD (Atkinson and Lewis, 2000) algorithms.

The commonly used algorithm is the parametric method MLC and its use includes applications in the subtropical biome in Argentina (Zak et al., 2004), land use and land cover (LULC) change in coastal Egypt (Shalaby and Tateishi, 2007). Besides applications being in different geographic locations, the MLC was observed to outperform other parametric methods of MD and PPD (Tso and Mather, 2001), when data are normally distributed. However, success is not guaranteed in non-normally distributed data (Sohn and Rebello, 2002). There are incidences when non-parametric per-pixel methods performed better than parametric ones including MLC, for example by decision trees (Otukei and Blaschke, 2010, Rogan et al., 2002) and by spectral angle mapper (Nangendo et al., 2007).

Sub-pixel classification

Sub-pixel classification algorithms have one assumption, that of exhaustive definition of classes to be mapped (Campbell, 1996, Congalton and Green, 2008). They are also referred to as unmixing or soft classification methods, because they do not lead to definite classes but proportions of all classes. In coarser multispectral imagery, these assumptions are difficult to fulfil due to the presence of mixed pixels (Campbell, 1996, Wang and Jia, 2009). Multispectral images, such as the SPOT 5 and 6, have coarser pixels, making mapping of vegetation types or species difficult due to mixed spectral signatures. Mixed pixels result when cover classes are smaller than spatial resolution of the sensor in use (Zhu, 2005). Sub-pixel classification aims to reduce the effect of pixel mixing.

Specific examples of algorithms that perform pixel unmixing in forest mapping and modelling are linear spectral unmixing (Kuusinen et al., 2013, Weng and Lu, 2008), spectral mixture analysis (SMA) (Thorp et al., 2013), multiple endmember spectral mixture analysis (MESMA) (Roberts et al., 1998) and the mixture tuned matched filtering (MTMF) (Jia et al., 2006). All these methods involve unmixing using estimation of endmembers representing the cover classes for each pixel.

Proportional images from sub-pixel methods are important in mapping and monitoring of forest characteristics due to their recognition of the spatially heterogeneous mixture of species, shadow, soil, and epiphytes compared to just one cover type (Goodwin et al., 2005). Each proportional map shows the approximate sub-pixel abundance and spatial distribution of that endmember (Adams et al., 1986). Another advantage of these methods is their ability to detect and map proportions of small features occurring at sub-pixel level such a less dominant cover type such as sparse trees (Tompkins et al., 1997).

MTMF is different from other unmixing methods since it requires no prior knowledge or identification of all endmembers (Mehr and Ahadnejad, 2013). The abundance of endmembers is estimated by maximising responses of the known, user-defined, endmembers while minimising the unknown, hence the words “matched filtering” (Williams and Jr, 2002). Some studies recorded improvements in classification after using these sub-pixel classifiers (Bastin, 1997, Fisher and Pathirana, 1990, Foody, 1996, Gottlicher et al., 2009). MTMF had a higher accuracy than per-pixel classification method of SAM in mapping forest canopy fuel attributes (Jia et al., 2006).

This study examines among other things, the application pixel unmixing to discriminate semi-deciduous and evergreen forest species in South Africa’s Wild Coast region using both field spectral and multispectral data. The rationale is that within multispectral pixels there are mixtures of semi-deciduous and evergreen indigenous forests species. Masking is done before classification to restrict processing only to subtropical forests. The exclusion of areas of no interest is common in sub-pixel classification since it reduces the potential for spectral confusion (Foody, 2002a).

Against this wide background on classifiers, it is evident that there are no universally agreed upon algorithms, due to differences in environments, features of interest and data distribution.

3.3.2 Forest management programmes using multispectral imagery

International initiatives on forest monitoring using remote sensing are either being done by United Nations (UN) agencies, International Non-Governmental Organisations and researchers. The United States of America's national agencies of National Aeronautics and Space Administration (NASA) and United States Geological Survey (USGS) are also active in this field since they own most of the operational satellites. For most of the global forest monitoring programmes, images from the Landsat programme have been widely used, for example, the Forest Resource Assessment (FRA) and the Global Forest Watch programme (Hansen et al., 2013). The Global Forest Watch programme by the World Resources Institute (WRI), launched in February 2014, is the most recent effort in mapping global forest cover changes. A global online map of forest gains and losses is a product of this initiative (Hansen et al., 2013). Other sensors used include Advanced Very High Resolution Radiometer (AVHRR) in the AVHRR Global Land Cover (Loveland et al., 2000) and MODIS in the MODIS Land Cover Classification product (Hansen et al., 2000). These multispectral images were chosen due to the need for most of these programmes to have world coverage. However, the success of national and local level applications of these global programmes has been limited.

There are also national and regional programmes in place, which apply remote sensing. Notable examples include land cover or forest monitoring systems in Australia (ADE, 2014, Lehmann et al., 2015), USA's Forest Inventory and Analysis (FIA) (Barrett and Gray, 2011) Germany, European Union's CORINE (EEA, 2007) Programmes, the Democratic Republic of Congo (DRC), Zambia, Indonesia, Ecuador and Paraguay (UN-REDD, 2012). Some specifically monitor forest fires (Barrett and Gray, 2011) or forest health (Olsen et al., 1999). All in all, remote sensing has been recognised for its ability to monitor forests and hence the wide usage in different parts of the world as a management tool.

3.3.3 Tree phenology and multispectral remote sensing

Phenology is one the important characteristic of forest species, which is essential for forest management. Phenology refers to the timing of the plant processes (Wu et al., 2014), including the growing season and shedding of leaves by deciduous trees. Remote sensing has been instrumental in monitoring vegetation especially the growing season, through mapping dynamics of green vegetation (Hmimina et al., 2013). These phonological dynamics are not only important to forest management but they also determine the biogeochemical fluxes of carbon dioxide (Garrity et al., 2011). Therefore, forest phenology is essential, as it determines how much carbon dioxide is being sequestered by forests at any particular time (Richardson et al., 2009). For instance, deciduous forest species sequester less carbon during winter, when they lose many leaves. Semi-deciduous trees are those, which shed their leaves to cope with stress conditions (Calvão and Palmeirim, 2011). Evergreen on the other hand cope with stress internally while maintaining an intact green foliage (Calvão and Palmeirim, 2011).

A time series of multispectral remote sensing data have been used to map phenological characteristics either using vegetation indices (VIs) such as the normalised difference vegetation index (NDVI) (Zhang and Goldberg, 2011). Garrity et al. (2011) noted that remote sensing applications to tree phenology are becoming important in global change studies. A notable state in deciduous forests phenology is fall foliage coloration, which is the stage when the greenness decreases during senescent stage in the fall (Zhang and Goldberg, 2011). Studies have shown the existence of a correlation between NDVI and the greenness in deciduous forests (Blackburn and Milton, 1995), coniferous forests (Jönsson et al., 2010) and semi-arid shrubland (Kennedy, 1989).

Forest species may be classified based on their leaf conditions during the fall season. Cover classification based on phenology is possible (Leinenkugel et al., 2013, Rautiainen et al., 2009) especially if remote sensing data used coincide with leaf fall or the winter regeneration period. Remote sensing mapping of phenological classes (in deciduous and evergreen forest) has been mainly conducted using per-pixel algorithms and multispectral data (Achard and Estreguil, 1995). Different multispectral sensors were used to perform phenology-based classification (Leinenkugel et al., 2013, Zhang and Goldberg, 2011).

The classification of different phenological-based classes is done through measuring greenness on images. However, sensor characteristics, vegetation types and surface background features all affect the applicability of these models in different environments (Drake et al., 1999, Purevdorj et al., 1998).

3.3.4 The relevance of SPOT 5 and 6 in subtropical forest characterisation

Among the multispectral sensors used in previous studies on forest change and phenological classification are MODIS (Walker et al., 2012), AVHRR, Landsat (Knorn et al., 2009, Kozak et al., 2008) and SPOT HRVIR HRV (Rautiainen et al., 2009). These were mostly medium resolution sensors. With a spatial resolution of 10 metres, SPOT 5's High Resolution Geometrical (HRG) images fall under the medium resolution sensors. In the present study, SPOT 5 imagery for the years 2005 and 2009 was classified to allow forest change analysis (Chapter 5). However, the 2013 SPOT image had to be resampled to 10m to allow a comparison of the classified map with the 2005 and 2009 products from SPOT 5. As shown in the table below, the four multispectral bands are located in the green, red, near infrared and mid infrared portions of the electromagnetic spectrum. In this thesis, nanometres (nm) are used as the measure of wavelength. The spectral characteristics of SPOT 5 HRG images are summarised in Table 3.1 below.

Table 3.1: SPOT 5 Spectral properties (CNES, 2005)

Band	Band Width	Spatial Resolution
Band 1	500-590 nm (Green)	10m
Band 2	610-680 nm (Red)	10m
Band 3	780-890 nm (Near infrared)	10m
Band 4	1580-1750 nm (Mid infrared)	10 m

The SPOT 6 satellite that was launched on the 9th of September 2013 with four multispectral and one panchromatic bands (Yuan et al., 2014). SPOT 6 has a spatial resolution of 6 metres among its multispectral bands and the four bands located in the blue, green, red and near infrared parts of the electromagnetic spectrum. Like other very high resolution (VHR) images such as Rapideye, Geoeye-1 and WorldView 2, SPOT 6 has an advantage of enhanced capabilities, stereo, monoscopic and multiview images (Stumpf et al., 2014). SPOT 6 sensor is a multispectral sensor with 5 bands including the panchromatic one, with a swath of 60 km and revisit frequency of about 3 days (Airbus Defence and Space, 2014). The multispectral band specifications for SPOT 6 images are shown in Table 3.2 below:

Table 3.2: Band specifications for SPOT 6 images (Airbus Defence and Space, 2014)

Band Number	Wavelength	Spatial Resolution
Band 1	Blue (0.455 – 0.525 µm)	6 m
Band 2	Green (0.530 – 0.590 µm)	6 m
Band 3	Red (0.625 – 0.695 µm)	6 m
Band 4	Near-Infrared (0.760 – 0.890 µm)	6 m

The state of the indigenous forests in 2013 was examined after SPOT 6 imagery classification. Chapter 8 integrated SPOT 6 multispectral with field spectral data to determine proportions of semi-deciduous and evergreen forests using sub-pixel classification. The high spatial resolution meant an improved sub-pixel characterisation of the subtropical forests. The location of the sensor's high spatial resolution bands make it ideal for a study of this nature. Similar studies include use of SPOT 6 and other high resolution imagery in characterising aquatic vegetation (Allen and Suir, 2014) and estimating seasonal leaf area index using Rapideye (Tillack et al., 2014).

3.4: Hyperspectral remote sensing applications in forests

Species discrimination using multispectral remote sensing is often challenging due to spectral overlaps and the spectral and spatial resolution being low (Rosso et al., 2005);

hence the need for hyperspectral remote sensing. Hyperspectral remote sensing, or imaging spectroscopy, consists of three groups, that is, spaceborne, airborne and field based. Field-based hyperspectral remote sensing, also referred as field spectroscopy, makes use of spectrometers or spectroradiometers to measure canopy and leaf spectra. Airborne and spaceborne hyperspectral data is acquired in the form of hyperspectral images. While field spectroscopy measures in situ reflectance, hyperspectral images do provide top of the atmosphere (TOA) measurements, which can be modelled to top of the canopy (TOC). Hyperspectral remote sensing acquires data in as wide range of spectra that enables users to extract differences in spectral signatures (Aspinall et al., 2002). These images detect very narrow bands, for example 2 to 4 nm and hyperspectral sensors may record different absorption features such as chlorophyll (Franklin, 2001). However, one of the problems of hyperspectral data use has been access especially of some airborne hyperspectral platforms such as AVRIS particularly by most developing countries.

Hyperspectral remote sensing is more suitable for identifying spectral differences between species that have vast differences in leaf angle, crown structure and colour (Cochrane, 2000). Species discrimination normally works for monotypic stands that occur in large stratifications (Zomer et al., 2009). The two general groups for species discrimination methods are empirical and physical based methods. These methods are used to identify and discriminate dominant plant species and functional types using empirical and physically-based methods (Dennison and Roberts, 2003). Empirical based methods, which rely on known leaf and canopy spectra therefore make adoption of methods in other environments a challenge (Schull et al., 2011). The physical based approach is based on the radiative transfer model of canopy spectral invariants. Canopy spectra were used to measure forage quality using regression modelling (Guo et al., 2010).

3.4.1 Forest leaf properties and spectral behaviour

In forests, leaves contribute more to the total reflectance. The most notable factors are solar angle, plant chemistry, leaf chemistry, climatic conditions, surface conditions and plant structure (Barrett and Curtis, 1999). Species discrimination and classification exploits the spectral behaviour of different species when exposed to light from the sun or artificial sources. The generalised spectral curve differs with different forest species and this is depicted by the behaviour in certain portions of the electromagnetic spectrum. The success of a spectral discrimination exercise depends on the chosen spectral sections of the spectrum (Vaiphasa et al., 2007). The vegetation reflectance curve depicts a certain unique shape that is determined by the above factors, which differ with different species. Besides the leaf's internal structure, water content and other leaf-based factors, it is worth noting that there are other factors, which affect reflectance in forest leaves and canopies. Factors affecting vegetation reflectance include phenological stage, leaf properties (leaf area and leaf angle distribution), vegetation height, tree size, fractional cover of vegetation, background effect, as well as health and water content of leaves (Woodstock et al., 2002).

In order to understand spectral discrimination in a forest, there is a need to know the behaviour and influences of different factors within the main wavelength regions. These unique sections of vegetation reflectance curve are the visible bands, red edge, near infrared and mid-infrared sections. In the visible bands, variability of reflectance curves is mainly due to species' different reflectance to visible light sources (Curran, 1989), especially at the cell wall-air interface of both mesophyll sponge and palisade (Barrett and Curtis, 1999). At wavelengths 500-750 nm, there is absorption due to pigments such as chlorophylls a and b, carotenes and xanthophyll (Barrett and Curtis, 1999). In the red-edge zone, there is separation of species that have leaf structure, pigments and water content (Curran, 1989). The near-infrared region is characterised by species' spectra differing more due to differences in internal leaf structure such as intercellular volume (Curran, 1989). There is high reflectance and low absorption because of the leaf's internal structure especially between 750 and 1350 nm (Barrett and Curtis, 1999). Internal structure and foliar biochemical contents of the leaf determines dissimilarity in the mid-infrared zone (Curran, 1989). There are absorption features between 1350 and 2500 nm due to water content in leaves. (Barrett and Curtis, 1999).

Although hyperspectral remote sensing is ideal for species discrimination, it is susceptible to data redundancy problems at band level (Adam and Mutanga, 2009, Bajwa et al., 2004). There are also concerns on the use of hyperspectral remote sensing, which include the influence of atmospheric variation, soil background, leaf distribution and orientation (Asner et al., 2000). This is mainly a problem in arid and semi-arid environments. The data redundancy issues are often solved by methods for wavelength selection, also termed band selection or dimension reduction methods.

3.4.2 Dimension reduction methods

The presence of many bands in hyperspectral data is problematic due to covariance matrix inversion (Vaiphasa et al., 2007), a scenario called the Hughes phenomenon (Sreekala and Subodh, 2011). There is also the risk of overfitting the classification due to redundancy imposed by co-linearity of the bands (Mutanga et al., 2009). It does become necessary to reduce band number by selecting the most relevant ones. Dimension reduction, therefore, reduces processing burden as well as deepens the understanding regarding appropriate regions for indigenous forest discrimination. High dimensionality introduces redundancy since most of the neighbouring wavelength bands have highly correlated information (Chan and Paelinckx, 2008) therefore presenting need for selection methods. Dimension reduction procedure there seek to identify wavelengths bands which are optimal for discriminating the target variable without losing information (Adam and Mutanga, 2009).

Among the methods used in species discrimination are the partial-least square (Peerbhay et al., 2013), principal component analysis (Castro-Esau et al., 2004, Gutiérrez et al., 2014), wavelet transform (Bruce et al., 2002). stepwise discriminant analysis (Manjunath et al., 2013, Vyas et al., 2011), genetic algorithms (Vaiphasa et al., 2007), integrating Kruskal-Wallis with Classification and Regression Trees (CART) (Fernandes et al., 2013); and sequential forward floating (Nakariyakul and Casasent, 2009). Of note is another hierarchical method that involves One-Way Analysis of Variance ANOVA with posthoc and CART (Adam and Mutanga, 2009). In the present study, the selected bands were evaluated using the Jeffries-Matusita or Bhattacharya distance methods (Fernandes et al., 2013, Schmidt and Skidmore, 2003). The step-by-step explanation of the hierarchical method of dimension reduction method used in this study is contained in the Methodology chapter.

3.4.3 Species discrimination methods used in hyperspectral remote sensing

Many factors affect light reflectance of vegetated surfaces. In forests, leaves contribute more to the total reflectance. Most notable factors are solar angle, plant chemistry, leaf chemistry, climatic conditions, surface conditions and plant structure (Barrett and Curtis, 1999). Species discrimination and classification exploit the spectral behaviour of different species when exposed to light from the sun or artificial sources. The generalised spectral curve differs with different forest species and this is depicted by the behaviour in certain portions of the electromagnetic spectrum. The success of a spectral discrimination exercise depends on the chosen spectral sections of the spectrum (Vaiphasa et al., 2007). The vegetation reflectance curve depicts a certain unique shape that is determined by the above factors, which differ with different species.

The spectral profile of forest leaves and canopies is manipulated differently by various classifiers to achieve species discrimination. Examples of the classifiers used in species discrimination using hyperspectral remote sensing include the linear discriminant analysis (LDA) Clark (Clark et al., 2005), partial-least square discriminant analysis (PLS-DA) (Peerbhay et al., 2013), neural networks (Armando et al., 2013), Naïve Bayes (Bickel and Levina, 2004) and random forest algorithm (Chan and Paelinckx, 2008). These classifiers differ in the way they use statistics to make the discrimination. Some studies refer to them as machine learning algorithms. Each of the classifiers has had success in different studies as shown by a few examples. LDA, PLSDA and RF were the three classifiers tested for accuracy in the discrimination of subtropical forest species at leaf-scale using the selected wavelengths from the hierarchical method.

Linear methods work with an assumption of multi-normality of the data or that the ratio between observations and variables greater than 2 or 3 (Ballabio et al., 2006). The methods identify linear combinations of features describing or separating two or more classes by maximising the between group variance while minimising within group variance (Gromski et al., 2014). Among its advantages is the issue of being simple and fast to execute, although it struggles with large numbers of classes (Gromski et al., 2014). It is noteworthy, however, that the current study only had 15 classes, hence the disadvantage of large numbers had less impact. In a study by (Clark et al., 2005), the LDA performed well in the identification of tropical rain forest species.

PLSDA is a linear method which searches for variables and directions at a multivariate scale to explain the class categories (Paz-Kagan et al., 2014). It is based on the partial least square regression of categorical variables or continuous data. (Gromski et al., 2014) The strengths of the model were evaluated using the overall accuracy and Kappa coefficient values. Despite it being used in species discrimination, the method may also be used for wavelength selection. Previous research on species discrimination using PLS-DA include discriminating six commercial forest species (Peerbhay et al., 2013) and corn from grasses and weeds (Longchamps et al., 2010).

Although the Random Forest (RF) is also useful as a dimension reduction technique (Ismail and Mutanga, 2011), it was used as a classifier for leaf-scale discrimination of subtropical forest species in the present study. Breiman (2001) defined the RF as non-parametric classifier consisting of tree-like structures with each tree selecting the most important class. The pixel will then be allocated the most popular class among the submissions from various individual trees. The RF is part of "ensemble learning" algorithms, which create many classifies and aggregate their result for final classification (Liu et al., 2013). Unlike other methods, more trees give a limiting value for the generalisation error thereby avoiding over-fitting of the model (Breiman, 2001). The method also possesses an internal validation mechanism called 'out-of-bag bootstrapping (OOB) estimate of error', hence the method does not require further validation (Chan and Paelinckx, 2008). Examples of the use of the random forest method with high accuracy include discrimination of tree species (Dalponte et al., 2012), papyrus vegetation (Adam et al., 2012) and in ecotope mapping (Chan and Paelinckx, 2008).

3.4.4 Upscaling of field spectroscopy and its integration with hyperspectral and multispectral imagery

Field spectroscopy on its own has shown ability to establish phenological changes (Carvalho et al., 2013, Cole et al., 2014) while multispectral images did the same on their own (Tillack et al., 2014). The capabilities of the two on their own coupled with the availability of the high spatial resolution SPOT 6 imagery motivated the present study, especially the last part on data integration and sub-pixel classification. The upscaling of field spectroscopy has been done to model leaf level reflectance to top of the canopy (TOC) and top of the atmosphere (TOA) measurements (Cho et al., 2010, Kempeneers et al., 2004). Canopy reflectance can also be simulated from leaf reflectance using radiative transfer models such as 4SAIL, PROSAIL and PROSPECT-SAILH (Cho et al., 2008, Jacquemoud et al., 2009).

The integration of field spectroscopy data has been mainly with hyperspectral images, from both spaceborne and airborne platforms due to similar high spectral resolution. Notable examples include the integration of spectroscopic data with hyperspectral imagery to discriminate tropical forest species (Clark et al., 2005). However, there are also examples of integration of field spectroscopy with multispectral data in vegetation studies (Curatola Fernández et al., 2013, Mutanga et al., 2015). One of the challenges of the integration with multispectral imagery is to do with spectral resolution differences. Field spectroscopy data cover a wider spectral range than multispectral remote sensing. In previous studies, resampling field spectra was done to Sumbandila (Oumar and Mutanga, 2010), Quickbird (Fernández et al., 2013) and to WorldView-2 (Mutanga et al., 2015) sensors in order to overcome this challenge.

3.5: Summary

In summary, the subtropical part of the forest biome of South Africa face threats, which are linked to the consumption by communities both in urban and local communities. In this chapter, evidence is presented to confirm remote sensing as a key tool in forest management. Different remote sensing data sources and classifiers were presented with their previous success in analysing forest characteristics. The classifiers used in field spectroscopy and multispectral images are many and each has its own merits and demerits. This review also shows that there is no universally accepted classifier, since performance varies with field of application, features and environment of interest. Therefore, in both forest change analysis and species discrimination, an effort is made to identify the most suitable classifier. There is much information that can be derived from field spectral and multispectral data including forest type, forest change and species discrimination. The information is presented at leaf, pixel and sub-pixel levels.

Multispectral images give a synoptic view of forest conditions while field spectroscopy allows more spectral characterisation. This research is thus motivated by other integration studies in the past, as well as prospects of improved characterisation of forests through data integration.

Methodology

4.1: Introduction

As explained earlier in Chapter 1, this chapter is an overarching one in which all the methods and data analysis techniques used are presented. A description of the sampling design and field data collection processes is provided first.

4.2: Sampling design

Sampling is a process employed to select a number of units for measurement in order to make accurate estimations about conditions in the area of study (Franklin, 2010). The sampling procedure used was stratified random sampling, which was best suited for collecting unbiased data that allows broader scale inferences to be drawn. Stratified random sampling is a probability sampling technique that divides the study area into two or more non-overlapping sub-populations (strata) that are sampled using different inclusion probability rules (Gregoire and Valentine, 2004). The selected sampling technique was suitable for this study since it is more forest specific than other land cover types. The lack of land cover homogeneity in the study area made stratified random sampling ideal for this kind of study as well. Non-forested and forested areas were the two strata types.

A division of the study area into forested land and non-forested land was necessary. The inclusion probability was 0.95 for forested lands and 0.05 for non-forested lands. An inclusion probability allows for the insertion of a rule for sample selection (Gregoire and Valentine, 2004); that is, either from a forested or non-forested portion of the study area. The formula used for calculating the sampling frame is shown in Equation 1 below. Selected points acted as central points for 30*30 square quadrats for the collection of independent and additional data such as land cover type and dominant species.

$$n = \left(\frac{tCV}{E}\right)^2 \qquad \textit{(Equation 1)}$$

Where: n is the number of sample units

E is the allowable percentage of error

CV represents confidence interval

t is the value from the t distribution table (Erk et al., 2003)

A confidence interval is a measure of variability of size or density of a study area's forests (Erk et al., 2003). The allowable percentage of error of 5%, confidence interval of 30, and a **t** value of 2 were selected in calculating sample size. The calculated sampling size was 100 sampling units but some sites turned out to be inaccessible and thus only 71 points were analysed. Higher values of confidence interval, such as 30, normally work for forests whose size and density are not uniform (Erk et al., 2003). The selected points are shown in Figure 4.1 below.

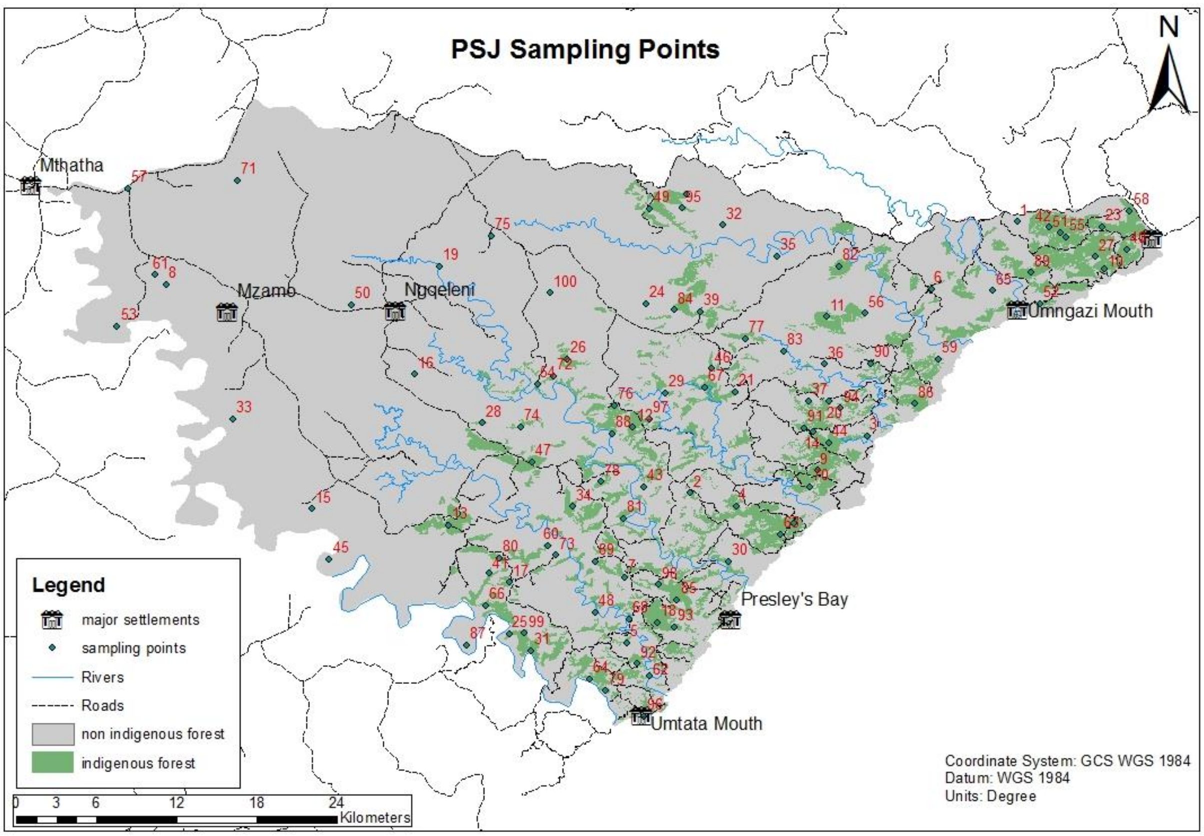

Figure 4.1: Sampling points in the study area in Port St Johns.

The 71 data points mentioned above were for collecting field data used in forest change analysis (Chapter 5). The field spectral measurements were made from 24 random points out of the 71 selected. A total of 132 leaf spectra were collected from these points and used in Chapter 6 and 7 while 24 spectral reflectance samples from dominant species were used in Chapter 8.

4.3: Primary Data collection

Data for this study were collected from a number of sources, including field-collected data, multispectral images and leaf spectral measurements. The following sections explain the data collection techniques used.

4.3.1 Field data collection

Ancillary field data were collected for the period May-July 2013. The research team (that included forest officers from DAFF) identified the species within sampling plots by either their Botanical or Xhosa names. The randomly selected points were navigated using a handheld centimetre level precision Ashtech®ProMark2™ Global Positioning System (GPS). Upon reaching the selected sites, field data for cover, canopy species, altitude and other forest related variables were collected within a 30m square quadrat, using the selected point as a centre of this quadrat. The research team that navigated its way into one of the forest patches to collect field data is shown in Plate 4.1.

Plate 4.1: An example of a section of one of the indigenous forests in the study area

4.3.2 Multispectral data used

SPOT 5 and 6 scenes with four multispectral bands were sourced from the South African National Space Agency (SANSA). The SPOT 5 multispectral bands were from the High Resolution Geometrical 2 (HRG 2) sensor and the SPOT 6 instrument. These images were used in multispectral analysis for forest change analysis and improved forest cover mapping. The spatial resolution of the two instruments SPOT 5 and 6 are different at 10m and 6m respectively. SPOT 5 and 6 were chosen as sensors of choice due to their availability and affordability and general convenience in developing countries, such as South Africa. There was no SPOT 5 imagery for 2013 hence the mixture of the sensors. All the images used were for the same season (period between March to July) and selection of the years 2005, 2009 and 2013 were mainly due to the availability of clear images in that same season. However, the spectral bands and wavelength ranges covered by the respective bands are the same. Spatial resolution was applied to all the images in order to render them comparable. SPOT 6 imagery was resampled to 10m resolution.

4.3.3 Spectral measurements of forest species' leaf spectra

Ground-based hyperspectral data were collected using a spectroradiometer, Spectral Evolution PSR-3500. Hyperspectral remote sensing is quantified by the percentage of light emitted from a surface compared to all light directed to the object of interest that is incident on the sample (Armando et al., 2013). In-situ spectral measurements were made during the day when the sun angle was equal or greater than 45º. This instrument has a wavelength range of 350-2500 nm and a spectral resolution of 3 nm for wavelength interval 350-700 nm, 10 nm at 700-1500 nm and 7 nm at 1500-2100 nm. The spectroradiometer had a leaf clip with an internal light source for measuring leaf reflectance. A leaf clip with an internal power source has the ability to measure reflectance with less distortion from the soil background and other small species (Vaiphasa et al., 2005). The instrument was calibrated using a white reflectance panel after every 15 minutes to minimise variation due to changes in sun angle during measurements. This procedure was meant to limit the effect of bidirectional reflectance.

Data collection involved leaf preparation and leaf spectral measurement. Five samples were collected from different parts of each tree's canopy. The spectral response of each forest species at each sampling site was measured 5 times; this was from leaves coming off different parts of the tree canopy. All in all data was collected from 24 sampling sites in the study area therefore we obtained 24 spectra for dominant species (used in Chapter 8) and 132 leaf reflectance samples (used in Chapter 6 and 7). Plate 4.2 below illustrates the spectroradiometer and the attached leaf clip used in collecting leaf spectra.

Plate 4.2: The Spectral Evolution Spectroradiometer PSR3500 series

Fifteen dominant indigenous species (listed in Table 4.1 below) were identified.

Table 4.1: Number of reflectance samples measured in this study

Botanical Name	Number of samples
Brachylaena discolour	5
Buxus natalensis	16
Cassine palilosa	4
Celtis Africana	10
Cryptocarya latifolia	10
Ficus natelensis	6
Grewia lasiocarpa	5
Halleria lucida	5
Harpephyllum caffrum	5
Heywoodia lucens	10
Millettia grandis	15
Millettia sutherlandii	5
Mimusops caffra	10
Searsia chirindensis	5
Vepris undulate	10
Total	**132**

4.4: Data Analysis

This section presents methods used in multispectral, hyperspectral (spectral discrimination), classifier development and improvement of multispectral images using field spectroscopy data. The study employed ENVI Image Analysis software for analysis multispectral images and as well their integration with field spectroscopy with data. Data analysis for selection of optimal wavelengths and species discrimination at leaf scale were conducted in R Statistical Computing software (R Development Core Team, 2008). In some most cases different classifier require a different R package and these are mentioned under the data analysis methods of the respective classifiers.

4.4.1 Methods used in multispectral analysis of forest changes.

Spot 5 and 6 multispectral images were pre-processed by way of geometric and atmospheric correction to eliminate location distortions and errors due to atmospheric constituents respectively. The study used ENVI 5.0 software for all multispectral analysis. The atmospheric correction algorithm called Quick Atmospheric Correction (QUAC) was employed, which makes use of central wavelengths and their radiometric calibration (Bernstein et al., 2008). The method has advantages in terms of speed and avoiding calculation of first-order radiation transport when compared to the physics-based models like Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH) (Bernstein et al., 2012). Output images represented surface reflectance scaled into byte-signed integers and used a reflectance scale factor of 10000. Images for the years 2005, 2009 and 2013 underwent the same QUAC procedure before the subsequent step of supervised hard classification.

A land cover-based classification was conducted in the form of supervised hard classification. Forest Managers at the Umtata Office of DAFF assisted in identifying various forest-based land cover classes on the multispectral images of the period 2004-2013. The main motivation for using DAFF officials was that most of the images in this range were historical and these officials already had several years’ experience working in the study areas. As such, they could identify land cover features easily as well as provide some context. The main classes identified were water, bare/built-up, grassland/pasture, woodland, less dense forest and dense forest. These classes were adopted and modified from the United States Geological Survey's (USGS) Land Use Land Cover (LULC) levels. Four supervised classification algorithms were tested on the 2013 SPOT 6 image, namely maximum likelihood, minimum distance, spectral angle mapper (SAM) and spectral information divergence (SID). The four algorithms perform different statistical procedures to allocate unknown pixels to different classes. Given these differences, it was imperative to evaluate their performance in land cover classification with special interest in changes in subtropical forests.

a) Maximum Likelihood Algorithm (MLA)

Maximum likelihood algorithm (MLA) is a hard classification technique, which calculates the probability of any pixel being a member of any of the cover classes and assigns a pixel to its most likely class (highest probability value) (Atkinson and Lewis, 2000, Shafri et al., 2007). This classifier uses statistics to allocate classes to the rest of the image based on their location in relation with the equi-probability contour around training data set points. These contours represent the probability of membership to a certain class and they tend to decline away from the mean centre (Mather and Koch, 2011). The parameters of location, shape and size of the ellipse represent the mean, variance and covariance of the features (Mather and Koch, 2011). It works when distribution of training data is based on a normal Gaussian model (Jensen, 2005, Tan et al., 2011). MLA uses the following discriminant function in allocating pixels of the image a class:

$$g_i(x) = \ln p(w_i) - \frac{1}{2}\ln|\sum i| - \frac{1}{2}(x - m_i)t \sum i^{-1}(x - m_i) \qquad \text{Equation 2}$$

Where:

$p(w_i)$ is the probability of w_i class occurring that is assumed equal for all classes

x is n-dimensional data (n represents the number of bands)

i represents class

m_i represents mean vector

$|\sum i|$ is the determinant of covariance matrix in class w_i

$\sum i^{-1}$ is the inverse matrix of the determinant of covariance matrix in class w_i

(Shafri et al., 2007).

The discriminant $g_i(x)$ was calculated for all the classes and for each pixel, the class with the highest value was selected as its final class.

b) Minimum Distance classifier

The minimum distance algorithm uses the spectral feature space's Euclidean distance between the value of the unknown pixels and class means (Atkinson and Lewis, 2000) to assign unknown pixels to different classes. The method estimates class mean vectors and then assigns pixels to classes whose mean is at a minimum distance from the pixel data vector (Dwivedi et al., 2004). There is an option of users defining the distance threshold and if a pixel is further than the user-defined distance, it is classified as 'unknown'. In this study, no distance threshold was defined since the aim was to classify all pixels and then evaluate the classification using independent data. In such a scenario, unclassified pixels would have complicated the classification.

The minimum distance classifier has the main advantage of being quick in its calculation but its main disadvantage is the assumption that classes are symmetric in a multispectral space (Dwivedi et al., 2004). In cases of no symmetric boundaries between classes, the minimum distance algorithm is likely to cause a misclassification of pixels (Hubert-Moy et al., 2001).

c) Spectral Angle Mapper (SAM)

The Spectral Angle Mapping (SAM) algorithm uses the coefficient of proportionality (cosine theta) to allocate classes to unknown pixels (Mather and Koch, 2011) and this coefficient is a measure of difference in the shapes of spectral curves. The method compares spectral similarity by calculating the angle between reference spectrum and each pixel vector in an n-dimensional space (Kruse et al., 1993). Dimensionality is determined by the number of bands on the multispectral images. The smaller the angle, the closer the target is to reference spectrum.

In the present study, the maximum angle was not specified to limit the presence of unclassified pixels. The advantages of SAM include being simple and time efficient due to its linearity (Garcia-Allende et al., 2008). Another advantage this technique has is that illumination differences across landscapes do not distort the final classification result (Harken and Sugumaran, 2005). There is more emphasis given to target reflectance characteristics by suppressing the influence of shading effects and assumes that data are normally distributed (Petropoulos et al., 2010).

d) Spectral Information Divergence (SID)

Spectral Information Divergence (SID) is a spectral classification method that uses a divergence measure to match pixels to reference spectra. SID considers each pixel to be a random sample, defines each pixel's probability distribution and assesses the probabilities between the spectra to measure the similarity between two pixels (Chang, 1999). The smaller the divergence, the more likely the pixels are similar and pixels with a measurement greater than the specified maximum divergence threshold are not classified (Du et al., 2004). The formula for determining SID is well explained in Chang (1999) where it outperformed the spectral angle mapper. Its main advantage is that of being a random probabilistic approach as opposed to a SAM's deterministic approach (Chang, 1999). In this study, SID was used for per-pixel instead of mixed pixel classification.

e) Accuracy Assessment

The performance of the four classification algorithms were evaluated using overall accuracy and the Kappa coefficient from a confusion matrix. The confusion matrix is the most widely used method of measuring accuracy in remote sensing (Foody, 2002b). There are many accuracy measures that can be derived from a confusion matrix, all with their strengths and weaknesses (Lark, 1995). Some studies recommended use of two or more measures from the confusion matrix (Muller et al., 1998). In this study, overall accuracy and the Kappa coefficient were chosen to capture the accuracy levels of the classification methods. Although other accuracy methods have been proposed (Pontius and Millones, 2011) in place of Kappa, this study used Kappa due to its continued use (Cracknell and Reading, 2014, Rozenstein and Karnieli, 2011). Another point to note is that the main metric for accuracy assessment was overall accuracy and Kappa was there to confirm overall accuracy results. Another reason for using Kappa is that this study adhered to the good practices on sampling design, response design and analysis thereby improving the performance of Kappa (Olofsson et al., 2014). Although Kappa is highly correlated to overall accuracy (Olofsson et al., 2014), the study used both methods as way of performing a double confirmation of the accuracy. The independent data was then used for validation using the confusion matrix.

Accuracy assessment is a measure for map quality and in this case goes further and evaluates the performances of different algorithms on the 2013 SPOT 6 imagery. It also helps in understanding errors (Foody, 2002a) within satellite image data. Overall accuracy is defined as the percentage of correctly classified pixels and is calculated by the following formula based on the confusion matrix:

$$Overall\ accuracy = \frac{\sum_i a_{ii}}{N} \qquad \text{Equation 3}$$

Where $\sum_i a_{ij}$ = sum of diagonal cells (the correctly classified points)

N = total number of sample pixels

Overall accuracy ranges from 0-100%, where higher percentages mean higher accuracy levels of the classification method. Although there is no acceptable overall accuracy threshold for land cover classification, this study adopted 85% from an earlier study (Thomlinson et al., 1999). Overall accuracy was supported by the Kappa coefficient that measures levels of agreement between the classified image and ground truth data. The Kappa coefficient was calculated from the confusion matrix using the following formula:

$$\text{Kappa} = \frac{\text{N}\sum_i a_{ii} - \sum_i a_{ii} + a+_i}{N^2 - \sum_i a_i + a+_i} \qquad \text{Equation 4}$$

Where a_{ii} = pixels from the $_i$th class that have been classified as $_i$th class

$a+_i$ = is the $_i$th column marginal (sum of row entries)

N = total number of samples pixels (Hubert-Moy et al., 2001)

The values of Kappa range from 0-1 with values closer to 1 depicting high level of agreement between the classified map and validation data. Kappa results were interpreted using the rules mentioned in Table 4.2 and adapted from a related study (Landis and Koch, 1977).

4.4.2 Selection of significant wavelengths for species discrimination

Pre-processing of field spectroscopy data involved using a moving average and spectrum differential processing to eradicate soil background effects. The pre-processing technique also removed high frequency noise. The first step in this scenario was visualising the mean spectra for the observed 15 indigenous forest species in order to assess if spectral separability was possible using all wavelengths. The Spectral Evolution Spectroradiometer's inbuilt software converted canopy spectral measurements to reflectance measurements in percentage. As shown in Figure 5.1 in chapter 5, plotting mean spectra for all the species in all wavelengths showed less information on separability. The spectral profiles of all forest species depicted less variation compared to profiles of forests and other surfaces like grassland, hence the use of statistical methods to identify significant bands and their separability.

The comparability of the indigenous forest species and hyperspectral data dimensionality were the major challenges in indigenous species classification. The Shapiro-Wilk test was included as a preliminary statistical test for assessing the data's fulfilment of the assumption of normality. The hierarchical method for dimension reduction was used. It involves One Way Analysis of Variance (ANOVA) with post hoc analysis, as well as Classification and Regression trees (Breiman et al., 1984), as used in previous studies (Adam and Mutanga, 2009, Padalia et al., 2013, Visser et al., 2013).

After determining significant wavelength spectral separability, the Jeffries-Matusita distance method measured their spectral separability. Below are the four general steps taken. Data analysis for selection of wavelengths was conducted using different packages of R Statistical Computing Software (R Development Core Team, 2008).

a) One Way ANOVA with post hoc correction

The need to test and select significant bands for species discrimination makes this stage essential. At this stage, what is tested is whether there is a significant difference in species reflectance in different bands or not. Some authors used this step as a first step towards species discrimination (Adam and Mutanga, 2009). While others preferred methods such as" wrapper feature selection (Vaiphasa et al., 2005), genetic search algorithms (Vaiphasa et al., 2007), sequential forward floating selection (Serpico and Bruzzone, 2001) and principal component analysis (Armando et al., 2013, Lee and Seung, 1999, Tsai et al., 2007). Band selection/dimension reduction is critical in the spectral separability exercise because it reduces the problem of high dimensional complexity, wavelengths correlations and data redundancy (Balabin and Safieva, 2011, Vaiphasa et al., 2007).

A One-Way Analysis of Variance (ANOVA) with Bonferroni correction at 95% confidence intervals ($p < 0.05$) was used. One way ANOVA is a statistical test of differences in mean spectral reflectance values for all combinations of 15 forest species at each measured wavelength band. These two techniques assist in narrowing down to significant bands for indigenous species discrimination. The three conditions/assumptions of ANOVA are that data should be randomly sampled, normally distributed and data type be interval/ratio (Barrett and Curtis, 1999). The spectral reflectance used met all ANOVA criteria. A significant difference among species' reflectance at each wavelength was determined using the null hypothesis for ANOVA's F-test, stating that there is no significant difference between pairs of species at each wavelength. The research hypothesis stated that there was a significant difference in the species reflectance of subtropical forest species between different wavelengths. The following formula summarises both the null and research hypotheses:

$$H_0: \mu_{350} = \mu_{351} = \mu_{352} = \mu_{353} \dots\dots\dots. = \mu_{2500}$$

$$H_1: \mu_{350} \neq \mu_{351} \neq \mu_{352} \neq \mu_{353} \dots\dots\dots. \neq \mu_{2500} \qquad \text{Equation 5}$$

Where: H_0 represents Null Hypothesis

μ_x is the mean reflectance of the measured 15 forests species at $_x$ spectral wavelength band from (350nm to 2500nm)

ANOVA tested the above hypothesis using an F test, which is calculated from within-group and between-group variances. A set of equations below best illustrates how the ANOVA procedure is calculated:

$$ANOVA\ F\ statistic = \frac{s_w^2}{s_b^2} \qquad \text{Equation 6}$$

Where: s_w^2 represents the within group variance

s_b^2 represents the between-groups variance (Walford, 2011).

The next stage after ANOVA was a post-hoc comparison procedure, Bonferroni, which controls the rate of performing a Type 1 error across multiple combinations. A Type 1 error represents the probability of rejecting a null hypothesis by mistake. The rationale behind the tests is that when using ANOVA, the F-statistic only indicates a difference between the means somewhere among the combinations. The post-hoc procedure, therefore, compares each mean with every other mean and reduces the probability of committing a Type 1 error. The adjustment is done in R statistical software where the resulting p values are evaluated for a significant difference of the different wavelengths among the different species combinations. The results from the ANOVA test indicate at which wavelengths forest species are most likely to be spectrally different, hence the need for further selection of most optimal spectral regions using the classification and regression trees method.

b) Classification and regression trees algorithm

The classification and regression trees (CART) method analyses the explanatory variables and makes binary divisions to reduce deviance in the response variable (Lawrence and Wright, 2001). The method has been used in classification and recursive partitioning for the past 30 years (Breiman et al., 1984). In this case, the explanatory variables are the spectral reflectance values while the species name lists are the response variables. Unlike results from ANOVA, results from CART do not guarantee separability of species based on individual wavelength bands (Visser et al., 2013). CART classifies explanatory variables using a two-stage approach of selecting the best fit for each response variable, as well as the best overall fit (Berk, 2008). In both stages, the method uses the sum of squares to split the data first to determine the best fit for each predictor and finally for the overall best fit. Within and between variance among the response variables determine the sum of squares measure (Berk, 2008). After these two stages, data splits into two subsets. Training data is used in selecting wavelength bands for splitting after searching for possible variable combinations. This allows the selection of an optimum number of bands for species classification (Visser et al., 2013). CART algorithm repeats the two-stage splitting process on the two subsets and the next subdivisions until there is a set of homogenous nodes, a process called recursive partitioning. The output of this method is a graph, which resembles an inverted tree showing main/root node being the trunk, splitting nodes branches and final/terminal nodes being the leaves.

The final homogenous nodes therefore show the grouping of reflectance values based on species. Information about the bands that allow the discrimination of these species comes in the form of rules for splitting at each node. Classification of final nodes is according to the response variables; that is, species name. However, it does not show the separability of the identified wavelengths in discriminating subtropical indigenous forest species. The next section, therefore, tested the separability of these identified bands using a distance measure called the Jefferies-Matusita (JM) separability index. An evaluation of the importance of the previous step of ANOVA was conducted by comparing results from CART analysis using the bands from the 99% confidence level regions against the full set of bands.

c) Spectral separability analysis

After selecting the significant bands, Jeffries-Matusita (JM) separability index was used to test the sensitivity of pairs of classified classes, that is, the different subtropical indigenous species. JM measures the average distance between two class density functions (Fernandes et al., 2013). The main reason for performing spectral separability was to minimise chances of Type 1 error (Vaiphasa et al., 2005) hence the need to confirm the separability of the selected wavelengths. The measure accurately quantifies spectral separability between pairs of variables and is calculated from the Bhattacharya distance (Adam and Mutanga, 2009, Glenday, 2008, Padalia et al., 2013, Vaiphasa et al., 2005). In this study, the JM distance method evaluated the separability of the different species using the statistically significant wavelengths selected in previous sections of ANOVA with posthoc and CART. The significant spectral bands used in this separability analysis were selected from one-way ANOVA with Bonferroni correction and CART. Calculation of the JM separability index was based on the following equation (Equation 5):

$$JM_{ij} = \sqrt{2(1 - e^{-BD})} \qquad \text{Equation 7}$$

Where $$BD = \frac{1}{8}\left(\mu_i - \mu_j\right)^T \left(\frac{C_i + C_j}{2}\right)^{-1} \left(\mu_i - \mu_j\right) + \frac{1}{2} In\left(\frac{\frac{1}{2}\left|C_i + C_j\right|}{\sqrt{\left|C_i\right| \mathrm{x} \left|C_j\right|}}\right) \qquad \text{Equation 8}$$

BD represents Bhattacharya distance

i and j are the spectral responses,

C is the covariance matrix of i and j,

μ is the mean vector of spectral response,

T is the transposition function and

$|C|$ is the determinant of C. (Glenday, 2008)

The output for JM distance analysis is a spectral distance ranging between 0 and 2 (Vaiphasa et al., 2005). JM distance values evaluate separability between pairs of species. A separability index of about ≤ 1.95 is widely accepted as depicting a strong separability (Glenday, 2008) between the indigenous forest species. A JM distance value of 2 depicts a classification procedure that is 100% accurate while 0 implies that selected signatures are totally inseparable (Lasaponara and Masini, 2007). The JM distance value, therefore, determined if reflectance at the selected optimal wavelengths were showing separability. This is translated to the ability of reflectance at the selected wavelengths to discriminate the 15 subtropical forest species.

4.4.3 Developing and evaluating classifiers for species discrimination

Using the selected significant wavelengths, all measurements were then divided into two, one (65%) for classifier development and the other (35%) for testing the classifiers. The overall aim of classifiers is to assign each pixel to predefined classes and help predict classes for new instances (Li et al., 2006). In designing the best method for indigenous forests, three machine learning based classifiers were performed. The three classifiers included in this section consisted of Linear Discriminant Analysis (LDA), Partial Least Squares Discriminant Analysis (PLS-DA), and Random Forest (RF) analysis. All data manipulation steps were employed using relevant tools (packages) in R Statistical Computing software.

a) Linear discriminant analysis (LDA)

Linear discriminant analysis (LDA) uses statistics to find linear combinations of features that can discriminate data into different classes. In some studies, the method is referred as Fischer's linear discriminant analysis (Guimet et al., 2006, Koger et al., 2003). The method works when there are many continuous independent and one categorical dependent variable. LDA is implemented using scatter matrix analysis by finding a linear transformation which best discriminates the classes and then classifies the data using a distance matrix within the transformed space (Li et al., 2006). When the number of classes is more than two, the matrices, transformation and classification are calculated using the following set of equations (9-11). The intra-class matrix is obtained using the first formula (equation 4).

$$\widehat{\sum}_w = S_1 + \cdots\cdots\cdots S_n = \sum_{i=1}^{n} \sum_{x \in C_i} (x - \bar{x}_i)\,(x - \bar{x}_i)' \qquad \text{Equation 9.}$$

Inter-class matrix is then obtained using the following calculation:

$$\widehat{\sum}_b = \sum_{i=1}^{n} m_i (\bar{x}_i - \bar{x})(\bar{x}_i - \bar{x})' \qquad \text{Equation 10}$$

Where n is the number of classes

m_i represents the number of training samples of each class

$\bar{x}$ reflects the total mean vector (Li et al., 2006).

Regarding the intra and inter-class matrices (Equations 9 and 10), a linear transformation **Φ** is calculated that is ultimately used in the classification of training data. The classification of a new feature z is achieved using:

$$argmin\; d(z\Phi, \bar{x}_k\Phi) \qquad \text{Equation 11}$$

Where $\bar{x}_k$ is the centroid of k-th class

d is a distance metric such as Euclidean distance or cosine measure (Li et al., 2006).

The LDA classifier was developed and evaluated on independent data using the MASS package in R, a package focussed on applied statistics (Venables and Ripley, 2002).

b) Partial Least Squares Discriminant Analysis (PLS-DA)

Partial least squares (PLS) method is a multivariate form of multiple regression that fits training data into a species discrimination model. PLS is similar to the principal component analysis (PCA) whereby information in the form of a large number of collinear variables are compressed into few non-correlated components making up a prediction function (Dorigo et al., 2007). The less important factors carry information from random spectral noise and background effects. PLS differs from PCA in that it only compresses the most important information from the variables and this reduces the overfitting of data, a typical stepwise regression analysis problem (Huang et al., 2004). The utility of PLS performs both dimension reduction and classification in a single operation (Dorigo et al., 2007). When the PLS is applied to classification of dependent variables, then it is called partial least squares discriminant analysis (PLS-DA). In PLS-DA a set X of variables uses partial least squares regression to describe the categories on a set Y of predictor variables (Pérez-Enciso and Tenenhaus, 2003).

The method was interrogated for its ability to discriminate subtropical forest species. Several studies have found that the method performs more accurately compared to the traditional regression techniques (Hansen and Schjoerring, 2003, Huang et al., 2004) due to its ability to manipulate large number of variables with co-linearity (Pérez-Enciso and Tenenhaus, 2003). In this case, the method was used in the classifier development process using the selected wavelength bands from the previous chapter on wavelength band selection. PLS-DA discrimination was conducted using the DISCRIMINER package in R (Pérez-Enciso and Tenenhaus, 2003).

c) Random Forest (RF)

Random forest (RF) is a tree based classifier which uses the bagging technique to classify the training dataset and it achieves this using the random feature subspace and out-of-bag estimates (Breiman, 2001, Chan and Paelinckx, 2008). It belongs to ensemble classification methods, which use a variety of methods to do the classification. The methods work by constructing a large number of classification trees from the training dataset using random feature selections and then votes for the most popular ones to be adopted (Breiman, 2001).

The method selected the final output from the popularity of the individual trees making up the model. Although validation of the RF could be done using the out-of-bag (OOB) estimation (Breiman, 2001), this study used a training dataset instead. The rationale behind ensemble classifiers, like RF, is that they achieve higher accuracy compared to methods that use one learning algorithm (Chan and Paelinckx, 2008). Among the advantages of the RF is its ability to handle high dimensional data (Gislason et al., 2004) as well as accurately classify in cases where amongst the explanatory variables there is no single or small group that can distinguish classes (Breiman, 2001).

Overall accuracy and Cohen's Kappa coefficient were calculated in the next section as a method of comparing the performance of the RF with the other two methods (LDA and PLSDA). The algorithm was processed using the RF package in R, which is based on Breiman and Cutler's random forests (Breiman, 2001).

d) Comparison of the discriminant methods

Two techniques were used to evaluate the performance of the selected classifiers on the independent validation dataset. The two techniques are the overall accuracy and the Cohen's Kappa coefficiency. These two were chosen due to their evaluating categorical classification ability to work data, which is not normally distributed. The overall accuracy is calculated from the confusion matrix and is interpreted as the percentage of correctly classified cases (Foody, 2002b). The method calculates overall accuracy by dividing correctly classified samples (diagonal values on a confusion matrix) by the total number of samples. However, some studies have criticised it for the failure to sideline correct classifications due to chance (Congalton, 1991, Rosenfield and Fitzpatricklins, 1986). The Cohen's Kappa coefficient was therefore used to deal with chance agreement as suggested in previous studies (Smits and Dellepiane, 1999).

The Cohen's Kappa quantitatively compares the level of agreement between classified and true datasets. Weighted kappa values were also incorporated to deal with classifications that may be due to chance (Ben-David, 2008). The statistics can be calculated either with or without weighting. Both methods make calculations based on the differences between the observed and expected agreement (Viera and Garrett, 2005). The method was widely used to evaluate classification results (Koedsin and Vaiphasa, 2013, Naidoo and Hill, 2006, O'Grady et al., 2013, Pu, 2010). The unweighted Cohen's Kappa statistic was calculated using the equation below (equation 10):

$$k = \frac{p_o - p_c}{1 - p_c} \quad \text{Equation 12}$$

Where p_o is the proportion of pixels with observed agreement, and

p_c is expected theoretical proportion by chance selection (Cohen, 1960)

The equal-spacing weighting method includes a weighting factor for each cell that uses the following formula:

$$w_{ij} = \frac{1-|i-j|}{g-1} \qquad \text{Equation 13}$$

Where i,j represents the location of cells, and
g is the number of categories. (Cohen, 1968)

There is no one agreed interpretation of Kappa values (O'Grady et al., 2013) but these values were interpreted using values table of conclusions from Landis and Koch (1977). The Kappa thresholds and their corresponding interpretation are shown in Table 4.2 below. A final decision was made based on the calculated Kappa values. The Kappa values, in turn, show the level of agreement between the predicted and actual classification results. The best classifier is one that has higher accuracy levels and one, which shows a high agreement between predicted and reality. Shown in Table 4.2 below are the interpretation rules that were adopted:

Table 4.2: Interpretation of Kappa (Landis and Koch, 1977)

Kappa value	Interpretation
< 0	"No agreement"
0.01-0.20	"Slight agreement"
0.21-0.40	"Fair agreement"
0.41-0.60	"Moderate agreement"
0.61-0.80	"Substantial agreement"
0.81-0.99	"Almost perfect agreement"

Conclusions were made on the best method for discriminating the indigenous forests of the Wild Coast region of South Africa. These conclusions took into consideration some of the underlying assumptions of the different methods.

4.4.4 Sub-pixel classification using field spectral and multispectral data

Before performing sub-pixel classification, a mask was created using the per-pixel classification algorithm (MLC) to remove non-forest portions of the study area. The integration of per-pixel and sub-pixel classifiers is through the preliminary masking of the image before performing the latter method. The mask was built on the classified image from the first section on per-pixel classification based forest change analysis. According to Foody (2002a), conducting masking before sub-pixel classification improve the resulting proportional maps since it avoids spectral confusion. Using the 2013 classified map, a mask was developed using the areas classified as indigenous forests. This was used to mask out non-forest areas from the original 2013 images. Per-pixel classification refers to algorithms that allocate each pixel to one and only one class based on a logic that a pixel can only fully be a member of a class or not . Sub-pixel classification techniques, on the other hand, allow each pixel to have multiple and partial memberships to identified classes (Wang, 1990).

a) Integrating field spectral and SPOT 6 multispectral data

Leaf reflectance spectra were resampled to SPOT 6 bands and then assessed in terms of their accuracy in phenological classification of subtropical indigenous forests. Resampling was the method of choice because of its ability to integrate field spectra with multispectral images (Oumar and Mutanga, 2010). The rationale is to integrate the strengths of multispectral and field spectroscopy to improve the classification of subtropical indigenous forests. The combined framework for this method includes hard classification, as shown in Figure 4.2 below:

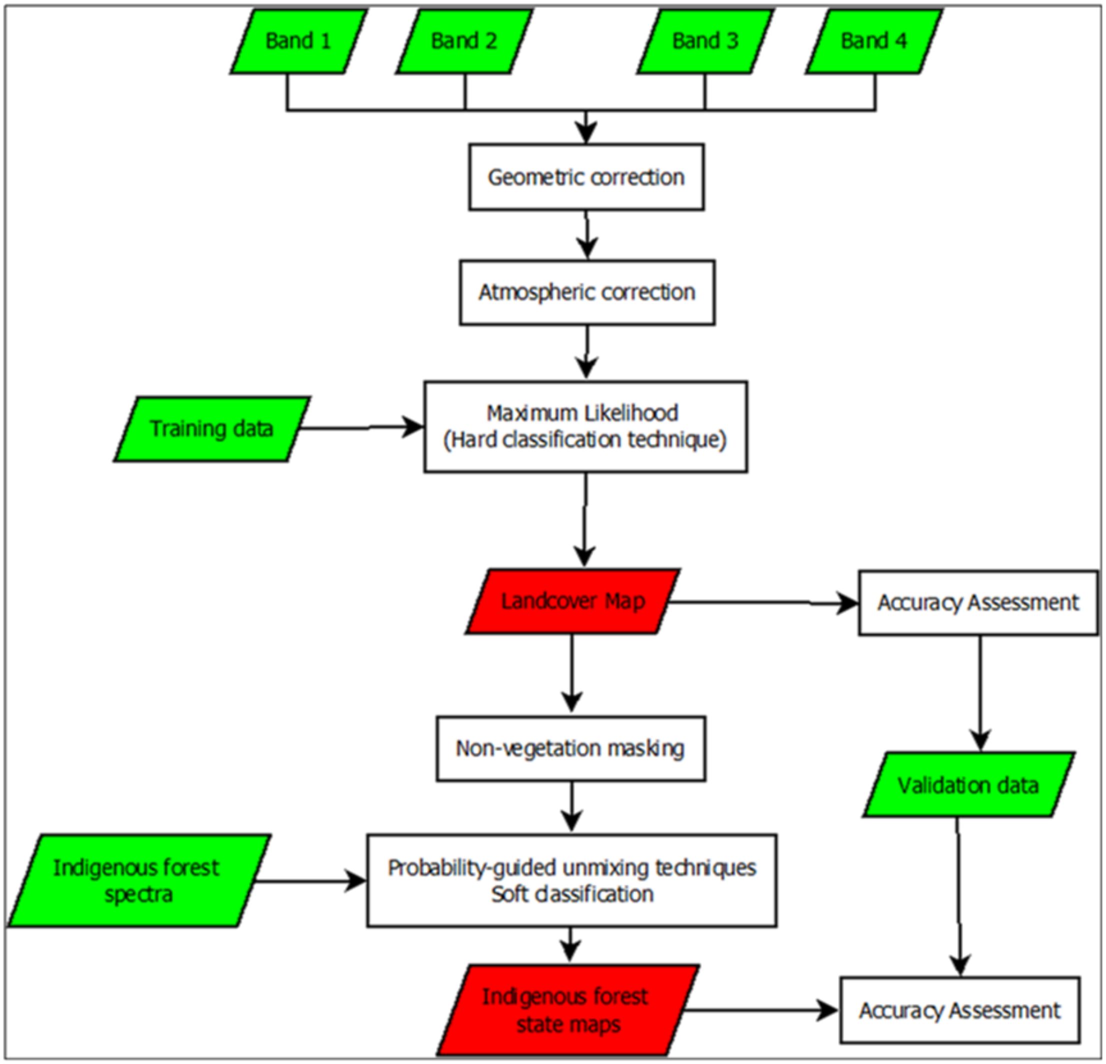

Figure 4.2: Outline of methodology for improving forest classification. (Adapted from Curatola Fernández et al. (2013))

Combining per-pixel and sub-pixel classification techniques can improve mapping of cover variables as witnessed in previous research studies, including bracken fen status classification (Fernández et al., 2013), and tropical vegetation (Gottlicher et al., 2009). In the present study, land cover mapping using a per-pixel classification algorithm provided a non-forest mask used to remove areas not classified as subtropical forests from the 2013 SPOT 6 image. This image was used in the sub-pixel classification, integrated with field spectroscopy data.

b) Sub-pixel discrimination of semi-deciduous and evergreen forest species

Sub-pixel classification was achieved in this study by using a partial unmixing and sub-pixel abundance estimation method called Mixture-Tuned Matched Filtering (MTMF) (Boardman, 1998, Williams Parker and Hunt, 2002). The method quantifies abundances of the endmembers within each pixel using a combination of linear spectral unmixing and matched filter methods. Matched filtering is used when maximising the response of the known endmember without knowing other endmembers of an unknown background (Dopido et al., 2011). MTMF incorporates linear unmixing through mixed pixel leverage and feasibility-induced constraints (Dopido et al., 2011).

MTMF was chosen over other unmixing methods due to its ability to give better results from a sample with few endmembers as well its elimination of false positives from abundance images (Dehaan and Taylor, 2003). The method also calculates an output infeasibility score based on the interaction of the target spectrum and composite background. Other researchers have used the MTMF in mapping leafy spurge, a noxious weed, (Mundt et al., 2007, Williams Parker and Hunt, 2002), and also irrigation-induced salinisation (Dehaan and Taylor, 2003). Results from unmixing methods like the MTMF are highly dependent on input endmembers. Thus, changes in endmembers lead to changes in results.

Results from MTMF are two MF score images showing the degree of matching of each endmember (semi-deciduous and evergreen forests) in each image pixel as well as two infeasibility images. The MF score maps show the relative degree of match of each pixel with the training spectrum (Mitchell and Glenn, 2009). The correctly classified pixels are shown in the respective MF score maps with values closer to 1 and low infeasibility values. Infeasibility values are in the form of noise sigma values, hence the lower the values the less the background noise. A 2-D scatterplot was then used to determine the best matches to the endmember spectra by plotting the MF score against infeasibility.

The interactive classification using the scatterplot was used based on previous examples from a study on leafy splurges (Mitchell and Glenn, 2009). Ground truth data then evaluated the performance of MTMF using the producer’s, user's and overall accuracy values. These were calculated from an error/confusion matrix. The producer's accuracy is the fraction of correctly classified pixels with regard to all pixels of that ground truth class.

4.5: Summary

This chapter presented all methods used to meet the objectives of the study and their respective results (Chapters 5-8). Data collection and analysis were done at leaf, canopy and top-of-atmosphere levels. Four per-pixel classification algorithms were tested for their accuracy in classifying the study area using the confusion matrix. By applying the selected method on 2005 and 2009 multispectral images, forest change analysis was conducted to quantify changes over the periods 2005-2009 and 2009-2013. The hierarchical method was used to identify optimal bands for the discrimination of sub-tropical forest species at leaf level (Adam and Mutanga, 2009). The selected three machine learning algorithms for the subsequent leaf level discrimination were LDA, PLSDA and RF. MTMF, a sub-pixel classification technique, was selected for mapping the proportions of the phenological groups. Overall accuracy and Kappa coefficient were selected for validation of the classification exercise at leaf and top-of atmosphere.

Multi-temporal Analysis of Subtropical Forest Changes between 2005 and 2013

5.1: Introduction

The conservation of subtropical forests in the coastal regions of South Africa remains one of the big tasks of national government. In the light of the prevailing conditions, this section aims to assess land cover change at four-year intervals for the years 2005, 2009 and 2013 with a special focus on the subtropical indigenous forests. Earlier research has shown that selective logging causes increased vulnerability to fires (Cochrane, 2001), alters forest composition and structure and diminishes animal and forest resources (Nepstad et al., 1992)

Forest change also causes other negative effects such as forest area reduction, forest edge increase, and subdivision of large forested areas (Laurance et al., 2000). Threats to wildlife survival and changes in tree and animal species composition are some of the specific impacts. Forest changes occur at varying spatial scales; there is a need to understand the dynamics of these changes and landscape dynamics in the region to aid the sustainable management of the forests. The study area along the Wild Coast of South Africa has a unique landscape comprising subtropical forests, woodlands, grasslands, rivers and wetlands.

Since there are a number of classification algorithms, the one with highest accuracy was adopted and incorporated in Chapter 8. Besides mapping forest change, this chapter paves way for Chapter 8 where there is an integration of field spectral and SPOT 6 data. Having decided on the best method, classification of the images from past years would allow the quantification of subtropical forest changes in the area. The focus of this chapter was to monitor forest change using multispectral remote sensing imagery from SPOT 5 and SPOT 6. Specifically, the chapter serves to:

- evaluate the performance of 4 different classification algorithms (maximum likelihood, minimum distance (MD), spectral angle mapper (SAM) and spectral information divergence (SID) in mapping land cover classes (such as forests, woodland, water, bare/built-up and grassland) and

- quantify forest changes between 2005 and 2013 using multispectral imagery for years the 2005, 2009 and 2013.

Conclusions were then drawn based on the observed forest change trends from 2005 to 2013. Recommendations for sustainable management of the forests would then be made based on the changes identified.

5.2: Results

5.2.1 Comparing four classification methods using the 2013 SPOT 6 image

In the light of the first objective of determining the best classification method for land cover classes using multispectral, the 2013 SPOT 6 image was classified using the MLC, MD, SAM and SID. The following maps (Figures 5.1 - 5.4) show classification results from the four algorithms.

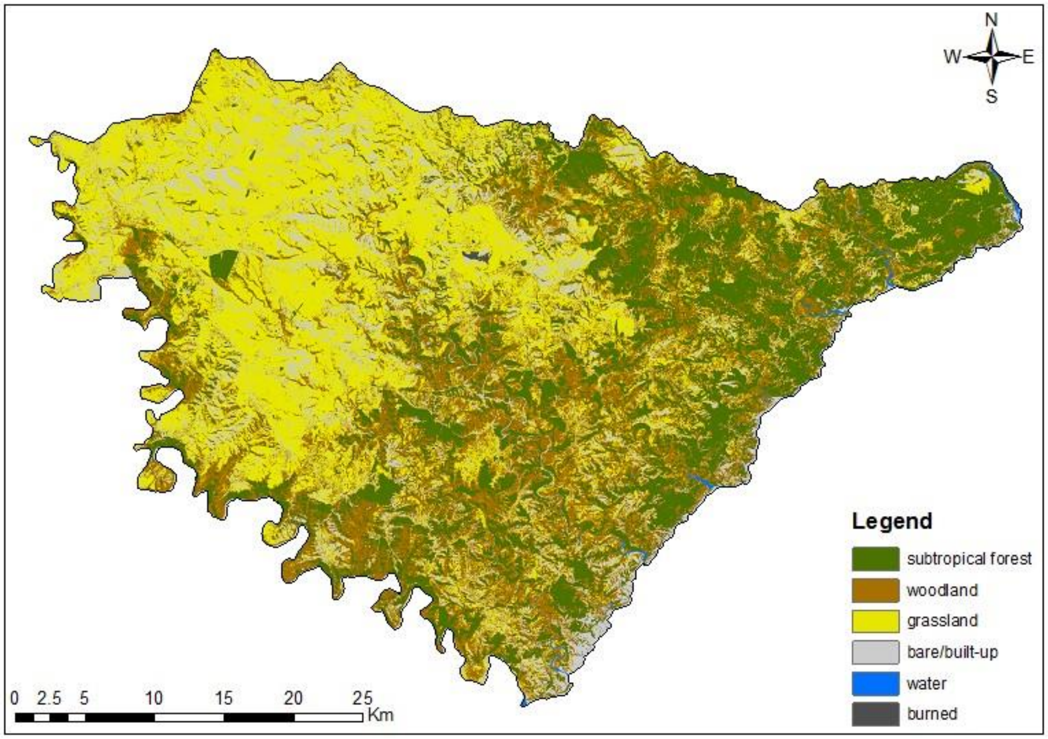

Figure 5.1: MLC classification results for the 2013 image

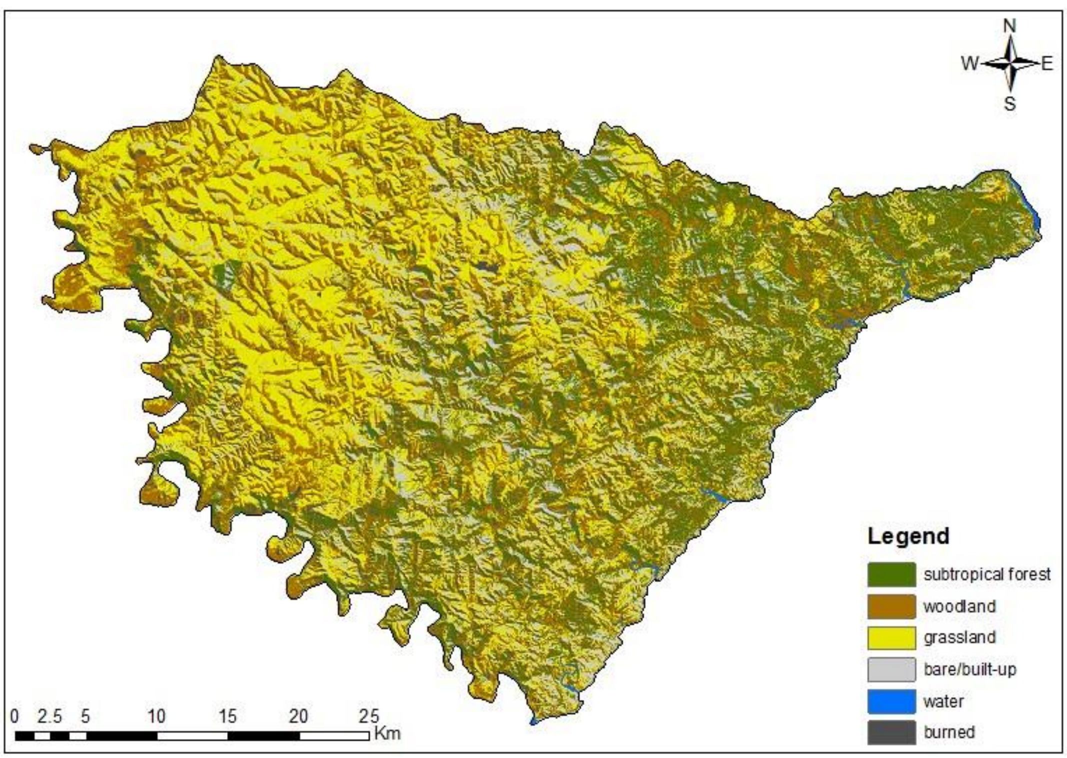

Figure 5.2: MD classification results for the 2013 image

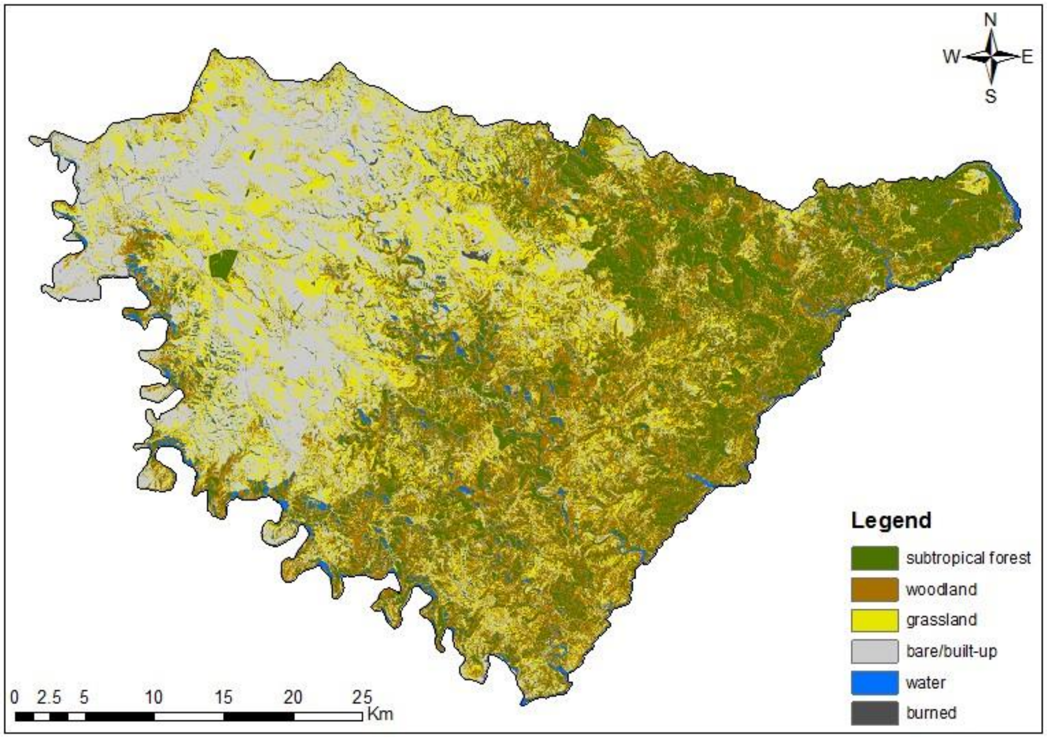

Figure 5.3: SAM classification results for the 2013 image

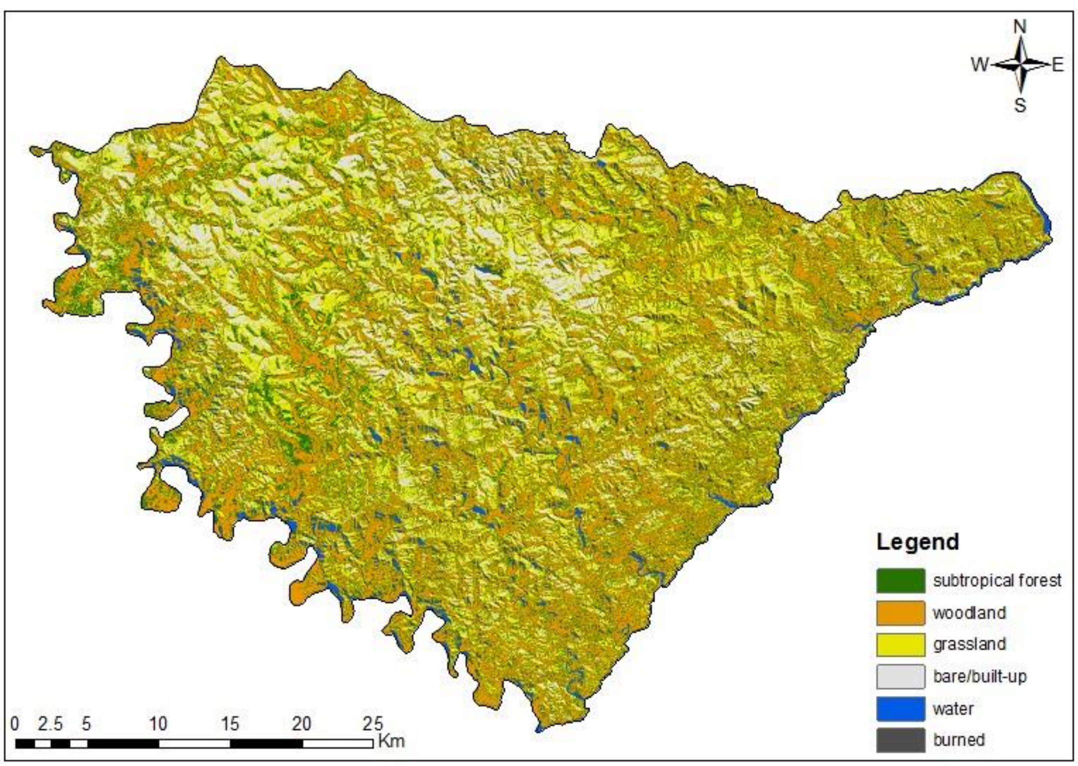

Figure 5.4: SID classification results for the 2013 image

The maps were evaluated for accuracy using confusion matrix-derived metrics of overall accuracy and Kappa coefficient. Determining the best classification was achieved by comparing the overall accuracy and kappa coefficient values of the resultant maps from the four different classification algorithms. Confusion matrices for individual classification methods are shown in Tables 10.1 - 10.4, which are in Appendix 1. The summary of the results of this exercise are presented in the following table (Table 5.1).

Table 5.1: Summary of confusion matrices of the four classification algorithms

Algorithm	**Overall Accuracy**	**Kappa Coefficient**	**Kappa interpretation**
Maximum Likelihood	88.75	0.69	Substantial agreement
Minimum distance	43.66	0.18	Slight agreement
Spectral Angle Mapper	42.25	0.004	No agreement
Spectral Information Divergence	32.39	0.04	Slight agreement

According to the accuracy results presented in Table 5.1 above, the MLC algorithm is the most accurate method when compared to the other three methods of MD, SAM and SID. With an overall accuracy of 88.75% and a Kappa coefficient of 0.69, MLC shows high accuracy as well as a substantial agreement between observed and classified data.

Consequently, mapping of subtropical forests and other land cover classes was based on MLC because of its high accuracy and levels of agreement between the classified map and reality on the ground. The resulting maps from classification of images of the three years of 2005, 2009 and 2013 are presented in the next section.

5.2.2 The state of indigenous forests, woodlands and other land cover for the years 2005, 2009 and 2013

The maximum likelihood classification algorithm was applied to images from the SPOT 5 HRG sensor for 2005, 2009 and 2013. The final land cover maps for the years 2005, 2009 and 2013 provided the state of subtropical forests, woodlands and other land cover classes. The following three maps (Figures 5.5, 5.6 and 5.7) present the state of forests woodlands for the years 2005, 2009 and 2013. The first one depicts the situation that was prevailing in the study area in 2005 and the subtropical forests have a wider coverage than the 2009 and 2013 maps in Figures 5.5 and 5.6. The forests are mainly concentrated along the coastal regions of the study area.

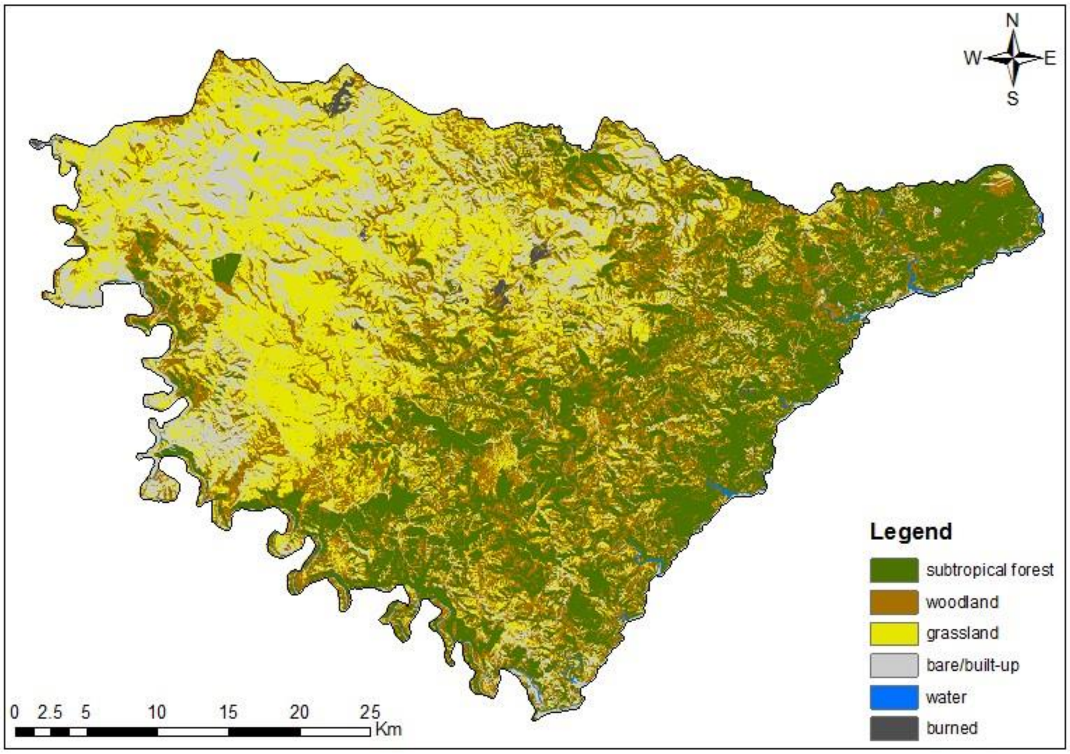

Figure 5.5: The state of the environment in 2005

According to the classification results shown by the above map (Figure 5.5), area coverage of the subtropical forests in 2005 was about 46700.96 hectares. In the classification maps, the subtropical forests are referred to as natural forests (presented in dark green) and they are distinguished from woodlands based on tree height when mature. In 2005, most of the coastal portions of the study area were covered by subtropical forest. Figure 5.6 and 5.6 provide maps of the forests and other land cover classes in the years 2009 and 2013.

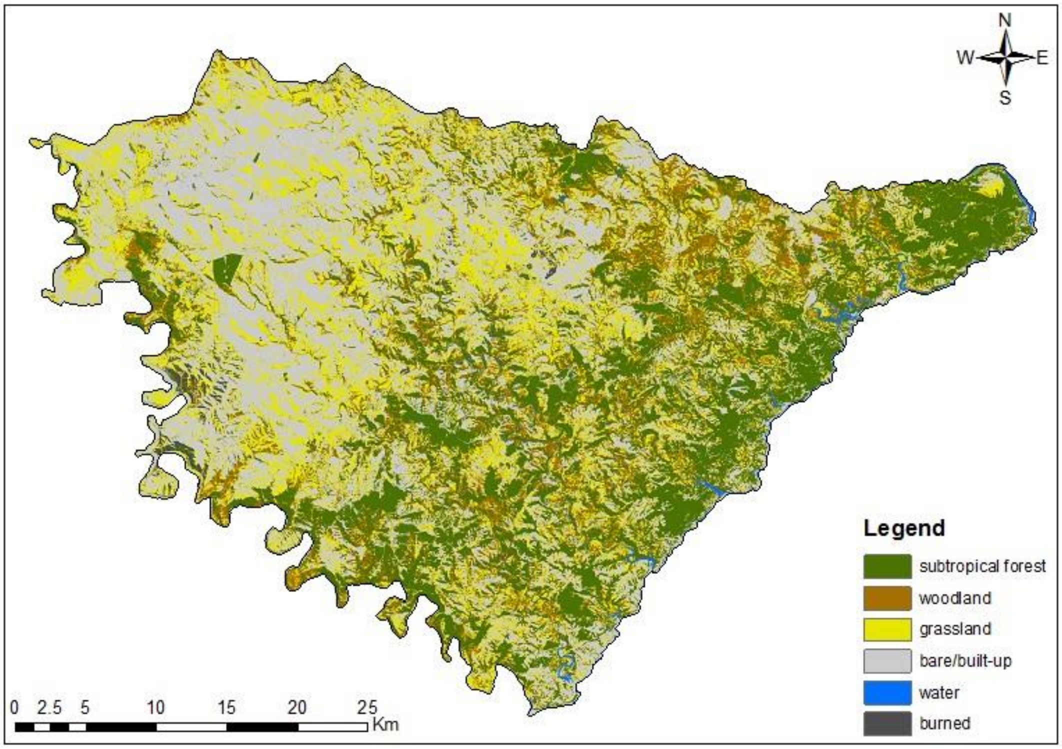

Figure 3: The state of the environment in 2009

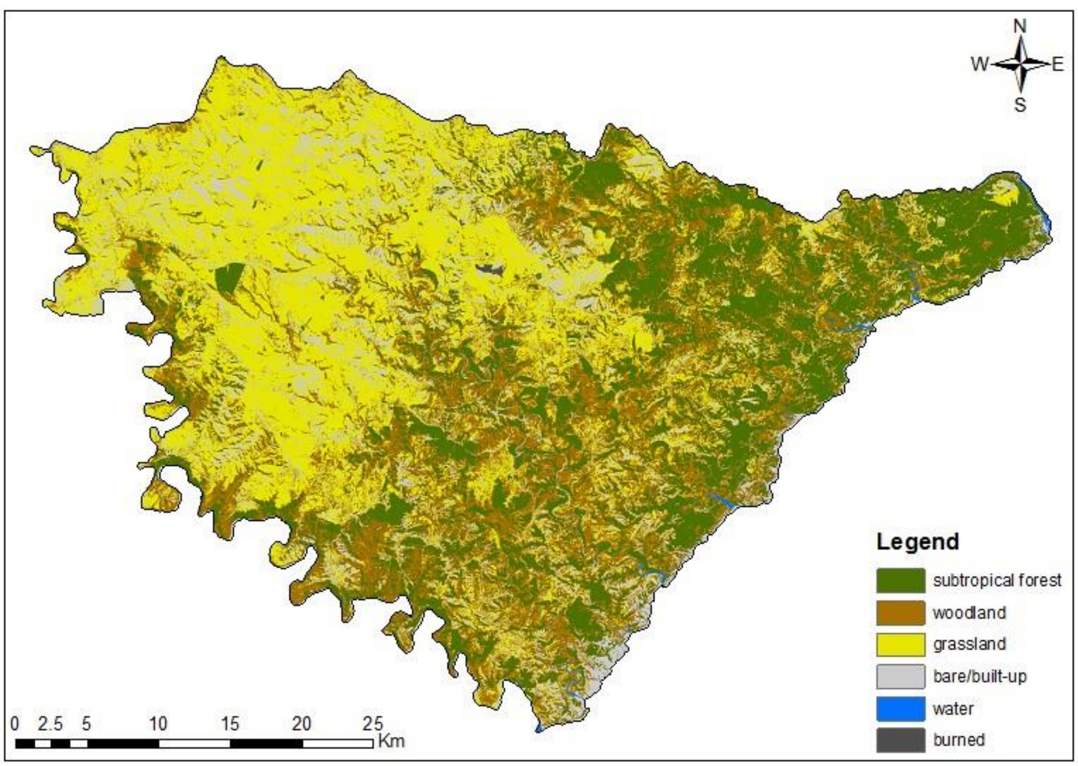

Figure 4: The state of the environment in 2013

The forests, woodlands and other land cover types areal coverage in 2005, 2009 and 2013 is presented in Table 5.2 (in hectares). The figures show a decrease in subtropical forests from 2005 to 2013 in the study area. Much of the change was witnessed between 2005 and 2009 compared to the period between 2009 and 2013.

Table 5.2: The coverage of indigenous forests and other cover classes (in hectares)

Cover Class	2005	2009	2013
subtropical forest	46700.96	43052.54	42105.56
woodland	43607.48	44140.30	44882.11
grassland	51427.68	41386.30	60687.73
Bare/built-up	26176.8	37613.51	20584.79
water	651.68	784.21	548.7264
burned	827.6	2392.48	554.2812
Total	**169392.20**	**169369.34**	**169363.20**

The trends in Table 5.2 show that while subtropical forests are decreasing in area, woodlands and grasslands have been increasing. The above results can also be evaluated in terms of differences between the periods 2005-2009 and 2009-2013 are shown in Table 5.3 in the next section.

5.5.3 Change analysis for the periods 2005-2009 and 2009-2013

Visual interpretation of maps and a quantification of the land cover classes show a decline in indigenous forests in the study area. The coverage of the different land cover classes can be interpreted in terms of the difference change between the two four-year periods of 2005-2009 and 2009-2013 (Table 5.3 below).

Table 5.3: Land cover change differences between periods 2005-2009 and 2009

Cover Class	2005-2009 Change in ha	% Change 2005-2009	2009-2013 Change in ha	% Change 2005-2009
natural forest	-3648.42	-7.81	-946.98	-2.20
woodland	532.82	1.22	741.81	1.68
grassland	-10041.38	-19.53	19301.43	46.64
bare/built-up	11436.71	43.69	-17028.72	-45.27
water	132.53	20.34	-235.48	-30.03
burned	1564.88	189.09	-1838.20	-76.83

As can be inferred from Table 5.3, the subtropical forests decreased in area in both periods 2005-2009 and 2009-2013 by 3648.42 and 946.98 hectares respectively. These changes translate to -7.81% and -2.20% change for the two respective periods. From a conservation point of view, this is a considerable change in forest cover in an 8-year period. The significance of the land cover change were then analysed using a student t-test. In this case, the two periods of 2005-2009 and 2009-2013 were analysed to see if the observed trends were significantly different. The null hypothesis was that there is no significance difference between 2005-2009 and 2009-2013. The student t-test results are presented in Table 5.4 below.

Table 5.4: Testing for significance between area for classes in 2005 and 2009

	2005-2009	***2009-2013***
Mean	-3.81	-1.023533333
Variance	49537768.02	133480834.3
Observations	6	6
Pearson Correlation	-0.953371181	
Hypothesized Mean Difference	0	
df	5	
t Stat	-0.000371217	
P(T<=t) one-tail	0.499859084	
t Critical one-tail	2.015048372	

P(T<=t) two-tail	0.999718167	
t Critical two-tail	2.570581835	

The results of the t-test show that p>0.05 (p=0.999 from Table 5.4 above) hence the null hypothesis was rejected. The null hypothesis stated that cover changes between the two periods (2005-2009 and 2009-2013) were significantly different (p< 0.05) at 95% confidence interval). It can thus be concluded that the trends in land cover change in the area between the two periods have not changed significantly. Although, the statistical test tested changes in all cover classes, there is a need for intervention to reduce the subtropical forests changes in this biome.

5.3: Discussion

In comparing the classification algorithms on the SPOT 6 image for 2013, the maximum likelihood (88.75% overall accuracy and 0.69 Kappa) outperformed the other three algorithms. After adopting maximum likelihood in classifying multispectral images for 2005 and 2009,The overall accuracy and kappa coefficient values for MLC were highest, hence the most accurate among the selected four algorithms. Results show the method having the highest level of agreement between classified and ground truth data. The superiority of the method in classifying the 2013 image is similar to and thus reinforces the findings of earlier studies on mapping land cover in an urban setup (Dewan and Yamaguchi, 2008), forest species using (Pu, 2010), mapping mangrove species (Wang et al., 2004), forested forests and peatlands (Townsend and Walsh, 2001). The performance of MLC has been better when compared with certain classifiers in some past studies. Examples include its studies by Al-Ahmadi and Hames (2009), comparison with artificial neural network (Erbek et al., 2004) and with object-based method (Wang et al., 2004).

The multi-temporal analysis revealed a negative changes occurring within subtropical forests and other land cover classes within the study area. The observed trend in the subtropical forests further confirm the threats posed to these forests from a number of physical and human-induced factors as presented in earlier studies (Lawes and Obiri, 2003b, Shackleton et al., 2013). The local authorities and the central government have stated there are programmes to limit forest loss in the study area, but this study illustrates deterioration trends.

While subtropical forests show a decrease, the opposite is true for woodlands over the same periods (2005-2009 and 2009-2013). The increase in woodlands over the years can be explained by their invasive and pioneer species capabilities. This is supported by an earlier study which found that woodland tree species, such as *Acacia karoo,* invade abandoned fields on Wild Coast (Shackleton et al., 2013). They in turn, however, allow succession that later gives way to the re-introduction of subtropical forests.

5.4: Conclusion

The chapter compared the performance of four supervised classification methods (maximum likelihood, minimum distance, spectral angle mapper and spectral information divergence) over the study area in South Africa's Wild Coast using SPOT 6 imagery. The supervised maximum likelihood classification performed best in this area comprising subtropical forests, woodlands and other land cover classes. The Kappa coefficient of the method showed the highest level of agreement compared to other methods. In this case, MLC proved its capability of classifying a study area that covered predominantly subtropical forests better than the three other methods of MD, SAM and SID. MLC highlighted the importance of linear per-pixels methods compared to the non-parametric methods of SAM and SID.

The importance of MLC is not restricted to this chapter's objective of quantifying forest change but it was also evaluated in Chapter 8 of its ability to combine with a sub-pixel classifier to discriminate semi-deciduous and evergreen forest species. It is in the same chapter that will also evaluate the integration of field spectra and multispectral data.

The spatio-temporal analysis of subtropical forests changes from 2005-2013, revealing a decreasing trend in forests and an increase in woodlands and bare/built-up lands. Multispectral imagery from the SPOT 5 HRG and SPOT 6 sensors proved their capability in mapping land cover in landscapes dominated by forests. The hectares lost in subtropical forests and related increase in other land cover classes give an indication of potential forest loss drivers which should be addressed. The t-test indicates that there are no significant changes in the general land cover change over the two periods (2005-2009 and 2009-2013) and again this calls for more intervention efforts in conservation in the area. There is a need to improve on the sustainable use of subtropical forests on the Wild Coast and this should be addressed by all the stakeholders, namely traditional leaders, communities, business owners, national and local government departments.

Overall, this chapter not only identifies the best method for land cover classification, it also shows the trends in forest changes, which can aid decision making in sustainable forest management. The final maps and figures of changes may be used by decision makers such as DAFF management, local municipalities and traditional leaders in making choices that foster the sustainable use of forests. The method and imagery from the SPOT series of data can therefore provide much needed data to assist monitoring. There are chances of continuing with such a forest monitoring programme using the forthcoming EO-SAT 1 (a national satellite programme).

Selection of Optimal Wavelengths for Subtropical Forest Species Discrimination

6.1: Introduction

The ability to distinguish features such as forests, soil and rocks through the application of hyperspectral remote sensing has led to an increase in remote sensing use in natural resource management. Hyperspectral sensors have advantages over multispectral ones, which are limited in both spatial and spectral resolution (Vaiphasa et al., 2005). The identification of forest species through the minor spectral variation due to structure and biochemistry of leaves (Clark, 2011, Zhang et al., 2012) is possible when using hyperspectral remote sensing and discrimination methods can be classified into two general groups: empirical and physically based methods. The use of field spectroscopy in discriminating terrestrial vegetation has been utilised in studies regarding tropical mangrove species (Vaiphasa et al., 2005), coniferous forests (Lukes et al., 2011) as well as commercial plantations (Peerbhay et al., 2013).

The present chapter focused on investigating the capability of hyperspectral remote sensing to discriminate indigenous forest species. Spectral reflectance data acquired using a spectroradiometer (Spectral Evolution PSR-3500) fitted with a leaf clip with an artificial light source was used. The underlying hypothesis of this study is that it is possible to separate different forest species based on their unique spectral reflectance. Data were analysed by applying the four steps in normality testing: One-way Analysis of Variance (ANOVA), classification and regression tree (CRT) analysis and validating the identified wavelengths bands using the Jeffries-Matusita distance method. This chapter assesses the spectral properties of indigenous subtropical forest species, and identifies the significant wavelengths for indigenous species discrimination. It also evaluates the separability of the identified wavelengths.

6.2: Results

The indigenous species under inspection are *Brachylaena discolour, Buxus natalensis, Cassine palilosa, Celtis africana, Cryptocarya latifolia, Ficus natelensis, Grewia lasiocarpa, Halleria lucida, Harpephyllum caffrum, Heywoodia lucens, Millettia grandis, Millettia sutherlandii, Mimusops caffra, Searsia chirindensis* and *Vepris undulate.* An initial exploration of spectral measurements depicted the general spectral profile of vegetation. A spectral curve to visualise the average reflectance of subtropical forest species from the study area is presented in Figure 6.1 below.

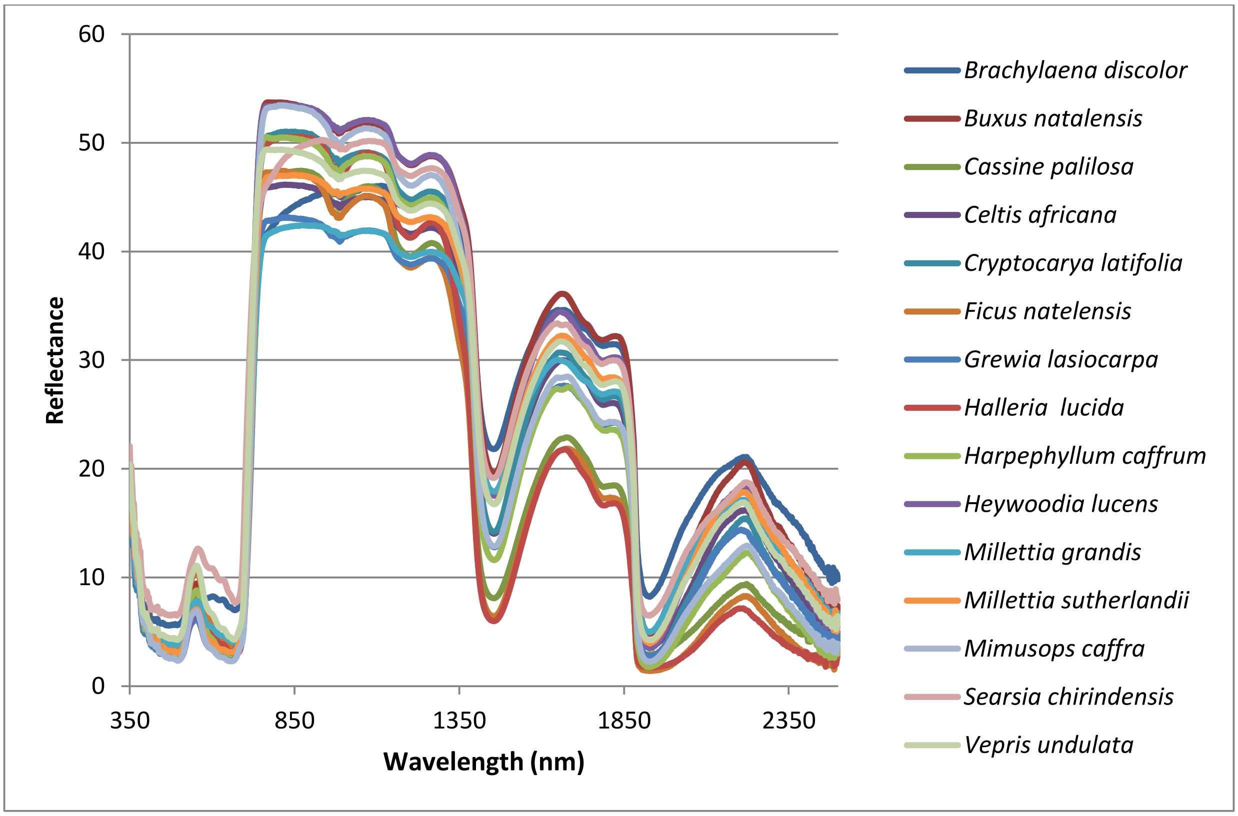

Figure 6.1: Mean spectral reflectance of the identified indigenous forest species

The plot of the mean spectra above shows the general trends of the reflectance and little information on reflectance regions that are likely to be spectrally separable.

6.2.1 Band selection

The selection of significant wavelengths for species discrimination was achieved by applying the three stage hierarchical method involving ANOVA with post hoc correction, Classification and Regression Tree analysis and Jeffries Matusita distance method (Adam and Mutanga, 2009).

a) Significant differences between wavelength bands using One-Way ANOVA with Bonferroni correction.

One way ANOVA investigated all the wavelength bands for significant differences in the spectral reflectance of different subtropical forest species. In this case, the null hypothesis formulated states that; there is a significant difference in mean leaf spectral reflectance among the different wavelength bands. The ANOVA results indicated that all wavelength bands, except for 11, have p values of less than 0.05; hence, the null hypothesis was rejected and the research hypothesis was accepted for the 2098 bands. The p-values are illustrated in Figure 6.2 below and they show higher values occurring between 350 and 450nm.

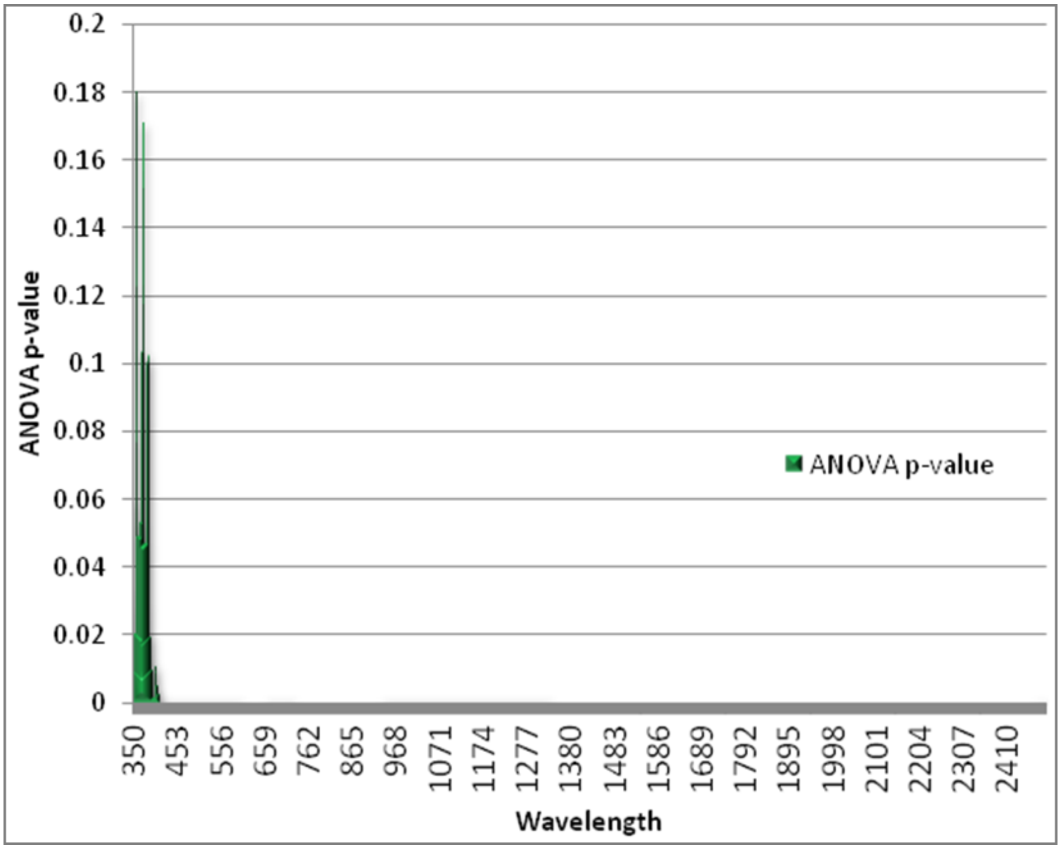

Figure 6.2: The distribution of p-values after One Way ANOVA (Wavelength in nanometres)

Although ANOVA is good at investigating the difference among a group of variables, it does not show that one variable is more different from the rest (Barrett and Curtis, 1999). Hence, a post-hoc test was employed to test for differences among pairs of species. Instead of making conclusions based on these results, the Bonferroni correction method was performed to minimise the probability of performing a Type 1 error. At the 95% confidence, ANOVA with Bonferroni correction results indicated that all except 144 wavelength bands had $p < 0.25$ resulting in the rejection of the null hypothesis (H_0) and acceptance of an alternative hypothesis (H_1). As shown in the Figure 6.3 below, wavelength bands that were accepted for further analysis ($p<0.05$) were mainly located in higher wavelengths. The wavelength bands that proved to be not significantly different from each other were located at 350-436, 439-441, 443, 449, 517-568 nanometres.

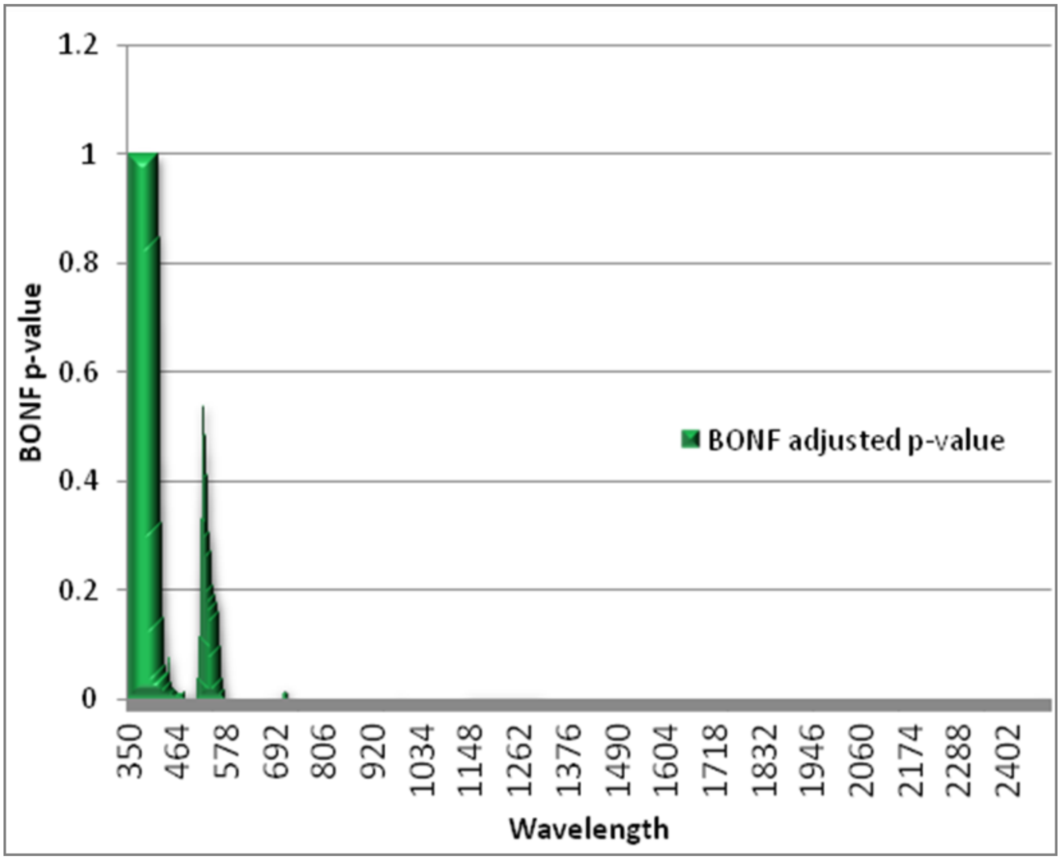

Figure 6.3: The distribution of Bonferroni corrected p-values among the reflectance at different wavelength bands.

It was therefore deduced that the remaining 2007 wavelength bands have mean reflectance spectra, which are significantly different from each other. According to the hierarchical method, this indicates the existence of a combination of reflectance spectra among this group that can spectrally discriminate the indigenous forest species. The results from ANOVA with Bonferroni correction method became inputs into the classification and regression tree analysis, described in the next section.

b) Selection of significant wavelength bands using Classification and Regression Tree analysis (CART)

Using repetitive partitioning and modelling, the CART model managed to identify the optimal wavelengths from the significantly different ones identified by One-Way ANOVA with Bonferroni correction. The following tree diagram summarises the decision of the tree method and the identified wavelengths (prefixed by V). The branches to the right fulfil the condition on the branching node (YES) while those on the left do not (NO). The method has discarded other wavelengths that do not contribute significantly to the discrimination of the identified subtropical forest species. The CART results are presented in the form of a tree in Figure 6.4 below. According to these results, the method identified 17 wavelengths that can spectrally differentiate the identified 15 subtropical forest species.

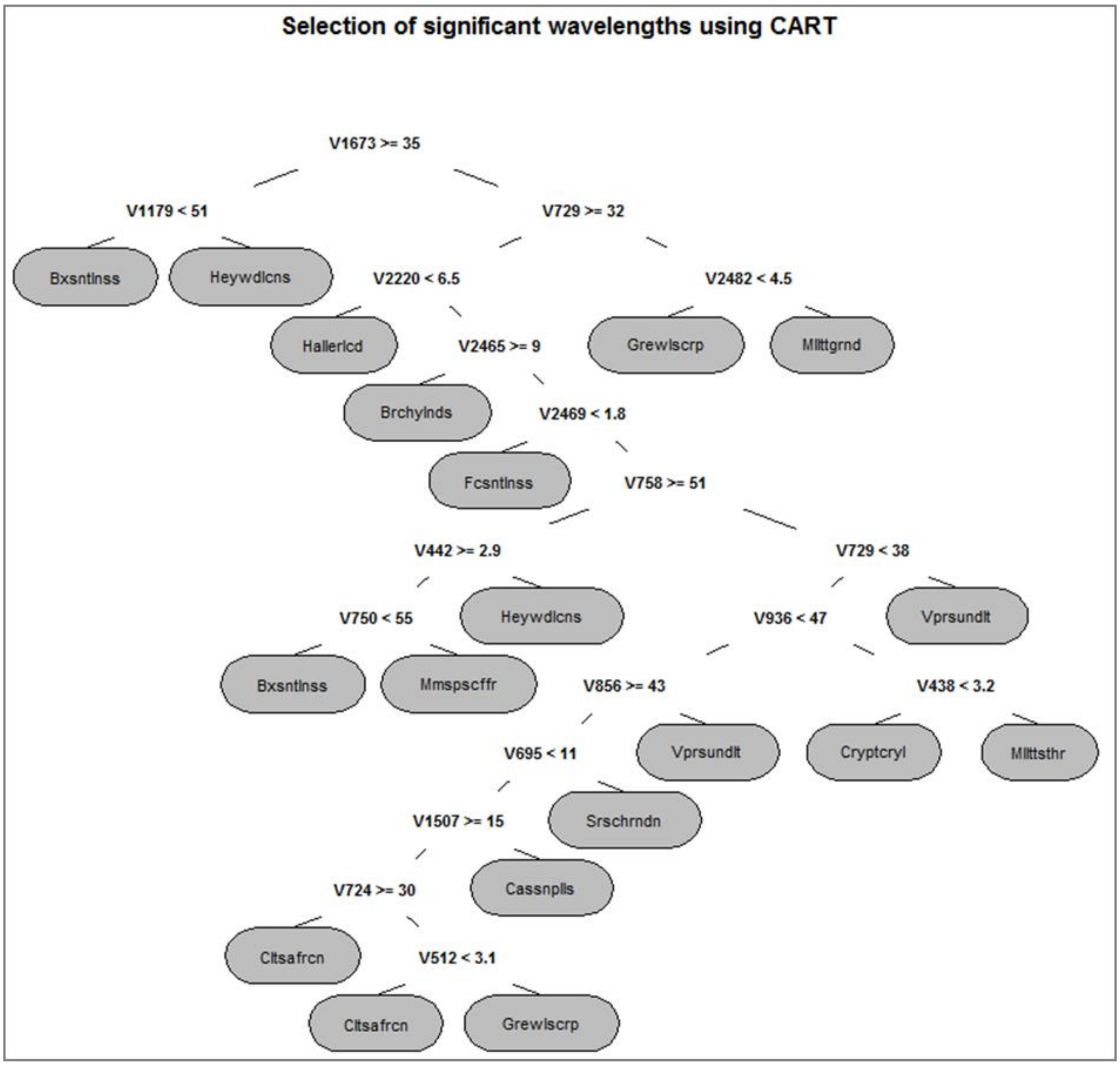

Figure 6.4: The Classification and Regression tree showing optimal wavelengths for indigenous species discrimination.

The CART procedure identified 17 wavelength bands that are more significant for the discrimination of the subtropical indigenous species. These wavelengths were 438, 442, 512, 695, 724, 729, 750, 758, 856, 936, 1179, 1507, 1673, 2220, 2465, 2469 and 2482 nanometres. Lastly, the spectral separability of the identified wavelengths was evaluated using the Jeffries-Matusita (JM) distance method, as shown in the next section.

c) Separability analysis

The JM separability results (Table 6.1 below) show separability of the identified wavelengths in their discrimination of the respective indigenous forest species The majority of combinations in Table 6.1 had distance values greater than 0.05, which is interpreted as a sign of high levels of separability. The values are interpreted as showing a 100% accuracy in separability when they are equal or closer to 2 while 0 implies that selected signatures are totally inseparable (Lasaponara and Masini, 2007). In other words, the JM distance method also works as a method of evaluating the preceding steps, that is, one-way ANOVA and the classification and regression tree (CART) methods. Table 6.1 below summarises the JM distances between the identified wavelengths, which have an implication on their spectral separability.

Table 6.1: JM Distance values showing spectral separability values for selected significant wavelengths

	438	442	512	695	724	729	750	758	856	936	1179	1507	1673	2220	2465	2469
442	0.00															
512	0.02	0.03														
695	0.57	0.61	0.44													
724	2.00	2.00	2.00	2.00												
729	2.00	2.00	2.00	2.00	0.27											
750	2.00	2.00	2.00	2.00	1.42	0.90										
758	2.00	2.00	2.00	2.00	1.48	1.00	0.01									
856	2.00	2.00	2.00	2.00	1.60	1.14	0.03	0.01								
936	2.00	2.00	2.00	2.00	1.59	1.10	0.01	0.01	0.01							
1179	2.00	2.00	2.00	2.00	1.23	0.60	0.12	0.18	0.25	0.19						
1507	1.85	1.86	1.82	1.56	1.17	1.60	1.93	1.94	1.96	1.96	1.92					
1673	2.00	2.00	2.00	1.99	0.04	0.39	1.44	1.50	1.61	1.60	1.27	0.88				
2220	1.74	1.75	1.70	1.27	1.64	1.88	1.99	1.99	1.99	2.00	1.99	0.15	1.40			
2465	0.41	0.43	0.28	0.02	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.61	1.99	1.35		
2469	0.32	0.35	0.21	0.06	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.65	1.99	1.41	0.01	
2482	0.28	0.31	0.17	0.07	2.00	2.00	2.00	2.00	2.00	2.00	2.00	1.68	1.99	1.46	0.02	0.00

Table 6.1 indicates that the selected wavelengths for subtropical forest species are statistically separable. The table also shows less accuracy (values close to zero) in separability between wavelengths that are in the visible portion of the electromagnetic spectrum. However, this phenomenon is only present when pairing wavelengths from the visible portion among themselves.

6.3: Discussion

In this chapter, the issue of dimension reduction for the discrimination of subtropical forest species was analysed. A preliminary analysis of the mean spectra for individual species yields provided no information on the location of optimal wavelengths for species discrimination. The shape and location of absorption features of all the 15 subtropical forest species appear similar, hence difficult to differentiate through visual inspection. The similarity of the species is due to leaf anatomy and biochemical properties that have close resemblance. However, the spectral reflectance of the different subtropical species are not exactly the same due to differences in biochemical concentrations as well as pigment concentration (Martin et al., 1998).

The hierarchical approach identified the 17 wavelengths that are essential for subtropical indigenous forest species and these are 438, 442, 512, 695, 724, 729, 750, 758, 856, 936, 1179, 1507, 1673, 2220, 2465, 2469 and 2482 nm. These wavelengths are located in the visible, red-edge, near infrared (NIR) and mid-infrared (MIR) portion of the electromagnetic spectrum. The presence of wavelengths in the red-edge further confirms the importance of this region in spectral discrimination of different vegetation species (Vrindts et al., 2002). Similar studies have found different portions of spectrum being more important and these include shortwave infrared (SWIR) for discriminating soybean from weeds (Gray et al., 2009), red edge as well as NIR regions for papyrus discrimination (Adam and Mutanga, 2009). Another point worth noting is that among the optimal wavelengths are four bands from the visible portion of the spectrum which are similar to previous research on tropical forest species (Clark et al., 2005).

Spectral variability among the species is due to water content (Grant, 1987), leaf structure and biochemistry (such as chlorophyll content, epiphyll and herbivory) (Clark et al., 2005). While this may not be the first study on field spectroscopy used in spectral discrimination, dimensions and number of species involved work toward providing novel information on indigenous subtropical species identification and monitoring. The following studies managed to apply similar methods on few predictor variables: five tropical mangrove species (Koedsin and Vaiphasa, 2013), four swamp wetland species (Adam and Mutanga, 2009), discriminating two crops from coniferous weeds (de Castro et al., 2012), and two Eucalyptus species (Arumugasundaram et al., 2011).

The study has demonstrated the applicability of the hierarchical methodology in selecting significant wavelengths (Adam and Mutanga, 2009, Vaiphasa et al., 2005) in subtropical indigenous tree species of South Africa. Despite the potential presented in this study, one should take note that spectra measured using a leaf clip and artificial light were used. The complexity introduced by a real-world scenario include the following factors: effect of background vegetation; soils and water; difference between artificial light and the sun; difference in canopy formations and changes in daily climatic conditions (Ramsey and Jensen, 1996).

6.4: Conclusion

This chapter clearly demonstrates that spectral characterisation of the subtropical indigenous forests is possible using field spectroscopy. From the above results, the leafy-level spectral discrimination of indigenous forest species along the coastal region of South Africa is possible using in-situ spectra measurements. Based on this chapter's results, the following conclusions are made:

- The methods used (One-way ANOVA with Bonferroni correction and CART) successfully identified wavelengths that are not correlated, statistically significant and spectrally separable. The potential of the statistical methods that form the hierarchical method in selecting optimal wavelengths for subtropical indigenous forest species discrimination is demonstrated in the present study.
- The discrimination of the subtropical forest species identified the following optimal 17 wavelength bands in the Visible (438, 442, 512 and 695 nm), Near Infrared

(729, 750, 758, 856, 936, 1179, 1507 and 1673 nm) and Mid-infrared (2220, 2465, 2469 and 2482 nm) as spectrally separable.

- The selected 17 wavelengths are spectrally separable as shown by the results from the JM distance analysis were values closest to 2. These high values show 100% accuracy separability between sets of wavelengths.

The information presented in this chapter is useful in large-scale species discrimination of indigenous species based on airborne or spaceborne hyperspectral images. The selected optimal wavelengths for subtropical forest species discrimination were recorded for use in the next chapter on classifier selection using field spectroscopy and machine learning methods. These wavelengths, therefore, were inputs into model optimisation and evaluation.

Subtropical Forest Species Discrimination Using Field Spectroscopy

7.1: Introduction

Subtropical forests along the Wild Coast region of South Africa are part of the Maputaland-Pondoland-Albany biodiversity hotspot (Shackleton et al., 2013). The whole region is estimated to have 50 000 hectares (ha) of indigenous forest fragments (Berliner, 2011). Subtropical forests play a critical role in supporting livelihoods, as well as carbon sequestration. Remote sensing has proven its usefulness in broad classification of forests and monitoring forest change in humid tropics (Hansen et al., 2008). Field spectroscopy, a form of remote sensing, permits species discrimination at leaf and canopy levels on its own. With the high floral richness along Wild Coast (Lawes and Obiri, 2003a), their spectral discrimination provides scientific knowledge that can aid their management. It will also add to what is known about these forests. Species discrimination at leaf or canopy levels provides the necessary spectral information about forests and it can support wider area discrimination. The applications of spatial species discrimination maps is very useful in biodiversity assessments of an area (Lucas et al., 2008), as well as supporting forest management by government departments (DAFF and DEA), as well as local authorities.

Vegetation classification is often difficult due to the comparability (or lack of it) of the different species types (Jia et al., 2011). Discrimination of forest species in humid environments is often difficult because of high plant diversity, which translates into high spectral variation Clark (Clark et al., 2005). Leaf-scale spectral variations are mainly due to leaf biochemical properties and morphology (Asner, 1998, Clark et al., 2005, Roberts et al., 2004). However, a number of classifiers have been successfully used in species discrimination in various studies (Gutiérrez et al., 2014, Somers and Asner, 2013). The classifiers are also referred to as machine learning methods due to their extensive use of statistical computations to analyse data and make predictions. Some of the widely used classifiers for this type of discrimination include the linear discriminant analysis (LDA)

(Clark et al., 2005), partial-least squares discriminant analysis (PLSDA), neural networks (de Castro et al., 2012), and RF (Chan and Paelinckx, 2008).

The objective of this chapter was to identify the best classifier for the discrimination of the dominant subtropical forest species among the LDA, PLSDA and RF. This chapter utilised selected optimal wavelengths (detailed in the preceding chapter). Field collected spectral details were divided into training (65%) and testing (35%) data; that is, for calibrating and validating the respective classifiers. Therefore, 99 samples were used as the training data set while 33 observations were used as the validation data set.

The selection of the best classifier was based on accuracy metrics of overall accuracy and Cohen's Kappa coefficient, derived from the confusion matrix. The data collection and analysis methods used in this chapter are fully explained in Chapter 4. Conclusions were then made on the best among the three methods for the discrimination of subtropical forest species.

7.2: Results

7.2.1 Species discrimination techniques

The following are results showing the performance of the four classification algorithms on discriminating the subtropical indigenous forest species.

a) Linear discriminant analysis technique

When an LDA-based classifier was applied to independent validation data, the overall accuracy was 86.05%. The same LDA classifier's application on validation data can be illustrated by the diagram below (Figure 7.1), which plots LD1 against LD2, the first and second discriminants used in modelling the data.

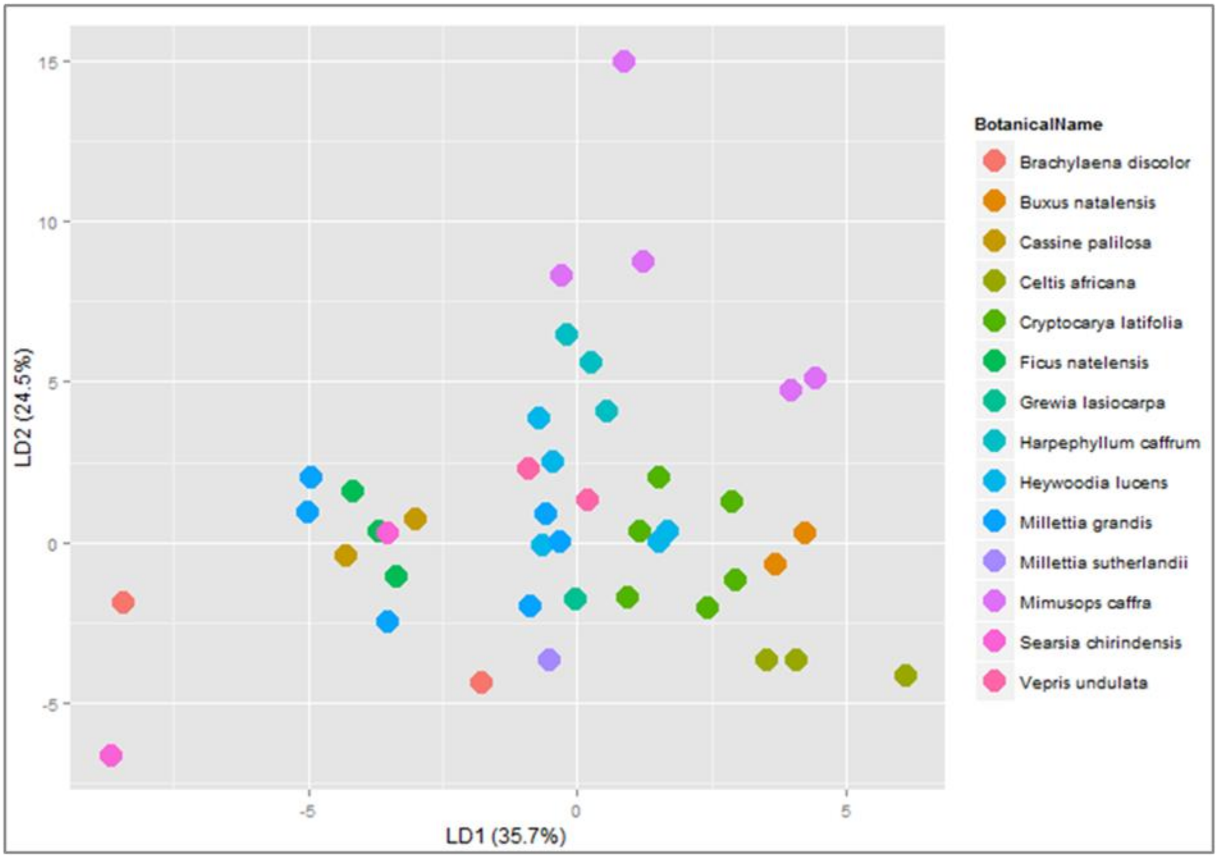

Figure 7.1: Scatterplot showing indigenous species classification based on two major discriminants (LD1 and LD2).

The results above depict a classification using the LDA based classifier with an overall accuracy level of 86.05%. The Cohen's Kappa coefficient for this classifier was 0.8460. Based on this Kappa coefficient, it was concluded that there was an almost perfect agreement between LDA results and validation data.

b) The partial least square discriminant analysis (PLSDA) classifier

The performance of the classifier was evaluated by using the overall accuracy percentage when the model was applied to the independent validation data set. The overall accuracy of this method was 0.627907. The interpretation is that if independent data is classified by the classifier, the probability of the correct discrimination of all species is approximately 62.79%. The Cohen's Kappa coefficient for the method was 0.1394. The two measures show that the classification using PLSDA had slight agreement between classification results and validation data.

c) The random forest classifier

The classifier ranged the selected wavelength bands based on their importance in the classifier. Figure 7.2 below show the importance of the selected wavelengths in discriminating the 15 sub-tropical forest species.

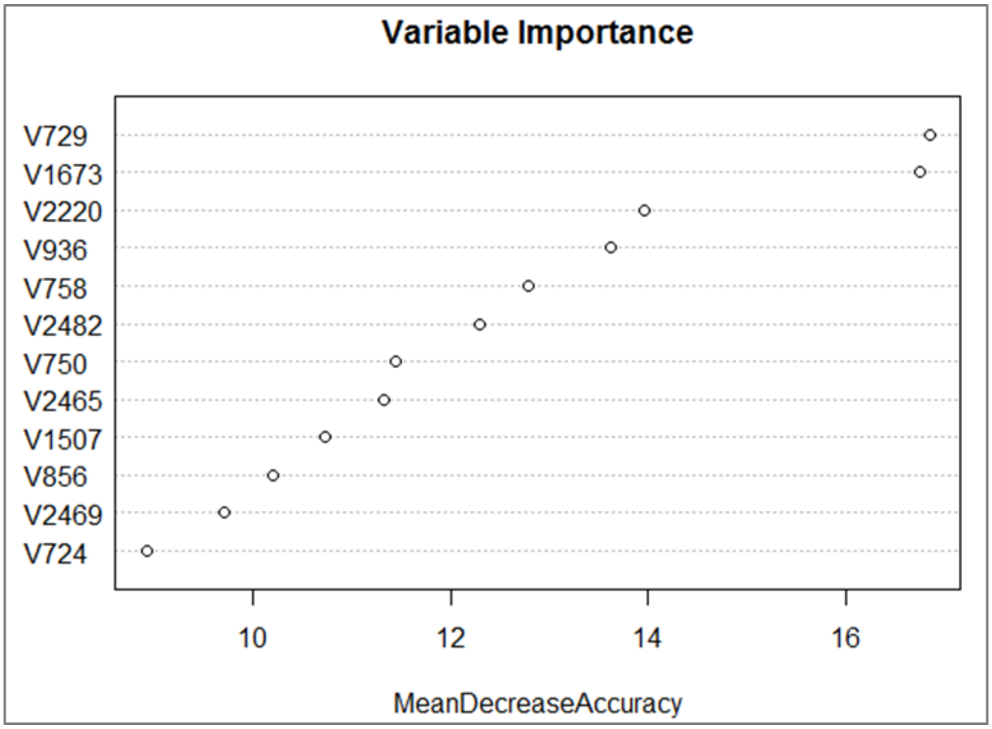

Figure 7.2: Variable importance

According to Figure 7.2 above, RF identified the 729nm wavelengths as the most important while the 724nm one ranked last in variable importance. The selected wavelength bands were inserted into a random forest classifier using the training data set. When the classifier was applied on independent data, there was an overall accuracy of 37.21% meaning the resulting discrimination is accurate by approximately 37.21%. Further analysis of the discrimination results using the Cohen's Kappa evaluation yielded an unweighted Kappa coefficient of 0.31746. Accuracy assessment results showed a very low overall accuracy but the Kappa illustrated a fair agreement between RF results and validation data.

7.2.2 Accuracy assessment results for the three algorithms

The decision on the algorithm to use for subtropical indigenous forests was reached after comparing the Cohen's Kappa coefficients for the three coefficients. Among the various machine-learning classifiers used in this chapter, the one with the highest Cohen's Kappa coefficient was the Linear Discriminant Analysis (LDA) followed by the Partial Least Squares Discriminant Analysis (PLSDA) and lastly the Random Forest classifiers. The rest of the values are shown in Figure 7.3 below:

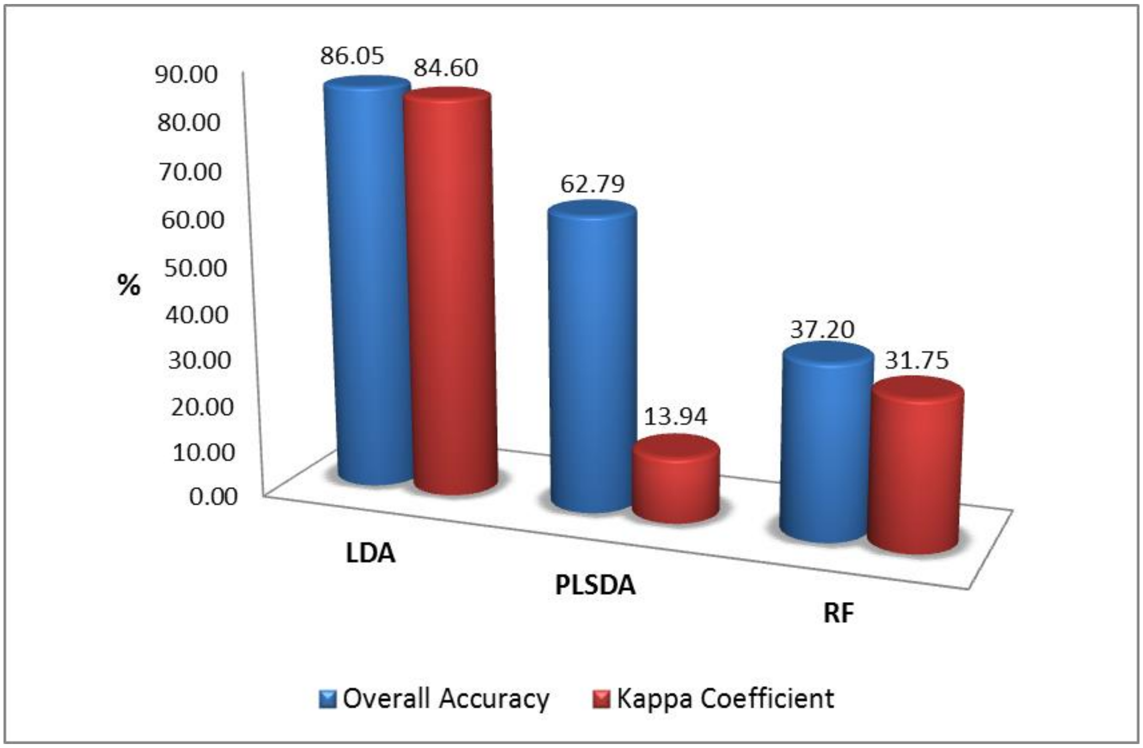

Figure 7.3: Overall Accuracy and Cohen's Kappa coefficients for LDA, PLSDA and RF

This section demonstrates that the LDA based classifier performs better at discriminating subtropical forest species than the other two approaches. Both overall accuracy and Cohen's Kappa coefficient for LDA were higher when compared to similar statistics for PLSDA and Random forest. According the overall accuracy values shown above (Figure 7.3), the LDA had highest accuracy followed by PLSDA and lastly RF. However, when considering Cohen's Kappa coefficient values, LDA had highest agreement between species discrimination results and ground truth data followed by RF and lastly PLSDA. The overall interpretation of both overall accuracy and Cohen's Kappa identify LDA as being the best classifier for sub-tropical forest species discrimination among the three.

7.3: Discussion

Using the optimal wavelengths selected in the previous section, this chapter presented classifier optimisation and evaluation of three classifiers viz; LDA, PLSDA and RF. Of these three methods, the LDA (86.05% overall accuracy and an 84.60% Kappa coefficient) displayed the highest accuracy in comparison to PLSDA and RF. Both overall accuracy and Cohen's Kappa values confirmed the superiority of LDA in discriminating subtropical forest species at leaf level. If the Cohen's Kappa values are interpreted according to Landis and Koch (1977), LDA discrimination results had an almost perfect agreement with validation data compared to PLSDA's slight agreement and RF's fair agreement.

The performance of the LDA was consistent with its performance in other studies where it satisfactorily classified tropical forest species (Castro-Esau et al., 2006, Feret and Asner, 2011). In a way, these results showed the ability of a parametric discriminant method (LDA) performing better than a non-parametric one (RF) in discriminating subtropical forest species at the leaf level. This provides evidence that conventional parametric methods like the LDA perform better in certain environments than non-parametric ones.

The performance of the LDA, without comparing it to the other two PLSDA and RF, also vindicates the strength of the hierarchical method of selecting wavelengths (in Chapter 6). The selected wavelengths have led to species discrimination with high accuracy levels. If the selected wavelengths had not been optimal for the observed species' discrimination, accuracy levels would most likely have been low. This chapter is also further proof that although subtropical forests have high species and spectral variations, machine learning algorithms such as the LDA are able to discriminate them using field spectra.

7.4: Conclusion

This chapter has demonstrated the ability of the LDA in the identification of a classifier for discriminating subtropical forest species with satisfactory accuracy. The number of indigenous forest species classified in this study also shows the ability of the approach in discriminating more than five spectrally significant forest species. The results demonstrate further opportunity in using field spectroscopy data in the classification of hyperspectral imagery from airborne and spaceborne platforms such as NASA's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) and EO-1 Hyperion.

The application of the three methods and evaluation of their performance on independent data were done with an overall aim of meeting one of the study's key objectives. The objective addressed in this chapter is that of identifying the best classifier for subtropical species discrimination. Based on the results obtained, the following conclusions are made:

1. At leaf-scale, the LDA is highly accurate, compared to PLSDA and Random Forest in the discrimination of subtropical indigenous forest species. Accuracy assessment of the three methods using independent data resulted in LDA, PLSDA and Random Forest classifiers having overall accuracies of 86.05 %, 62.79 % and 37.2 % respectively.
2. The Cohen's Kappa coefficient also proved that LDA discrimination results had the highest level of agreement between classified and ground truth data. The agreement level is higher than PLSDA and RF discrimination.
3. The study proves that LDA based classifier managed to classify 15 species using the leaf spectral reflectance whose optimal wavelength dimensionality had been reduced by the hierarchical method. This approach should be a useful guideline for subtropical indigenous forest species classification in other similar environments.

Discriminating Semi-deciduous and Evergreen Subtropical Forests Species Using Integrated Multispectral and Field Spectroscopy

8.1: Introduction

High-resolution multispectral images such as SPOT 6 are becoming widely available at affordable rates and their applications are widespread in forestry monitoring, for example assessing changes in vegetation structure and so forth (see Chapter 5). Field spectroscopy on the other hand improves the spectral analysis of vegetation using several bands. While field spectroscopy is good at discrimination of species at the leaf level, multispectral images provide larger cover classification. There is a need for characterisation of indigenous forests as a way of further understanding their natural and human-induced changes. The current and previous chapters have detailed analysis on significant wavelength selection, species discrimination at leaf level and multispectral-based forest change analysis (Chapters 6, 7 and 8 respectively). The assimilation of field spectroscopy data with multispectral data is a highly complex and difficult task due to spectral and spatial differences. In this chapter, the simulated field spectral data were combined with 2013 SPOT 6 imagery to perform sub-pixel classification of forests into evergreen or semi-deciduous.

In deciduous or coniferous classification of forests, the main considerations are tree leaves and how the trees produce their seeds. The location and prevailing conditions in the area result in the trees being either semi-deciduous or evergreen. Deciduous refers to trees that lose their leaves during winter and in the Wild Coast the duration of shedding leaves is small hence the term semi-deciduous. However, there is also variability within semi-deciduous and evergreen forest species that can be attributed to leaf structure. Dicotyledonous leaves have more airspaces within their spongy mesophyll tissue than monocotyledonous leaves of same age and thickness (Raven et al., 2005). Research has noted that dicotyledonous trees have a higher reflectance in the NIR than monocotyledonous (Gausman and Weidner, 1985).

The chapter also seeks to: (1) manipulate spectral feasibility of high spatial resolution multispectral imagery such as SPOT 6 and field spectroscopy data to discriminate semi-deciduous and evergreen forest species and (2) to evaluate its performance on using independent data. The ground level field of view (FOV) were chosen with one target (that is one tree species belonging to one phenological group) while SPOT 6 imagery had mixed pixels in most forest patches. Mixed pixels are a combination of the spectra of the targets that they contain (Biewer et al., 2009) in this case, semi-deciduous and evergreen subtropical forest species.

The sub-pixel classification and validation procedures conducted in this chapter are explained in detail in Chapter 4 (methodology) under data analysis section. An evaluation of the classification was done using the error/confusion matrix using the locational data from the ground-collected data. Overall, producers and user's accuracy levels were calculated from the matrix. The results of both classification and accuracy assessments are presented in the next sub-section of this chapter.

8.2: Results

The following sub-section examines the results of resampling, sub-pixel classification and the subsequent accuracy evaluation. The aim is to provide proof of the integration of multispectral and field spectroscopy data in characterisation of subtropical forests.

8.2.1 Resampled spectra

The resampled mean spectra of semi-deciduous and evergreen forest species did not show much variation. When the resampled spectra were combined with multispectral imagery for sub-pixel classification the results were images showing proportions of the two classes in each pixel. This is illustrated in Figure 8.1 below.

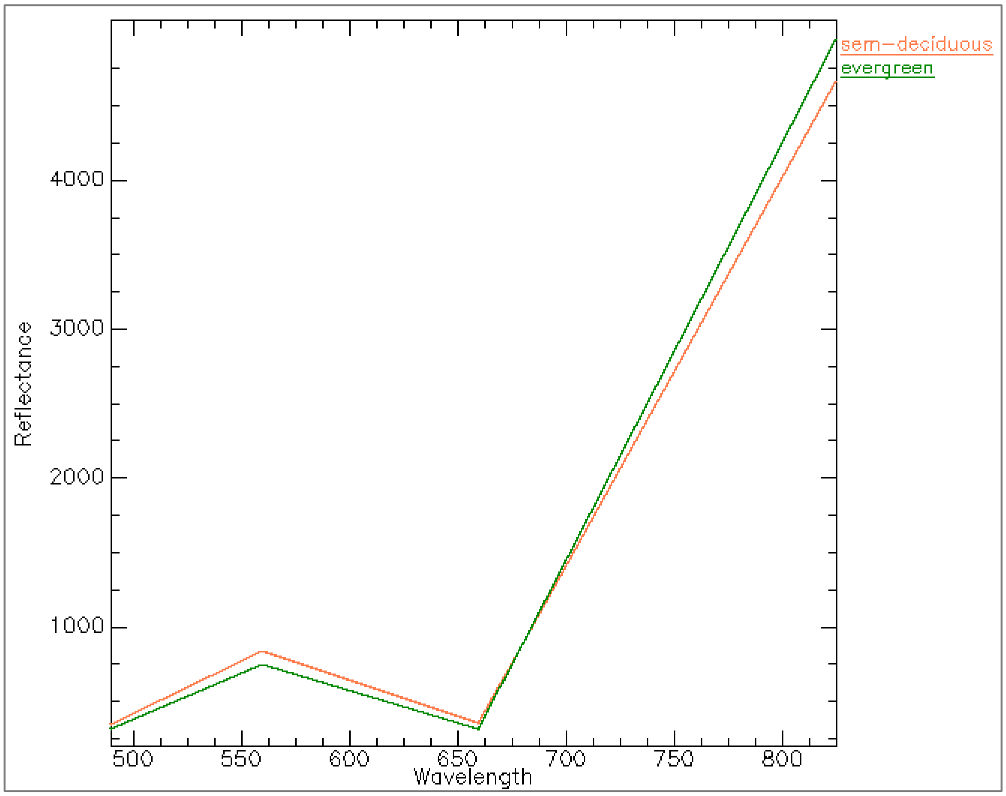

Figure 8.1: Resampled mean spectra for semi-deciduous and evergreen forest species.

The reflectance curve for resampled spectra shows that there is spectral variability in the green (between 525 and 600 nm) and near infrared (between 525 and 600 nm) portions of the electromagnetic spectrum. The resampled spectra that were later incorporated into the sub-pixel classification of the subtropical forests and the results are presented in the next section.

8.2.2 Sub-pixel classification into semi-deciduous and evergreen forest

Sub-pixel classification results show the proportions of the indigenous forests that are semi-deciduous or evergreen in each pixel within the subtropical forests. The two maps below show MF (matched filter) scores for semi-deciduous (Figures 8.2) and evergreen (Figure 8.3) subtropical forest species. These maps show the proportions of the two phenological classes that are within each pixel.

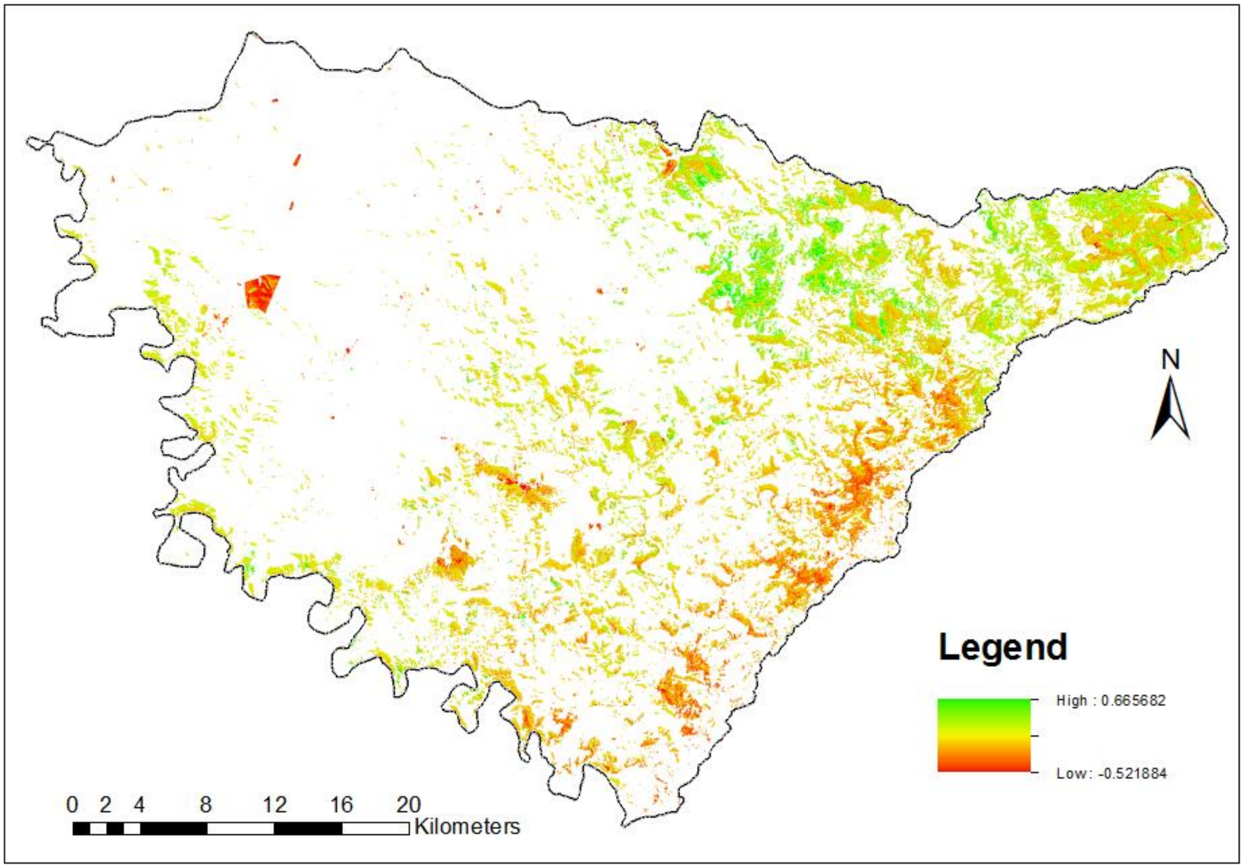

Figure 8.2: MF Score map showing proportions of semi-deciduous subtropical forest species in each pixel

Semi-deciduous subtropical forests have higher proportions in inland areas, as shown in Figure 8.2. Higher MF score values show higher proportions of the abundance of the respective class. In the case of semi-deciduous subtropical forests of the Wild Coast, these higher values (between 0.5 and 1 MF scores) are mainly located inland. The map shows that the highest MF score is approximately 0.666 while the lowest one is -0.522. When a pixel has an MF score of less than zero, the method interpreted it as one occupied by background features which are not in the same class as the class being mapped. However, proportions of semi-deciduous forests are low along coastal forests as presented by almost red colour along the coast. The proportions for evergreen subtropical forests are shown in the map below (Figure 8.3).

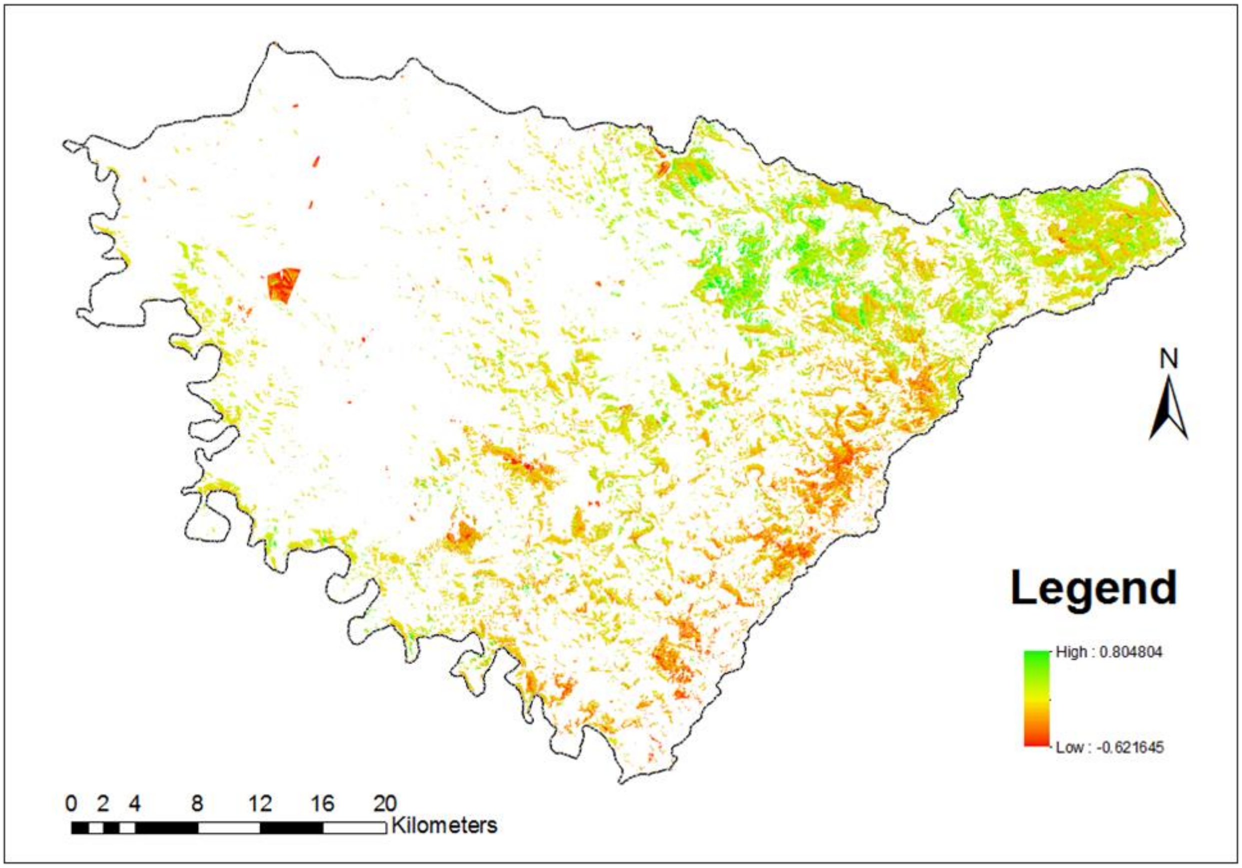

Figure 8.3: MF Score map showing proportions of semi-deciduous subtropical forest species

The above map (Figure 8.3) shows evergreen forest species proportions through MF scores from an MTMF sub-pixel classification procedure. Contrary to the proportions of semi-deciduous forest species, the evergreen forest proportions are higher along the coast and to the north-eastern part (around Port St Johns area). With MF score values ranging between -0.622 and 0.805, there are indications some pixels are almost entirely covered by evergreen forest species. A comparison of highest MF scores of the two phenological classes, shows that the evergreen classification has the highest MF score of 0.805 compared to 0.667 for semi-deciduous. The infeasibility maps for semi-deciduous and evergreen forests are shown in the appendix section (Figure 10.1 and 10.2 respectively).

It is possible to “harden” the soft classification results or allocate each pixel to a single class using a 2-D scatterplot. Allocating the pixels to one of the classes allows accuracy assessment of the above sub-pixel classification using the mixture-tuned matched filtering method. The hardening processing is shown in Figure 8.4 below where a 2D scatterplot is made pitting MF score and infeasibility maps for semi-deciduous forest. The selection of pixels with MF scores with values higher than 0 (shown in purple in Figure 8.4 below) highlighted pixels that were classified as outright semi-deciduous. Pixels with MF score values less than 0 were not included in either semi-deciduous since they show the presence of background features not belonging to the semi-deciduous class.

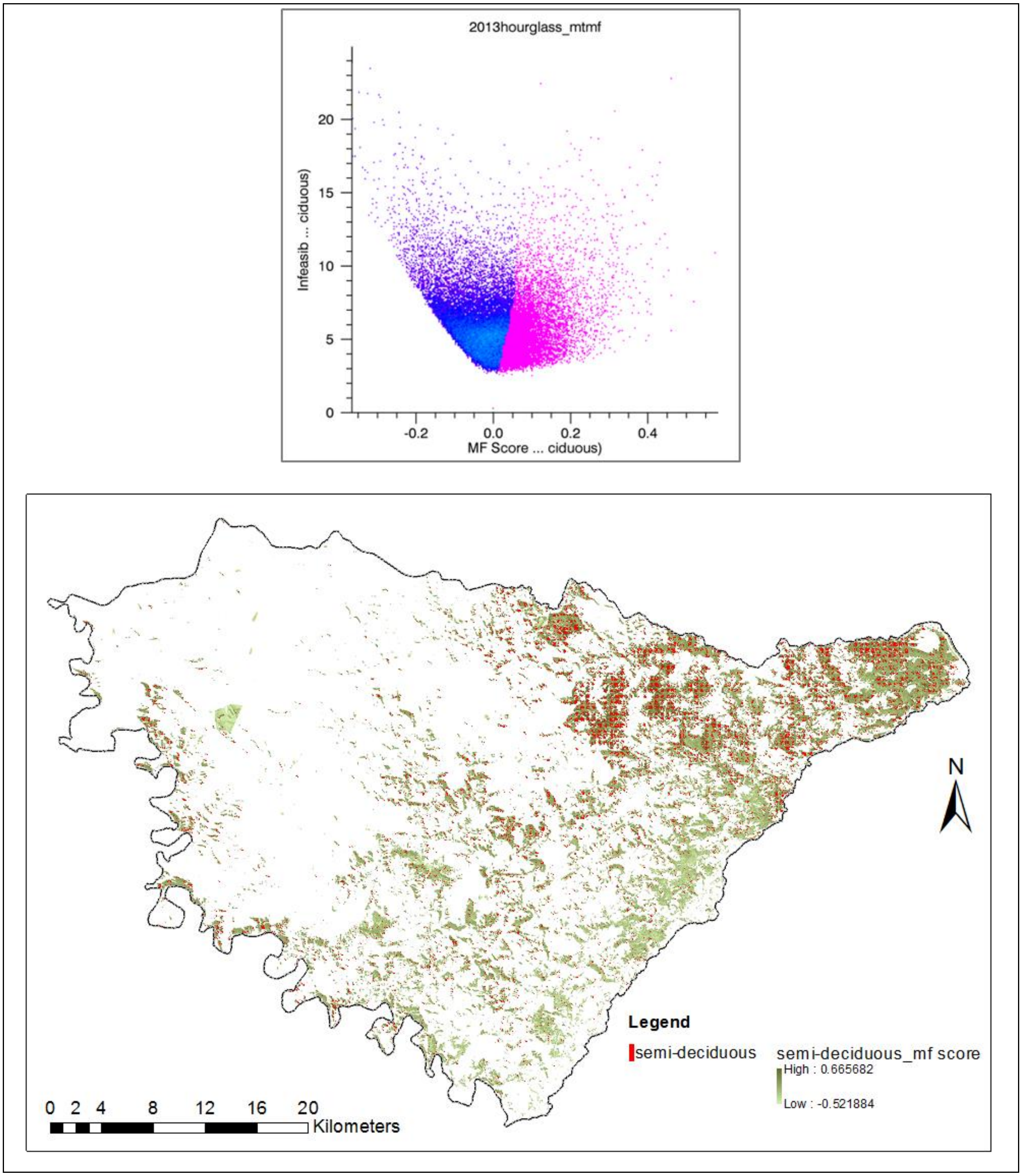

Figure 8.4: Scatterplot and map showing semi-deciduous classification

The pixels shown in red are the ones classified as definite semi-deciduous subtropical forest in the study area. The application of the 2D scatterplot selection of evergreen forests is shown in Figure 8.5 below:

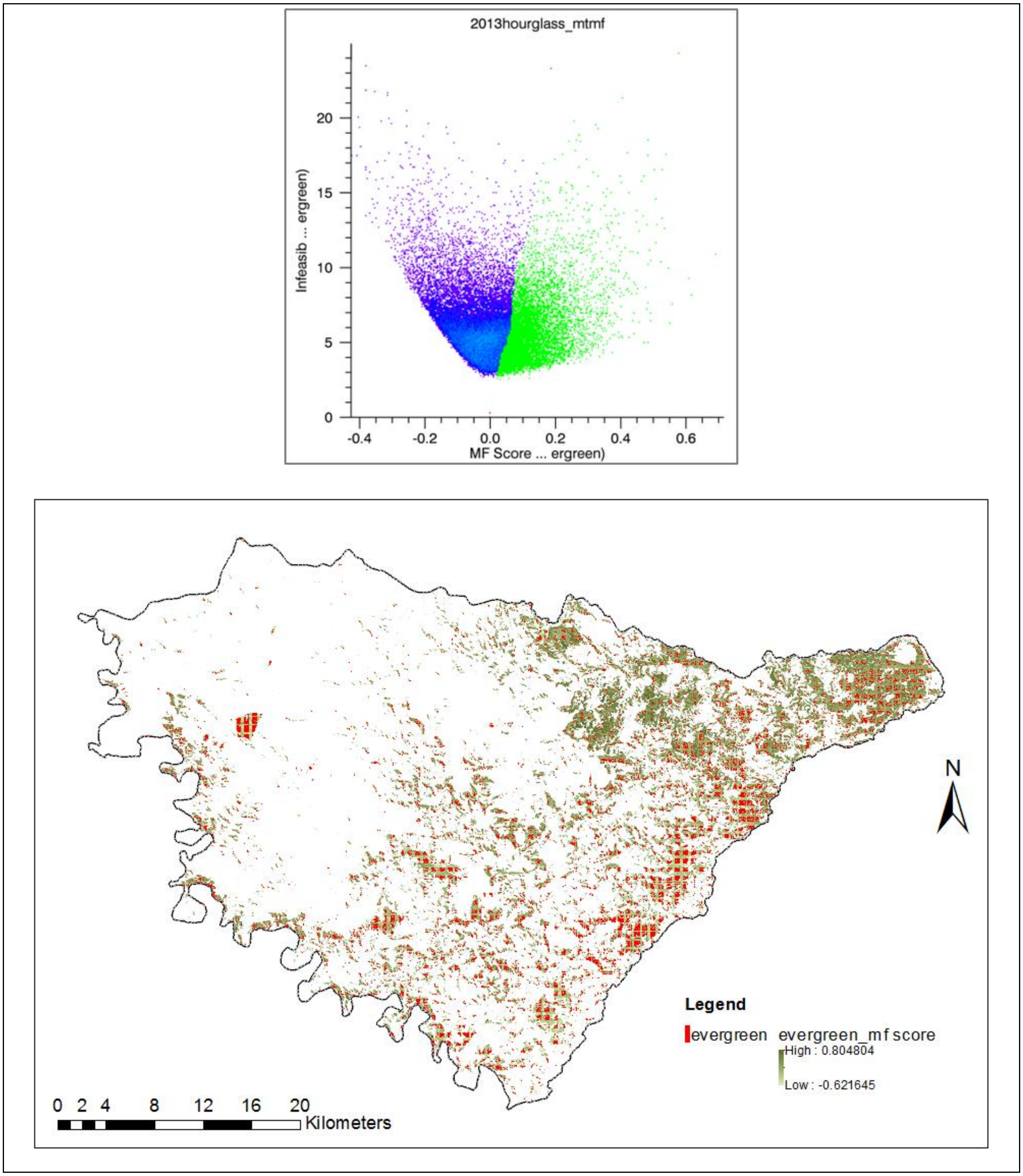

Figure 8.5: Scatterplot and map showing evergreen forests

The 2D scatterplot in Figure 8.5 above shows the selected evergreen forest pixels based on the MF scores and infeasibility values. The selected pixels are shown in green in the scatterplot and mapped in red for clarity. Results show that evergreen forests are mainly located along the coast and the north-eastern tip (approximately within an 8 km radius from Port St Johns) of the study area.

After combining the two maps for pixels that were outright semi-deciduous and evergreen forest, some pixels were not put into either of the classes. In other words, some pixels were not classified into either of the two classes after the hardening process. These pixels would have attained MF scores of less than 0 in both semi-deciduous and evergreen MF score maps. An evaluation of the MTMF method for mapping proportions of semi-deciduous and evergreen forest species for each pixel within subtropical forests is presented in the sub-section.

8.2.3 Evaluating classification results using confusion matrix

Accuracy assessment yielded the following confusion matrix from which overall accuracy, user's and producer's accuracy coefficients for the all classifications and the respective phenological classes were taken. Table 8.1 presented the confusion matrix from the evaluation of the discrimination of subtropical semi-deciduous and evergreen forest species in the study area.

Table 8.1: A confusion matrix for soft classification results

	Ground truth					
Classified		**Semi-deciduous**	**Evergreen**	**Total**	**User's accuracy**	**Producer's accuracy**
	Semi-deciduous	8	1	9	0.8889	0.6154
	Evergreen	5	10	15	0.6667	0.9091
	Total	13	11	**24**		

The overall accuracy of the whole sub-pixel classification is 75%. The conclusion is that there are 75% chances of any pixel on the final maps being correctly classified as semi-deciduous or evergreen forest. The producer's accuracy values for semi-deciduous and evergreen were 61.54% and 90.91% respectively. These percentages show the percentages of ground truth correctly classified. Based on the ground truth data, evergreen points from ground truth data were more accurately classified as 90.91% compared to 61.54% for the semi-deciduous ones.

Reliability figures of the two classified maps semi-deciduous and evergreen forest species) were examined using user's accuracy values. The classified maps were 88.89% and 66.67% reliable for semi-deciduous and evergreen forest respectively. If one uses the classified map and navigates to any pixel classified as semi-deciduous, there is an 88.89% chance that it will actually be reflecting a semi-deciduous forest species. The same applies to evergreen pixels from the classified map that had a 66.67% chance of being evergreen on the ground.

8.3: Discussion

Mixed-tuned matched filter method successfully performed sub-pixel classification of proportions of semi-deciduous and evergreen species within the subtropical forests of South Africa's Wild Coast. Using validation data, comprising of 24 samples, the method had an overall accuracy of 75%, which is classified as fair. The producer's and user's accuracy values show that the method is reliable in mapping both semi-deciduous and evergreen forest species. However, applying some form of hard classification using the 2-D scatterplot shows that not all pixels are allocated to the two classes of semi-deciduous and evergreen forests. These are the pixels whereby the MF score is less than 0 and the infeasibility is slightly higher. Pixels with very low (less than 0) MF scores and high infeasibility values were not selected as a way of rejecting false positives from the classification.

The results further strengthens the effectiveness of combining classifiers (maximum likelihood and MTMF) as well as different spectral data sources (SPOT 6 imagery and field spectroscopy data) in subtropical forest classification at both pixel and sub-pixel levels. The acknowledgement of the supervised maximum likelihood emanates from the fact that the image used in this chapter had been masked using a subtropical forest mask from a land cover classification in Chapter 5. The strengths of using multiple classifier resonates with past studies in land cover classification (Steele, 2000). While per pixel classification is generally accurate in terms of land cover classification (which identified the coverage of the subtropical forests), sub-pixel classification went ahead and mapped the proportions of semi-deciduous and evergreen species within these forests.

8.4: Conclusion

The chapter has highlighted the effectiveness of combining multispectral remote sensing data from the SPOT 6 sensor and field spectroscopy data in the discrimination of semi-deciduous and evergreen forest species. The resulting maps show proportions of semi-deciduous and evergreen forest species within each pixel of the subtropical forests. The two data sources with their different spatial scale combine well to identify various forest proportions, an essential element of large scale monitoring of this fragile biome in South Africa. The rich and diverse forest species that are within the Wild Coast's subtropical forests need protection, hence phenological classification provides another dimension to available spatial data about these forests.

Although, this chapter explored the phenological classification for only one year, that is 2013, there is room for a continuous monitoring of the forest changes and spatial implication of these two broad classes. A comparison between years will require data to be collected within similar climatic conditions and around the same time of the year. Further analysis within these species may look at phenological classification in summer, spring and winter seasons in order to have information regarding forest conditions in all seasons.

Integrating the two data sources obtained at different scales also supported the value of a multiscale approach to forest modelling and monitoring. The scale issue was addressed by exploiting spectral resolution. Field spectroscopy was resampled to the same spectral coverage as the multispectral SPOT 6 imagery, thereby allowing the sub-pixel classification of the subtropical forests into proportions of semi-deciduous and evergreen forest species.

Synthesis and Conclusion

9.1: Introduction

The indigenous forests of South Africa face a number of challenges that threaten their existence. The majority of these indigenous forests are located along the Wild Coast of the Eastern Cape and KwaZulu Natal Provinces. The subtropical biome contains much of the country's biodiversity despite it being small and fragmented (Eeley et al., 2001). The need to assess the status of subtropical forests on South Africa's Wild Coast is mainly motivated by growing population, as well as declining yields from subsistence agriculture and remittances from migrant labour (Shackleton et al., 2013). Remote sensing as a spatial analysis tool provides answers to conservation related questions, such as where and how much change has occurred in the forests.

The results-based chapters (Chapter 5-8) have investigated subtropical forest species along the Wild Coast at different scales and spectral levels. In this chapter, a synthesis of the study's findings, recommendations and directions for future research are provided. The present study has successfully quantified forest changes between 2005 and 2013, determined optimal wavelengths for subtropical forest discrimination, selected best classifier for leaf scale discrimination and identified semi-deciduous from evergreen forests at sub-pixel level. The discrimination of semi-deciduous and evergreen forest species made use of integrated field spectral and multispectral data as well as two classifiers. This is after showing the strength of multispectral integration of these data sources. The main findings of this study can be grouped into four broad themes based on the objectives of the study. There are all explained in the following objective-derived sub sections:

9.1.1 Determining the best supervised classification algorithm for mapping subtropical forest changes

The MLC proved to be the best classifier compared to MD, SAM and SID in classifying different land cover classes, including subtropical forest. The performance of the MLC also highlights the superiority of a linear per-pixel compared to non-parametric per-pixel methods (SAM and SID). After comparing the respective classification algorithms, this study confirmed that medium resolution images such a SPOT 5 can play an important role in assessing forest change. Declining trends of the subtropical forest areal coverage over the two periods of 2005-2009 and 2009-2013 were identified. That notwithstanding, the student t-test revealed that although figures suggest a decrease in forest cover, change among all the classes between the two periods is not significant. These trends in forest change call for conservation efforts geared towards improved management of indigenous forests along the Wild Coast of South Africa.

9.1.2 Selection of optimal wavelengths for subtropical forest species discrimination using field spectroscopy

Results proved that the important wavelengths for discriminating subtropical forest species are located in the visible, red edge, near infrared and mid infrared portions of the electromagnetic spectrum. The selection and evaluation of the optimal wavelengths has been demonstrated in Chapter 5. After identifying 15 different species from sampling points, only 17 wavelengths were optimal for their spectral discrimination. The optimal wavelengths were 438, 442, 512 and 695 nm (in the visible); 729, 750, 758 nm (red edge); 856, 936, 1179, 1507 and 1673 nm (near infrared) and 2220, 2465, 2469 and 2482 nm (mid-infrared) portions of the electromagnetic spectrum. By managing to identify significant optimal wavelengths, the study confirmed that the indisputable capability of the hierarchical method in this task. Thus the hierarchical method, comprising One-way ANOVA with Bonferroni correction, CART and JM distance, successfully identified the optimal wavelengths and evaluated their separability. Although the method was initially applied to the discrimination of papyrus vegetation (Adam and Mutanga, 2009), this study proved its application in subtropical forest species. Upscaling studies and other forms of extrapolation may therefore concentrate on the observed wavelengths and their general location on the electromagnetic spectrum.

9.1.3 Identifying the best classifier for leaf level discrimination of subtropical forest species

Using the selected wavelengths in the preceding chapter, the LDA has proven its capability to discriminate subtropical forest species at leaf level. Based on the accuracy metrics, there is evidence that the LDA outperformed PLSDA and RF methods. On a general note, it proves the importance of linear machine learning algorithms in species discrimination compared to non-parametric ones (e.g. RF). PLSDA is another parametric algorithm that was outperformed by the LDA, but its accuracy levels were higher than RF, again confirming the importance of parametric methods.

9.1.4 Discriminating proportions of semi-deciduous and evergreen forest species using sub-pixel classification after integrating multispectral imagery and field spectroscopy

Integrating multispectral (SPOT 6) and field spectra data led to the successful discrimination of semi-deciduous and evergreen subtropical forests at sub-pixel level. Field spectra of the semi-deciduous and evergreen subtropical forest species was collected in the field as point data and integrated with high-resolution multispectral data. The subsequent sub-pixel classification served to upscale hyperspectral to multispectral data. The proportional maps of the two classes are a form of upscaling, since they discriminate semi-deciduous and evergreen forests for the whole study area. The method also proved the importance of multiple classifiers, as proportional maps were a product of MLC and MTMF. The MLC provided a general land cover classification of which was used to create a mask to remove non-forested parts of the study before sub-pixel analysis. The study also highlighted the importance of Mixed-Tuned Matched Filtering (MTMF) at sub-pixel level classifications since it concentrated on the provided classes (semi-deciduous and evergreen), while supressing the unknown.

9.2: Conclusion

A declining trend of subtropical forests has been identified; species discrimination at leaf level is achievable using field spectra; so is the integration of SPOT 6 and field spectra for mapping semi-deciduous and evergreen forests species. These conclusions are made based on the following observations from this study:

- The MLC is the best classification algorithm (88.75% overall accuracy and a Kappa coefficient of 0.69) for mapping land cover classes (including subtropical forest) in the study area. The other algorithms that were outperformed are MD (43.66% overall accuracy and Kappa coefficient of 0.18), SAM (42.25% overall accuracy and Kappa coefficient of 0) and SID (32.39% overall accuracy and Kappa coefficient of 0.04).

- An MLC based forest change analysis using SPOT 5 and 6 showed a decrease in forest areal cover during both periods 2005-2009 (3648.42 ha) and 2009-2013 (946.98 ha). The two values show a decreasing temporal trend in forest cover in the area of 7.81% and 2.20% for the 2 periods respectively. The t-test proved that the changes in all land cover classes over the two periods are not significantly different ($p>0.05$).
- Out of the 2150 wavelengths, the hierarchical method (involving One-Way ANOVA with Bonferroni correction and CART) identified only 17 optimal ones for subtropical forest species discrimination. The selected 17 are 438, 442, 512, 695, 724, 729, 750, 758, 856, 936, 1179, 1507, 1673, 2220, 2465, 2469 and 2482 nm. They were located in the visible, red-edge, near infrared and mid-infrared portions of the electromagnetic spectrum. The JM distance method confirmed (most sets had index values of > 1 and closer to 2.0) the ability of the selected wavelengths to do species discrimination by measuring separability between sets of the selected ones.
- In this study, the LDA proved its capability to discriminate subtropical forest species since it performed better in comparison to the PLSDA and RF. It is essential to include the linear based statistical methods when performing leaf-level discrimination of subtropical forest species.
- Integrated multispectral and field spectral data managed discriminate the proportions of semi-deciduous and evergreen indigenous forest species with 75% overall accuracy. The proportions were discriminated at sub-pixel level using the Mixture Tuned Matched Filtering (MTMF). These results do not only prove integration of multispectral and field spectroscopy data but also served to upscale hyperspectral to multispectral data for subtropical forest characterisation.

9.3: Recommendations

Forest resources are facing immense pressure from other land uses, hence their monitoring is essential, especially in a country like South Africa, where the forest biome only covers 0.1-0.2% of the total terrestrial area (Castley and Kerly, 1996). However, there are no indications that technological advances are embraced in national decision-making processes. The future of forest conservation, especially subtropical forests, is not very bleak. Developing a forest monitoring programme based on SPOT 5 HRG and SPOT 6 multispectral imagery can provide much-needed information about the state of the indigenous forests, such as the subtropical type in the Wild Coast region. In light of the findings of this study, the following are perceived research directions in as far as subtropical forests are concerned:

- Although the parametric methods (MLC and LDA) were better in this study, further studies may confirm this with other subtropical forest stands along the coast of South Africa or other countries with similar climatic conditions.
- There is potential for a similar integration methodology between field spectroscopy and multispectral imagery with red-edge band(s), such as WorldView2, Rapideye or ESA's Sentinel 1, to yield additional information about the subtropical forests. Characteristics like phenology and even their species make-up may be easily detected if monitoring is done over time.
- Another point of departure may be simulating field spectra to top-of-canopy reflectance or measuring canopy reflectance and integrate with multispectral data for further characterisation of subtropical forests.
- Other characteristics such as plant water differences may also be investigated in subtropical forests.

References

ACHARD, F. & ESTREGUIL, C. 1995. Forest classification of Southeast Asia using NOAA AVHRR data. *Remote Sensing of Environment,* 54**,** 198-208.

ADAM, E. & MUTANGA, O. 2009. Spectral discrimination of papyrus vegetation (Cyperus papyrus L.) in swamp wetlands using field spectrometry. *ISPRS Journal of Photogrammetry and Remote Sensing,* 64**,** 612–620.

ADAM, E. M., MUTANGA, O. & RUGEGE, D. 2012. Discriminating the papyrus vegetation (Cyperus papyrus L.) and its co-existent species using random forest and hyperspectral data resampled to HYMAP. *International Journal of Remote Sensing,* 33**,** 552-569.

ADAMS, J. B., SMITH, M. O. & JOHNSON, P. E. 1986. Spectral mixture modeling: A new analysis of rock and soil types at the Viking Lander 1 Site. *Journal of Geophysical Research: Solid Earth,* 91**,** 8098-8112.

ADE 2014. National Inventory Report 2012. Canberra, Australia: Australian Department of the Environment (ADE).

AFRICA, S. 1998. National Veld and Forest Fire Act, . *No. 101 of 1998.* Pretoria: Government Printer.

AIRBUS DEFENCE AND SPACE. 2014. *SPOT 6/SPOT 7 Technical Sheet* [Online]. Available: http://www.geo-airbusds.com/files/pmedia/public/r12317_9_spot6-7_technical_sheet.pdf [Accessed 25/11/ 2014].

AL-AHMADI, F. S. & HAMES, A. S. 2009. Comparison of four classification methods to extract land use and land cover from raw satellite images for some remote arid areas, Kingdom of Saudi Arabia *JKAU; Earth Science,* 20**,** 167-191.

ALIBER, M. & HART, T. G. B. 2009. Should subsistence agriculture be supported as a strategy to address rural food insecurity? *Agrekon* 48**,** 434-458.

ALLEN, Y. C. & SUIR, G. M. 2014. Using high-resolution, regional-scale data to characterize floating aquatic nuisance vegetation in coastal Louisiana Navigation Channels. Vicksburg: US Army Engineer Research and Development Center.

ARMANDO, F., JOSÉ, L., JOSÉ, M., JOSÉ, X., JOÃO, P. & PEDRO, M.-P. 2013. Comparison between neural networks and partial least squares for intra-growth ring wood density measurement with hyperspectral imaging. *Computers and Electronics in Agriculture,* 94**,** 71–81.

ARUMUGASUNDARAM, S., GHOSH, M., VEERASAMY, S. & RAMASAMY, Y. 2011. Species discrimination, population structure and linkage disequilibrium in Eucalyptus camaldulensis and Eucalyptus tereticornis using SSR Markers. *PLOS One,* 6.

ASNER, G., WESSMAN, C., BATESON, C. & PRIVETTE, J. 2000. Impact of Tissue, Canopy, and Landscape Factors on the Hyperspectral Reflectance Variability of Arid Ecosystems. *Remote Sensing of Environment,* 74**,** 69-83.

ASNER, G. P. 1998. Biophysical and Biochemical Sources of Variability in Canopy Reflectance. *Remote Sensing of Environment,* 64**,** 234-253.

ASNER, G. P., KELLER, M., PEREIRA, J. R., ZWEEDE, J. C. & SILVA, J. N. M. 2004. Canopy damage and recovery after selective logging in Amazonia: field and satellite studies. *Ecological Applications,* 14**,** 280-298.

ASPINALL, R. J., MARCUS, W. A. & BOARDMAN, J. W. 2002. Considerations in collecting, processing, and analysing high spatial resolution hyperspectral data for environmental investigations. *Journal of Geographical Systems,* 4**,** 15-29.

ATKINSON, P. M. & LEWIS, P. 2000. Geostatistical classification for remote sensing: an introduction. *Computers & Geosciences,* 26**,** 361-371.

AXELSSON, A. L., STÅHL, G., SÖDERBERG, U., PETERSSON, H., FRIDMAN, J. & LUNDSTRÖM, A. 2010. National forest inventory report: Sweden. *In:* GSCHWANTNER, T., LAWRENCE, M. & MCROBERTS, R. E. (eds.) *National forest inventories. Pathways for common reporting.* Heidelberg: Springer.

BAJWA, S. G., BAJCSY, P., GROVES, P. A. & TIAN, L. F. 2004. Hyperspectral image data mining for band selection in agricultural applications. *Transactions of the ASAE,* 47**,** 895-907.

BALABIN, R. & SAFIEVA, R. 2011. Biodiesel classification by base stock type (vegetable oil) using near infrared spectroscopy data. *Anal Chim Acta,* 689**,** 190-197.

BALLABIO, D., MAURI, A., TODESCHINI, R. & BURATTI, S. 2006. Geographical classification of wine and olive oil by means of classification and influence matrix analysis (CAIMAN). *Analytica Chimica Acta,* 570**,** 249-258.

BARRETT, E. C. & CURTIS, L. F. 1999. *Introduction to environmental remote sensing,* Cheltenham, Stanley Thornes.

BARRETT, T. M. & GRAY, A. N. 2011. Potential of a national monitoring program for forests to assess change in high-latitude ecosystems. *Biological Conservation,* 144**,** 1285-1294.

BASTIN, L. 1997. Comparison of fuzzy c-means classification, linear mixture modelling and MLC probabilities as tools for unmixing coarse pixels. *International Journal of Remote Sensing,* 18**,** 3629-3648.

BEN-DAVID, A. 2008. Comparison of classification accuracy using Cohen's Weighted Kappa. *Expert Systems with Applications,* 34**,** 825-832.

BENNIE, A. 2011. Questions for Labour on Land, Livelihoods and Jobs: A Case Study of the Proposed Mining at Xolobeni, Wild Coast. *South African Review of Sociology,* 42**,** 41-59.

BERK, R. 2008. *Statistical Learning from a Regression Perspective,* New York, Springer.

BERLINER, D. The conservation status of forests on the Eastern Cape's Wild Coast, South Africa. Fifth Natural Forest and Woodlands Symposia, 2011 Richards Bay. Department of Agriculture, Forestry and Fisheries.

BERNSTEIN, L. S., ADLER-GOLDEN, S. M., SUNDBERG, R. L. & RATKOWSKI, A. J. In-scene-based atmospheric correction of uncalibrated VISible-SWIR (VIS-SWIR) hyper- and multi-spectral imagery. Remote Sensing of Clouds and the Atmosphere XIII, 2008 Cardiff, United Kingdom. SPIE Proceedings.

BERNSTEIN, L. S., JIN, X., GREGOR, B. & ADLER-GOLDEN, S. M. 2012. Quick atmospheric correction code: algorithm description and recent upgrades. *Optical engineering,* 51**,** 111719.

BICKEL, P. J. & LEVINA, E. 2004. Some theory for Fisher's linear discriminant function,'naive Bayes', and some alternatives when there are many more variables than observations. *Bernoulli***,** 989-1010.

BIEWER, S., ERASMI, S., FRICKE, T. & WACHENDORF, M. 2009. Prediction of yield and the contribution of legumes in legume-grass mixtures using field spectrometry. *Precision Agriculture,* 10**,** 128-144.

BLACKBURN, G. A. & MILTON, E. J. 1995. Seasonal variations in the spectral reflectance of deciduous tree canopies. *International Journal of Remote Sensing,* 16**,** 709-720.

BOARDMAN, J. Leveraging the high dimensionality of AVIRIS data for improved sub-pixel target unmixing and rejection of false positives: mixture tuned matched filtering. Summaries of the Seventh Annual JPL Airborne Geoscience Workshop, 1998 Pasadena, CA. JPL Publication.

BREIMAN, L. 2001. Random forests. *Machine learning,* 45**,** 5-32.

BREIMAN, L., FRIEDMAN, J., STONE, C. J. & OLSHEN, R. A. 1984. *Classification and regression trees,* Boca Raton, Chapman & Hall/CRC.

BRIGHAM, T., CHIHONGO, A. & CHIDUMAYO, E. 1996. Trade in woodland products from the Miombo region. *In:* CAMBELL, B. (ed.) *The Miombo in Transition: Woodlands and Welfare in Africa.* Bogor: CIFOR.

BROSIUS, J. P. 1997. Endangered Forest, Endangered People: Environmentalist Representations of Indigenous Knowledge. *Human Ecology,* 25**,** 47-69.

BRUCE, L. M., KOGER, C. H. & JIANG, L. 2002. Dimensionality reduction of hyperspectral data using discrete wavelet transform feature extraction. *Geoscience and Remote Sensing, IEEE Transactions on,* 40**,** 2331-2338.

CALVÃO, T. & PALMEIRIM, J. M. 2011. A comparative evaluation of spectral vegetation indices for the estimation of biophysical characteristics of Mediterranean semi-deciduous shrub communities. *International Journal of Remote Sensing,* 32**,** 2275-2296.

CAMPBELL, J. B. 1996. *Introduction to Remote Sensing,* New York, Taylor & Francis Group.

CARVALHO, S., SCHLERF, M., VAN DER PUTTEN, W. H. & SKIDMORE, A. K. 2013. Hyperspectral reflectance of leaves and flowers of an outbreak species discriminates season and successional stage of vegetation. *International Journal of Applied Earth Observation and Geoinformation,* 24**,** 32-41.

CASTLEY, G. H. & KERLY, K. I. H. 1996. The paradox of forest conservation in South Africa. *Forest Ecology and Management,* 85**,** 35-46.

CASTRO-ESAU, K. L., SÁNCHEZ-AZOFEIFA, A. G., RIVARD, B., WRIGHT, J. S. & QUESADA, M. 2006. Variability in leaf optical properties of Mesoamerican trees and the potential for species classification. *American Journal of Botany,* 93**,** 517-530.

CASTRO-ESAU, K. L., SÁNCHEZ-AZOFEIFA, G. A. & CAELLI, T. 2004. Discrimination of lianas and trees with leaf-level hyperspectral data. *Remote Sensing of Environment,* 90**,** 353-372.

CAWE, S. G. 1996. A floristic classification of the indigenous forests of Transkei, South Africa. *In:* VAN DER MAESEN, L. J. G., VAN DER BURGT, X. M. & VAN MEDENBACH DE ROOY, J. M. (eds.) *The Biodiversity of African Plants.* Springer Netherlands.

CHAN, J. C.-W. & PAELINCKX, D. 2008. Evaluation of Random Forest and Adaboost tree-based ensemble classification and spectral band selection for ecotope mapping using airborne hyperspectral imagery. *Remote Sensing of Environment,* 112**,** 2999-3011.

CHANG, C.-I. Spectral information divergence for hyperspectral image analysis. Geoscience and Remote Sensing Symposium, 1999. IGARSS '99 Proceedings., 1999 Hamburg, Germany. IEEE 1999 International, 509-511.

CHO, M., SOBHAN, I., SKIDMORE, A. & LEEUW, J. Discriminating species using hyperspectral indices at leaf and canopy scales. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 3-11 Jul 2008 2010 Beijing, China. ISPRS.

CHO, M. A., SKIDMORE, A. K. & ATZBERGER, C. 2008. Towards red-edge positions less sensitive to canopy biophysical parameters for leaf chlorophyll estimation using properties optique spectrales des feuilles (PROSPECT) and scattering by arbitrarily inclined leaves (SAILH) simulated data. *International Journal of Remote Sensing,* 29**,** 2241-2255.

CHRISTENSEN, P. & RINGVALL, H. A. 2013. Using statistical power analysis as a tool when designing a monitoring program: experience from a large-scale Swedish landscape monitoring program. *Environmental Monitoring and Assessment,* 185**,** 7279-7293.

CLARK, M., L. 2011. Identification of Canopy Species in Tropical Forests Using Hyperspectral Data. *Hyperspectral Remote Sensing of Vegetation.* CRC Press.

CLARK, M., ROBERTS, D. & CLARK, D. 2005. Hyperspectral discrimination of tropical rain forest tree species at leaf to crown scales. *Remote Sensing of Environment,* 96**,** 375-398.

CNES. 2005. Resolutions and spectral modes. Available: http://www2.astrium-geo.com/files/pmedia/public/r451_9_resolutionspectralmodes_uk_sept2010.pdf [Accessed 04/08/2013].

COCHRANE, M. 2000. Using vegetation reflectance variability for species level classification of hyperspectral data. *International Journal of Remote Sensing,* 21**,** 2075-2087.

COCKS, M. L. & WIERSUM, K. F. 2003. The significance of plant diversity to rural households in Eastern Cape province of South Africa. *Forests, Trees and Livelihoods,* 13**,** 39-58.

COHEN, J. 1960. A coefficient of agreement for nominal scales. *Education and Psychological Measurement,* 20**,** 37-46.

COHEN, J. 1968. Weighted kappa: Nominal scale agreement provision for scaled disagreement or partial credit. *Psychological Bulletin,* 70**,** 213-220.

COLE, B., MCMORROW, J. & EVANS, M. 2014. Spectral monitoring of moorland plant phenology to identify a temporal window for hyperspectral remote sensing of peatland. *ISPRS Journal of Photogrammetry and Remote Sensing,* 90**,** 49-58.

CONGALTON, R. G. 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sensing of Environment,* 37**,** 35-46.

CONGALTON, R. G. & GREEN, K. 2008. *Assessing the accuracy of remotely sensed data: Principles and Practices,* Boca Raton, CRC Press.

COWLING, R. M., GIBBS RUSSELL, G. E., HOFFMAN, M. T. & HILTON-TAYLOR, C. 1989. Patterns of plant species diversity in Southern Africa. . *In:* HUNTLEY, B. J. (ed.) *Biotic diversity in Southern Africa. Concepts and Conservation.* Cape Town: Oxford University Press.

COWLING, R. M., RICHARDSON, D. M., SCHULZE, R. E., HOFFMAN, M. T., MIDGLEY, J. J. & HILTON-TAYLOR, C. 1997. Species diversity at the regional scale. *In:*

COWLING, R. M., RICHARDSON, D. M. & PIERCE, S. M. (eds.) *Vegetation of Southern African.* Cambridge: Cambridge University Press.

CRACKNELL, M. J. & READING, A. M. 2014. Geological mapping using remote sensing data: A comparison of five machine learning algorithms, their response to variations in the spatial distribution of training data and the use of explicit spatial information. *Computers & Geosciences,* 63**,** 22-33.

CURATOLA FERNÁNDEZ, G. F., SILVA, B., GAWLIK, J., THIES, B. & BENDIX, J. 2013. Bracken fern frond status classification in the Andes of southern Ecuador: combining multispectral satellite data and field spectroscopy. *International Journal of Remote Sensing,* 34**,** 7020-7037.

CURRAN, P. J. 1989. Remote sensing of foliar chemistry. *Remote Sensing of Environment,* 30**,** 271-278.

DAFF 2012. Strategic Plan 2012/13-2016/17. *In:* DEPARTMENT OF AGRICULTURE, F. A. F. (ed.). Pretoria: Government Printers.

DAFF 2014. National Forest Act: List of protected tree species. *In:* DEPARTMENT OF AGRICULTURE, F. A. F. (ed.). Pretoria: Government Printer.

DALPONTE, M., BRUZZONE, L. & GIANELLE, D. 2012. Tree species classification in the Southern Alps based on the fusion of very high geometrical resolution multispectral/hyperspectral images and LiDAR data. *Remote Sensing of Environment,* 123**,** 258-270.

DE CASTRO, A.-I., JURADO-EXPÓSITO, M., GÓMEZ-CASERO, M.-T. & LÓPEZ-GRANADOS, F. 2012. Applying Neural Networks to Hyperspectral and Multispectral Field Data for Discrimination of Cruciferous Weeds in Winter Crops. *The Scientific World Journal,* 2012.

DEHAAN, R. & TAYLOR, G. R. 2003. Image-derived spectral endmembers as indicators of salinisation. *International Journal of Remote Sensing,* 24**,** 775-794.

DENNISON, P. & ROBERTS, D. 2003. Endmember selection for multiple endmember spectral mixture analysis using endmember average RMSE. *Remote Sensing of Environment,* 87**,** 123-135.

DEPARTMENT OF WATER AFFAIRS AND FORESTRY 2006. Rivers of South Africa at 1:500 000 scale. *In:* SERVICES, D. R. Q. (ed.). Pretoria, South Africa: Government Printers.

DEWAN, A. M. & YAMAGUCHI, Y. 2008. Using remote sensing and GIS to detect and monitor land use and land cover change in Dhaka Metropolitan of Bangladesh during 1960–2005. *Environmental Monitoring and Assessment,* 150**,** 237-249.

DOPIDO, I., ZORTEA, M., VILLA, A. & PLAZA, A. 2011. Unmixing prior to supervised classification of remotely sensed hyperspectral images. *Geoscience and Remote Sensing,* 8**,** 760-764.

DORIGO, W. A., ZURITA-MILLA, R., DE WIT, A. J. W. & BRAZILE, J. 2007. A review on reflective remote sensing and data assimilation techniques for enhanced agroecosystem modeling. *International Journal of Applied Earth Observation and Geoinformation,* 9**,** 165-193.

DORREN, L. K. A., MAIER, B. & SEIJMONSBERGEN, A. C. 2003. Improved Landsat-based forest mapping in steep mountainous terrain using object-based classification. *Forest Ecology and Management,* 183**,** 31-46.

DRAKE, N. A., MACKIN, S. & SETTLE, J. J. 1999. Mapping Vegetation, Soils, and Geology in Semiarid Shrublands Using Spectral Matching and Mixture Modeling of SWIR AVIRIS Imagery. *Remote Sensing of Environment,* 68**,** 12-25.

DRAMSTAD, W. E., FJELLSTAD, W. J., STRAND, G. H., MATHIESEN, H. F., ENGAN, G. & STOKLAND, J. N. 2002. Development and implementation of the Norwegian monitoring programme for agricultural landscapes. *Journal of Environmental Management,* 64**,** 49–63.

DU, Y., CHANG, C.-I., REN, H., CHANG, C.-C., JENSEN, J. O. & D'AMICO, F. M. 2004. New hyperspectral discrimination measure for spectral characterization. *Optical Engineering,* 43**,** 1777-1786.

DWIVEDI, R. S., KANDRIKA, S. & RAMANA, K. V. 2004. Comparison of classifiers of remote-sensing data for land-use/land-cover mapping. *Current Science,* 86**,** 328-335.

EEA 2007. CLC2006 technical guidelines (technical report no 17). Copenhagen, Denmark: European Environment Agency (EEA).

EELEY, H. A. C., LAWES, M. J. & REYERS, B. 2001. Priority areas for the conservation of subtropical indigenous forest in southern Africa: a case study from KwaZulu-Natal. *Biodiversity & Conservation,* 10**,** 1221-1246.

ERBEK, F. S., ÖZKAN, C. & TABERNER, M. 2004. Comparison of maximum likelihood classification method with supervised artificial neural network algorithms for land use activities. *International Journal of Remote Sensing,* 25**,** 1733-1748.

ERK, A. R., MARTIN, G. L. & GILMORE, D. W. 2003. Measuring and Monitoring Forest Resources. *In:* YOUNG, R. A. & GIESE, R. L. (eds.) *Introduction to Forest Ecosystem Science and Management.* Hoboken: John Wiley & Sons.

FAO 2000. Forest Resource Assessment 2000. *In:* FAO (ed.). Rome, Italy: Food and Agriculture Organization of United Nations,.

FERET, J. B. & ASNER, G. P. 2011. Spectroscopic classification of tropical forest species using radiative transfer modeling. *Remote Sensing of Environment,* 115**,** 2415-2422.

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 Journal of Photogrammetry and Remote Sensing,* 80**,** 80-90.

FERNÁNDEZ, G. F. C., SILVA, B., GAWLIK, J., THIES, B. & BENDIX, J. 2013. Bracken fern frond status classification in the Andes of southern Ecuador: combining multispectral satellite data and field spectroscopy. *International Journal of Remote Sensing*.

FISHER, P. F. & PATHIRANA, S. 1990. The evaluation of fuzzy membership of land cover classes in the suburban zone. *Remote Sensing of Environment,* 34**,** 121-132.

FJELLSTAD, W., MATHIESEN, H. & STOKLAND, J. 2001. Monitoring Norwegian agricultural landscapes: the 3Q program. *In:* GROOM, G. & REED, T. (eds.) *Strategic landscape monitoring for the Nordic countries.* Copenhagen: TemaNord.

FOODY, G. M. 1996. Approaches for the production and evaluation of fuzzy land cover classifications from remotely-sensed data. *International Journal of Remote Sensing,* 17**,** 1317-1340.

FOODY, G. M. 2002a. Hard and soft classifications by a neural network with a non-exhaustively defined set of classes. *International Journal of Remote Sensing,* 23**,** 3853-3864.

FOODY, G. M. 2002b. Status of land cover classification accuracy assessment. *Remote sensing of environment,* 80**,** 185-201.

FRANKLIN, J. 2010. *Mapping species distributions - spatial inference and prediction,* Cambridge, Cambridge University Press.

FRANKLIN, S. E. 2001. *Remote sensing for sustainable forest management,* Boca Raton, Lewis Publishers.

FUNG, T., MA, Y. H. F. & SIU, W. L. 2003. Band selection using hyperspectral data of subtropical tree species. *Geocarto International,* 18**,** 3-11.

GARCIA-ALLENDE, P. B., CONDE, O. M., MIRAPEX, J., CUNILLAS, A. M. & LOPEZ-HIGUERA, J. M. 2008. Data Processing Method Applying Principal Component Analysis and Spectral Angle Mapper for Imaging Spectroscopic Sensors. *IEEE Sensors Journal,* 8**,** 1310-1316.

GARRITY, S. R., BOHRER, G., MAURER, K. D., MUELLER, K. L., VOGEL, C. S. & CURTIS, P. S. 2011. A comparison of multiple phenology data sources for estimating seasonal transitions in deciduous forest carbon exchange. *Agricultural and Forest Meteorology,* 151**,** 1741-1752.

GAUSMAN, H. W. & WEIDNER, V. R. 1985. Plant leaf optical properties in visible and near infrared light. *Applied Optics,* 24**,** 3305-3416.

GELDENHUYS, C. J. Requirements for improved and sustainable use of forest biodiversity: examples of multiple use forest in South Africa. *In:* POKER, J., STEIN, I. & WERDER (EDS.), U., eds. Proceedings Forum Biodiversity Treasures in the World's Forests, 3-7 July 1998 1999. Alfred Toepfer Akademie fur Naturschutz, 72-82.

GELDENHUYS, C. J. & MACDEVETTE, D. R. 1989. Conservation status of coastal and montane evergreen forest. *In:* HUNTLEY, B. J. (ed.) *Biotic Diversity in Southern Africa,.* Cape Town: Oxford University Press.

GISLASON, P. O., BENEDIKTSSON, J. A. & SVEINSSON, J. R. Random Forest classification of multisource remote sensing and geographic data. Geoscience and Remote Sensing Symposium, IGARSS '04. Proceedings, 20-24 Sept. 2004 2004. IEEE International, 1049-1052.

GLENDAY, J. 2008. Carbon storage and emissions offset potential in an African dry forest, the Arabuko-Sokoke Forest, Kenya. *Environmental Monitoring and Assessment,* 142**,** 85-95.

GOETZ, S., BACCINI, A., LAPORTE, N., JOHNS, T., WALKER, W., KELLNDORFER, J., HOUGHTON, R. & SUN, M. 2009. Mapping and monitoring carbon stocks with satellite observations: a comparison of methods. *Carbon balance and management,* 4.

GONG, P. & YU, B. 2001. Conifer species recognition: effects of data transformation. *International Journal of Remote Sensing,* 22**,** 3471-3481.

GOODWIN, N., COOPS, N. C. & STONE, C. 2005. Assessing plantation canopy condition from airborne imagery using spectral mixture analysis and fractional abundances. *International Journal of Applied Earth Observation and Geoinformation,* 7**,** 11-28.

GOTTLICHER, D., OBREGÓN, A., HOMEIER, J., ROLLENBECK, R., NAUSS, T. & BENDIX, J. 2009. Land-cover classification in the Andes of southern Ecuador using Landsat ETM+ data as a basis for SVAT modelling. *International Journal of Remote Sensing,* 30**,** 1867-1886.

GRANT, L. 1987. Diffuse and specular characteristics of leaf reflectance. *Remote Sensing of Environment,* 22**,** 309-322.

GRAY, C. J., SHAW, D. R. & BRUCE, L. M. 2009. Utility of Hyperspectral Reflectance for Differentiating Soybean (Glycine max) and Six Weed Species. *Weed Technology,* 23**,** 108-119.

GREGOIRE, T. G. & VALENTINE, H. T. 2004. *Sampling Strategies for Natural Resources and the Environment by,* Boca Raton, Chapman and Hall/CRC.

GRIFFITHS, M. E. & LAWES, M. J. 2006. Biogeographic, Environmental, and Phylogenetic Influences on Reproductive Traits in Subtropical Forest Trees, South Africa. *Ecography,* 29**,** 614-622.

GRISCOM, H., MILLER, S., GYEDU-ABABIO, T. & SIVANPILLAI, R. 2010. Mapping land cover change of the Luvuvhu catchment, South Africa for environmental modelling. *Geojournal,* 75**,** 163-173.

GROMSKI, P. S., XU, Y., CORREA, E., ELLIS, D. I., TURNER, M. L. & GOODACRE, R. 2014. A comparative investigation of modern feature selection and classification approaches for the analysis of mass spectrometry data. *Analytica Chimica Acta,* 829**,** 1-8.

GROSSMAN, D. & GANDAR, M. V. 1989. Land transformation in South African savanna regions. *South African Geographical Journal,* 71**,** 38-45.

GUIMET, F., BOQUÉ, R. & FERRÉ, J. 2006. Application of non-negative matrix factorization combined with Fisher's linear discriminant analysis for classification of olive oil excitation–emission fluorescence spectra. *Chemometrics and Intelligent Laboratory Systems,* 81**,** 94-106.

GULDIN, J. M. & GULDIN, R. W. 2003. Forest Management and Stewardship. *In:* YOUNG, R. A. & GIESE, R. L. (eds.) *Introduction to Forest Ecosystem Science and Management.* Hoboken: John Wiley & Sons.

GUO, X., WILMSHURST, J. & LI, Z. 2010. Comparison of laboratory and field remote sensing methods to measure forage quality. *International journal of environmental research and public health,* 7**,** 3513-3530.

GUTIÉRREZ, L., GUTIÉRREZ-PEÑA, E. & MENA, R. H. 2014. Bayesian nonparametric classification for spectroscopy data. *Computational Statistics & Data Analysis,* 78**,** 56-68.

HANSEN, M., DEFRIES, R., TOWNSHEND, J. & SOHLBERG, R. 2000. Global land cover classification at 1 km spatial resolution using a classification tree approach. *International Journal of Remote Sensing,* 21**,** 1331-1364.

HANSEN, M. C., POTAPOV, P. V., MOORE, R., HANCHER, M., TURUBANOVA, S. A., TYUKAVINA, A., THAU, D., STEHMAN, S. V., GOETZ, S. J., LOVELAND, T. R., KOMMAREDDY, A., EGOROV, A., CHINI, L., JUSTICE, C. O. & TOWNSHEND, J. R. G. 2013. High-resolution global maps of 21st-century forest cover change. *Science,* 342**,** 850-853.

HANSEN, M. C., STEHMAN, S. V., POTAPOV, P. V., LOVELAND, T. R., TOWNSHEND, J. R. G., DEFRIES, R. S., PITTMAN, K. W., ARUNARWATI, B., STOLLE, F. & STEININGER, M. K. 2008. Humid tropical forest clearing from 2000 to 2005 quantified by using multitemporal and multiresolution remotely sensed data.

Proceeding of the National Academy of Sciences of the United States of America, 105**,** 9439-9444.

HANSEN, P. M. & SCHJOERRING, J. K. 2003. Reflectance measurement of canopy biomass and nitrogen status in wheat crops using normalized difference vegetation indices and partial least squares regression. *Remote sensing of environment,* 86**,** 542-553.

HARKEN, J. & SUGUMARAN, R. 2005. Classification of Iowa wetlands using an airborne hyperspectral image: a comparison of the spectral angle mapper classifier and an object-oriented approach. *Canadian Journal of Remote Sensing,* 31**,** 167-174.

HEYMAN, O., GASTON, G. G., KIMERLING, A. J. & CAMPBELL, J. T. 2003. A per-segment approach to improving aspen mapping from high-resolution remote sensing imagery. *Journal of Forestry,* 101**,** 29-33.

HMIMINA, G., DUFRÊNE, E., PONTAILLER, J. Y., DELPIERRE, N., AUBINET, M., CAQUET, B., DE GRANDCOURT, A., BURBAN, B., FLECHARD, C., GRANIER, A., GROSS, P., HEINESCH, B., LONGDOZ, B., MOUREAUX, C., OURCIVAL, J. M., RAMBAL, S., SAINT ANDRÉ, L. & SOUDANI, K. 2013. Evaluation of the potential of MODIS satellite data to predict vegetation phenology in different biomes: An investigation using ground-based NDVI measurements. *Remote Sensing of Environment,* 132**,** 145-158.

HUANG, Z., TURNER, B. J., DURY, S. J. & WALLIS, I. R. 2004. Estimating foliage nitrogen concentration from HYMAP data using continuum removal analysis. *Remote Sensing of Environment,* 93**,** 18-29.

HUBERT-MOY, L., COTONNEC, A., DU, L. L. & CHARDIN, A. 2001. A comparison of parametric classification procedures of remotely sensed data applied on different landscape units. *Remote Sensing of Environment,* 75**,** 174-187.

HUMPHREYS, J. R., O’REILLY-WAPSTRA, J. M., HARBARD, J. L., DAVIES, N. W., GRIFFIN, A. R., JORDAN, G. J. & POTTS, B. M. 2008. Discrimination between seedlings of Eucalyptus globulus, E. nitens and their F1 hybrid using near-infrared reflectance spectroscopy and foliar oil content. *Silvae Genetica,* 57**,** 262-269.

HÜTTICH, C., HEROLD, M., STROHBACH, B. & DECH, S. 2011. Integrating in-situ, Landsat, and MODIS data for mapping in Southern African savannas: experiences of LCCS-based land-cover mapping in the Kalahari in Namibia. *Environmental Monitoring and Assessment,* 176**,** 531-547.

ISMAIL, R. & MUTANGA, O. 2011. Discriminating the early stages of Sirex noctilio infestation using classification tree ensembles and shortwave infrared bands. *International Journal of Remote Sensing,* 32**,** 4249-4266.

ISMAIL, R., MUTANGA, O. & AHMED, F. 2008. Discriminating Sirex noctilio attack in pine forest plantations in South Africa using high spectral resolution data. *In:* KALACSKA, M. & SANCHEZ-AZOFEIFA, G. A. (eds.) *Hyperspectral Remote Sensing of Tropical and Sub-Tropical Forests.* Boca Raton: CRC Press.

JACQUEMOUD, S., VERHOEF, W., BARET, F., BACOUR, C., ZARCO-TEJADA, P. J., ASNER, G. P., FRANÇOIS, C. & USTIN, S. L. 2009. PROSPECT + SAIL models: A review of use for vegetation characterization. *Remote Sensing of Environment,* 113**,** S56-S66.

JENSEN, J. R. 2005. *Introductory Digital Image Processing: A Remote Sensing Perspective,* Upper Saddle River, NJ, Prentice Hall.

JIA, G. J., BURKE, I. C., KAUFMANN, M. R., GOETZ, A. F. H., KINDEL, B. C. & PU, Y. 2006. Estimates of forest canopy fuel attributes using hyperspectral data. *Forest Ecology and Management,* 229**,** 27-38.

JIA, K., WU, B., TIAN, Y., ZENG, Y. & LI, Q. 2011. Vegetation classification method with biochemical composition estimated from remote sensing data. *International Journal of Remote Sensing,* 32**,** 9307-9325.

JOHNSON, C. T. 1983. The forests and trees of Transkei. *Veld and Flora,* 69**,** 26–27.

JÖNSSON, A. M., EKLUNDH, L., HELLSTRÖM, M., BÄRRING, L. & JÖNSSON, P. 2010. Annual changes in MODIS vegetation indices of Swedish coniferous forests in relation to snow dynamics and tree phenology. *Remote Sensing of Environment,* 114**,** 2719-2730.

KAKEMBO, V. 2009. Vegetation patchiness and implications for landscape function: The case of Pteronia incana invader species in Ngqushwa Rural Municipality, Eastern Cape, South Africa. *Catena,* 77**,** 180-186.

KANGAS, A. 2006. Assessing the World's Forests. *In:* KANGAS, A. & MALTAMO, M. (eds.) *Forest Inventory.* Dordrecht: Springer Netherlands.

KE, Y., QUACKENBUSH, L. J. & IM, J. 2010. Synergistic use of QuickBird multispectral imagery and LIDAR data for object-based forest species classification. *Remote Sensing of Environment,* 114**,** 1141-1154.

KEMPENEERS, P., BACKER, S., DELALIEUX, S., STERCKX, S., DEBRUYN, W., COPPIN, P. & SCHEUNDERS, P. 2004. Upscaling of spectroradiometer data for stress detection in orchards with remote sensing. *SPIE Remote Sensing.* Gran Canaria, Spain.

KENNEDY, P. J. 1989. Monitoring the phenology of Tunisian grazing lands. *International Journal of Remote Sensing,* 10**,** 835-845.

KENT, M. & COKER, P. 1992. *Vegetation description and analysis: a practical approach,* Boca Raton, CRC Press.

KLEYNHANS, C. J., THIRION, C. & MOOLMAN, J. 2005. A Level I River Ecoregion classification system for South Africa, Lesotho and Swaziland. Pretoria, South Africa.: Resource Quality Services, Department of Water Affairs and Forestry.

KNORN, J., RABE, A., RADELOFF, V. C., KUEMMERLE, T., KOZAK, J. & HOSTERT, P. 2009. Land cover mapping of large areas using chain classification of neighboring Landsat satellite images. *Remote Sensing of Environment,* 113**,** 957-964.

KOEDSIN, W. & VAIPHASA, C. 2013. Discrimination of Tropical Mangroves at the Species Level with EO-1 Hyperion Data. *Remote Sensing,* 5**,** 3562-3582.

KOGER, C. H., BRUCE, L. M., SHAW, D. R. & REDDY, K. N. 2003. Wavelet analysis of hyperspectral reflectance data for detecting pitted morningglory (Ipomoea lacunosa) in soybean (Glycine max). *Remote Sensing of Environment,* 86**,** 108-119.

KOZAK, J., ESTREGUIL, C. & OSTAPOWICZ, K. 2008. European forest cover mapping with high resolution satellite data: The Carpathians case study. *International Journal of Applied Earth Observation and Geoinformation,* 10**,** 44-55.

KRUSE, F. A., LEFKOFF, A. B., BOARDMAN, J. B., HEIDEBREICHT, K. B., SHAPIRO, A. T. & BARLOON, P. J., & GOETZ, A. F. H. 1993. The Spectral Image Processing System (SIPS)—interactive visualization and analsis of imaging spectrometer data. *Remote Sensing of Environment,* 44**,** 145 – 163.

KRUSE, F. A. & PERRY, S. L. 2009. Improving multispectral mapping by spectral modeling with hyperspectral signatures. *Journal of Applied Remote Sensing,* 3.

KUUSINEN, N., TOMPPO, E. & BERNINGER, F. 2013. Linear unmixing of MODIS albedo composites to infer subpixel land cover type albedos. *International Journal of Applied Earth Observation and Geoinformation,* 23**,** 324-333.

LANDIS, J. R. & KOCH, G. G. 1977. An application of hierarchical kappa-type statistics in the assessment of majority agreement among multiple observers. *Biometrics,* 33**,** 363-374.

LARK, R. M. 1995. Components of accuracy of maps with special reference to discriminant analysis on remote sensor data. *International Journal of Remote Sensing,* 16**,** 1461-1480.

LASAPONARA, R. & MASINI, N. Statistical evaluation of spectral capability of satellite QuickBird data in detecting buried archaeological remains. 27th EARSeL Symposium: Geoinformation in Europe, 2007 Bolzano. Millpress.

LAURANCE, W. F., VASCONCELOS, H. L. & LOVEJOY, T. E. 2000. Forest loss and fragmentation in the Amazon: implications for wildlife conservation. *Oryx,* 34**,** 39-45.

LAWES, M. J. & OBIRI, J. A. F. 2003a. Canopy gaps in subtropical forest in South Africa: size of the species pool and not the number of available niches limits species richness. *Journal of Tropical Ecology,* 19**,** 549-556.

LAWES, M. J. & OBIRI, J. A. F. 2003b. Using the spatial grain of regeneration to select harvestable tree species in subtropical forest. *Forest Ecology and Management,* 184**,** 105-114.

LAWRENCE, R. L. & WRIGHT, A. 2001. Rule-based classification systems using classification and regression tree (CART) analysis. *Photogrammetric Engineering and Remote Sensing,* 67**,** 1137-1142.

LEE, D. & SEUNG, H. 1999. Learning the parts of objects by non-negative matrix factorization. *Nature,* 401**,** 788-791.

LEHMANN, E. A., CACCETTA, P., LOWELL, K., MITCHELL, A., ZHOU, Z.-S., HELD, A., MILNE, T. & TAPLEY, I. 2015. SAR and optical remote sensing: Assessment of complementarity and interoperability in the context of a large-scale operational forest monitoring system. *Remote Sensing of Environment,* 156**,** 335-348.

LEINENKUGEL, P., KUENZER, C., OPPELT, N. & DECH, S. 2013. Characterisation of land surface phenology and land cover based on moderate resolution satellite data in cloud prone areas — A novel product for the Mekong Basin. *Remote Sensing of Environment,* 136**,** 180-198.

LI, T., ZHU, S. & OGIHARA, M. 2006. Using discriminant analysis for multi-class classification: an experimental investigation. *Knowledge and Information Systems,* 10**,** 453-472.

LIU, L., JING, X., WANG, J. & ZHAO, C. 2009. Analysis of the changes of vegetation coverage of western Beijing mountainous areas using remote sensing and GIS. *Environmental Monitoring and Assessment,* 153**,** 339-349.

LIU, M., WANG, M., WANG, J. & LI, D. 2013. Comparison of random forest, support vector machine and back propagation neural network for electronic tongue data classification: Application to the recognition of orange beverage and Chinese vinegar. *Sensors and Actuators B: Chemical,* 177**,** 970-980.

LONGCHAMPS, L., PANNETON, B., SAMSON, G. & LEROUX, G. D. 2010. Discrimination of corn, grasses and dicot weeds by their UV-induced fluorescence spectral signature. *Precision Agriculture,* 11**,** 181-197.

LÖTTER, M. C., MUCINA, L. & WITKOWSKI, E. T. F. 2014. Classification of the indigenous forests of Mpumalanga Province, South Africa. *South African Journal of Botany,* 90**,** 37-51.

LOVELAND, T. R., REED, B. C., BROWN, J. F., OHLEN, D. O., ZHU, Z., YANG, L. & MERCHANT, J. W. 2000. Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. *International Journal of Remote Sensing,* 21**,** 1303-1330.

LOVETT, G. M., BURNS, D. A., DRISCOLL, C. T., JENKINS, J. C., MITCHELL, M. J. & RUSTAD, L. 2007. Who needs environmental monitoring? *Frontiers in Ecological Environment,* 5**,** 253-260.

LOW, A. B. & REBELO, A. G. 1996. Vegetation of South Africa, Lesotho and Swaziland. Pretoria: Department of Environmental Affairs and Tourism,.

LUCAS, R., BUNTING, P., PATERSON, M. & CHISHOLM, L. 2008. Classification of Australian forest communities using aerial photography, CASI and HyMap data. *Remote Sensing of Environment,* 112**,** 2088-2103.

LUKES, P., RAUTIAINEN, M., STENBERG, P. & MALENOVSKY, Z. 2011. Empirical test of the spectral invariants theory using imaging spectroscopy data from a coniferous forest. *International Journal of Applied Earth Observation and Geoinformation,* 13**,** 668-675.

MALLINIS, G., KOUTSIAS, N., TSAKIRI-STRATI, M. & KARTERIS, M. 2008. Object-based classification using Quickbird imagery for delineating forest vegetation polygons in a Mediterranean test site. *ISPRS Journal of Photogrammetry and Remote Sensing,* 63**,** 237-250.

MANJUNATH, K. R., KUMAR, T., KUNDU, N. & PANIGRAHY, S. 2013. Discrimination of mangrove species and mudflat classes using in situ hyperspectral data: a case study of Indian Sundarbans. *GIScience & Remote Sensing,* 50**,** 400-417.

MARCEAU, D. J. & HAY, G. J. 1999. Remote sensing contributions to the scale issue. *Canadian Journal of Remote Sensing,* 25**,** 357-366.

MARTIN, M. E., NEWMAN, S. D., ABER, J. D. & CONGALTON, R. G. 1998. Determining forest species composition using high spectral resolution remote sensing data *Remote Sensing of Environment* 65**,** 249–254.

MATHER, P. M. & KOCH, M. 2011. *Computer Processing of Remotely-Sensed Images: An Introduction,* Chichester, Wiley-Blackwell.

MEER, F. V. D., SCHMIDT, K., BAKKER, W. & BIJKER, W. 2002. New environmental remote sensing systems. *Environmental Modelling with GIS and Remote Sensing.* CRC Press.

MEHR, G. S. & AHADNEJAD, V. 2013. Using the mixture-tuned matched filtering method for lithological mapping with Landsat TM5 images. *International Journal of Remote Sensing,* 34**,** 8803-8816.

MELGANI, F. & BRUZZONE, L. 2004. Classification of hyperspectral remote sensing images with support vector machines. *Geoscience and Remote Sensing, IEEE Transactions on,* 42**,** 1778-1790.

MERTZ, O., MÜLLER, D., SIKOR, T., HETT, C., HEINIMANN, A., CASTELLA, J.-C., LESTRELIN, G., RYAN, C. M., REAY, D. S., SCHMIDT-VOGT, D., DANIELSEN, F., THEILADE, I., NOORDWIJK, M. V., VERCHOT, L. V., BURGESS, N. D., BERRY, N. J., PHAM, T. T., MESSERLI, P., XU, J., FENSHOLT, R., HOSTERT, P., PFLUGMACHER, D., BRUUN, T. B., NEERGAARD, A. D., DONS, K., DEWI, S., RUTISHAUSER, E. & SUN, Z. 2012. The forgotten D: challenges of addressing forest degradation in complex mosaic landscapes under REDD+. *Geografisk Tidsskrift-Danish Journal of Geography,* 112**,** 63-76.

MILLS, A. J. & COWLING, R. M. 2006. Rate of Carbon Sequestration at Two Thicket Restoration Sites in the Eastern Cape, South Africa. *Restoration Ecology,* 14**,** 38-49.

MITCHELL, J. J. & GLENN, N. F. 2009. Subpixel abundance estimates in mixture-tuned matched filtering classifications of leafy spurge (Euphorbia esulaL.). *International Journal of Remote Sensing,* 30**,** 6099-6119.

MON, M. S., MIZOUE, N., HTUN, N. Z., KAJISA, T. & YOSHIDA, S. 2012. Factors affecting deforestation and forest degradation in selectively logged production forest: A case study in Myanmar. *Forest Ecology and Management,* 267**,** 190-198.

MULLER, S. V., WALKER, D. A., NELSON, F. E. & AUERBACK, N. A. 1998. Accuracy assessment of a land-cover map of the Kuparuk river basin, Alaska: considerations for remote regions. *Photogrammetric Engineering and Remote Sensing,* 64**,** 619-628.

MUNDT, J. T., STREUTKER, D. R. & GLENN, N. F. Partial unmixing of hyperspectral imagery: theory and methods. Proceedings of the American Society for Photogrammetry and Remote Sensing, May 7-11, 2007 2007 Tampa, Florida.

MUNYATI, C., SHAKER, P. & PHASHA, M. 2011. Using remotely sensed imagery to monitor savanna rangeland deterioration through woody plant proliferation: a case study from communal and biodiversity conservation rangeland sites in Mokopane, South Africa. *Environmental Monitoring and Assessment,* 176**,** 293-311.

MUTANGA, O., ADAM, E. & ADJORLOLO, C. 2015. Evaluating the robustness of models developed from field spectral data in predicting African grass foliar nitrogen concentration using WorldView-2 image as an independent test dataset.

International Journal of Applied Earth Observation and Geoinformation, 34**,** 178-187.

MUTANGA, O. & SKIDMORE, A. 2004. Integrating imaging spectroscopy and neural networks to map grass quality in the Kruger National Park, South Africa. *Remote Sensing of Environment,* 90**,** 104-115.

MUTANGA, O., VAN, J. & KUMAR, L. 2009. Imaging spectroscopy (hyperspectral remote sensing) in southern Africa: an overview. *South African Journal of Science,* 105**,** 193-198.

NAIDOO, R. & HILL, K. 2006. Emergence of indigenous vegetation classifications through integration of traditional ecological knowledge and remote sensing analyses. *Environmental management,* 38**,** 377-387.

NAKARIYAKUL, S. & CASASENT, D. P. 2009. An improvement on floating search algorithms for feature subset selection. *Pattern Recognition,* 42**,** 1932-1940.

NANGENDO, G., SKIDMORE, A. K. & VAN OOSTEN, H. 2007. Mapping East African tropical forests and woodlands — A comparison of classifiers. *ISPRS Journal of Photogrammetry and Remote Sensing,* 61**,** 393-404.

NATIONAL ENVIRONMENTAL MANAGEMENT: BIODIVERSITY ACT 2004. South Africa. http://www.acts.co.za/national-environmental-management-biodiversity-act-2004/index.html.

NEPSTAD, D. C., BROWN, I. F., LUZ, L., ALECHANDRE, A. & VIANA, V. 1992. Biotic impoverishment of Amazonian forests by rubber tappers, loggers and cattle ranchers. *Advances in Economic Botany,* 9**,** 1-14.

O'GRADY, D., LEBLANC, M. & GILLIESON, D. 2013. Relationship of local incidence angle with satellite radar backscatter for different surface conditions. *International Journal of Applied Earth Observation and Geoinformation,* 24**,** 42-53.

OBIRI, J., LAWES, M. & MUKOLWE, M. 2002. The dynamics and sustainable use of high-value tree species of the coastal Pondoland forests of the Eastern Cape Province, South Africa. *Forest Ecology and Management,* 166**,** 131-148.

OLOFSSON, P., FOODY, G. M., HEROLD, M., STEHMAN, S. V., WOODCOCK, C. E. & WULDER, M. A. 2014. Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment,* 148**,** 42-57.

OLSEN, A. R., SEDRANSK, J., EDWARDS, D., GOTWAY, C. A., LIGGETT, W. & RATHBUN, S. 1999. Statistical issues for monitoring ecological and natural resources in the United States. *Environmental Monitoring and Assessment,* 54**,** 1–45.

OTUKEI, J. R. & BLASCHKE, T. 2010. Land cover change assessment using decision trees, support vector machines and maximum likelihood classification algorithms. *International Journal of Applied Earth Observation and Geoinformation,* 12**,** S27-S31.

OUMAR, Z. & MUTANGA, O. 2010. Predicting plant water content in Eucalyptus grandis forest stands in KwaZulu-Natal, South Africa using field spectra resampled to the Sumbandila Satellite Sensor. *International Journal of Applied Earth Observation and Geoinformation,* 12**,** 158-164.

PADALIA, H., KUDRAT, M. & SHARMA, K. P. 2013. Mapping sub-pixel occurrence of an alien invasive Hyptis suaveolens (L.) Poit. using spectral unmixing technique. *International Journal of Remote Sensing,* 34**,** 325-340.

PAZ-KAGAN, T., SHACHAK, M., ZAADY, E. & KARNIELI, A. 2014. A spectral soil quality index (SSQI) for characterizing soil function in areas of changed land use. *Geoderma,* 230–231**,** 171-184.

PEERBHAY, K. Y., MUTANGA, O. & ISMAIL, R. 2013. Commercial tree species discrimination using airborne AISA Eagle hyperspectral imagery and partial least squares discriminant analysis (PLS-DA) in KwaZulu Natal, South Africa. *ISPRS Journal of Photogrammetry and Remote Sensing,* 79**,** 19-28.

PÉREZ-ENCISO, M. & TENENHAUS, M. 2003. Prediction of clinical outcome with microarray data: a partial least squares discriminant analysis (PLS-DA) approach. *Human Genetics,* 112**,** 581-592.

PETERSEIL, J., WRBKA, T., PLUTZAR, C., SCHMITZBERGER, I., KISS, A., SZERENCSITS, E., REITER, K., SCHNEIDER, W., SUPPAN, F. & BEISSMANN, H. 2004. Evaluating the ecological sustainability of Austrian agricultural landscapes—the SINUS approach. *Land Use Policy,* 21**,** 307-320.

PETIT, S. 2009. The dimensions of land use change in rural landscapes: lessons learnt from the GB Countryside Surveys. *Journal of Environmental Management,* 90**,** 2851–2856.

PETROPOULOS, G. P., VADREVU, K. P. & XANTHOPOULOS, G. 2010. A comparison of spectral angle mapper and artificial neural network classifiers combined with Landsat TM imagery analysis for obtaining burnt area mapping. *Sensors,* 10**,** 1967-1985.

PONTIUS, R. G. & MILLONES, M. 2011. Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. *International Journal of Remote Sensing,* 32**,** 4407-4429.

PORT ST JOHN'S LOCAL MUNICIPALITY 2010. Spatial Development Framework (Review 2010). Port St John's, South Africa.

PORTER-BOLLAND, L., ELLIS, E. A., GUARIGUATA, M. R., RUIZ-MALLÉN, I., NEGRETE-YANKELEVICH, S. & REYES-GARCÍA, V. 2012. Community managed forests and forest protected areas: An assessment of their conservation effectiveness across the tropics. *Forest Ecology and Management,* 268**,** 6-17.

PU, R. 2010. Mapping urban forest tree species using IKONOS imagery: preliminary results. *Environmental Monitoring and Assessment,* 172**,** 199-214.

PUREVDORJ, T. S., TATEISHI, R., ISHIYAMA, T. & HONDA, Y. 1998. Relationships between percent vegetation cover and vegetation indices. *International Journal of Remote Sensing,* 19**,** 3519-3535.

R DEVELOPMENT CORE TEAM 2008. *R: A language and environment for statistical computing,* Vienna, R Foundation for Statistical Computing.

RAHLAO, S., MANTLANA, B., WINKLER, H. & KNOWLES, T. 2012. South Africa's national REDD+ initiative: assessing the potential of the forestry sector on climate change mitigation. *Environmental Science & …*.

RAMSEY, E. W. & JENSEN, J. R. 1996. Remote sensing of mangrove wetlands: relating canopy spectra to site-specific data. *Photogrammetric Engineering and Remote Sensing* 62**,** 939–948.

RASOLOFOSON, R. A., FERRARO, P. J., JENKINS, C. N. & JONES, J. P. G. 2015. Effectiveness of Community Forest Management at reducing deforestation in Madagascar. *Biological Conservation,* 184**,** 271-277.

RAUTIAINEN, M., NILSON, T. & LÜKK, T. 2009. Seasonal reflectance trends of hemiboreal birch forests. *Remote Sensing of Environment,* 113**,** 805-815.

RAVEN, P. H., EVERET, R. F. & EICHHORN, S. E. 2005. *Biology of Plants,* New York, W. H. Freeman.

RICHARDSON, A. D., HOLLINGER, D. Y., DAIL, D. B., LEE, J. T., MUNGER, J. W. & O'KEEFE, J. 2009. Influence of spring phenology on seasonal and annual carbon balance in two contrasting New England forests. *Tree Physiology,* 29**,** 321-331.

ROBERTS, D. A., GARDNER, M., CHURCH, R., USTIN, S., SCHEER, G. & GREEN, R. O. 1998. Mapping Chaparral in the Santa Monica Mountains Using Multiple Endmember Spectral Mixture Models. *Remote Sensing of Environment,* 65**,** 267-279.

ROBERTS, D. A., USTIN, S. L., OGUNJEMIYO, S., GREENBERG, J., DOBROWSKI, S. Z., CHEN, J. & HINCKLEY, T. M. 2004. Spectral and Structural Measures of Northwest Forest Vegetation at Leaf to Landscape Scales. *Ecosystems,* 7**,** 545-562.

ROGAN, J., FRANKLIN, J. & ROBERTS, D. A. 2002. A comparison of methods for monitoring multitemporal vegetation change using Thematic Mapper imagery. *Remote Sensing of Environment,* 80**,** 143-156.

ROMIJN, E., HEROLD, M., KOOISTRA, L., MURDIYARSO, D. & VERCHOT, L. 2012. Assessing capacities of non-Annex I countries for national forest monitoring in the context of REDD+. *Environmental Science & Policy,* 19–20**,** 33-48.

ROSENFIELD, G. H. & FITZPATRICKLINS, K. 1986. A coefficient of agreement as a measure of thematic classification accuracy. 52**,** 223-227.

ROSSO, P. H., USTIN, S. L. & HASTINGS, A. 2005. Mapping marshland vegetation of San Francisco Bay, California, using hyperspectral data. *International Journal of Remote Sensing,* 26**,** 5169-5191.

ROZENSTEIN, O. & KARNIELI, A. 2011. Comparison of methods for land-use classification incorporating remote sensing and GIS inputs. *Applied Geography,* 31**,** 533-544.

SALOVAARA, K. J., THESSLER, S., MALIK, R. N. & TUOMISTO, H. 2005. Classification of Amazonian primary rain forest vegetation using Landsat ETM+ satellite imagery. *Remote Sensing of Environment,* 97**,** 39-51.

SANSA. 2014. Eyes in the Sky inspiring the youth. Available: http://www.sansa.org.za/earthobservation/resource-centre/news/424-eyes-in-the-sky-inspiring-the-youth [Accessed 05/07/2014].

SCHMIDT, K. S. & SKIDMORE, A. K. 2003. Spectral discrimination of vegetation types in a coastal wetland. *Remote Sensing of Environment,* 85**,** 92-108.

SCHOLES, R. J. 2004. Woodlands in South Africa. *In:* LAWES, M. J., EELEY, H. A. C., SHACKLETON, C. M. & GEACH, B. G. S. (eds.) *Indigenous forests and woodlands in South Africa: policy, people and practice.* Pietermaritzburg: University of KwaZulu-Natal Press.

SCHOLES, R. J. & HALL, D. O. 1996. The carbon budget of tropical grasslands, savannas and woodlands. *In:* BREYMEYER, A. I., HALL, D. O., MELILLO, J. M. & AGREN, G. I. (eds.) *Global change: effects on coniferous forests and grasslands.* New York: John Wiley & Sons.

SCHULL, M., KNYAZIKHIN, Y., XU, L., SAMANTA, A., CARMONA, P., LEPINE, L., JENKINS, J., GANGULY, S. & MYNENI, R. 2011. Canopy spectral invariants, Part 2: Application to classification of forest types from hyperspectral data. *Journal of Quantitative Spectroscopy & Radiative Transfer,* 112**,** 736-750.

SERPICO, S. B. & BRUZZONE, L. 2001. A new search algorithm for feature selection in hyperspectral remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing,* 39**,** 1360 - 1367.

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. *The South African Journal of Science,* 100**,** 658-664.

SHACKLETON, C. M. 2001. Re-examining local and market-orientated use of wild species for the conservation of biodiversity. *Environmental Conservation,* 28**,** 270-278.

SHACKLETON, C. M., SHACKLETON, S. E., BUITEN, E. & BIRD, N. 2007a. The importance of dry woodlands and forests in rural livelihoods and poverty alleviation in South Africa. *Forest Policy and Economics,* 9**,** 558-577.

SHACKLETON, C. M., TIMMERMANS, H. G., NONGWE, N., HAMER, N. & PALMER, R. 2007b. Direct-use values of non-timber forest products from two areas on the Transkei Wild Coast. *Agrekon* 46**,** 135-156.

SHACKLETON, R., SHACKLETON, C., SHACKLETON, S. & GAMBIZA, J. 2013. Deagrarianisation and Forest Revegetation in a Biodiversity Hotspot on the Wild Coast, South Africa. *PLoS ONE,* 8.

SHAFRI, H. Z. M., SUHAILI, A. & MANSOR, S. 2007. The performance of maximum likelihood, spectral angle mapper, neural network and decision tree classifiers in hyperspectral image analysis. *Journal of Computer Science,* 3**,** 419-423.

SHALABY, A. & TATEISHI, R. 2007. Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the Northwestern coastal zone of Egypt. *Applied Geography,* 27**,** 28-41.

SHAPIRA, U., HERRMANN, I., KARNIELI, A. & BONFIL, D. J. 2013. Field spectroscopy for weed detection in wheat and chickpea fields. *International Journal of Remote Sensing,* 34**,** 6094-6108.

SIVANPILLAI, R., SRINIVASAN, R., SMITH, C. T., MESSINA, M. G. & WU, X. B. 2007. Estimating regional forest cover in East Texas using Advanced Very High Resolution Radiometer (AVHRR) data. *International Journal of Applied Earth Observation and Geoinformation,* 9**,** 41-49.

SMITS, P. C. & DELLEPIANE, S. G. 1999. Quality assessment of image classification algorithms for land-cover mapping: a review and a proposal for a cost-based approach. *International Journal of Remote Sensing,* 20**,** 1461-1486.

SOHN, Y. & REBELLO, N. S. 2002. Supervised and unsupervised spectral angle classifiers. *Photogrammetric Engineering and Remote Sensing,* 68**,** 1271-1280.

SOMERS, B. & ASNER, G. P. 2013. Invasive Species Mapping in Hawaiian Rainforests Using Multi-Temporal Hyperion Spaceborne Imaging Spectroscopy. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing,* 6**,** 351-359.

SOUTH AFRICA 1998. National Forests Act, . *No. 84 of 1998.* Pretoria: Government Printer.

SREEKALA, G. B. & SUBODH, S. K. 2011. Hyperspectral Data Mining. *Hyperspectral Remote Sensing of Vegetation.* CRC Press.

STAHL, G., ALLARD, A., ESSEEN, P. A., GLIMSKAR, A. O., HEDSTROM, R. A. & SVENSSON, J. 2011. National inventory of landscapes in Sweden (NILS)—scope, design and experiences from establishing a multiscale biodiversity monitoring system. *Environmental Monitoring and Assessment,* 17**,** 579–595.

STATISTICS SA. 2011a. Nyandeni Local Municipality. Available: http://beta2.statssa.gov.za/?page_id=993&id=nyandeni-municipality.

STATISTICS SA. 2011b. Port St John's Local Municipality. Available: http://beta2.statssa.gov.za/?page_id=993&id=port-st-johns-municipality [Accessed 31/04/2014].

STEELE, B. M. 2000. Combining multiple classifiers: an application using spatial and remotely sensed information for land cover type mapping. *Remote sensing of environment,* 74**,** 545-556.

STUMPF, A., MALET, J. P., ALLEMAND, P. & ULRICH, P. 2014. Surface reconstruction and landslide displacement measurements with Pléiades satellite images. *ISPRS Journal of Photogrammetry and Remote Sensing,* 95**,** 1-12.

SUNDERLIN, W. D., ANGELSEN, A., BELCHER, B., BURGERS, P., NASI, R., SANTOSO, L. & WUNDER, S. 2005. Livelihoods, forests, and conservation in developing countries: An Overview. *World Development,* 33**,** 1383-1402.

TAN, K. C., LIM, H. S. & JAFRI, M. Z. M. Comparison of neural network and maximum likelihood classifiers for land cover classification using landsat multispectral data. IEE Conference on Open Systems, September 25 - 28, 2011 Langkawi, Malayia. IEEE, 241-244.

TEGLER, B., SHARP, M. & JOHNSON, M. A. 2001. Ecological monitoring and assessment network's proposed core monitoring variables: an early warning of environmental change. *Environmental Monitoring and Assessment,* 67**,** 29–56.

THOMLINSON, J. R., BOLSTAD, P. V. & COHEN, W. B. 1999. Coordinating methodologies for scaling landcover classifications from site-specific to global: Steps toward validating global map products. *Remote Sensing of Environment,* 70**,** 16-28.

THORP, K. R., FRENCH, A. N. & RANGO, A. 2013. Effect of image spatial and spectral characteristics on mapping semi-arid rangeland vegetation using multiple endmember spectral mixture analysis (MESMA). *Remote Sensing of Environment,* 132**,** 120-130.

TILLACK, A., CLASEN, A., KLEINSCHMIT, B. & FÖRSTER, M. 2014. Estimation of the seasonal leaf area index in an alluvial forest using high-resolution satellite-based vegetation indices. *Remote Sensing of Environment,* 141**,** 52-63.

TOMPKINS, S., MUSTARD, J. F., PIETERS, C. M. & FORSYTH, D. W. 1997. Optimization of endmembers for spectral mixture analysis. *Remote Sensing of Environment,* 59**,** 472-489.

TOWNSEND, P. A. & WALSH, S. J. 2001. Remote sensing of forested wetlands: application of multitemporal and multispectral satellite imagery to determine plant community composition and structure in southeastern USA. *Plant Ecology,* 157**,** 129-149.

TRIMBLE, M. & VAN AARDE, R. 2011. Decline of birds in a human modified coastal dune forest landscape in South Africa. *PloS One,* 6.

TSAI, F., LIN, E. K. & YOSHINO, K. 2007. Spectrally segmented principal component analysis of hyperspectral imagery for mapping invasive plant species. *International Journal of Remote Sensing,* 28**,** 1023-1039.

TSO, B. & MATHER, M. P. 2001. *Classification Methods for Remotely Sensed Data,* London, Taylor and Francis.

UN-REDD 2012. UN-REDD Programme.

VAIPHASA, C., ONGSOMWANG, S., VAIPHASA, T. & SKIDMORE, A. K. 2005. Tropical mangrove species discrimination using hyperspectral data: A laboratory study. *Estuarine, Coastal and Shelf Science,* 65**,** 371-379.

VAIPHASA, C., SKIDMORE, A., BOER, W. & VAIPHASA, T. 2007. A hyperspectral band selector for plant species discrimination. *ISPRS Journal of Photogrammetry and Remote Sensing,* 62**,** 225-235.

VENABLES, W. N. & RIPLEY, B. D. 2002. *Modern Applied Statistics with S,* London, Springer.

VIERA, A. J. & GARRETT, J. M. 2005. Understanding interobserver agreement: the kappa statistic. *Fam Med,* 37**,** 360-363.

VISSER, F., WALLIS, C. & SINNOTT, A. M. 2013. Optical remote sensing of submerged aquatic vegetation: opportunities for shallow clearwater streams. *Ecology and Managemqent of Inland Waters,* 43**,** 388-398.

VON MALTITZ, G., MUCINA, L., GELDENHUYS, C., LAWES, M., EELEY, H., ADIE, H., VINK, D., FLEMMING, G. & BAILEY, C. 2013. Classification system for South African indigenous forests: An objective classification for the Department of Water Affairs and Forestry. *Environmentek Report ENV-P-C 2003-017.* Pretroria: CSIR.

VRINDTS, E., BAERDEMAEKER, D. J. & RAMON, H. 2002. Weed detection using canopy reflection. *Precision Agriculture,* 3**,** 63-80.

VYAS, D., KRISHNAYYA, N. S. R., MANJUNATH, K. R., RAY, S. S. & PANIGRAHY, S. 2011. Evaluation of classifiers for processing Hyperion (EO-1) data of tropical vegetation. *International Journal of Applied Earth Observation and Geoinformation,* 13**,** 228-235.

WALFORD, N. 2011. *Practical Statistics for Geographers and Earth Scientists,* Chichester, J. Wiley.

WALKER, J. J., DE BEURS, K. M., WYNNE, R. H. & GAO, F. 2012. Evaluation of Landsat and MODIS data fusion products for analysis of dryland forest phenology. *Remote Sensing of Environment,* 117**,** 381-393.

WANG, F. 1990. Fuzzy supervised classification of remote sensing images. *IEEE Transactions on Geoscience and Remote Sensing,* 28**,** 194-201.

WANG, L. & JIA, X. 2009. Integration of soft and hard classifications using extended support vector machines. *Geoscience and Remote Sensing Letters,* 6.

WANG, L., SOUSA, W. P., GONG, P. & BIGING, G. S. 2004. Comparison of IKONOS and QuickBird images for mapping mangrove species on the Caribbean coast of Panama. *Remote Sensing of Environment,* 91**,** 432-440.

WEATHERSA 2014. How are the dates of the four seasons worked out? : South African Weather Service.

WENG, Q. & LU, D. 2008. A sub-pixel analysis of urbanization effect on land surface temperature and its interplay with impervious surface and vegetation coverage in Indianapolis, United States. *International Journal of Applied Earth Observation and Geoinformation,* 10**,** 68-83.

WILLIAMS, P. A. & JR, H. E. R. 2002. Estimation of leafy spurge cover from hyperspectral imagery using mixture tuned matched filtering. *Remote Sensing of Environment,* 82**,** 446-456.

WILLIAMS PARKER, A. J. & HUNT, E. R. J. 2002. Estimation of leafy spurge cover from hyperspectral imagery using mixture tuned matched filtering. *Remote Sensing of Environment,* 82**,** 446-456.

WOODCOCK, C. & HARWARD, V. J. 1992. Nested-hierarchical scene models and image segmentation. *International Journal of Remote Sensing,* 13**,** 3167-3187.

WOODSTOCK, C. U., MACOMBER, S. A. & KUMAR, L. 2002. Vegetation mapping and monitoring. *In:* SKIDMORE, A. (ed.) *Environmental Modelling with GIS and Remote Sensing.* London: CRC Press.

WU, C., GONSAMO, A., GOUGH, C. M., CHEN, J. M. & XU, S. 2014. Modeling growing season phenology in North American forests using seasonal mean vegetation indices from MODIS. *Remote Sensing of Environment,* 147**,** 79-88.

WU, H. & LI, Z. L. 2009. Scale issues in remote sensing: A review on analysis, processing and modeling. *Sensors,* 9**,** 1768-1793.

WULDER, M., NELSON, T. & SEEMANN, D. 2007. Using spatial pattern to quantify relationship between samples, surroundings, and populations. *Environmental Monitoring and Assessment,* 131**,** 221-230.

XU, C., LI, Y., HU, J., YANG, X., SHENG, S. & LIU, M. 2012. Evaluating the difference between the normalized difference vegetation index and net primary productivity as the indicators of vegetation vigour assessment at landscape scale. *Environmental Monitoring and Assessment,* 184**,** 1275-1286.

YAGOUB, H., BELBACHIR, A. H. & BENABADJI, N. 2014. Detection and mapping vegetation cover based on the Spectral Angle Mapper algorithm using NOAA AVHRR data. *Advances in Space Research,* 53**,** 1686-1693.

YOCCOZ, N. G., NICHOLS, J. D. & BOULINIER, T. 2001. Monitoring of biological diversity in space and time. *Trends in Ecology & Evolution,* 16**,** 446-453.

YU, Q., GONG, P., CLINTON, N., BIGING, G., KELLY, M. & SCHIROKAUER, D. 2006. Object-based detailed vegetation classification with airborne high spatial resolution remote sensing imagery. *Photogrammetric Engineering and Remote Sensing,* 72**,** 799-811.

YUAN, L., ZHANG, J. & SHI, Y. 2014. Damage mapping of powdery mildew in winter wheat with high-resolution satellite image. *Remote Sensing,* 6**,** 3611-3623.

ZAK, M. R., CABIDO, M. & HODGSON, J. G. 2004. Do subtropical seasonal forests in the Gran Chaco, Argentina, have a future? *Biological conservation,* 120**,** 589-598.

ZHANG, F., TIYIP, T., DING, J., SAWUT, M., TASHPOLAT, N., KUNG, H., HAN, G. & GUI, D. 2012. Spectral reflectance properties of major objects in desert oasis: a case study of the Weigan-Kuqa river delta oasis in Xinjiang, China. *Environmental Monitoring and Assessment,* 184**,** 5105-5119.

ZHANG, X. & GOLDBERG, M. D. 2011. Monitoring fall foliage coloration dynamics using time-series satellite data. *Remote Sensing of Environment,* 115**,** 382-391.

ZHU, H. 2005. Linear spectral unmixing assisted by probability guided and minimum residual exhaustive search for subpixel classification. *International Journal of Remote Sensing,* 26**,** 5585-5601.

ZOMER, R., TRABUCCO, A. & USTIN, S. 2009. Building spectral libraries for wetlands land cover classification and hyperspectral remote sensing. *Journal of Environmental Management,* 90**,** 2170-2177.

ZWIGGELAAR, R. 1998. A review of spectral properties of plants and their potential use for crop/weed discrimination in row-crops. *Crop Protection,* 17**,** 189-206.

Appendices

Appendix 1: Additional Results (Per-pixel classification)

The following results are confusion matrices for the individual classification algorithms of 2013 SPOT 6 image.

Table 10.1: Confusion matrix for MLC classification on the 2013 SPOT 6 image.

	Ground Truth					
Class	**grassland**	**subtropical forest**	**woodland**	**Total**	**Producer's Accuracy**	**User's Accuracy**
grassland	7	1	0	**8**	0.88	0.88
subtropical forest	0	52	2	**54**	0.91	0.96
woodland	1	4	4	**9**	0.67	0.44
Total	**8**	**57**	**6**	**71**		

Overall Accuracy 88.73 %, Kappa coefficient 0.69

Table 10.2: Confusion matrix for MD classification on the 2013 SPOT 6 image

	Ground Truth					
Class	**grassland**	**subtropical forest**	**woodland**	**Total**	**Producer's Accuracy**	**User's Accuracy**
grassland	6	1	0	**7**	75	85.71
subtropical forest	1	25	3	**29**	43.86	86.2069
woodland	0	19	0	**19**	26.76	0
Other classes	1	12	3	**16**		
Total	**8**	**57**	**6**	**71**		

Overall accuracy 43.66, Kappa coefficient 0.18

Table 10.3: Confusion matrix for SAM classification on the 2013 SPOT 6 image

	Ground Truth					
Class	**grassland**	**subtropical forest**	**woodland**	**Total**	**Producer's Accuracy**	**User's Accuracy**
grassland	3	2	0	**5**	37.5	60
subtropical forest	0	27	6	**33**	47.37	81.82
woodland	2	22	0	**24**	0	0
Other classes	3	6	0	**9**		
Total	**8**	**57**	**6**	**71**		

Overall accuracy 42.25, Kappa coefficient 0.004

Table 10.4: Confusion matrix for SID classification on the 2013 SPOT 6 image

	Ground Truth					
Class	**grassland**	**subtropical forest**	**woodland**	**Total**	**Producer's Accuracy**	**User's Accuracy**
grassland	5	5	5	**15**	62.5	33.33
subtropical forest	2	18	1	**21**	31.58	85.71
woodland	0	32	0	**32**	0	0
Other classes	1	2	0	**3**		
Total	**8**	**57**	**6**	**71**		

Overall Accuracy 32.39 %, Kappa coefficient 0.0353

Appendix 2: Additional Results (Sub-pixel classification)

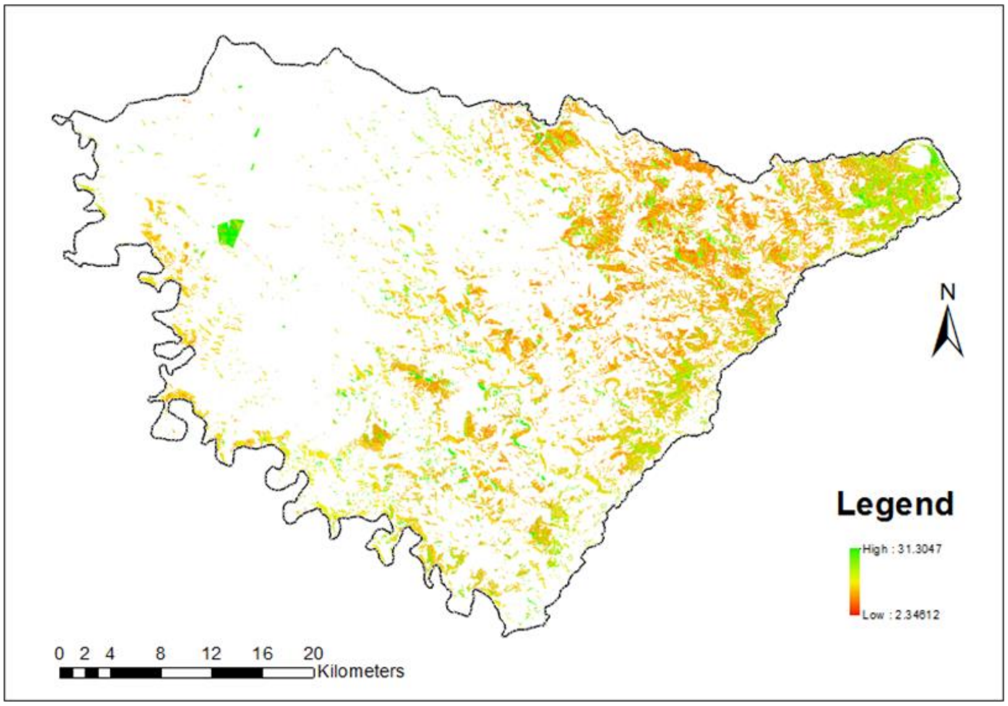

Figure 10.1: Semi-deciduous infeasibility map

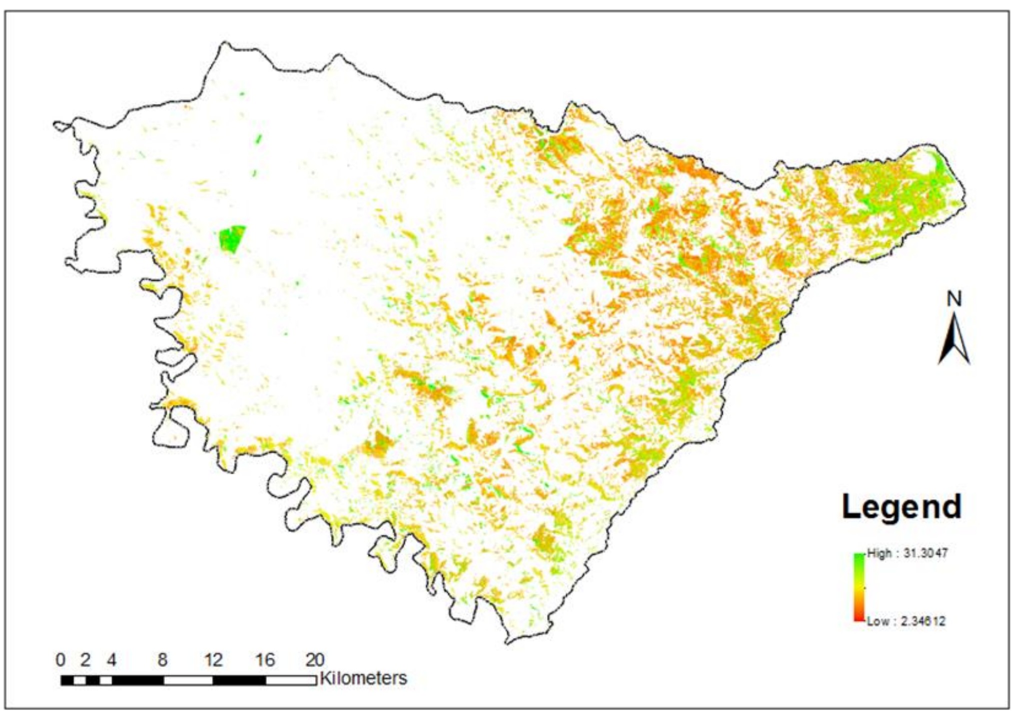

Figure 10.2: Evergreen infeasibility map