Discriminating wetland vegetation species in an African savanna using hyperspectral data

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Submitted in fulfilment of the academic requirements for the degree of Master of
Science in the Discipline of Geography in the
School of Environmental Sciences, Faculty of Science and Agriculture.

University of KwaZulu-Natal,
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May 2010

Declaration

This study was undertaken in fulfillment of a Geography Masters Degree and represents the original work of the author. Any work taken from other authors or organizations is duly acknowledged within the text and references chapter.

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Pride Mafuratidze

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Supervisor: Professor Onisimo Mutanga

Dedication

Dedicated to my wife Loreen and our son Panashe

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Abstract

Wetland vegetation is of fundamental ecological importance and is used as one of the vital bio-indicators for early signs of physical or chemical degradation in wetland systems. Wetland vegetation is being threatened by expansion of extensive lowland areas of agriculture, natural resource exploitation, etc. These threats are increasing the demand for detailed information on vegetation status, up-to-date maps as well as accurate information for mitigation and adaptive management to preserve wetland vegetation. All these requirements are difficult to produce at species or community level, due to the fact that some parts of the wetlands are inaccessible. Remote sensing offers non-destructive and real time information for sustainable and effective management of wetland vegetation. The application of remote sensing in wetland mapping has been done extensively, but unfortunately the uses of narrowband hyperspectral data remain unexplored at an advanced level. The aim of this study is to explore the potential of hyperspectral remote sensing for wetland vegetation discrimination at species level. In particular, the study concentrates on enhancing or improving class separability among wetland vegetation species. Therefore, the study relies on the following two factors; a) the use of narrowband hyperspectral remote sensing, and b) the integration of vegetation properties and vegetation indices to improve accuracy. The potential of vegetation indices and red edge position were evaluated for vegetation species discrimination. One-way ANOVA and Canonical variate analysis were used to statistically test if the species were significantly different and to discriminate among them. The canonical structure matrix revealed that hyperspectral data transforms can discriminate vegetation species with an overall accuracy around 87%. The addition of biomass and water content variables improved the accuracy to 95.5%. Overall, the study demonstrated that hyperspectral data and vegetation properties improve wetland vegetation separability at species level.

Acknowledgments

Firstly, I would like to thank almighty God who gave me the strength, health, and wisdom to finish this research. Also, there are so many people who left what they were doing just to give advice and assist me in completing this project.

Without Professor Onisimo Mutanga, my supervisor, who acted as a friend and brother during my M Sc research, this could not have been done. Sometimes I was hesitant to give him my drafts for his critical comments, but his comments, support, guidance, and assistance helped me to understand and extend my scientific reasoning.

I would also like to thank Elhadi Adam, as a friend and a colleague. His assistance in providing the fieldwork data and ideas made my life easier and his critical comments are really appreciated.

I extend my gratitude to Land Resources International (LRI), especially James Broadie and Rory Hickson who gave me the opportunity to study and get work experience at the same time.

Many thanks to Dr Riyad Ismail, Zakariyyaa Oumar, Mohammed Oumar, Vimbai Rachel Jenjezwa and Moses Azong Cho for assisting me with all the scientific techniques and methods which were used to complete this study.

I would also like to thank my family and friends for their moral support and encouragement.

Finally, I thank my wife, Loreen, for giving me her tender love and support. I also thank her for her prayers.

List of abbreviations

ANOVA	Analysis of Variance
ASD	Analytical Spectral Device
AVHRR	Advanced Very High Resolution Radiometer
CASI	Compact Airborne Spectrographic Imager
CI	Carter Index
CVA	Canonical Variate Analysis
DW	Dry Weight
GMI	Gitelson and Merzylak Index
LAI	Leaf Area Index
LE1	Linear Extrapolation
LIDAR	Light Detection and Ranging
Lin-Inter	Linear Interpolation
MFD	Maximum First Derivative
MIR	Mid-Infrared
NIR	Near-Infrared
NDVI	Normalized Difference Vegetation Index
RADAR	Radio Detection and Ranging
REP	Red Edge Position
RESP	Red Edge Spectral Parameter
ROSIS	Reflective Optics System Imaging Spectrometer
PWC	Plant Water Content
SR	Simple Ratio
SWIR	Shortwave Infrared
TIR	Thermal Infrared
TVI	Transformed Vegetation Index
VIs	Vegetation Indices
VNIR	Visible and Near-infrared
VOG_a	$Vogelmann_a$
W	Leaf Sample Weight

Chapter One:

Introduction

1.1 Background

Wetlands in an African savanna are alluring, dynamic, and complex unique natural systems that provide substantive hydrological systems, biological and ecological diversity (Kotze and Breen, 1994; UNESCO, 2008). A ‘wetland’ is defined as a land where the water table is usually at or near the surface or which is saturated for long enough period to promote features such as water tolerant vegetation that can survive in wet-altered soils (Cowardin *et al.*, 1979). There are many types of wetlands including springs, mires, bogs, floodplains, coral reefs, long sand beaches, vleis, seeps, extensive reed and papyrus swamps, coastal lakes, estuaries, and mangrove swamps (Collins, 2001; Schmidt and Skidmore, 2003; UNESCO, 2008). These wetlands are hard-working ecosystems that provide a critical habitat for fauna and flora including vegetation species and wildlife animals (Collins, 2001).

There are approximately 120 000 wetlands in South Africa that cover approximately 7% of South Africa’s surface area (Wetlands South Africa, 2009). From those 120 000 wetlands mapped by the National Wetland Inventory in South Africa, only 12 sites have been recognised by the Ramsar Convention (Ramsar, 1971), including the iSimangaliso Wetland Park in KwaZulu-Natal, Langebaan on the west coast in the Western Cape, Barberspan in North West Province, Blesbokspruit in Gauteng, and De Hoop vlei in the Cape (Wetlands South Africa, 2009). Wetlands are essential in an arid, water-scarce country such as South Africa, yet an estimated 30% to 60% of South Africa’s wetlands have been destroyed by housing, roads, infrastructure, and agricultural development (Kotze and Breen, 1994; Begg, 1989; Working for wetlands in SANPARKS, 2004). Due to the limited availability of valuable information in South Africa on the distribution and state of wetlands, it is a serious impediment for the adequate identification, monitoring, protection, and management of wetland resource.

Mapping and assessment of wetlands require a greater understanding of the following three variables: wetland (hydrophytic) vegetation, hydric soil, and wetland hydrology (Mitsch and Gosselink, 1993; Collins, 2001). In the case of iSimangaliso Wetland Park, the problem of extensive lowland areas for agriculture and natural resource exploitation is affecting the hydrology and salinity of the wetland system (Kotze and Breen, 1994). Also the land use changes within certain parts of the park are related to the closure of the iSimangaliso Wetland Park estuary mouth by sedimentation, and the reduction in the supply of critical resources (Collins, 2001).

The effects of the above mentioned problems can only be noticed through ecological changes. Hydrophytic vegetation is of fundamental ecological importance and is used as one of the vital bio-indicators for early signs of any physical or chemical degradation in wetland systems (Demuro and Chisholm, 2003; Belluco *et al.*, 2006; Adam and Mutanga, 2009). Therefore, acquiring accurate information for identification and monitoring of vegetation species distribution and quantity is an important technical task for sustainable management of wetlands (Schmidt and Skidmore, 2003). As a result, the spectral response of floristic characteristics of wetlands play a vital role in monitoring water quality, environment stress management, natural resource inventory and managing human impacts on wetlands (Mitsch and Gosselink, 1993; Van Aardt and Waynne, 2001; Adam and Mutanga, 2009).

Schmidt and Skidmore (2003), Vaiphasa *et al.* (2005), and Adam and Mutanga (2009) suggest that protection and restoration programmes of wetland vegetation require up-to-date spatial and taxonomic information. Previously, researchers and scientists had been using optical interpretation and prior knowledge of vegetation to provide qualitative assessments of vegetation characteristics (Clark *et al.*, 2005). In addition, these researchers used traditional floristic mapping methods which are labour-intensive, time-consuming and expensive. Also, some places are inaccessible since most wetlands are waterlogged and swampy, which allows only a small area to be covered for study (Lee and Lunetta, 1996; Schmidt and Skidmore, 2003; Adam and Mutanga, 2009).

One of the most important tools that are being used to monitor changes in wetland vegetation is remote sensing (Kotze *et al.*, 1995; Lee and Lunetta, 1996; Schmidt and

Skidmore, 2003; Xie *et al*., 2008). The introduction of remote sensing in vegetation studies has brought the uses of a non-destructive and direct method of assessing and monitoring vegetation species from local to global scales (Datt, 1999). Adam and Mutanga (2009) recognised that remote sensing offers a practical and cost-effective means to quantify and discriminate the vegetation parameters of the vegetation species as well as making field sampling more focused and efficient. Satellite or airborne imagery provides permanent records useful for monitoring the extent, type, and location of environmental changes in wetland communities (Datt, 1999). Since the early 1980s, remotely sensed imagery has become commonly used to improve identification of vegetation species (Howland, 1980; Begg, 1989; Kotze *et al.*, 1995; Green *et al.*, 1998; Asner *et al.*, 2000; Curran *et al.*, 2001; Hirano *et al.*, 2003; Mutanga *et al.*, 2003; Schmidt and Skidmore, 2003; Xie *et al*., 2008; Adam and Mutanga, 2009).

Multispectral remote sensing has been widely used to monitor vegetation status, but unfortunately this system has limited capability for accurate identification of vegetation species. Due to its coarse spectral resolution it creates ambiguous differentiation among vegetation species (Schmidt and Skidmore, 2003). Multispectral sensors cannot effectively determine either the fine scale spatial heterogeneousness or narrow ecotones common in most wetlands (Siciliano *et al.*, 2008). Multispectral data provide a wider view and lower cost needed for its application in different vegetation studies, but have shown ineffectiveness when distinguishing vegetation species (Ndzeidze, 2008).

However, over the past few decades, advances in sensor technology have improved remote sensing and discrimination of wetland vegetation at species level, with the development of hyperspectral sensors. In contrast to data from multispectral remote sensing, hyperspectral data are of high spectral resolution of narrow channels less than 10 nm and the data consist of a large number of very narrow contiguous bands between 350 nm and 2500 nm in the electromagnetic spectrum (Kokaly and Clark, 1999; Van Aardt and Waynne, 2001; Kokaly, 2001). With the help of hyperspectral remote sensing, vegetation parameters such as biomass (Tucker, 1979; Sun *et al.*, 1991; Moreau and Toan, 2003; Mutanga and Skidmore, 2004) and water content (Cochrane, 2000; Mutanga *et al.*, 2003) have been accurately measured and quantified. These narrow spectral bands also allow the detection of fine details of vegetation species, which could otherwise be masked by broadband sensors (Schmidt and Skidmore, 2003; Mutanga *et al.*, 2003).

Since wetlands are waterlogged and swampy, the spectral reflectance will be affected by atmospheric interference, soil background, and segmental water, which eventually lead to spectral noise. To overcome this problem, this study concentrated on the red edge region (680nm to 750 nm) which is insensitive to soil background and atmospheric interferences (Guyot *et al.,* 1992; Clevers, 1999; Mutanga and Skidmore, 2007; Cho, 2007). Red edge is defined as the wavelength of the inflection point of reflectance slope that is located between the red trough and near infrared (NIR) plateau (Collins, 1978; Curran *et al.,* 2001; Mutanga, 2004). The second method was the application of vegetation properties to enhance the spectral separability among the vegetation species that ultimately increases the accuracy.

Biophysical and biochemical parameters have an impact on discriminating wetland species since they vary as a function of plant species and hydrologic regime (Mutanga and Skidmore, 2004; Curran *et al.,* 2001; Pu *et al.,* 2003). This was supported by Schmidt and Skidmore (2003), who point out that all vegetation contains similar biochemical constituents, but these vary in their proportions (in terms of absorption and reflectance). The variation in those proportions is what is used to discriminate different plants even if they receive the same amount of water as in the case of a wetland.

However, to date, there are no studies to the best of our knowledge that have been undertaken to establish what the effects of these vegetation properties are on spectral reflectance of wetland vegetation. Most previous studies have concentrated on mapping and discriminating wetland vegetation species rather than investigating the effects of vegetation properties on reflectance spectra (Asner and Martin, 2008). In the present research, because of time constraints, only biomass and water content variables were investigated.

Most of the wetlands in iSimangaliso Wetland Park receive varying amounts of rainfall throughout the year that means all the plant absorbs different amount of water per given area. Since the most abundant chemical in leaves is water that may constitute up to 70% (Kokaly *et al.,* 2009; Ustin *et al.,* 2004; Vaiphasa *et al.,* 2005; Asner and Martin, 2008), quantification of canopy water content can be very useful. Every vegetation species absorbs and stores water differently; hence the variation in plant water content can be used as a means to discriminate wetland plants using hyperspectral remote sensing (Collins, 1978; Jago and Curran, 1995). Asner and Vitousek (2005) managed to detect and distinguish two invasive nitrogen fixer and understory herb species, *Morella faya* and *Hedychium gardnerianum*, using quantification of foliar nitrogen and plant water content.

However, most of the previous researchers' conclusions on the aboveground biomass and water content quantification are not directly applicable to wetland vegetation discrimination at species level. Also, when discriminating vegetation species, raw data (bands) might not be effective because of overlap and noise that is associated with other parts of the electromagnetic spectrum. Moreover, when detecting spectral reflectance of submerged aquatic vegetation at any scale, variation in biophysical and biochemical properties must be considered.

It is critical to note that hyperspectral remote sensing has focussed on the estimation of both biochemical properties and biophysical properties of vegetation or species discrimination independently, without a clear cut attempt to integrate the products in improving species mapping. Several maps, algorithms and models have now been developed to predict biomass and other structural properties of vegetation at reasonable accuracies. The question is, can the integration of this available ancillary information with hyperspectral data improve species discrimination?

The main aim of this study was to investigate the potential of hyperspectral remote sensing (using field spectrometry) for vegetation species discrimination at field level. In particular, leaf spectral reflectance at canopy level of four wetland vegetation species was measured for spectral separability. To test the utility of ancillary vegetation structural information, this study quantified vegetation properties (plant water content and aboveground biomass) and combined them with hyperspectral data in discriminating vegetation species. The study sets itself to the following aim and objectives.

1.2 Aim and objectives

Based on the issues articulated above, the research will focus on the potential of the red edge position to identify and map different wetland vegetation at species level using hyperspectral data. The main objectives are:

- to evaluate the ability of hyperspectral remote sensing data in discriminating wetland vegetation at species level using the red edge position,
- to test and compare the performance of the red edge position against other vegetation indices,
- to test different red edge extraction techniques to distinguish hydrophytic vegetation, and
- to investigate if there is an improvement in species discrimination by combining vegetation structural and biochemical characteristics with hyperspectral data.

1.3 Research questions

i. How useful are red edge parameters to wetland vegetation discrimination at species level as compared to other vegetation indices?

ii. Which hyperspectral vegetation indices can be used to discriminate wetland vegetation species calculated from wavelengths in the red edge region?

iii. How important are quantified biochemical and biophysical properties of vegetation on vegetation discrimination at species level?

1.4 Study area

Lake St Lucia was declared South Africa's first Natural World Heritage Site by UNESCO on 1 December 1999, and its name was changed to Greater St Lucia Wetland Park which was then renamed on 1 November 2007 to iSimangaliso Wetland Park. This was done in an effort to give the wetland a unique African identity. The wetland site is registered under one of the Ramsar sites. This large wetland area has 280km² of near pristine terrestrial, wetland, estuarine, coastal, and marine environments, and it covers about 328 000 hectares which is why it is regarded as the largest estuarine area on the African continent. The iSimangaliso Wetland Park is located between Maphelana in the south and Kosi Bay near the border of Mozambique in the north, and it is between longitudes 32º21′ and 32º 34′ E latitudes 27 º 34′S and 28 º 24′ S as shown in Figure 1.1. It has a mean annual temperature of about 21 °C. Around the iSimangaliso Wetland Park, rainfall is not available throughout the year and it is spatially highly variable in the Park. Depending on the location in the park, rainfall ranges from 1200mm to 1300 mm per annum with approximately 60 % of the rainfall in summer (UNESCO, 2008).

The park supports extraordinary ecological and biological diversity due to its location that is between tropical and subtropical biota (Collins, 2001). In the iSimangaliso Wetland Park, there are many different wetland vegetation species including those in salt marshes (e.g. *Juncus krausii, Salicornia spp., and Ruppia maritima*); Saline reed swamps (*Phragmites mauritianus*); Sedge Swamp (*Eleocharis limosa*) and Echinochloa floodplain grassland (*Echinochloa pyramidalis, Eriochloa spp., and Cyperus spp*.), but the most dominant species are found in freshwater reed and papyrus swamps (*Phragmites australis and Cyperus papyrus*). In total, four species were identified as being the most common species that generally grow at the same place. These were *Cyperus papyrus, Phragmites australis, Echinochloa pyramidalis,* and *Thelypteris interrupta*. *Cyperus papyrus* and *Phragmites australis* cover approximately 7 000ha in the Park.

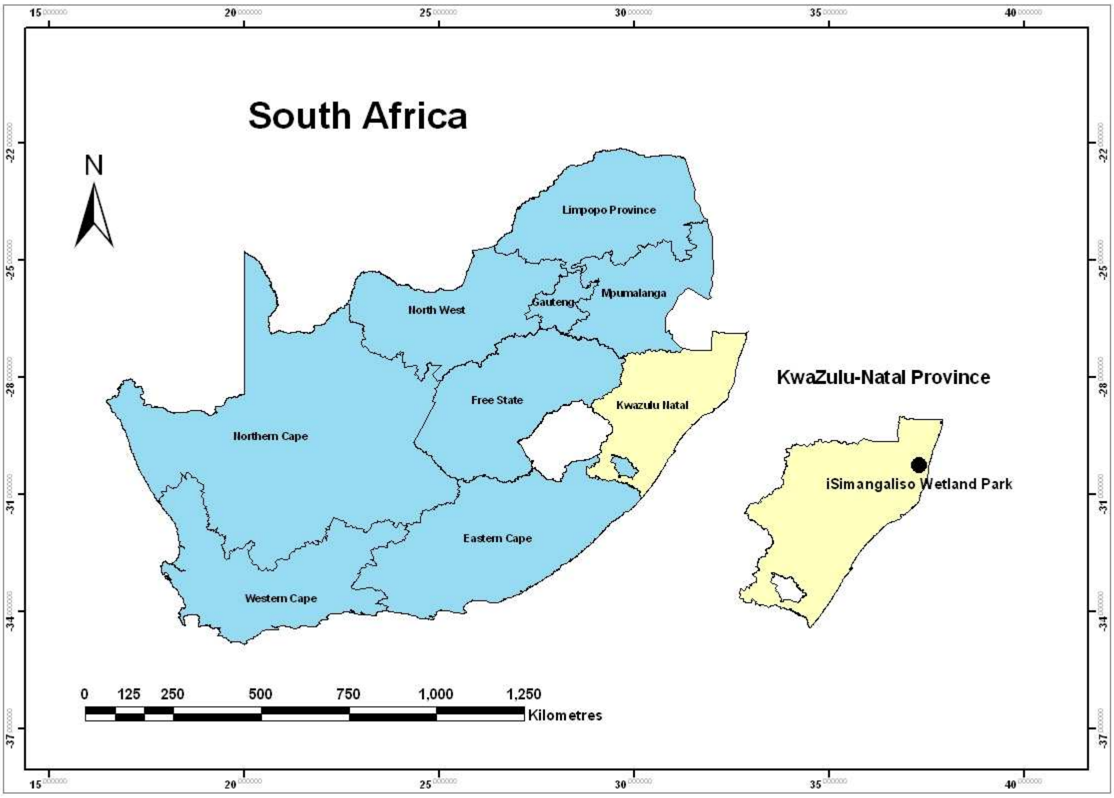


Figure 1.1 The location of the study area iSimangaliso Wetland Park in KwaZulu-Natal Province, South Africa.

1.5 Thesis outline

In Chapter 1 background is provided of wetlands' vegetation and the importance of remote sensing, especially the availability of narrow bands (data). In Chapter 2, the review of literature regarding application of remote sensing in wetland vegetation is summarised and the potential of hyperspectral technology for discriminating wetland vegetation at the species level is demonstrated. The possibility of using vegetation properties (biochemical and biophysical properties) in vegetation species discrimination is also discussed.

In Chapter 3 the methods used to carry out the research are discussed. An explanation is given of how the field spectral measurements, aboveground biomass, plant water content, vegetation indices, and red edge position were calculated. All the statistical analysis methods used to check if there were significant differences between wetland vegetation species are outlined. The use of discriminant analysis techniques in differentiating vegetation species is also investigated.

In Chapter 4 the results of the relationship between spectral reflectance, vegetation indices, and the red edge position are summarized. A comparison between vegetation indices and the red edge derivatives in discriminating wetland vegetation at species level is also done in this chapter. In Chapter 5 the results of discriminating wetland vegetation at species level using vegetation indices and vegetation properties is provided. These two chapters are in the form of articles for publication.

In Chapter 6 the research is summarized and the aim and objectives of the thesis are synthesized.

Chapter Two:

Literature Review

2.1 Introduction

The wetlands of the iSimangaliso Wetland Park are important as productive natural ecosystem remnants offering wildlife habitat, tourist destinations, and water quality at a given time or over a continuous period. Wetland vegetation has compositional and structural characteristics that provide specialized habitats for a range of important wetland-dependent species. Wetland vegetation may also provide a range of locally important goods for local communities such as reeds for weaving, grazing areas for domestic stock, and services to downstream users such as flood attenuation and nutrient retention (Kotze and Breen, 1994; Schmidt and Skidmore, 2003; Working for Wetlands in SANPARKS, 2004).

However, in the iSimangaliso Wetland Park, problems such as drainage of extensive lowland areas for agriculture and the exploitation of natural resources are affecting the hydrology and salinity of the wetland system. The other problems that affect the iSimangaliso Wetland Park ecology is the land use changes within certain parts of the park related to the closure of the estuary mouth by sedimentation, and the reduction in the supply of critical resources. The threat arose from the transformation of the upper portion of the Mfolozi Swamps by agriculture (Collins, 2001; UNEP, 2001). Schmidt and Skidmore (2003) suggest that there are long-term threats to wetlands that require an investigation into vegetation species that are available right now and these threats include pollution, sea level rise, climatic change, and ground subsidence from gas extraction.

Wetland vegetation has undergone considerable changes and most wetlands are rapidly being lost or degraded because of human activities, which bring the need to protect and preserve them (Dini *et al.,* 1998). A thorough understanding of relationships between vegetation species distribution and accurate knowledge is vital for the development, implementation, and monitoring of wetland vegetation (Dini *et al.,* 1998; Schmidt and Skidmore, 2003). When working with wetland vegetation for management of sustainability and integrated wetland conservation strategies, the most important thing is the acquisition of accurate knowledge about the natural relationships of plants because it makes the interpretation of structure, development, and distribution of ecological plant communities in the landscape much easier based on the study of plant groups (Schmidt and Skidmore, 2003). This led to the introduction of remote sensing which has been used for a long time to monitor vegetation status.

2.2 Remote sensing and spectral characteristics of wetland vegetation

Specifically, remote sensing data is acquired using hand held spectrometers, aerial photography, and airborne or satellite sensors based on the detection of electromagnetic radiation (Provoost *et al.*, 2005; Curran *et al.,* 1990). Currently, there are two main techniques used to acquire remote sensing data, namely, active sensors and passive sensors. Active sensors (LIDAR and RADAR) are systems that emit energy that is directed at a target and later measure the return signal after the target reflects energy back to the sensor. Passive sensors measure solar energy that is naturally available. Passive sensors are the most common sensors used for the acquisition of detailed data on vegetation species.

The electromagnetic waves emitted by the sun are partially absorbed, partially transmitted, and partially reflected by the different materials on the earth’s surface (Provoost *et al.,* 2005; Lillesand and Kiefer, 1994). Remote sensing data offer the opportunity to detect these signals that are also affected by atmospheric conditions and the earth’s surface in general and vegetation in great detail. The reflected radiance measured by the sensor is converted to reflectance values that are defined as the ratio of the intensity of the reflected light to the intensity of the incoming light as a function of the wavelength. Features on the earth’s surface have different spectral signatures due to differences in chemical and physical properties (Provoost *et al.*, 2005) which are eventually detected by spectroradiometers devices such as an Analytical Spectral Device (ASD). The ASD measures continuous spectral bands between 350nm and 2500nm throughout the visible (350nm to 700nm), NIR (700nm to 1300nm), Mid-Infrared (MIR), and Thermal Infrared (TIR) (1300nm to 2500nm) regions of the electromagnetic spectrum (Kumar *et al.,* 2001; Lillesand and Kiefer, 2000). The interaction of electromagnetic radiation with the leaves is dependent upon many factors including cuticular composition and structure, cellular organization, intercellular air spaces, biomass, Leaf Area Index (LAI), cytoplasmic inclusions, pigments, water content, emissivity characteristics, and temperature (Kumar *et al.,* 2001; Lillesand and Kiefer, 2000; Provoost *et al.*, 2005; Siciliano *et al.*, 2008; Schmidt and Skidmore, 2003).

Provoost *et al.* (2005) and Curran *et al.* (1990) found that absorption is strong in the violet (< 400nm), blue and red (from 400nm to 700nm) part of the spectrum that is caused by the composition and concentration of chlorophyll and pigments (e.g. anthocyanin, lutein, ß and ά carotenoids, and xanthophyll), which result in lower reflectance. The characteristics of the upper epidermis and the refractive index of the cuticular wax determine the reflectance from the leaf surface, but the anatomical structure of the leaf also contributes significantly to NIR reflectance (Provoost *et al.*, 2005). As shown in Figure 2.1, from 495nm to 570nm which is the green part of the solar spectrum indicate an increase in energy reflectance causing plants to show a green colour. This results in low reflectance in the visible wavelengths and strong increased reflectance of the near infrared that appears around 690nm (Curran *et al.*, 1990). Green plants hardly absorb NIR because the energy content of the shortwave infrared part of the solar spectrum is insufficient to trigger photochemical reactions, and this part of the energy spectrum is not absorbed by chlorophyll a, chlorophyll b, or carotene (Kumar *et al.*, 2001; Adam and Mutanga, 2009).

The contrast between red absorption and NIR reflection, known as the ‘red edge’, is the evident spectral characteristic with more information content for vegetation spectra (Dawson and Curran, 1998; Mutanga, 2004; Cho and Skidmore, 2006). ‘Red edge’ is defined as being the wavelength of the inflection point of reflectance slope that is located between two of the most widely used wavelength regions used for narrow band vegetation studies, the red trough and NIR plateau in the 680nm to 750nm regions of vegetation spectra (Collins, 1978; Curran *et al.,* 2001; Mutanga, 2004). The absorption of the red part of the spectrum is due to the combined effects of polymer forms of strong chlorophyll, and the high multiple scattering of radiation in the leaf mesophyll causes high reflectance in the NIR part of the spectrum (Liang, 2003; Cho and Skidmore, 2006). A significant advantage of the use of the red edge position is that it is relatively insensitive to variations in illumination conditions and to the reflectance of the soil background but it is highly correlated to vegetation greenness parameters (Mutanga and Skidmore, 2007). The position of the red edge has been successfully used in vegetation studies as an indicator of physiological changes in vegetation studies (Collins, 1978; Jago and Curran, 1995). From Figure 2.1 it can be noted that between wavelengths 700nm and 1300nm (Visible and Near Infra-Red (VNIR) and lower Shortwave Infrared (SWIR)) there is high reflectance of energy. This high reflectance is caused scattering of electromagnetic radiation due to the arrangement of cellular and discontinuities in the refractive index within the leaf. Finally, SWIR region (1300nm to 2600nm) is characterized by strong water absorption bands and minor absorption of biochemical content dominating the gradually decreasing reflectance of green vegetation (Kumar *et al*., 2001).

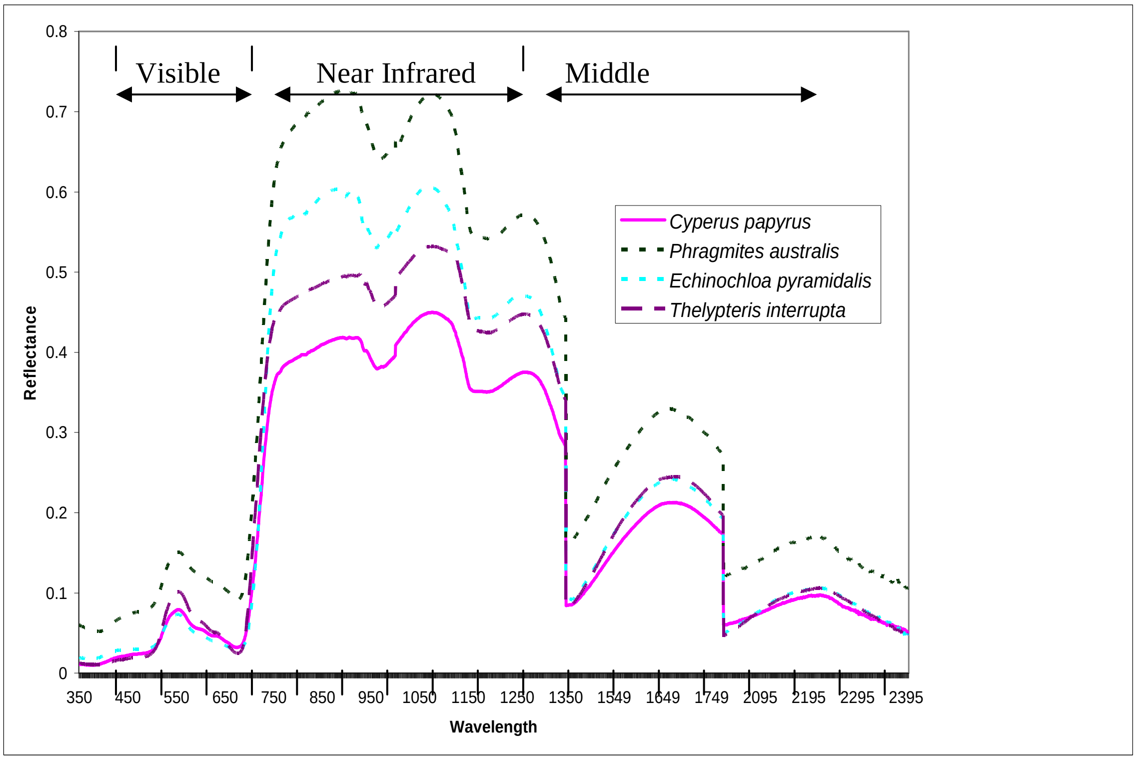


Figure 2.1 Reflectance curves of different types of wetland vegetation species in the iSimangaliso Wetland Park (December 2009, ASD measurements).

Spectral properties of wetland vegetation are related to biochemical and biophysical properties rather than species and its spectral reflectance is influenced by soil background and hydrologic regime (Guyot, 1990). This interference causes low spectral reflectance in vegetation spectrum especially in the NIR region where water is highly absorbed (Cochrane, 2000). Within a single species, plants show a variety of phenological, morphological, and physiological conditions, complicating the spectral separability of vegetation types based on species composition (Schmidt and Skidmore, 2003; Asner, 1998). Estimating biophysical and biochemical constituents of vegetation with imaging spectrometry is a difficult task, since several overlapping absorption features influence plant reflectance (Curran *et al*., 1992; Curran *et al*., 2001; Siciliano *et al*., 2008).

The spectral response at either leaf or canopy level can be affected by leaf internal structure, leaf age, phenological stages, angle of view, atmospheric properties, spectral mixture, moisture content, illumination angle, biochemical and biophysical properties (nitrogen, biomass, plant water content, LAI, phosphorus, chlorophyll content, anthocyanin, lutein, ß and ά carotenoids, and xanthophylls) (Cochrane, 2000). Accurate knowledge of different spectral response is very important for discrimination of wetland vegetation at species level since there is no uniqueness in spectral signatures (Kumar *et al*., 2001; Kamaruzaman and Kasawani, 2007). Biomass and chlorophyll content of wetland vegetation species are thought to vary greatly as a function of the plant species and hydrologic regime (Anderson, 1995; Adam and Mutanga, 2009). Plant water content, cellulose and other plant properties are recorded as being an influence in the spectral reflectance of vegetation that determines the strong absorption in mid-infrared and an increase in near infrared leaf reflectance (Kumar *et al*., 2001).

2.3. Application of remote sensing in wetland vegetation mapping

Previously, some studies have been investigating the possibility of providing well-timed data for identifying and monitoring wetland vegetation and this has been categorized as an important part of wetlands vegetation restoration (Govender *et al*., 2007; Schmidt and Skidmore, 2003). Therefore, the detection, mapping, and monitoring of changes in these natural ecosystems becomes very important. Monitoring wetland vegetation requires quantitative, accurate, and regular collection of information that has made the use of remote sensing a most important tool (Schmidt and Skidmore, 2003). Over the past few decades, imagery has been acquired from a wide range of sensors, some with high spatial resolution and low spectral resolution, and some with coarse spatial resolution and high spectral resolution. The first remote sensing method used to map wetland vegetation was aerial photography with low spatial resolution (Howland, 1980; Jensen *et al.*, 1986; Kamaruzaman and Kasawani, 2007; Adam and Mutanga, 2009). The drawback of aerial photography, as noted in these studies, is that it has coarse spatial resolution and low spectral resolution, thereby affecting the actual vegetation mapping (Jensen *et al.*, 1986; Klemas and Dobson, 1993; Smith *et al.*, 2004; Adam and Mutanga, 2009). Considering the increased use of remote sensing data, aerial photography has been less frequently used since it is not practically possible to map and monitor wetland vegetation on a regional scale. Nowadays, multispectral and hyperspectral remote sensing is used to monitor wetland vegetation on a regular basis, which requires high temporal resolution and regular collection of data (Klemas and Dobson, 1993).

Multispectral remote sensing was introduced in the mapping and monitoring of vegetation with different spatial resolutions ranging from sub-metre to kilometres and with different temporal resolutions ranging from 30 minutes to weeks or months (Key *et al.*, 2000). Using traditional multispectral data, the most common classification techniques used by some previous researchers to classify wetlands vegetation were supervised classification (Parallelepiped classification, Minimum Distance Classification, Mahalanobis Distance Classification, Nearest Neighbour Classification, and Maximum Likelihood Classification) and the unsupervised classification (K means and Clustering). Multispectral remote sensing proved to be a very useful tool and some previous researchers have been successful in discriminating broad vegetation communities (Smith *et al.*, 2004) and in mapping salt marsh vegetation (Belluco *et al.*, 2006). Ndzeidze (2008) reviewed the utility of Landsat imagery from 1973 to 2007 for change detection and established whether wetlands and related land cover classes in the drainage basin could be classified for the Upper Noun Basin, Cameroon. From his research, it was found that the study failed to detect significant changes in the Upper Noun drainage basin from 1973 to 2007 using multispectral and temporal Landsat satellite images. Eventually, Ndzeidze had to rely on his knowledge of the study area and information from past fieldwork to identify and distinguish wetland and related land use and land cover.

Bellluco *et al.* (2006) used multispectral data from ROSIS (Reflective Optics System Imaging Spectrometer), CASI (Compact Airborne Spectrographic Imager), MIVIS (Multispectral Infrared and Visible Imaging Spectrometer), IKONOS and Quickbird in The San Felice salt marsh in the northern part of the Venice Lagoon, Italy. To distinguish among five dominant vegetation species which were *Juncus, Spartina, Limonium, Sarcocornia,* and *Salicirnia*. The authors obtained an overwhelming overall accuracy and Kappa coefficient for all the species ranging from 74.6 % to 99.2 % and from 0.59 to 0.99 respectively. The authors performed a simple band averaging which resulted in reduction of noise, but by doing this the authors were reducing spectral resolution that significantly reduced the number of reference pixels and gives misleading information calculated from confusion matrix statistics.

Shahraini *et al.* (2003) also used multispectral data for mapping the spatial extent of lakes and coastal wetlands in Hirmand, Puzak and Sabury lakes, Iran, using imagery from Landsat TM, Advanced Very High Resolution Radiometer (AVHRR)-LAC and AVHRR-GAC. The authors showed the potential of Landsat TM, AVHRR-LAC and AVHRR-GAC data for mapping of lakes, coastal wetlands, coastal mixed pixels between water and land, and the transitional regions of wetlands using training data and different supervised classification methods (Maximum likelihood, Mahalanobis distance, Minimum distance, and Parallelepiped classification).

However, there is a need for more research to investigate the possibility of using biochemical and biophysical parameters to discriminate wetland vegetation at species level. Discrimination of wetland vegetation species by using multispectral remote sensing was found to be unsatisfactory since it has few bands that cannot describe vegetation spectra in detail (Schmidt and Skidmore, 2003). Also, multispectral remote sensing data cannot utilize the red edge region that is insensitive to atmospheric interference and soil background (Smith *et al.*, 2004; Adam and Mutanga, 2009). Due to its coarse spectral and spatial resolutions, multispectral remote sensing has been found to be ineffective to either discriminate vegetation since some vegetation species has almost the same spectral signatures or detect any spectral changes associated with chemical or physiological changes in plants (Sun *et al.,* 2008). Due to the fact that wetland vegetation is densely populated, the use of broadband remote sensing with its coarse spectral resolution might not produce the required results.

2.4 Hyperspectral remote sensing and improvement in discrimination of wetland vegetation at species level using spectral reflectance

Hyperspectral remote sensing, also known as 'imaging spectrometery', 'imaging spectroscopy', 'ultraspectral imaging', 'hyperspectral spectroscopy' and 'narrow-band imaging', is a relatively new technology that is currently being used for vegetation studies (Govender *et al*., 2007, Adam and Mutanga, 2009). These names for hyperspectral remote sensing are often used interchangeably with each other, but the only way to differentiate them depends on the aim of the scientist or researchers' intended application. Imaging spectrometry usually refers to the use of particular spectral absorption features in the scene to uniquely identify materials (Kerekes, 2006), while imaging spectroscopy involves measuring the spectral distribution of photon energies (as wavelengths or frequencies) associated with radiation that may be transmitted, reflected, emitted, or absorbed upon passing from one medium to another (Kerekes, 2006; Adam and Mutanga, 2009).

Hyperspectral remote sensing involves acquisition of the digital images in hundreds of narrow continuous spectral bands between 350nm and 2500nm throughout the visible (350nm to 700nm), NIR (700nm to 1300nm), MIR and TIR (1300nm to 2500nm) regions of the electromagnetic spectrum (Govender *et al*., 2007) as shown in Figure 2.1. Hyperspectral remote sensing acquires images with high spectral resolution of individual bands less than 10nm over a continuous spectrum. Since hyperspectral remote sensing has so many narrow bands, it can detect detailed vegetation features that might otherwise be masked within broader bands of multispectral sensors (Schmidt and

Skidmore, 2003; Mutanga *et al*., 2003). High spectral resolution sensors provide sensitive fine-scale data on biochemical and biophysical parameters that can be used to discriminate, classify, monitor, and assess wetland vegetation species (Li *et al.*, 2005). This is done with the intention of up-scaling the measurements to airborne or satellite sensors (Rosso *et al.*, 2005; Vaiphasa *et al.*, 2005).

Over the past few decades many problems were recorded when discriminating wetland vegetation at species level using multispectral remotely sensed data. This has necessitated the possibility of separating different vegetation species based on foliar spectral reflectance using greater detailed hyperspectral remotely sensed data.

In Madeira Bay, Florida, USA, Hirano *et al*. (2003) classified ten vegetation classes using data they acquired from AVIRIS and the detailed Everglades Vegetation Database. The following vegetation classes including buttonwood forest, red mangrove forest, white mangrove forest, white mangrove scrub, herbaceous prairie, saw grass, spike rush and lather leaf exotics were classified using ENVI spectral angle mapper (SAM) with producer's accuracy ranging from 41.9% for buttonwood forest to 100% for spike rush and an overall accuracy of 65.7%.

Spectral discrimination of salt marsh was also done by Artigas and Yang (2005) in the New Jersey Meadowlands, USA. In this research, four common wetland species were selected for discrimination namely, *Phragmites australis*, *Spartina alternifolia, Spartina patens* and *Distichlis spicata*. Leaf spectral reflectance was ascertained using Analytical Spectral Devices, FieldSpec ® Full Range spectroradiometer. Findings from this research showed that it was possible to classify salt marshes using the red edge region between 600 nm and 680nm, usually under fall conditions. The red edge first derivative showed the highest potentially useful information to discriminate among wetland vegetation species.

At Lake Onkivesi, Finland, Valta-Hulkkonen *et al.* (2003) classified seven aquatic vegetation categories including *Phragmites australis*, *Equisetum fluviatile*, *Schoenoplectus lacustris*, *Stratiotes aloides,* and *Sagittaria sagittifolia* using a Leica

RC30 camera equipped with a 153 mm focal length lens and UAGS 13260 lens, and a Kodak 1443 colour infrared film. The authors used visual and digital classification (maximum likelihood classifier) of hydrophytic vegetation and achieved an overall accuracy of 81% and 83% respectively. Schmidt and Skidmore (2003) used a GER 3700 spectrometer to test the spectral separability of salt marshes on the island of Schiermonnikoog, Netherlands. They measured about twenty-seven salt marsh species including *Spartina townsendii, Salicornia europaea, Atriplex portulacoides, Juncus gerardi, Artemisia maritime, Elymus athericus, Phragmites australis* and *Scirpus maritime.* For spectral discrimination, the Jeffries–Matusita distance and the Bhattacharyya distance were applied and resulted in an overall accuracy of 91%.

In 2004, van Til *et al.* investigated the use of the GER 2600 field spectrometer for discriminating coastal dune vegetation. The leaf spectral reflectance measurements were taken in May and June 2001 for ten herbaceous vegetation types. Multivariate analysis and Redundancy analysis were calculated to determine the percentage of explained variance of coastal dune vegetation. The better discrimination was achieved in the bands between 370nm and 690nm for end of May and between 370nm and 460nm for end of June. This research noted that the bands between 730nm and 930nm were not able to discriminate salt marsh vegetation. The overall percentages of explained variance for raw data for both May and June were 82 % and 75 % respectively, after the data were transformed.

Vaiphasa *et al.* (2005) used hypespectral remotely sensed data for spectral separability of sixteen tropical mangrove species using laboratory data that avoids the difficulties of field conditions. They conducted their research in Chumporn, Thailand using laboratory data with the intention of reducing costs and up-scaling their research in the future application of airborne hyperspectral sensors. The leaf spectral measurements were conducted using ASD. Using a wrapper feature selection tool they selected only bands that were the best combination for species discrimination. They applied one-way Analysis of Variance (ANOVA) and Jeffries–Matusita distance measure using those four bands to determine if species were spectrally separable. They produced an overall accuracy of 80%, but 5 out of 10 of the *Rhizophoraceae* family were spectrally similar.

From this study it was noted that tropical mangrove species did not have sufficient spectral information due to their similarity in pigment substances.

Pengra *et al.* (2007) used Hyperion data to classify monodominant *Phragmites australis* in the coastal wetlands of the west coast of Green Bay, Northen America Great Lakes. The authors used minimum noise fraction to reduce systematic sensor noise that has an influence on the image analysis. Spectral correlation mapper was applied to determine the spectral similarity among different reflectance spectra by calculating the spectral angles, such that positive and negative correlations between samples could be distinguished. *Phragmites australis* was discriminated from nine other land cover classes such as cat tail, mixed emergent vegetation, scrub and shallow water. They concluded that 3.4 % of the study area was covered by *Phragmites australis* which was supported by an overall accuracy of 81.4%.

Andrew and Ustin (2008) focused on the role of environmental characteristics in the spectral separability of *Lepidium latifolium* from other species. They used minimum noise fraction, mixture tuned matched filtering, and Jeffries–Matusita distances for discrimination of species in three different locations: the Rush Ranch Open Space Preserve, the Greater Jepson Prairie Ecosystem, and the Cosumnes River Preserve, in California, USA. The discriminant techniques were applied to reduce noise, dimensionality of hyperspectral data, and to detect objects that differ subtly from the ground (Green *et al*., 1998; Andrew and Ustin, 2008). The authors managed to get distinct differences of species using high spectral resolution sensors Hymap for Rush Ranch imagery and then HyVista Corporation for Jepson Prairie and Cosumnes imagery. These fine spectral resolution sensors sample wavelengths of 450nm to 2500nm with 150 to 200 contiguous bands of 5nm to 10nm bandwidths. In Rush Ranch, *Lepidium* was distinguished from *Salicornia, Distichlis, Centaurea solstitialis*, water, and litter with an overall accuracy of 90%. In Jepson Prairie, *Lepidium* was differentiated from typha, agriculture, soil, *Centaurea calcitrapa*, water, and litter with an overall accuracy of 88%. Finally, in the Cosumnes River Preserve, the authors managed to discriminate *lepidium* from agriculture, trees, litter and soil where a 93.6% overall accuracy was achieved.

Sun *et al*. (2008), in the Arboretum of the Institute of Botany, Chinese Academy of Science in Beijing, showed the potential of hyperspectral data for wetland vegetation species discrimination using their spectral reflectance characters. The authors chose eleven wetland vegetation species for discrimination which were *Cyperus alternifolius, Cyperus papyrus, Pontederia cordata, Nymphaea tetragona, Hydrocleys nymphoides, Nymphoides peltatum, Pistia stratiotes, Azolla imbircata, Vallisneria asiatica, Potamogeton malaianus, Hydrilla verticillata*. The spectral reflectances of these eleven species were acquired using an SVC GER 1500 hand held spectrometer. The first derivative reflectance, second derivative reflectance, continuum removal, and Mahalanobis distance were used for selecting bands that could be used for wetland vegetation discrimination at species level. All these methods showed all the bands that had a greater possibility of species discrimination through their results. The bands that were selected for species discrimination are located between 410nm and 999nm i.e. in the chlorophyll and water absorption region (red edge).

Although all these techniques were able to successfully discriminate wetland vegetation at species level successfully, there is a growing interest by researchers for more investigation into what exactly cause spectral reflectance difference. There are many factors which causes spectral reflectance differences including atmospheric properties, spectral mixture, soil moisture content, illumination angle, biochemical and biophysical properties (nitrogen, biomass, plant water content, LAI, phosphorus, and chlorophyll content, anthocyanin, lutein, ß and ά carotenoids, and xanthophylls). The question that arises from all these previous studies is: Is it possible to use quantified measures of biochemical and biophysical properties for vegetation species discrimination? And can they also improve or enhance the overall accuracy and to what extent can we apply them.

2.5 Application of quantified biochemical and biophysical properties for discrimination of wetland vegetation at species level

For the past few decades, hyperspectral remote sensing has been proven to be useful for wetland vegetation species discrimination at leaf and canopy level (Artigas and Yang, 2005; Hirano *et al.,* 2003; Schmidt and Skidmore, 2003; Vaiphasa *et al*., 2005; Cho, 2007; Kamaruzaman and Kasawani, 2007; Sun *et al.*, 2008; Adam and Mutanga, 2009). These wetland vegetation species have biochemical and biophysical properties that influence spectral reflectance and there is a need for researchers to develop a method that will use these vegetation parameters to distinguish them. Quantifying and estimating biochemical and biophysical properties of wetland vegetation species has been playing a vital role in monitoring the changes of ecological systems such as vegetation quality, vegetation stress, and vegetation nutrient cycles at local, regional, and global scales (Asner, 1998; Kokaly *et al.*, 2009).

Various biophysical and biochemical attributes that influence vegetation spectral reflectance were recognised as being plant water content (Wessman *et al.*, 1988; Anderson, 1995; Asner, 1998; Ustin *et al.*, 1998), pigment composition and content (Lichtenthaler *et al.*, 1996), chlorophyll content, and biomass (Asner, 1998; Mutanga, 2004; Adam and Mutanga, 2009). This was also supported by Kokaly *et al.* (2009) who suggested that water is the most abundant chemical in leaves and can constitute up to 70% of chemical. Remote sensing offers the opportunity to explore the possibility of using these vegetation properties for species discrimination since it has never been done in any wetland vegetation discrimination at species level to our knowledge. Traditional methods have been found to be time-consuming and not cost-effective and some of the wetland areas are inaccessible because they are swampy and waterlogged. Since plants' water content and biomass were found to be important in the ecological studies reviewed, this study focuses only on those two vegetation attributes due to the fact that they require spatial assessment repetitively and objectively.

To date there have been few studies done on the estimation and quantification of biomass and plant water content for wetland vegetation discrimination at species level. The quantification of aboveground biomass and water content of wetland vegetation will develop sufficient information for understanding, mapping, identifying, managing, and modelling vegetation species physical composition, roles, and dynamics in wetland vegetation systems (Phinn *et al.*, 2008; Adam and Mutanga, 2009). Previous studies have shown that there is a relationship between plant water content and biomass that can be exploited in the discrimination of wetland vegetation (Moreau and Le Toan, 2003;

Phinn *et al*., 2008). The first attempt to discriminate vegetation species using biochemical properties was done by Wessman *et al.* (1988), where lignin and nitrogen content in the foliage was used.

2.6 The uses of red edge hyperspectral indices in wetland vegetation discrimination at species level

Vegetation indices (VIs) have been used in remote sensing for a long time and have been shown to be useful in discriminating between different vegetation types. VIs are ratios of reflectance values at different wavelengths or formulations using simple operations between reflectances at given wavelengths (Mutanga and Skidmore, 2004; Wamunyima, 2005).

For the past few decades, vegetation indices based on spectral reflectance measurements have been used as a reliable non-destructive method for measuring biophysical and biochemical parameters of plants (Datt, 1999; Aparicio *et al.*, 2000). Mutanga (2004) and Jensen (2000) suggested that vegetation indices are usually used because they remove the variability caused by canopy geometry, and soil background and they act as radiometric measures that function as an indicator of relative abundance and activity of green vegetation. The logic behind the use of vegetation indices is that they contrast reflectances in the red and near infrared regions of the electromagnetic spectrum and, as a result, scientists are able to use that difference for vegetation analysis (Todd *et al*., 1998; Mutanga and Skidmore, 2004; Aparicio *et al.,* 2000). Many studies have been conducted which examine the correlation between VI and diverse measures of canopy structure and plant composition, such as chlorophyll content, Nitrogen concentration of leaves, green and dry biomass, phosphorus content, water content and LAI (Mutanga and Skidmore, 2004; Wamunyima, 2005).

The most widely used vegetation indices are the Simple Ratio (Jordan, 1969) and the NDVI (Rouse *et al.*, 1973; Tucker, 1979). Other vegetation indices were developed to counter the effects of canopy geometry, soil background, sun view angles, and atmospheric conditions. These are the Perpendicular Vegetation Index (Richardson and Wiegand, 1977), the Weighted Difference Vegetation Index (Clevers, 1988), the Soil

Adjusted Vegetation Index (Huete, 1988), the Transformed Soil Adjusted Vegetation Index (Baret and Guyot, 1991), the Modified Soil Adjustment Vegetation Index (Qi *et al.*, 1994), the Modified Normalized Difference Vegetation Index (Liu and Huete 1995), the Renormalized Difference Vegetation Index (Roujean and Breon, 1995), the Triangular Vegetation Index (TVI) (Broge and Leblanc, 2000), the Chlorophyll Absorption Ration Index and the Modified Chlorophyll Absorption Ration Index which was developed as an improvement on Chlorophyll Absorption Ration Index (Daughtry *et al.,* 2000).

The improvement of technology brought the use of hyperspectral remote sensing that acquires data in narrow bands (many channels). There are different vegetation indices that were developed to make use of these narrow bands in the red edge region that are referred to as red edge hyperspectral indices (Wamunyima, 2005). Since the red edge region is not usually disturbed by vegetation water absorption, it's relatively much easier to apply these vegetation indices. The red edge hyperspectral indices are calculated using the narrow channels within the red edge region of the reflectance spectrum of vegetation that is located between 680 nm and 750 nm. Some of the developed indices include Vogelmann$_a$ (VOG_a) (Vogelmann *et al.*, 1993), the Red Edge Spectral Parameter (RESP), the Carter Index (CI), the Inverse Carter Index (Carter, 1994), and the Gitelson and Merzylak Index (GMI) (Gitelson and Merzylak, 1997). These are not only the red edge hyperspectral indices which have been developed, but for this research only indices of interest were selected and their equations are shown in Table 3.2 as RESP (Equation 3.2.1), CI (Equation 3.2.2), GMI (Equation 3.2.3), NDVI (Equation 3.2.4), SR (Equation 3.2.5), TVI (Equation 3.2.6), and VOG_a (Equation 3.2.7).

2.7 Red edge position

The red edge (680nm to 750nm) (Figure 2.1) is defined as a rise in the vegetation reflectance from the red part of the visible spectrum to the near infrared part. The absorption of the near infrared part of the spectrum is due to the combined effects of polymer forms of strong chlorophyll adding closely spaced absorption bands to the far red shoulder of the main chlorophyll band and the high multiple scattering of radiation in the leaf mesophyll (Liang, 2003). The red edge uses three parameters for all the calculations that are the red edge position (REP), amplitude, and slope (Cho and Skidmore, 2006; Mutanga and Skidmore, 2004). Wamunyima (2005) noted that at REP the slope of the vegetation spectral curve is at its maximum within the 680nm to 750nm range. The amplitude is the first derivative value at the maximum slope position within 680nm to 750nm range (Dawson and Curran, 1998; Pu *et al.*, 2003; Cho and Skidmore, 2006). Previous vegetation studies show that REP shifts according to changes of plant health, biomass, leaf chlorophyll content, seasonal patterns and phonological state (Mutanga and Skidmore, 2004; Cho, 2007; Adam and Mutanga, 2009, Belanger *et al.*, 1995; Munden *et al.*, 1994). The red edge position shifts toward the longer wavelength due to an increase in the amount chlorophyll content which absorbs electromagnetic radiation in the red trough. This absorption widens the trough and hence pushes the red edge towards the longer wavelengths. A reduction in chlorophyll results in higher reflectance in the red and hence a shift of the red edge towards the shorter wavelengths.. Through observing these shifts, red edge position can effectively be used to discriminate wetland vegetation species with varying amounts of chlorophyll.

There is a variety of analytical techniques that are being used to extract the red edge position as a means to classify vegetation, such as four point interpolation (Linear), Gaussian, linear extrapolation, Maximum first derivative, Lagrangian interpolation, polynomial fitting, and high order curve fitting techniques which have been developed to minimize errors in determining the red edge position (Dawson and Curran, 1998; Pu *et al.*, 2003; Cho, 2007; Shafri *et al.*, 2006). The aim of this study is to provide an alternative method or technique for determining the red edge position that can be used to discriminate wetland vegetation species. A number of studies have been using analytical techniques for various reasons such as discriminating vegetation species and estimating biophysical and biochemical properties for example nitrogen content, leaf area index, chlorophyll content, fresh ground biomass or dry biomass (Mutanga, 2004; Mutanga and Skidmore, 2004; Cho and Skidmore, 2006; Sun *et al.*, 2008). Only a few selected techniques were used in this present research, especially the linear extrapolation technique developed by Cho and Skidmore (2006) which is a technique that has never been used for wetland vegetation species discrimination.

2.8 Lessons learnt from the review

Wetland vegetation species are very important to many living things including animals, birds, and human beings. It is very important to have a clear picture of what exactly is found in a particular wetland area in terms of vegetation species so as to conserve them. Multispectral remote sensing has been used to monitor changes in wetland vegetation, but it's relatively difficult to analyse vegetation (discrimination, classification, or mapping) due to low spectral resolution. This has resulted in the introduction of hyperspectral remote sensing which uses narrow continuous spectral bands to discriminate different wetland vegetation species. Internationally, the use of the red edge position for wetland vegetation species discrimination has been successfully applied with favourable results. Red edge extraction techniques and vegetation indices have been improved or developed and found to be more reliable. However, in the South African context no red edge extraction techniques have been used for wetland vegetation species discrimination. Linear extrapolation is a technique that was developed to control variations caused by soil background effects as well as atmospheric induced variations. Of particular interest is the response of the red edge to variation in the biophysical and biochemical properties of different vegetation species. Since the red edge region uses non-water absorption bands with minimum atmospheric interference it is capable of discriminating wetland vegetation species in the South African context. Leaf structure and shape, water content, biomass, and the concentration of biochemicals are all functions of vegetation leaves that can improve the discrimination of vegetation.

2.9 Conclusion

Wetland vegetation discrimination at species level is critical to government departments such as the Department of Water Affairs and Forestry, the Department of Rural Development and Land Reform, and the Department of Environment Affairs and Tourism, since they need to conserve wetlands. The critical component for monitoring and managing ecosystems and preserving biological diversity is the discrimination of wetland vegetation which requires accurate knowledge of the distribution of plant species (Schmidt and Skidmore, 2003). This accurate knowledge is obtained from the use of laboratory and field spectroscopy (remote sensing), which will be quantified and be used in vegetation discrimination. Vegetation species have variations in canopy reflectance due to biochemical and biophysical properties that are being detected by high spectral resolution sensors. This information is critical to distinguish vegetation species from one another. This review has shown the potential of hyperspectral remote sensing data for wetland vegetation discrimination at species level.

It is critical to note that hyperspectral remote sensing has focussed on the estimation of either biochemical properties, biophysical properties of vegetation as well as species discrimination independently, without a clear cut attempt to integrate the products in improving species mapping. Several maps, algorithms and models have now been developed to predict biomass and other structural properties of vegetation at reasonable accuracies. The question is, can this available ancillary information be integrated with hyperspectral data to improve species discrimination?

Chapter Three:

Methodology

3.1 Introduction

In this chapter, an outline is given of the sampling methods, leaf spectral measurements, biochemical and biophysical variables, hyperspectral vegetation indices, and red edge extraction techniques used to discriminate wetland vegetation species using hyperspectral data.

3.2 Field spectral measurements

Canopy spectral measurements used in this study were recorded on the 29th December 2009 between 10:00 am and 02:00 pm under sunny and cloudless conditions. Measurement of hyperspectral leaf reflectance was acquired at canopy level using a hand-held field spectroradiometer (FieldSpec Pro, Analytical Spectral Device) over the 350nm to 2500nm wavelength region at 1.4nm sampling intervals fitted with a 25° field of view fibre optic. The instrument has a spectral sampling resolution of 1.4nm, a spectral interval of 3nm between 350nm and 1 000nm, a spectral sampling resolution of 2 nm, and a spectral interval of 10nm between 1 000nm and 2 500nm. Radiance measurements were optimized and calibrated before the first measurement was taken. A calibrated white reference Spectralon calibration panel was used on the leaf clip every 10 to 15 measurements to offset any change in the atmospheric conditions and irradiance of the sun. Only the spectral range between 670nm and 780nm was analysed since the research was mainly focused on the red edge position for vegetation species discrimination.

Field sites were selected using two sampling techniques which are random sampling and purposive sampling. Random points were generated on a land cover map produced from an ASTER image using ArcMap’s extension Hawth's Analysis Tool. When any of the random point was inaccessible, purposively selected sampling was applied. Using GPS, these points were then located in the field sites. A total of 41 vegetation plots of 3m by 3m were taped in the field and the plot size was viewed as suitable. Then three subplots of 0.5m by 0.5m were randomly selected from within plot to measure the spectral reflectance which resulted in a total of 7 to 15 field spectrometer measurements. A total of 50 samples per vegetation species were selected for measurements. In the iSimangaliso Wetland Park, there are many different vegetation species, which is very rich in endemic taxa, but the dominant vegetation species were identified as *Cyperus papyrus*, *Phragmites australis*, *Echinochloa pyramidalis,* and *Thelypteris interrupta*. These four wetland vegetation species were selected for this study and their measurements were recorded based on density and estimation of percentage cover (covering at least 40% of the area) (Table 3.1.).

Measurements of biomass were taken after the leaf spectral measurements were taken. The biomass from each plot was clipped, after all dry material was removed from the clipped plants, and then fresh biomass was measured immediately using a digital weighing scale. The aboveground biomass was determined by dividing the weight of the harvested grass by the surface area of the subplot (Mutanga and Skidmore, 2004).

Table 3.1 Four dominant wetland vegetation species of Great St Lucia Wetland Park, KwaZulu Natal Province, South Africa

Species	Proposed Code	Family	No of Plots	No of Measurements
Cyperus papyrus	CP	Cyperaceae	15	134
Phragmites australis	PA	Poaceae	9	111
Echinochloa pyramidalis	EP	Graminae	7	101
Thelypteris interrupta	TI	Thelypteridaceae	10	113

The red edge indices were computed from all possible two band combination indices involving 80 bands in the red edge region (670nm to 750nm). These vegetation indices (Table 3.2) were selected because they are the most widely used indices for estimating biomass and water content for vegetation studies. For example, NDVI has shown that it can solve the saturation problem in estimating biomass (Mutanga and Skidmore, 2004)

Table 3. 2 Vegetation indices

Vegetation Indices used for wetland vegetation species discrimination using reflectance spectra			
Vegetation Index	**Formula**	**Reference**	**Equation**
Red Edge Spectral Parameter (RESP)	R_{750} / R_{710}	Gupta *et al.*,2003	3.2 1
Carter Index (CI)	R_{695} / R_{760}	Carter, 1994	3.2 2
Gitelson and Merzylak Index (GMI)	R_{750} / R_{700}	Gitelson and Merzylak, 1997	3.2 3
Normalized Difference Vegetation Index (NDVI)	(R_{746} - R_{730}) / (R_{746} +R_{730})	Rouse *et al.*, 1973	3.2 4
Simple Ratio (SR)	R_{755} / R_{706}	Jordan, 1969	3.2 5
Transformed Vegetation Index (TVI)	$\sqrt{(((R_{755}-R_{730})/(R_{730}+R_{755})) + 0.5)}$	Rouse *et al.*, 1973	3.2 6
Vogelmann$_a$ (VOG_a)	R_{740} / R_{720}	Vogelmann *et al.*, 1993	3.2 7

R is the Reflectance

3.3 Plant water status

Soon after canopy spectral measurements were acquired a total of 50 plant water samples were taken. Leaves were cut and weighed to obtain leaf sample weight (W). Then the plant water samples were stored over ice in a portable refrigeration unit and were immediately taken to the laboratory for water measurements. After several hours, the samples were taken off ice and well dried of any surface moisture with a filter paper. Samples were then oven dried at 70 °C for 24h and weighed to determine dry weight (DW). Plant water content (PWC) was determined as detailed by Liu *et al.*, (2004):

$$PWC\ (\%) = [(W-DW) / (W)] * 100 \qquad \text{Eq.3.4. 1}$$

Where,

PWC- Plant water content,
W – Sample fresh weight, and
DW – sample dry weight.

The 50 plant water measurements were then used for analysis.

3.4 Red edge position algorithms

To assess morphological structures and chemical content of vegetation, it is vital to apply numerical methods computed from reflectance or derivative spectra. A number of techniques for REP extraction have been proposed in the literature on remote sensing and their uses depend on the purpose of the application. The red edge position was determined by various techniques of analysis such as, linear interpolation, inverted Gaussian, linear extrapolation, maximum first derivative, and Lagrangian (Dawson and Curran, 1998; Cho and Skidmore, 2006; Shafri *et al.,* 2006; Pu *et al.,* 2003 The response is indicated in section 3.4 under methodology page 31. Of the five methods listed above only three spectral derivatives were used in this study, linear interpolation, linear extrapolation and maximum first derivative. Curran *et al.,* (1990) suggested that spectral derivatives are used to resolve or enhance absorption features that might be masked by interfering background absorption. Also compared to Lagrangian and inverted Gaussian, the spectral derivatives helps to reduce the continuum caused by leaf biochemicals and canopy background effects (Curran *et al.,* 1991; Dawson and Curran, 1998). As a result, the spectral derivatives have become popular in remote sensing as compared to the lagrangian and inverted Gaussian models, hence the derivatives were used in this study.

3.4.1 Linear interpolation technique (Lin- Inter)

Baret *et al.* (1987) developed a simple method based on linear interpolation. This method assumes that the reflectance curve at the red edge can be simplified to a straight line centred around the midpoint between the reflectance in the NIR usually at about 780nm and the reflectance minimum of the chlorophyll absorption feature usually at about 670nm. The REP is then estimated by a simple linear equation using the slope of the line (Guyot *et al.*, 1992) that is between four wavebands (670nm, 700nm, 740nm, and 780 nm). The REP is determined by using a two-step calculation procedure:

(i) Calculation of the reflectance at the inflexion point (R_{re}):

$$R_{re} = (R_{670} + R_{780})/2 \qquad \text{Eq.3.5.1. 1}$$

Where R is the reflectance

(ii) The red edge wavelength or red edge position was calculated as follows:

$$REP = 700 + 40[(R_{re} - R_{700})/(R_{740} - R_{700})] \qquad \text{Eq.3.5.1. 2}$$

700 and 40 are constants resulting from interpolation or wavelength interval between 700 nm and 740 nm.

3.4.2 Maximum first derivative reflectance (MFD)

This technique locates the REP as the maximum first derivative of the reflectance spectrum in the region of the red edge using high-order curve fitting techniques. The maximum first derivative spectrum was employed to enhance absorption features that might be masked by interfering background absorption (Curran *et al.*, 1990). The first derivative was calculated using a first-difference transformation of the reflectance spectrum and it was derived from:

$$FDR_{(\lambda i)} = (R_{\lambda(j+1)} - R_{\lambda(j)}) / \Delta_{\lambda} \qquad \text{Eq.3.5.2. 1}$$

Where,

FDR is the first derivative reflectance at a wavelength *i* midpoint between wavebands j and j+1,

$R_{\lambda(j)}$ is the reflectance at the j waveband,

$R_{\lambda(j+1)}$ is the reflectance at the j+1 waveband, and

Δ_{λ} is the difference in wavelengths between j and j+1.

3.4.3 Linear extrapolation technique (LE1)

Cho and Skidmore (2006) developed the linear extrapolation technique to (i) mitigate the destabilising effect of the multiple peaks on the correlation between chlorophyll and REP, and (ii) track variation in slope near 700nm and 725 nm, where derivative peaks occur. Multiple peaks of spectra of four species in this study were found at 705nm, 720nm, 724nm, 730nm, 763nm and 767nm (Figure.3.1). Cho and Skidmore (2006) observed these multiple peaks at 700nm, 720nm, 730nm and 760nm in shrub and tree spectra. It could be observed from the first derivative curves that the double peak feature is located between 700nm and 770nm. The new technique is based on linear extrapolation of two straight lines through two points on the far-red (680nm to 700 nm) and two points on the NIR (725m, to 760nm) flanks of the first derivative reflectance spectrum of the red edge region (Eq.3.5.3.1 and Eq.3.5.3.2). The REP is then defined by the wavelength value at the intersection of the straight lines.

Far red line: $FDR = m_1\lambda + c_1$ Eq.3.5.3.1

NIR line: $FDR = m_2\lambda + c_2$ Eq.3.5.3.2

Where m and c represent the slope and intercept of the straight lines. At the intersection, the two lines have equal λ (wavelength) and FDR values. Therefore, the REP which is the λ at the intersection is given by:

$REP = -(c_1 - c_2) / (m_1 - m_2)$ Eq.3.5.3. 3

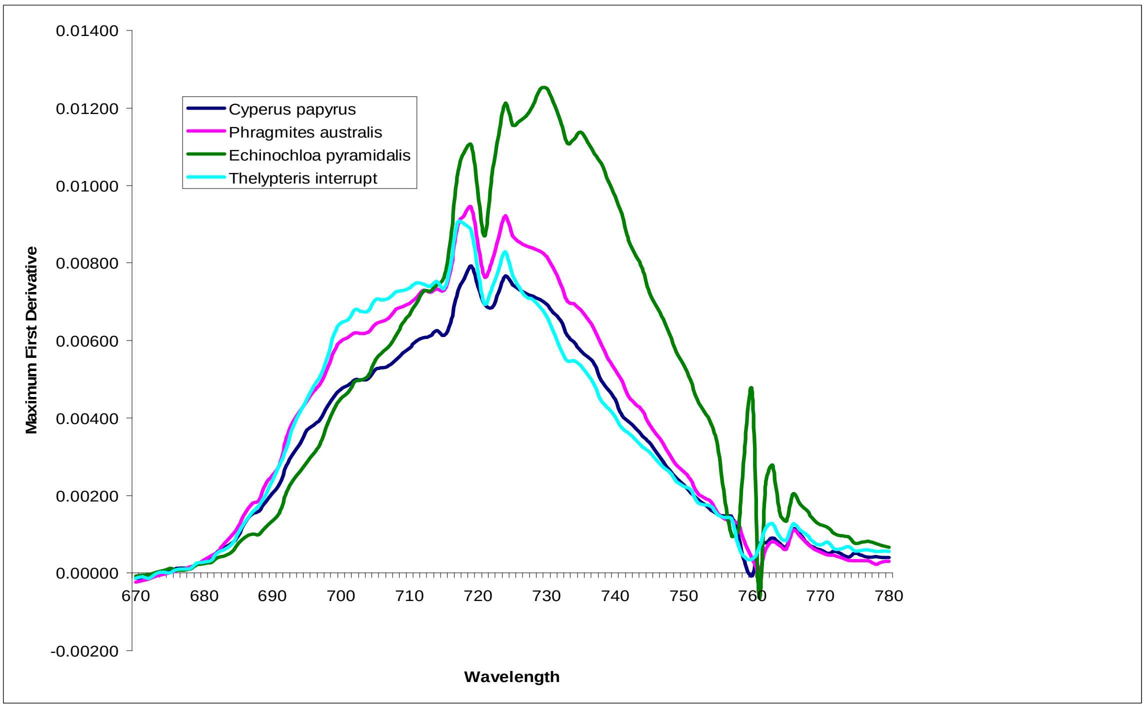


Figure 3.1 Mean maximum first derivatives of four species showing multiple red edge peaks.

3.5 Data analysis

3.5.1 Statistical test

In this research, only bands from 670nm to 780nm (Red edge region) were selected because it is relatively less sensitive to atmospheric and soil background effects (Shafri *et al.*, 2006). A statistical test was performed to compare the spectral responses of the four individual wetland vegetation species and determine if there was any significant difference among them. A two-step procedure was applied to adequately discriminate species using REPs and vegetation indices. Firstly, one-way ANOVA was performed using REP and vegetation indices. The research hypothesis that the means of the reflectance between the pairs of species (CP, PA, EP and TI) were significantly different i.e. null hypothesis, H_0: $\mu_1 = \mu_2 = \mu_3 = \mu_4$ versus alternative hypothesis, H_1: $\mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4$ was tested, where μ_1, μ_2, μ_3, and μ_4 are the mean reflectance of canopy indices from *Cyperus papyrus* (CP), *Phragmites australis* (PA), *Echinochloa* *pyramidalis* (EP), and *Thelypteris interrupta* (TI). The test was applied using 95% confidence interval ($p < 0.05$).

Second, in order to determine which pair of species means differ, a post hoc Bonferroni test was applied. The Bonferroni test simply calculates a new pairwise alpha to keep the familywise alpha value at 0.05 (or another specified value depending on the application). Familywise error represents the probability that any one of a set of comparisons or significance tests is a Type I error. Type I error is a true null hypothesis that is rejected incorrectly. When running multiple hypothesis testing, the likelihood that one or more are significant due to chance (Type I error) increases (Feise, 2002; Vaiphasa *et al.*, 2005). The Bonferroni test helps to reduce Type I error.

3.5.2 Discriminating wetland vegetation species using spectral reflectance

In multivariate analysis of spectroscopic data, it is normal to collect and compare vegetation spectra from different samples. The variability between the groups or within groups cannot be observed without using multiple variables in a multivariate set-up. Discriminant analysis is one such technique that can achieve this analysis. Rencher (1995) defines discriminant analysis as being a method of distinguishing among classes of objects based on linear functions of multiple variables. In this study, there were four groups (vegetation species) of six pairs which created a function for discriminating between CP and PA, CP and EP, CP and TI, PA and EP, PA and TI, and EP and TI.

Canonical variate analysis (CVA) (also called multiple discriminant analysis or canonical discriminant analysis) was used as a suitable technique that could fairly discriminate the wetland vegetation species. The main reason why CVA was used for wetland vegetation species discrimination is that it investigates the relationship between given groups of variables, and the best discrimination between groups will be obtained by maximizing the ratio of the among-group variation to the within-group variation. CVA is a multivariate analysis technique which discriminates among pre-specified, well-defined groups of sampling entities based on a suite of characteristics (Mutanga, 2004). For all the data that was used in the present research, there were four species that were sampled, and from these samples each species was classified into one of *g* groups. As a result there were four groups with the total variation that were seen as the combination of among-group variation and within-group variation. The technique is given information about groups which in turn produces new variables that minimizes the within group variance while maximizing the among-group variance in canonical scores. The canonical variates can be calculated from the eigenvectors of the ratio of the among-group sum that is *g* groups with variables measured on each of a number of observations, and this will be equal to the number of groups minus one (g-1), or the number of variables in the analysis. Since there were four groups i.e. *Cyperus papyrus* (CP), *Phragmites australis* (PA), *Echinochloa pyramidalis* (EP), and *Thelypteris interrupta* (TI), it means that CVA = 4-1 and the result is 3 roots. A root refers to the Eigenvalues that are associated with the respective canonical function.

According to Mutanga (2004), the first canonical function defines the specific linear combination of new variables that maximizes the ratio of among-group to within group variance in any single dimension. The use of such analysis produces linear combinations of new variables called 'canonical variates' (or latent variables). The first discriminant function provides the best separation among classes because the classes produce linear combinations with largest correlations, while the second set of linear combinations also shows the largest correlation subject to the condition that they are orthogonal to the first canonical variates and so forth. The interpretation of the variables in each discriminant function is as follows: the larger the standard coefficient, no matter what the sign is, either negative or positive, the greater is the power of the respective variable to discriminate between groups. In the present research, all the data from the results of REPs and vegetation indices were entered into the analysis based on their ability to increase group separation, although the main focus was to observe how the new technique, linear extrapolation, performed compared to other REPs and vegetation indices.

The main objective of canonical analysis in this application was to obtain a low-dimensional representation of the data that highlights as accurately as possible the true differences existing amongst groups of wetland vegetation species. Accuracy assessment was done using error matrix to evaluate if the research managed to fulfil its objective of discriminating wetland vegetation species. An error matrix displays records in terms of number of predicted classes and actual land cover revealed by sample site results. It lists the actual land cover types of the reference data in the columns and the predicted classes in the rows (Table 4.3). Overall accuracy is the sum of the correctly classified pixels divided by the total number of test pixels. The user's accuracy shows which samples that are correctly classified within individual categories. This measure of accuracy is calculated for each row by dividing the proportion of correctly classified pixels in a class by the total number of pixels in that class. On the other hand, the producer's accuracy is a measure of how accurate the image pixels have been classified. The producer's accuracy is derived by dividing the number of correct pixels in one class divided by the total number of pixels as derived from reference data (Story and Congalton, 1986).

To show if there was a measure of agreement or accuracy with the reference data, Kappa analysis was applied. The Kappa statistic incorporates the off diagonal observations of the rows and columns as well as the diagonal to give a more robust assessment of accuracy than overall accuracy measures do. The values of Kappa range from -1 to +1, with -1 indicating perfect disagreement, 0 indicating no agreement, and +1 indicating perfect agreement between training and test data. The results of Kappa (K_{hat}) statistic are expressed according to Landis and Koch (1977) as follows:

Kappa (K_{hat}) Statistic	Strength of Agreement
< 0.00	Poor
0.00-0.20	Slight
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Substantial
0.81-1.00	Almost Perfect- Perfect

The equation of K_{hat} is defined as follows:

= (Observed agreement - Chance agreement) / (1 - Chance agreement) Eq.3.6.2. 1

3.5.3 Discriminating wetland vegetation species using vegetation indices integrated with quantified measures of water content and biomass.

In this study, quantified water content and biomass, and vegetation indices were used to determine if there was any improvement in wetland vegetation species discrimination. To determine if vegetation properties increased the discriminatory power, quantified water content and biomass, and vegetation indices (RESP, GMI, CI, and SR) that produced favourable results in the first test, were used in this second test. In this study, to check whether the introduction of water content and biomass variables had improved the discrimination of wetland vegetation at species level, the same discrimination techniques or procedures were used.

A statistical test was also used to compare among the spectral responses of the 4 individual wetland vegetation species and to determine if there was any significant difference among them. A two-step procedure was applied to adequately discriminate species using vegetation biochemical and biophysical parameters and vegetation indices. One-way ANOVA was performed on all vegetation indices and quantified measures of water content and biomass. The research hypothesis that the means of the reflectance between the pairs (CP vs. PA, CP vs. EP, CP vs. TI, PA vs. EP, PA vs. TI, and EP vs. TI) were different i.e. null hypothesis, H_0: $\mu_1 = \mu_2 = \mu_3 = \mu_4$ versus alternative hypothesis, H_1: $\mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4$ was tested, where μ_1, μ_2, μ_3 ,and μ_4 are the mean reflectance of canopy indices from CP, PA, EP, and TI. Then Bonferroni test was applied to determine which pair of species means differed.

Chapter Four:

Discriminating wetland vegetation at species level using reflectance spectra: a comparison between vegetation indices and the red edge position

4.1 Overview

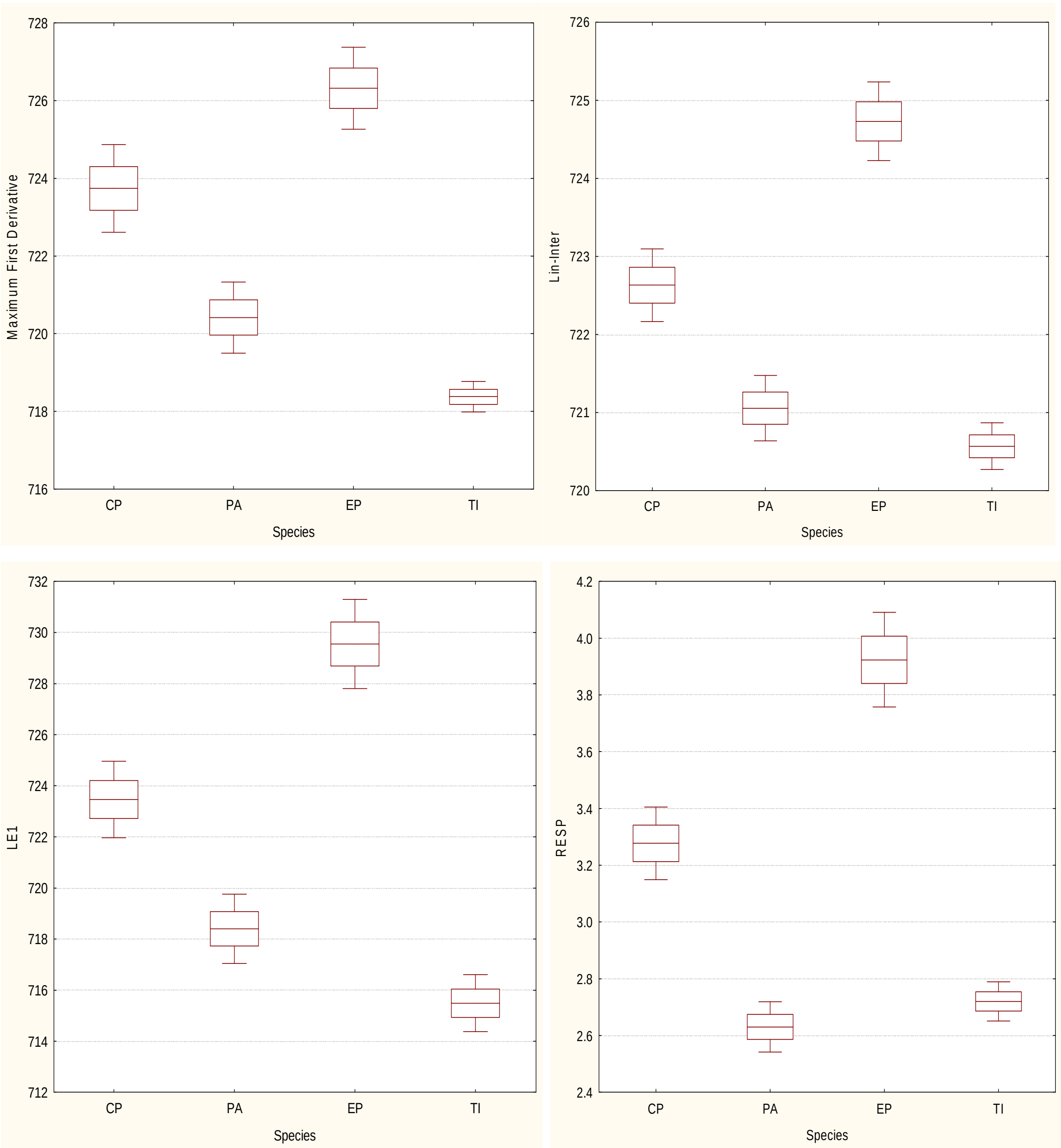
Most wetland vegetation species have similar spectral reflectance curves hence this poses a problem when trying to discriminate between them using traditional methods such as visual interpretation. Nevertheless, it's possible to discriminate wetland vegetation species potentially on the basis of amplitude using hyperspectral remote sensing. Schmidt and Skidmore, (2003) noted that, although the spectral reflectance curves of different wetland vegetation species might look similar, it is possible to discriminate these species using hyperspectral remote sensing techniques such as vegetation indices and the red edge position. Such hyperspectral transformations can be combined with advanced linear or nonlinear models, multivariate statistical analysis technique such as discriminant analysis techniques (mahalanobis distance, Jeffries–Matusita distance, Canonical variate analysis, and classification trees).

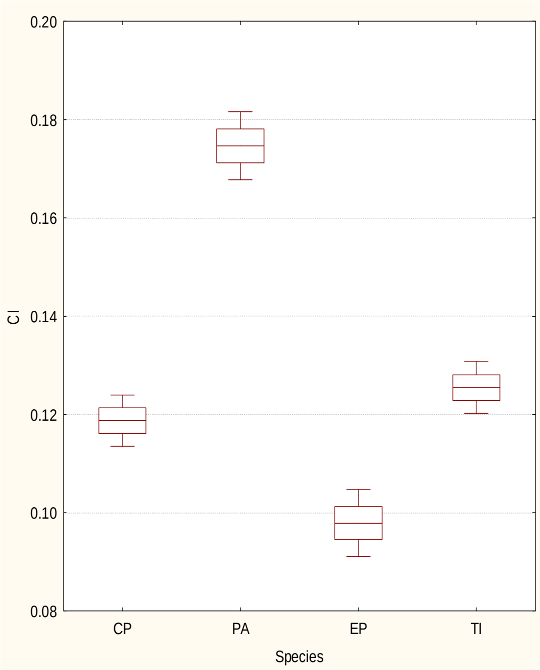
4.2 Discriminating wetland vegetation using vegetation indices and the red edge position

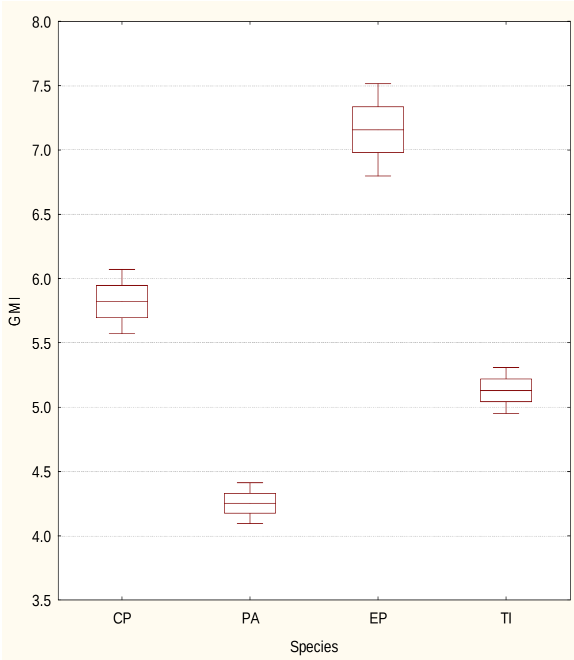
The results from one-way ANOVA showed that there is a significant difference among all the species means for all vegetation indices (RESP, CI, GMI, VOG_a, NDVI, SR, and TVI) and REPs (MFD,Lin-Inter, and LE1) i.e. the null hypothesis, Ho: H_0: $\mu_1 = \mu_2 = \mu_3 = \mu_4$ was rejected for all the indices. ANOVA proved that these vegetation species were spectrally different using different indices.

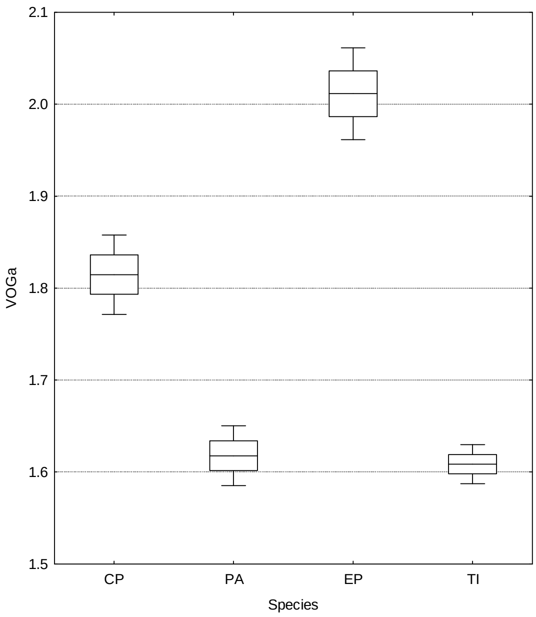
The use of one-way ANOVA indicated that hyperspectral remote sensing data can be used to distinguish wetland vegetation at species level. REPs and vegetation indices have shown that the reflectance spectra of most vegetation species were statistically different with a 95% confidence level. From Figure 4.1 the REPs show that EP has the highest mean of reflectance spectra of all other species which is around 726nm, followed by CP, PA, and TI with means of 723nm, 719nm, and 717nm respectively.

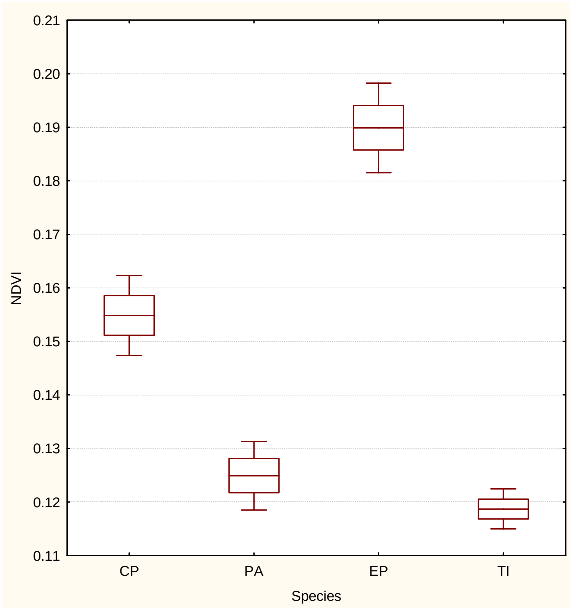
Vegetation indices produced different results such that SR, RESP, and GMI yielded same order of ranking which starts with the highest mean for EP followed by CP, TI, and PA. CI showed that PA has the highest mean of all other vegetation species with a mean of 0.174659, followed by TI, CP, and EP with means of 0.125460, 0.118736, and 0.097873 respectively. The box plots of VOG_a, NDVI, and TVI indicated that EP had the highest mean followed by CP, PA, and TI.




CI
0.20
0.18
0.16
0.14
0.12
0.10
0.08
CP
PA
EP
TI
Species


GMI
8.0
7.5
7.0
6.5
6.0
5.5
5.0
4.5
4.0
3.5
CP
PA
EP
TI
Species


VOGa
2.1
2.0
1.9
1.8
1.7
1.6
1.5
CP
PA
EP
TI
Species


NDVI
0.21
0.20
0.19
0.18
0.17
0.16
0.15
0.14
0.13
0.12
0.11
CP
PA
EP
TI
Species

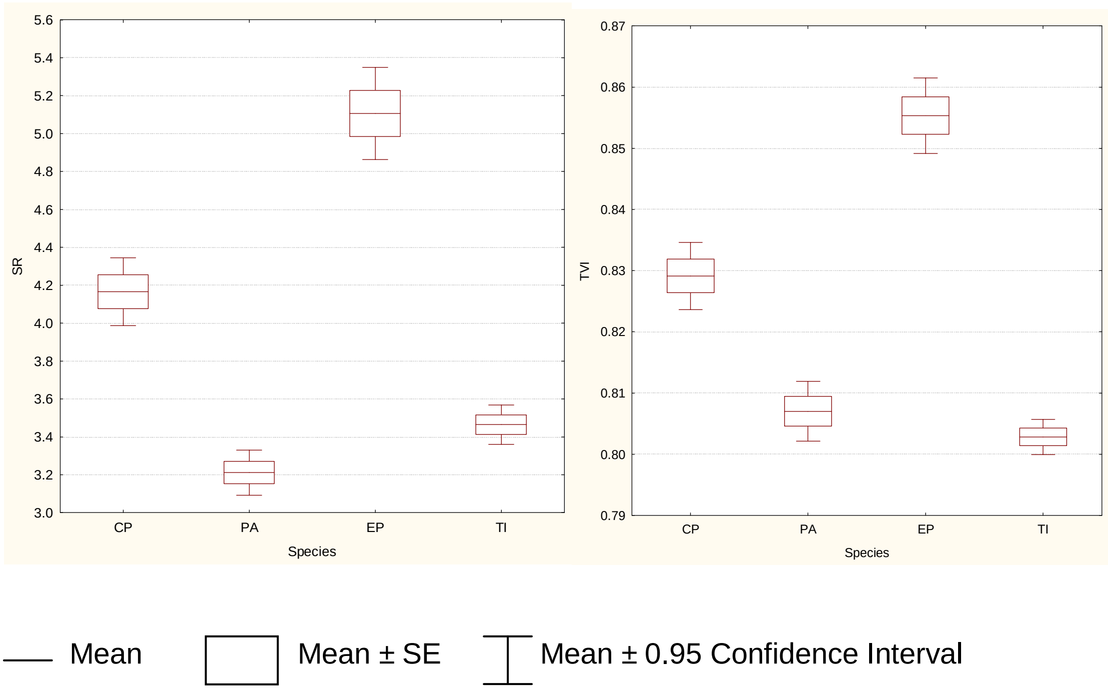


Figure 4.1 Box plots showing the spread of mean, standard error, and Confidence Interval of each vegetation species produced by REPs and vegetation indices.

Overall, most of the indices yielded p values less than 0.01, but CI showed that there was no significant difference between species with a p value of 0.07509 as shown in Figure 4.2.

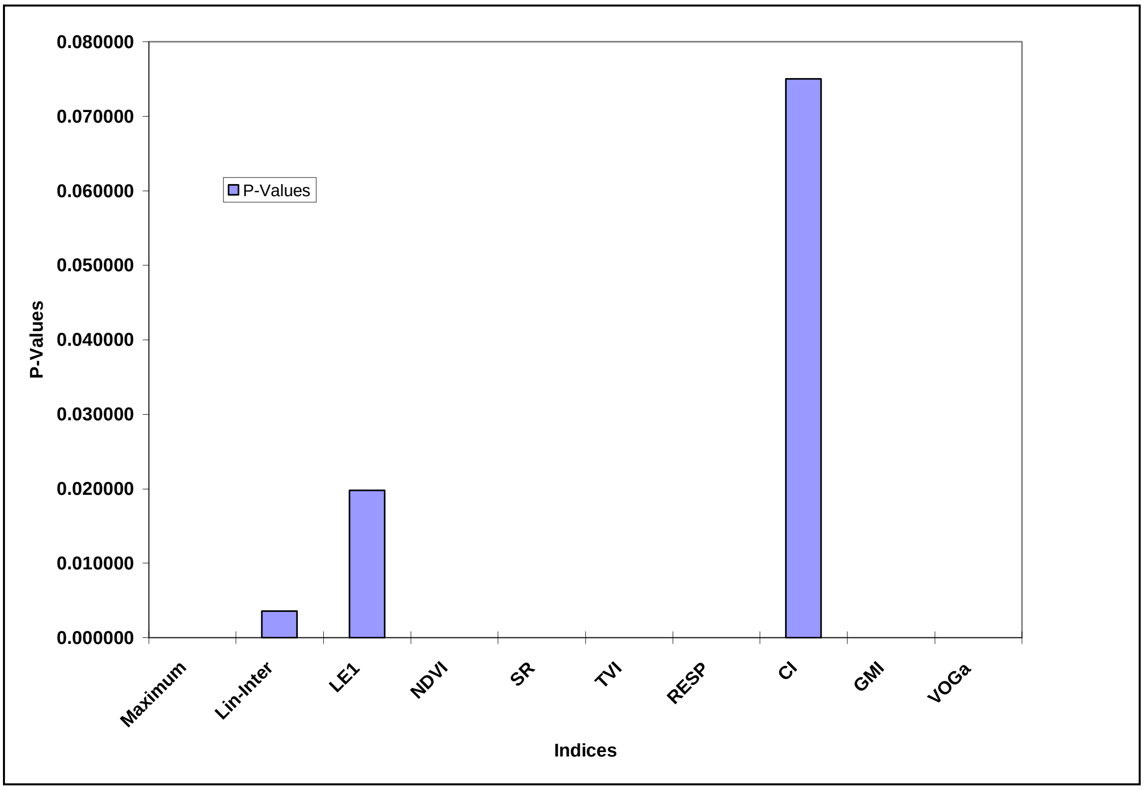


Figure 4.2 Results of ANOVA test showing overall p values of four species from different vegetation indices notably MFD, Lin-Inter, LEI, NDVI, SR, TVI, RESP, CI, GMI, and VOG_a**.**

One-way ANOVA test did not show which pairs of means were different. To determine which pairs of means differ, the post hoc Bonferroni test was applied which is basically used for multiple comparisons. From the pair's means, it can be noted that different vegetation species have different spectral responses and this can help to discriminate them. After the Bonferroni test was computed, it was observed that some of the species were not significantly different, especially when using vegetation indices as compared to the REPs (Figure 4.3). Most species pairs were able to be differentiated using REPs than all vegetation indices except GMI. All vegetation indices could not discriminate all the species excluding GMI which produced highly significant p values with the minimum of 0.000000 and maximum of 0.00066 as shown in Figure 4.3. RESP, VOG_a, NDVI, and TVI showed that the pair of PA and TI was not statistically different with a p value of one. CI showed that the pair of CP and TI was not statistically different with a p value of 0.713578. SR also showed no statistical difference between PA and TI.

Maximum first derivative and linear extrapolation showed that all the vegetation species were statistically different. Linear interpolation produced the same results as RESP which showed that there was no significant difference between PA and TI with a p value of 0.641440.

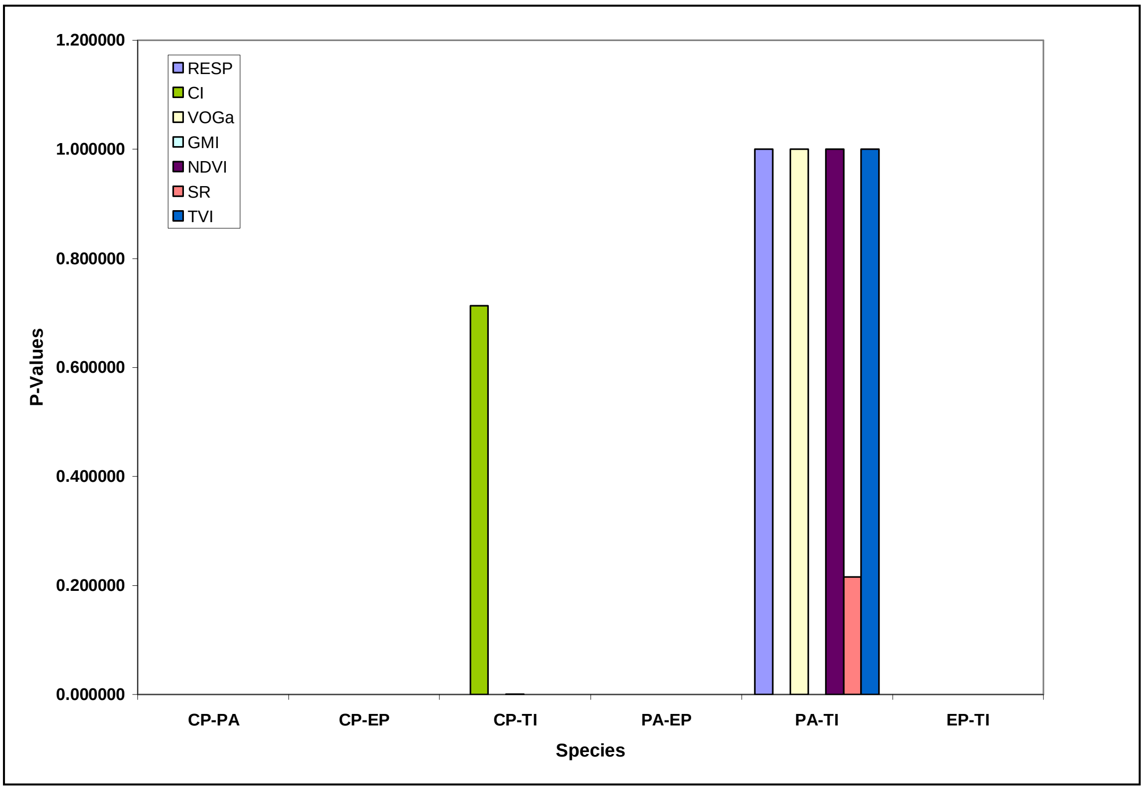


Figure 4.3 Results of one-way ANOVA test showing the difference between all four species (6 pairs) using RESP, CI, NDVI, SR, TVI, GMI, and VOG_a after the Bonferroni adjustment.

When all the REPs extracted from maximum first derivative, linear extrapolation and linear interpolation was compared, maximum first derivative and linear extrapolation showed the highest potential of discriminating wetland vegetation species than linear interpolation (Figure 4.4). In general, REPs, except linear interpolation showed that they can be used for vegetation discrimination with lower p values than vegetation indices.

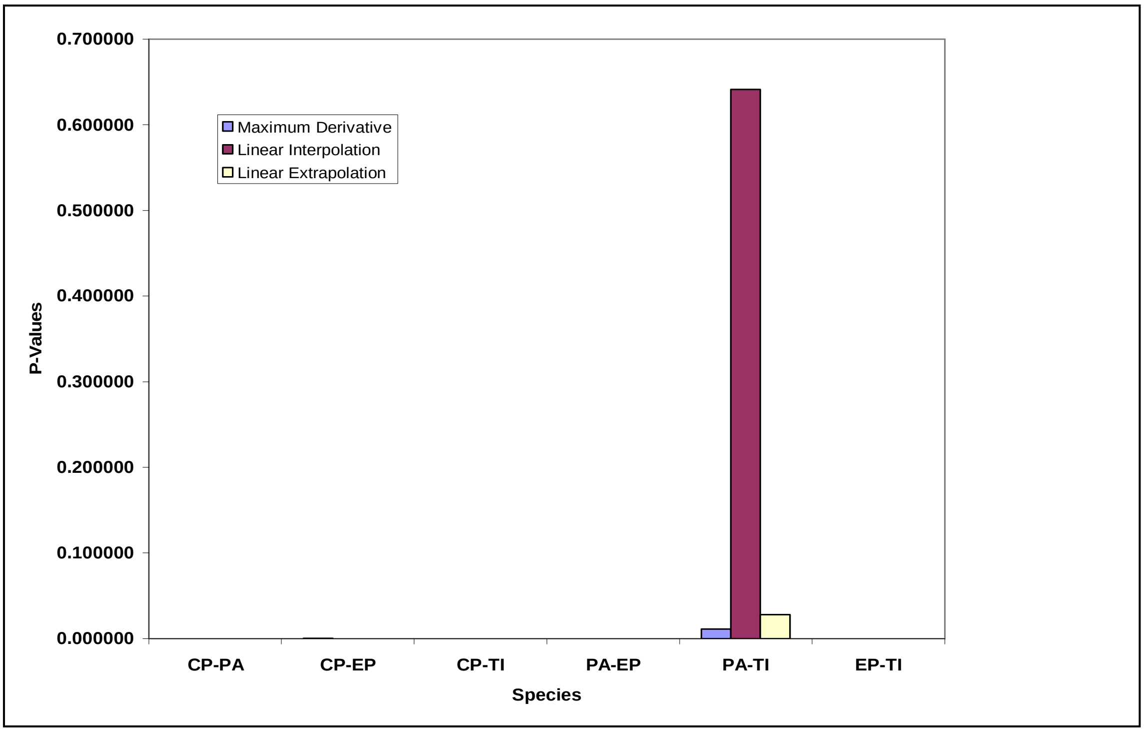


Figure 4.4 Results of one-way ANOVA test showing the difference between all four species (6 pairs) using MFD, Lin-Inter, and LEI after Bonferroni adjustment.

4.3 Canonical variate analysis results

To support and further extend the results of one-way ANOVA test, CVA was applied. CVA can discriminate among the species and is capable of ranking the important remote sensing variables in the discrimination process. CVA proved to be very useful in discriminating wetland vegetation species because from the results, it showed that there was a highly significant difference between species with Wilks' lambda of 0.0737251 and p value of less than 0.0000. If the Wilks' lambda is in the range of one it shows that there won't be a discriminatory power in the model, but if it is around 0.0, as was obtained in the study, it shows that there is a discriminatory power in the model. CVA was applied with a standard method and tolerance of 0.001.

From the results in Table 4.1, root 1 showed that vegetation indices, CI, GMI, and LE1 had relatively more power of discriminating wetland vegetation species with highest factor structure coefficients of -0.542223, 0.303967 and 0.25979 respectively. Linear extrapolation method showed that it has more power of discriminating vegetation species than when compared to other REPs (maximum first derivative and linear interpolation) since it has a highest factor structure coefficient of 0.25979. The second canonical function is marked by variables VOG_a followed by NDVI, RESP, and TVI and to a lesser extent SR and Lin-Inter. The third canonical function shows that the largest contribution was provided by GMI followed by SR, RESP, LE1, and TVI respectively.

Table 4. 1 Factor structure matrix representing the correlation between the variables and the canonical functions

	Root 1	Root 2	Root 3
Maximum	-0.013753	-0.683907	-0.005173
Lin-Inter	0.048586	-0.769295	0.220014
LE1	0.25979	-0.758011	0.24693
NDVI	0.074005	-0.851914	0.219431
SR	0.202803	-0.831706	0.282193
TVI	0.077425	-0.843625	0.225851
RESP	0.166538	-0.852697	0.254418
CI	-0.542223	0.608658	-0.170163
GMI	0.303967	-0.758661	0.312395
VOGa	0.115917	-0.868219	0.204568
Eigenvalues	3.4642	1.9331	0.7226

The scatter plots in Figure 4.5 and Figure 4.6 show the position of the hydrophytic vegetation species classes in the canonical space. Although there were three functions or roots that were produced, root 1 versus root 2 produced better results compared to root1 versus root 3 and root 2 versus root 3 on how these wetland vegetation species differ when the CVA was run. Even though root 1 versus root 2 showed that vegetation species were separable, there was a sizeable confusion between CP and EP.

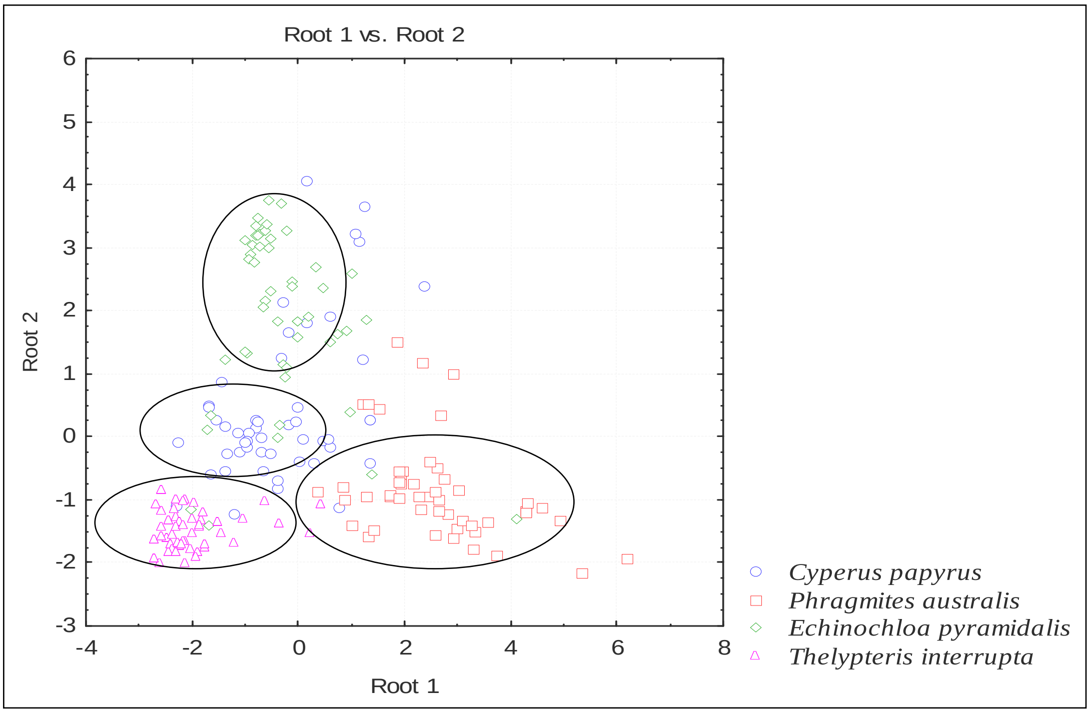


Figure 4.5 Scatter plot of canonical roots (root 1 vs root 2) produced by CVA.

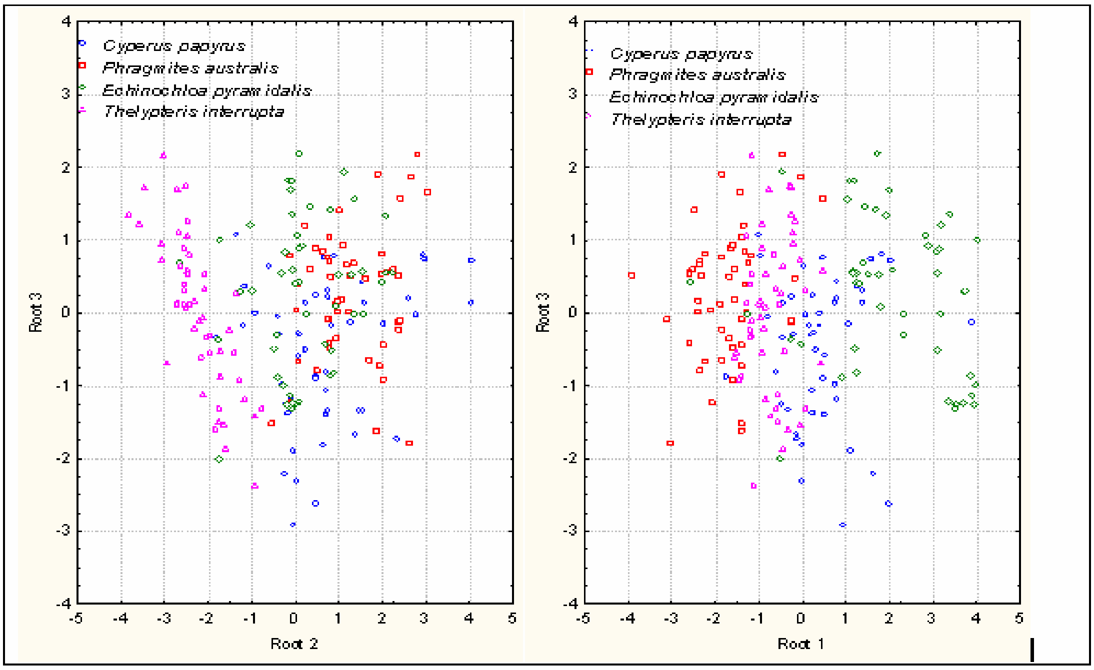


Figure 4.6 Scatter plots of canonical roots (root 1 vs root 3 and root 2 vs root 3) produced by CVA.

From Table 4.2, which shows the means of canonical variables to determine the nature of the discrimination for each canonical root, the results show that the first canonical function discriminates mostly between the PA and other wetland vegetation species. This is followed by TI and CP, and to a lesser extent EP. In the second canonical function, EP was discriminated mostly followed by TI, PA, and CP. The third canonical function seems to distinguish mostly between CP and other wetland vegetation species; however, the magnitude of the discrimination is much smaller and this can be noted in Table 4.1 which shows that the Eigenvalue of the third canonical function is much smaller than the first and second canonical function. The Eigenvalue of the third canonical function is 0.7226 compared to the first and second canonical functions with Eigenvalues of 3.4642 and 1.9331 respectively.

Table 4. 2 Means of canonical variables to determine the nature of the discrimination for each canonical root

Species	Root 1	Root 2	Root 3
CP	0.55331	-0.69016	-1.37209
PA	-2.96247	0.87026	0.10329
EP	0.31154	-1.86877	0.89374
TI	2.097624	1.688666	0.375062

Table 4. 3 An error matrix of four wetland vegetation species

From Table 4.3, it can be noted that, of those 50 samples per wetland vegetation species that were mapped as CP, PA, EP, and TI only 40, 47, 37, and 50 samples were correctly assigned to CP, PA, EP, and TI on the ground, resulting in a 80%, 94%, 74%, and 100% user's accuracy respectively. Also from Table 4.3, it can be seen that 40 out of 55 samples of CP were correctly classified as CP, resulting in a producer's accuracy of 77%. On 51 samples of PA, 47 samples were correctly classified as PA, resulting in a producer's accuracy of 94%. Of the 42 samples of EP, *only* 37 samples were correctly classified as EP, which resulted in a producer's accuracy 88%. Finally, of the 56 samples of TI, 50 samples were correctly classified as TI, resulting in a producer's accuracy of 89%. The overall accuracy was 87% with a kappa coefficient of 0.83 which was almost perfect according to Landis and Koch's (1977) strength of agreement.

Species	CP	PA	EP	TI	Commission Error (%)	User Accuracy (%)
CP	40	2	4	4	20	80
PA	2	47	1	0	6	94
EP	10	2	37	2	26	74
TI	0	0	0	50	0	100
Omission Error (%)	23	6	12	11		
Producer Accuracy (%)	77	94	88	89		
Overall Accuracy (%)	87					
Kappa statistic	0.83					

4.4 Discussion

This study investigated whether the spectral information of wetland vegetation at species level could be used to discriminate vegetation species. This was done by using vegetation indices and the REPs variables. Canonical variate analysis was used to discriminate among the species as well as ranking the most important hyperspectral transforms in the discrimination process.

4.4.1 Predictive performance of discriminant analysis

It was tested whether the REPs (Lin-Inter, MFD, and LE1) can discriminate wetland vegetation species better than vegetation indices (RESP, CI, NDVI, SR, TVI, GMI, and VOG_a). All the calculations were done using the wetland vegetation species reflectance spectra collected per species. The application of one-way ANOVA to test if there were significant differences among wetland vegetation species has helped to determine if there was any chance of species separability. To support the study, the results obtained from one-way ANOVA test and Boniferroni adjustment test confirmed that there was a significant difference among hydrophytic vegetation by showing which ones were statistically different and not statistically different.

The results of this study confirmed that it is a reliable method to discriminate hydrophytic vegetation using REPs and vegetation indices as shown by one-way ANOVA test and the Boniferroni adjustment test on Figure 4.3 and Figure 4.4. Previous studies have also shown that the red edge region is relatively insensitive to atmospheric interference, to variations in illumination conditions, and to the reflectance of the soil background (Guyot *et al.*, 1992; Mutanga, 2004). This has made the use of the red edge region to discriminate wetland vegetation species feasible. Linear interpolation and maximum first derivative were used in this research, but were not as useful as the proposed linear extrapolation technique. The linear extrapolation technique which was developed by Cho and Skidmore (2006) to tackle the problem of multiple peaks on the correlation between chlorophyll and REP and variation in slope, proved to be more useful than linear interpolation and maximum first derivative since it is least sensitive to canopy properties and structure (Cho and Skidmore, 2006). Cho and Skidmore (2006) suggested that linear extrapolation was more sensitive to leaf chlorophyll content with minimal effect of LAI and leaf mass compared to linear interpolation and maximum first derivative. Overall, the red edge parameters extracted from hyperspectral data are important because they are comprised of many narrow bands that are linked to important biochemical and biophysical properties of plants (Kokaly, 2001; Cho and Skidmore, 2006; Mutanga, 2004; Siciliano *et al.*, 2008). These results are comparable to those of Mutanga (2004) who found that the visible red absorption as well as REPs can discriminate between treatment groups of tropical grass containing different levels of nitrogen concentration.

The application of red edge hyperspectral indices or vegetation indices as they are known seems to produce invariable results with a slight difference and most of these VIs were significant other than CI. Red edge hyperspectral vegetation indices balance the absorption towards the red reflectance and towards the near infrared regions of the spectrum by utilizing all the bands that are around the inflection point derived from maximum first derivative. All vegetation indices couldn't discriminate all the species excluding GMI which produced highly significant p values with the minimum of 0.000000 and maximum of 0.00066. All other vegetation indices (RESP, VOG_a, and CI) had one pair they couldn't discriminate which might be a result of utilizing bands in the longer wavelength than GMI which uses 700nm and 750nm bands which lie on the red edge slope.

CVA as suggested by Mutanga (2004) helped to reduce dimensionality in the hyperspectral data set to three canonical functions, and to describe and explore the difference between REPs and vegetation indices in discriminating wetland vegetation species. Using CVA, it was observed that canonical functions assist in showing which of the REPs and vegetation indices had discriminatory power when utilizing hyperspectral remote sensing data for wetland vegetation discrimination at species level. CVA has further revealed that CI, GMI, LE1, SR, and RESP had relatively more power to discriminate wetland vegetation species since they had the highest factor structure coefficients in the first canonical function as shown in Table 4.1. The results from CVA have also shown that the first canonical function has a high magnitude of discriminating wetland vegetation species since it has higher Eigenvalues than the second and third functions. The only unexpected result was that, after CVA was run, vegetation indices, especially GMI and CI, showed more power of discriminating wetland vegetation species than linear extrapolation did. This was not expected since the application of this new technique on vegetation species discrimination on six species done by Cho (2007) which were *Hedera, Rhododendron, Prunus, Corylus, Malus, and Aesculus* proved to have more power for species discrimination. In his study Cho (2007) proved that linear extrapolation had a slight edge in discriminating species over linear interpolation and maximum first derivative. The results obtained in this study have shown that REPs and vegetation indices can be accurately used for wetland vegetation species discrimination because they produced an overall accuracy of 87% with K_{hat} of 0.83 and producer's accuracy ranging from 71% (CP) to 92% (PA) after accuracy assessment was done.

4.5 Conclusion

In this study two main objectives were dealt with which were:

1. To evaluate the ability to detect detailed wetland vegetation types with hyperspectral data using red edge position, and

2. To test different red edge extraction techniques for estimating different hydrophytic vegetation.

From this study it can be conclude that:

- Spectral reflectance measurements of hydrophytic vegetation at canopy level can be used to discriminate CP, TI, EP, and PA. This means that the mean spectral reflectance of wetland vegetation varies from the other species mixed within the same ecosystem.

- Canonical functions computed from REPs and vegetation indices can be used to discriminate among groups of wetland vegetation species.

- Red edge region has relatively more information that can be used to discriminate wetland vegetation species. Vegetation indices computed from canonical functions showed that they have greater discriminatory power than REPs, except linear extrapolation.

Overall, the result which was obtained in this research has confirmed that hydrophytic vegetation can be discriminated using spectral reflectance at species level. This study also confirmed how hyperspectral remote sensing is useful when identifying and mapping wetland vegetation.

The study demonstrated that it is possible to discriminate wetland vegetation species at canopy level using reflectance spectra computed from canonical functions. However, the biophysical and biochemical properties of vegetation vary from species to species. It is therefore imperative to add these properties as independent variables to discriminate wetland vegetation species. In the next chapter, biomass and water content variables will be used to discriminate wetland vegetation species.

Chapter Five:

Integrating measures of biochemical and biophysical properties with vegetation indices to improve wetland vegetation discrimination at species level

5.1 Overview

The discrimination of wetland vegetation at species level has a very important influence on attempts to mitigate ecosystem deterioration. Different wetlands in developing countries, especially in Africa, have come under much pressure since their hydrology and salinity are being damaged by exploitation of their natural resources, and as a result they need to be monitored and conserved for future generations. There are many bio-indicators such as wetland vegetation, hydric soil, and wetland hydrology that can be used to check if there is any wetland change, but vegetation is one of the most important factors that can be used (Demuro and Chisholm, 2003). To monitor a large area, remote sensing comes into play since it is very practical and cost-effective and it has been successfully used for vegetation studies for a long time (Ross, 1981; Guyot and Baret, 1988; Curran *et al.*, 1992). Vegetation indices have been developed to monitor the changes in ecological systems. These vegetation indices operate by contrasting intense chlorophyll pigment absorptions in the red region against the high reflectance due to multiple scattering in the near infrared region (Todd *et al.*, 1998). Asner (1998) suggested that biophysical and biochemical properties of vegetation can be quantified and used for vegetation mapping since species differ in their structural and biochemical content characteristics. However, to date, no studies to our knowledge have quantified these biophysical and biochemical parameters and combined them with hyperspectral data for vegetation species discrimination. This study was carried out in the wetlands of iSimangaliso Wetland Park and the results are described in the next section.

5.2 Discriminating wetland vegetation at species level using a combination of biochemical and biophysical properties with vegetation indices

One-way ANOVA results at 95 % confidence level ($p < 0.05$) indicated that there was a significant difference among wetland vegetation species. The means of each and every vegetation index (RESP, CI, GMI, and SR), water content and biomass variables showed that wetland vegetation species can be distinguished using their means. As shown in Figure 5.1, for quantified water content the highest mean is for TI followed by EP, CP, and finally PA. The box plot of quantified biomass showed the highest mean for CP followed by PA, EP, and TI in that order.

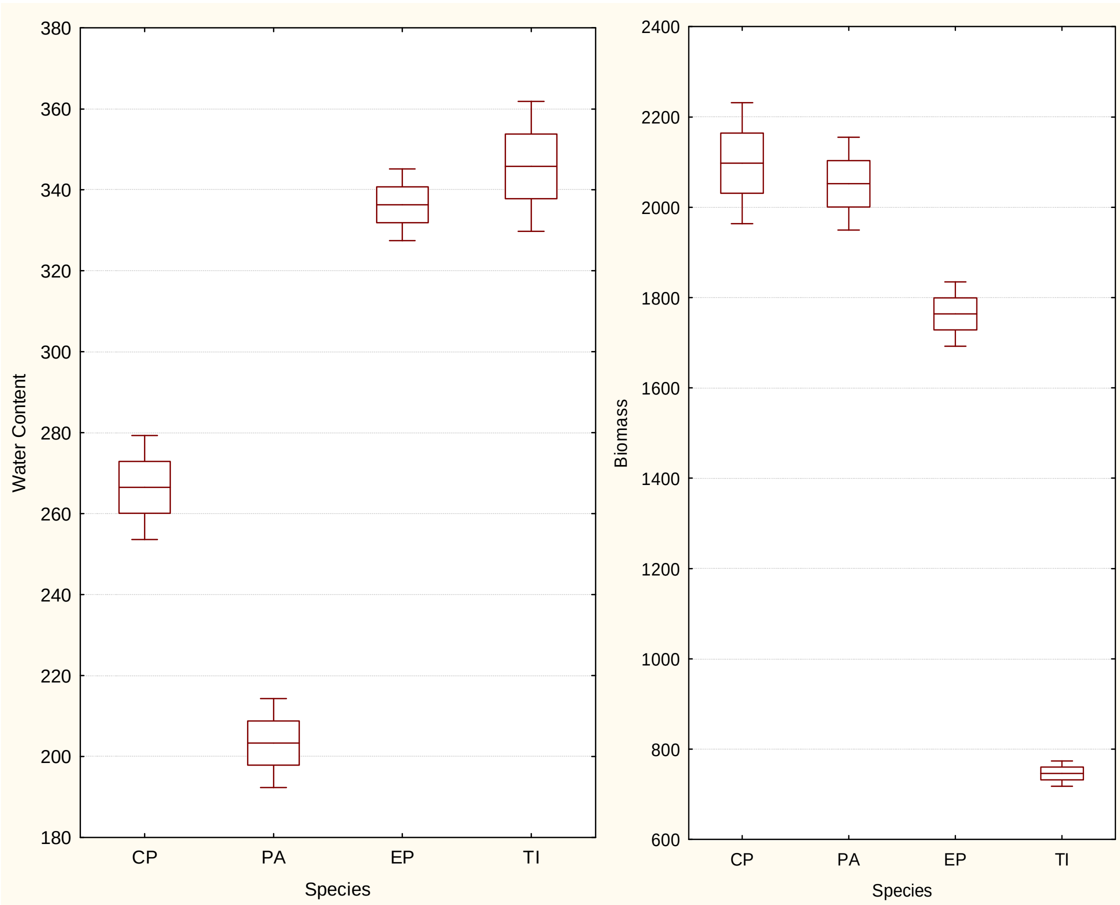


Figure 5.1 Box plots showing the spread of mean, standard error, and Confidence Interval of each vegetation species produced water content and biomass variables.

From all the vegetation indices, and measures of water content and biomass that were applied, their overall p values were less than 0.0004, except CI that had a p value of 0.075029 as shown in Figure 5.2. One-way ANOVA test did not show which pairs of means were different. Therefore, to determine which pairs of means differ, the post hoc Bonferroni test was applied. Figure 5.3 shows all the p values of vegetation indices, and quantified water content and biomass. The Bonferroni test showed that some vegetation indices (RESP and SR) were not able to differentiate between PA and TI. Also CI failed to distinguish between CP and TI. GMI was the only vegetation index that managed to distinguish all the vegetation species. Water content and biomass variables couldn't discriminate between EP and TI, and CP and PA.

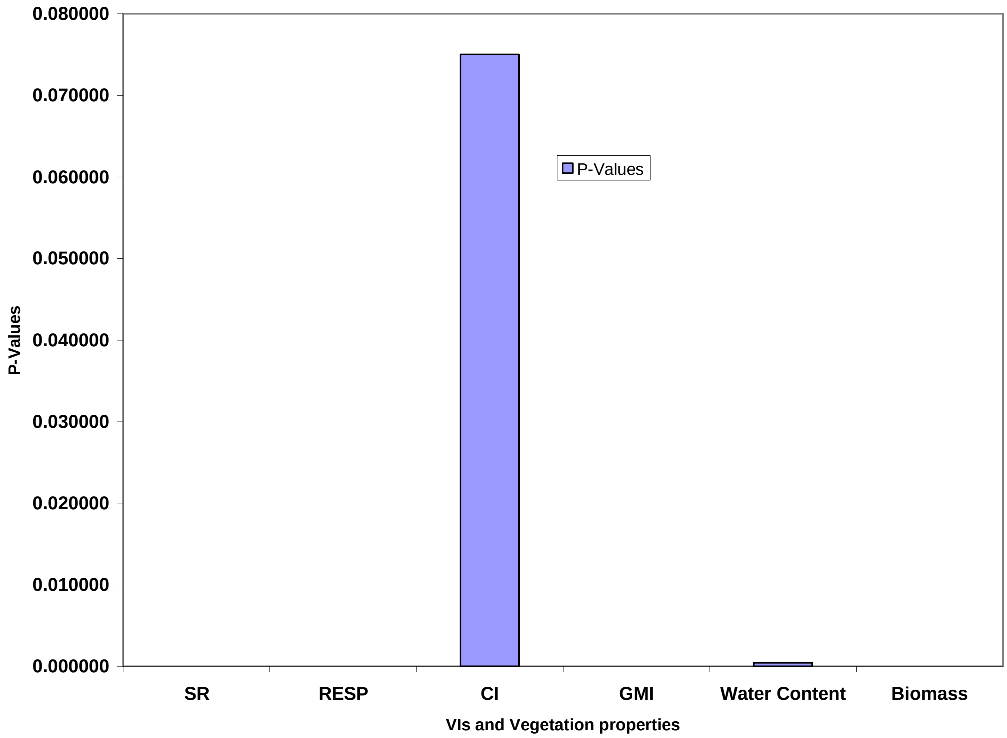


Figure 5.2 Results of ANOVA test showing overall p values of four species from different vegetation indices and vegetation properties.

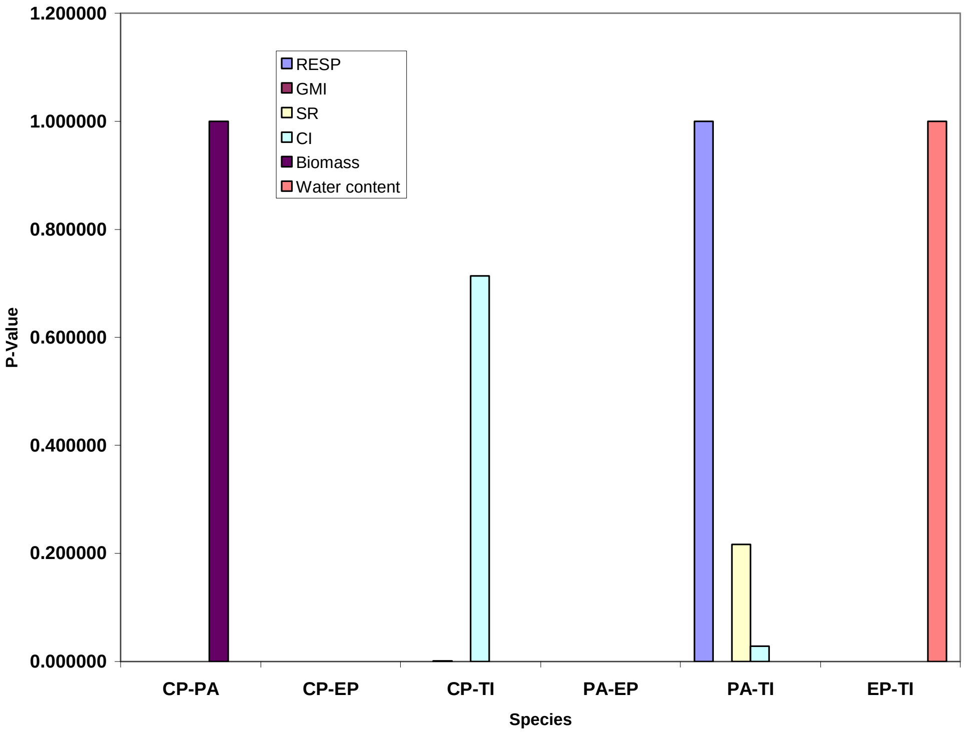


Figure 5.3 Results of one-way ANOVA test showing the p values of all four species (6 pairs) using RESP, GMI, CI, SR, and measures of plant water content and biomass after Bonferroni adjustment.

Although the results of one-way ANOVA indicated that the indices were able to distinguish among wetland vegetation at species level, it is very difficult to determine which one of the indices, quantified water content or biomass, had the best discriminatory power. As a result, canonical variate analysis was applied to test if the introduction or addition of quantified water content and biomass had improved the discriminatory power. The results of CVA supported that all the species were statistically different with a Wilk's lambda of 0.0217327. The first canonical function shown in Table 5.1 contains the largest proportion of the explained variance with an Eigenvalue of 9.78499. The highest factor structure coefficient is contained in the quantified water content and biomass with coefficients of -0.432514 and 0.421967 respectively. This was followed by CI, GMI, SR, and RESP in that order. The highest factor structure coefficient in the second canonical function shows that RESP, SR, and quantified biomass made the largest contribution, and to a lesser extent GMI. The third canonical function also shows that the highest factor structure coefficient is in the CI, quantified biomass, and in GMI and SR to a lesser extent.

Table 5.1 Factor structure matrix representing the correlation between the variables and the canonical functions

	Root 1	Root 2	Root 3
SR	-0.178442	0.832607	0.293838
RESP	-0.160428	0.855823	0.281673
CI	0.338479	-0.495210	-0.674013
GMI	-0.237049	0.727677	0.336985
Water Content	-0.432514	0.056009	0.080464
Biomass	0.421967	0.791681	0.441068
Eigenvalues	9.78499	1.69537	0.58288

Table 5.2 shows the means of canonical variable representing the correlation between the wetland vegetation at species level and the canonical roots. The results in Table 5.2 showed that the first canonical root discriminates mostly between PA species and other species, followed by TI species, and to a lesser extent EP species. The second canonical function discriminates mostly between EP species and other wetland vegetation species, followed by TI group. In the third canonical function, it can be noted that CP species can be mostly discriminated as compared to other vegetation species, and this is followed by PA group, and to a lesser extent EP group. However, the magnitude of the discrimination is much smaller, and this can be noted in Table 5.1 which shows that the Eigenvalue of the third canonical function is much smaller than the first and second canonical function.

Table 5.2 Means of canonical variables representing the correlation between the wetland vegetation species and the canonical function

Species	Root 1	Root 2	Root 3
CP	1.45706	0.22934	1.252645
PA	4.35233	-0.36384	-0.734683
EP	-2.44813	1.86333	-0.403674
TI	-3.36126	-1.72883	-0.114288

The scatter plot in Figure 5.4 shows positions of wetland vegetation species in the canonical space. All the species in the scatter plot are positioned distinctly among them. The positioning of the canonical scores shows a gradient from *Thelypteris interrupta*, followed by *Echinochloa pyramidalis*, and *Cyprus papyrus* to *Phragmites australis.* Figures 5.5 and 5.6 show the scatter plots of canonical root 1 versus root 3 and root 2 versus root 3 respectively. The results in these scatter plots clearly indicate that only the first canonical function, followed by the second canonical function, makes the highest contribution to wetland vegetation species discrimination. The scatter plot of canonical root 1 versus root 3 shows that it can be also used to distinguish between wetland vegetation at species level to a lesser extent than root 2 versus root 3, although it cannot separate between *Echinochloa pyramidalis* and *Thelypteris interrupta.* Also, from Figure 5.3 it can be noted that there is no confusion between species except for a minimal confusion between *Cyprus papyrus* and *Phragmites australis.*

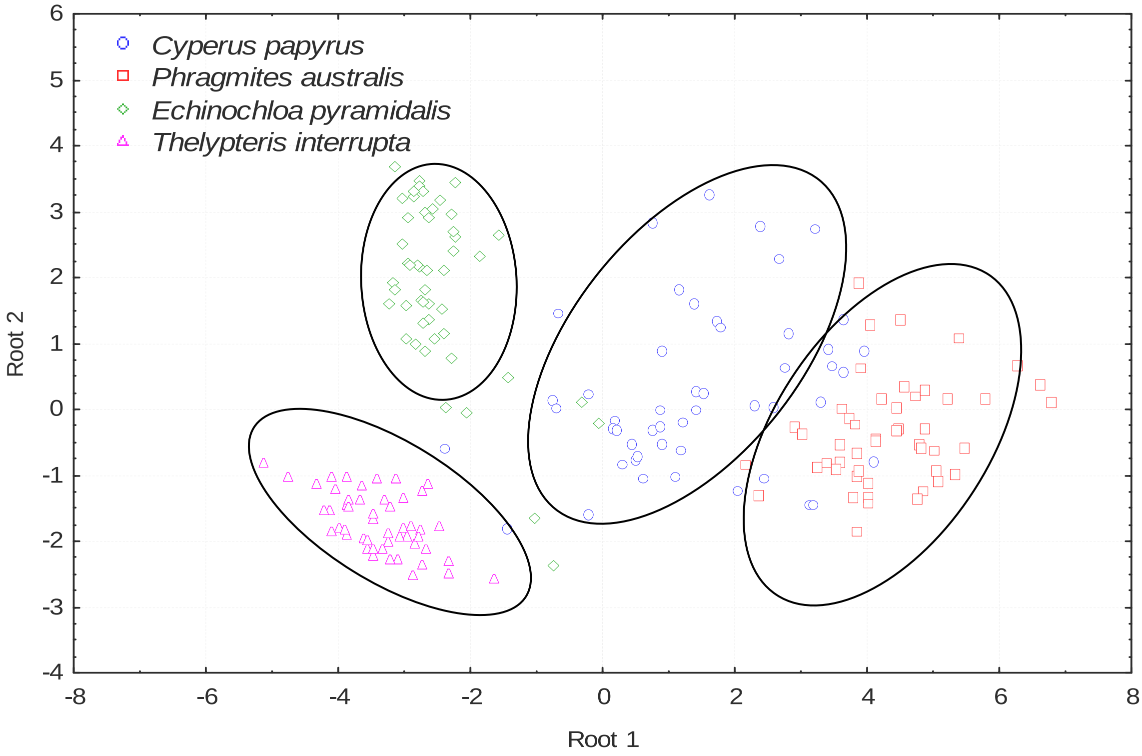


Figure 5. 4 Scatter plot of canonical roots (root 1 versus root 2) produced by CVA.

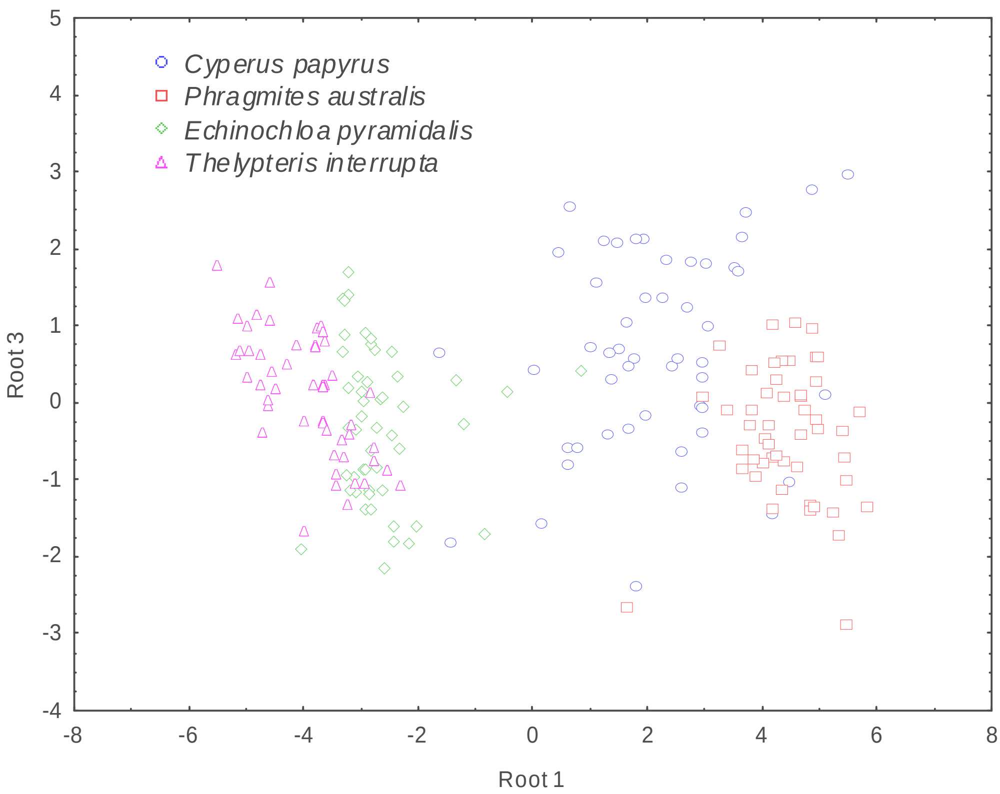


Figure 5. 5 Scatter plot of canonical roots (root 1 versus root3) produced by CVA.

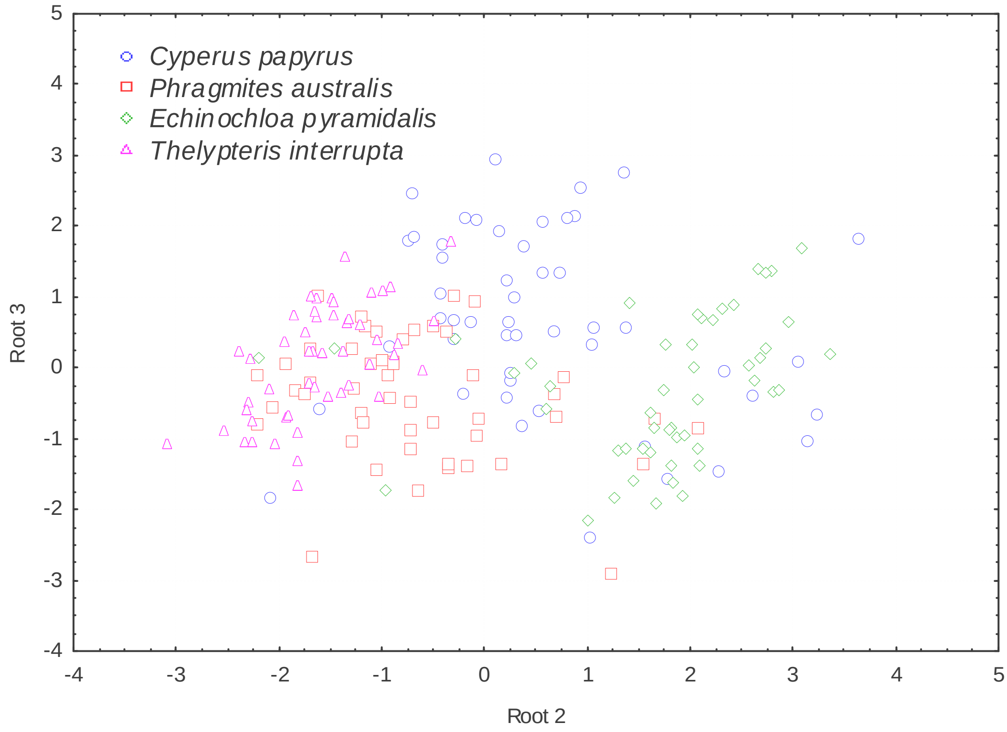


Figure 5. 6 Scatter plot of canonical roots (root 2 versus root3) produced by CVA.

To determine if measures of biochemical and biophysical properties of vegetation had improved the discriminatory power, quantified water content and biomass was added as canonical variables. The addition of water content and biomass variables was seen as a major improvement on vegetation species discrimination. But to determine the actual percentage of improvement made by water content and biomass measures, the confusion matrix or error matrix was calculated for those two variables as seen in Table 5.3. The overall accuracy and Kappa statistic showed that, wetland vegetation species can be classified into their respective groups with overall accuracy of 82 % and Kappa statistic of 0.76 respectively. The classification rate that was achieved by adding water content and biomass variables in the canonical variate analysis indicted their discriminatory power.

Table 5.3 An error matrix of four wetland vegetation species showing Producer Accuracy, Omission Error, User Accuracy, Commission Error, and Overall Accuracy as percentages and Kappa Statistic using water content and biomass variables only

Species	CP	PA	EP	TI	Commission Error (%)	User Accuracy (%)
CP	32	10	6	2	36	64
PA	10	40	0	0	20	80
EP	5	0	42	3	16	84
TI	0	0	0	50	0	100
Omission Error (%)	32	20	12	10		
Producer Accuracy (%)	68	80	88	90		
Overall Accuracy (%)	82					
Kappa statistic	0.76					

Table 5.4 An error matrix of four wetland vegetation species showing Producer Accuracy, Omission Error, User Accuracy, Commission Error, and Overall Accuracy as percentages and Kappa Statistic using quantified water content and biomass, and vegetation indices

Species	CP	PA	EP	TI	Commission Error (%)	User Accuracy (%)
CP	45	3	1	3	10	90
PA	1	49	0	0	2	98
EP	1	0	47	2	6	94
TI	0	0	0	50	0	100
Omission Error (%)	4	2	2	8		
Producer Accuracy (%)	96	98	98	91		
Overall Accuracy (%)	95.5					
Kappa statistic	0.94					

To further investigate the effectiveness of water content and biomass measures to discriminate wetland vegetation species and to explain the observed patterns or changes, the samples were classified using Fisher's linear discriminant function with proportional to group size prior probabilities (McGarigal *et al.*, 2000; Mutanga, 2004). From Table 5.4, it can be noted that, of those 50 samples per wetland vegetation species that were mapped as CP, PA, EP, and TI only 45, 49, 47, and 50 samples were correctly assigned to CP, PA, EP, and TI, resulting in a 90%, 98%, 94%, and 100% user's accuracy respectively. Also all the vegetation species were correctly classified as CP, PA, EP, and TI, and achieved producer's accuracy of 96%, 98%, 98%, and 91% respectively. The overall accuracy and kappa coefficient of 95.5% and 0.94 was obtained respectively. The addition of water content and biomass variables increased the discriminatory power by 8.5%.

5.3 Discussion

In this section, the potential of hyperspectral data in conjunction with biochemical and biophysical properties of vegetation to discriminate wetland vegetation species is discussed. The main aim is to investigate if there is any improvement in vegetation species discrimination after the introduction of water content and biomass as independent variables.

5.3.1 Integrating quantified water content and biomass, and vegetation indices to discriminate wetland vegetation at species level

Vegetation indices have been widely used for wetland vegetation discrimination (Cho and Skidmore, 2006), but the motivation for the present study was to determine if there was any improvement in vegetation species discrimination with the introduction of biochemical and biophysical parameters. To achieve this proposed goal, the quantified water content and biomass as independent variables were used in conjunction with vegetation indices in the vegetation species discrimination.

The results confirmed that discriminating different wetland vegetation at the species level is improved using vegetation indices with the addition of water content and biomass variables. As suggested by Mutanga (2004), CVA provides an insight into the relationship among the wetland vegetation species, thereby showing the importance of hyperspectral remote sensing. The study has shown that canonical functions extrapolated from water content and biomass variables in combination with vegetation indices can be used for vegetation species separability. The result indicates that quantified water content and biomass of vegetation can be used to distinguish between species since they produced an overall accuracy of 82% and a Kappa statistic of 0.76, respectively. The addition of water content and biomass variables as ancillary information to vegetation indices improved the overall accuracy of species discrimination from 87% as shown in Table 4.3 to 95.5% as shown in Table 5.1, increasing the percentage overall accuracy by 8.5%.

The CVA results have shown that the highest factor structure coefficient for the first canonical function is in the water content and biomass variables. This shows the importance of differences in the structural properties of vegetation species in discriminating among them.

The scatter plot of canonical roots in Figure 5.4 shows the relative positions of species along the canonical axes, and this gives an insight into the relationships among the wetland vegetation species. As shown in Figure 5.4, the vegetation species in the canonical space are clearly located in their own space. *Thelypteris interrupta* is positioned to the lower left side, followed by *Echinochloa pyramidalis* positioned in the top left side of the canonical space, then followed by *Cyperus papyrus* in the middle, and *Phragmites australis* positioned in the bottom right of the feature space. This positioning shows the gradient of vegetation species, thereby confirming the discriminatory power of hyperspectral remote sensing data in combination with the structural characteristics of the species themselves.

This study has shown that the availability and improvement in remote sensing processing techniques for measuring the structural variables of vegetation is an important step towards improving species discrimination. Generated maps from empirical or physically based models showing the distribution of vegetation biochemical and biophysical characteristics can be input as extra ancillary information, in combination with hyperspectral data to improve the mapping of wetland vegetation species as shown in this study.

5.4 Conclusion

In this study, the aim was to discriminate wetland vegetation species using the red edge hyperspectral vegetation indices with the help of water content and biomass variables. The results in this study have shown that:

- The use of measures of biochemical and biophysical properties of plants in conjunction with vegetation indices calculated from hyperspectral remote sensing data improved the discrimination of wetland vegetation at species level.
- With the addition of plant water content and biomass variables, wetland vegetation species were classified into their respective classes with an overall accuracy of 95.5%. By adding quantified water content and biomass the overall accuracy was increased by 8.5%.
- Ancillary information can effectively be used in conjunction with hyperspectral remote sensing data (vegetation indices) to discriminate vegetation species.

Overall, the study has indicated that it is possible to discriminate wetland vegetation at species level using water content and biomass variables, and vegetation indices derived from hyperspectral data.

Chapter Six:

Conclusion

6.1 Introduction

The wetlands of iSimangaliso Wetland Park are important as productive natural ecosystem remnants offering wildlife habitat, tourist destinations, and good water quality at a given time or over a continuous period. These wetlands are functional ecosystems that provide a critical habitat for fauna and flora. Vaiphasa *et al*. (2005) suggest that there are other end users who recognise the importance of wetlands such as forestry, fisheries, and environmental conservation. In wetland studies there are three variables which must be recognised which are wetland (hydrophytic) vegetation, hydric soil, and wetland hydrology (Cowardin *et al.*, 1979). The most important variable when it comes to any wetland change is the wetland vegetation. Hydrophytic vegetation is of fundamental ecological importance and is used as one of the most important bio-indicators for early signs of any physical or chemical degradation in wetland systems (Demuro and Chisholm, 2003; Belluco *et al.*, 2006; Adam and Mutanga, 2009). Wetland vegetation as one of the natural resources, is declining because of the influence of natural disturbance and either intentionally or unintentionally harmful human activities (Vaiphasa *et al.*, 2005; Adam and Mutanga, 2009). As a result, there are now groups which are trying to develop methods for the sustainable management of these wetlands e.g Ramsar Convention and UNESCO. Therefore, there is a need for accurate, precise, and up-to-date spatial information on the current status of wetland vegetation as a prerequisite for the sustainable management of wetland systems (Green *et al.*, 1998).

Remote sensing is regarded as one of the best methods for monitoring and mapping wetlands at local, regional, or global scales (Van Aartd and Waynne, 2001; Schmidt and Skidmore, 2003; Adam and Mutanga, 2009). Currently, there is extensive use of remote sensing for identifying, monitoring, modelling, and discriminating wetland vegetation species using their spectral reflectance (Lee and Lunetta, 1996; Demuro and Chisholm, 2003; Belluco *et al.*, 2006; Hirano *et al.*, 2003; Vaiphasa et al., 2005; Adam and Mutanga, 2009). However, remote sensing is inconclusive in the discrimination of wetland vegetation at species level in the South African context. There is a major disadvantage in South Africa because there is not much information on previous studies for wetland vegetation spectral libraries. The use of multispectral remote sensing for wetland vegetation mapping has been done internationally with reasonable results (Baret *et al.*, 1987; Shahraini *et al.,* 2003; Belluco *et al.,* 2006; Ndzeidze, 2008), but this application was inconclusive when it came to fine details of vegetation, for example, biochemical and biophysical properties. This raised the idea of developing hyperspectral remote sensing with narrow contiguous spectral bands between visible and shortwave infrared regions which have already proved to be a useful tool for wetland vegetation discrimination at species level (Schmidt and Skidmore, 2003; Hirano *et al.,* 2003; Vaiphasa *et al.,* 2005; Sun *et al*., 2008; Adam and Mutanga, 2009). This application of hyperspectral remote sensing has not yet been done extensively to our knowledge in the South African context, except that by Adam and Mutanga (2009). Therefore, in the present study, the aim was to further explore the potential of hyperspectral remote sensing data with its narrow bands to discriminate wetland vegetation at species level in the iSimangaliso Wetland Park, KwaZulu Natal, South Africa. Vegetation indices and the red edge position were used to discriminate wetland vegetation species using spectral reflectance and the biochemical and biophysical properties of vegetation. In order to achieve this goal, the following main objectives were set and achieved:

- to evaluate the ability of hyperspectral remote sensing data in discriminating wetland vegetation at species level using the red edge position,
- to test and compare the performance of red edge position against vegetation indices,
- to test different red edge extraction techniques to distinguish hydrophytic vegetation, and
- to investigate whether there is an improvement in species discrimination by combining vegetation structural and biochemical characteristics with hyperspectral data.

6.2 The use of vegetation indices and REPs for wetland vegetation discrimination at species level

The discrimination of vegetation species using their spectral reflectance was addressed in this study (Chapter 4) by evaluating the potential of the red edge position and hyperspectral vegetation indices to distinguish *Phragmites australis, Thelypteris interrupta, Cyperus papyrus,* and *Echinochloa pyramidalis* species from each other. Canonical variate analysis showed that we can discriminate vegetation species using vegetation indices and REPs as canonical variables. The analysis helps to indicate which one of the canonical variables (vegetation indices and REPs) performed better compared to others. The hyperspectral vegetation indices performed much better than REPs in red edge region. Some vegetation indices especially VOG_a, RESP and CI showed that they had relatively more power of discriminating wetland vegetation species with highest factor structure coefficients than other variables. The overall accuracy obtained was 87% after accuracy assessment. The significant finding in this study is that vegetation indices yielded a superior discriminatory power than REPs when it comes to discriminating wetland vegetation at species level. This finding however needs to be further investigated with more data.

6.3 Introducing vegetation properties for discriminating wetland vegetation at species level

CVA was applied to determine the discriminatory power of variables (vegetation indices and vegetation properties) that were used in this study. In the first paper (Chapter 4), vegetation indices produced 87% overall accuracy compared to 82% of water content and biomass variables in the second paper (Chapter 5). CVA in Chapter 5 showed that water content and biomass variables had superior discriminatory power than did vegetation indices since they had highest factor structure coefficients. The combination of vegetation indices and quantified water content and biomass produced an overall accuracy of 95.5% after accuracy assessment. Comparing results from chapter 4 and chapter 5 shows that the overall accuracy increased by 8.5%. In general, this study showed that vegetation properties can be used to discriminate vegetation species with more discriminatory power than vegetation indices alone. Ancillary information proved that it can effectively be used in conjunction with hyperspectral remote sensing data (vegetation indices) to discriminate vegetation species.

6.4 Synthesis

This study has shown the potential of hyperspectral remote sensing in wetland vegetation spectral separability at species level in the iSimangaliso Wetland Park, KwaZulu Natal, South Africa. Evidently, from this study, it can be noted that the visible and near infrared regions (red edge region) of the electromagnetic spectrum are very important for discriminating wetland vegetation at species level. Spectral reflectance of wetland vegetation was used to evaluate the effectiveness of vegetation indices as compared to the red edge position. The performance of vegetation indices was favourable compared to REPs due to differences in the pigment content (causes of absorption differences in the visible region) and canopy structure (or internal leaf structure in the near infrared) characterized by a plateau of high reflectance (Schmidt and Skidmore, 2003). The use of these vegetation indices overcame the problem of saturation due to the use of narrow bands (hyperspectral) data.

However, when quantified vegetation properties (plant water content and aboveground biomass) were added in as discriminatory variables, the overall discriminatory power increased as well. Of particular importance was the overall performance of plant water content and biomass variables, which yielded highest factor structure coefficients of -0.432514 and 0.421967 respectively.

In summary, it was highlighted in the study that adding biochemical and biophysical parameters of vegetation to remotely sensed data improves the discrimination of vegetation species. Furthermore, the study has shown the potential of discriminating wetland vegetation at species level using data obtained by hand-held field spectrometer with the possibility of up-scaling field and laboratory data to airborne and satellite remote sensing.

6.5 Limitation of the study

One of the limitations of the study was the fact that the study area was waterlogged and swampy; therefore it was very difficult to collect the leaf spectral reflectance measurements. Sampling was done on areas that were reasonably accessible. Also, the field work was done in December in the summer, and usually it rains most of the time. For future studies on discrimination of wetland vegetation at species level it might be a good idea if the leaf spectral reflectance measurements could be taken in winter or a dry season to improve accessibility and reduce the effect of atmospheric obscurities.

6.6 Conclusion and recommendations

The main objective was to investigate the potential of narrow band remote sensing to discriminate wetland vegetation species at field level. The second objective was to investigate whether the addition of quantified vegetation properties (biochemical and biophysical properties) can improve the discrimination of vegetation species. It was revealed in this study that the information contained in narrow bands data and vegetation properties can be used to achieve these goals. Finally, it was concluded that hyperspectral vegetation indices and quantified vegetation parameters based on wavelengths located in the red edge region can accurately discriminate vegetation species at canopy level.

This study was the first attempt to discriminate wetland vegetation using a combination of quantified vegetation properties and hyperspectral vegetation indices. Therefore, future research in wetland vegetation species discrimination either at field level, or at airborne or satellite level should investigate the possibility of using quantified vegetation properties in addition to the spectral data. In addition, vegetation properties such as nitrogen, phosphorous, lignin, chlorophyll content, and leaf area index could be quantified to study their characteristics, and how the differences of these parameters may improve the accuracy of wetland vegetation discrimination. Since discriminating vegetation species at field level using traditional remote sensing (aerial photography) is time consuming, not cost-effective and suffers the disadvantage of some parts of the study area being inaccessible, it is recommended that the study be up-scaled to the application of airborne and satellite hyperspectral remote sensing. In terms of temporal and spatial resolution, airborne or satellite remote sensing offers a good coverage of local, regional, and global scale even in some areas that are difficult to access and also offers a repetitive acquisition of wetland vegetation imagery for developing and improving sustainable management methods.

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