WETLAND ECOTONES: TESTING REMOTE SENSING TECHNIQUES TO MAP ECOTONES IN A FYNBOS EMBEDDED WETLAND

By DANIëLLE AFTON SEYMOUR

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Supervisor: Prof. H.M. de Klerk

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DECLARATION

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SUMARY

Various researchers starting as early as 1903, have developed many definitions of an ecotone (Clements 1905; Livingston 1903; Odum & Barrett 1971). The definition by Holland (1988) described ecotones as zones of transition between adjacent ecological systems, having a set of unique characteristics defined by space and time scales, and by the strength of interactions between adjacent ecological systems (Holland 1988). This definition paves the way for research that may exemplify various aspects of landscape ecology and spatial heterogeneity. Although a niche of high scientific interest, ecotonal research is very understudied, especially research on using Remote Sensing to identify and map fine-scale wetland ecotones. A bibliometric analysis and literature review showed that limited research has been conducted on wetland ecotones in southern Africa, however with sufficient literature covered on wetland delineation, classification, and mapping.

Wetlands which are highly dynamic and considered moving entities in a landscape due to their varying hydroperiods, are especially challenging to map. Two main experiments were carried out both of which used Machine Learning (ML) algorithms namely Random Forest (RF) and the naïve Bayes classifier. The aim of the first experiment was to review and test remote sensing techniques to accurately identify and map distinct vegetation communities within the Du Toits River wetland, Western Cape South Africa. The second experiment was then to use probabilistic classification measures to map and characterize the ecotones prevailing in a fynbos embedded wetland ecosystem. The study used freely available satellite imagery namely Landsat 8 Surface Reflectance Tier 1, and Sentinel-2 MSI: MultiSpectral Instrument, Level-2A, obtained from the United States Geological Survey (USGS) through open-source resources such as Google Earth Engine (GEE).

This research suggests that Random Forest (RF) classifier showed great potential in accurately mapping landcover, specifically four distinct and dominant vegetation types within the wetland namely *Prionium serratum, Psoralea pinnata* (referred to as palmiet wetland vegetation*)*, a condensed group of *Pteridium aquilinum*, *Restio paniculatus* and *Merxmuellera cincta* (referred to as Sclerophyllous Wetland Vegetation), and Temporary Wetland Fynbos. RF results showed little spectral confusion between classes and produced moderate to high overall accuracies for classifications run through both the winter and summer seasons.

The efficacy of using the fuzzy logic i.e. supervised probabilistic measures to identify and map ecotones in a spatially heterogenous landscape was showcased. Probabilistic mapping and fuzzy graphs showed complex and diverse ecotones within the wetland. It was evident that clear ecotones in the form of rapid and sharp high probabilities of one vegetation type intersected and replaced

another. These ecotones may provide useful information about wetland ecosystem functioning and how vegetation zones may contribute to wetland ecosystem services (e.g. flood attenuation and carbon storage).

Using a per-pixel based approach to map ecotones is highly useful as ecotones are more complex in reality and mapping them as single vector lines is not useful nor accurate. Although this study aimed to identify and map fine-scale wetland ecotones, further research using even finer scale data and in-depth field analysis that specifically focuses on the identified and mapped ecotonal areas will be significant.

KEY WORDS

alluvial fan, ecotone, image classification, Landsat-8, probabilistic classifier, remote sensing, Sentinel-2, wetland, wetland ecotones

OPSOMMING

Verskeie navorsers wat so vroeg as 1903 begin het, het baie definisies van 'n ekotoon ontwikkel (Clements 1905; Livingston 1903; Odum & Barrett 1971). Die definisie deur Holland (1988) het ekotone beskryf as sones van oorgang tussen aangrensende ekologiese sisteme, met 'n stel unieke eienskappe wat gedefinieer word deur ruimte en tydskale, en deur die sterkte van interaksies tussen aangrensende ekologiese sisteme (Holland 1988). Hierdie definisie baan die weg vir navorsing wat verskeie aspekte van landskapekologie en ruimtelike heterogeniteit kan illustreer. Alhoewel 'n nis van hoë wetenskaplike belang is, word ekotonale navorsing baie onderbestudeer, veral navorsing oor die gebruik van Afstandswaarneming om fynskaalse vleiland-ekotone te identifiseer en te karteer. 'n Bibliometriese analise en literatuuroorsig het getoon dat beperkte navorsing oor vleiland-ekotone in Suider-Afrika gedoen is, maar met voldoende literatuur gedek oor vleilandafbakening, klassifikasie en kartering.

Vleilande wat hoogs dinamies is en beskou word as bewegende entiteite in 'n landskap as gevolg van hul wisselende hidroperiodes, is veral uitdagend om te karteer. Twee hoofeksperimente is uitgevoer wat albei Masjienleer (ML) algoritmes gebruik het, naamlik Random Forest (RF) en die naïewe Bayes klassifiseerder. Die doel van die eerste eksperiment was om afstandswaarnemingstegnieke te hersien en te toets om afsonderlike plantegroeigemeenskappe in die Du Toitsrivier-vleiland, Wes-Kaap Suid-Afrika akkuraat te identifiseer en te karteer. Die tweede eksperiment was dan om waarskynlikheidsklassifikasiemaatreëls te gebruik om die ekotone wat in 'n fynbos ingebedde vleiland-ekosisteem heers te karteer en te karakteriseer. Die studie het vrylik beskikbare satellietbeelde gebruik, naamlik Landsat 8 Surface Reflectance Tier 1, en Sentinel-2 MSI: MultiSpectral Instrument, Level-2A, verkry van die Verenigde State se Geologiese Opname deur middel van oopbronbronne soos Google Earth Engine (GEE).

Hierdie navorsing dui daarop dat Random Forest (RF) klassifiseerder groot potensiaal getoon het in die akkurate kartering van landbedekking, spesifiek vier duidelike en dominante plantegroeitipes binne die vleiland, naamlik *Prionium serratum*, *Psoralea pinnata* (na verwys as palmiet-vleilandplantegroei), 'n gekondenseerde groep *Pteridium aquilinum*, *Restio paniculatus* en *Merxmuellera cincta* (na verwys as sklerofilagtige vleilandplantegroei), en Tydelike Vleilandfynbos. RF resultate het min spektrale verwarring tussen klasse getoon en matige tot hoë algehele akkuraatheid getoon vir klassifikasies wat deur beide die winter en somerseisoene loop.

Die doeltreffendheid van die gebruik van die fuzzy logika d.w.s. toesighoudende waarskynlikheidsmaatreëls om ekotone in 'n ruimtelik heterogene landskap te identifiseer en te karteer, is ten toon gestel. Probabilistiese kartering en fuzzy grafieke het komplekse en diverse ekotone binne die vleiland getoon. Dit was duidelik dat duidelike ekotone in die vorm van vinnige en skerp hoë waarskynlikhede van een plantegroeitipe gekruis en 'n ander vervang het. Hierdie ekotone kan nuttige inligting verskaf oor vleiland-ekosisteemfunksionering en hoe plantegroeisones kan bydra tot vleiland-ekosisteemdienste (bv. vloeddemping en koolstofberging).

Die gebruik van 'n per-pixel-gebaseerde benadering om ekotone te karteer is baie nuttig aangesien ekotone in werklikheid meer kompleks is en om dit as enkelvektorlyne te karteer is nie nuttig of akkuraat nie. Alhoewel hierdie studie daarop gemik was om fynskaalse vleiland-ekotone te identifiseer en te karteer, sal verdere navorsing deur gebruik te maak van selfs fyner skaaldata en meer in-diepte veldanalise wat spesifiek op hierdie geïdentifiseerde en gekarteerde ekotonale gebiede fokus, betekenisvol wees.

TREFWOORDE

alluviale vleiland, ekotoon, beeldklassifikasie, Landsat-8, probabilistiese klassifiseerder, afstandswaarneming, Sentinel-2, vleiland, vleiland-ekotone

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CONTENTS

TABLES

FIGURES

APPENDICES

ACRONYMS AND ABBREVIATIONS

CFR	Cape Floristic Region
EO	Earth Observation
GEE	Google Earth Engine
GIS	Geographical Information Systems
GIT	Geographic Information Technology
HGM	Hydro geomorphic
HHNRC	Hottentots-Holland Nature Reserve Complex
L8	Landsat 8 Collection
NASA	National Aeronautics and Space Administration
NBA	National Biodiversity Assessment
NDVI	Normalized Difference Vegetation Index
NFEPA	National Freshwater Ecosystem Priority Areas
NIR	Near-Infrared
NWI	National Wetland Inventory
NWM	National Wetland Map
NWVD	National Wetland Vegetation Database
MNDWI	Modified Normalized Difference Water Index
MSW	Moving Split Window
PCRS	Projected Coordinate Reference System
RF	Random Forest
RS	Remote Sensing
S2: MSI L2A	Sentinel-2: MultiSpectral Instrument, Level-2A
SANBI	South African National Biodiversity Institute

SAWCS	South African Wetland Classification System
SWIR	Short-wave Infrared
VI	Vegetation Indices
USGS	United States Geological Survey

CHAPTER 1: INTRODUCTION

"Mapping is fundamental to the process of lending order to the world."

- Robert Rundstrum, 1926

1.1 ECOTONES, WETLANDS AND REMOTE SENSING

As early as the beginning of the 20th century there has been substantial research interest in defining and understanding ecotones. Various researchers within the realm of landscape ecology have aimed at defining what an ecotone is; describing it as stress lines connecting points of accumulated or abrupt change (Livingston 1903); environmentally stochastic stress zones (Clements 1905); or a transition zone between two adjacent ecosystems with greater species richness (Odum & Barrett 1971). What is common amongst these definitions is that ecotones are boundaries and/or lines, points, or zones of change in the structure or composition of a landscape or ecosystem. The late 80s saw attributes that were more expressive added to the definition of an ecotone e.g. "a zone of transition between adjacent ecological systems, having a set of unique characteristics defined by space and time scales and by the strength of interactions between adjacent ecological systems" (Holland 1988). As landscape ecology deals with the study of spatial patterns, how a landscape is structured and the effect thereof on ecological processes (Pickett & Cadenasso 1995) is of significance to this study.

1.1.1 Ecotones

Additional definitions and expressions of ecotones have developed in the later years of the 21st century with each definition progressing in dimensionality as reviewed by Hufkens, Scheunders & Ceulemans (2009). Researchers have argued that ecotones are a unique ecosystem in their own right and that species richness and abundance tend to peak in ecotonal areas because these areas may hold species from two or more neighbouring communities (Kark 2007). However, other researchers argue that this may not always be the case but rather that ecotones may serve as either barriers or corridors between gene pools (di Castri, Hansen & Naiman 1988); and that "boundaries that fluctuate dramatically in space and time will be relatively poor in species" (di Castri, Hansen & Naiman 1988, p.10).

1.1.2 Inland Aquatic Ecosystems

In South Africa, inland aquatic ecosystem biodiversity comprises of "river and inland wetland ecosystem types as well as their associated species" (Van Deventer et al. 2018). These ecosystems are among the most productive, yet most threatened in the world especially as result of "flow modification, invasive alien species, overexploitation, water pollution, and the destruction and/or fragmentation of habitat", and the degree and magnitude of pressures are poorly understood and not well monitored (Van Deventer et al. 2018, p.56).

Approximately 87% of wetlands in the Western Cape are threatened and in a moderate to heavily modified or degraded condition due to "inappropriate development, drainage, poor agricultural practices, human-induced erosion or infestation by invasive alien species (Helme & Rebelo 2016, p.159). Consequently, the need for freshwater inland systems research and restoration in South Africa is compelling with rivers and wetlands at the forefront of this need, as freshwater security is essential to human well-being and livelihood. International policy and legislation (e.g. the Ramsar Convention) over the years has placed emphasis on implementing laws that protect and conserve wetlands due to the ecosystem services they provide in both anthropogenic and ecological contexts. The Convention on Wetlands, commonly known as the Ramsar Convention, is an international government body of more than 90 countries that are interested in worldwide wetland conservation. The Ramsar Convention define wetlands as "areas of marsh, fen, peatland, or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish, or salt, including areas of marine water the depth of which at low tide does not exceed 6 m" (Ramsar Convention on Wetlands 2018).

The National Water Act of South Africa (1998) defines wetlands as "land which is transitional between terrestrial and aquatic systems where the water table is usually at or near the surface, or the land is periodically covered with shallow water, and which land in normal circumstances supports or would support vegetation typically adapted to life in saturated soil" (Republic of South Africa 1998). It is noted that land-water transitions are important transitions between terrestrial and aquatic ecosystems as these are sites where nutrient concentrations change due to water flows between them, and therefore are important buffers between upland terrestrial and aquatic ecosystems (Holland, Whigham & Gopal 1990, p.171). Vegetation is typically expected to change between wetland habitat and terrestrial habitat as one commonly finds hydrophyte vegetation which is adapted to saturated soil conditions and typical of wetland conditions as opposed to terrestrial environmental conditions.

1.1.3 Remote Sensing and Conservation

The relevance and use of Remote Sensing (RS) has seen substantial growth and importance in conservation and ecological sciences (Pettorelli et al. 2017) with the launch of a journal titled *Remote Sensing in Ecology and Conservation* in 2014 by Wiley and the Zoological Society of London. The aim of this journal was to provide an open-access platform journal "that aims to support communication and collaboration among experts in remote sensing, ecology and conservation science" (Pettorelli et al. 2017, p.53). Moreover, de Klerk, Burgess & Visser (2018, p.127) note that data derived from remote sensing holds a lot of potential to provide finer scale data that is continuous in both space and time. A number of global studies have focused on studying ecotone types using RS (Hennenberg et al. 2005; Hou & Walz 2014; Johnston & Bonde 1989; de Klerk, Burgess & Visser 2018; Hans Ole Ørka et al. 2012) with examples ranging across biomes and land-use boundaries.

1.2 SIGNIFICANCE OF WETLAND ECOTONE MAPPING

In the face of climate change, conservation efforts have increased globally as many fauna, flora and biomes continue to be under threat, with climate change identified as one of the key pressures on inland aquatic ecosystems (Van Deventer et al. 2018). Wetlands provide a number of ecological and economic functions such as "water quality improvement, flood regulation and protection, groundwater recharge, shoreline stabilisation, fish and wildlife habitat, agriculture production, aesthetics and biological productivity" (Nhamo, Magidi & Dickens 2017). Wetlands are especially sensitive to climate change "as they are delicately balanced between terrestrial and aquatic influences, where species may already find refuge from desiccation" (Helme & Rebelo 2016, p.162). Wetland research thus need to be prioritised as significant and invaluable.

Consequently, ecotones which are considered transitional areas where two adjacent ecosystems in the case of wetlands are the transition from aquatic to terrestrial or, the wetland boundary- connect as abrupt points of change, will be important to map and understand as integral functioning of wetlands. Therefore, because there are limited studies on using RS to map and monitor wetland ecotones in southern Africa, the purpose of this study is to use remotely sensed data and techniques to map, identify and characterize ecotones within an alluvial fan wetland. This study focused on the Du Toits River wetland, which is a weakly channelled alluvial fan wetland situated in the north-western margin of the Theewaterskloof Dam. Literature notes that the wetland is dominated by the endemic South African Red Listed wetland species namely, *Prionium serratum*- commonly known as palmiet (Rebelo, Emsens, et al. 2018). Palmiet vegetation is argued to be an important ecosystem engineer in wetlands due to its deep and extensive root structure which is said to have stabilized river valleys within the Cape Floristic Region (Job 2014). However, this unique endemic species continues to be highly threatened with degradation and threats such as channel erosion, land-cover change (e.g. draining and clearing of wetlands for agricultural land), pollution from agricultural run-off and invasive alien vegetation infestations (Rebelo, Emsens, et al. 2018). Moreover, the wetland comprises of sclerophyllous wetland species such as sedges/rushes, restios, grasses, herbs, shrubs, and bulbous plants (Sieben, Mtshali & Janks 2014). Additionally, at some portions of the wetland one finds the presence of Sandstone Fynbos species that belong to three Fynbos vegetation units namely the Hawequas Sandstone Fynbos, Elgin Shale Fynbos and Kogelberg Sandstone Fynbos.

1.3 RESEARCH PROBLEM FORMULATION

As there is limited research on wetland ecotone mapping, a study that looks at fine-scale ecotones within a fynbos embedded wetland using Remote Sensing, can be of value to add to the fundamental emphasis of wetland processes and ecosystem services such as flood attenuation, sediment trapping and carbon storage. Various studies have focused on classification, delineation and mapping of wetland extent and vegetation (van Deventer et al. 2020; Deventer et al. 2018; Van Deventer et al. 2016; Nhamo, Magidi & Dickens 2017). The South African National Wetland Map (NWM) which provides up to date information on the location, spatial extent and ecosystem types of aquatic inland and estuarine ecosystems map ecotones between rivers or inland wetlands and estuaries as river-estuary ecotones (van Deventer et al. 2020). This study therefore aimed to add to the theoretical framework of wetlands as key ecosystems in a landscape, and to explore RS techniques that have the potential to enhance understanding these remarkably dynamic systems and their associated ecotones at a local scale. This study may also add valuable information to the conservation and management of wetland systems that are currently under severe threat in South Africa, using time and cost-efficient methods such as Remote Sensing.

1.4 RESEARCH AIMS AND OBJECTIVES

To use novel remote sensing approaches and field-based surveys to map and characterize ecotones within a fynbos embedded alluvial fan wetland.

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

1. Review literature to develop a definition of wetland ecotones; identify potential remote sensing methods to map wetland ecotones.
2. Report on the ecology, geomorphology, and provide an overview of the study area.
3. Develop a sampling scheme and collect field data to identify indicators of palmiet wetland vegetation, sclerophyllous wetland vegetation and fynbos species.
4. Apply Machine Learning approaches to map vegetation cover in the wetland by means of supervised classification methods.
5. Test probabilistic fuzzy classification methods to map wetland ecotones; identify, map, and characterize wetland ecotones.

1.5 RESEARCH METHODOLOGY DESIGN AND THESIS STRUCTURE

Geographic Information Technology (GIT) encompassing Geographic Information Systems (GIS) and Remote Sensing (RS) is a science and technology that helps us understand the earth as a system by mapping and therefore visualizing components and processes on earth (Guo et al. 2017). Remote

Sensing is a method within GIS that allows one to manipulate, interpret and analyse data from satellite imagery non-invasively without coming into contact with the object observed or monitored (Pettorelli et al. 2015). Remote Sensing also makes it possible to collect data "over greater spatial and temporal extents than is possible through field-based methods" (Pettorelli et al. 2015). This in turn allows for monitoring of developments and patterns that develop on the Earth's surface, which may aid in predicting global change accurately enough to support policy makers in making sound decisions concerning the protection of our environment. This research is explorative in nature as it involves testing various remote sensing methods to map and identify ecotones in a fynbos wetland ecosystem. The research approach is deductive as the study makes use of existing remote sensing algorithms. The data used in the study will be empirical and quantitative as satellite imagery and *in situ* soil and vegetation observations and surveys will be done.

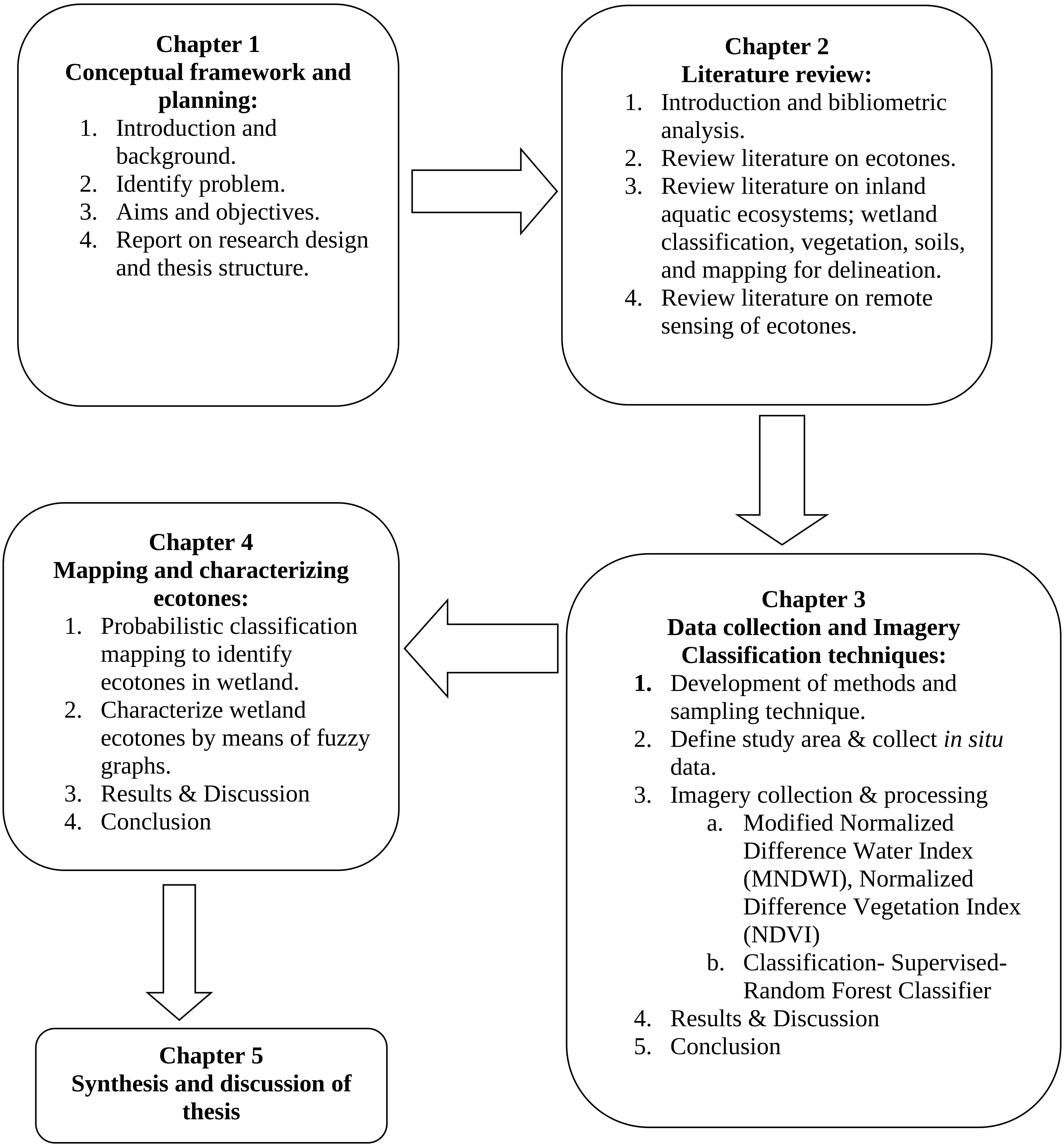


Figure 1.1 Research Design

As shown above, this chapter (Chapter 1) provided an introductory background into the study as well as to explain the rationale and significance of this research. The planning and development of the research is outlined in the aims and objectives. Chapter 2 provides an overview of relevant literature on ecotones, wetlands, and remote sensing. Literature related to ecotones will be sourced mainly from landscape ecology fields and wetland ecology. This chapter will also review current and existing remote sensing literature that deals with mapping of ecotones. The aim of Chapter 3 investigates a set of decisions on which remote sensing data to use, development of a sampling scheme and to identify a monitoring frequency for the study. Secondary data such as climate, vegetation, and geomorphology relevant to the study area will be sourced. Chapter 3 investigates using spectral indices such as the Normalized Difference Vegetation Index (NDVI) and Modified Normalized Difference Water Index (MNDWI), and supervised, machine learning classification methods to map different land cover classes in the study area to distinguish between wetland and fynbos habitat. Chapter 4 further investigates identifying, mapping, and characterizing ecotones within the study area using probabilistic classification methods. Lastly, Chapter 5 synthesizes and concludes all findings while commenting on the value of the study and providing recommendations for further research based on this study.

CHAPTER 2: ECOTONES, WETLANDS AND MAPPING LITERATURE REVIEW

"*The best visualizations never celebrate the data; instead, they make us learn about worldly phenomena and forget about the data*."

-Kirk Goldsberry, 2013

2.1 INTRODUCTION AND BIBLIOMETRIC ANALYSIS

As this study covers aspects from both landscape ecology and Earth Observation, a bibliometric search and review was conducted to find peer-reviewed literature that will assist in illustrating three objectives which guides the literature review content of this study. The bibliometric review is divided into three main sections that covers literature pertaining to ecotones; wetlands and the mapping of wetlands; and lastly, probabilistic per-pixel approaches to mapping ecotones.

This bibliometric review made use of Elsevier's abstract and citation database namely Scopus which was accessed via the Stellenbosch University library electronic database (https://www-scopus-com.ez.sun.ac.za/search/form.uri?display=basic#basic). The papers identified and deemed useful to this study were saved, downloaded, and exported to the Mendeley referencing system.

The first objective of the review was to search for published literature that contained the word ecotone as well as the definition of an ecotone. The purpose of this objective was mainly to get an idea of, and to draw a good summary of the various definitions of an ecotone described over the past decade and to refine to one definition that will be used throughout this study. The terms "ecotone" and "definition" were used while limiting the search to the past 10 years i.e. "2010-Present". Articles were selected as document type (this limited the search to peer-reviewed, internationally accredited journal articles specifically), resulting in 23 articles being identified. The search was refined to subject area criteria namely, "Environmental Science; Earth and Planetary Science; Agricultural and Biological Sciences". These subject areas were selected in order to limit the search specifically to ecotone studies in environmental, remote sensing, landscape, and biological sciences. Keywords were limited to "Ecotone, Biodiversity, Ecology, Image Classification" and importantly, the English language was selected. This search resulted in 10 articles which were exported as CSV to an Excel workbook for analysis. Of the 10 articles, five made reference to the definition of an ecotone (Cantonati et al. 2020; Erdôs et al. 2011; Hanberry 2020; H.O. Ørka et al. 2012; Ranson, Montesano & Nelson 2011) while another five articles did not give a definition of ecotone (Elliott & Whitfield 2011; MacGregor-Fors 2010; San-José et al. 2010; Schultz, Franco & Crone 2012; Vieira et al. 2016) but rather encompassed case studies that discussed various aspects of ecotones, ecological boundaries, edges, and the edge effect. What was common amongst the articles is that each dealt with the aspect of change or transition between various types of biomes, or ecosystems. The terms gradient, transition, zone, boundary, edge, and ecotone were the main terms of reference in all the abstracts of the 10 articles.

The second objective of the bibliometric search was to investigate the status of literature that explores mapping of wetlands**.** The purpose of this was to get a sound comprehension of the literature (local and global) that covers wetland mapping, whether it be mapping wetland extent and delineation, or wetland vegetation mapping. Search terms included "wetland" and "map"; and "remote sensing" or "earth observation" or "MODIS" or "Landsat" or "aerial photography" or "LiDAR" or "SPOT" or "Radar" or "Sentinel". The search was also limited to "2010-Present", resulting in 145 articles. Keywords used were "Remote Sensing, Wetlands, Wetland, Satellite Imagery and Mapping"; and input language selected was "English". This resulted in 128 articles of which 30 articles were randomly selected and exported for further reading and analysis.

The results from this second search generated articles that explore various case studies of researching the dynamics of wetland ecosystems (Arshad, Eid & Hasan 2020; Fang et al. 2018; Valderrama-Landeros et al. 2020; Zhang et al. 2020) using Remote Sensing, along with wetland vegetation mapping and delineation (Campbell & Wang 2019; Chang et al. 2020; Hamandawana, Atyosi & Bornman 2020; Jiao et al. 2019; Yeo et al. 2020). However, not all 30 papers addressed wetland delineation or wetland vegetation mapping explicitly which was the initial aim of the search. Overall, all the articles have a commonality in the sensor data used, namely Landsat datasets (Hamandawana, Atyosi & Bornman 2020; Masina et al. 2020; Olmanson et al. 2020; Walter & Mondal 2019), LiDAR (Campbell & Wang 2019; Pilant et al. 2020; Rapinel et al. 2019), Sentinel-1 or Sentinel-2 (Chang et al. 2020; Fitoka et al. 2020; Hakdaoui et al. 2019; Lefebvre et al. 2019; Mahdianpari et al. 2020; Pena-Regueiro et al. 2020) and MODIS data (Edvardsson et al. 2019). The RS methods adopted in mapping spatial extent, vegetation and change detection in wetlands include a variety of data types and supervised classification algorithms. Data types were raw spectral bands, the Normalized Difference Vegetation Index, Normalized Difference Water Index (Pena-Regueiro et al. 2020; Rupasinghe & Chow-Fraser 2019; Yeo et al. 2020), and Soil Adjusted Vegetation Index (Arshad, Eid & Hasan 2020). Supervised Classification of imagery for wetland mapping, assessing and change detection used Random Forest, and Support Vector Machine (SVM) algorithms, on per-pixel and object-based (Object-Based Image Analysis, OBIA) approaches, (Fitoka et al. 2020; Fu et al. 2017;

Hakdaoui et al. 2019; Hamandawana, Atyosi & Bornman 2020; Mahdianpari et al. 2020; Olokeogun & Kumar 2020; Pilant et al. 2020; Walter & Mondal 2019).

The third objective of the bibliometric search was aimed at finding literature that used probability mapping to describe and map ecotones. The search terms “probability” and “ecotone” and “map” were used, limited to the past 10 years i.e. “2010-present”, resulting in eight articles which were exported. These eight articles speak to various RS techniques used to study ecotones in different landscape settings. For example, a study by Vitali et al. (2019) looked at spatio-temporal patterns of pine recruitment and encroachment across anthropogenic upper treeline ecotones in Southern Europe (Vitali et al. 2019). Fedrigo et al. (2018) used a Random Forest model to produce high accuracy “maps of stand type probability, including areas of transition (the ‘ecotone’) between rainforest and eucalypt forest” in south-east Australia (Fedrigo et al. 2018). Ørka et al. (2012) describe using the binomial logistic regression approach to produce a probability map that is suitable for monitoring changes in the extent and location of a subalpine zone (i.e. the transition between forest and alpine vegetation communities) (Hans Ole Ørka et al. 2012). More relevant to this study are two articles that resulted from the search i.e. the use of supervised probabilistic classification methods to map ecotones between two vegetation types in the Agulhas Plain, South Africa (de Klerk, Burgess & Visser 2018); and the use of “ hierarchical modelling and Bayesian inference to predict the probability of wetland presence as a continuous gradient with the explicit consideration of spatial structure” thus identifying wetland extent, ecotones and hydrological connections (Humphreys et al. 2017).

Although this bibliometric search was used to guide the literature review chapter, additional literature beyond the past decade was sourced to get a holistic review of research that has been done on ecotones, wetlands, and the mapping and/or monitoring thereof.

2.2 LANDSCAPE ECOLOGY: ECOTONES

When researching different types of ecosystems, it is important to take into consideration the whole landscape. Landscape ecology, which is concerned with studying the “reciprocal effects of spatial pattern on ecological processes” (Pickett & Cadenasso 1995, p.31), is an important umbrella term when delving further into the studies of specific biomes and ecosystems in ecology. Moreover, it is important to note that landscapes are made up of a mosaic of different areas that are differentiated by biotic and abiotic structures or compositions- ultimately known as landscape heterogeneity.

2.2.1 Ecotone, Ecological Boundary or Patch?

According to Cadenasso, Pickett, Weathers & Jones (2003), landscapes consist of two types of structures namely patches and boundaries. A patch is defined as “volumes that can be distinguished compositionally, structurally, or functionally from adjacent volumes at a given scale” (Cadenasso, Pickett, Weathers & Jones 2003, p.751). The example given by Cadenasso and colleagues (2003) to describe a patch is of a research question that focuses on forest fragments; the landscape will then be divided into patch types that are forest and those that are non-forest. Here, the patch described as forest will be assumed to be homogenous in structure, in contrast with the structure of patches identified as non-forest (Cadenasso, Pickett, Weathers & Jones 2003, p.751). Boundaries are then noted as the component which “marks patch limits; they are the zones between two neighbouring patches” (Cadenasso, Pickett, Weathers & Jones 2003, p.751). Strayer and colleagues furthermore argue that “[e]cologists use the term boundary (or edge) to refer to a wide range of conceptual and tangible structures” (Strayer et al. 2003, p.738). Ultimately, it is important to note that specific locations in a landscape can serve as a patch or boundary, depending on the question that the research is addressing. An example proposed by Cadenasso and colleagues (2003, pp.751–752) to highlight that the same physical space in a landscape can serve as a boundary for one research question, and as a patch for a different research question is given as follows. An estuary can be a considered as a patch for research questions that address its function and ecosystems services such as being a nursery ground for fish. However, it can also be considered a boundary between freshwater and saltwater or marine systems in another research question. Hence, this leads one to question whether the term ecotone is similar or equal to the terms patch or boundary in landscape ecology.

It is important to make mention of the detailed account of an ecotone definition that Odum & Barrett (1971) describe, which sets the tone for the next section of this literature review which aims to find a working definition of ecotone for this study: "A transition between two or more diverse communities as, for example, between forest and grassland, or between a soft bottom and hard bottom marine community. It is a junction zone or tension belt which may have considerable linear extent but is narrower than the adjoining community areas themselves. The ecotonal community commonly contains many of the organisms of each of the overlapping communities and, in addition, organisms which are characteristic of and often restricted to the ecotone. Often, both the number of species and the population density of some of the species are greater in the ecotone than in the communities flanking it. This tendency for increased variety and density at community junctions is known as the edge effect" (Odum & Barrett 1971) in di Castri, Hansen & Naiman (1988, p.49). Therefore, based on these definitions and linkages provided between them, this study will consider an ecotone analogous to an ecological boundary.

2.2.2 Ecotone definitions and characteristics

It can be said that researchers follow the definition of Clements (1905) which contends that ecotones are distinctly defined in terms of a spatially rapid vegetation change. This is evident in a study by Walker, Wilson, Steel, Rapson, Smith, King & Cottam (2003, p.579) who define an ecotone as a " zone where directional spatial change in vegetation (i.e. qualitative and quantitative species composition) is more rapid than on either side of the zone (Lloyd, McQueen, Lee, Wilson, Walker & Wilson, 2000)" (Walker et al. 2003, p.579). However, Holland (1988) defined an ecotone as being "a zone of transition between adjacent ecological systems, having a set of unique characteristics defined by space and time scales and by the strength of interactions between adjacent ecological systems" (Holland 1988). This definition not only speaks to vegetation changes per se, but to a transition in any ecological system and may include a transition between any habitat forms or landscape mosaics such as aquatic-terrestrial, forest-fynbos or freshwater-marine systems.

The properties and characteristics of ecotones are essential to discuss when trying to understand the definition of an ecotone. Various researchers have documented different properties of ecotones and their unique characteristics in both spatial and temporal extents, or specific ecosystems. Walker and colleagues (2003) express several general properties of ecotones such as "vegetational sharpness, physiognomic change, occurrence of a spatial community mosaic, many exotic species, ecotonal species, spatial mass effect, and species richness higher or lower than either side of the ecotone". To support these generalizations, Walker et al. (2003, p.579) attempt to sample five types of ecotones in order to explore the prevalence of these properties, and base their definition of ecotones as rapid vegetation changes, on their findings across a diversity of ecosystems i.e. scattered mangroves, through salt marsh, rush-marsh, scrub and woodland to pasture ecosystems. This study used methods such as quadrat vegetation sampling with various statistical analysis and algorithms to identify the types of ecotones and their properties. The study found that ecotones displayed sharp changes in species composition; change in plant physiognomy; community mosaics; some unique ecotonal species; more species occurred frequently in the ecotone than in adjacent habitat; and that in one ecotone species richness was higher than in the adjacent habitat. In summary, the study concluded that ecotone characteristics depend on a particular ecological setting or environment and the ecology of the species present, rather than being definite general ecotone properties (Walker et al. 2003).

Additionally, a study by Kamel (2003) noted that there are different types of ecotones which can be classified according to the factors which affect their characteristics, and which is the most unstable part of an ecosystem due to its sensitivity to environmental changes. This means that an ecotone will be classified based on the environmental stress and biological interactions that form the ecotone. The results of this study led to ecotones being grouped into three main classifications with the first being climatic ecotones which can be subdivided into thermo-ecotone where temperature is the main limiting factor; and hygro-ecotone where humidity is the main limiting factor. The second ecotone classification is edaphic ecotones which is controlled by the edaphic (soil condition) factors. Edaphic ecotones can be subdivided into a further three categories namely geo-ecotone which is affected by either soil texture or soil depth or both; hydro-ecotone which is affected by the status of water in the soil; and lastly chemo-ecotone which is affected by soluble ions in the soil. The third and final ecotone classification as identified by Kamel (2003) is biological ecotones. This ecotone classification can be subdivided into external biological ecotone which concerns the boundaries between adjacent ecosystems and need the same demands to survive; and secondly internal biological ecotone which concerns "the relations between individuals in the same ecosystem, especially at the period of change from one aspect to another" (Kamel 2003, p.1559).

Holland, Whigham & Gopal (1990) delve further into the characteristics of ecotones in wetlands. In coastal wetland ecosystems such as estuaries, temporal variability may have an impact on the ecotone e.g. the exchange of material between upstream rivers or open water bodies and estuaries downstream occur once or twice daily due to the tidal cycles (Holland, Whigham & Gopal 1990). Additionally, inland wetland ecotones allow for the exchange of nutrients and material across boundaries. Holland, Whigham & Gopal (1990) refer to these as transfers across lateral boundaries, which include "transfers from the upland to the wetland (upland-wetland ecotone), or from the wetland into open water (wetland-open water ecotone), from groundwater aquifers into soils or across vegetation zones with each zone dominated by different species (wetland-wetland ecotones)" (Holland, Whigham & Gopal 1990, p.174). Importantly, wetland open-water ecotones may change spatially as wetlands expand into open water areas such as lakes, or as wetlands erode (Holland, Whigham & Gopal 1990). This is important to consider in this study as the Du Toits River wetland, which is an alluvial fan, expands into the open waters of the Theewaterskloof Dam.

Kark (2007) describes an ecotone as a zone where ecological communities, biotic regions or ecosystems coincide and often rapidly shift from one ecosystem or region to another. Kark (2007) also notes that ecotones occur along ecological gradients which are created as a result of spatial shifts in elevation, climate, soil, nutrients and various other environmental factors. It is further argued that ecotones "commonly coincide with areas of sharp climatic transition along environmental gradients" and show a diversity of boundary types. These boundaries range from natural, to human generated ecotones e.g. fire breaks, urban structures, forest edge clear-cuts etc. (Kark 2007). As previously noted, it is evident that ecotones do occur within aquatic and terrestrial systems and have both spatial and temporal properties that vary across ecosystem types or biomes (Holland, Whigham & Gopal 1990).

The past ten years has shown an array of literature written about ecotones and their characteristics; Hufkens, Scheunders & Ceulemans (2009) review and highlight the trends and issues that have dominated research about ecotones between 1996-2006. Moreover, Senft (2009) based their Masters dissertation on species diversity patterns at ecotones. The study aimed to clarify species richness patterns at ecotones and the underlying mechanisms of these patterns. It was found that generally, higher species richness did not occur within the ecotone than the adjacent vegetation, and "that the species present were mostly also present on either side of the transition, with very few species unique to the ecotone" (Senft 2009). This is similar to results that Walker et al. (2003) found and is described in earlier text. In summary, ecotones can be seen as distinct zones of rapid change or the spaces between adjacent ecological habitats that show unique ecological properties (Cadenasso, Pickett, Weathers & Jones 2003; Holland, Whigham & Gopal 1990; Odum & Barrett 1971). Furthermore, ecotones are said to have areas of high turnover and species diversity, and often species that are unique to the ecotone (Kark 2007). However, other researchers have counter-argued this and found different results that show relatively less species diversity in the ecotone than to adjacent habitats (Hou & Walz 2014; Senft 2009). Ultimately, the Holland (1988) definition which describes the ecotone as a transition zone between neighbouring ecological systems that is characterized by unique properties which are defined by space and time scales, and by the strength of interactions between the adjacent ecological systems, will provide the foundation of this study. This is based on the idea that characteristics of ecotones will be influenced by interactions between two adjacent ecosystems with unique properties i.e. between and from upland fynbos and palmiet or peatland conditions.

2.2.3 Freshwater Ecosystems: Ecotones and Wetlands

Freshwater ecosystems, a tangible yet finite resource, refers to "all inland water bodies whether fresh or saline, including rivers, lakes, wetlands, sub-surface waters and estuaries" and are said to face high levels of threat with more than half of South Africa's river and wetlands being threatened (Van Deventer et al. 2018). Highly valuable to humans and biodiversity, freshwater ecosystems thus need effective conservation actions to ensure a sustainable supply for future needs. Rivers and wetlands are crucial for the survival of all living species and provide essential ecosystem services such as the provision of water, flood attenuation, water and flood regulation and erosion control (Van Deventer et al. 2019, p.33). These ecosystem contributions or services are just a few to mention, however, the value of inland aquatic ecosystems and freshwater on earth is immeasurable.

As the focus of this study is to map and understand the characteristics of wetland ecotones, it is important to keep in mind the definition of a wetland, classification, vegetation types, and soils of wetlands in South Africa specifically, to gain a deeper and better understanding of how to approach identifying and mapping ecotones in a wetland. The National Water Act (1998) define wetlands as “the land which is transitional between terrestrial and aquatic systems where the water table is usually at or near the surface, or the land is periodically covered with shallow water, and which land in normal circumstances supports or would support vegetation typically adapted to life in saturated soil.” If one is to break down this definition into different parts, it can be said that there are three distinct attributes to a wetland ecosystem i.e. transition between terrestrial and aquatic systems; the periodic inundation of shallow water; and typically, hydrophytic vegetation presence. This is also the only legislated wetland definition in the country (Department of Water Affairs and Forestry 2005; Ollis et al. 2013; Republic of South Africa 1998). It is worth mentioning that in a global context, Tiner (2016) notes that wetland is a generic term that is used to define “the universe of wet habitats including marshes, swamps, bogs, fens, and seasonally waterlogged areas. Wetlands are environments subject to permanent or periodic inundation or prolonged soil saturation sufficient for the establishment of hydrophytes and/or the development of hydric soils or substrates unless environmental conditions are such that they prevent them from forming” (Tiner 2016, p.1). Thus it is important to recognize that although wetlands may differ in various biomes across the globe with “regional differences in hydrologic regimes, climate, soil-forming processes, and geomorphologic settings”, common distinctive characteristics of these ecosystems is the presence of varying periods of saturation, hydric soils and wetland plant communities which have evolved over time (Tiner 2016, p.1).

As previously mentioned, ecotones are said to be zones of change or transition from one ecological system, community, or region to another. Therefore, one carefully needs to consider three things as guiding principles when defining wetland ecotones, especially in the context of this thesis:

1. At which point is there a change from terrestrial or upland fynbos habitat to wetland habitat?
2. Which factors will determine this change: is it hydrology, soil, vegetation or all three combined?
3. Based on its definition, is a wetland therefore itself simply the ecotone between land and water? Or can ecotones exist within a wetland and how?

Holland, Whigham & Gopal (1990) provide two wetland types namely tidal wetlands and inland wetlands to represent the ecotones in these systems. According to Holland, Whigham & Gopal (1990, p.172) tidal wetlands encompass tidal salt marshes, tidal freshwater marshes and brackish tidal wetlands whilst inland wetland ecosystems are inland freshwater marshes, northern peatlands and swamps. Moreover, Holland, Whigham & Gopal (1990) note that wetlands have external and internal boundaries with distinct vegetation types and thus some wetland ecotones can be clearly delineated while others difficult to distinguish. In conclusion, it can be said that ecotones will have different characteristics depending on the type of ecosystems that are adjacent to one another as well as the overall biogeographic region: “Ecotones are necessarily context dependent: they don’t exist without areas of relatively homogeneous composition, they don’t exist without defined communities, and they are dependent on a user-defined spatial extent” (Senft 2009).

As wetlands are highly dynamic and complex ecosystems, factors such as the biogeographic setting, geology, vegetation cover, and inundation levels of the area of interest are important to consider when attempting to identify and map ecotones therein.

2.2.4 Measuring and Mapping of Ecotones

As there is a plethora of definitions of ecotones, similarly there are various approaches to measuring or quantifying ecotones. Researchers have used methods such as looking at beta diversity (species turnover) which is often used when studying gradients (Williams 1996; Williams, De Klerk & Crowe 1999). Beta-diversity refers to “the change in species as one moves between habitats, communities or ecosystems” (Kark 2007; Williams 1996) and is a useful way to see patterns and trends of change between communities. Kark (2007) also notes that the measuring of ecotones often depends on the data that is available. Literature in the bibliometric search also showed that ecotones have been mapped and measured using a variety of RS sensor data such as the coarse scale MODIS (Fox, Vandewalle & Alexander 2017), LiDAR (Jenkins & Frazier 2010; Moradkhani, Baird & Wherry 2010; H.O. Ørka et al. 2012), medium resolution sensors such as Landsat (Bharti, Adhikari & Rawat 2012; Galgamuwa, Wang & Barden 2020; Xu et al. 2018; Yang et al. 2015), through to finer spatial (high spatial resolution) scale data such as QuickBird and GeoEye (Beck et al. 2015).

An example of a study that uses RS to map ecotones is by Hou & Walz (2014) who attempt to extract small biotopes and ecotones from multi-temporal RapidEye data and high resolution normalized digital surface model. The study aimed to combine object-based, and per-pixel image analysis. Importantly, the Normalized Difference Vegetation Index and Normalized Difference Water Index were used in the classification process. Whereas de Klerk, Burgess & Visser (2018) use supervised probabilistic classification methods to investigate the “location, width and character of ecotones between acid Sandstone and alkaline Limestone fynbos on the Agulhas plain at the southern tip of Africa, known for rapid speciation of plants and exceptional plant biodiversity at the global scale" (de Klerk, Burgess & Visser 2018). The results of both these studies show the efficacy of imagery classification and analysis in mapping and understanding ecotones at different scales and in different ecological systems. It is also noted in literature that soil moisture plays an important role in controlling plant distribution and community composition across ecotones (Kamel 2003; Marfo et al. 2019). Therefore soil moisture properties will also be important to consider in this study as RS techniques will be applied to map and delineate ecotones within a wetland, where soil inundation and surface reflection may play a role in the classification of vegetation types and ultimately, the mapping of the ecotones within the system.

Kark (2007) further notes that other research methods have been used to detect and quantify ecotones such as "simulation modelling, geographic information systems (GIS), remote sensing, and statistical tools that enable quantification and analysis of ecotones of different types and over several spatial scales", and which often depends on available data (Kark 2007, p.3). When using GIS as a means of quantifying ecotones, two spatial models are applied namely vector (point, line or polygon features) and raster (pixel or x-y based features) (Kark & van Rensburg 2006). Using a vector model approach may be useful for human-induced features (or even human-made ecotones) as these will often appear linear. Moreover, Kark & van Rensburg (2006) note that a vector-based approach will allow for the calculation of area, length, "fractal dimensions and the analysis of spatial relationships between features" (Kark & van Rensburg 2006, p.33). However, it is further argued that the use of vector models may have contributed to "boundary regions being ignored, appearing as a one-dimensional line on the map, with emphasis given to the comparison between units defined as more homogenous (e.g. distinct vegetation communities or ecoregions)" (Kark & van Rensburg 2006, p.33). This argument is reinforced by de Klerk, Burgess & Visser (2018) who note that on most maps-whether paper or a GIS database- ecotones are often presented as a single line "regardless of their actual extent on the ground, or whether they are derived from field mapping (e.g. SANBI 2006-), expert synthesis (Dinerstein et al. 2017), or statistical analysis of gridded databases (Linder et al. 2012)" (de Klerk, Burgess & Visser 2018, p.125). Moreover, it can be said that the characteristics such as the strength and breadth of different ecotones can vary substantially and that a single hard line cannot be an appropriate or accurate means of mapping ecotones (de Klerk, Burgess & Visser 2018; Williams 1996). As boundaries, edges and ecotones are much more complex in reality than in theory, a raster-based approach may thus be more appropriate as it can be applied over multiple spatial scales (Kark & van Rensburg 2006) and the cells or pixels in a raster are "given a different value so that the location of ecotones and steepness of gradients" can be more easily mapped and analysed. For example, de

Klerk, Burgess & Visser (2018) make use of fuzzy probabilistic classifiers to assign graded (fuzzy) membership to imagery in order to map the location, extent and characteristics of ecotones at a landscape level between two vegetation types in the Agulhas Plain, South Africa. It is important to note that generally, traditional hard classifiers present a feature in binary classes, whereas fuzzy classifiers assign graded membership to pixels (de Klerk, Burgess & Visser 2018) and therefore probabilistic soft classifiers might be deemed more useful in this study as it provides "a probability distribution over a set of classes, where each pixel is assigned a strength membership value for each class being mapped" (de Klerk, Burgess & Visser 2018, p.128).

Another example of a per-pixel RS method to quantify and map ecotones is the application of the moving split window (MSW) method (van der Maarel 1976) which enables one to detect regions "where the variance of neighbouring samples along a gradient is highest. The basic idea is to detect edges by finding the areas with the highest rate of change among adjacent pixels" (Kark & van Rensburg 2006, p.34). The MSW technique is one of the most popular multivariate techniques in literature used to detect and map ecotones along one-dimensional data such as transects (Brownstein et al. 2013; Choesin & Boerner 2002; Hennenberg et al. 2005; Johnston & Bonde 1989; Walker et al. 2003). In using the MSW technique, transects are usually subjectively positioned; gradient-oriented and placed perpendicular to areas that are presumed to be boundary/boundaries (Choesin & Boerner 2002; Erdos et al. 2014). Typically, at one end of a transect a window is assigned and split into two half windows, which are ultimately compared using a dissimilarity function. Windows are then shifted along the transect and computed along all positions of the transect, repeatedly until the end of the transect. Where the dissimilarity function is plotted against spatial boundaries, peaks will appear i.e. boundaries and/or ecotones (Erdos et al. 2014). In the case of using the MSW method to analyse satellite imagery, plots/transects are the pixels of the image which are then compared based on their reflectance (Chang et al. 2003; Erdos et al. 2014).

As the above section of the review has highlighted that ecotones are generally expected to be ecological areas of high transition and change, a more detailed account of per-pixel methods to detect and map ecotones, and which data is most suitable to use will be discussed following a preceding review of wetland classification, vegetation, soils, and mapping of wetlands.

2.3 SOUTH AFRICAN INLAND AQUATIC ECOSYSTEMS

The Freshwater Consulting Group on account of the South African National Biodiversity Institute (SANBI) have compilated and provided a user manual titled *Classification System for Wetlands and other Aquatic Ecosystems in South Africa* (Ollis et al. 2013) which aims to describe and classify inland wetlands and aquatic ecosystems. This classification system is based on the principle that hydrology and geomorphology determines the way in which an aquatic ecosystem functions (Ollis et al. 2013). Therefore, a hydrogeomorphic (HGM) approach to "wetland classification is founded (Brinson 1993), whereby hydrological and geomorphological characteristics are used to distinguish primary wetland units" (Ollis et al. 2013, p.5). Simply stated, the South African Wetland Classification System (Ollis et al. 2013) aims to describe wetlands in terms of the profile of the "basin where water is stored, and the main inputs and outputs of water in that basin" (Sieben, Mtshali & Janks 2014, p.2) and has a six-tiered structure:

> "The tiered structure progresses from Systems (Marine vs. Estuarine vs. Inland) at the broadest spatial scale (Level 1), through Regional Setting (Level 2) and Landscape Units (Level 3), to Hydrogeomorphic (HGM) Units at the finest spatial scale (Level 4). At Level 5, Inland Systems are distinguished from each other based on the hydrological regime and, in the case of open waterbodies, the inundation depth- class".

Source Ollis et al. (2013, p.5)

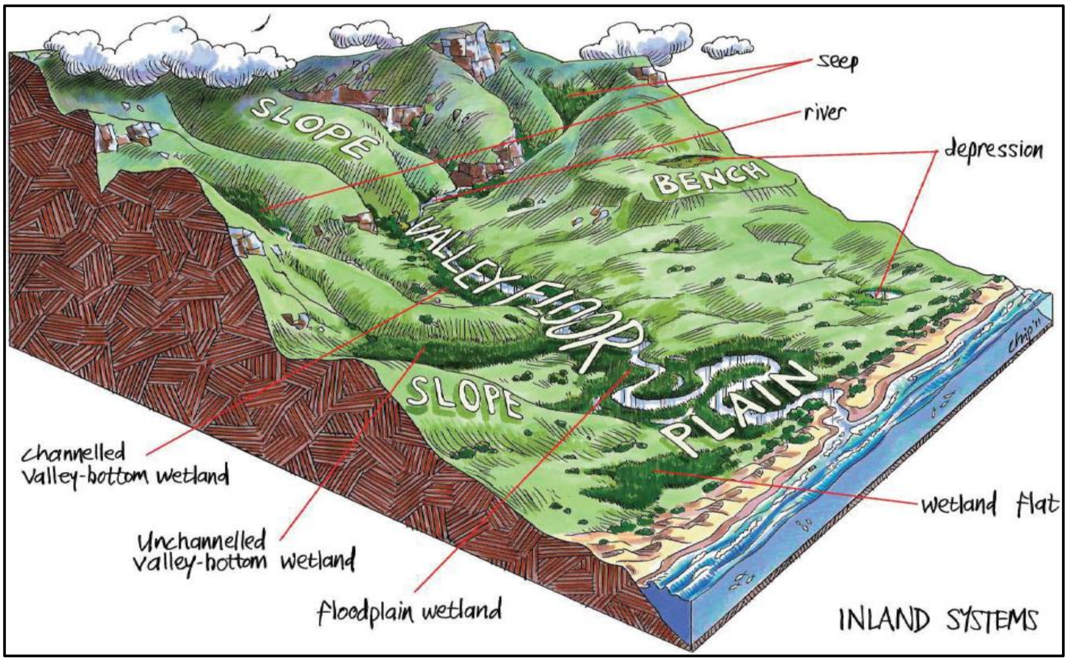
Wetlands are classified under the Level 4 structure of the guideline namely the Hydrogeomorphic (HGM) unit, i.e. "the main 'unit' by which a single wetland can be recognized" (Sieben, Mtshali & Janks 2014, p.2). The HGM units are distinguished based on landform, hydrological characteristics and hydrodynamics (Ollis et al. 2013, p.18). Wetlands are grouped as a unique type of inland aquatic ecosystem (Ollis et al. 2013) based on the definition which highlights that a wetland is distinctly considered an ecosystem transitioning between aquatic and terrestrial habitats (Republic of South Africa 1998).

In South Africa, a wide range of existing ecosystem services are potentially provided by these six wetland types, broadly categorized as: supporting services, regulating services, provisioning services, and cultural services (Van Deventer et al. 2019). Supporting services include "soil formation, primary production, nutrient cycling, water recycling"; regulating services include "air quality, local climate regulation, global climate regulation, water regulation, flood hazard regulation, storm hazard regulation, pest regulation, regulation of human diseases, noise and visual buffering"(Van Deventer et al. 2019, p.33). Provisioning services include the provision of fresh water, food, fibre, fuel, "genetic resources, natural medicines and pharmaceuticals, ornamental resources, clay, mineral, aggregate harvesting, energy harvesting from natural air and water flows"(Van Deventer et al. 2019, p.33). Lastly cultural ecosystem services which include "cultural heritage, recreation and tourism, aesthetic value, spiritual and religious value, inspirational value, social relations, educational and research"(Van Deventer et al. 2019, p.33).

2.3.1 Wetland classification

The purpose of wetland classification is to create and support an inventory of wetlands by "standardising and defining terms to describe wetland types to allow successful wetland conservation and management" (Finlayson & van der Valk 1995) in Grenfell et al. (2019, p.2). Wetland classification systems are usually based on a selected wetland definition which Grenfell et al. (2019) argue is often based on the definition by Cowardin et al. (1979), which requires that a wetland meets one or more of the following criteria: "(1) it supports hydrophytes at least periodically, (2) the substrate is composed of undrained hydric soil and/or (3), the substrate is non-soil and is saturated or covered by shallow water at some time during the growing season of each year" (Grenfell et al. 2019, p.2). It is evident that these criteria are also listed in the National water Act (1998) definition of a wetland.

The traditional wetland classification guide of Ollis et al. (2013) categorize six broad wetland types based on their HGM units. These six types are floodplain wetland, channelled valley-bottom wetland, unchannelled valley-bottom wetland, depression, seep and lastly, a wetland flat (Ollis et al. 2013).



Source: Ollis et al. (2013, p.17)

Figure 2.1 Illustration of the landscape setting of the inland systems of South Africa, based on the HGM units

Although wetland classifications are aimed at creating a standardized inventory and guide for how to identify and classify wetlands across the country, Grenfell et al. (2019) argue that the current classification system (Ollis et al. 2013) is not always accurate in that wetlands do not always fit neatly into a category. In addition, depending on the spatial and temporal scale of observation, different processes will be at play in a system, and affects which wetland type is assigned to a specific study area. Grenfell and colleagues (2019) introduced a genetic classification system that is focused on the mode of wetland formation, and is based on the "understanding that genetic processes impact on the outcome hydrology, sedimentology, geomorphology, ecosystem service provision, and long-term dynamics of wetlands in drylands" (Grenfell et al. 2019, p.1). This genetic classification describes four wetland types based on the sediment source; i.e. colluvial, alluvial, Aeolian and geochemical, which are then subdivided into eight wetland types namely; hillslope seep, floodplain, valley-bottom, plain, blocked-valley, alluvial fan, aeolian depression, and geochemical depression (Grenfell et al. 2019, p.1). It is important to briefly note the process of wetland formation within a landscape before discussing the different wetland types. Grenfell et al. (2019) state that "wetlands usually occur in areas of flow accumulation concentration, whether from surface flow (channel or surface runoff) or inter-flow (within soil and bedrock), or occasionally at locations of groundwater discharge" (Grenfell et al. 2019, p.2). Furthermore, due to extensive semi-arid conditions that are associated with the sub-tropical high pressure belt in southern Africa, the majority of wetlands occur along drainage lines (Grenfell et al. 2019).

Ultimately, when classifying wetlands, it is important that one thinks about the wetlands historically as part of the landscape, not as single units, but rather as systems that are interconnected with drainage lines in the landscape (Grenfell et al. 2019).

2.3.2 Wetland vegetation

As established in the above section, it can be said that there are different types of wetlands, each characterised by unique topography, geomorphological features and/or a combination of hydrology regimes and vegetation types. However, the most important characteristic that determines habitat conditions in a wetland is the hydrology regime i.e. water flow in and out of the wetland (Mitsch & Gosselink 2000). Hydrological conditions determine whether a wetland is temporarily or permanently flooded; contains flowing or still-standing water; has channelled or diffuse flow; inundated or saturated soils; and ultimately where various types of sediments are deposited in the wetland (Sieben, Mtshali & Janks 2014). These wet, and damp habitat conditions in turn influence vegetation composition, as wetland vegetation respond to hydrology and topography, by forming zones of either dominant plant species, or a complex mosaic of diverse plant species (Richards 2001). Sieben, Mtshali & Janks (2014) additionally note that water quantity and quality are the two most important aspects that affect plant communities in wetland environments. Wetland vegetation are adapted to growing in substrates that are anaerobic (i.e. devoid of oxygen) for at least some parts of the year, and are affected by altered soil chemistry influenced by prolonged periods of saturation and inundation (Department of Water Affairs and Forestry 2005; Richards 2001; Sieben, Mtshali & Janks 2014). Tiner (2016, p.26) additionally argues that vegetation itself has a substantial effect on the hydrology of a site. It must be noted that vegetation (hydrophytes), hydrology and soil (hydromorphic) conditions are the three determining factors of wetland ecosystem presence (Department of Water Affairs and Forestry 2005; Ollis et al. 2013; Richards 2001; Sieben, Mtshali & Janks 2014).

Vegetation is one of the most visible aspects of a wetland environment and plays an important role in wetland functioning (Sieben, Mtshali & Janks 2014) such as slowing down overland runoff, soaking and storing rainwater to replenish the groundwater table, help bind soil together and reduce soil erosion, and helping with intercepting and trapping sediment and silt from land runoff thus filtering and purifying water flowing through the wetland (Richards 2001). Moreover, literature has noted that some species remove toxins in their tissues through sequestration and trap sediments in an "anoxic environment where anaerobic bacteria reduce many nutrients to a gaseous form. Both of these processes have a positive impact on water quality (Cronk & Fennessy 2001)" in (Sieben, Mtshali & Janks 2014, p.4).

Classification of plants according to occurrence in wetlands

A global approach to identifying wetland vegetation is based on the classification by Reed (1988) who primarily attempted to delineate wetlands, and wetland vegetation by using a wetland-indicator species approach. This entails categorizing vegetation based on their most likely occurrence in wetlands and non-wetlands, into four groups namely obligate wetland (ow) species, facultative wetland (fw) species, facultative (f) species and facultative dry-land (fd) species with an estimated percentage of occurrence in wetlands as displayed in the table below:

Table 2.1 Classification of plants according to occurrence based on Reed (1988) in Department of Water Affairs & Forestry (2005)

Obligate wetland (ow) species	Almost always grows in wetlands (>99% of occurrences).
Facultative wetland (fw) species	Usually grow in wetlands (67-99% of occurrences) but occasionally are found in non-wetland areas.
Facultative (f) species	Are equally likely to grow in wetlands and non-wetlands (34% - 66% occurrences).
Facultative dry-land (**fd**) species	Usually grow in non-wetland areas but sometimes grow in wetlands (estimated probability 1- 34%)

However, a more recent reference of this classification approach is in Brand et al. (2018, p.8) who refer to Tiner (Tiner 1999) and Cronk & Fennessy (2001) as references to wetland indicator plants i.e. the degree to which species are associated with wetlands:

Table 2.2 Classification of plants according to occurrence in wetlands based on Tiner (1999) and Cronk & Fennessy (2001) in Brand et al. (2018)

Obligate wetland (**OBL**)	estimated probability >99% in wetlands.
Facultative wetland (**FAWC**)	estimated probability 67% - 99% in wetlands.
Facultative (**FAC**)	estimated probability 34% - 66% in wetlands
Facultative Upland (**FACU**)	estimated probability 67% - 99% occur outside wetlands, occasionally found in wetlands (estimated probability 1% - 33%)
Obligate Upland (**UPL**)	estimated probability >99% occur outside wetlands.

These two tables show that the classification approaches are the same, except that the category names and abbreviations have changed from the original Reed (1988) classification i.e. Obligate wetland previously abbreviated (ow) is now (OBL), Facultative wetland previously (fw) is (FAWC), Facultative species previously (f) is now (FAC), Facultative dry-land previously (fd) is now Facultative Upland (FACU) and an additional category has been added namely Obligate Upland (UPL) (Brand et al. 2018). Furthermore, it is contended that wetlands are generally characterised by grasses, although sedges are often the dominant plants occurring in the wettest parts of a wetland (Sieben, Mtshali & Janks 2014).

The National Wetland Vegetation Database (Sieben, Mtshali & Janks 2014) under the support of the Water Research Commission (WRC) provides a comprehensive report of wetland vegetation in South Africa. The purpose of this report was to compile a standardized database of vegetation data for wetlands across the country so that sound conservation planning, and monitoring can be implemented nationally. Vegetation occurring in wetlands are important in terms of their indicator value as they can assist ecologists to "interpret the environmental conditions and changes therein in the wetlands" (Sieben, Mtshali & Janks 2014, p.iii). This database of vegetation looks at vascular plants as an important feature as they are present in all wetlands. Thus, the application of the database is suitable for application to wetlands and riparian areas across the country, regardless of their diversity in the different bioregions of the country (Sieben, Mtshali & Janks 2014).

A brief account of inland wetland vegetation based on vegetation cover and vegetation form is described below and referenced from both the South African Wetland Classification System, hereafter referred to as SAWCS (Ollis et al. 2013) and National Wetland Vegetation Database (NWVD) (Sieben, Mtshali & Janks 2014). Ollis and colleagues (2013) contend that vegetation cover characteristics affect the composition of biota within an inland wetland and the ecosystem functions that the wetland can perform. The SAWCS (2013) recognizes two categories of vegetation cover in an inland wetland namely vegetated- with four sub-categories- and unvegetated, which is not further sub-divided and consists of either bare substratum, open water or a fluctuation between these two states (Ollis et al. 2013, p.57). The four sub-categories of vegetation form in the vegetated category include aquatic vegetation, herbaceous vegetation, shrubs/thicket vegetation and forest which are each briefly described:

Aquatic Vegetation

Aquatic vegetation encompasses plants that are "found principally on or below the water surface" and are categorized into three groups namely floating aquatic vegetation, submerged aquatic vegetation and algal mat. However, although emergent macrophytes "are plants that are rooted in the substratum of an aquatic ecosystem but that emerge above the water surface (if present), with most of the plant structures visible above the surface" they are not considered aquatic vegetation. This is because emergent macrophytes do not primarily occur on or below the water surface and should be classified as herbaceous vegetation or if they are woody, as shrubs/thicket or forest vegetation (Ollis et al. 2013, p.58).

Herbaceous vegetation

These are non-woody vegetation types found in wetlands, and include several sub-categories namely, geophytes, grasses, herbs/forbs, sedges, rushes, reeds, restios and palmiet. Refer to APPENDIX A for a detailed description of each herbaceous vegetation types as described in Ollis et al. (2013, p.60).

Shrubs/thicket vegetation

According to the SAWCS, these are self-supporting, multi-stemmed woody plants that are less than five metres in height and include young trees and trees that are small and stunted due to environmental conditions, and true shrubs. Furthermore, it is noted that dense stands of shrubs is called thicket (Ollis et al. 2013).

Forest wetlands

For forest inland wetlands, the SAWCS notes that these systems are characterised by woody vegetation, dominantly trees with a canopy cover of >75%. Forest wetlands may be further subdivided into riparian forests i.e. “a community of trees (i.e. a forest) occurring in the riparian zone of a river”, and forested wetland (or swamp forest) which is “a community of trees (i.e. a forest) occurring in soils that are permanently saturated or seasonally inundated with non-saline water” (Ollis et al. 2013, p.62).

The National Wetland Vegetation Database (NWVD) (2014) assigns eight main clusters of wetland vegetation which aligns with the Mucina & Rutherford (2006) South African Vegetation Map:

- Main Cluster 1: Sclerophyllous Wetland Vegetation
- Main Cluster 2: Swamp Forest
- Main Cluster 3: Subtropical Wetland
- Main Cluster 4: Estuarine, Brackish, and Saline Wetland Vegetation
- Main Cluster 5: Montane Grassy Wetland Vegetation
- Main Cluster 6: Temperate Grassy Wetland Vegetation
- Main Cluster 7: Short Lawn Grassy Wetland Vegetation
- Main Cluster 8: Hydrophytic Vegetation

For this study, a detailed list of species for Sclerophyllous Wetland Vegetation as described in the NWVD (Sieben, Mtshali & Janks 2014, pp.32–38) is attached as APPENDIX B. This list was used in field data collection, as a means of reference for identifying plants found within the Du Toits River wetland.

Sclerophyllous Wetland Vegetation

This vegetation type is the first main cluster and the most clearly defined of the eight main clusters in the NWVD (Sieben, Mtshali & Janks 2014). The NWVD report these plants as species communities that occur or grow exclusively on nutrient-poor substrates and Table Mountain Group Sandstone dominantly in the Western Cape (Sieben, Mtshali & Janks 2014). This environment is characteristic of the Cape Floristic Region (CFR) and Fynbos biome (Rebelo et al. 2006) conditions, and encompass a mixture of vegetation dominantly shrubs, restios and tough, hardy mostly needle-leaved sclerophyllous grasses and sedges (Sieben et al. 2017; Sieben, Mtshali & Janks 2014). Sieben, and colleagues (2014) additionally note that some sclerophyllous vegetation communities may also be found in parts of the Eastern Cape and Limpopo provinces, where nutrient-poor Sandstones are also present. Although included in the NWVD representing 321 plots and 700 species resulting from data analysis (Sieben, Mtshali & Janks 2014), sclerophyllous vegetated wetlands have historically been under sampled, most likely due to upland vegetation in the fynbos biome drawing more attention (Sieben et al. 2017).

A more recent study by Sieben, Kotze, Job & Muasya (2017) present an overview and classification of wetland vegetation found within sandstone fynbos or related vegetation types that occur on extremely nutrient-poor substrates. As mentioned above, this is sclerophyllous vegetation (Main Cluster 1 of the NWVD), and should not be referred to as Fynbos vegetation as “it is not restricted to the temperate Fynbos biome, but it is mostly dominated by sclerophyllous shrubs and graminoids as an adaptation to the unique environmental conditions in these wetlands” (Sieben et al. 2017, p.55). From this study, it was noted that wetlands in the Fynbos biome are unique and quite unusual in the context of wetland vegetation in general which in most cases in South Africa, have “distinct vegetation dominated by graminoids, mostly from the family Cyperaceae, that stands out from the vegetation in the uplands, independent of the biome they are located in (Sieben, Mtshali & Janks 2014). It is highlighted that many of the plants in these wetlands are closely related to the upland fynbos plants surrounding these wetlands, and belonging to the same families such as Restionacae, Ericaceae, Proteaceae, Asteraceae and Rosaceae (Mucina & Rutherford 2006; Sieben et al. 2017; Sieben, Mtshali & Janks 2014).

Furthermore, Sieben, Mtshali & Janks (2014) mention that when researching this vegetation type, taxonomical issues may arise in distinguishing between sclerophyllous vegetation and upland fynbos especially among Restionacae and Ericaceae species. However, they further note that on a plot basis, this vegetation type is not species-rich when compared to upland fynbos. Consequently, this means that it may be difficult to distinguish between sclerophyllous vegetation and upland fynbos vegetation for this study, and careful analysis must be considered with the Remote Sensing classification results. Soil conditions will be included from field observations to determine or solve any potential confusion between vegetation types.

Note that the purpose of this project is to test and explore whether Remote Sensing can efficiently detect ecotones within a fynbos embedded wetland system. Therefore, although vegetation cannot be used as a primary and single indicator of wetland presence, it will be the main feature used to derive patterns of plant composition and changes from Remote Sensing imagery and techniques, to potentially identify fine-scale ecotones. Additional indices such as the Modified Normalized Difference Water Index (MNDWI) to determine the surface water level during the wet and dry season will also be used for supplementary analysis.

2.3.3 Wetland soils

From the previous sections it can be inferred that wetlands are commonly characterised by three determining factors that have a knock-on effect on one another i.e. the hydrological regime (how water moves in and out of the wetland as well as the frequency and duration of inundation and saturation), may affect the soil morphology and chemistry (hydromorphic soils) in the wetland, and this in turn may affect the vegetation that will inhabit the wetland (Ollis et al. 2013). This argument is supported in Job (2014) who also notes that the "presence and retention of water in a landscape is a key defining feature of a wetland, where water is held long enough to saturate soils to sufficient depth to influence the plants that grow there, and for characteristics indicative of flooded soil to develop" (Job 2014, p.9). Because environmental conditions differ across the world, wetland soils in the southern African context will be discussed and therefore relevant literature covering information on wetland soils in South Africa will be consulted.

Wetlands encompass a tremendously wide range of hydrological regimes from temporarily (or seasonal) to permanently saturated, which is typically reflected in the morphology of mineral wetland soils (Job 2014). The term 'hydromorphic soil' is associated with wetlands and is characterised by prolonged and repeated periods of saturation which develop anaerobic (oxygen-devoid) soil conditions (Department of Water Affairs and Forestry 2005). Furthermore, it is noted that prolonged anaerobic conditions may result in a change in the chemical characteristics of the soil (Department of Water Affairs and Forestry 2005). Hydromorphic soils display unique characteristics (in both colour and texture) resulting from these intermittent periods of saturation, and soil components such as iron and manganese which are insoluble under aerobic conditions become soluble under anaerobic soil conditions (as in wetlands) and can be percolated from a soil profile. Iron is said to be the most abundant element in soil and results in the general red and brown colour of many soils. Under anaerobic conditions, once most of the iron has been dissolved out of soil due to prolonged anaerobic conditions, the soil profile consists of a greyish, greenish or bluish colour, and is said to be "gleyed" (Department of Water Affairs and Forestry 2005). Common in seasonally or temporarily saturated wetlands, is a fluctuating water table, which results in alternations between aerobic and anaerobic conditions. This in turn can cause dissolved iron to become insoluble again, resulting in the formation of mottles (Department of Water Affairs and Forestry 2005). Richards (2001) notes that condensed levels of iron in mineral soil material under aerobic soil conditions, may result in the development of yellow, orange, red or black mottles.

Additionally, the SAWCS (Ollis et al. 2013) refer to 'substratum type' which is one of the descriptors (level 6 of the classification system) of classifying Inland Systems. The guide further reinforces that for wetlands, when classifying the substratum type, it is important to consider the soil profile and not just the surface substratum. This is because "soil profile has a significant influence on the formation and functioning of a wetland ecosystem, including the way in which water enters and flows through a wetland" (Ollis et al. 2013, p.51). The substratum types for Inland Systems include the following categories:

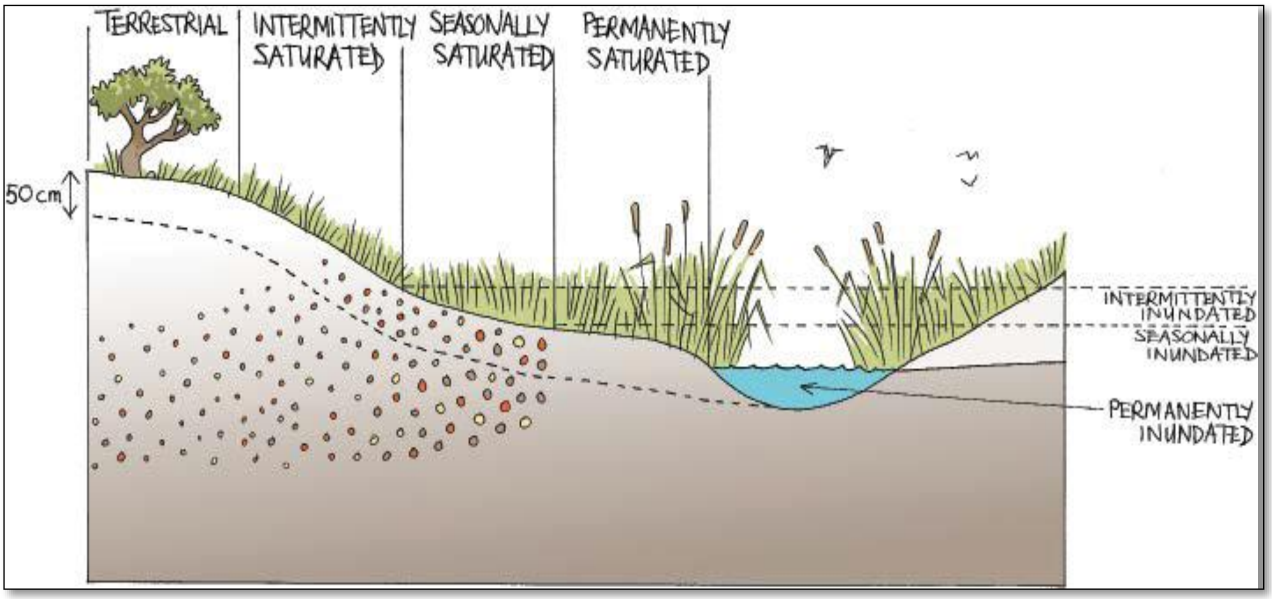
1. Rocky substrata: bedrock, boulders, cobbles, and pebbles/gravel.
2. Mineral soil (>10% organic carbon): sandy soil, silt (mud), clayey soil, and loamy soil.
3. Organic soil (>10% organic carbon): Peat (>30% organic carbon), and <30% organic carbon.
4. Salt crust is another unique type of substratum included in the Classification System but not applicable to this study.

Organic soil vs mineral soils

According to Ollis et al. (2013) organic carbon is one of the abundant components in any soil, however, with varying amounts in different soil types. The soil classification system in South Africa contends that "topsoil with an average organic carbon content of at least 10% throughout a vertical distance of 200 mm is defined to be an organic soil" (Soil Classification Working Group 1991). Organic soils are mostly made up of accumulated organic material that consists of varying stages of decayed plant and animal remains and "tend to occur in environments where the rate of decay of organic matter is substantially slower than the rate of production. Such conditions occur in areas that are saturated with water for long periods in most years (i.e. in wetlands that are permanently or near-permanently saturated)"(Ollis et al. 2013). Occasionally some organic soils can be classified as peat but not always. Fundamentally, peat can be defined as "a sedentarily (in-situ) accumulated material comprising of at least 30% (dry mass) of dead organic matter" (Joosten & Clark 2002). Whereas mineral soils are all other non-organic soils and can be described based on their texture. These include sand-, silt, and/or clay-sized rock and mineral fragments" (Ollis et al. 2013).

Ultimately:

"Wetland vegetation and mottling of the soil are generally absent from the terrestrial zone, while the intermittently saturated zone generally has some wetland vegetation and sparse mottling of the soil. The seasonally saturated zone generally supports significant wetland vegetation (mostly grasses and sedges), and the soil is often greyish in colour with many mottles. Mostly wetland vegetation (sedges, rushes, and reeds) occurs in the permanently saturated zone, where the soils are generally grey in colour with few or no mottles, and seasonal to permanent inundation is common. Due to the above-mentioned relationships between the hydrology, soils, and vegetation of a wetland, in the absence of long-term hydrological records (which is usually the case), soil morphology and/or vegetation can be used as indicators of the hydrological regime of a wetland by those with adequate experience. Soil morphology characteristics are the result of long-term hydrological conditions, while the vegetation within a wetland is an indicator of recent conditions" (Ollis et al. 2013, p.41). This is key in analysing the soil and vegetation in my study area as soil and vegetation will speak to the ecotone characteristics.



Source: Ollis et al. (2013)

Figure 2.2 Schematic of a cross-section through a hypothetical wetland displaying the various zones of saturation and inundation that could occur in a wetland. The diagram also shows how vegetation and soils in the upper ground surface (50cm) layer typically responds to the hydroperiod (in Ollis et al. (2013), modified from Kotze 1996)

2.3.4 Mapping and Monitoring wetlands

The need for increased capacity and prioritization of wetland research has increased over the years as scientists have shown that these valuable ecosystems are increasingly under threat (Van Deventer et al. 2019; Van Deventer et al. 2018; Ramsar Convention on Wetlands 2018). One important aspect to wetland conservation and management is the availability of national wetland inventories with accompanying maps of the location of wetlands. These provide information on a countries wetland resources which may lead to better monitoring, management and restoration efforts (Tiner 2016). The universal term for identifying where wetlands are and how they are located within the landscape is wetland delineation. Wetland delineation refers to the "determination and marking of the boundary of a wetland marking the outer edge of the temporary zone of wetness" in either a field-based or desktop application (Department of Water Affairs and Forestry 2005, p.28). There are four factors to consider as indicators in delineating a wetland (Department of Water Affairs and Forestry 2005, pp.5–6) namely:

1. The terrain unit indicator which helps in identifying where and in what parts of the landscape a wetland is most likely to occur.
2. The soil form indicator as identified by the Soil Classification Working Group (1991) which are soils that show signs of prolonged and frequent saturation.
3. The soil wetness indicator which identifies characteristics or 'morphological signatures' that develop in the soil as a result of various periods of frequent and prolonged saturation.
4. Lastly, the vegetation indicator which identifies hydrophytic vegetation that are adapted to saturated soil conditions.

These indicators are important in determining wetland presence and once identified, may also be used as a baseline for mapping the location and extent of wetlands which can be added to national wetland inventory datasets or repositories.

The National Wetland Inventory (NWI) for South Africa is housed within the South African National Biodiversity Institute (SANBI) who holds the current repository of national spatial data and information for wetlands. Moreover, the National Wetland Inventory (NWI) is the originator for the National Wetland Map (NWM) which was the principal wetland input in national planning projects such as the National Freshwater Ecosystem Priority Areas (NFEPA) (Nel et al. 2011) and National Biodiversity Assessment (Van Deventer et al. 2018; Driver et al. 2012; Job et al. 2018). Job et al. (2018) notes that the NWI receives and integrates wetland data and information from numerous and a wide range of sources typically with "different mapping scales, coverage and accuracies"(Job et al. 2018, p.2). It is impossible to approach wetland conservation and management in a holistic or systematic manner whether at national, provincial, local or catchment scale without having good baseline information that are provided by wetland inventories (Job et al. 2018). It is further argued that this does not imply waiting for the perfect data to create a good inventory, but rather involves "investing in ongoing improvements while making use of the best available data to develop policy and guidance that is appropriate to regional conditions and wetland characteristics" (Job et al. 2018, p.2). Since its first inception, the National Wetland Map, henceforth referred to as the NWM, has encountered a number of improvements over the years, with the latest being the NWM5 (version 5) which was published in 2020. Job et al. (2018) noted that wetland inventories at any scale (national, provincial, local etc) must continuously be updated and improved and not regarded as absolute. This is showcased in the NWM 5 which aims to enhance and improve the existing and previous NWMs. The South African NWM5 (2020) provides information on the "location, spatial extent and ecosystem types of two of the three broad aquatic ecosystems, namely, estuarine and inland aquatic (freshwater) ecosystems"(van Deventer et al. 2020, p.66). This version of the NWM comes with the following improvements:

(i) "the extent of wetlands mapped in NWM5, compared to previous versions of the NWMs;
(ii) the improved extent of inland wetlands mapped in focus areas in NWM5 relative to NWM4;
(iii) the type of cover associated with the wetlands (inundated, vegetated or arid);
(iv) the ecotone between rivers and estuaries; and
(v) level of confidence for the inland wetlands in terms of how well the extent and hydrogeomorphic units were captured for each sub-quaternary catchment of South Africa" (van Deventer et al. 2020, p.66)

van Deventer and colleagues (2020) also note that the intention of the NWM5 is to inform users of both the improvements and the "shortcomings of the NWM5 so that it is appropriately used in planning and decision making, whilst enabling better planning for the wetland inventory of South Africa" (van Deventer et al. 2020, p.68). An important issue to take note of is that the NWM5 does not represent fine-scale ecotones which this study aims to, but rather focuses on river-estuary ecotones. This is understandable as the scale at which ecotones are mapped in this study, may be too small for a large extent of spatial data such as a national wetland layer. Fine-scale ecotones may thus rather be included in catchment-based layers. van Deventer et al. (2020) recommend that future improvements of the NWM should focus on catchment-based improvements, mainly in strategic water-source areas, areas that experience high development pressures, and areas with low confidence designation.

It is noted in literature that the mapping of wetlands is not always an easy task as the boundaries of most wetlands are not always clearly defined by abrupt changes from wetland to terrestrial habitat. However, there is usually a gradual transition in soil and vegetation characteristics that is linked to the "declining frequency and duration of saturation of the soil, as one moves away from the centre of the wetland" (Job et al. 2018, p.3). This must be considered when attempting to map the transition i.e. ecotones within the Du Toit River wetland where it may be challenging to clearly define and distinguish visible changes between upland fynbos and wetland habitat. Job et al. (2018) note that finding a point along the moisture gradient at which to draw the wetland boundary can especially be a daunting task if the mapping is solely relying on detection from remote sensing imagery. Researchers have also scripted the challenges of mapping wetlands which include the fact that wetlands are not unified by one single or common landcover-type or vegetation form such as a forest that is populated by trees, grasslands by grass, and shrublands by shrub (Gallant 2015). Instead, wetlands in their dynamic capability can support varying vegetation types as detailed above in 2.3.2. These wetland vegetation communities can either be monodominated by a few single species or a heterogenous mosaic of multiple species (e.g. sclerophyllous) in different life forms (Gallant 2015). The common presence of water in wetlands whether permanent, seasonal, or temporary, also has its challenges when mapping wetlands. Gallant (2015) states that the presence of water can signify that it is at the Earth's surface, or below the surface in the rooting zone of plant, and where the varying water levels "impose strong controls in wetlands, and the magnitude of change in water levels influences the relative abundance of species and rate of vegetation succession" (Gallant 2015, p.10939).

Gallant (2015) continues to suggest another factor that makes wetlands hard to map remotely is that "they are highly dynamic in ways that substantially alter their reflectance and energy backscatter properties", and " individual species can exhibit significant variation in energy responses (spectrally and in terms of backscatter geometry) within a growing season at different stages of their development" (2015, p.10939). The third factor Gallant (2015) alludes to is that the often steep environmental gradients in and around the edges of wetlands may create narrow ecotones "that are often below the spatial resolving capacity of remote sensors. Sharp contrasts in characteristics of energy response at the land-water interface can be exploited to aid mapping in some wetland settings" (Gallant 2015, p.10940). Lastly, it is emphasized that these interchanging conditions illustrate wetlands as a moving-target in a Remote Sensing perspective as wetlands present "more of a moisture regime than a cover type" (Gallant 2015, p.10940).

2.4 PRINCIPLES OF REMOTE SENSING

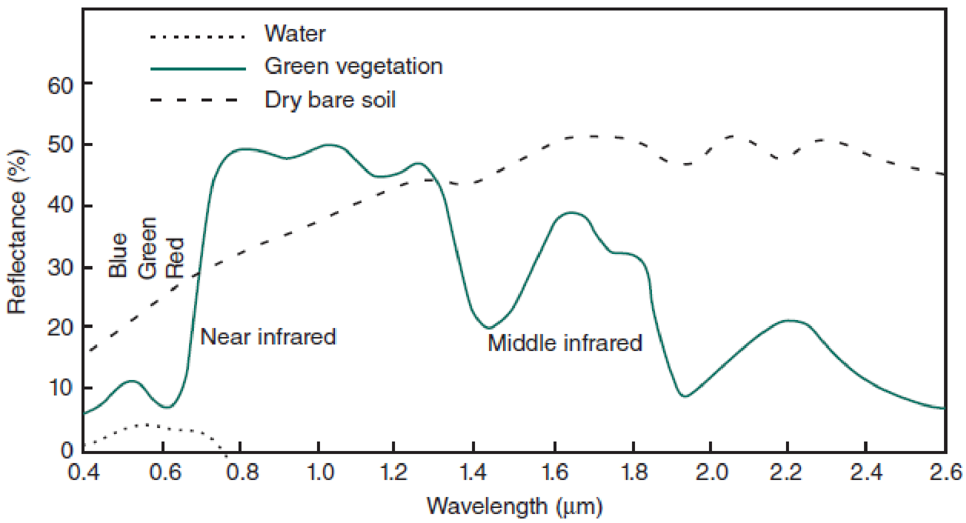
Remote Sensing (RS) is said to be the art and science of acquiring information about an object, area, or phenomenon on the Earth's surface (land and ocean) without being in direct physical contact with it (Bakker et al. 2001; Wegman et al. 2016), and forms a part of the broader theme of Earth Observation (EO). RS can provide consistent long-term EO data at both local and global scales without being labour-intensive and time-consuming, as opposed to in-field observations and data collection (Wang et al. 2010; Wegman et al. 2016). RS has increased in popularity since its first application and publication in Africa by Wicht (1945) who saw the value of it to provide important back drop information about infrastructure and natural processes (de Klerk & Buchanan 2016). Furthermore, it can be said that RS methods are based on the concept that information is derived from image data acquired by sensors such as aerial cameras, scanners or radar, which create a representation of real world phenomena (Bakker et al. 2001). RS encompasses acquiring information about the Earth's surface at one point in time using systems such as "sensors onboard airborne (aircraft, balloons) or space-borne (satellites, space shuttles) platforms" (Kumar & Singh 2013, p.406). These sensors record data in different parts of the Electromagnetic spectrum (EMS) as RS relies on measurement of electromagnetic energy (Bakker et al. 2001). There are three key aspects to the resolution of RS systems namely spatial, spectral, and temporal, and all sensors need to trade-off these three properties due to storage, processing, and bandwidth properties (Longley et al. 2015). Spatial resolution refers to the size of an object that can be resolved and is mostly measured in pixel size (often measured in metres); spectral resolution (bands) refer to the parts of the electromagnetic spectrum that are measured as different objects reflect and emit different types and amount of radiation in the EMS (Longley et al. 2015; Wegman et al. 2016). Lastly, temporal resolution (number of days) or repeat cycle refers to the frequency that images are collected for the same area (Longley et al. 2015).

2.4.1 The Electromagnetic Spectrum

Electromagnetic energy and radiation are described as a spectrum of continuous wavelengths that are measured in nanometres (nm) (Wegman et al. 2016). The Electromagnetic spectrum (EMS) comprises various radiations such as the visible spectrum which is a range perceivable by the human eye (approximately 400-700 nm), ranging from blue to red. However, Wegman et al. (2016) note that "the visible spectrum is just a small part of radiation used in remote sensing" and that radiation in the near and mid-infrared (NIR and MIR), and thermal infrared (TIR) carries a lot more useful information about the earth's surface (2016, p.48). Simply stated, the sun, which is the primary source of illumination on the Earth, emits radiation which is absorbed, transmitted and reflected by different surfaces in a distinguishing manner (spectral response), which is then transmitted back to space and recorded by sensors on satellites or planes (Wegman et al. 2016).

2.4.2 Spectral Reflectance Signatures

As noted above, different surfaces on Earth absorb, reflect, and transmit different amounts of radiation, which can be referred to as spectral resolution or spectral reflectance/response/signature. It is also noted that RS systems may capture "data in one part of the spectrum (referred to as a single band) or simultaneously from several parts (multiband or multispectral) (Longley et al. 2015, p.177). The spectral resolution of a dataset is defined by the number of bands across the entire spectrum and which allows for the differentiation of surface properties (Wegman et al. 2016). Furthermore, Wegman et al. (2016) notes that based on these different reflectance properties, RS data analysis intends to differentiate surface or land cover types such as water, vegetation, soil, and urban structures. Vegetation is said to absorb mostly blue and red light for photosynthesis which is why it appears green to the human eye while reflecting NIR radiation and depending on the state of vegetation (Wegman et al. 2016). Figure 2.3 below displays the spectral signatures of water, green vegetation, and dry bare soil as an example of the spectral responses in the EMS of three surfaces on Earth (Longley et al. 2015).



Source: Longley et al. (2015)

Figure 2.3 Spectral signatures of water, vegetation, and dry bare soil

2.4.3 Active and Passive Sensors

As mentioned above, Remote Sensing uses sensor devices to record and measure electromagnetic energy (Bakker et al. 2001). There are two types of sensors namely active and passive sensors

(Wegman et al. 2016). Passive sensors are those that sense natural radiation which are either reflected or emitted from the earth's surface and include optical sensors, where sensors detect "radiation in the visible, near-, middle- and thermal-infrared wavelength regions, reflected/scattered or emitted from the earth, forming images resembling photographs taken by a camera/ sensor located high up in space" (Kumar & Singh 2013, p.406). Whilst active sensors are those which produce their own electromagnetic radiation such as LiDAR (Kumar & Singh 2013). Additionally, Wegman et al. (2016) suggest that active sensors illuminate the Earth artificially by "actively emitting and receiving radiation in the form of radio waves (Radar; wavelengths ranging from 3 to 24 cm) or laser pulses (Light Detection and Ranging (LiDAR); typically in the NIR wavelengths)" (2016, p.49).

2.4.4 Remote Sensing Sensors

High spatial resolution data and/or fine scale spatial resolution is often less than 10 m, and ranges from 0.5-10 m with IKONOS, QuickBird, OrbView-3 and SPOT-5 (Satellite Pour l'Observation de la Terre-5) being commonly used systems (Wang et al. 2010, p.9649). Moreover, one of the great advantages of fine scale spatial resolution data is that "it greatly increases the accuracy of identification and characterization of small objects at spatial scales which were previously only available from airborne platforms" (Wang et al. 2010, p.9649). However, as data such as QuickBird and GeoEye are expensive and difficult to obtain repeat temporal coverage, freely available medium resolution optical sensors such as MODIS, Sentinel and Landsat, are more feasible and relevant to this study. These datasets are easily accessible, time and cost-efficient that can be used and stored in open-source software such as Quantum GIS (QGIS), and cloud-computing platforms such as Google Earth Engine (GEE). Google Earth Engine is a cloud-based computing platform that publicly avails ready to use geospatial datasets such as a variety of "satellite and aerial imaging systems in both optical and non-optical wavelengths, environmental variables, weather and climate forecasts and hindcasts, land cover, topographic and socio-economic datasets"(Gorelick et al. 2017, p.18).

Landsat 8 data will be used in this study with a spatial resolution of 30 m which is a useful scale for identifying landscape patterns (Wegman et al. 2016) such as ecotones as done by de Klerk, Burgess & Visser (2018). Additionally, Sentinel-2 MSI: MultiSpectral Instrument, Level-2A data will be used as well since the bands of Sentinel-2 (European Space Agency 2015) have a finer resolution (10 m and 20 m) than Landsat 8 and may be useful for understanding vegetation distribution at a small landscape scale. Note that there are inconsistencies in the literature whereby some researchers refer to Landsat and Sentinel imagery as high spatial resolution data (Chen et al. 2016; Lück-Vogel et al. 2016). However, in this study, Landsat 8 and Sentinel-2 data are referred to as medium resolution as their spatial resolutions are within the ranges of 10 m-60 m (Sentinel-2: MSI, Level 2-A), and 30 m-

100 m (Landsat 8) (Guo et al. 2017; de Klerk et al. 2016; Wang et al. 2010; Zhang et al. 2017) which is not as fine scale as QuickBird, GeoEye or SPOT etc.

Landsat 8 Surface Reflectance Tier 1

Since the early 1970s, the Landsat satellites have provided multispectral imagery of the Earth's surface which has improved the understanding of the Earth's land processes, change detection and the impact humans have on the environment (U.S. Geological Survey 2016). The first Landsat satellite was launched in 1972 followed by Landsat 2 and 3 which were launched in 1975 and 1978 respectively, with similar configurations as Landsat 1 (U.S. Geological Survey 2016, p.3). In 1984 Landsat 4 was launched with an additional instrument called the Thematic Mapper (TM) and an improved ground resolution of 30 m and three new channels/bands. Landsat 5, a duplicate of Landsat 4, was also launched in 1984 whilst Landsat 6 failed to achieve orbit in 1993 but was equipped with an additional 15 m-panchromatic (PAN) band. By 1993 Landsat 7 was launched and "performed nominally until the Enhanced Thematic Mapper Plus (ETM+) sensor's Scan Line Corrector (SLC) failed in May 2003. Since that time, L7 has continued to acquire useful image data in the "SLC-off" mode" (U.S. Geological Survey 2016, p.3). Importantly, Landsat 8 (L8) is the latest freely available series of imagery in the Landsat mission (launched in 2013) and is said to provide robust, high performing, cloud-free and extremely high quality data of all the landmass and near-coastal areas on Earth (U.S. Geological Survey 2016). The L8 has a 16-day repeat cycle averaging a collection of 22-23 images of a location per year (Zhu 2017). The Landsat 8 Surface Reflectance Tier 1 (SR T1) dataset is atmospherically corrected surface reflectance from the Landsat 8 OLI/TIRS satellites. Images in this dataset contains five visible and Near-Infrared (NIR) bands, and two Shortwave-Infrared (SWIR) bands processed to orthorectified surface reflectance (U.S. Geological Survey 2016; USGS 2017). Table 2.3 details the characteristics of L8 OLI bands. It has been noted on NASA's website that Landsat 9 was launched in September 2021 (https://landsat.gsfc.nasa.gov/landsat-9/landsat-9-overview) with improved capabilities and orbiting time for increased temporal coverage of observations of the Earth's surface.

Table 2.3 Band characteristics of Landsat 8 OLI and *TIRS* Bands (µm)

Band number	Band description	Wavelength (µm)	Resolution
1	Coastal/Aerosol	0.435 - 0.451	30m
2	Blue	0.452 - 0.512	30m
3	Green	0.533 - 0.590	30m
4	Red	0.636 - 0.673	30m
5	NIR	0.851 - 0.879	30m
6	SWIR-1	1.566 – 1.651	30m
10	*TIR-1*	*10.60 – 11.19*	*100m*
11	*TIR-2*	*11.50 – 12.51*	*100m*
7	SWIR-2	2.107 – 2.294	30m
8	Pan	0.503 – 0.676	15m
9	Cirrus	1.363 – 1.384	30m

Source: Google Earth Engine (2021)

Literature also notes that Landsat data is most useful in large-scale vegetation studies and change detection (Chen, Michishita & Xu 2014; Fang et al. 2018; Matsushita et al. 2007; Zhu 2017). Often, Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) have been fused together to create datasets of high temporal frequency and high spatial resolution observations (Zhang et al. 2017).

Sentinel-2 MSI: MultiSpectral Instrument, Level-2A

The Sentinel collections are a constellation of satellites developed by the European Space Agency to "operationalize the Copernicus program, which include all-weather radar images from Sentinel-1A and 1B, high-resolution optical images from Sentinel-2A and 2B, ocean and land data suitable for environmental and climate monitoring from Sentinel-3, as well as air quality data from Sentinel-5P" (Google Developers 2021). This study used the Sentinel-2 (S2): MultiSpectral Instrument, Level 2-A (Surface Reflectance) data which is a wide-swath (290 km), high quality and multispectral imaging mission. The temporal frequency of S2 imagery is a global five-day revisit frequency with 13 spectral bands i.e. "four bands at 10 m, six bands at 20 m and three bands at 60 m spatial resolution" (European Space Agency 2015, p.9) which provides data that is suitable for assessing the state and change of vegetation, soil and water cover (European Space Agency 2015; Google Developers 2021). Table 2.4 below provide the band characteristics of the multispectral bands of the Sentel-2 MSI, Level 2-A imagery:

Table 2.4 Band characteristics of Sentinel-2 MSI: MultiSpectral Instrument, Level-2A

Band number	**Band description**	**Wavelength** (µm)	**Resolution**
1	Aerosols	443.9 (S2A) - 442.3 (S2B)	60m
2	Blue	496.6 (S2A) - 492.1 (S2B)	10m
3	Green	560 (S2A) - 559 (S2B)	10m
4	Red	664.5 (S2A) - 665 (S2B)	10m
5	Red Edge 1	703.9 (S2A) -703.8 (S2B)	20m
6	Red Edge 2	740.2 (S2A) -739.1 (S2B)	20m
7	Red Edge 3	782.5 (S2A) -779.7 (S2B)	20m
8	NIR	835.1 (S2A) - 833 (S2B)	10m
8A	Red Edge 4	864.8 (S2A) - 864 (S2B)	20m
9	Water vapor	945 (S2B) - 943.2 (S2B)	60m
11	SWIR-1	1613.7 (S2B)-1610.4 (S2B)	20m
12	SWIR-2	2202.4(S2A) -2185.7 (S2B)	20m
AOT	Aerosol Optical Thickness		10m
WVP	Water Vapor Pressure		10m
SCL	Scene Classification Map		20m
TCI_R	True Color Image, Red channel		10m
TCI_G	True Color Image, Green channel		10m
TCI_B	True Color Image, Blue channel		10m
MSK_CLDPRB	Cloud Probability Map		20m
MSK_SNWPRB	Snow Probability Map		10m
QA60	Cloud mask		20m
QA60 Bitmask	Bit 10: Opaque clouds 0: No opaque clouds 1: Opaque clouds present Bit 11: Cirrus clouds 0: No cirrus clouds 1: Cirrus clouds present		

Source: Google Earth Engine (2021)

2.4.5 Processing Remote Sensing data

As the above section has highlighted various sensors and datasets available in RS, focusing on Landsat 8 and Sentinel-2 data, it is important to also mention that remotely sensed imagery needs to undergo digital image processing or pre-processing to be useful in applications (Walz 2002). This is because RS data are affected by various “electronic, geometric, mechanical and radiometric distortions” and if left uncorrected would reduce the accuracy of the information extracted and thereby also reduce the usefulness of the data (Bernstein 1976, p.41). In order to correct RS sensor data, internal and external errors have to be determined which need to be both measurable and predictable (1976). Walz (2002) notes that satellite data needs to be entered into a “standardized system of coordinates so that it can be combined with other spatial information” and thus sensor errors can then be detected and corrected where necessary (Walz 2002, p.288). Pre-processing of RS data typically includes fundamental correction steps for sensor geometry and terrain-induced geometric distortions which is often referred to as orthorectification (Wegman et al. 2016). Pre-processing of imagery includes a variety of steps such as radiometric correction (Bakker et al. 2001; Wegman et al. 2016) atmospheric correction, image correction, enhancement, transformation, and classification (Kumar & Singh 2013; Zhu 2017). These processes are briefly described below and followed by a detailed discussion of image classifications which is the main theme of Chapter 3.

Image correction -According to Kumar & Singh (2013) the data that is recorded by sensors often encompass errors that are related to geometry and brightness value of the pixels and thus are corrected by using "suitable mathematical models, which are either definite or statistical models" (Kumar & Singh 2013). Furthermore, other image correction approaches have been used in the mapping of change detection and these include atmospheric correction, cloud and cloud shadow detection as well as image compositing, fusions and metrics (Zhu 2017).

Image enhancement -The principle of image enhancement is to modify the image by changing the pixel brightness values so that the visual impact of the image is more suitable or improved (Kumar & Singh 2013). These image enhancement techniques are accomplished by deriving new brightness values of pixels from either existing values, or "from the brightness values of a set of surrounding pixels" (Kumar & Singh 2013, p.407). An example of a classical band combination for the enhancement of vegetation in imagery are band 4-band 3-band 2, which highlights the differences between vegetation and no vegetation in an image, and the vegetation ultimately appears red using this combination (Wegman et al. 2016).

Image transformation- In terms of image transformation, Kumar & Singh (2013) note that the multispectral character of an image allows it to be transformed spectrally to a new set of image components or bands with a specific purpose in order to extract information that is more evident to the content of an image. It is noted that the pixel values of the new components of an image is still similar or related to the original spectral bands via a linear operation (Kumar & Singh 2013).

Image classification- The overall objective of image classification is to assign classes or themes to all pixels in an image with different classes of land use or land cover. To label or classify land cover and land use, two methods of image classification are adopted in RS namely supervised and unsupervised classification.

2.5 IMAGE CLASSIFICATION

Image classification which can also be referred to as land cover classification, is the process of converting multiple input layers into groups of pixels with similar characteristics where the resulting pixel values may be used to identify land cover classes that are "either defined a priori (supervised classification) or a clustering algorithm (unsupervised classification) (Wegman et al. 2016, p.245). Earlier research has suggested that the principle of image classification, is that pixels are assigned to a class based on "its feature vector, by comparing it to predefined clusters in the feature space" which result in a classified image (Bakker et al. 2001). Furthermore, Bakker et al. (2001) emphasize that the "crux of image classification is in comparing it to predefined clusters, which requires definition of the clusters and methods for comparison" (Bakker et al. 2001, p.196).

2.5.1 The Process Of Image Classification

Researchers (Bakker et al. 2001; Lu & Weng 2007; Perumal & Bhaskaran 2010) have highlighted a number of procedures for the general workflow of image classification i.e. selecting and preparing suitable sensor data; determining clusters in a suitable feature space (supervised or unsupervised); defining and selecting training samples, extracting signatures, selecting a suitable classification algorithm, running the classification; and post-classification or validation (accuracy assessments) (Bakker et al. 2001; Lu & Weng 2007; Perumal & Bhaskaran 2010). Image classification serves a specific goal which is to convert image data into thematic data (Bakker et al. 2001), and is useful to quantify landscape features for modelling and various other landscape or ecological analysis (Wegman et al. 2016). In turn, Wegman et al. (2016) infers that image classification is a fairly subjective process and involves balancing options in almost every step of the workflow. Their take on the classification workflow highlights 10 detailed steps to follow (Wegman et al. 2016):

1. Defining why one wants a classified image and how one will use it.
2. Defining the study area.
3. Define classes by selecting or developing a classification scheme.
4. Selecting the imagery (resolution, sensor, and date).
5. Prepare the imagery for classification (image corrections).
6. Collect and generate ancillary data (such as spectral indices or texture).
7. Choose a classification approach (feature space: supervised or unsupervised).
8. Collect training and validation data (in field data where possible).
9. Creating and modelling a classified map.
10. Assess the classification accuracy, and revisit previous steps for refinement if necessary (e.g., collecting additional or better training and ancillary data).

2.5.2 Supervised and Unsupervised Classification

In terms of classification approaches namely unsupervised and supervised, unsupervised classification involves the identification of "natural groups, or structures, multi-spectral data" (Kumar & Singh 2013, p.407). Additionally, in an unsupervised classification approach, there is minimum user interaction -it is statistically and computer-led- and it requires interpretation after the classification as "the division of classes is carried out automatically by a classification algorithm" or a decision rule (Walz 2002, p.290). In contrast, supervised classification refers to a classification process of sampling classes of "known identity (ground truth sites) to classify pixels of unknown identity" (Kumar & Singh 2013, p.410). Supervised classification is user or analyst dependent as the analyst trains the computer to distinguish distinct land cover classes thereby developing spectral signatures for each land cover class (Walz 2002). In essence, this means that a supervised classification will develop spectral signatures for all the pixels in an image, search the entire scene for similar signatures, and group this as a land cover class. There are a number of supervised classification methods such as Maximum Likelihood (ML), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Neural Networks (NN) and the decision-tree classifier Random Forest (RF) (Myburgh & van Niekerk 2014; Perumal & Bhaskaran 2010; Wegman et al. 2016). Maximum likelihood classification is the most stable and most commonly used supervised classifier and assumes that "the populations from which the training samples are drawn are multivariate-normal in their distribution" (Kumar & Singh 2013, p.407). However, other classifiers such as Random Forest (Breiman 2001) has increased in popularity over the years (Bargiel & Herrmann 2011; Fu et al. 2017; Poona et al. 2016).

The classification of images into a thematic map remains a challenge due to various factors such as landscape heterogeneity and complexity of a study area, and therefore, the selected RS data as well as image processing and classification approaches chosen may affect the success of a classification (Lu & Weng 2007). Lu & Weng (2007) note that because both airborne and space-borne data vary in spatial, radiometric, temporal and spectral resolutions, it is essential that one understands the strengths and weakness of each data type before selecting it for classification. One can thus summarize image classification into three main objectives; to group similar features, to separate dissimilar ones, and to assign class labels to match spectral classes with information classes. This is so that one can obtain insight into the data with regards to ground cover and surface characteristics using various RS approaches and algorithms. Image classification using Landsat 8 Surface Reflectance Tier 1 and Sentinel-2: MSI, Level-2A data to create a thematic map of the vegetation cover and distribution of a fynbos embedded alluvial fan wetland, will be explored in Chapter 3 using the Random Forest classifier (research objective 4).

2.5.3 Per-Pixel Based Mapping And Fuzzy Classification Approaches

Traditionally, hard classifiers such as "agglomerative, divisive/partitioning, moving window, and rate of change approaches"(de Klerk, Burgess & Visser 2018) produce classified images with binary outputs where the general rule is 'one pixel-one class', which essentially means that a pixel either must be a full member of a class, or not (Melgani 2000). This method of processing however is not very useful in producing maps for data that is naturally mixed or non-binary, especially in heterogenous ecological systems where a pixel may cover more than one vegetation type within. This scenario may especially be true when using data such as Landsat with a resolution of 30 m, in a relatively small wetland such as the Du toits River wetland, where more than one vegetation type may most likely occur within and across the boundaries of a 30 m pixel. In this case, it may result in the classified image having a number of mixed pixels, which hard classifiers consider an unresolved pixel or a misclassification (Ozesmi & Bauer 2002).

There are two approaches in RS which can extract information from remotely sensed data namely using a per-pixel based approach, where an image pixel is the fundamental unit under analysis; and object-based, where image objects are first created and then subjected to further analysis (Devi & Jinji 2015). Zhang (2014) contends that using per-pixel based mapping may result in a "salt-and-pepper" effect in heterogenous landscapes but these issues can be overcome by using Object-Based Image Analysis (OBIA) techniques "which first decompose an image scene into relatively homogeneous areas and then classify these areas instead of pixels" (Zhang 2014, p.10). However, by using a per-pixel approach, mixed pixels can be used as the main representative of fuzzy boundaries, or ecotones. The classical Bayes classifier is an example of one classifier that supports the fuzzy logic whereby a classified image can consist of mixed pixels that will store probability values for more than one class and rules out the idea that one pixel can only belong to one definite class. In essence, the Naïve Bayes classification is a simple probabilistic classifier based on the Bayes' Theorem which assumes that there is independence between features, and determines the probability of a feature with prior knowledge (prior probability) and current evidence i.e. it depends on conditional probability (Zhang 2016). This study will adopt a per-pixel approach using the Bayesian-based class probability classification and fuzzy graphs to map ecotones or vegetation change/turnover in the wetland (research objective 5).

2.6 LITERATURE EVALUATION AND CONCLUSION

The bibliometric analysis showed that limited research has been conducted on wetland ecotones especially in southern Africa. The literature reviewed in this chapter pertaining to the ecotone debate of whether one must use the words ecotone, ecological boundary, or patch, highlighted that although termed differently and used differently in various scientific approaches, all three these terms may be used interchangeably in the context of this study. Ultimately, ecotones were defined for this study as distinct zones of change or transition between adjacent ecological ecosystems and having unique characteristics that are defined by space and time scales. This chapter also delved into a theoretical framework of wetlands in a South African context, highlighting the wetland classification system used in the country, the HGM units or wetland types, vegetation types found as well as the soils typically found in wetlands in the country. The review covered the debates around wetland classification and the need for wetlands to be seen as integrated parts of a landscape and not as single units in a landscape. The review further touched on whether wetlands are seen as ecotones in a landscape and whether internal biological ecotones may exist within wetlands. Ultimately, internal wetland ecotones were of interest and not so much wetlands as a whole being an ecotone in a landscape. Furthermore, the literature review highlighted some discrepancies in the spelling of some wetland vegetation species in vegetation databases for example, *Epischoenis gracilis* (Fischer et al. 2019) vs *Epischoenus gracilis* (Sieben, Mtshali & Janks 2014); and *Isolepis prolifera* (Fischer et al. 2019) vs *Isolepis prolifer* (Sieben, Mtshali & Janks 2014). A review of wetland delineation and mapping in South Africa was provided with reference to the latest updated National Wetland Inventory, and how this inventory maps and describes ecotones. The chapter also provided a brief background on remote sensing, how it works, the types of remote sensing data, and the approaches to land use/landcover classification.

CHAPTER 3: REMOTE SENSING OF SPATIAL HETEROGENOUS LANDSCAPES- LANDCOVER CLASSIFICATION OF A FYNBOS EMBEDDED WETLAND

"In cartography, as in medicine, art and science are inseparable. The perfect map blends art and science into an effective tool of visual communication."

-Dr Keith Harries, 1999

3.1 ABSTRACT

Multispectral supervised classification is a commonly used and popular approach to land use and landcover mapping whereby training data is used to train a classification algorithm the identity of different features in a landscape. Wetlands are typically challenging to map due to their diverse and often fluctuating conditions influenced by varying hydroperiods and are especially heterogenous in the case of being embedded within a fynbos system, as they are subject to the same environmental conditions as Fynbos vegetation. This chapter aimed to map the different vegetation cover in the Du Toits River wetland using Landsat 8 Surface Reflectance Tier 1, and Sentinel-2 MSI: MultiSpectral Instrument, Level-2A imagery during both the winter 2020 and summer 2020/2021 season by means of Random Forest, a supervised classification method which fits decision trees to changing subsets of training data. The results showed that Random Forest classifier in R provided robust results and great promise in spectrally discriminating and classifying two dominant palmiet wetland vegetation types, namely *Prionium serratum* and *Psoralea pinnata*, a sclerophyllous wetland vegetation class comprising wetland ferns, restios and grasses, and Fynbos (temporary wetland) vegetation within the system. The classification accuracy for Landsat 8 winter was 78% and summer 79% with kappa values of 0.74 and 0.75 respectively. Sentinel-2 generally performed better with overall accuracies of 76% (winter) and 81% (summer), and kappa values of 0.72 and 0.78. Additional spectral indices such as the MNDWI to display seasonal hydroperiods and varying NDVI values for the different communities in the wetland were calculated and mapped. It is concluded that the wetland is a unique heterogenous system with a spatial mosaic of ecotones between wetland, sclerophyllous wetland, and temporary wetland fynbos vegetation.

3.2 INTRODUCTION

Remote Sensing (RS) of the Earth's surface has long been recognized in ecology as a time-saving, non-labour-intensive and consistent long-term means of monitoring ecosystems and their surrounding environment at different scales-both local and global (Pettorelli et al. 2017; Wang et al. 2010). Landscape ecology which deals with studying the "reciprocal effects of spatial pattern on ecological processes" (Pickett & Cadenasso 1995), is a topic of interest in RS where the primary objective is to understand Earth processes from a spatial perspective while using technology to map and monitor trends and patterns. More specifically, image classification and/or land cover classification is a commonly used RS technique whereby satellite imagery goes through the process of converting multiple input layers into groups of pixels with similar characteristics; which are ultimately used to identify land cover classes on the Earth's surface by means of two methods i.e. supervised or unsupervised classification (Wegman et al. 2016, p.245). This study which deals with mapping vegetation cover and distribution within a fynbos embedded wetland is the first step to mapping and understanding wetland ecotones. In landscape ecology ecotones have been noted in the literature to be important sites within a landscape where transitions between neighbouring ecological systems are "characterized by unique properties which are defined by space and time scales, and by the strength of interactions between the adjacent ecological systems"(Holland 1988). Although diverse and dynamic across the globe, wetland inventory and mapping has seen substantial growth over the years with various studies attempting to efficiently and accurately detect, delineate and map wetlands at various scales in the landscape (Gallant 2015; Job et al. 2018; Rebelo, Finlayson & Nagabhatla 2009; Richards 2001; Sieben, Mtshali & Janks 2014). Limited research has been done on mapping wetland ecotones (save for a chapter by Holland, Whigham & Gopal (1990) which accounts for characterizing aquatic-terrestrial or wetland ecotones), and thus this research aimed to be a steppingstone in bridging that gap. This chapter forms part of a two-part process to mapping wetland ecotones where the main objective was to identify and utilize robust and efficient supervised classification methods to map distinct vegetation cover within a fynbos embedded wetland system that is subject to high spatial heterogeneity. Spectral signatures which are measurements of the spectral response of different features at the different bands of a satellite sensor (Ozesmi & Bauer 2002), is a useful way of discriminating spectral differentiation of classes, especially in wetlands where there may be overlapping spectral signatures and fluctuating hydroperiods due to their diversity (Gallant 2015; Ozesmi & Bauer 2002). Spectral signatures as well as spectral indices were explored in addition to landcover classification for this study.

3.3 STUDY AREA

With wetlands excelling towards a growing decline in the Western Cape- approximately 87% threatened and in a moderate to heavily modified or degraded condition (Helme & Rebelo 2016)- it is important that the location, extent, and ecological state of wetlands be identified so that sound conservation and management decisions can be put into effect to protect these important ecosystems. Generally, wetlands provide numerous ecosystem services such as carbon storage, flood attenuation, sediment trapping, stream flow regulation, phosphate and nitrate removal, habitats for unique fauna and flora, and other aesthetic services such as education and research, tourism and cultural significance (Van Deventer et al. 2019; Fischer et al. 2019; Ramsar Convention on Wetlands 2018). The Du Toits River Wetland is an alluvial fan wetland (Grenfell et al. 2019) where features within the wetland are upstream channelled proximal alluvial fan, and distal portions have the distributary channels which are diffuse and move over time. It starts off upstream (at the bridge) as a channelled valley-bottom wetland with a channelled river of the Du Toits River (Fischer et al. 2019). In the middle section it becomes weakly channelled and sometimes unchannelled. In the lower reaches (toe) it becomes a major alluvial fan with multiple channels and tributaries that feed the fan with very fine sediment that would have had channel reforming. For this study, the Ollis et al. (2013) classification system does not work for this study area – it is one of the examples of why the classification system does not work- although similar in many respects to a valley-bottom wetland as described by Ollis et al. (2013).

Situated north-west of the Theewaterskloof Dam in the Western Cape of South Africa (Figure 3.1), this wetland is one of three key wetlands in the area that contribute largely to the enhancement of water quality entering the Theewaterskloof Dam which is a crucial water supply for human use, "primarily for domestic and industrial water supply to Cape Town metro as well as for irrigation more locally" (Fischer et al. 2019, p.23). The wetland is situated in a high rainfall and high rainfall intensity catchment with a total rainfall of 1241 mm/year and rainfall intensity of 86 mm-the maximum for South Africa is 140 mm (Snaddon et al. 2018, p.34).

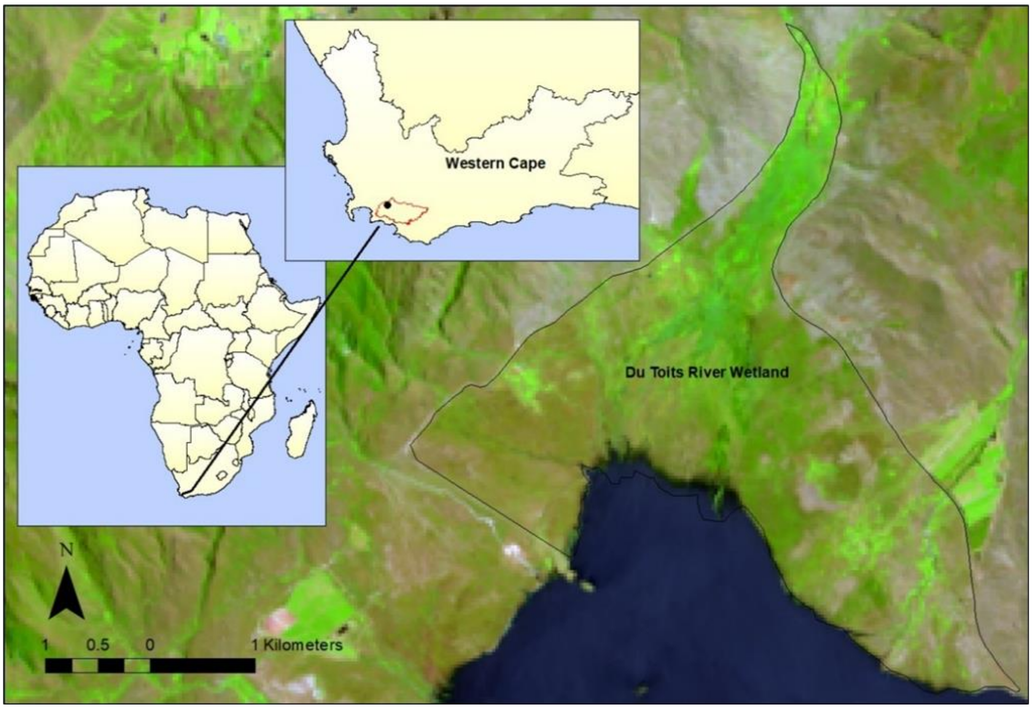


Figure 3.1 Study area where the area of interest is demarcated by a solid black line surrounding the alluvial fan with the Theewaterskloof Dam situated further south. Black dot in map insert shows the wetland location within the Theewaterskloof catchment (red outline) in the Western Cape province of South Africa

In addition, Fischer et al. (2019, p.13) note that the Du Toits River wetland has three varying underlying geomorphological features from upstream to further down at the toe of the wetland. Table 3.1 below highlights the key geomorphology and hydrological features of the Du Toits River wetland:

Table 3.1 Key hydrogeomorphic units (HGM) i.e. wetland type and hydrological features of the Du Toits River wetland.

HGM units listed from upstream to downstream of the wetland:	1. Channelled valley-bottom 2. Weakly channelled/unchannelled valley-bottom 3. Channelled valley-bottom with multiple channels on a major alluvial fan and from tributaries feeding the fan.
Hydro-geological type setting:	Table Mountain Group sandstone, with HGM 2 having possible links with groundwater.
Predominant hydrological zones:	Predominantly permanent zone in HGM 2 and good representation of temporary, seasonal, and permanent zones in HGM 1 and 3.
Sediment type:	Predominantly sandy sediments with organic soil deposits especially in HGM 2.

Source: Adopted from Fischer et al. (2019, p.13)

Grenfell et al. (2019, p.13) note that alluvial fans typically form at "locations of loss of confinement as a stream discharges onto a receiving basin of very low gradient" which is evident in the Du Toits wetland. Valley-bottom wetlands are commonly known in arid environments to be void of hydrophytic vegetation (Grenfell et al. 2019). In South Africa, although generally small units in the landscape, wetlands have distinct vegetation types distinguishing them from their surrounding terrestrial habitats (Sieben et al. 2017). According to Sieben, Mtshali & Janks (2014), the most common wetland plants are largely grasses but sedges are often dominant in the wettest part of the wetland.

Wetlands in the Cape Floristic Region

Mucina and Rutherford (2006) highlight two wetland types that occur and are restricted to the Cape Floristic Region (CFR) (within which the Du Toits River wetland falls) namely Cape Lowland Freshwater wetlands which occur on nutrient-poor sandstone substrates, and Cape Vernol Pools (Sieben et al. 2017, p.55). Wetlands that occur on nutrient-poor substrates are typically found within but not restricted to the Fynbos Biome in the Western Cape (Sieben, Mtshali & Janks 2014). Fynbos is an evergreen, fire-prone shrubland, naturally dominated by the influence of "hot summer fires at intervals of 10-30 (or more extremely 5-50 years), which are fuelled by the fine-leaved shrubs and especially by the Restionacae" present in this biome (Rebelo et al. 2006). Fynbos is endemic to the Cape Floral Kingdom which is the smallest floral Kingdom in the world that grows on the nutrient-poor substrates of sandstone and quartzites of the Table Mountain Group sandstones of the Western Cape, and parts of the Southern to Eastern Cape. Importantly, Sieben et al. (2017) note that wetlands that occur within fynbos systems are "subject to these same stresses and disturbances, and, in addition, they need to cope with anoxic soils" (Sieben et al. 2017, p.54).

The nutrient-poor environment of wetlands in the Table Mountain Group sandstone account for the creation of conditions where "organic matter breaks down slowly and in some cases, peat layers develop over the acidic sandy substrate" (Sieben et al. 2017). These wetlands are also often characterized by the similar plants found in upland fynbos, namely "sclerophyllous (hardy, mostly needle-leaved) shrubs and graminoids from the family Restionacae, but the more typical graminoids of families like Poaceae and Cyperaceae also occur" (Sieben et al. 2017, p.55).

Table 3.2 Common plant species found in the Du Toits River wetland

Plant group:	**Species:**
Sedges/rushes	*Carpha glomerata* *Cyperus thunbergii* *cf Epischoenis gracilis* *Isolepis prolifera* *Prionium serratum*-Ollis et al. (2013) classify this as a robust shrub (palmiet).
Grasses	*Merxmuellera cincta*
Restios	*Elegia capensis* *Restio paniculatus,*
Bulbous plants	*Wachendorfia thyrsiflora*
Herbs	*Laurembergia repens*
Shrubs	*Cliffortia strobilifera* *Rubus fructicosus* (alien species)
Fern	*Pteridium aquilinum* *cf Thelypteris confluens*
Trees	*Acacia mearnsii (alien species)* *Psoralea aphylla* *Psoralea pinnata* *Brabejum stellatifolium* *Searsia augustifolia*

Source: Adopted from Fischer et al. (2019).

Although similar in composition, sclerophyllous wetland vegetation is not referred to as fynbos vegetation because it is not restricted to the Fynbos biome, but it is dominated by "sclerophyllous shrubs and graminoids as an adaptation to the unique environmental conditions in these wetlands" (Sieben et al. 2017, p.55). Majority of the Du Toits River wetland is managed and protected by Cape Nature i.e. the Hottentots-Holland Nature Reserve Complex (HHNRC) (CapeNature 2017), and is situated almost entirely in the Theewaterskloof World Heritage site (Fischer et al. 2019; Snaddon et al. 2018). The wetland is said to be justifiably in a pristine condition as there are relatively low impacts due to the limited occurrence of alien species e.g. *Acacia mearnsii*, but the presence of indigenous species such as *Isolepis prolifera*, and *Pteridium aquilinum*, that are tolerant of or favoured by high levels of human disturbance (Fischer et al. 2019). In the case of the Du Toits River wetland, a mixture of palmiet wetland and sclerophyllous wetland vegetation is found (Sieben, Mtshali & Janks 2014) embedded within three vegetation units of the Sandstone Fynbos group namely Elgin Shale, Hawequas Sandstone, and Kogelberg Sandstone (Rebelo et al. 2006).

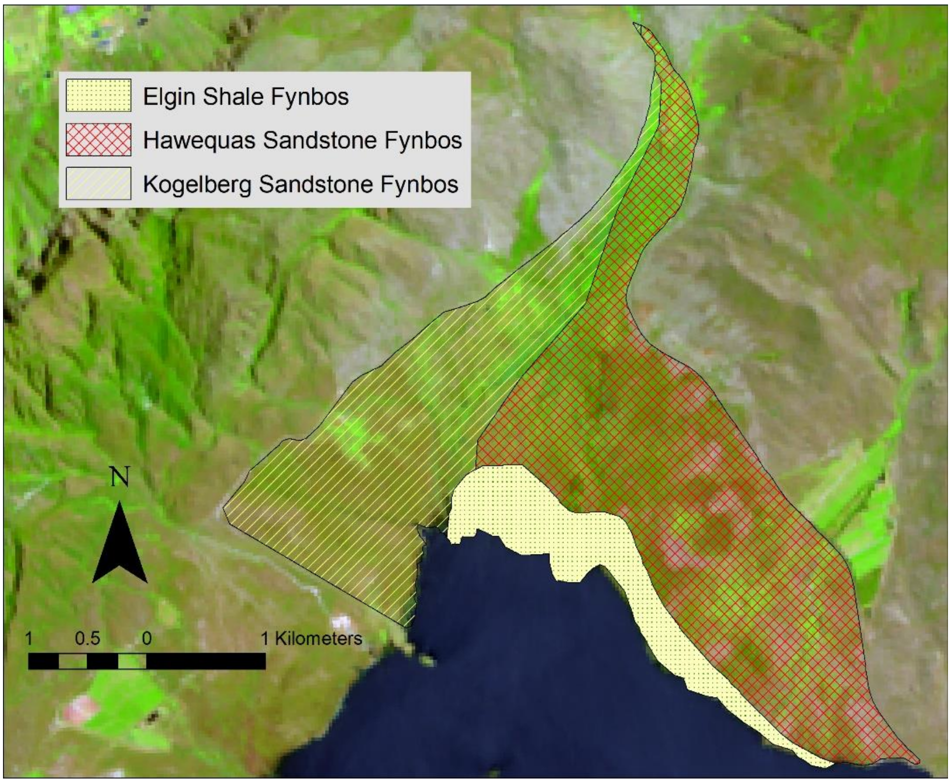


Figure 3.2 Three Fynbos Biome vegetation types that occur within in the study area namely Hawequas Sandstone Fynbos, Kogelberg Sandstone Fynbos and Elgin Shale Fynbos. This Fynbos Vegetation Unit Classification is based on the Rebelo et al. (2006) National Vegetation Map for South Africa, Lesotho and Swaziland. The data is provided as a shapefile available on the SANBI BGIS website and is the 2018 final version of the latest updated National Vegetation Map

Note that hereafter Fynbos is referred to as temporary wetland fynbos and not terrestrial or upland fynbos as in this case although field observations indicated the presence of Fynbos species belonging to the Cape Floristic Region (see APPENDIX H), the fynbos is exposed to periods (seasonal or temporary) of inundation at some point throughout the year. These were supported by soil observation made in field.

Table 3.3 below describe the vegetation types as decided on after field data collection. Initial field work indicated that *Prionium serratum* and *Psoralea pinnata* can be distinguished from each other and represent different categories within the palmiet class.

Table 3.3 Seven distinct landcover classes for Random Forest classification

Landcover class	**Description:**	
Prionium serratum	Commonly known as palmiet, and are considered ecosystem engineers in wetlands, creating deep peat conditions (Job 2014; Rebelo et al. 2019; Rebelo, Somers, et al. 2018; Sieben, Mtshali & Janks 2014).	Palmiet Wetland Vegetation (Wetland subtype-1)
Psoralea pinnata	An erect shrub, or small tree, commonly known as fountain bush, that can reach an estimated height of 4 m and typically grows along streams and saturated environments (Palmer & Pitman 1973).	
Sclerophyllous Wetland Vegetation	This cluster comprises a grouping of *Pteridium aquilinum* (Bracken fern), *Restio paniculatus, Elegia capensis* and wetland grasses such as *Merxmuellera cincta* (Sieben, Mtshali & Janks 2014). These three vegetation communities were grouped as one class in the classification as they often co-occurred in the wetland.	Sclerophyllous Wetland Vegetation-condensed with the occasional occurrence of intermittent terrestrial and fynbos vegetation (Wetland subtype-2)
Temporary Wetland Fynbos	Fynbos species belonging to the CFR such as *Protea neriifolia*, *Berzelia abrotanoides*, *Leucadendron conicum, Leucadendron coniferum* and *Metalasia muricata* (Rebelo et al. 2006).	
Bare soil/sandstone	All visible sandy deposits around active, exposed channels and eroded channels, or exposed and degraded areas of land.	
Degraded	This class is vegetation that is not ground-truthed or sampled but visually appears as degraded vegetation (possibly burnt) from previous farming practices and water extraction.	
Water	All openly visible water and channels/tributaries.	

According to Sieben, Mtshali & Janks (2014) there have been numerous studies that verify that it is viable to distinguish individual species from their spectral signature, "but it is often complicated by the fact that part of the signature is determined by the physical environment, mixtures of species or the health of plant populations" (Sieben, Mtshali & Janks 2014, p.5). The purpose of this chapter was thus to explore imagery classification techniques that efficiently differentiate the various vegetation types that belong to wetland (palmiet), sclerophyllous wetland vegetation and temporary wetland fynbos vegetation within the Du Toits River wetland.

3.4 METHODS

To achieve the aims of creating a thematic landcover map of the study area, quantitative methods were adopted. Each step of the classification process (Wegman et al. 2016) is detailed below.

3.4.1 Field data collection

The first set of field data collection took place between 21-23 October 2020 (spring) and the second took place between 7-9 June 2021 (winter). It is argued that it is ideal to collect field data (for training or verification) that corresponds with or is close to the date and time of imagery being used in a classification (Wegman et al. 2016). This is to ensure that the conditions on the ground have not changed significantly (Wegman et al. 2016) in comparison to what is being represented in the imagery, but this is not always possible or realistic. Factors such as time and money constraints need to be considered as well as the nature of the study area as some areas may be remote, inaccessible, or situated in difficult terrain.

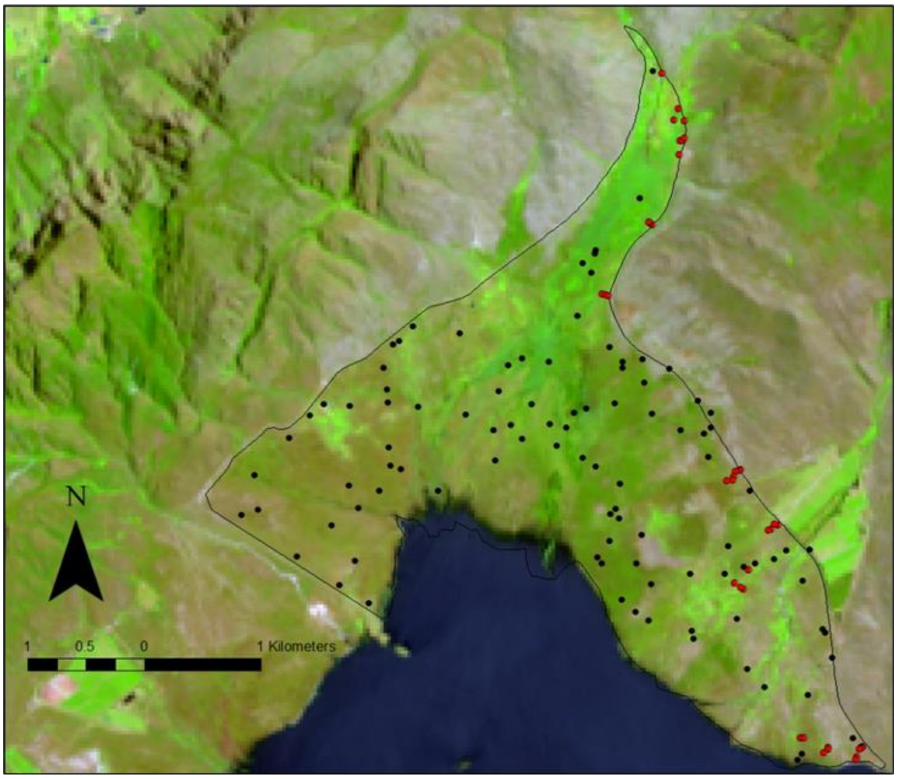


Figure 3.3 Random Sampling points created in ArcMap represented as red dots. The total samples collected in field during October 2020 and June 2021 are presented as black dots

A transect line approach was planned but not used due to accessibility constraints where deep, hidden channels made it impossible to traverse the transects. Therefore, a simple random sampling approach (Wegman et al. 2016) was adopted with quadrats being placed randomly across the wetland to cover the full extent of the wetland as defined in this study, and ultimately to sample all vegetation types within the wetland. A random sampling map was created in ArcGIS 10.7.1, however, due to limited accessibility (private property and waterlogging), samples were collected as close as possible to the accessible random points as generated in ArcMap. A sum of 40 samples were collected across both collection periods. A handheld Garmin GPS (eTrex 10) was used to collect geographic coordinates and the elevation of all samples recorded. At these sites, 1x1 metre quadrats were placed approximately 10-20 m apart to ensure at least two quadrats were sampled per pixel (for Sentinel-2 imagery), due to the heterogenous vegetation in the wetland with a mixture of wetland, fynbos and terrestrial (or non-wetland) species. Within each quadrat, the species were recorded along with their estimated frequency of occurrence (% cover). These data suggested the following three overall vegetation groups were present: palmiet wetland vegetation, sclerophyllous wetland vegetation or Fynbos (referred to as temporary wetland fynbos) vegetation. From this data, each quadrat was assigned to a vegetation class belonging to one of the three vegetation groups. Where an individual species covered a percentage higher than 50%, that specific species was then used as an indicator species to determine whether a quadrat was palmiet wetland, sclerophyllous wetland, or temporary wetland fynbos habitat. See APPENDIX H for the full data collection collated sheets.

Additionally, soil conditions were observed and recorded using a Munsell Colour Chart to visually identify soils that were indicative of wetland conditions vs non-wetland conditions. Soil samples were taken at 50 cm, and then 100 cm from the surface. Relevant literature guides such as the South African Wetland Classification System (Ollis et al. 2013) and the National Wetland Vegetation Database (Sieben, Mtshali & Janks 2014) were consulted to assist in grouping plants into the different classes of vegetation. Where plant identifications were not found in books or literature, photographs were taken in field and searched online using both Google search (websites such as SANBI's PlantZAfrica http://pza.sanbi.org/), and a plant identifier mobile application called PlantSnap.

Figure 3.4 are photos taken in field of soil auger samples collected within quadrats, demarcated at 50 cm and 100 cm from the surface. Soil colour patterns can provide an indication of the water regime; where soils are well drained (typically mineral soils), there is enough oxygen to oxidize irons in the soil resulting in brown, red or yellow soil (Richards 2001). Where soils are saturated and anaerobic (devoid of oxygen), iron is leached from the soil and soils become grey, sometimes gleyed depending on the period of saturation (Richards 2001). Lastly, where soils are wetter (especially for longer periods of time), the presence of water reduces the rate of decomposition of organic matter resulting in darker, blacker, and higher organic matter (Job 2014; Richards 2001). If anaerobic soils in wetlands dry up or are drained, one often finds the presence of mottles which are iron oxides that form red or orange spots in the soil. Mottles are useful indicators of drained wetlands after long periods of saturation, and also evidence of wetland loss in an area (Job 2014; Richards 2001). Field observations have shown that where palmiet wetland vegetation i.e. *Prionium serratum*, *Psoralea pinnata* (fountain bush) and also *Zantedeschia aethiopica* (arum lily) were dominantly present; soils were deeper, wetter (permanently saturated) and darker in colour with higher organic matter -sometimes clay (photos a and b)-as commonly found in peatlands (Job 2014; Sieben 2012). This class is thus referred to as wetland vegetation subtype-1 in this study which is considered to be ‘pure’ wetland habitat and/or peatland conditions. Where soils were damp to dry; sandy to sandy loam; brown, red, and grey in colour (photos c and d), species such as *Pteridium aquilinum* (i.e. Bracken fern), *Merxmuellera cincta* (grass) were found. This class was thus considered the sclerophyllous (SWV) group i.e. subtype-2 of the overall wetland vegetation in this study as it was characterized by properties belonging partly to wetland and/or drier fynbos habitat conditions. The dominant Temporary Wetland Fynbos (photos e and f) areas although sometimes saturated, generally showed much drier, sandier, and coarser soils than in the wetland, and sclerophyllous wetland vegetation communities. There were no signs of mottling in any of the soil samples taken in field.

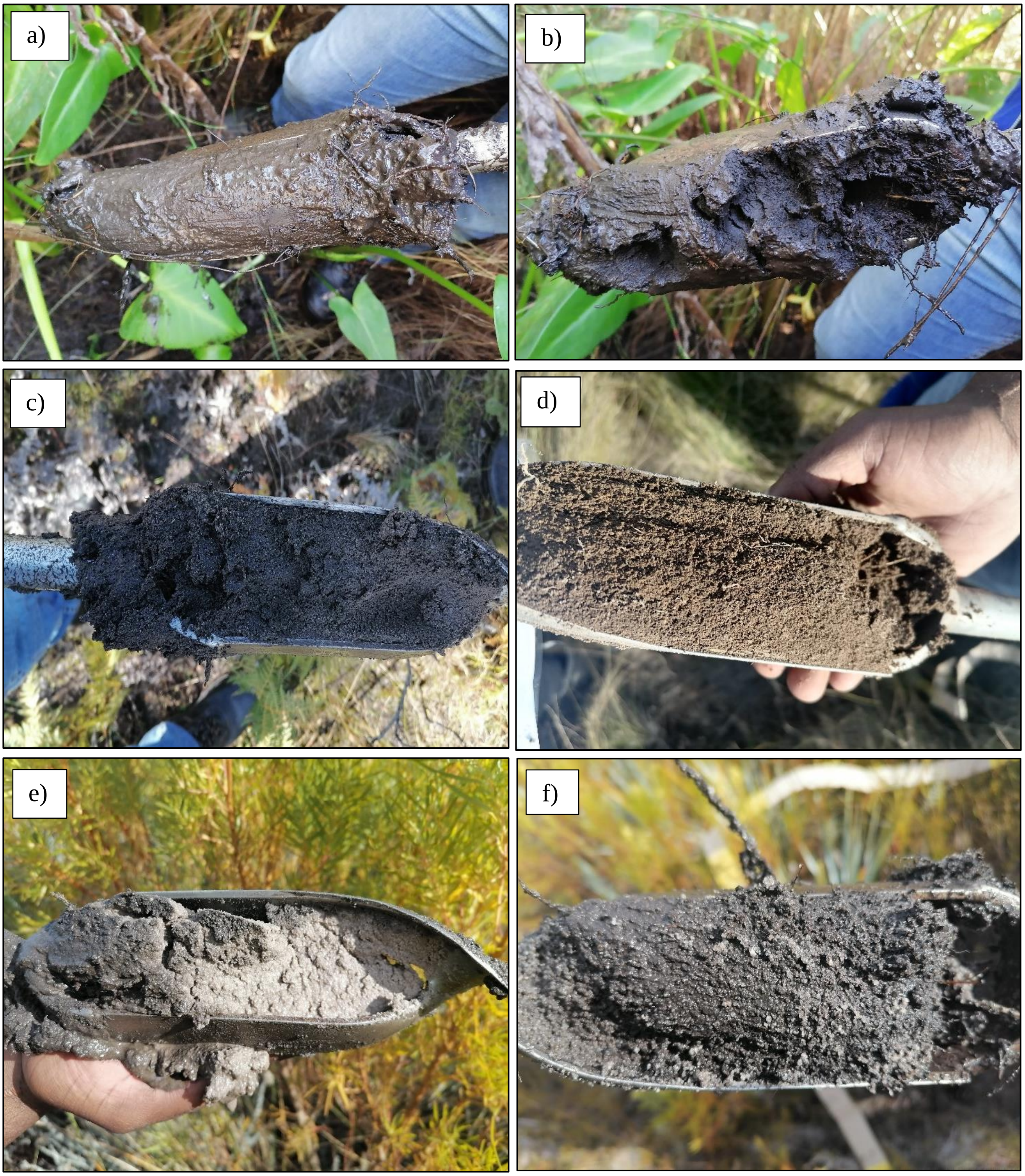


Figure 3.4 Soil auger profile photos taken in field at quadrats with dominant presence of a) *Prionium serratum* (Palmiet) & *Zantedeschia aethiopica* (Arum lily); b) *Psoralea pinnata* (fountain bush); c) *Pteridium aquilinum* (i.e. Bracken fern), d) *Merxmuellera cincta* (grass); Fynbos species such as e) *Berzelia abrotanoides* & *Metalasia muricata* and f) *Leucadendron coniferum* with very small fragments of dry palmiet wetland vegetation

3.4.2 Multispectral Imagery Classification

Since the early advent of RS and GIS in the 1960s, extensive literature has been written on the efficacy of satellite imagery for land use and land cover classification (Ahmad & Quegan 2012; Foody et al. 1992; Lu & Weng 2007; Melgani 2000; Perumal & Bhaskaran 2010; Shih & Chen 1994; Sun et al. 2013) using a variety of methods and algorithms, with improvements in approaches to date (Pettorelli et al. 2017; Wegman et al. 2016). RS poses imperative coverage for mapping and quantifying landcover features or landscape patterns (Wegman et al. 2016), which is often useful in data and knowledge creation to assist ecologists, conservation managers and decision makers (Buchanan et al. 2009; de Klerk & Buchanan 2016; Wegman et al. 2016). The aim of this chapter was to create a thematic map of vegetation cover in the Du Toits River wetland that comprises of a mosaic of palmiet wetland vegetation, sclerophyllous wetland vegetation and sandstone fynbos as described above, using the Random Forest classifier. The result classified maps were then used to test RS approaches to map internal biological ecotones (i.e. between or among community) within a fynbos embedded wetland. In essence, this would be mapping and characterizing ecotones among palmiet wetland vegetation (i.e. *Prionium serratum* and *Psoralea pinnata*), and sclerophyllous wetland vegetation (i.e. wetland grasses and restios), along with Temporary Wetland Fynbos vegetation. To limit non-target classes that were not of interest surrounding the wetland, the study area was clipped to the wetland boundary and non-target landcover classes that remained within the wetland boundary, namely, water, bare soil/sandstone, and degraded landcovers were identified. This resulted in seven distinct landcover classes developed as set out in Table 3.3.

3.4.2.1 Imagery acquisition and pre-processing

Various RS imagery has been used to map ecotones such as the coarse scale MODIS (Fox, Vandewalle & Alexander 2017), LiDAR (Jenkins & Frazier 2010; Moradkhani, Baird & Wherry 2010; H.O. Ørka et al. 2012), medium resolution sensors such as Landsat (Bharti, Adhikari & Rawat 2012; Galgamuwa, Wang & Barden 2020; Xu et al. 2018; Yang et al. 2015), through to finer spatial (high spatial resolution) scale data such as QuickBird and GeoEye (Beck et al. 2015). Note that this study follows Guo et al. (2017), Zhang et al. (2017) and Wang et al. (2010) who refer to Landsat 8 and Sentinel-2 imagery as medium resolution. Landsat 8 OLI Surface Reflectance Tier 1 imagery was sourced through Google Earth Engine (GEE), as the spatial resolution of this imagery is 30 m which is a relatively coarse, medium spatial resolution optical sensor. These datasets are typically cloud free and pan-sharpened upon acquisition (U.S. Geological Survey 2016). Additionally, finer resolution imagery namely Sentinel-2 MSI: MultiSpectral Instrument, Level-2A data was sourced as it has a spatial resolution of 10 m which is ideally suited for monitoring fine scale vegetation, soil, and inland water as prevalent in this study area. Temporal resolution of satellite imagery acquisition is important for landcover classifications and further enhancements such as spectral indices (e.g. Vegetation Indices) as one typically wants the vegetation in the selected study area to be at its optimum 'greenness' to be captured efficiently (Wegman et al. 2016). More so, the temporal resolution of imagery used in a hydrological index such as the Modified Normalized Difference Water Index (MNDWI) (Xu 2006) will be to select imagery during and after the high rainfall season of an area of interest to capture waterlogged or inundated areas efficiently. The study area is located within the Cape Floristic Region (CFR) consequently experiencing Mediterranean-type climate, with wet winters and moderately intense drought-prone summers (Midgley et al. 2003; Rebelo et al. 2017; Van Wilgen 1984). For this study, to define which months satellite images will have reflectance that correspond to winter and summer situations of a wetland within a fynbos system, fire danger index (Rebelo et al. 2006; Van Wilgen 1984) months for this area were selected as this index considers parameters such as temperature, humidity, and rainfall, which is expected to influence how the vegetation absorbs and reflects incoming solar radiation. Sieben et al. (2017) also note that wetlands in fynbos environments, are likely subjected to the same fire regime as the surrounding landscape as they are frequently "located in open landscapes where fires can travel uninhibited" (Sieben et al. 2017, p.60). The date of satellite imagery spans the months June 2020, July 2020, and August 2020 for high rainfall months i.e. the winter period, and December 2020, January 2021, and February 2021 for the dry, hot summer months i.e. fire season (CapeNature 2017; Van Wilgen 1984). In South Africa, December initiates the start of summer season, ending in February the following year. The justification for this temporal selection is based on the rainfall and fire regime characteristics for the study area as described below in Table 3.4:

Table 3.4 Climatic conditions for the Du Toits River wetland within the Hottentots-Holland Nature Reserve Complex (HHNRC)

<table>
<tr><th>Rainfall for Du Toits River wetland:</th><th colspan="3">Average Temperatures (HHNRC):</th></tr>
<tr><td rowspan="2">Total rainfall: 1241 mm/year</td><td rowspan="3">Winter</td><td>Maximum</td><td>Minimum</td></tr>
<tr><td rowspan="2">June: 16℃
July: 17℃
August: 15℃</td><td rowspan="2">June: 4℃
July: 3℃
August: 2℃</td></tr>
<tr><td rowspan="2">Rainfall intensity: 86 mm</td></tr>
<tr><td rowspan="2">Summer</td><td rowspan="2">December: 27℃
January: 33℃
February: 33℃</td><td rowspan="2">December: 10℃
January: 11℃
February: 11℃</td></tr>
<tr><td>Rainfall seasonality: Winter</td></tr>
</table>

Source: Snaddon et al. (2018, p.34); CapeNature (2017, p.16)

3.4.2.2 Spectral Indices

Literature notes that spectral indices have several advantages over the initial use of original reflectance for three main reasons: 1) they can dramatically enhance the identification of landcover types in both a visual or automated image interpretation; 2) many of the indices involve "mathematical division of bands, which has a normalizing effect on illumination variability within a single scene and also between scenes"; and 3) they are useful in describing the actual physical measures of land surface (e.g. the degree of vegetation cover, vegetation stress or water stress in vegetation) (Pettorelli 2013; Wegman et al. 2016). Spectral indices namely the Modified Normalized Difference Water Index (MNDWI) and Normalized Difference Vegetation Index (NDVI) are both explored in this chapter in order to substantiate the results of the landcover classification.

Modified Normalized Difference Water Index (MNDWI)

Wetlands are known to be influenced by hydrological regimes which determine whether a wetland is temporarily or permanently flooded, contains flowing or still standing water, has channelled or diffuse flow, inundated or saturated soils; and where various types of sediments are deposited in the wetland (Grenfell et al. 2019; Sieben, Mtshali & Janks 2014). The wet and damp conditions in wetlands consequently influence the vegetation composition and state, as vegetation typically respond to the hydrology and topography of a landscape and thus form zones of either dominant plant species, or an intricate mosaic of different plants (Richards 2001). The MNDWI was computed as this index extracts waterlogged areas and displays inundation efficiently while blocking out noise such as soil, built-up areas and vegetation (Xu 2006).

In computing an MNDWI, three results may be produced; water will have greater positive values as it is absorbs more MIR light, built-up areas will have negative values, and soil and vegetation will also have negative values as both reflect more MIR light (Jensen 2005; Xu 2006). Hence, this index is useful to infer where waterlogged areas are in both wet and dry season, giving an idea of inundation from a surface reflectance aspect, as well as the hydrology of the wetland. This in turn may speak to the species composition of the different vegetation communities within the wetland. The MNDWI (Xu 2006) algorithm is as follows:

Note that the SWIR1 band is referred to as MIR (middle-infrared) in the original Xu (2006) publication.

$$MNDWI = \frac{Green - SWIR1}{Green + SWIR1} \qquad \text{Equation 3-1}$$

where:

Green	is reflectance of the green band i.e. Band 3 in L8 data;
SWIR1	is the middle short-wave infrared i.e. Band 6 in L8 data

The MNDWI algorithm was performed in ArcGIS 10.7.1 on L8 imagery for the wet season i.e. June 2020-August 2020 (winter composite) when most rainfall is recorded in the area (CapeNature 2017, p.16), and the months December 2020-February 2021(summer composite) i.e. the dry season (Van Wilgen 1984). The Spatial Analysis tool, Map Algebra and Raster Calculator was used to calculate the MNDWI algorithm. This process was repeated on Sentinel-2: MSI, Level-2A data where:

Green	is reflectance of the green band i.e. Band 3 in Sentinel-2: MSI, Level-2A imagery;
SWIR1	is the middle short-wave infrared i.e. Band 11 in Sentinel-2: MSI, Level-2A imagery

Note that because the imagery used are composites that span across three months for each season, when extracting the necessary bands for the MNDWI algorithm (i.e. Band 3 and Band 6 for L8 data and Band 3 and Band 11 for Sentinel-2 data), these were reduced to the median of each band for every month stacked in the composite. See APPENDIX C for the code generated to obtain raw L8 and Sentinel-2: MSI, L2A imagery from GEE.

Normalized Difference Vegetation Index (NDVI)

Vegetation Indices (VIs) that are derived from airborne, field or satellite data are contended to be useful in displaying significant empirical and theoretical evidence that they are related to various vegetation parameters, and are thus used to test and measure different vegetation properties (Mašková, Zemek & Květ 2008). Healthy vegetation typically displays very low reflectance in the red region of the spectrum due to “photosynthetic absorption of light and very high reflectance in the NIR due to scattering processes at the leaf level. With decreasing photosynthetic activity, the difference between red and NIR will decrease, and the red to NIR ratio flattens” (Wegmann 2016, p.222). This contrasting characterization is called the ‘red edge’ and is ultimately what most VIs are based on (Wegmann 2016). The NDVI (Kriegler et al. 1969; Rouse, J.W. et al. 1974) is the most common and widely used VI which has proven to be highly correlated with vegetation cover, biomass, “net primary production, leaf area index (LAI), fraction of absorbed photosynthetically active radiation, carbon assimilation and evapotranspiration” (Pettorelli et al. 2011, p.16; Wegmann 2016). The NDVI (Rouse, J.W. et al. 1974) algorithm is as follows:

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad \text{Equation 3-2}$$

where:

NIR	is reflectance of the green band i.e. Band 8 for Sentinel-2: MSI, Level-2A imagery;
RED	is reflectance of the red Band 4 for Sentinel-2: MSI, Level-2A imagery.

NDVI maps were generated in R using Sentinel-2: MSI, Level-2A composite images for the wet season (i.e. June 2020-August 2020) and the dry season (December 2020, January 2021-February 2021). See APPENDIX D for the NDVI code generated in R. In computing an NDVI, green leaves or vegetation with high chlorophyll content will have high visible light absorption and high NIR reflectance, resulting in positive NDVI values. Noise such as bare soil, clouds and concrete will have values close to zero, while water will have negative values (Pettorelli et al. 2011). This VI analysis can assist in discriminating between classes and vegetation types.

3.4.2.3 Supervised Classification

Supervised classification is one of two image classification methods in RS. It is the process whereby a user will train an algorithm using a subset of known training data to assign identity and classify unknown pixels in an image (Bakker et al. 2001; Perumal & Bhaskaran 2010; Wegman et al. 2016). Apart from selecting a suitable classifier, the key to successful classification with high accuracy, is the quality, thematic depth and number of training data (Myburgh & van Niekerk 2014; Wegman et al. 2016). The supervised classification approach was chosen because the study area was accessible to collect *in situ* data and there was sufficient literature to substantiate known vegetation cover for the area, (Fischer et al. 2019; Rebelo et al. 2017; Rebelo et al. 2019; Rebelo, Emsens, et al. 2018; Sieben, Mtshali & Janks 2014) making a priori class decision more applicable and relevant. There are a number of supervised classifiers, for instance maximum likelihood (ML), nearest neighbour (NN), artificial neural networks (ANN), support vector machines (SVM) and decision trees such as Random Forest (RF) (Myburgh & van Niekerk 2014; Perumal & Bhaskaran 2010; Wegman et al. 2016). The classifier algorithm selected for this study is Random Forest (RF) because it is the most frequently used as a standard approach in a number of image classification studies with high classification accuracies (Bargiel & Herrmann 2011; Fu et al. 2017; Mellor et al. 2013; Poona et al. 2016; Xie, Sha & Yu 2008). Although not the most recent image classification algorithm, Maximum Likelihood (ML) is still commonly used and is often shown to be very stable (de Klerk et al. 2016; Neware & Khan 2018; Perumal & Bhaskaran 2010; Xie, Sha & Yu 2008). Therefore, a ML classification was initially tested as a means of getting an idea of the possible classification outcomes of vegetation distribution based on what was observed in field.

3.4.2.4 Random Forest Classifier

A supervised classification method which fits decision trees to changing subsets of training data, and once a large number of trees is generated, the most popular class is identified and classified, is called Random Forest (Breiman 2001; Wegman et al. 2016). Breiman (2001) provides a definition for random forest as a "classifier consisting of a collection of tree-structured classifiers $\{h(x, \Theta_k), k = 1,...\}$ where the $\{\Theta_k\}$ are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input x" (Breiman 2001, p.6). Random Forest (RF) classification was generated and run in R on cloud-masked, Landsat 8 SR Tier 1 filtered winter 2020 and summer 2020/2021 composites, and on finer scale Sentinel-2: MSI, Level-2A imagery for the same date ranges.

The model used 200 trees and 4 randomly selected predictors per split and an 80/20 split, where 80% was used as training data and 20% as testing data (see APPENDIX E for the full code). Training data points were collected in the field (see 3.4.1) and then combined with points created within GEE as feature collection, point geometries. These training data points were converted to a CSV file in GEE, exported and converted to a shapefile for use in R, ensuring that the Projected Coordinate Reference System (PCRS) remained consistent i.e. WGS 84 / UTM zone 34S (EPSG: 32734).

For Landsat 8 data, bands 2 (Blue), 3 (Green), 4 (Red), 5 (Near-Infrared i.e. NIR), 6 (Shortwave-Infrared i.e. SWIR-1) and 7 (SWIR-2) were specified in the prediction. The SWIR-1 (1.566 – 1.651 µm) and SWIR-2 (2.107 – 2.294 µm) bands were included for Landsat 8 classification as vegetation also has fairly high reflectance values in these parts of the spectrum (Longley et al. 2015). For Sentinel-2 data, bands 2 (Blue), 3 (Green), 4 (Red) and 8 (NIR) were specified in the classifier prediction. Bands 2 (Blue), 3 (Green) and 4 (Red) are the bands in which vegetation has the highest absorption in the electromagnetic spectrum, and highest reflectance in the NIR band (Longley et al. 2015).

Landcover classes included *Prionium serratum* and *Psoralea pinnata* within Wetland Vegetation (i.e. palmiet wetland subtype-1), *Pteridium aquilinum, Restio paniculatus and Merxmuellera cincta* were grouped as a condensed class within Sclerophyllous Wetland Vegetation (i.e. wetland subtype-2), Temporary Wetland Fynbos, Bare soil/sandstone, Water and Degraded (see Table 3.3). Palmiet Wetland Vegetation and Sclerophyllous Wetland Vegetation (SWV) are split as belonging to two subtypes of overall wetland vegetation based on the National Wetland Vegetation Database (Sieben, Mtshali & Janks 2014). Moreover, field observations have shown that soils in the SWV quadrats were sandier and drier, rather than the deeper, organic (peat conditions) found within Palmiet Wetland Vegetation quadrats. The bare soil, degraded vegetation, and water landcover classes were additionally added in order to reduce misclassification of unassigned pixels.

Ultimately, these distinct groups of vegetation along with bare soil and water are the final landcover classes as they are significantly visible and occur as dense clusters that can be spectrally identified by a satellite, and because "phenology has been shown to be valuable in discriminating wetland species" (Rebelo, Somers, et al. 2018). Spectral reflectance values from imagery were coded in R and exported to CSV (for graph generation) to see how each landcover class reflects in the selected band wavelengths, and how they can be spectrally discriminated. This is similar to a study by Rebelo, Somers, et al. (2018) which looked at the plant functional trait data and spectral reflectance (in field measurements) of 22 palmiet wetland species, which include many of the key species found in the Du Toits River wetland (Table 3.2).

3.4.2.5 Accuracy Assessments

Uncertainty and error are almost always present and inevitable in GIS and RS as it "arises from the way that GI users conceive of the world, how they measure and represent it, and how they analyze their representations of it" (Longley et al. 2015, p.99). Moreover, classified maps are never a perfect representation of reality, and evaluating the accuracy of these are essential to inform users of the limitations of produced maps (Wegman et al. 2016). Errors and uncertainty in classified maps may occur due to various reasons such as spectral confusion, incorrect locations of objects in a map, or pixels and/or objects being assigned incorrect labels (Wegman et al. 2016).

The standard method of measuring and calculating errors in classifications is to produce a contingency table or confusion matrix which evaluates the performance of a classification (Chen et al. 2016; Longley et al. 2015; Pande-Chhetri et al. 2017; Wegmann 2016). The layout of a confusion matrix is not standardized, but commonly consists of rows and columns that summarize and compare the actual target values or validation data, with those classified and predicted by the classifier or machine learning model (Longley et al. 2015; Wegman et al. 2016). The quantifying of accuracy metrics involves using statistics to measure which classes performed well and which need improvement. These metrics include overall accuracy, producers' accuracy, consumer's accuracy, and kappa coefficient. Overall accuracy refers to the total amount of correctly classified pixels or samples; producer's accuracy is the accuracy from the map producer's perspective and is calculated as the proportion of correctly classified pixels per class (omission error); while consumer's accuracy looks at the accuracy from the perspective of a user of the map and is calculated as "the number of correct predictions relative to the total number of times a class was predicted", i.e. (commission error) (Wegman et al. 2016, p.272). The kappa coefficient is the summary of the confusion matrix but "subtracts agreement that could have occurred by chance alone" (Wegman et al. 2016, p.272), or estimates agreements between reference (validation) data and predicted data that occur by chance (Longley et al. 2015). Other researchers have counterargued the efficacy of using a kappa value as a measure of accuracy and note that it should be completely disregarded and replaced with two simpler parameters: quantity disagreement and allocation disagreement (Pontius & Millones 2011). Accuracy assessments for the RF classifications were produced where traditional metrics such as overall accuracy, kappa, consumer's accuracy (percentage commission) and producers' accuracy (percentage omission) were considered and analyzed, along with sensitivity and specificity statistics for each class.

3.5 RESULTS AND DISCUSSION

3.5.1 Modified Normalized Difference Water Index

Below are results for a Modified Normalized Difference Water Index (MNDWI) (Xu 2006) performed in ArcMap. These maps display the extraction of waterlogged areas. MNDWI values range between a maximum value of 1 to a minimum value of -1 (Xu 2006). High values i.e. > 0 to +1 is water (water absorbs more light in the MIR/SWIR wavelength of the spectrum) and low values i.e. < 1 are in this case 'noise' such as soil, sediment deposits and vegetation (these reflect more light in the MIR/SWIR wavelength of the spectrum).

From the outputs in Figure 3.5 and Figure 3.6 it is evident that the main water channel-although weak- is located at the head of the wetland with smaller discontinuous alluvial tributaries flowing downstream towards the dam. Richards (2001) notes that in wetlands, the water table lies close to or above the soil surface and is influenced by climatic and seasonal changes resulting in varying periods of saturation throughout the year i.e. permanently saturated (all year); seasonally saturated (flooded for 5-11 months) or temporarily saturated (flooded 1-4 months). During the winter period, most rainfall is recorded (CapeNature 2017), and thus the wetland groundwater table recharges resulting in the water table being at its highest after the wet season. This is most likely why MNDWI values are higher in the summer MNDWI outputs. Rebelo et al. (2017) substantiate this observation by noting that after the rainy winter season, wetlands are at their highest water levels and thus easier to detect in the landscape.

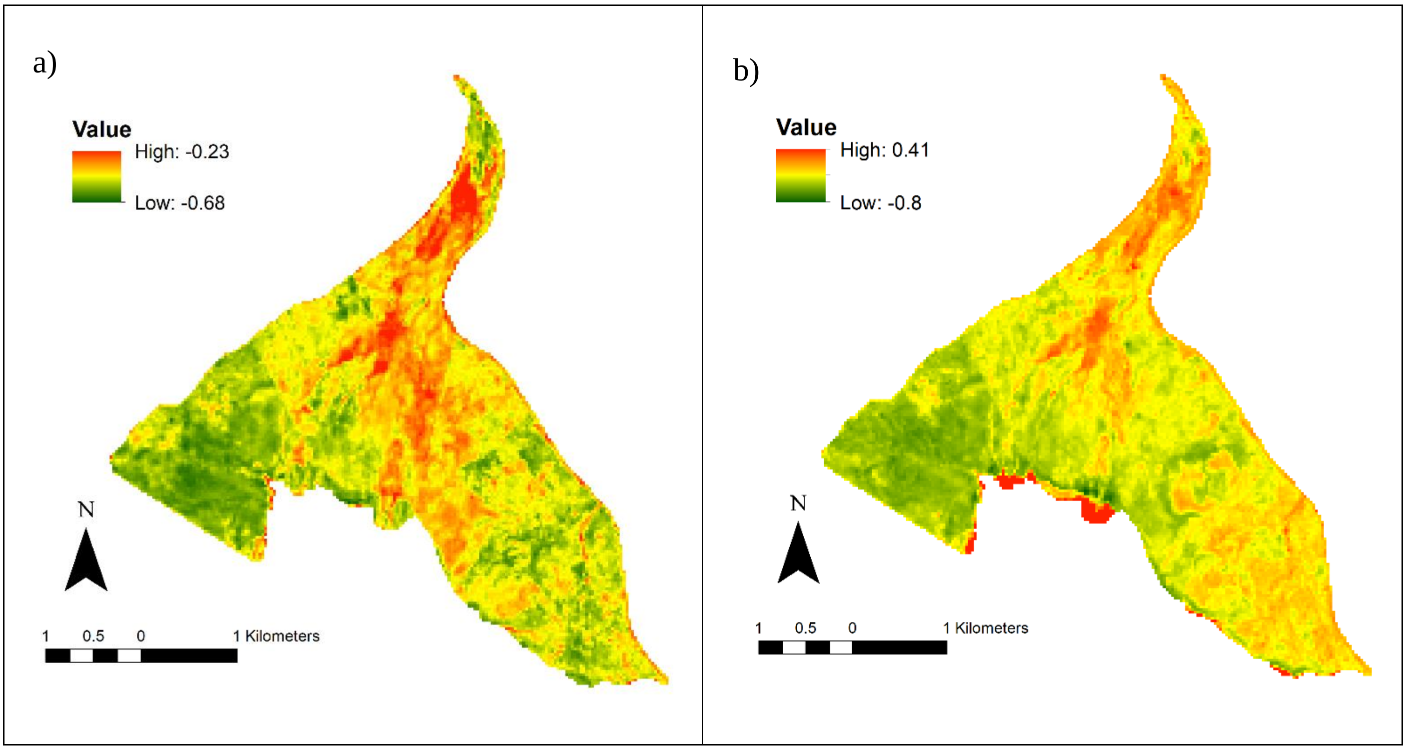


Figure 3.5 MNDWI created in ArcMap using Landsat 8 SR T1 for a) winter composite; b) summer composite

The MNDWI using Landsat 8 data performed well in displaying surface water as dominantly inundated through the main channel and centre of the wetland during both the wet and dry season. This indicates that centre of the wetland is a permanent channel with diffuse flows downstream towards the dam, while the outer areas towards the wetland boundary are seasonally saturated.

Sentinel-2: MSI, Level-2A data with 10 m (Figure 3.6) resolution provided defined visualization of permanent narrow streams and channels. It is also evident that the southern and south-eastern areas of the lower wetland are seasonally saturated towards the wetland boundary. This is substantiated by the damp sandy loam and often gleyed soils in this area found from the 100 cm mark soil profile as observed in field. According to Richards (2001) gleying is a process that occurs “when prolonged saturation reduces the level of mineral soils. The colours grey, and to a lesser extent blue and green, dominate in gleyed soil material” (2001, p.22). Soil profile photos were taken in field (displayed in Figure 3.4) showing the various soils at different zones of saturation and vegetation types in the wetland.

The far south-western areas show incredibly low MNDWI values which indicate that the vegetation may be degraded from previous farming and water extraction practices, or this is upland fynbos habitat where very little to no wetland subtype vegetation and wetland soils are present.

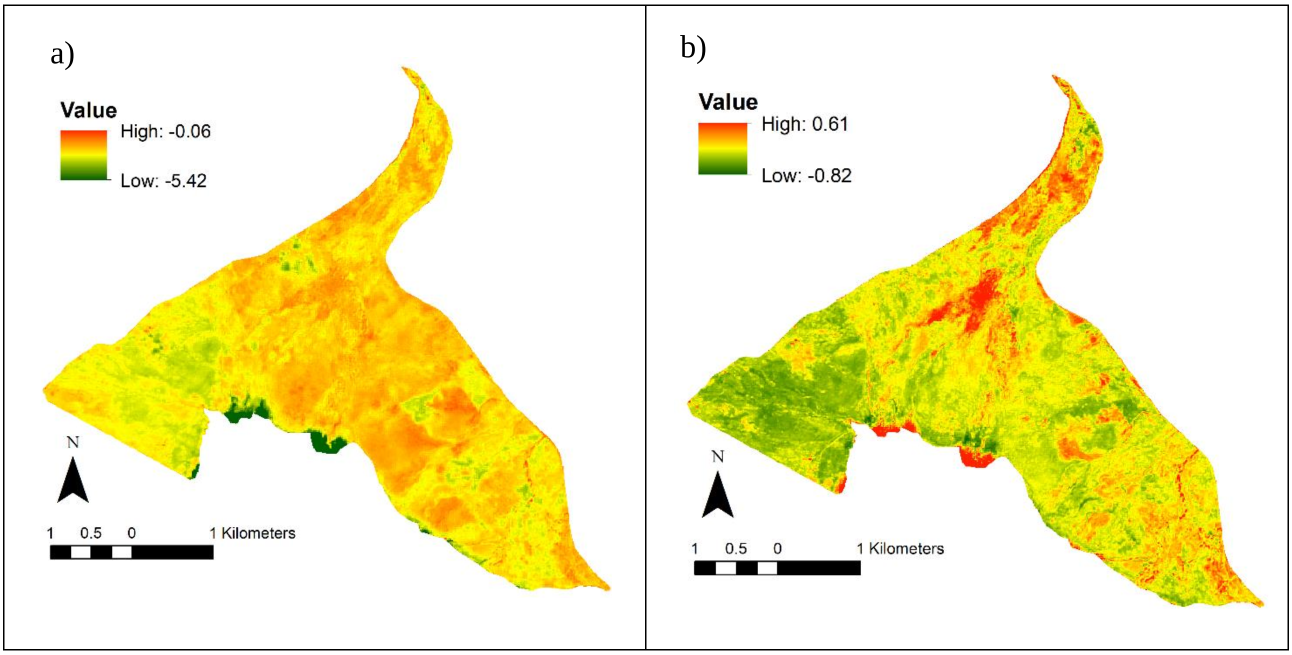


Figure 3.6 MNDWI created in ArcMap using Sentinel-2: MSI, Level-2A imagery for a) winter composite; b) summer composite

According to Job (2014) the "presence and retention of water in the landscape is a key defining feature of a wetland, where water is held long enough to saturate soils to sufficient depth to influence the plants that grow there, and for characteristics indicative of flooded soil to develop" (2014, p.9). Although the MNDWI gives an estimation of the hydrology and flooding regime of the wetland from a surface water aspect, it is a substantial way to analyze the Du Toits wetland hydrology, while additional soils observations can aid in showing how this correlates with the classification and identification of vegetation within in the wetland.

3.5.2 Normalized Difference Vegetation Index

The result output maps of NDVI values for both the wet and dry season of 2020 and 2021 are shown below in Figure 3.7. NDVI values typically range between -1 and +1 and are shown in the legends on the right-hand side of each map. High NDVI values indicate higher differences in the red edge wavelengths, and are good indicators of vegetation health, high vegetation activity and greenness (Wegman et al. 2016). Values that are 0 and below, are typically non-vegetated, while negative values indicate the presence of water (Wegman et al. 2016).

It is evident that the different vegetation types have varying NDVI values, some moderately low in shades of dark green to light green and some fairly high in shades of yellow to bright red approaching +1 values. The vegetation located to the centre and head of the wetland which are the dominant palmiet wetland vegetation species (i.e. *Prionium serratum* and *Psoralea pinnata*) as well as other obligate wetland species, show fairly high NDVI values. These differences in the NDVI values are a good way of discriminating between different species in a heterogenous landscape. Moreover, the NDVI values do show slight, but not significant variations between the wet and dry season which also may speak to wetland vegetation vs fynbos vegetation health and stress in the wet and dry season.

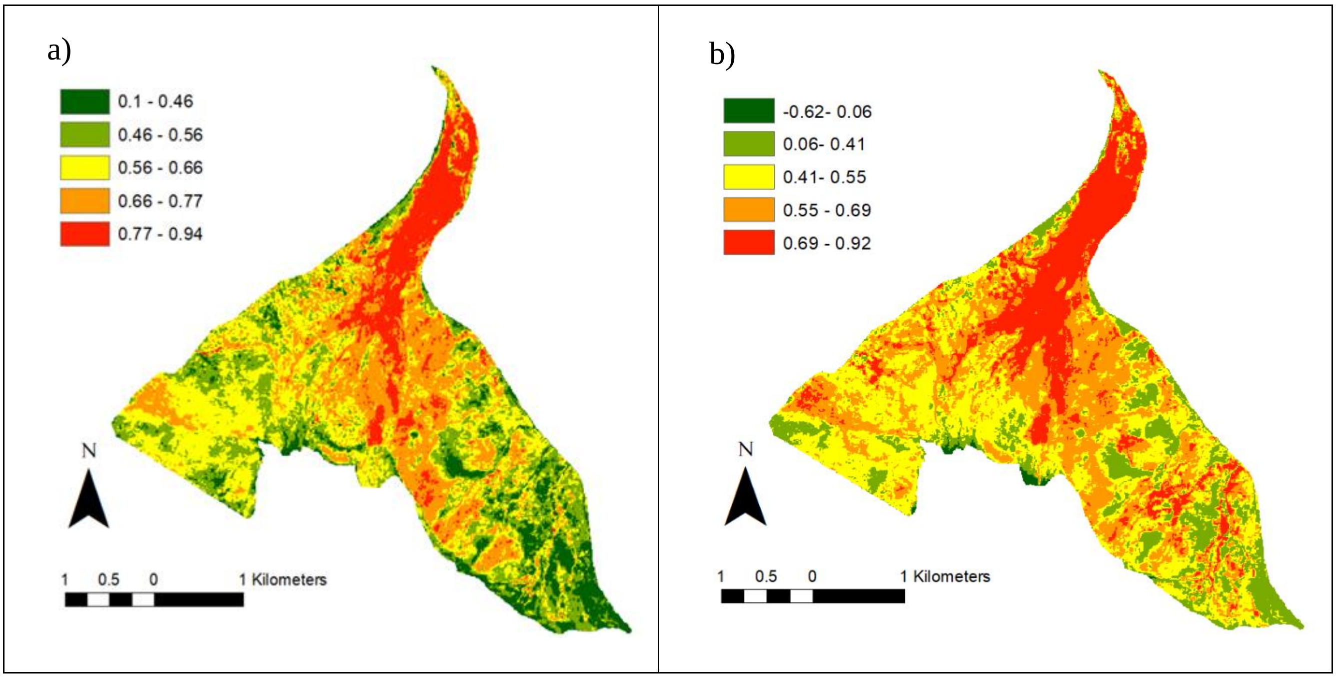


Figure 3.7 NDVI values for a) wet season i.e. June, July and August 2020 composite and b) dry season i.e. December 2020, January 2021, and February 2021 composite for Sentinel-2: MSI, Level-2A imagery

The slightly higher NDVI values in winter indicate that wetland species in this area are healthy during the wet season as precipitation increases and consequently the water table increases after the heavy winter rains, giving life to peatland and hydrophytic vegetation (Rebelo et al. 2017). This is validated by rainfall values described by Snaddon et al. (2018) who note that the annual total rainfall is 1241 mm/year, rainfall intensity 86 mm and the rainfall seasonality is winter i.e. the growing season for wetland vegetation. The average NDVI value for winter (i.e. June 2020-August 2020) is 0.62 and the standard deviation is 0.12. The average decreases in summer (i.e. December 2020-February 2021) at 0.55 and the standard deviation 0.16.

Sieben, Mtshali & Janks (2014) note that water quantity and quality are the of the most important aspects that influence plant communities in wetland environments. Wetland vegetation are typically adapted to growing in substrates that are anaerobic (i.e. devoid of oxygen) for at least some parts of the year, and are affected by altered soil chemistry influenced by prolonged periods of saturation and inundation (Department of Water Affairs and Forestry 2005; Richards 2001; Sieben, Mtshali & Janks 2014). Tiner (2016) additionally argues that vegetation itself has a substantial effect on the hydrology of a site. *Prionium serratum* especially has an effect on the fluvial processes, sediment deposition and filtering of water in wetlands. Job (2014, p.15) note that the “dense growth of robust palmiet stems and its very dense root mass, provide formidable frictional resistance to flood flows, dissipating their energy and trapping any sediment”. The plant is thus considered an ecosystem engineer where “the occurrence and proliferation of palmiet in foothill streams eventually plugs the river, turning the river into a wide valley-bottom wetland” (Sieben 2012, p.8) as evident in the Du Toits River wetland. In terms of the relationship between the presence and retention of water in a wetland and vegetation that occur, Rebelo et al. (2006) note that fynbos belonging to the Cape Reed family such as Restionacae (i.e. *Restio paniculatus, Elegia capensis* and *Elegia filacae* which are present in the Du Toits wetland) and Asteraceae species, are adapted to well-leached nutrient-poor soils and high annual rainfall as prevalent in the Western Cape and specifically in this catchment where annual rainfall is 1241 mm/year (Snaddon et al. 2018). This could be why Fynbos species are found on the outer areas of the wetland, away from the main wetland channel.

3.5.3 Image Classification

Random Forest classifier was performed on multispectral Landsat 8 SR T1 and Sentinel-2: MSI, Level-2A data. Although the resolution of multispectral data is coarse, it is useful in looking at region scale vegetation studies. In order to assess and validate the performance of the RF classifier, confusion matrices for each of the output maps are shown in Table 3.5 to Table 3.8. In each confusion matrix, columns represent the reference (or validation) data and rows are the classified pixels as predicted by the classifier. The diagonals represent the number of correctly classified pixels, and these cells are shaded in green. The percentage error of commission (over-mapping) and consumer’s accuracy of each class runs across the last bottom rows of the table. Whereas the percentage errors of omission (under-mapping) and producer’s accuracy of each class runs down the last two columns of the table, with additional metrics such as sensitivity and specificity percentages for each class.

3.5.3.1 Random Forest results

Before running a classification, it is important to check and analyse the training data to see reflectance values of each class in the various bands (wavelengths) selected for the prediction. As different objects and surfaces emit and reflect various types and amounts of radiation, selecting which part of the electromagnetic spectrum to measure is critical in RS (Longley et al. 2015). In this case it is imperative to identify which bands are most useful in discriminating the different vegetation types within the wetland. Literature notes that vegetation phenology has long been known to be useful in discriminating species for vegetation mapping as single species spectra may vary "throughout the growing season due to variations in the amount and ratios of plant pigments, leaf water content, plant height, canopy effects, leaf angle distribution and other structural characteristics" (Gilmore et al. 2008). Spectral signature and/or response curves are thus useful in displaying valuable information at each wavelength of the Electromagnetic Spectrum (EMS); for instance, Bands 2-4 i.e. Blue, Green and Red bands of most satellite imagery encompass the visible wavelengths of the EMS where chlorophyll and leaf pigments are absorbed (Wegman et al. 2016). The NIR wavelength tells us about leaf and canopy structure, and the SWIR wavelengths are where water content are absorbed (Wegman et al. 2016). The graphs below provide useful information as to how the different landcover classes in the classification respond at different wavelengths of the EMS in L8 SR T1 and Sentinel-2: MSI, L2A imagery:

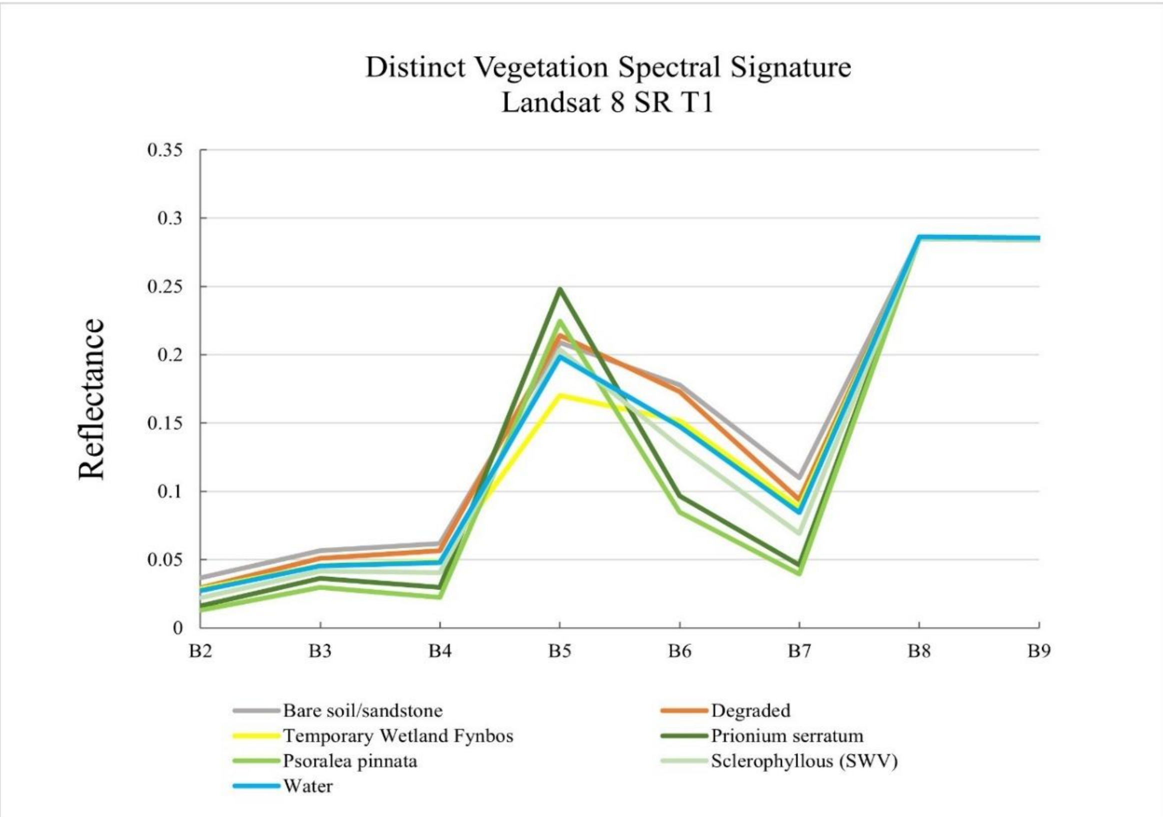


Figure 3.8 Spectral signature curve for the Distinct Landcover classification using Landsat 8 SR T1 winter imagery

As displayed in Figure 3.8, the spectral response of all seven landcover classes show variations at the different wavelengths (i.e. bands). In bands 2-4 all the classes have similar reflectance with palmiet wetland vegetation (*Prionium serratum* and *Psoralea pinnata*) having slightly lower reflectance than the other classes. Throughout the EMS in winter imagery, Palmiet Wetland Vegetation, SWV, Degraded vegetation and Water have very close spectral reflectance. Thus, it would be expected that these classes are not suitable to map using coarse scale data such as Landsat 8 with 30 m resolution, especially during the winter season as seen in Figure 3.8.

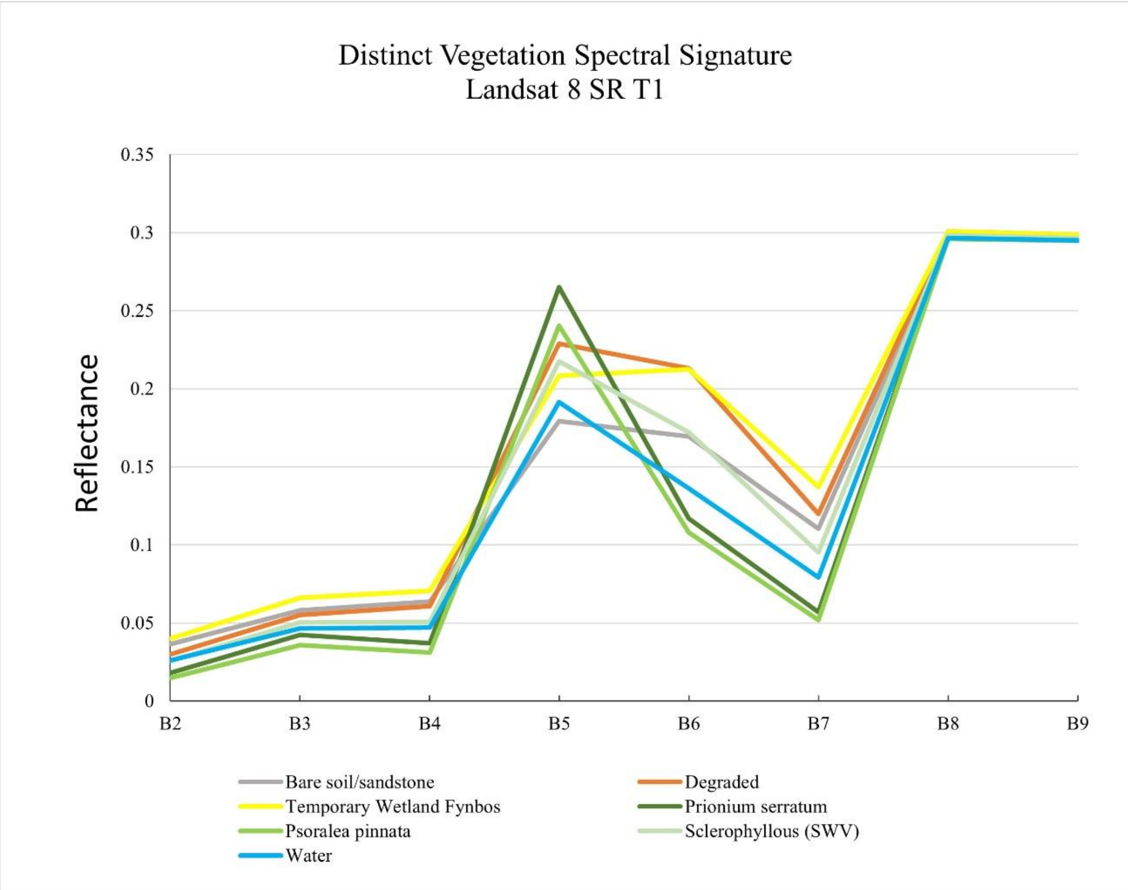


Figure 3.9 Spectral signature curve for the Distinct Landcover classification using Landsat 8 SR T1 summer imagery

In summer L8 imagery, the landcover classes have slightly different spectral responses. In bands 2-4 i.e. the visible wavelengths of the EMS where chlorophyll and leaf pigments are most absorbed (Wegman et al. 2016), Temporary Wetland Fynbos has fractionally higher reflectance values than all the other landcover classes. Figure 3.9 also shows that Palmiet Wetland Vegetation i.e. *Prionium serratum* has the highest spectral reflectance in bands 2-6 and significantly drops in bands 6-9 (i.e. the NIR wavelengths which speak to leaf and canopy structure). There is visible intertwining of the spectral responses for *Psoralea pinnata*, SWV, Temporary Wetland Fynbos and Degraded vegetation at band 4-5. This may speak to the phenology of these communities in summer.

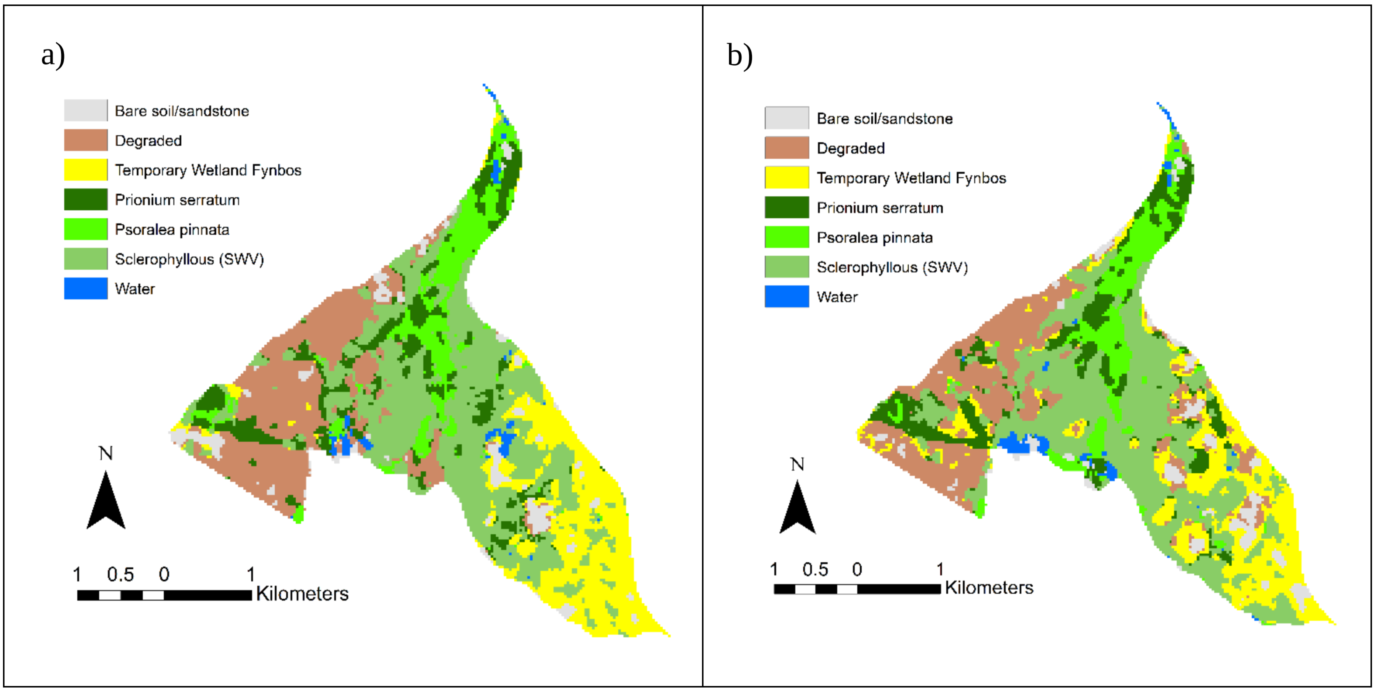


Figure 3.10 Outputs of the Random Forest classifier for a) winter 2020 composite and b) summer 2020/2021 composite with seven distinct landcover classes using Landsat 8 SR T1 imagery

Figure 3.10 demonstrate that the RF classifier using L8 imagery with 30 m resolution performed well and visually discriminated the landcover classes, even though the spectral responses show high similarities for each class in the spectral response graphs. By analysing the confusion matrices as in Table 3.5 and Table 3.6, it is evident that when using L8 data, Palmiet Wetland Vegetation performs well with low errors of omission (EO) for *Prionium serratum* (19.6% in winter; 23.2% in summer) and high producer’s accuracy (80.4% winter; 76.8% summer). *Psoralea pinnata* similarly has low percentages of omission (27.4% in winter; 24.2% in summer) and moderately high producer’s accuracy i.e. 72.6% in winter and 75.8% in summer (see Table 3.9). These two vegetation types are only confused with other vegetation such as SWV in 5 pixels and confused in a total of 3 pixels with Temporary Wetland Fynbos, Bare soil, and Degraded vegetation. The palmiet class similarly has low over-mapping errors (i.e. errors of commission, or EC) where *Prionium serratum* has 23.7% EC in winter, and 27.1% EC in summer with high consumer’s accuracies i.e. 76.3% in winter and 72.9% in summer. Contrastingly, *Psoralea pinnata* has a slightly decreased error of commission in summer (25% in winter; 16.1% in summer) and very high consumer’s accuracy (75% winter; 83.3% in summer, see Table 3.9).

The SWV group (primarily wetland ferns, grasses and restios, see Table 3.3) also have moderately low omission errors at 26% in L8 winter imagery and slightly decreased 21.1% in L8 summer imagery. When looking at the visual outputs as well, it is evident that this group is mapped as spread across the outer-most soil gradients towards the road, while Palmiet Wetland Vegetation occurs dominantly through the middle channel of the wetland. In L8 data the SWV class has a high error of commission in winter (35.1%) compared to summer (21.1%).

Table 3.5 Confusion matrix with accuracy metrics for the seven distinct landcover classes, Random Forest classification using Landsat 8 SR T1 winter imagery (Figure 3.10, a)

	Classified data									
Reference data	*Prionium serratum*	*Psoralea pinnata*	SWV	Temporary Wetland Fynbos	Bare soil/sandstone	Degraded	Water	**Row Totals**	**EO %**	**PA %**
Prionium serratum	45	9	1	0	0	0	1	**56**	19.6	80.4
Psoralea pinnata	11	45	4	1	1	0	0	**62**	27.4	72.6
SWV	1	4	37	3	3	2	0	**50**	26	74
Temporary Wetland Fynbos	0	0	6	41	1	0	0	**48**	14.6	14.6
Bare soil/sandstone	0	1	2	1	26	0	1	**31**	16.1	83.87
Degraded	1	0	6	1	2	46	0	**56**	17.9	82.14
Water	1	1	1	0	13	0	47	**63**	25.4	74.6
Column Totals	**59**	**60**	**57**	**47**	**46**	**48**	**49**	**366 (TP)**		
Sensitivity %	76.3	75	64.9	87.2	57	96	95.9			
Specificity %	96.4	94.4	95.8	97	98	97	94.9			
EC %	23.7	25	35.1	12.8	43.5	4.2	4.1			
CA %	76.3	75	64.9	87.2	56.5	95.8	95.9			
Overall Accuracy %	78									
Kappa:	0.74									

EO= Errors of omission; PA= Producer's accuracy; EC= Errors of commission; CA= Consumer's accuracy; TP=Total pixels

Table 3.6 Confusion matrix with accuracy metrics for the seven distinct landcover classes, Random Forest classification using Landsat 8 SR T1 summer imagery (Figure 3.10, b)

	Classified data									
Reference data	*Prionium serratum*	*Psoralea pinnata*	SWV	Temporary Wetland Fynbos	Bare soil/sandstone	Degraded	Water	**Row Totals**	**EO %**	**PA %**
Prionium serratum	43	7	1	1	3	0	1	56	23.2	76.8
Psoralea pinnata	13	50	1	1	0	0	1	66	24.2	75.8
SWV	1	2	45	5	2	2	0	57	21.1	78.9
Temporary Wetland Fynbos	0	0	3	37	1	3	0	44	15.9	15.9
Bare soil/sandstone	0	0	2	1	27	2	1	33	18.2	81.82
Degraded	0	0	3	3	2	41	0	49	16.3	83.67
Water	2	1	2	0	11	0	47	63	25.4	74.6
Column Totals	59	60	57	48	46	48	50	**366 (TP)**		
Sensitivity %	72.8	83.3	78.9	78.7	59	85	95.9			
Specificity %	96	95.1	96.1	97.8	98	97	94.9			
EC %	27.1	16.7	21.1	22.9	41.3	14.6	6			
CA %	72.9	83.3	78.9	77.1	58.7	85.4	94			
Overall Accuracy %	79									
Kappa:	0.75									

EO= Errors of omission; PA= Producer's accuracy; EC= Errors of commission; CA= Consumer's accuracy; TP=Total pixels

Temporary Wetland Fynbos vegetation has low errors of omission and commission in both winter and summer. Table 3.5 and Table 3.6 show 14.6% (winter) and 15.9% (summer) EO, while the errors of commission (EC) are 12.8% (winter) and an increased 22.9% (summer). Bare soil/sandstone generally has low errors of omission i.e. 16.1% in winter imagery and 18.2% in summer. This class is however largely over-mapped with 43.5% in winter and 41.3% in summer. The tables show that bare soil is commonly confused with water, i.e. it is confused in 14 pixels, and in summer it is confused with water in 12 pixels. Degraded vegetation similarly has low classification errors i.e. 17.9% EO in winter and 16.3% EO in summer. This vegetation class also has a very low error of commission in winter i.e. 4.2% and 14.6% in summer and very high consumer's accuracies i.e. 95.8% in winter and 85.4% in summer. Water has low and acceptable classification errors in both L8 winter and summer imagery; in winter the EO is 25.4% and the error of commission is 4.1%. While in summer, water also has 25.4% EO and 6% EC.

The overall accuracy of the Landsat 8 classifications is 78% with a kappa value of 0.74 for winter imagery, while L8 summer imagery classification performed slightly better with 79% overall accuracy and a kappa of 0.75. This suggests that coarse scale data such as Landsat 8 with 30 m resolution performs well in spectrally discriminating and classifying distinct vegetation groups in a heterogenous system, especially during the summer period.

The spectral signature responses for the seven landcover classes using Sentinel-2: MSI, Level-2A imagery are displayed below to highlight how each class responds in the different wavelengths of Bands 2-12 in Sentinel-2: MSI, L2A imagery. Note that in Sentinel-2: MSI, Level-2A data there is no Band 10.

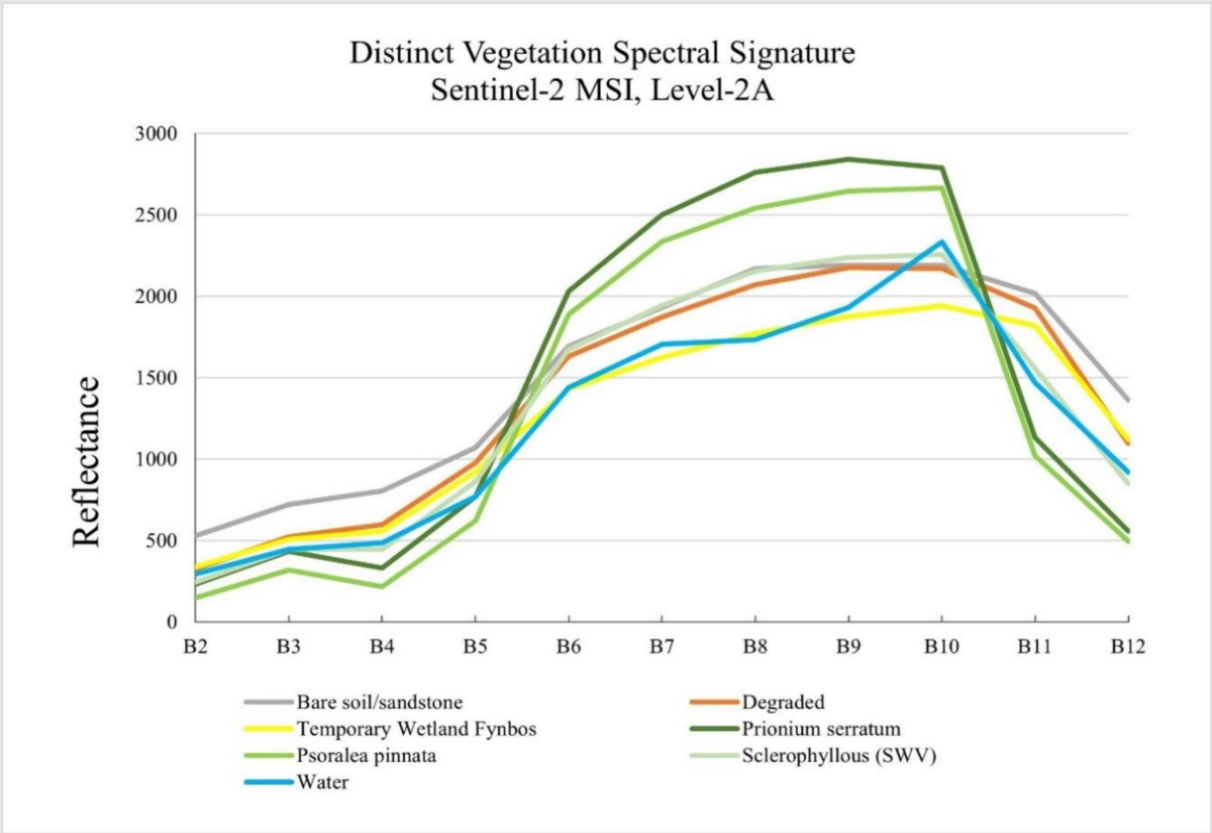


Figure 3.11 Spectral signature profiles for the seven distinct classes in Sentinel-2: MSI, Level-2A winter 2020 imagery

In analysing the spectral responses in Figure 3.11 and Figure 3.12, it is apparent that the dominant palmiet wetland vegetation namely *Prionium serratum* and *Psoralea pinnata* and water have similar reflectance through bands 2-4 but differs in the Red Edge (B5,6 & 7) and NIR (B8) bands. Literature notes that these types of trends makes mapping wetlands very challenging as they are “highly dynamic in ways that substantially alter their reflectance and energy backscatter properties”, and “ individual species can exhibit significant variation in energy responses (spectrally and in terms of backscatter geometry) within a growing season at different stages of their development” (Gallant 2015, p.10939).

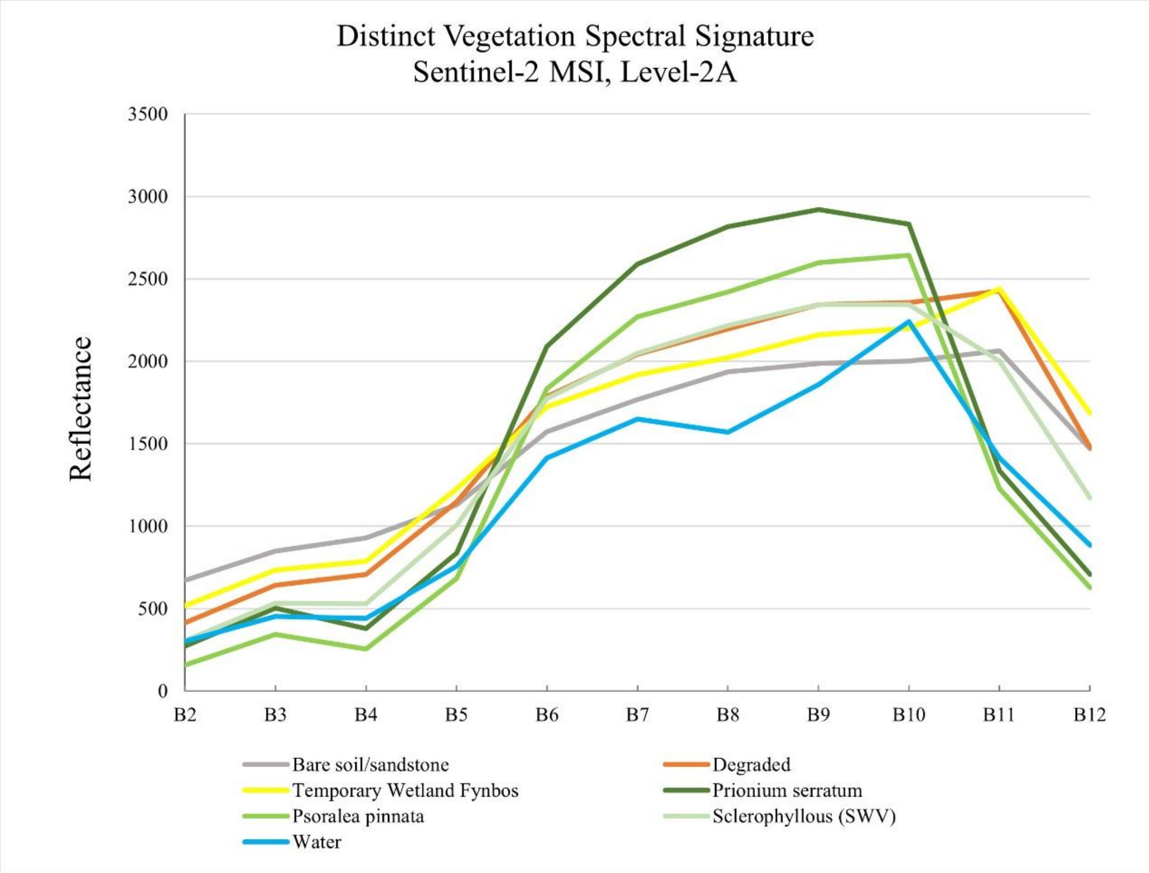


Figure 3.12 Spectral signature profiles for the seven distinct classes in Sentinel-2: MSI, Level-2A summer 2020_2021 imagery

Additionally, wetlands are seen as moving targets in RS due to their interchanging conditions, i.e. heterogeneity in vegetation cover and fluctuating hydroperiods which present wetlands as a moisture regime rather than cover type (Gallant 2015). Given that the Du Toits River wetland is a fynbos embedded wetland, these spectral response curves additionally assist in highlighting that Palmiet Wetland Vegetation have different spectral responses to dryer Temporary Wetland Fynbos vegetation. The response curves show that Sclerophyllous Wetland Vegetation and Degraded vegetation have similar spectra, which could mean that the degraded areas may be dry, degraded and burnt ferns or grass (i.e. *Pteridium aquilinum, Restio paniculatus or Merxmuellera cincta*). In bands 2-4 Temporary Wetland Fynbos has higher distinct spectra from the other three vegetation types, but quite similar reflectance to degraded vegetation and may be signs of vegetation stress in Temporary Wetland Fynbos. This trend changes in the three Red Edge bands i.e. B5, B6 and B7 as well as B8, the NIR band where wetland Fynbos has lower reflectance than the three vegetation types (*Prionium serratum*, *Psoralea pinnata* and Sclerophyllous) but similar reflectance to bare soil. All classes show a decline in reflectance in the SWIR bands i.e. B11 and B12. It is important to note that fluctuating water level as evident in the Du Toits River wetland (Figure 3.5 and Figure 3.6) may also influence or change the spectral reflectance of vegetation (Ozesmi & Bauer 2002).

Figure 3.13 are the resultant output maps of RF classifier run on a winter composite (Figure 3.13 a) and a summer composite (Figure 3.13 b). The RF classifier was run on each season imagery in order to get an idea of vegetation occurrence and changes between wet (growing) season and dry (flowering) seasons. Table 3.7 and Table 3.8 below indicate that the Palmiet Wetland Vegetation class had generally acceptable classification errors i.e. *Prionium serratum* had a 20.7% omission and 22% commission, while *Psoralea pinnata* had a low 16.9% omission and 18.3% commission in the winter season. These percentages are confidently low which illustrate that RF spectrally discriminates these two palmiet wetland vegetation subtypes quite well on Sentinel-2: MSI, L2A imagery using the seven-class approach. Although *Psoralea pinnata* is a common wetland tree typically occurring in Hawequas Sandstone Fynbos systems (Rebelo et al. 2006; Sieben et al. 2017), it has been argued by Rebelo, Emsens, et al. (2018) that *Psoralea pinnata* (and *Pteridium aquilinum)* are some of the key species characterizing degraded fragments of what should be pristine wetland (dominated by *Prionium serratum*) in the Du Toits River wetland.

In summer these values fluctuate where *Prionium serratum* decreased to 14% omission and 16.9% commission- relatively lower than in winter imagery. *Psoralea pinnata* has a decreased omission value of 14.8% and 13.3% commission in summer. *Psoralea pinnata* bloom from October to December (Palmer & Pitman 1973), hence the change in reflectance from winter compared to summer as seen in the above map outputs. The seasonal differences in the classification speak to the phenology of the vegetation and how it absorbs and radiates energy to receiving satellites at various life stages and growing seasons, suggesting that fynbos embedded wetlands may provide better mapping accuracies in the dryer, flowering season (i.e. spring to summer). The classification results also correspond with the differences in NDVI values as shown in Figure 3.7. Where NDVI values are high i.e. ranging between 0.77-0.94 (winter) and 0.69-0.92 (summer), the RF classified images indicate that these are areas of dense *Prionium serratum* and *Psoralea pinnata* occurrence. Spectral signature graphs in Figure 3.11 and Figure 3.12 show that these two vegetation have very similar reflectance in the spectrum and may be difficult to distinguish as separate classes of vegetation. However, the efficacy of RF classifier successfully distinguishes these two unique peatland vegetation.

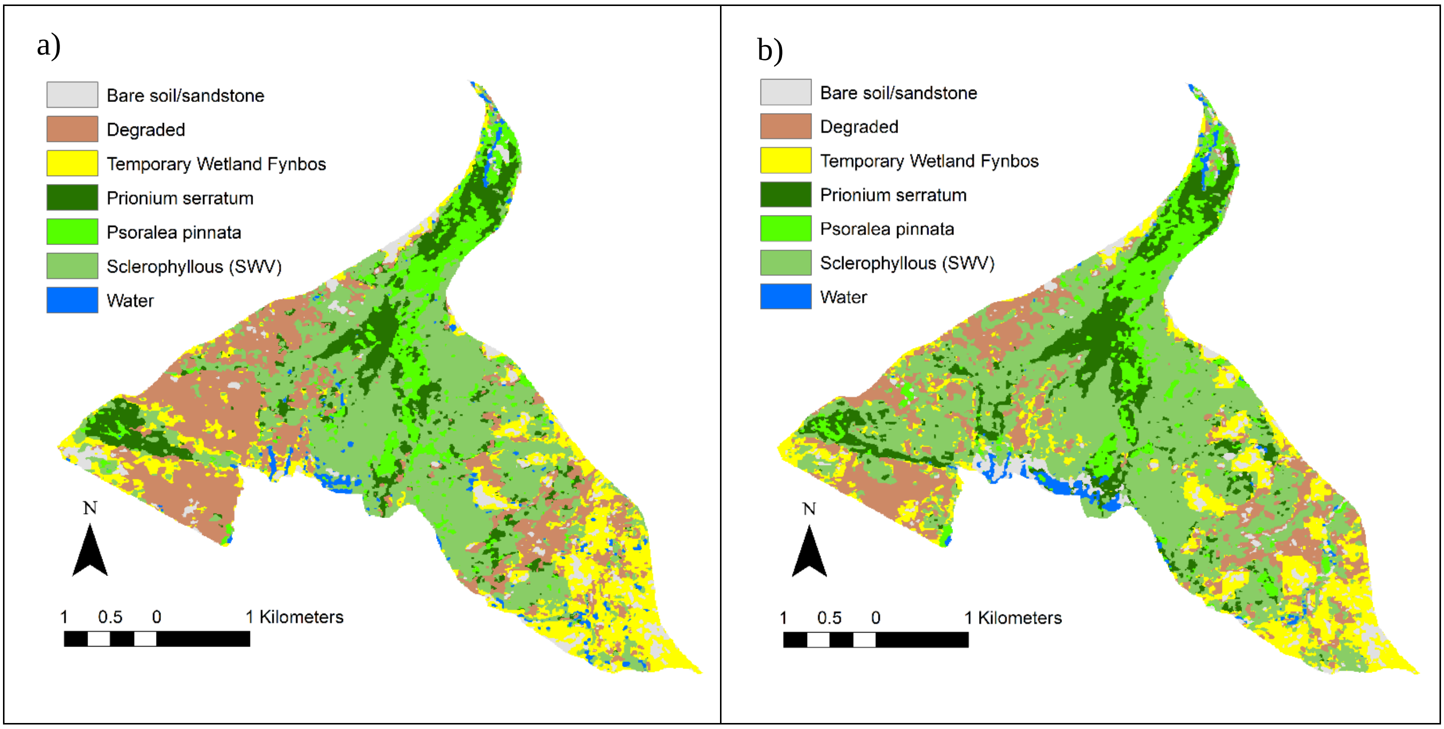


Figure 3.13 Map outputs of the Random Forest classifier for a) winter 2020 composite and b) summer 2020/2021 composite with seven distinct landcover classes using Sentinel-2: MSI, Level-2A imagery

It is evident from the matrices that the sclerophyllous (SWV) group are slightly over-generalized at a 31.6% commission for Sclerophyllous Wetland Vegetation and 27.7% commission for Temporary Wetland Fynbos in the winter season. In summer these two vegetation communities have 17.5% and 29.8% commission errors. Furthermore, these two classes are moderately under-mapped in some areas of the wetland i.e. SWV at 36.1% in winter, and 30.9% omission in summer; while Fynbos is at 29.2% in omission winter; and a significantly decreased 8.3% omission in summer. Figure 3.11 and Figure 3.12 show that SWV and Fynbos have similar spectra to the Degraded and Bare soil classes. Although this is a fynbos embedded wetland, spectral signatures of Temporary Wetland Fynbos show a clear distinction from wetland vegetation. This could be due to Temporary Wetland Fynbos having varied structural composition that are determined by factors such as floristic maturity, "fire (intensity, season, frequency, veld age, past fire history, lottery recruitment from seed banks following fire), and thus the same community may vary in species composition and abundance between fires" (Rebelo et al. 2006). These areas also show lower NDVI values in the dry season i.e. shaded light green (values 0.46-056 in winter and 0.06-0.41 in summer) in Figure 3.7, adequately spectrally discriminating Fynbos from the surrounding wetland shrubs and trees that have higher NDVI values. Similar to the observation of wetland vegetation, it is suggested that Temporary Wetland Fynbos vegetation maps more accurately in summer imagery.

Table 3.7 Confusion matrix with accuracy metrics for the seven distinct landcover classes, Random Forest classification using Sentinel-2: MSI, Level-2A winter 2020 imagery (Figure 3.13 a)

		Classified data									
		Prionium serratum	*Psoralea pinnata*	SWV	Temporary Wetland Fynbos	Bare soil/sand stone	Degraded	Water	**Row Totals**	**EO %**	**PA %**
Reference data	*Prionium serratum*	46	7	2	0	0	2	1	**58**	20.7	79.3
	Psoralea pinnata	7	49	3	0	0	0	0	**59**	16.9	83.1
	SWV	3	4	39	5	0	8	2	**61**	36.1	63.9
	Temporary Wetland Fynbos	0	0	5	34	5	2	2	**48**	29.2	29.2
	Bare soil/sandstone	0	0	1	4	37	0	4	**46**	19.6	80.4
	Degraded	2	0	7	2	1	36	2	**50**	28	72
	Water	1	0	0	2	3	0	38	**44**	13.6	86.4
	Column Totals	**59**	**60**	**57**	**47**	**46**	**48**	**49**	**366 (TP)**		
	Sensitivity %	78	82	68	72	80	75	78			
	Specificity %	96	97	93	96	97	96	98			
	EC %	22	18.3	31.6	27.7	19.6	25	22.4			
	CA %	78	81.7	68.4	72.3	80.4	75	77.6			
	Overall Accuracy %	76									
	Kappa:	0.72									

EO= Errors of omission; PA= Producer's accuracy; EC= Errors of commission; CA= Consumer's accuracy; TP=Total pixels

Table 3.8 Confusion matrix with accuracy metrics for the seven distinct landcover classes, Random Forest classification using Sentinel-2: MSI, Level-2A summer 2020/2021 imagery (Figure 3.13 b)

		Classified data									
		Prionium serratum	*Psoralea pinnata*	SWV	Temporary Wetland Fynbos	Bare soil/sand stone	Degraded	Water	**Row Totals**	**EO %**	**PA %**
Reference data	*Prionium serratum*	49	6	2	0	0	0	0	**57**	14	86
	Psoralea pinnata	5	52	2	0	0	0	2	**61**	14.8	85.2
	SWV	5	0	47	6	1	6	3	**68**	30.9	69.1
	Temporary Wetland Fynbos	0	0	2	33	1	0	0	**36**	8.3	91.7
	Bare soil/sandstone	0	1	1	3	37	1	6	**49**	24.5	75.5
	Degraded	0	0	2	4	1	41	1	**49**	16.3	83.7
	Water	0	1	1	1	6	0	37	**46**	19.6	80.4
	Column Totals	**59**	**60**	**57**	**47**	**46**	**48**	**49**	**366 (TP)**		
	Sensitivity %	83	87	82	70	80	85	76			
	Specificity %	97	97	93	99	96	97	97			
	EC %	16.9	13.3	17.5	29.8	19.6	14.6	24.5			
	CA %	83.1	86.7	82.5	70.2	80.4	85.4	75.5			
	Overall Accuracy %	81									
	Kappa:	0.78									

EO= Errors of omission; PA= Producer's accuracy; EC= Errors of commission; CA= Consumer's accuracy; TP=Total pixels

Bare soil/sandstone has an omission error of 19.6% (winter) and 24.5% (summer), while commission errors for this class remain 19.6% during winter and summer. Limited information is known about the Degraded landcover class as these areas were not sampled due to inaccessibility, waterlogging and safety reasons. Therefore, visual observations were made from Google Earth which appear to be degraded or dead vegetation that may belong to the SWV group i.e. *Pteridium aquilinum, Restio paniculatus or Merxmuellera cincta* and/or Temporary Wetland Fynbos. The Degraded vegetation class has low errors of omission i.e. 28% (winter) and 16.3% (summer). This class similarly has moderately low errors of commission (25% winter; 14.6% summer) and high consumers accuracy (75% in winter and 85.4 in summer, see Table 3.9). The omission errors for water are fairly low i.e. 13.6% EO in winter (Table 3.7) and 19.6% in summer (Table 3.8). The confusion matrices show that water has low commission percentages i.e. 22.4% in winter (Table 3.7) and 24.5% in summer (Table 3.8). The classification of this class performed quite well, distinctly displaying some parts of the channelled river and its tributaries. The presence of water in the classified images corroborate the presence of waterlogged areas in the Sentinel-2: MSI, L2A MNDWI outputs in Figure 3.6. The kappa value for both seasons imagery is at 0.72 and 0.78 while the overall accuracy of both Sentinel-2: MSI, L2A Random Forest classified images stands at 76% (winter classification) and a high 81% (summer classification) which is a good level of accuracy.

Table 3.9 below provide a summary of the overall statistics for each landcover class for both Landsat 8 and Sentinel-2 sensors. From this table it is evident that generally the classification performed best using the Sentinel-2: MSI, Level-2A imagery with the highest overall accuracy i.e. 81%, kappa statistic i.e. 0.78 and frequently high consumer’s and producer’s accuracies for all classes. High accuracies are shaded green cells.

Table 3.9 Overall summary statistics of how each landcover class performed in both Landsat 8 SR T1 and Sentinel-2: MSI, Level-2A imagery using the Random Forest classifier

			Consumers Accuracy:							**Producers Accuracy:**						
	OA:	**KS:**	*P. serratum*	*P. pinnata*	SWV	TW Fynbos	Bare soil	Degraded	Water	*P. serratum*	*P. pinnata*	SWV	TW Fynbos	Bare soil	Degraded	Water
Sensor and Season:																
L8 Winter	0.78	0.74	76.3	75	64.9	87.2	56.5	95.8	95.9	80.4	72.6	74	14.6	83.87	82.14	74.6
L8 Summer	0.79	0.75	72.9	83.3	78.9	77.1	58.7	85.4	94	76.8	75.8	78.9	15.9	81.82	83.67	74.6
Sentinel-2: MSI, L2A Winter	0.76	0.72	78	81.7	68.4	72.3	80.4	75	77.6	79.3	83.1	63.9	29.2	80.43	72	86.36
Sentinel-2: MSI, L2A Summer	0.81	0.78	83.1	86.7	82.5	70.2	80.4	85.4	75.5	86	85.2	69.1	91.7	75.5	83.7	80.4

OA= Overall Accuracy; KS= Kappa Statistic; *P. serratum*= *Prionium serratum*; *P. pinnata*= *Psoralea pinnata*; SWV= Sclerophyllous Wetland Vegetation; TW Fynbos= Temporary Wetland Fynbos

3.6 CONCLUSION

In assessing the accuracy and classification errors of the Random Forest results, it is apparent that the classifier performed well in displaying the spread of different vegetation and other landcover such as bare soil and water in the Du Toits River wetland. Consistently across both datasets i.e. Landsat 8 and Sentinel-2: MSI, Level-2A, the classifier displayed the spread of the Palmiet Wetland Vegetation i.e. *Prionium serratum* and *Psoralea pinnata* distinctly at the centre of the wetland. Other wetland vegetation such as sclerophyllous group of grasses, ferns and restios, along with Fynbos vegetation are spread predominantly on the outer boundary of the wetland, and with patches intertwined towards the centre of the wetland. Although confusion between classes was quite low, it can be improved by adding more training data that is based on alternative ground- truth methods, especially in the western areas of the wetland that were not sampled *in situ*. The MNDWI and NDVI results, and analyses substantiate the classification of the different landcovers within the wetland. Evidently, where there are higher MNDWI values and higher soil wetness, palmiet wetland vegetation is dominant. Where MNDWI values are lower, with lower soil wetness, temporary wetland fynbos and sclerophyllous vegetation are found. The NDVI outputs correspondingly show that the distribution of wetland vegetation (palmiet etc) at the centre of the wetland have higher NDVI values while the wetland grasses, ferns, restios spread to the outer boundary and which belong to the SWV group, and Fynbos have moderate to lower maximum NDVI values.

Based on the then working definition of an ecotone by Holland (1988) which described ecotones as transition zones between neighbouring ecological systems that are characterized by unique properties which are defined by space and time scales, and by the strength of interactions between the adjacent ecological systems; this study therefore contends that ecotones will exist where there are vegetation shifts with distinct properties in vegetation and soil composition. For example, the ecotone can exist where there are distinct vegetation changes from the center of the wetland where *Prionium serratum* and *Psoralea pinnata* dominantly and densely occur, to the outer edges of the wetland moving towards the mountainous gradient where grasses, ferns and Fynbos occur. This change is supported by soil observations which indicate that where there are deeper, wet, and organic soils with peatland species such as *Prionium serratum, Zantedeschia aethiopica and Psoralea pinnata*. A transition occurs to soil conditions that are sandy to sandy loam, not always wet where sclerophyllous vegetation is classified and found, and Fynbos is dominantly found in drier areas. Internal biological ecotones may exist among the different vegetation communities as well. It is thus acknowledged that the whole wetland is a complex mosaic ecotone with patches of internal ecotones within. It can be concluded from this chapter that ecotones within the wetland are not linear but may be spatially disjunct.

CHAPTER 4: REMOTE SENSING OF WETLAND ECOTONES

"*Impossible to map the world–we select and make graphics so that we can understand it.*"

-Roger Tomlinson, 1981

4.1 ABSTRACT

Remote Sensing (RS) data and techniques have become increasingly popular to use for observational studies and monitoring in ecology due to its ability to obtain large amounts of data over greater spatial and temporal scales than is possible through field-based methods. Remote sensing is an especially effective means of detecting and monitoring spatiotemporal aspects of ecotones where one vegetation type (or ecosystem) transitions into another. The frequent revisit times of satellites enable monitoring of the dynamics typical of some ecotones. Probabilistic, supervised classification of Sentinel-2 MSI: MultiSpectral Instrument, Level-2A, imagery was used to identify, map, and characterize wetland ecotones. The resultant output probability map, along with fuzzy probability graphs developed for six transects placed across the wetland, were able to map complex and dynamic wetland ecotones between two distinct types of palmiet wetland vegetation, sclerophyllous wetland vegetation, and Fynbos species belonging to the Cape Floristic Region. Results showed 1) abrupt (under 10 m), sharp ecotones within palmiet (peat) wetland vegetation groups, 2) sharp, narrow ecotones (under 10 m) between palmiet wetland, sclerophyllous wetland, and fynbos (temporary wetland) communities, and 3) distinct and complex ecotones within the sclerophyllous wetland vegetation and temporary wetland fynbos dominated areas of the wetland. Probabilistic classification methods are deemed useful in mapping fine-scale, abrupt ecotones, especially for wetlands that are dynamic entities in a landscape. This study highlights the efficacy of using probability, per-pixel RS approaches to map ecotones that are complex units in reality, rather than using binary classifications or vector line mapping approaches. The findings of this study suggest that there is great potential and need for wetland ecotone mapping as core areas in understanding wetland ecosystem processes, and perhaps understanding embedded, alluvial fan wetland formation and functioning.

4.2 INTRODUCTION

Ecological boundary, gradient, edge, edge boundary, ecocline and ecotone are terms that have been crucial in landscape ecology studies, all being used interchangeably due to the lack of shared and unified definitions of each (Cadenasso, Pickett, Weathers, Bell, et al. 2003). Hufkens, Scheunders & Ceulemans (2009) provide a review of the various terms and definitions of ecotone research in vegetation ecology and summarize the trends, techniques and discrepancies between definitions and their scientific applications. Hufkens and colleagues' (2009) review provided a good basis to refine and select a working definition for this study which aimed to identify and map internal biological (i.e. between individuals in the same ecosystem/community) ecotones within a spatially heterogenous fynbos embedded wetland, using a supervised probabilistic classification. In this study ecotones are defined by Holland (1988) as zones of "transition between adjacent ecological systems, having a set of characteristics uniquely defined by space and time scales and by the strength of the interactions between adjacent ecological systems"(Holland 1988; Holland, Whigham & Gopal 1990). For this research, ecotones are considered zones of vegetation change and 'chaos' i.e. harbouring vegetation species from both adjacent ecosystems at varying probabilities. Researchers have noted that while substantial research in landscape ecology has focused on discrete ecological regions, communities and systems, ecotones or zones of transition have received less attention (Kark 2005) although they have long been a topic of interest to scientists (Clements 1905; Livingston 1903; Odum & Barrett 1971) due to their effects on landscape diversity and patterns (Whittaker 1960). Described as unique units in a landscape, ecotones are responsible for various landscape functions which include; movement of animals and seeds across the transition, high biological diversity, speciation, high rate of primary and secondary production, and refuge areas for species under changing conditions (climatic and human induced), highlighting that ecotones contribute to ecosystem integrity (Kark 2005; Kark 2007; Walker et al. 2003; Williams 1996). Alternatively, researchers have also noted that ecotones sometimes show less or lack species diversity than in adjacent habitats (Hou & Walz 2014; Senft 2009; Walker et al. 2003). Hence, although understudied, ecotones provide a good ground for studying natural communities.

Ecotones often occur along ecological gradients that are created by spatial shifts in elevation, soil, climate and various other environmental parameters (Kark 2005) and in the case of wetlands, may occur at various points of hydrogeomorphic units (HGM) (Ollis et al. 2013). These HGM units are determined and influenced by landform, hydrological characteristics and hydrodynamics (Ollis et al. 2013), which in turn determine the geomorphologic and alluvial processes that occur within a wetland. Soils may thus be key components in analysing wetland ecotones as wetlands sustain hydromorphic soils which are distinctly different to soil conditions in terrestrial habitats, and are influenced by varying periods of flooding (Ollis et al. 2013; Richards 2001). This mean that when studying wetland ecotones, vegetation composition along with soil and hydrological aspects need to be considered. Holland, Whigham and Gopal (1990) note that wetlands like all other ecosystems have internal and external boundaries that separate distinct vegetation patches, with various ecological processes and transfers occurring at these boundaries or ecotones. It can also be argued that wetlands as a component in the landscape may be regional-scale ecotones based on the wetland definition

(Republic of South Africa 1998) which recognize these ecosystems as land-water transitions: “land which is transitional between terrestrial and aquatic systems where the water table is usually at or near the surface, or the land is periodically covered with shallow water, and which land in normal circumstances supports or would support vegetation typically adapted to life in saturated soil”. One type of South African peatland, called palmiet wetlands are one of the most significant, yet highly threatened wetlands due to channel erosion, alien vegetation invasion, draining for agricultural land, and pollution from agricultural runoff (Rebelo, Emsens, et al. 2018). Palmiet wetlands are dominated by *Prionium serratum* (or *P. serratum*), an endemic and red list South African sedge-like shrub with deep, extensive root systems-that can go up to three meters deep in permanently inundated wetlands (Sieben, Mtshali & Janks 2014)- and which are argued to have stabilized river valleys within the Cape Floristic Region (CFR). Consequently, palmiet typically form unchannelled valley-bottom wetlands where peat beds accumulate (Job 2014). Valley-bottom wetlands, generally occur along a valley floor and are often linked to upstream or adjoining river channels (Ollis et al. 2013), are discontinuous and may have reaches that are both channelled and unchannelled (Grenfell et al. 2019).

For this study, internal (i.e. among community) wetland ecotones are of interest in an alluvial fan wetland dominated by dense *Prionium serratum* stands, and being embedded within a Fynbos system with alluvial channels that deposit and retain varying amounts of sediment, water, and organic material (Fischer et al. 2019; Snaddon et al. 2018). This study identifies four vegetation types in the wetland system namely *Prionium serratum* and *Psoralea pinnata* both of which fall within the palmiet (peat) wetland vegetation group; sclerophyllous wetland vegetation (i.e. wetland ferns, grasses and restios which frequently co-occur including, *Pteridium aquilinum*, *Merxmuellera cincta* and *Restio paniculatus*, henceforth termed SWV)*;* and Temporary Wetland Fynbos (species belonging to the endemic Cape Floristic Fynbos biome). Literature has noted that these fynbos embedded wetlands are often subject to the same environmental conditions as Fynbos vegetation that are prone to thriving in nutrient poor, well leached soils, and adapted to Mediterranean climate of the Western Cape with high rainfall winters and hot, dry summers (Rebelo et al. 2006; Sieben et al. 2017; Van Wilgen 1984). This chapter aimed to use probabilistic fuzzy classification to identify, map and characterize fine-scale, internal wetland ecotones in an alluvial fan fynbos embedded wetland.

4.3 STUDY AREA

The Du Toits River wetland is a dynamic alluvial fan wetland embedded between two Fynbos covered mountain slopes with a weakly channelled river (Fischer et al. 2019; Snaddon et al. 2018) that feeds and filters into the Theewaterskloof Dam. The Theewaterskloof Dam, located near the town of Villiersdorp in the Western Cape province of South Africa, has a capacity of 480 million m³ and surface area of 48 km² making it the seventh largest dam in South Africa (Musungu & Jacobs 2015). Locally, the dam is the largest in the Western Cape and is one of the main sources of water to the City of Cape Town (Fischer et al. 2019). Surrounding the dam, are three key wetlands namely the Du Toits River wetland, the Elandskloof wetland and the Vyeboom wetland where rain falling on the surrounding mountain catchment areas filters through these wetlands and then enters the dam, contributing to improving the water quality and regulating flow into the dam (Fischer et al. 2019). The Du Toits River wetland is driven by unique wetland-fynbos conditions induced by the underlying Table Mountain Group sandstone substrates, resulting in a heterogenous mosaic of palmiet wetland, sclerophyllous wetland, and Fynbos vegetation groups (Rebelo et al. 2017; Rebelo et al. 2015; Sieben et al. 2017). The Du Toits River wetland provides important regulating ecosystem services including sediment trapping (also referred to as erosion control), carbon storage, flood attenuation, phosphate and nitrate removal (Fischer et al. 2019; Rebelo et al. 2019; Snaddon et al. 2018) and water supply. Figure 4.1 below shows the four dominant vegetation types that are of interest for this chapter to map internal wetland ecotones.

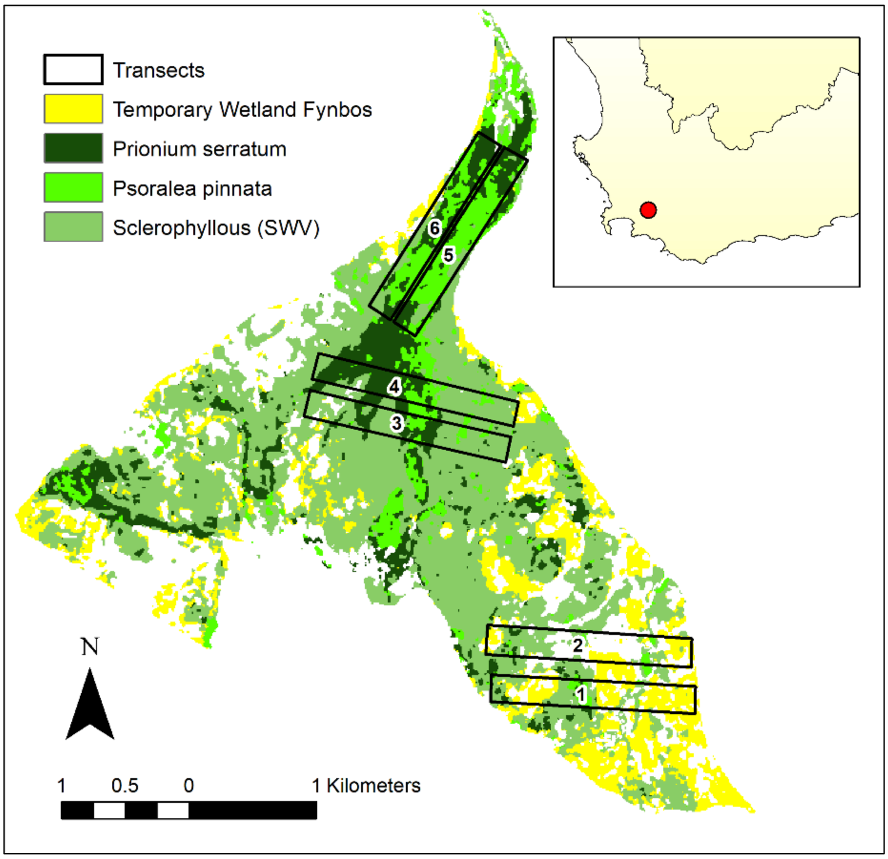


Figure 4.1 Classified image of the main landcover within the Du Toits River wetland. The four distinct vegetation zones established for vegetation analysis: *Prionium serratum*, *Psoralea pinnata* (i.e. palmiet wetland vegetation), *Pteridium aquilinum*, *Restio paniculatus*, *Merxmuellera cincta* (grouped as SWV) and Temporary Wetland Fynbos. The red dot in the insert map represents the location of the wetland within the Western Cape. Placement of transects are labelled 1, 2, 3,4, 5 and 6

4.4 METHODS

A supervised image classification approach, namely the class probability classifier was applied to a cloud-free Sentinel-2: MSI, Level-2A -with 10 metre spatial resolution-sourced from Google Earth Engine (GEE)- summer composite spanning the months December 2020, January 2021, and February 2021. This imagery deemed the best for identifying and classifying vegetation types within the Du Toits wetland as this period is after the growing season for wetland vegetation, and flowering season of some Fynbos species. Training data polygons were created in ArcMap using the training samples tool.

4.4.1 Class Probability Classification

In order to identify a suitable classifier to map ecotones within the wetland, relevant literature identified in the bibliometric search was reviewed as possible approaches for example, Ørka et al. (2012) used a binomial logistic regression approach to produce a probability map that was suitable for monitoring changes in the extent and location of a subalpine zone i.e. the transition between forest and alpine vegetation communities; Fedrigo et al. (2018) used a Random Forest (RF) model to produce high accuracy maps of stand type probability, which included areas of transition i.e. the ecotone between rainforest and eucalypt forest in south-east Australia . Additionally, Humphreys et al. (2017) used a "hierarchical modelling and Bayesian inference to predict the probability of wetland presence as a continuous gradient with the explicit consideration of spatial structure" thus identifying wetland extent, ecotones, and hydrological connections. Similarly, de Klerk, Burgess and Visser (2018) use a soft classifier Bayesian-based probability map to provide probability distribution over a set of classes where pixels are "assigned a strength of membership value for each class being mapped" (de Klerk, Burgess & Visser 2018, p.128).

This study followed de Klerk, Burgess & Visser (2018) in using a naïve Bayesian-based probability map to identify mixed pixels with varying probabilities as ecotones or ecotone pixels. The Naïve Bayes classification is a simple probabilistic classifier based on the Bayes' Theorem which assumes that there is independence between features, and determines the probability of a feature with prior knowledge and current evidence i.e. it depends on conditional probability (Zhang 2016). The Bayesian-based Class Probability algorithm was performed in ArcMap 10.7.1 where classification training and verification data polygons were generated for four distinct vegetation types i.e. *Prionium serratum* and *Psoralea pinnata* within Palmiet Wetland Vegetation (subtype-1), Sclerophyllous Wetland Vegetation hereafter termed SWV (subtype-2), and Temporary Wetland Fynbos. These vegetation types have been grouped distinctly based on vegetation and soils prevalent within these communities (Sieben 2012; Sieben et al. 2017) and field observations that took place during June 2021. *Prionium serratum* and *Psoralea pinnata* were grouped as wetland vegetation subtype-1, as soils were generally very wet with organic filled peat and sometimes clay. The SWV cluster comprised a grouping of *Pteridium aquilinum* (commonly known as Bracken fern), *Restio paniculatus*, and wetland grasses such as *Merxmuellera cincta* (Sieben, Mtshali & Janks 2014). These areas consisted of sandy, to sandy loam, damp but sometimes dry soil conditions and considered sclerophyllous wetland vegetation subtype-2. The Temporary Wetland Fynbos class comprised of all species belonging to the CFR Fynbos biome such as *Protea neriifolia*, *Berzelia abrotanoides*, *Leucadendron conicum*, *Leucadendron coniferum* and *Metalasia muricata* (Rebelo et al. 2006) where soils were generally dryer, harder and much more coarse.

4.4.2 Training Data, Accuracy Assessment and Transects

Training data polygons were captured and based on the points collected in field and GEE (Chapter 3 3.4.1.5). A total of 120 polygons were digitized and split using an 80/20 split where 80% was used as training data and 20% as testing data to yield training (96) and verification (24) polygons distributed randomly for each of the four vegetation classes. Standard accuracy metrics were performed for the Probability classified image in R (version 4.1.1) using the caret package (Kuhn 2008) where overall accuracy, kappa, producer's accuracy, and consumer's accuracy were considered in the form of a confusion matrix. Note that within the accuracy script, the code takes the highest probability of a cell belonging to one of the four vegetation types and uses a function to turn this probability layer into a binary layer. The confusion matrix was thus run on a binary classification output raster of the four vegetation layers based on the initial class probability classified raster produced in ArcMap (see APPENDIX F for the accuracy assessment code generated in R).

In order to illustrate the nature of internal wetland ecotones, six transects were digitized and placed subjectively in such a way that it covered parts of each of the four distinct vegetation types at a particular known gradient. As the wetland is quite small and narrow- especially at the head of the wetland, transect sizes were set to 1.6 km in length and 200 m width, as it was expected that species composition changed across a few (less than 10) meters. The transect size was further justified by the spatial resolution of imagery which is 10 m (Sentinel-2: MSI, Level-2A), where fine-scale ecotones across a few meters may be mapped and analysed. Transects were created with specific measurements to create graphs of how the vegetation class probabilities changed over space. Vegetation class probabilities were binned over the 200 m width every 50 m along the 1.6 km length (which gave 32 'readings' along a transect for the graphs). Transects 1 and 2 were placed in the lower eastern parts of the wetland where Sclerophyllous Wetland Vegetation and Temporary Wetland Fynbos conditions were dominant. Here, soils were dryer, coarser and had less organic matter present as observed in field. Transects 3 and 4 were focused on identifying ecotones between *Prionium serratum*, *Psoralea pinnata* (palmiet wetland vegetation) and SWV which may speak to the transition from 'pure' palmiet wetland to the dryer sclerophyllous wetland conditions. Transects generally run from east to west, except for Transect 5 and Transect 6 that were placed running north-south due to the narrow size of the head of the wetland, and east-west transects would cover areas not within the delineated study area. These two transects were focused on looking at the ecotones within the wetland vegetation (palmiet) group i.e. running through densely vegetated areas of *Prionium serratum* and *Psoralea pinnata* where deeper, wetter, and more peat organic soils were present.

4.5 RESULTS AND DISCUSSION

4.5.1 Probabilistic Classification

The class probability map (Figure 4.2) of the four vegetation types showed that *Prionium serratum* and *Psoralea pinnata* had high and dense probabilities of occurrence at the head of the wetland, where the main channel flows with inundated soils that are rich in organic material/sediment (*sensu* field observations). These two vegetation types also spread sporadically southward down the middle wetland channel with smaller plants such as *Zantedeschia aethiopica* underneath their dense canopies. *Prionium serratum* was also classified as occurring in patches further south-west and south-east of the wetland, which are likely where narrow tributary channels occur. The class SWV was classified as having high probabilities toward the middle sections abutting/surrounding the *Prionium serratum* and *Psoralea pinnata* (east and west edges), and also occurred towards the nearest edge (toe) of the wetland approaching the open dam water. Additionally, SWV was found abutting the outer Temporary Wetland Fynbos edges as the soils dry out in the transition from palmiet wetland to upland Temporary Wetland Fynbos vegetation. At a local scale within the wetland, the SWV group may be regarded as the transitional area from pure (peat) wetland conditions to the dryer, sandier Fynbos conditions. These areas have a mixture of damp or sometimes dry, and sandy to sandy loam soil conditions which are very different than in the pure palmiet wetland areas where *Prionium serratum* and *Psoralea pinnata* are found (deeper, wetter, peat accumulated soils). Temporary Wetland Fynbos vegetation were classified as having high probabilities towards the outer edges of the wetland boundary with distinct soil conditions (dryer, coarser, and sandier soils) than in the 'pure' palmiet wetland and sclerophyllous areas. In terms of colour representation on the map (Figure 4.2) where pixels are bright red there are high probabilities of *Prionium serratum*; bright greens are high probabilities of *Psoralea pinnata*; blues are high probabilities of SWV; and the medium sand colour represents high probabilities of Fynbos vegetation. Where there is mixed colouration, or very dark hues (sometimes black) of these colours, the ecotone pixel is presented as a mixed pixel.

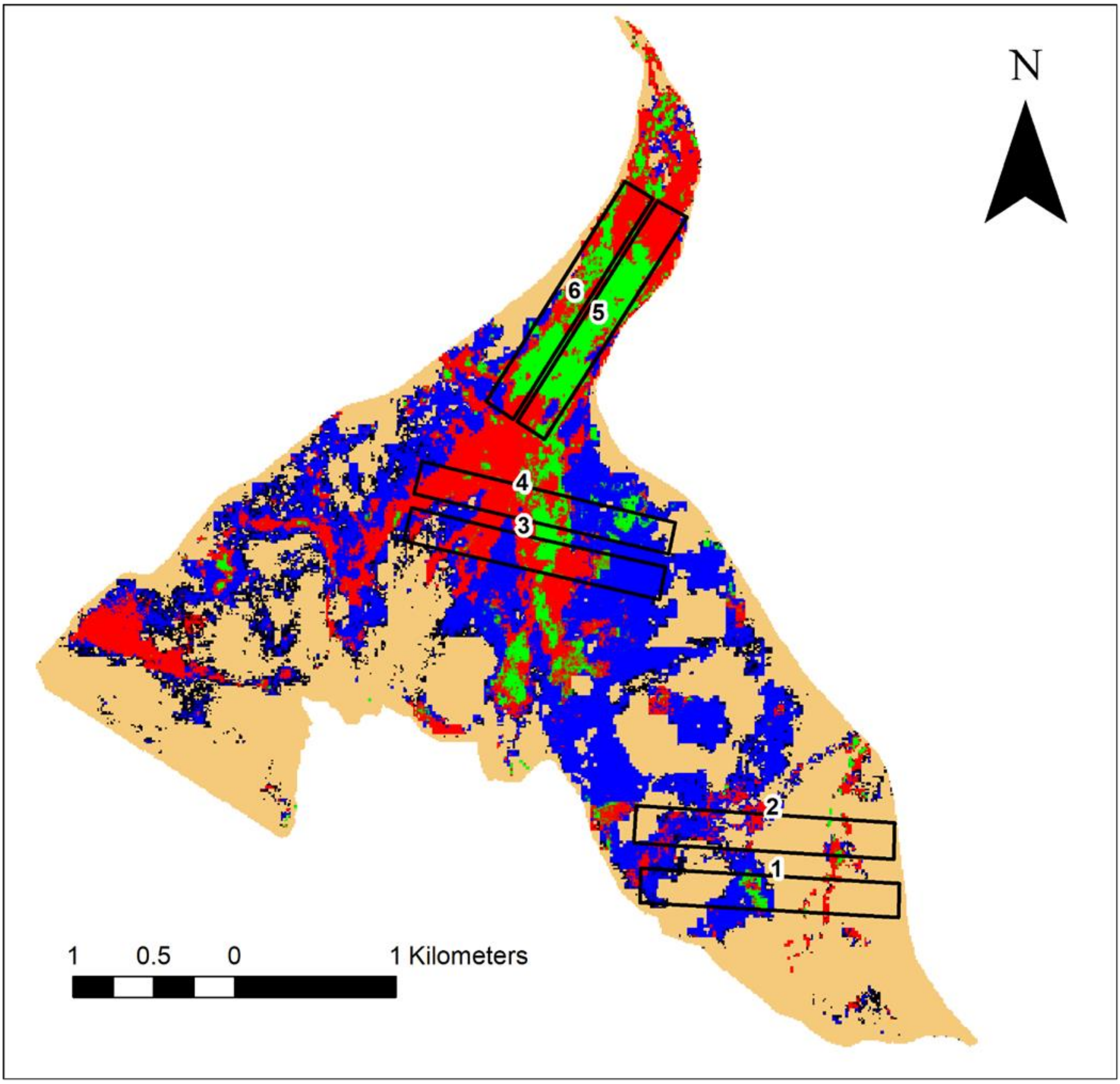


Figure 4.2 Class Probability value map (RGB) for the four distinct vegetation types in the Du Toits River Wetland i.e. *Prionium serratum* (red), *Psoralea pinnata* (green), SWV (blue) and Temporary Wetland Fynbos (medium sand) with transects outlined by black solid lines

When analysed closely, it is apparent in the probability map (Figure 4.2) that there are 'mixels' (mixed pixels) present which appear in hues that vary between the designated class colours. In remote sensing literature, mixed pixels are generally used in the context of being a problem of using coarser resolution data, and therefore being less sensitive to spatial complexity or heterogeneity (Rocchini 2007). However, in this study, mixed pixels are suggested to be a mixture of classes with varying probability values of at least two vegetation types (or more), leading to an ecotone pixel where there is a transition from one vegetation type to another over the space of a pixel width (10 m). This is concurrent with observations in the field. For example, if one checks the pixel values in the multi-layered raster with four band layers where each layer represents the probability of one of the four vegetation types being present, a pixel may have a 55% probability value for the red band (i.e. *Prionium serratum*) and a 44% probability value for the green band (i.e. *Psoralea pinnata*). This could mean that the specified pixel represents an ecotone that has high probabilities of both palmiet species present, with transitions occurring sharply and abruptly from *Prionium serratum* to *Psoralea pinnata* within the 10 m of Sentinel-2 pixel. Traditionally, in a binary classifier this would be regarded as an unresolved pixel, or that the spectral resolution is too coarse to provide a binary output of either vegetation types classified, thus the classifier might be struggling to distinguish between the two. Literature also notes that generally if the there is a decrease in spatial resolution, spectral heterogeneity is affected as these mixed pixels with varying probabilities threaten the capability of matching field heterogeneity with spectral heterogeneity (Rocchini 2007). However, this research suggests that the probabilistic approach supports what was seen in field, which is that species can co-occur within the frame of coarse spatial resolution data and can also change rapidly within the same geographical space as a rapid turnover, over a very fine spatial scale i.e. an ecotone pixel. Another example that demonstrates this argument is a pixel that included probability values for all four classified bands i.e., SWV (Blue) = 4%, *Psoralea pinnata* (Green) = 43%, *Prionium serratum* (Red) = 50% and Temporary Wetland Fynbos (Medium sand) = 2%. This example indicates high probabilities of palmiet wetland conditions, indicating rapid turnover between these two distinct palmiet wetland vegetation types. The probability classified map also indicates that the ecotones are two-dimensional, covering the extent of a pixel (10 m), defined by medium grain size (Strayer et al. 2003), and occurring as spatially disjunct patches between the four classified vegetation types. Ecotones in this alluvial fan, fynbos embedded wetland are patchy, narrow, generally sharp and abrupt which leads to nonlinear behaviour, emphasizing that these transitions are ecotones in the strict sense (di Castri, Hansen & Naiman 1988).

4.5.2 Accuracy Assessment

Standard accuracy measurements of the classification output were conducted in R (using the caret package) in order to verify the classified map with what was observed in field. Table 4.1 below provides a confusion matrix of the classified map which shows that the classifier had an 82.7% overall accuracy and a kappa of 0.77, which is a very good accuracy (Monserud & Leemans 1992). High producer's and consumer's accuracy (94-98%) together with low errors of omission and commission for *Prionium serratum* and *Psoralea pinnata* (2-5.8%), show that these two palmiet wetland vegetation classes are well separated in the probability classification. However there is some spectral confusion between the sclerophyllous wetland and Fynbos classes with around 50% of fynbos reference data being misclassified as sclerophyllous wetland. This might be due to species such as *Pteridium aquilinum* and *Restio paniculatus* having similar structural composition and growth forms as upland fynbos vegetation (Sieben 2014), resulting in the spectral reflectance and backscatter of these communities to a satellite being similar.

Table 4.1 Confusion matrix with accuracy metrics for the four vegetation classes, Class Probability classifier using Sentinel-2 MSI: MultiSpectral Instrument, Level-2A summer 2020/2021 imagery (Figure 4.2)

		Classified data						
		Prionium serratum	*Psoralea pinnata*	SWV	Temporary Wetland Fynbos	**Row Totals**	**EO %**	**PA %**
Reference data	*Prionium serratum*	98	2	4	0	**104**	5.8	94.2
	Psoralea pinnata	2	98	0	2	**102**	3.9	96.1
	SWV	0	0	44	7	**51**	13.7	86.3
	Temporary Wetland Fynbos	0	0	52	91	**143**	36.4	63.6
	Column Totals	**100**	**100**	**100**	**100**	**400 (TP)**		
	EC %	2	2	56	9			
	CA %	98	98	44	91			
	Overall Accuracy %:	82.75						
	Kappa:	0.77						

EO= Errors of omission; PA= Producer's accuracy; EC= Errors of commission; CA= Consumer's accuracy; TP=Total pixels

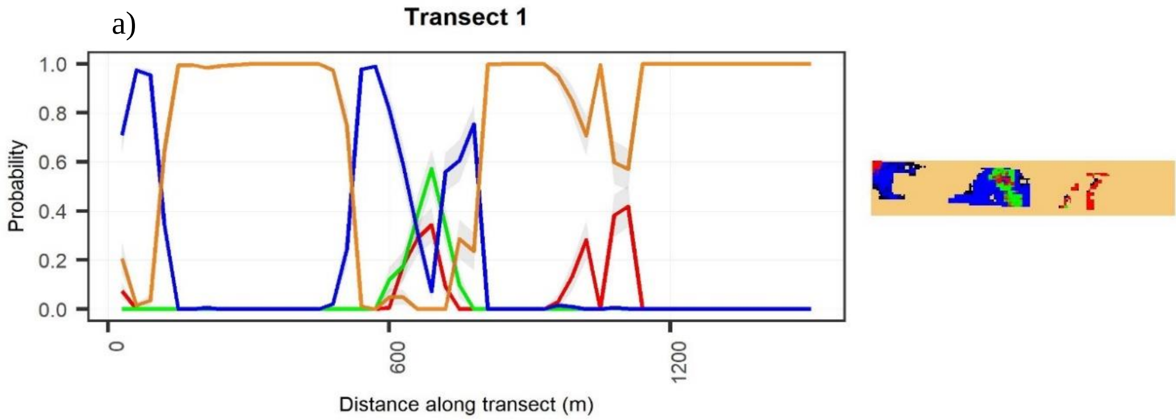
4.5.3 Probabilistic Ecotone Mapping

If one looks at the corresponding probability fuzzy graphs (Figure 4.3, see APPENDIX G for the code developed to generate the graphs), one can see how the lines of probability for the different vegetation type 'switch' dominance over the length of the transect for each of the transects identified.

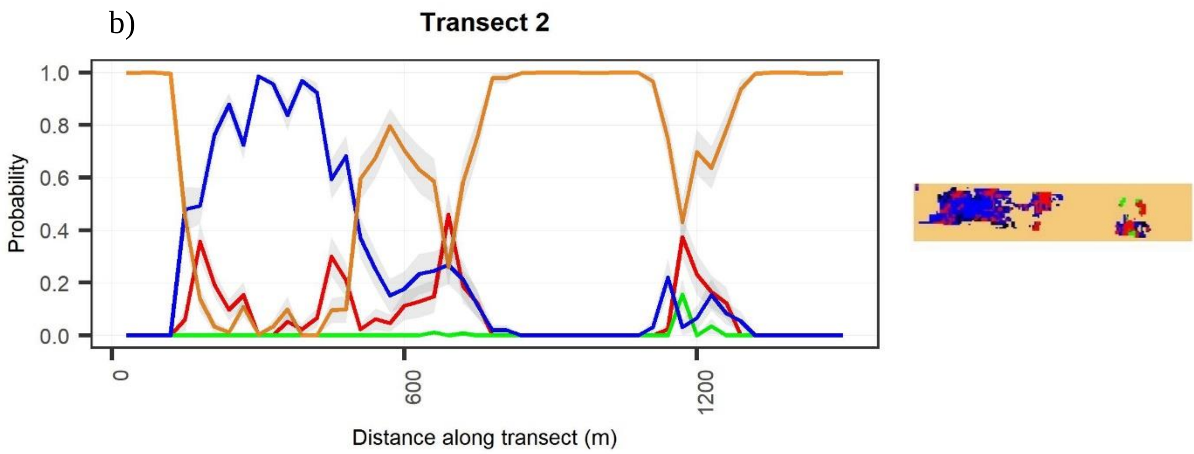
Transect 1 (Figure 4.3 a) which was placed in the far south-eastern corner of the wetland to focus on the sclerophyllous vegetation and Temporary Wetland Fynbos dominated areas, showed high probability values for fynbos vegetation as expected. At the western-most point of the transect, the graph shows little to no values probability values for *P. serratum* and *P. pinnata*, which then abruptly transitions into a few hundred meters of high probabilities of palmiet wetland occurrence at approximately 500-800 m of the transect. One must thus consider that this may be an area with hidden channels and tributaries resulting in spatial shifts, different elevations, water levels and peat soils present (Kark 2005). Field observations support this argument as it was evident that there were some narrow, hidden channels within the wetland. While walking in Fynbos dominated areas, one would easily step from dry Temporary Wetland Fynbos mini-slopes into sudden deep inundated channels filled with tall grasses and restios. Occasionally, single patches of randomly dispersed *Prionium serratum* was present. This reinforces and validates what the graphs present which is that species turnover occurs rapidly, and within a few metres' dominant vegetation zones transition/change rapidly and abruptly, speaking to spatial heterogeneity.

In the same geographical space i.e. Transect 2 (Figure 4.3 b), the transitions between Sclerophyllous Wetland Vegetation and Temporary Wetland Fynbos are much more complex and convoluted with varying probability values highlighting that these two types of vegetation transition far into the other. This may be due to these vegetation types having similar structural properties (Sieben, Mtshali & Janks 2014). Similar to Transect 1, the fuzzy graph for Transect 2 also shows a moderate coverage of *Prionium serratum* from the western side of the transect mixed with high, and then lower probabilities of sclerophyllous wetland, and higher occurrence of Fynbos vegetation again in the east. This suggests the idea that there may be hidden channels and tributaries which support wetland vegetation, which have changed the drier, coarser soils of the Fynbos to the wetter sandy, to sandy loam soils of the sclerophyllous vegetation. This indicates ecosystem processes of sediment shifting that will lead to a change in vegetation types.

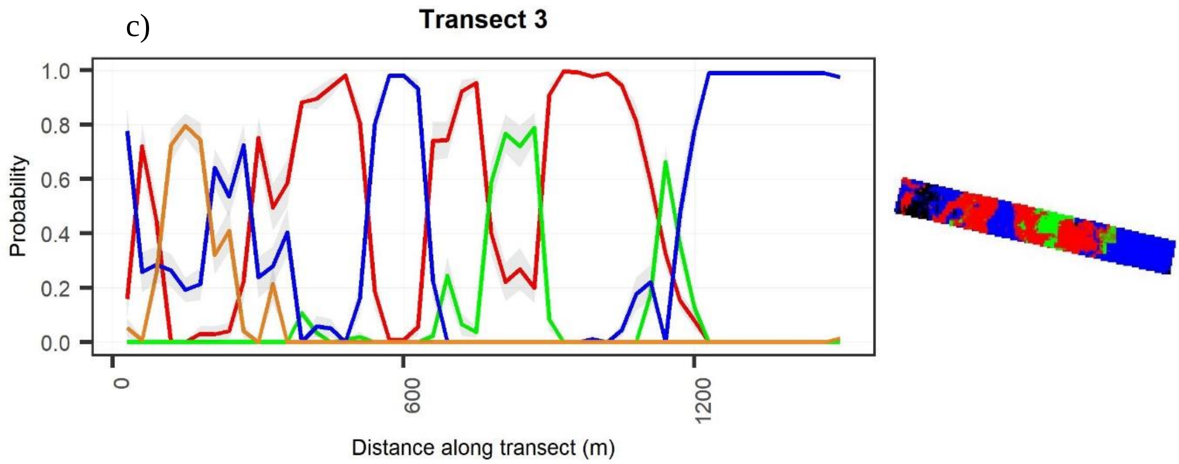
a)


Transect 1
Probability
1.0
0.8
0.6
0.4
0.2
0.0
0
600
1200
Distance along transect (m)

b)


Transect 2
Probability
1.0
0.8
0.6
0.4
0.2
0.0
0
600
1200
Distance along transect (m)

c)


Transect 3
Probability
1.0
0.8
0.6
0.4
0.2
0.0
0
600
1200
Distance along transect (m)

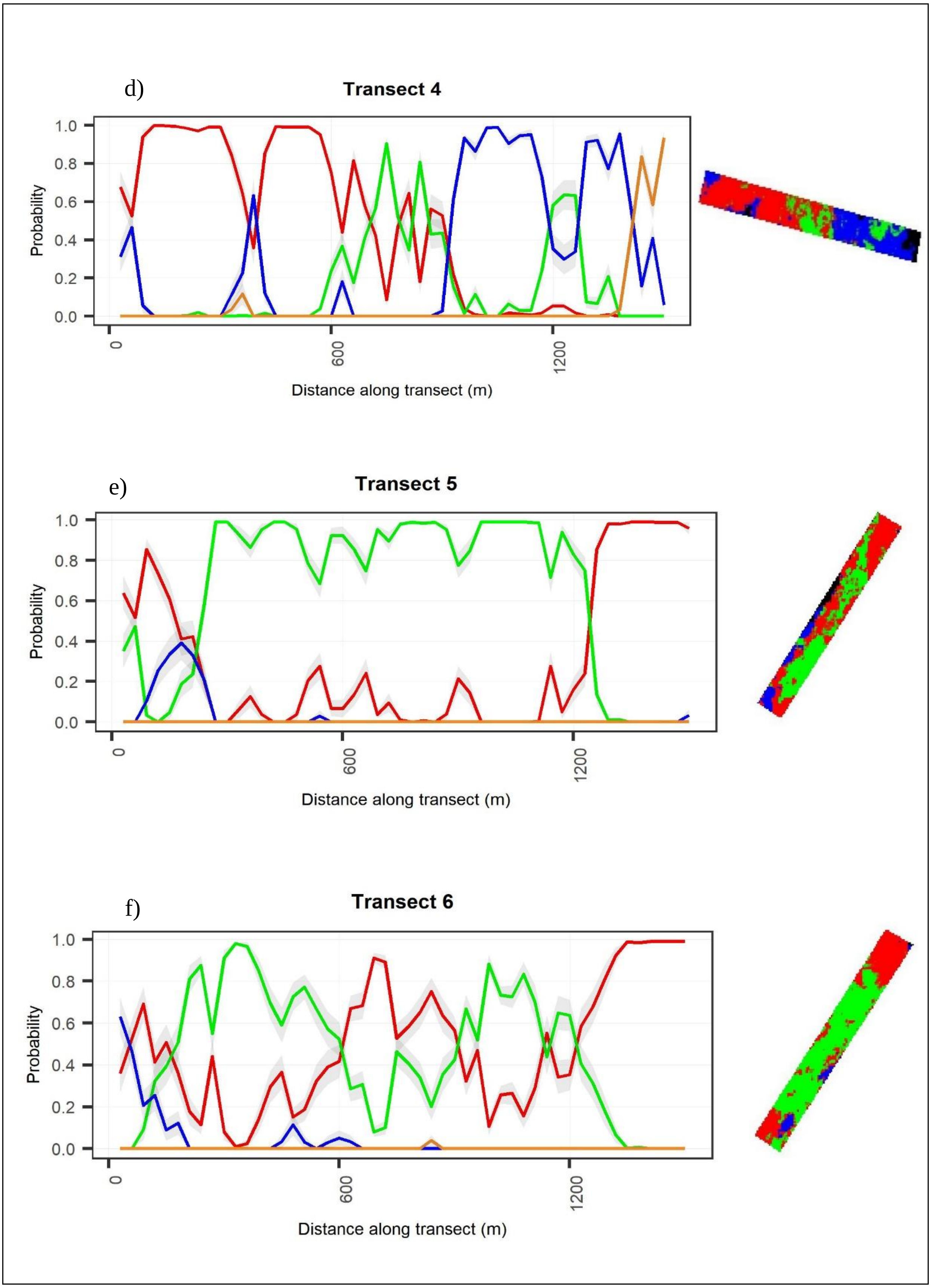


Figure 4.3 Probabilistic graphs (right) and associated map transects (left) of probability values for *Prionium serratum* (red), *Psoralea pinnata* (green), SWV (blue) and Temporary Wetland Fynbos (medium sand). For the graphs, class colours coincide with colours of the probability map in Figure 4.2. Values are binned at 50 m intervals over the 1600 m transect length. Ecotone pixels or 'mixed pixels' are displayed as varying saturated pixels within transects

Transect 3 (Figure 4.3 c) and Transect 4 (Figure 4.3 d) were placed in areas covering all four vegetation types but dominated by large patches of SWV (noted from field observations). In Transect 3, the graph supports this observation with high probability values for SWV and Temporary Wetland Fynbos in the western point of the transect. Additionally, transitions in this transect show different patterns along the transect length where there is a slow transition from high *Prionium serratum* values into low values for SWV, with a sudden abrupt and sharp transition into *Psoralea pinnata*, gradually then moving back into high probabilities of SWV. The graph displays an almost rippling effect where there is an intricate range of sharp changes between *Prionium serratum*, SWV and Temporary Wetland Fynbos between 0-300 m of the transect length. There are moderate occurrences of Temporary Wetland Fynbos around 20-400 m, and no occurrence approaching the eastern most point. Transect 4 on the other hand shows very low probability values for Temporary Wetland Fynbos with a sudden increased occurrence at approximately 1500 m of the transect. There are higher occurrences of palmiet wetland vegetation within this transect, transitioning abruptly into SWV for another couple of hundred meters where it then transitions abruptly back into high Fynbos areas with patches of *Psoralea pinnata* in between. This might be due to 'sediment islands' occurring between meandering alluvial channels.

The classified map and associated fuzzy graphs suggest that the transitions between and within wetland vegetation i.e. *Prionium serratum* and *Psoralea pinnata*, are abrupt with high probability values for either of the two vegetation types. This is most prominent in the main wetland channel (northern area of the wetland in (Figure 4.2) where ecotone pixels occur over a number of pixels (the mixed green and red pixels in Transect 5 and Transect 6). Transect 5 (Figure 4.3 e) shows an abrupt line of transition from high probabilities of *Prionium serratum* to higher probabilities of *Psoralea pinnata* across the length of the transect. At approximately 1500 m this changes rapidly from high *Psoralea pinnata* occurrence into abrupt high occurrence of *Prionium serratum*. Where another vegetation type such as the sclerophyllous class intersects (at approximately 100-200 m), a sudden island of sclerophyllous conditions is present followed by very high probabilities of *Psoralea pinnata*. This may be an indication that wetland species such as *P. serratum* and *P. pinnata* are clustering wetland vegetation types that often cause monodomination in a system (Gallant 2015) and spatially compete with smaller, finer wetland vegetation species. Soils in the palmiet wetland areas are distinctly different with a layer of damp, accumulated peat generally forming due to decaying animal and plant matter (Job 2014) which may account for the low probability value of Temporary Wetland Fynbos vegetation within this transect (Fynbos in general may likely not survive in these permanently wet and peat conditions). Transect 6 (Figure 4.3 f), occurring in the same geographical space as Transect 5 where palmiet wetland vegetation is dominant, show similar ecotonal conditions for the wetland group. Here the graph shows relatively high probabilities for both palmiet wetland vegetation types interchanging across the transect with low occurrences of sclerophyllous wetland vegetation. These interchanging inferences may be related to the main channel being deepest in Transect 5, possibly resulting in higher erosion control, sediment trapping and increased accumulation of peat than in adjacent areas.

Wetlands, like any other ecosystems have ecological boundaries (internal and external) that distinctly separate vegetation patches which in some cases can be clearly delineated, while for others it can be difficult to distinguish where one patch ends and the other begins (Holland, Whigham & Gopal 1990). This is partly true for the Du Toits River wetland where internal ecotones are quite complex but can be delineated, as the mixed pixels have shown. *Prionium serratum* and *Psoralea pinnata* have quite distinct spectral properties that distinguish them from other vegetation and thus making a clear distinction between Palmiet Wetland Vegetation, Sclerophyllous Wetland Vegetation and Temporary Wetland Fynbos communities. Holland, Whigham and Gopal (1990) refer to these types of transitions as wetland-wetland ecotones where there could be surficial or diffuse flow transfers across vegetation zones with each zone dominated by a specific species. This study therefore suggests that ecotonal areas in the wetland may have distinct hydrological and sedimentary properties due to their varying probabilities of comprising at least two vegetation types, which may be different to the conditions in areas with low species diversity and is dominated by one vegetation community. This in turn may affect the ecosystem services that this palmiet wetland system provides such as water flow regulation (i.e. storage and flood attenuation), climate regulation (i.e. carbon storage, energy exchange), and water quality regulation (i.e. retention/removal of excess nutrients or pollutants, and biogeochemical transformations) (Rebelo et al. 2019). For instance, flood attenuation and sediment trapping (and peat accumulation) properties may be entirely different in the palmiet wetland vegetated areas due to the extensive root systems of *Prionium serratum*, than in the sclerophyllous and fynbos areas where smaller and finer plants belonging to these communities may not be able to efficiently attenuate flows or trap sediment.

As hydrology is considered the primary driving force in wetlands, hydrologic conditions and changes affect the biotic and abiotic characteristics in a wetland such as salinity, nutrient availability, and soil anaerobiosis as well as the vegetation type found (Holland, Whigham & Gopal 1990; Tiner 1999). Wetland conditions in this palmiet dominated alluvial fan wetland may be affected by a number of factors including the velocity of flow in the channel and smaller streams, the direction of flow, and the zones of vegetation and their associated ecotones through which it flows. In the case of a high flooding period, water may move across the ecotones between palmiet wetland and sclerophyllous wetland or temporary wetland fynbos potentially causing changes in the regulating ecosystem services such as water flow regulation, erosion control or sediment trapping as it would be affected by the properties these wetland ecotones encompass. To understand these distinct properties, appropriate *in situ* water flow and quality, sedimentary, and nutrient measurements or observations must be done to corroborate this presumption. Wetland ecotones may also act as important buffering capacities in a landscape by regulating and reducing water flows through the wetland by slowing down overland runoff, soaking and storing rainwater to replenish the groundwater table, help bind soil together and reduce soil erosion, and helping with intercepting and trapping sediment and silt from land runoff thus filtering and purifying water flowing through the wetland (Richards 2001).

4.6 CONCLUSION

It has been established by this research that probabilistic per-pixel approaches to mapping complex wetland ecotones can advance the understanding of the structure and functioning of wetlands. Transect graphs highlight the efficacy of probability maps and per-pixel approaches to map and understand fine-scale ecotones in a heterogenous landscape where there are abrupt changes in dominance of vegetation. Mapping ecotones, with associated fuzzy (probability) graphs, as fuzzy mixed pixels provide opportunity for recognizing sharp, abrupt, and narrow ecotones at sub-pixel scale, where single lines and vector maps may disregard rapid species turnovers. Distinct, spatially disjunct, ecotones are represented by the saturated pixels in the probability map and where graphs show high probabilities of one vegetation type intersecting and changing rapidly into another. The probability maps and graphs effectively highlight the complexity of the transitions from one dominant vegetation type to another. In this study, palmiet wetland vegetation, namely Prionium serratum and Psoralea pinnata, although embedded within a fynbos system, have proven to be a dominating vegetation within the wetland, that often completely take over a wetland system leading to monodomination. This monodomination may increase regulating ecosystem services through sediment trapping, carbon storage and flood attenuation.

The methodology used in this paper to map ecotones in wetlands facilitate the understanding of the interaction between vegetation, hydrology, and soil. The flow of materials across the ecotones may be affected by these three components. This relates back to the definition of an ecotone by Holland (1988) who emphasizes that ecotones are characterized by space and time scales and by the strength of the interactions between adjacent ecological systems- adjacent systems being the two wetland vegetation subtypes and fynbos conditions. This probability, per-pixel approach may be useful in wetland conservation and management plans where time and funds are limited for the comprehensive field mapping of different wetland vegetation types and their ecotones, all of which are necessary to understand wetland functioning, spatial layout and how these factors affect prioritisation and management strategies of wetlands. The method of this research can provide additional metadata in wetland inventories offering valuable information relating to wetland formation, processes, and ecosystem services. Moreover, results provided insight into spatial heterogeneity and landscape mosaics where wetlands in the Cape Floristic Region are typically diverse and dynamic in species composition. Ultimately, the method demonstrated that variations in ecotones are due to varying density and diversity in palmiet wetland, sclerophyllous wetland, and fynbos vegetation communities occurring at different gradients and hydrogeomorphic units in the wetland.

CHAPTER 5: DISCUSSION AND CONCLUSION

This chapter presents a summary and critical review of all the findings of this study, especially pertaining to the experiments performed in Chapter 3 and Chapter 4. The aims and objectives are revisited and discussed in the context of the real-world problem being addressed and how this study contributes to existing knowledge of wetland ecotones and mapping. Limitations of the study and future research recommendations are provided, and conclusions are drawn.

5.1 REFLECTION OF RESEARCH AIMS AND OBJECTIVES

The overall aim of this study was to identify and use Remote Sensing (RS) approaches to efficiently map and characterize ecotones in an alluvial fan Fynbos embedded wetland. In order to achieve the overall aim of the study, five objectives were set. The first objective was to review literature to develop a definition of wetland ecotones and in this, identify literature that provide suggestions on potential remote sensing methods to map wetland ecotones. In essence, this first objective made up Chapter 2 of the study, namely the literature review. A bibliometric search and analysis conducted through Scopus, highlighted that limited research has been conducted on mapping wetland ecotones with most literature focusing on the aspect of change or transition (i.e. ecotones) between various types of biomes. The review however provided useful and comprehensive literature -local and global- that covered wetland mapping, whether it be mapping wetland extent and delineation, or the mapping of wetland vegetation. Therefore, a detailed account of wetland classification, vegetation and soils in South Africa, and the mapping thereof was reviewed and discussed in Chapter 2. The bibliometric search also aimed to identify literature that use probability mapping techniques to map ecotones, and to see whether these methods can be useful for all ecosystem types, including wetlands (aquatic-terrestrial systems) which resulted in a limited number of studies being identified (Fedrigo et al. 2018; Humphreys et al. 2017; de Klerk, Burgess & Visser 2018; Hans Ole Ørka et al. 2012; Vitali et al. 2019). The overall literature review provides a discussion of the principles of remote sensing and the various theories and methods behind image classification and per-pixel mapping approaches commonly used to detect and map ecotones or transitions in a landscape.

The second objective of the study, which was to report on the ecology, geomorphology, and to provide an overview of study area, ultimately formed a part of Chapter 3 where the study area was defined. This objective was necessary to get a deeper understanding of what type of wetland the Du Toits River wetland is, and to report on (based on literature) the vegetation, soil and hydrology of the wetland which ultimately guided the landcover classification conducted later in the chapter. Similarly, as part of the methods of Chapter 3, the third objective was to develop a sampling scheme and collect field data to identify indicators of palmiet wetland vegetation, sclerophyllous wetland vegetation and temporary wetland fynbos species. Again, this contributed to deeper understanding and verification information to supplement the landcover classification results produced later in the chapter. The fourth objective was to apply a Machine Learning (ML) approach to map vegetation cover in the wetland by means of supervised classification methods. The classifiers identified and attempted were Maximum Likelihood (as a robust technique, even though it is not a ML algorithm) and Random Forest, where the Random Forest generated in R provided robust results with high classification accuracies and effectively mapped distinct vegetation in the wetland. The Maximum Likelihood classification was not used in the final version of the research as it only provided a basis and feel for what the outcome of results potentially would be. These results highlighted the importance of the distinction between *Prionium serratum* and *Psoralea pinnata* vegetation classes within the palmiet wetland vegetation type. It is not often recognised that palmiet wetlands may consist of two distinct, closely co-occurring, and dominant vegetation types. Palmiet wetlands in South Africa are usually recognized by the presence of the renowned palmiet vegetation i.e. *Prionium serratum*, where this research has shown that *Psoralea pinnata* may also play an important role in peatland wetlands.

The fifth and final objective of this study was to test a per-pixel approach using a soft, probabilistic (fuzzy) classification to identify, map, and characterize wetland ecotones in the Du Toits River wetland. This was the main method adopted for Chapter 4. This objective was guided by the findings of Chapter 3 where the classification and *in situ* data offered comprehensive details on vegetation cover and what ecotones may be presented as in the wetland. The mapping of levels of saturation in colour representing the degree of probability of each of the four main vegetation types, together with the probability graphs for these vegetation types over six transects, demonstrated the ability to map and explain ecotones within the palmiet wetland, as well as between the palmiet wetland, sclerophyllous wetland vegetation and fynbos. The novelty in this study- specifically objective 5- is that although existing remote sensing techniques were used, this study showcased the efficacy of both binary and non-binary classification methods use in image classification of a heterogenous landscape. That is, that both these approaches were able to distinctly identify and map ecotones and patches in a wetland embedded within a Fynbos system, ultimately highlighting the efficacy of using RS to map and monitor heterogenous landscapes.

5.2 FINDINGS OF EFFICIENT RS TECHNIQUES TO MAP WETLAND ECOTONES

The two main experiments that were conducted for this study are comprised of Chapter 3 and Chapter 4. This section highlights the key findings for each chapter and an evaluation thereof. Chapter 3 titled "Remote Sensing of Spatial Heterogenous Landscapes- Landcover Classification of a Fynbos embedded wetland" showed that multispectral supervised classification methods namely Random Forest provided robust results and presented great promise in spectrally discriminating distinct vegetation within the Du Toits River wetland. Landsat 8 (30 m resolution) data and Sentinel-2 MSI: MultiSpectral Instrument, Level-2A (10 m resolution) was initially used. Four distinct vegetation groups were classified with high accuracies i.e., *Prionium serratum, Psoralea pinnata*, wetland ferns, grasses and restios (i.e., *Pteridium aquilinum, Restio paniculatus* and *Merxmuellera cincta*-grouped as Sclerophyllous Wetland Vegetation), and Temporary Wetland Fynbos along with three additional landcover classes namely Bare soil/sandstone, Degraded vegetation, and Water. This classification ultimately served as the first step in identifying internal wetland ecotones in a heterogeneous ecosystem (for chapter 4). Additional spectral indices such as the Modified Normalized Difference Water Index (MNDWI) and Normalized Difference Vegetation Index (NDVI) were included to corroborate the classification results and to set the context of the hydrology and vegetation composition in the wetland. Spectral signature graphs were additionally used to analyze and understand the spectral reflectance of classes at various wavelengths (bands) of the electromagnetic spectrum. This close analysis and continuous observation of imagery and how different vegetation types appear on imagery also provided the researcher with an accustomed eye for identifying palmiet wetland vegetation in a landscape. The methods of this chapter may also add valuable knowledge contribution for the teams who are involved in mapping and updating the National Wetland Inventory of South Africa (as highlighted in Chapter 2).

Chapter 4 titled “Remote Sensing of Wetland Ecotones” highlighted that a probabilistic classification (per-pixel) approach was able to map complex wetland ecotones between palmiet wetland vegetation, sclerophyllous wetland vegetation, and temporary wetland fynbos. Ecotones identified were generally sharp, narrow, and abrupt, and were represented as 'mixed pixels'. Traditionally, binary classifiers can only support or deal with binary outputs and see mixed pixels (or ‘mixels’) as an unresolved pixel. However, this probabilistic approach supported what was observed in field, which was that species turnover or 'change' can occur rapidly and be mapped within the medium resolution (10 m) of Sentinel-2 MSI: MultiSpectral Instrument, Level 2-A imagery. Therefore, mixels were not used in a traditional Remote Sensing meaning, but rather that mixels were areas of rapid species turnover. Ultimately, wetland ecotones were identified as patchy, narrow, abrupt, and spatially disjunct. Additionally, these ecotones were highlighted as useful in wetland mapping such as national or regional wetland inventories by providing valuable additional insight or metadata in relation to understanding wetland formation, processes, and ecosystem services. The methods and software’s used throughout this study were mainly free, open-source such Google Earth Engine, R, Quantum GIS (QGIS), and ArcMap (which is not open-source) and can easily be adopted or replicated. This reiterates the efficacy of using Remote Sensing as time, cost, and labour efficient means of mapping and monitoring heterogenous wetlands.

5.3 LIMITATIONS AND FUTURE RESEARCH RECOMMENDATIONS

One of the main limitations experienced in this research was the conditions or terrain of the study area where sampling was a challenge in deeply vegetated areas at the head of the wetland. The clusters of dense *Prionium serratum* and *Psoralea pinnata* stands were difficult to get through and not always safe as one could not see the depth of inundation. Therefore the first recommendation for future research would be to acquire a drone and use this to take photographs in the non-accessible areas as a means of quadrat sampling. Another limitation to sampling and ground-truthing in the western areas of the wetland was restricted by means of a locked gate at the head of the wetland. The gate limits access to the public by CapeNature, and in future the area manager of the Hottentots-Holland Reserve could be contacted or asked for assistance with accessing that area of the wetland. As highlighted in the results of both Chapter 3 and Chapter 4, Sentinel-2 imagery with a 10 m spectral resolution was able to map rapid species turnover with 10 m pixels as the study area was relatively small so the imagery suited the purpose. However, higher resolution imagery with even finer spatial resolution than 10 m may be considered for larger wetland areas. Chapter 4 has highlighted that wetland ecotones may be sites where unique wetland processes and ecosystem services may occur. Hence, although the main purpose of this study was to identify and map wetland ecotones, the results of this study can be used in further research to identify where these ecotones or mixed pixels are located, and ultimately can be sampled to physically understand what is happening in the field in these areas. Accuracy assessments in Chapter 3 and 4 analyzed accuracy metrics such as errors of commission and omission, overall accuracy, producer, and consumer's accuracy, and kappa. In future, the approaches of Pontius & Millones (2011) who suggest the use of quantity disagreement and allocation disagreement may be considered instead.

5.4 CONCLUSION

Remote Sensing has over the years proven to be a valuable means of monitoring the Earth in all its chaos and glory. This study added a valuable piece of information in the knowledge generation and community of Remote Sensing, as well as the wetland community. Emphasis was placed on identifying efficient methods for mapping landcover in a heterogenous wetland, and its associated ecotones. From the experiments explored in this thesis, a real-world problem, namely, to efficiently map wetland ecotones which is an understudied research niche was addressed.

Random Forest performed well using medium resolution data such as Landsat-8 and Sentinel-2, consistently displaying the spread of palmiet wetland vegetation distinctly across both datasets. Ecotones within the wetland are complex and essentially speak to spatial heterogeneity and its effect on landscape processes. Identifying and mapping ecotones is the first step to understanding ecological boundaries and patch metrics. Moreover, wetlands-and their associated ecotones-which are seen as moving entities in a landscape due to their varying hydroperiod conditions were efficiently mapped and overall, this wetland appears to be an interesting area to study natural communities in landscape ecology. Looking back on the three guiding principles when defining wetland ecotones, especially in the context of this thesis as noted in Chapter 2 namely,

1. At which point is there a change from terrestrial or upland fynbos habitat to wetland habitat?
2. Which factors will determine this change: is it hydrology, soil, vegetation or all three combined?
3. Based on its definition, is a wetland therefore itself simply the ecotone between land and water? Or can ecotones exist within a wetland and how?

It can be concluded that this study highlighted that ecotones or the point of change occurred where there was a rapid turnover from one vegetation type to another within the four wetland vegetation types identified and classified. The study also suggests that the wetland itself could be a complex ecotone or zone of transition between two fynbos mountain slopes, and with spatially disjunct internal (i.e. among community) ecotones within the wetland. Ultimately, results provided a good basis for further research on understanding wetland ecotones properties and the mapping thereof.

37 041 words

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APPENDIX A

Herbaceous vegetation of South African wetlands as described by Ollis et al. (2013):

Geophytes:	"non-woody plants, generally less than 2 m tall, that propagate by underground storage organs (i.e. bulbs, tubers, corms, rhizomes, or stolon's)".
Grasses:	"tuft-forming or creeping non-woody plants without brightly coloured flowering parts and with leaves that consist of three parts: leaf blade, leaf sheath and ligule (membrane or ring of hairs found between leaf blade and leaf sheath)".
Herbs/Forbs:	"non-woody flowering plants, generally less than 2 m tall, which are not sedges, rushes, reeds, restios, palmiet or geophytes".
Sedges:	"stiff, grass-like plants of the family Cyperaceae, sometimes referred to as 'nutgrasses'. Sedges are distinguished from grasses in that they generally do not have a leaf sheath (their leaves are attached directly to the culm or stem), or when they do, it is closed around the culm, whereas grasses have an open leaf sheath. The culms of many (but not all) sedges are triangular in cross section, while the culms of grasses are always cylindrical".
Rushes:	"stiff, non-woody plants of the genus Juncus, which grow in tufts of cylindrical unbranched stems with flowering parts branching off to the side of the stem near the apex. The so-called bulrush, *Typha capensis*, is usually considered to be a reed, not a rush".
Reeds:	"tall (up to 3 m), unbranched plants with stiff (semi-woody) stems or long, relatively stiff leaves, which generally grow at the water's edge with their roots submerged in water or saturated soil. *Phragmites australis* (common reed) is an example of a typical reed, with the stiff-leaved bulrush or cattail (*Typha capensis*) also considered to be a reed".
Restios	"plants of the family Restionaceae, which have very small leaves consisting only of scale-like sheathes that envelope the culms or stems; the sheaths are often brown, and the culms or stems green. Restios grow predominantly in the southwestern Cape, where they constitute one of the three main elements of Fynbos vegetation (the other two elements being proteas and ericas)".
Palmiet	"leafy *Prionium serratum* plants, commonly associated with rivers and valley-bottom wetlands. Palmiet tends to dominate systems, forming dense stands. It is a robust shrub with semi-woody stems. It produces a large root mass and deep rooting system able to grow through recently deposited sandy sediments and stabilise them".

Source Ollis et al. (2013, p.60)

APPENDIX B

The National Wetland Vegetation Database describing plants belonging to the Sclerophyllous Wetland Vegetation cluster group as described by Sieben, Mtshali & Janks (2014, pp.32–38):

Main Cluster 1: Sclerophyllous wetland vegetation communities (Sieben, Mtshali & Janks 2014)				
Veg type no.	**Community:**	**Description:**	**Indicator species:**	**Location:**
1	*Calopsis paniculata*	"commonly associated with riverine wetlands at the foothills of the Western Cape. It can occur both in monocultures as well as mixed with other species. It occurs on relatively fine-grained substrates. It mostly occurs in the Western Cape, but it has been recorded in the Southern Cape as well, where it is often also replaced by another restio, *Platycaulos callistachyos* in communities such as Community 1.5 *Cliffortia graminea* Community".	*Calopsis paniculata*	Western Cape, Eastern Cape
2	*Cliffortia strobilifera*	"associated with riverine wetlands of the Western Cape. This is a woody shrub that can become quite tall and can in that case also achieve mono-dominance. It is often co-occurring with Palmiet and *Calopsis paniculate"*.	*Cliffortia strobilifera*	Western Cape, Limpopo
3	*Cliffortia ferruginea – Merxmuellera cincta*	"restricted mainly to the Southern Cape, although the species *Cliffortia ferruginea* in some cases has also been found in the Agulhas plain and even on the Cape flats. This species can become quite weedy and starts dominating quite quickly and it even occurs together with some pioneer species in mown places next to roads in the Eastern Cape. This community might represent actually various communities and it is worth sampling in more detail".	*Cliffortia ferruginea, Merxmuellera cincta*	Southern Cape
4	*Isolepis costata*	"one of the most widespread species of this cluster and is also known from the grassland biome".	*Isolepis costata, Thelypteris confluens*	Southern Cape
5	*Cliffortia graminea*	"very restricted in its distribution but is very common in the wetlands of the Tsitsikamma region, where most wetlands are under pressure from plantation forestry that is often growing right at the edges of the wetlands. The community is rich in species but dominated by the shrubby *Cliffortia graminea* which superficially resembles a grass".	*Cliffortia graminea*	Southern Cape
6	*Carpha glomerata*	"dominated by the tall sedge *Carpha glomerata*, which sometimes nearly occurs as a monodominant species. It is particularly common in the Southern Cape. It grows in seasonally or permanently wet valley bottom wetlands".	*Carpha glomerata*	Southern Cape
7	*Cliffortia odorata*	"conspicuous round- leaved shrub that tends to occur in monocultures as it easily overgrows all other plant species in the community. It is typically associated with rivers, but it does also occur in valley bottom wetlands connected to a drainage network".	*Cliffortia odorata*	Southern Cape
8	*Wachendorfia thyrsiflora*	"most attractive of all Sclerophyllous Wetland Vegetation communities as it is dominated by the large yellow flowers of *Wachendorfia thyrsiflora*. It occurs in permanently wet valley bottom wetlands and is particularly common on the Humansdorp plains".	*Wachendorfia thyrsiflora, Senecio rigidus, Ursinia species, Panicum subalbidum*	Southern Cape
9	*Isolepis prolifer*	"first of the typical fynbos pioneer communities, that occur on open patches in between the fynbos or areas where streamflow prevents the establishment of larger plants. This community is dominated by *Isolepis prolifer*, a proliferous annual sedge that tends to grow in water of up to 20 cm deep".	*Isolepis prolifer*	Western Cape
10	*Juncus capensis*	"second pioneer community in the Sclerophyllous Wetland Vegetation but it tends to occur more on drier ground, in places that are only seasonally wet. It is dominated by *Juncus capensis*, a very variable species that tends to occur in quite species-rich communities".	*Juncus capensis*	Western Cape, Eastern Cape
11	*Laurembergia repens*	"community dominated by the species *Laurembergia repens*, which however has two different subspecies, with subspecies brachypoda occurring in the winter rainfall region as a creeping forb and subspecies repens in the summer rainfall region, which is more erect as a bush. So, even though the two subspecies have been lumped in this case, for the sake of oversight, they are structurally quite	*Isolepis inyangensis, Laurembergia repens, Fuirena species, Hypericum lalandii, Plectostachys serpyllifolia*	W Cape, E Cape, Limpopo

		distinct from each other. This community represents a pioneer community on wet and unstable substrates".		
12	*Juncus lomatophyllus*	"also more widespread outside of the Fynbos Biome. This is due to the fact that *Juncus lomatophyllus*, is more widespread and can be found on nutrient-poor substrates anywhere in the country. It is generally found as a pioneer community on unstable substrates and in the Fynbos, it grows in open patches in between the taller fynbos vegetation. It is particularly common in Limpopo Province".	*Juncus lomatophyllus*	W Cape, E Cape, Limpopo
13	*Epischoenus gracilis*	"dominated by the slender tuft-forming sedge *Epischoenus gracilis*, which is regularly found in Sclerophyllous Wetland Vegetation, but only rarely becomes dominant. In between the tufts this community is still quite rich in species with many fynbos shrubs found in the community".	*Epischoenus gracilis, Oxalis eckloniana*	Western Cape
14	*Elegia capensis*	"community is a typical fynbos community; in that it is dominated by Restios and is typically found along riverine wetlands in the lower mountain reaches in the Cape Fold Mountains. In most cases, the community is very species-poor, and it can reach monodominance, which is in stark contrast with the surrounding more drier parts of the landscape. The Restio *Elegia capensis* is a tall species and forms a very distinct growth form with the surrounding vegetation with its typical 'horsetail' shape".	*Elegia capensis*	Western Cape
15	*Elegia thyrsifera-Elegia neesii*	"represents a diverse group of fynbos plots that have few characteristics in common, most notably that they occur on sandy soils, are structurally very similar to the surrounding dryland vegetation and have a high species richness, with several species of Restios and Ericas. If more sampling takes place, it may well appear that this actually represents several communities".	*Ehrharta rupestis spp. tricostata, Tetria fimbriolata*	Western Cape
16	*Psoralea verrucosa*	"very diverse and probably heterogeneous, as it mainly consists of very variable plots that were part of a survey of springs in the Kamanassie Mountains but includes various other montane vegetation plots that have been done during the last few years. It is best to first sample more intensively in the Western Cape Mountains before any conclusions are drawn about these communities".		Kamanassie, Western Cape Mountains
17	*Elegia filacae*	"another wetland community that is structurally not distinguishable from the surrounding upland vegetation and represents 'typical fynbos', with a high proportion of dwarf shrubs, various species of Restios and several smaller forbs in between. It is best represented in the Cape of Good Hope Nature Reserve, but it can be found on various other places with deep sands and temporary to seasonal inundation as well, even in the lower parts of the Cape Fold Mountains. It is best recognizable by the abundance of the tussock-forming *Elegia filacea*".	*Elegia filacae, Elegia cuspidate, Cliffortia subsetacea, Restio distichus, Diastella divaricate, Bobartia indica, Tetraria fasciata, Erica laeta, Erica bruniades, Oxalis depressa*	Western Cape Southern Cape
18	*Berzelia lanuginosa*	"very characteristic fynbos wetland community and it is dominated by tall shrubs (up to 2 meters) of the family Bruniaceae which is one of the endemic families of the Western Cape. It is restricted to the southwestern coastline of the Western Cape which is the part of the province receiving the highest rainfall. The community occurs on sandy soils in temporarily to seasonally wet areas".	*Berzelia lanuginose Erica coloron, Ficinia capitella, Tetraria cuspidata*	Western Cape coast
19	*Merxmuellera stricta*	"dominated by the grass Merxmuellera stricta and does not look very much like typical fynbos, although there are many species of Ericaceae and Restionaceae that can occur within the matrix of grass. It is typically a northern element within the Sclerophyllous Wetland Vegetation and is commonly found in the Cedarberg all the way up to Namaqualand".	*Merxmuellera stricta*	Western Cape
20	*Pteridium aquilinum*	"even though it is dominated by a cosmopolitan species that is widespread within South Africa, is nonetheless typically a fynbos wetland, as elsewhere in the country, bracken fern (*Pteridium aquilinum*) does not venture into wetlands, but forms large carpets that are invading montane grassland, for example in the Drakensberg. The species has a wide tolerance, especially for nutrient-poor conditions, and it produces allelopaths, which are chemicals released in the soil that are toxic to other plants. It seems that only in specific circumstances this problematic plant can grow in wetlands, and it only invades the temporary zones on the	*Pteridium aquilinum*	Western Cape, Limpopo

		edges. It is quite possible that it has been stimulated by the forestry industry in the Tsitsikamma region as this species is quite common under plantation forestry worldwide".		
21	*Osmitopsis asteriscoides – Restio purpurascens*	"one of the most attractive fynbos wetland plant communities but it has a very limited distribution in the wettest and most pronounced winter rainfall sections of the Western Cape. The community is rich in species, particularly Erica's, Restio's and Brunia's, but the most conspicuous element is the large woody daisy *Osmitopsis asteriscoides* which has white flowers. It is typically found in seepage zones with a peaty substrate on the lower slopes of the sandstone mountains".	*Osmitopsis asteriscoides, Erica fontana, Elegia fenestrata, Berzelia abrotanoides, Cassytha ciliolata*	Western Cape
22	*Prionium serratum*	"another one of the typical sclerophyllous wetland types, dominated by the unique species palmiet (*Prionium serratum*). This species occupies the banks of mountain streams in the Western Cape but in certain circumstances in the foothills it chokes the river which starts to deposit its sediment which makes Palmiet thrive over a larger surface area. In this sense, Palmiet can be regarded as an ecosystem engineer (Sieben 2012) which is at the source of the creation of the wetland environment. It is together with Papyrus probably the only South African example of such a species. Palmiet is very common in rivers entering the foothills in the Southern Cape mountains and has created many wetlands there, which are however very fragile for erosion, and many have disappeared, most importantly the massive Duivenhoks River system. Palmiet represents a unique growth form, and it is very good in withstanding huge floods and plays an important role in flood attenuation and associated ecosystem services. This is mainly because of its extensive root system, very unusual for wetland plants, which can go up to three meters deep into a permanently inundated peatland. Palmiet is also found on the Msikaba group sandstones in Pondoland where it is often mixed with a larger group of species (in the Western Cape it can easily achieve monodominance) and often co-occurs with *Scleria angusta - Abildgaardia hygrophila* wetlands (3.33)".	*Prionium serratum*- palmiet	Western Cape, Pondoland
23	*Pennisetum macrourum*	"one of the most common Fynbos wetland types, particularly in the western part of the Western Cape. *Pennisetum macrourum*, even though it is a grass and not a restio, represents a typical fynbos element in that it is stiff and sclerophyllous, and is one of the few species of Sclerophyllous Wetland Vegetation that is also found on sandstone substrates in the north of the country, often together with *Cliffortia strobilifera. Pennisetum macrourum* wetlands are poor in species and can often achieve monodominance".		W Cape, E Cape, Limpopo
24	*Cyperus thunbergii*	common variant to the previous community. *Cyperus thunbergii* regularly occurs mixed in with *Pennisetum macrourum* in wetlands but there are many occasions where it actually becomes dominant. The community is most common in valley bottom wetlands on sandy soils with a temporary to seasonal inundation.	*Cyperus thunbergii*	Western Cape, Eastern Cape
25	*Elegia intermedia*	"community stands out in the very rich fynbos as it forms a monoculture of a single species of restio, *Elegia intermedia*, which is a reasonably tall species. It has been sampled in a single area in the Hottentots-Holland Mountains and is probably not very widespread as the dominant species is not known to have a wide distribution range. The community grows on a very coarse peat layer".	*Elegia intermedia, Campylopus stenopelma*	Hottentots Holland
26	*Anthochortus crinalis*	"community stands out by the abundance of the restio *Anthochortus crinalis*, which forms characteristic hummocks that give it the name 'orgy grass'. In the hollows between these hummocks different species can grow, but in general, this community is quite poor in species. The existence of several other species of Anthochortus growing in the same type of habitats, suggests that there are also similar communities like this occurring elsewhere in the extreme Southwestern tip of South Africa. This habitat has been sampled only in a limited way because of the access to these areas and is presently known only from a single study".	*Cliffortia tricuspidate, Ficinia argyropa, Anthochortus crinalis, Ehrharta setacea ssp. setacea, Ephischoenus villosus*	Hottentots Holland

27	*Elegia mucronata*	"community is typical for high altitude seepages in the Cape Fold Mountains but is so far restricted in its distribution range because of the limited sampling that was done in the high mountains of the Western Cape. However, the species *Elegia mucronata, Erica intervallaris* and *Grubbia rosmarinifolia* seem to be more widespread across the Western Cape, so it is very well possible that this community is more widespread. The community is structurally very diverse as the restio. *Elegia mucronata* forms a high stratum over an often short layer of small restios and dwarf shrubs".	*Restio subtilis, Elegia mucronate, Chrysitrix junciformis , Erica intervallaris, Tetraria capillacea*	Hottentots Holland

****

APPENDIX C

Code developed for obtaining raw satellite imagery in Google Earth Engine:
////Code developed by Daniëlle Seymour\\\\

Landsat 8 Surface Reflectance, Tier 1 raw imagery in Google Earth Engine:

```
///Insert Landsat Image Collection and filter by area using an imported shapefile\\
var image = ee.ImageCollection('LANDSAT/LC08/C01/T1_SR')
.filterBounds(WetlandExtent2);

///Function to cloud mask from the pixel qa band of Landsat 8 SR data. Bits 3 and 5 are cloud
shadow and cloud, respectively.\\
function maskL8sr(image) {
var cloudShadowBitMask = 1 << 3;
var cloudsBitMask = 1 << 5;

var qa = image.select('pixel_qa');

var mask = qa.bitwiseAnd(cloudShadowBitMask).eq(0)
 .and(qa.bitwiseAnd(cloudsBitMask).eq(0));

 return image.updateMask(mask).divide(10000)
 .select("B[0-9]*")
 .copyProperties(image, ["system:time_start"]);
}
///Filter imagery for Winter 2020 date ranges.\\\
///Create joint filter and apply it to Image Collection.\\\
var Winter2020 = ee.Filter.date('2020-06-01','2020-08-30');

var WinterFilter = ee.Filter.or(Winter2020);

var allsum = image.filter(WinterFilter);

///Make a Composite: Apply the cloud mask function, use the median reducer, and clip the
composite to our area of interest\\\
///create visualization parameters for composite\\\
var true_colour = {
		bands: ['B4', 'B3','B2'],
		min: 0,
		max: 0.3,
		gamma: [0.95, 1.1, 1]};

var composite = allsum
	.map(maskL8sr)
	.median()
	.clip(WetlandExtent2);

///Specify a projection\\\
var proj = ee.Projection('EPSG:32734');
print(proj);
```

```
///Display the Composite\\\
Map.addLayer(composite, true_colour,'Du Toits Wetland_Winter', 0);

///Export the image, specifying scale and region.\\\
Export.image.toDrive({
image: composite,
description: 'L8WinterComp_2020',
folder: 'Raw/Imagery/Reprojected',
scale: 30,
region: WetlandExtent2,
//crs: 'EPSG:32734',
//fileFormat: 'GeoTIFF'
 });

///Filter imagery for Summer 2020_2021 date ranges\\\
///Create joint filter and apply it to Image Collection.\\\
var sum20_21 = ee.Filter.date('2020-12-01','2021-02-28');
var SumFilter = ee.Filter.or(sum20_21);
var allsum = image.filter(SumFilter);

///Make a Composite: Apply the cloud mask function, use the median reducer, and clip the
composite to our area of interest\\\
///create visualization parameters for composite\\\
var true_colour = {
                bands: ['B4', 'B3','B2'],
                min: 0,
                max: 0.3,
                gamma: [0.95, 1.1, 1]};

var composite = allsum
            .map(maskL8sr)
            .median()
            .clip(WetlandExtent2);

///Specify a projection\\\
var proj = ee.Projection('EPSG:32734');
print(proj);

///Display the Composite\\\
 Map.addLayer(composite, true_colour,'Du Toits Wetland_Summer', 0);

///Export the image, specifying scale and region.\\
    Export.image.toDrive({
    image: composite,
    description: 'L8SummerComp_2020_2021',
    folder: 'Raw/Imagery/Reprojected',
    scale: 30,
    region: WetlandExtent2,
  //crs: 'EPSG:32734',
  //fileFormat: 'GeoTIFF'
 });
```

Sentinel-2 MultiSpectral Instrument: Level-2A raw imagery in Google Earth Engine:

```
///Insert Sentinel 2-A Image Collection and filter by area using an imported shapefile\\\
    var image = ee.ImageCollection('COPERNICUS/S2_SR')
    .filterBounds(WetlandExtent2);

///Function to mask clouds S2\\\
   var mask = function(image) {
   var QA60 = image.select(['QA60']);
   var clouds = QA60.bitwiseAnd(1<<10).or(QA60.bitwiseAnd(1<<11)); // this gives us cloudy
pixels
  return image.updateMask(clouds.not()); // remove the clouds from image
};

///Filter imagery for Summer 2020/21 date ranges \\\
///Create joint filter and apply it to Image Collection.\\\
   var Summer2020 = ee.Filter.date('2020-12-01','2021-02-28');
   var SummerFilter = ee.Filter.or(Summer2020);
   var allsum = image.filter(SummerFilter);

///Make a Composite: Apply the cloud mask function, use the median reducer, and clip the
composite to area of interest\\\
///create visualization parameters for composite\\\
 var rgbVis = {
                  bands: ['B4', 'B3','B2'],
                 min: 0,
                 max: 3000,
                 gamma: [0.95, 1.1, 1]};

 var composite = allsum
              .map(mask)
              .median()
             .clip(WetlandExtent2);

///Specify a projection\\\
 var proj = ee.Projection('EPSG:32734');
 print(proj);

///Display the Composite\\\
    Map.addLayer(composite, rgbVis,'Du Toits Wetland_Summer', 0);
    Map.setCenter(19.162248, -33.974126, 13);

///Export the image, specifying scale and region.\\\
   Export.image.toDrive({
   image: composite,
   description: 'S2JanFebComp_2021',
   folder: 'Raw/Imagery/Reprojected',
   scale: 10,
   region: WetlandExtent2
   //fileFormat: 'GeoTIFF'
 });
```

```
////Filter imagery for Winter 2020 date ranges\\\
///Create joint filter and apply it to Image Collection.\\\
     var Winter2020 = ee.Filter.date('2020-06-01','2020-08-30');
     var WinterFilter = ee.Filter.or(Winter2020);
     var allsum = image.filter(WinterFilter);

///Make a Composite: Apply the cloud mask function, use the median reducer, and clip the
composite to our area of interest\\\
///create visualization parameters for composite\\\
     var true_colour = {
                bands: ['B4', 'B3','B2'],
                min: 0,
                max: 3000,
                gamma: [0.95, 1.1, 1]};

 var composite = allsum
              .median()
              .clip(WetlandExtent2);

///Specify a projection\\\
  var proj = ee.Projection('EPSG:32734');
  print(proj);

///Display the Composite\\\
   Map.addLayer(composite, true_colour,'Du Toits Wetland_Winter', 0);
   Map.setCenter(19.162248, -33.974126, 13);

///Export the image, specifying scale and region.\\\
    Export.image.toDrive({
    image: composite,
    description: 'S2WinterComp_2020',
    folder: 'Raw/Imagery/Reprojected2',
    scale: 10,
    region: WetlandExtent2
   //fileFormat: 'GeoTIFF'
 });

///////////////////////////////////////////////////////End of script\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\\
```

APPENDIX D

Code developed in R for computing the Normalized Difference Vegetation Index:
###Code developed by Daniëlle Seymour####

Normalized Difference Vegetation Index in R:

```
###Load packages####
library(rgdal)
library(raster)
library(rasterVis)
library(caret)
library(randomForest)
library(e1071)
```

Winter NDVI:

```
rm(list=ls())
setwd("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Winter/Imagery_Winter")

#First import all files in a single folder as a list
rastlist1 <- list.files(path =
"C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Winter/Imagery_Winter",
pattern='.tif', all.files=TRUE, full.names=FALSE)
img<-
brick("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Winter/Imagery_Winter/S2Wi
nterCompRepro.tif")
names(img) <- c('B1', 'B2', 'B3', 'B4', 'B5', 'B6','B7', 'B8','B8A','B9','B10','B11', 'B12','AOT','WVP',
'SCL','TCI_R', 'TCI_G','TCI_B','MSK_CLDPRB','MSK SNWPRB', 'QA60', 'QA60 Bitmask')
names(img) <- paste0("B", c(1:23))

###NDVI calculation###
ndvi = ((img$B8-img$B4)/(img$B8+img$B4))
names(ndvi)= c('NDVI')
img = addLayer(img, ndvi)
plot(ndvi)
setwd("C:/Thesis_2021/Results_Mapwork/R/NDVI_")
writeRaster(ndvi, filename="Sentinel_NDVI_Winter.tif", format="GTiff", overwrite=TRUE)

###########################End of script#########################################
```

Summer NDVI:

```
rm(list=ls())
setwd("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Summer/Imagery_Summer")

#First import all files in a single folder as a list ##
rastlist1<list.files(path="C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Summer/Ima
gery_Summer", pattern='.tif', all.files=TRUE, full.names=FALSE)
img<brick("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Summer/Imagery_Summ
er/S2SummerCompRepro.tif")
```

```
names(img) <- c('B1', 'B2', 'B3', 'B4', 'B5', 'B6','B7', 'B8','B8A','B9','B10','B11', 'B12','AOT','WVP',
'SCL','TCI_R', 'TCI_G','TCI_B','MSK_CLDPRB','MSK SNWPRB', 'QA60', 'QA60 Bitmask')
names(img) <- paste0("B", c(1:23))

###Add NDVI to imagery###
ndvi = ((img$B8-img$B4)/(img$B8+img$B4))
names(ndvi)= c('NDVI')
img = addLayer(img, ndvi)
plot(ndvi)
setwd("C:/Thesis_2021/Results_Mapwork/R/NDVI_")
writeRaster(ndvi, filename="Sentinel_NDVI_Summer.tif", format="GTiff", overwrite=TRUE)

#####################################End of script#############################
```

APPENDIX E

Code developed in R for the Random Forest classifier:
###Based on code developed by Blessing Khavu, provided by Blessing Khavu as part of postgrad research group peer learning###

Winter RF:

```
###Random Forest Classification- to spectrally discriminate various landcover/vegetation of Du Toits Wetland###
###Spectral signature graph code developed by Daniëlle Seymour###
###This script uses the 7 distinct vegetation classification scheme###
###This is RF script for Winter 2020###Sentinel-2A, MSI Level-2A###
###Raw imagery processed in GEE: composite spans '2020-06-01','2020-08-31'###

###Load packages###
library(rgdal)
library(raster)
library(rasterVis)
library(caret)
library(randomForest)
library(e1071)

#############################Load Image, create list and brick raster###################
###List band and then brick the raster:
###Raster stack vs brick: how they store each band is different. The bands in a RasterStack are stored as links to raster data that is located somewhere on our computer.
###A RasterBrick contains all of the objects stored within the actual R object. In most cases, we can work with a RasterBrick in the same way we might work with a RasterStack.
###However a RasterBrick is often more efficient and faster to process - which is important when working with larger files.

rm(list=ls())
setwd("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Winter/Imagery_Winter")



#First import all files in a single folder as a list
rastlist1 <- list.files(path =
"C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Winter/Imagery_Winter",
pattern='.tif', all.files=TRUE, full.names=FALSE)
img<-
brick("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Winter/Imagery_Winter/S2WinterCompRepro.tif")
names(img) <- c('B1', 'B2', 'B3', 'B4', 'B5', 'B6','B7', 'B8','B8A','B9','B10','B11', 'B12','AOT','WVP',
'SCL','TCI_R', 'TCI_G','TCI_B','MSK_CLDPRB','MSK SNWPRB', 'QA60', 'QA60 Bitmask')
names(img) <- paste0("B", c(1:23))

#########################Plotting RGB image###################################
plotRGB(img * (img >= 0), r = 4, g = 3, b = 2, scale = 10000)
```

```
###########Load shapefile with class coordinates and class name i.e. Prionium serratum, Psoralea pinnata, Pteridium_Restio_Merx, Fynbos, Bare soil/sandstone, Water and Degraded###################
#######You can add it along with values of each band or do it in R###
trainData <-
shapefile("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/TrainingData_shp5/DistinctTraining5.shp")
head(trainData)

##################Extract values to the shapefile that you just loaded###########
#beginCluster() #to optimize all cores
roi_data <- extract(img, trainData, df=TRUE)
roi_data$Class <- as.factor(trainData$Class[roi_data$ID])
roi_data <- roi_data[roi_data$Class!="0",]
head(roi_data)

###Second option of extraction for signature plot###
roi_data <- extract(img, trainData, df=TRUE)
head(roi_data)
summary(roi_data)

###Create signature plot###
specs <- aggregate(roi_data, list(trainData$Class), mean, na.rm=TRUE)
specs
#instead of the first column, use row names
rownames(specs) <- specs[,1]
specs <- specs[,-1]
specs
setwd("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest")
write.csv(specs, "SpecsDistinct.csv")

#Create a vector of colour for the land cover classes for use in plotting
mycolor <- c('grey','red','yellow','dark green','light green','orange','blue')
#transform ms from a data.frame to a matrix
specs <- as.matrix(specs)
# First create an empty plot
plot(0, ylim=c(0,4000), xlim = c(1,12), type='n', xlab="Bands", ylab = "Reflectance")
##add the different classes
for (i in 1:nrow(specs)){
  lines(specs[i,], type = "l", lwd = 3, lty = 1, col = mycolor[i])
}
# Title
title(main="Spectral Profile of Distinct Classes-S2A", font.main = 2)
# Legend
legend("topleft", rownames(specs),
       cex=0.8, col=mycolor, lty = 1, lwd =3, bty = "n")

###########Set seed to make sure the same random sample is selected next time########
set.seed(200)
###Note: seed---Random number seed to use. If a value is provided, it will be used to initialize R's random number generator before the model is fitted. ##
```

```
###If a value is not provided (the default), the random number generator will be initialized from the
current time###########################################

################Split the data set into test and training data set##################
splitIndex <- createDataPartition(roi_data$Class,
                                  p = .80,
                                  list = FALSE,
                                  times = 1)
trainDF <- roi_data[ splitIndex,]
testDF  <- roi_data[-splitIndex,]
trainDF <- na.omit(trainDF)

########################Load the Column names###############
trainDF <- trainDF[, c('Class', "B1", "B2", "B3", "B4", "B5", "B6","B7", "B8","B9","B10","B11",
"B12")]
testDF <- testDF[, c('Class',"B1", "B2", "B3", "B4", "B5", "B6","B7", "B8","B9","B10","B11",
"B12")]

########################Build the Random Forest Model with Training Data###########
Fitcontrol <- trainControl("repeatedcv",
                           number=10,
                           repeats=1)
rf <- train(as.factor(Class) ~.,
            data = trainDF,
            method= "rf",
            trControl = Fitcontrol,
            preProcess = c("center", "scale"),
            importance = TRUE)

###Print the model summary from the Random Forest model###
print(rf)

###Check for the Variable importance####
plot(varImp(rf,scale=FALSE))

### Predict to a new Dataframe for a Map Output#######
pred <- predict(rf , newdata = testDF,  type= "raw")
confusionMatrix(pred, as.factor(testDF$Class))
img_pred <- predict(img, model=rf, na.rm=T)

###Plot the image in R###
levels(img_pred)
levelplot(img_pred,col.regions = c("white","red","yellow","dark green","light
green","orange","blue"),main = "Supervised Classification")

##########################Write Output Grid of the classified image################
setwd("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Winter/Outputs2")
writeRaster(r3, filename="Distinct_RF_Winter2.tif", format="GTiff", overwrite=TRUE)

##########################END OF SCRIPT##########################
```

Summer RF:

```
###Random Forest Classification- to spectrally discriminate various landcover/vegetation of Du Toits Wetland###
###Based on code developed by Blessing Khavu, provided by Blessing Khavu as part of postgrad research group peer learning####
###Spectral signature graph code developed by Daniëlle Seymour###
###This script uses the 7 distinct veg classification scheme###
###This is RF script for Summer 2020/2021###Sentinel-2A, MSI Level2-A###
###Imagery processed in GEE: composite spans '2020-12-01','2021-02-28'###
###Load packages###
library(rgdal)
library(raster)
library(rasterVis)
library(caret)
library(randomForest)
library(e1071)

#############################Load Image, create list and brick raster##################
####List band and then brick the raster: ###Raster stack vs brick: how they store each band is different. The bands in a RasterStack are stored as links to raster data that is located somewhere on our computer. ###A RasterBrick contains all of the objects stored within the actual R object. In most cases, we can work with a RasterBrick in the same way we might work with a RasterStack. ###However a RasterBrick is often more efficient and faster to process - which is important when working with larger files.

rm(list=ls())
setwd("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Summer/Imagery_Summer")
#First import all files in a single folder as a list
rastlist1 <- list.files(path =
"C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Summer/Imagery_Summer",
pattern='.tif', all.files=TRUE, full.names=FALSE)
img<-
brick("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Summer/Imagery_Summer/S2SummerCompRepro.tif")
names(img) <- c('B1', 'B2', 'B3', 'B4', 'B5', 'B6','B7', 'B8','B8A','B9','B10','B11', 'B12','AOT','WVP', 'SCL','TCI_R', 'TCI_G','TCI_B','MSK_CLDPRB','MSK SNWPRB', 'QA60', 'QA60 Bitmask')
names(img) <- paste0("B", c(1:23))


##########################Plotting RGB image#######################################
plotRGB(img * (img >= 0), r = 4, g = 3, b = 2, scale = 10000)

#######################Load shapefile with class coordinates and class name i.e. WV, SWV, Bare soil/sandstone, Water and Unknown####################
#######################You can add it along with values of each band or do it in R###
trainData <-
shapefile("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/TrainingData_shp5/DistinctTraining5.shp")

################Extract values to the shapefile that you just loaded###########
#beginCluster() #to optimize all cores
roi_data <- extract(img, trainData, df=TRUE)
```

```
roi_data$Class <- as.factor(trainData$Class[roi_data$ID])
roi_data <- roi_data[roi_data$Class!="0",]
head(roi_data)

###Second option of extraction for signature plot###
roi_data <- extract(img, trainData, df=TRUE)
head(roi_data)
summary(roi_data)

###Create signature plot###
specs <- aggregate(roi_data, list(trainData$Class), mean, na.rm=TRUE)
specs
# instead of the first column, use row names
rownames(specs) <- specs[,1]
specs <- specs[,-1]
specs
setwd("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest")
write.csv(specs, "SpecsDistinct2.csv")

#Create a vector of color for the land cover classes for use in plotting
mycolor <- c('grey','red','yellow','dark green','light green','orange','blue')
#transform ms from a data.frame to a matrix
specs <- as.matrix(specs)
# First create an empty plot
plot(0, ylim=c(0,4000), xlim = c(1,12), type='n', xlab="Bands", ylab = "Reflectance")
##add the different classes
for (i in 1:nrow(specs)){
  lines(specs[i,], type = "l", lwd = 3, lty = 1, col = mycolor[i])
}
#Title
title(main="Spectral Profile of Distinct Classes-S2A", font.main = 2)
#Legend
legend("topleft", rownames(specs),
       cex=0.8, col=mycolor, lty = 1, lwd =3, bty = "n")

###########Set seed to make sure the same random sample is selected next time########
set.seed(200)
###Note: seed---Random number seed to use. If a value is provided, it will be used to initialize R's
random number generator before the model is fitted. ###If a value is not provided (the default), the
random number generator will be initialized from the current time.
#################Split the data set into test and training data set###################
splitIndex <- createDataPartition(roi_data$Class,
                             p = .80,
                             list = FALSE,
                             times = 1)
trainDF <- roi_data[ splitIndex,]
testDF  <- roi_data[-splitIndex,]
trainDF <- na.omit(trainDF)

#########################Load the Column names. Edit them if you wish################
trainDF <- trainDF[, c('Class', "B1", "B2", "B3", "B4", "B5", "B6","B7", "B8","B9","B10","B11",
"B12")]
```

```
testDF <- testDF[, c('Class', "B1", "B2", "B3", "B4", "B5", "B6","B7", "B8","B9","B10","B11",
"B12")]

###############Build the Random Forest Model with Training Data############
Fitcontrol <- trainControl("repeatedcv",
                    number=10,
                    repeats=1)
rf <- train(as.factor(Class) ~.,
         data = trainDF,
         method= "rf",
         trControl = Fitcontrol,
         preProcess = c("center", "scale"),
         importance = TRUE)
predict(rf)

########Print the model summary from the Random Forest model##########
print(rf)
#######Check for the Variable importance####################
plot(varImp(rf,scale=FALSE))

#########Predict to a new Dataframe for a Map Output##################
pred <- predict(rf , newdata = testDF,  type= "raw")
confusionMatrix(pred, as.factor(testDF$Class))
img_pred <- predict(img, model=rf, na.rm=T)

####################Plot the image in R###########################################
levels(img_pred)
levelplot(img_pred,col.regions = c("white","red","yellow","dark green","light
green","orange","blue"),main = "Supervised Classification")
#3x3 mean filter
r3 <- focal(img_pred, w=matrix(1/9,nrow=3,ncol=3), median)

###########################Write Output Grid of the classified image#################
setwd("C:/Thesis_2021/Results_Mapwork/R/R_Random_Forest/RF_Summer/Outputs4")
writeRaster(r3, filename="Distinct_RF_Summer2.tif", format="GTiff", overwrite=TRUE)

##############################END OF SCRIPT################################
```

APPENDIX F

Code developed in R for the accuracy assessment of the probability classification:

```
####Based on code developed by Vernon Visser-provided by Helen de Klerk####

####Accuracy assessment code for the class probability map generated in ArcMap with four
vegetation layers###

###Load packages:
library(raster)
library(RStoolbox)
library(ggplot2)
library(rfUtilities)
library(sampling)
library(caret)

#Set working directory:
setwd("C:/Thesis_2021/Results_Mapwork/R/EcotoneMapping")


#ArcMap Bayesian classification raster:
classProb =
stack("C:/Thesis_2021/Results_Mapwork/R/EcotoneMapping/Class_Probability2/ClassProb_Outpu
t/ClassifiedImage/4ClassVeg.tif") #PCRS
classProb[classProb>100] = NA #Change all values above 100 to NA

#Function to create binary classification raster based on classProb raster (1= P.serratum ; 2=
P.pinnata ; 3= Pteridium_Restio_Merx; 4= Fynbos)
classProbPerc = function(perc){
  cpRast = classProb[[1]]
  cpRast[] = NA
  cpRast[ classProb[[1]]<=perc | classProb[[4]]<=perc ] = NA
  cpRast[ classProb[[1]]>perc & classProb[[2]]<=perc ] = 1
  cpRast[ classProb[[2]]>perc & classProb[[1]]<=perc ] = 2
  cpRast[ classProb[[3]]>perc & classProb[[4]]<=perc ] = 3
  cpRast[ classProb[[4]]>perc & classProb[[3]]<=perc ] = 4

  return(cpRast)
}

#90% threshold
classProb90 = classProbPerc(perc=90)
#plot(classProb90)
#Choose classified raster for accuracy testing:
rastClass = classProb90


#Read in testing data:
accShp =
shapefile("C:/Thesis_2021/Results_Mapwork/R/EcotoneMapping/Class_Probability2/TestSamples
2/Test2.shp")
```

```
head(accShp)
plot(accShp)

#Select random points:
sampleCells = cellFromPolygon(rastClass, accShp) #Get all possible raster cells overlapped by test
polyons
sampleCellClasses = lapply(sampleCells, function(x) rastClass[x]) #Get class values from rastClass
raster
sampleCellClasses
#Create list to store observed veg classes:
sampleClasses = list() #Create empty list that will be of same dimensions as "sampleCells" to store
veg classes
for(l in 1:length(sampleCells)){
  sampleClasses[[l]] = rep(accShp@data$class[l], length(sampleCells[[l]])) #Assign sample classes
to empty list
}

#Many of the cells have NA values, either because the classification is uncertain or the training
polygons do not overlap the
#classification raster. Below we remove these cells from our possible sampling cells:
sampleCellClassesNA = lapply(sampleCellClasses, function(x) which(is.na(x))) #Find all NA value
cells
for(l in 1:length(sampleCells)){
  if(length(sampleCellClassesNA[[l]])>0){
    sampleCells[[l]] = sampleCells[[l]][-sampleCellClassesNA[[l]]] #Remove all NA value cells
    sampleClasses[[l]] = sampleClasses[[l]][-sampleCellClassesNA[[l]]] #Remove all NA value cells
  }
}
#whichRemove = which(unlist(lapply(sampleCells, function(x) length(x)))==0)
#sampleCells = sampleCells[-whichRemove] #Remove from list empty elements
#sampleClasses = sampleClasses[-whichRemove] #Remove from list empty elements

#See how many cells available in each veg class:
table(unlist(sampleClasses))

#Put sample data into a dataframe:
sampleDat = data.frame(cellIDs=unlist(sampleCells), class=unlist(sampleClasses))
sampleDat

sum(is.na(sampleDat$class))

#Sample 100 records from each veg class
subSampleCells = strata(sampleDat, stratanames='class', size = c(100,100,100,100),
method='srswor')
subSampleCells = getdata(sampleDat,subSampleCells)

 #Get predicted veg classes for sample cells (from rastClass raster):
pred = rastClass[subSampleCells$cellIDs]
pred[pred==1] = 'Prionium serratum'
pred[pred==2] = 'Psoralea pinnata'
pred[pred==3] = 'Pteridium_Restio_Merx'
pred[pred==4] = 'Fynbos'
```

```
#Get observed veg classes for sample cells:
obs = subSampleCells$class

#Confusion matrix:
table(obs, pred)

#Get accuracy:
accuracy(pred, obs)

################################End of script#######################################
```

APPENDIX G

Code developed in R for mapping ecotones and their associated fuzzy graphs:

```
###Based on code developed by Vernon Visser-provided by Helen
 de Klerk####

###Ecotone mapping in Du Toits River Wetland###
###Class probability map is based on Random Forest classified images as done in Chapter 3###
###Aim of this script: to map internal wetland ecotones i.e. changes/transition in vegetation
composition from 'pure wetland'-Prionium serratum & Psoralea pinnata to sclerophyllous wetland,
mixture of wetland grasses, ferns, restios and dryer Fynbos conditions###

###Load packages###
library(rgdal)
library(raster)
library(rasterVis)
library(caret)
library(e1071)

#Set working directory:
setwd("C:/Thesis_2021/Results_Mapwork/R/EcotoneMapping")

#Read in Class Probability classified raster##Classified on 15 Sept 2021 based on RF classified
outputs in Chap3, so no additional accuracy measures done##
vegetation =
stack("C:/Thesis_2021/Results_Mapwork/R/EcotoneMapping/Class_Probability2/ClassProb_Outpu
t/ClassifiedImage/4ClassVeg.tif") #PCRS
names(vegetation) <- c(X4ClassVeg.1 = "Prionium_serratum", X4ClassVeg.2 =
"Psoralea_pinnata",X4ClassVeg.3 = "Pteridium_Restio_Merx", X4ClassVeg.4 = "Fynbos")
plot(vegetation)

#Get individual layers:
vegLayer1 =  vegetation[[1]]
vegLayer2 =  vegetation[[2]]
vegLayer3 =  vegetation[[3]]
vegLayer4 =  vegetation[[4]]

##Check each layer/class##
#vegLayer1
#vegLayer2
#vegLayer3
#vegLayer4

#Get shapefile of transect coordinates:
transShp =
shapefile("C:/Thesis_2021/Results_Mapwork/R/EcotoneMapping/Class_Probability2/Large
transects2/6_trans_1_6kmx200m.shp")
transShp

#Add ID column:
transShp$TRANSECT= 1:nrow(transShp@data)
```

```
#Extract values
trans1Dat = extract(vegLayer1, transShp)
transShp$prob1 = trans1Dat #Add values to shapefile
head(trans1Dat)

trans2Dat = extract(vegLayer2, transShp)
transShp$prob2 = trans2Dat
head(trans2Dat)

trans3Dat = extract(vegetation[[3]], transShp)
transShp$prob3 = trans3Dat
head(trans3Dat)

trans4Dat = extract(vegetation[[4]], transShp)
transShp$prob4 = trans4Dat
head(trans4Dat)

#View shapefile data:
transShp@data

#Get individual transects:
for(t in 1:length(transShp$TRANSECT)){
  trans = transShp[transShp$TRANSECT==t,]
  assign(paste0('trans',t), trans)
  rm(trans)
}
plot(trans1) #Plot one of these transects
plot(trans2)
plot(trans3)
plot(trans4)
plot(trans5)
plot(trans6)
plot(transShp)

#Function that will get mean probabilities for each layer (1 to 4) in 50 polygon bins (at
approximately every 50 m across the transect)
library(maptools)
library(rgeos)
library(geosphere)
 getProbsBins = function(trans){ #trans = transect for which you want to get data, e.g. trans1
  coords = trans@polygons[[1]]@Polygons[[1]]@coords #Get all polygon coordinates
  #Eastern-most point:
  minX = data.frame(matrix(coords[which(coords[,1]==min(coords[,1])),], ncol=2))
  minX = minX[1,]
  #Western-most point:
  maxX = data.frame(matrix(coords[which(coords[,1]==max(coords[,1])),], ncol=2))
  maxX = maxX[1,]
  #Northern-most point:
  maxY = data.frame(matrix(coords[which(coords[,2]==max(coords[,2])),], ncol=2))
  maxY = maxY[1,]
  #Southern-most point:
```

```
  minY = data.frame(matrix(coords[which(coords[,2]==min(coords[,2])),], ncol=2))
  minY = minY[1,] #Added this in case we get two coordinates that are the max, so we select only
one of them

  #Assign corners of polygons based on angle from E to W:
  if(minY[,1]<maxY[,1]){
    UL = minX
    LL = minY
    UR = maxY
    LR = maxX
  } else if(minY[,1]>maxY[,1]){
    UL = maxY
    LL = minX
    UR = maxX
    LR = minY
  }
  #Get corner coordinates in UTM projection:
  coordinates(UL) = ~X1+X2 #Transform to spatialPoints object
  proj4string(UL) <- CRS("+proj=utm +south +zone=34 ellps=WGS84") #Assign projection
  UL.latlon = spTransform(UL, CRS('+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs'))
#Reproject to UTM
  coordinates(UR) = ~X1+X2
  proj4string(UR) <- CRS("+proj=utm +south +zone=34 ellps=WGS84")
  UR.latlon = spTransform(UR, CRS('+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs'))
  coordinates(LR) = ~X1+X2
  proj4string(LR) <- CRS("+proj=utm +south +zone=34 ellps=WGS84")
  LR.latlon = spTransform(LR, CRS('+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs'))
  coordinates(LL) = ~X1+X2
  proj4string(LL) <- CRS("+proj=utm +south +zone=34 ellps=WGS84")
  LL.latlon = spTransform(LL, CRS('+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs'))

  #Find coordinates of midpoint between UL and LL points:
  bearingUL.LL = gzAzimuth(UL.latlon@coords, LL.latlon@coords) #Get bearing between UL and
LL
  distUL.LL = distGeo(UL.latlon, LL.latlon) #Get distance between UL and LL
  midUL.LL.latlon = data.frame(destPoint(p=UL.latlon, b=bearingUL.LL, d=distUL.LL/2)) #Get
coordinates of midpoint between UL and LL points
  coordinates(midUL.LL.latlon) = ~lon+lat #Transform to spatialPoints object
  proj4string(midUL.LL.latlon) <- CRS("+proj=longlat +ellps=WGS84 +datum=WGS84
+no_defs") #Assign projection
  midUL.LL = spTransform(midUL.LL.latlon, CRS('+proj=utm +south +zone=34 ellps=WGS84'))
#Reproject to UTM

  #Find coordinates of midpoint between UR and LR points:
  bearingUR.LR = gzAzimuth(UR.latlon@coords, LR.latlon@coords)
  distUR.LR = distGeo(UR.latlon, LR.latlon)
  midUR.LR.latlon = data.frame(destPoint(p=UR.latlon, b=bearingUR.LR, d=distUR.LR/2))
  coordinates(midUR.LR.latlon) = ~lon+lat
  proj4string(midUR.LR.latlon) <- CRS("+proj=longlat +ellps=WGS84 +datum=WGS84
+no_defs")
  midUR.LR = spTransform(midUR.LR.latlon, CRS('+proj=utm +south +zone=34 ellps=WGS84'))
```

```
  #Create 50 polygon bins across the length of transect (polygons are about 200 m wide and 1.6 km
long)
  distMidUL.LL.midUR.LR = pointDistance(midUL.LL.latlon, midUR.LR.latlon, longlat=T)
#Distance between midpoints
  distBreaks = distMidUL.LL.midUR.LR/50 #Get break distances (above distance divided by 50)
  bearingMidPts = gzAzimuth(midUL.LL.latlon@coords, midUR.LR.latlon@coords) #Get bearing
between midpoints
  bPolyList = {} #Create empty list for storing polygon bins
  for(b in 1:50){ #Loop through all bins while advancing the starting point by "break distance" along
the line between the midpoints each time
    if(b==1){
      bStart = midUL.LL.latlon@coords #For first break, use the midpoint between UL and LL
corners
    }
    bEnd = data.frame(destPoint(p=bStart, b=bearingMidPts, d=distBreaks)) #Calculate coordinates
"break distance" along the line between the midpoints
    bUL = data.frame(destPoint(p=bStart, b=c(bearingMidPts-90), d=50)) #Calculate UL coordinates
of polygon bin
    bUR = data.frame(destPoint(p=bEnd, b=c(bearingMidPts-90), d=50)) #Calculate UR coordinates
of polygon bin
    bLL = data.frame(destPoint(p=bStart, b=c(bearingMidPts+90), d=50)) #Calculate LL coordinates
of polygon bin
    bLR = data.frame(destPoint(p=bEnd, b=c(bearingMidPts+90), d=50)) #Calculate LR coordinates
of polygon bin
    bPoly = Polygon(rbind(bUL, bUR, bLR, bLL, bUL)) #Create polygon from above coordinates
    bPoly = Polygons(list(bPoly), ID=b) #Create polygon from above coordinates
    bPolyList[[b]] = list(bPoly) #Add polygon to polygons list
    bPolys = SpatialPolygons(unlist(bPolyList)) #Create multiple-polygon polygon
    bStart = bEnd #Reset starting coordinate to be end of last bin
  }
  proj4string(bPolys) <- CRS("+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs") #Assign
projection
  bPolysUTM = spTransform(bPolys, CRS('+proj=utm +south +zone=34 ellps=WGS84'))
#Reproject to UTM

  #Crop the vegetation raster to the extent of the transect in question, and mask:
  vegetationT = crop(vegetation, trans)
  vegetationT = mask(vegetationT, trans)

  #Get probability data:
  breakTransVals = extract(vegetationT, bPolysUTM) #Extract probability data from each layer
  breakTransMeans = lapply(breakTransVals, function(x) apply(x, MARGIN=2, mean, na.rm=T))
#Calculate mean value for each polygon bin
  breakTransSE = lapply(breakTransVals, function(x) apply(x, MARGIN=2, function(x) sd(x,
na.rm=T)/sqrt(length(x[!is.na(x)])))) #Calculate standard error value for each polygon bin
  #Add data to a data.frame:
  breakTransMeansGG = data.frame(brk=rep(c(1:50),4),
                               layer=rep(c(1:4),each=50),
                               prob = c(unlist(lapply(breakTransMeans, '[', 1)),
                                        unlist(lapply(breakTransMeans, '[', 2)),
                                        unlist(lapply(breakTransMeans, '[', 3)),
                                        unlist(lapply(breakTransMeans, '[', 4))),
```

```
                        se = c(unlist(lapply(breakTransSE, '[', 1)),
                               unlist(lapply(breakTransSE, '[', 2)),
                               unlist(lapply(breakTransSE, '[', 3)),
                               unlist(lapply(breakTransSE, '[', 4))))
 return(breakTransMeansGG)
}

transL = list(trans1, trans2, trans3, trans4, trans5, trans6) #Create list of all transect pointShape
objects
breakTransMeansGG = lapply(transL, getProbsBins) #Apply the function above to all of these
transect objects
ggDat = do.call(rbind, breakTransMeansGG) #Change format of the results above to get into one
dataframe
#test breakTransMeansGG step worked:
breakTransMeansGG
ggDat

#Add a column for the transect number. This also puts the transects in the correct order now:
ggDat$transect = factor(rep(paste0('trans',c(1:length(transShp$TRANSECT))), each=200),
                  levels=paste0('trans',c(1:length(transShp$TRANSECT))))
##check that the 'order is the same as the original ORIG_FID
head(ggDat$transect)

#Change percentage to probability:
ggDat$prob = ggDat$prob/100

#Get standard errors:
ggDat$SEupper = ggDat$prob + ggDat$se/100
ggDat$SElower = ggDat$prob - ggDat$se/100

#Plot the results for all transects:
library(ggplot2)
labels = c(trans1 = "Transect 1", trans2 = "Transect 2", trans3 = "Transect 3", trans4 = "Transect 4",
trans5 = "Transect 5",
        trans6 = "Transect 6")

#New titles for each transect
ggTransects = ggplot(ggDat) + #Specifies the dataset to use (ggDat) and the variables (x=brk,
y=prob) and the variables that determine the line colours
  geom_line(aes(brk, prob, colour=factor(layer), group=factor(layer))) + #Specifies it must be a line
plot
  geom_line(aes(brk, SEupper, colour=factor(layer), group=factor(layer))) + #Specifies it must be a
line plot
  geom_line(aes(brk, SElower, colour=factor(layer), group=factor(layer))) + #Specifies it must be a
line plot
  labs(x='Distance along transect (m)', y="Probability") + #x- and y-axis labels
  facet_wrap( ~ transect, ncol=1, labeller=labeller(transect = labels)) + #Creates the multiple plot
layout, facetting by transect number. You can change the number of plots in each row and column
here too.
  scale_color_manual(values=c("#ff0000","#00FF00","#0000FF","#F28C28" ), name = "", labels =
c("Prionium serratum", "Psoralea pinnata","Pter_Restio_Merx","Fynbos")) + #Specifies line
```

```
colours and used for legend editing. I sometimes use http://colorbrewer2.org to choose colours.
Here (name = "") specifies there must be no legend header
  scale_y_continuous(breaks=seq(0,1,0.2)) + #Change breaks along the y-axis
  scale_x_continuous(breaks=seq(0,100,20), labels=seq(0,3000,600)) + #Change breaks along x-
axis and their labels
  theme_bw() + #Changes overall plot colour to black and white theme
  theme(strip.background =element_rect(fill=NA), #Change other elements of the 'theme'. This
removes the facet label background colour
        axis.text.x = element_text(angle = 90, hjust = 1)) #This makes the x-axis labels vertical aligned
ggTransects

jpeg('C:/Thesis_2021/Results_Mapwork/R/EcotoneMapping/R_Outputs/figures/Transects_graphs2
021_50m.jpg', width=19, units='cm', res=600, height=50) #By changing the width and height you
can manipulate how the plot looks (e.g. if labels don't all fit, you can increase the size)
ggTransects
dev.off()

pdf("C:/Thesis_2021/Results_Mapwork/R/EcotoneMapping/R_Outputs/figures/Transects_graphs20
21_50m.pdf", width=11.69, height=8.27)
ggTransects
dev.off()

#Plot transect raster:
plot(vegetation)

####Plot individual transects together with their associated maps##
#Loop through each transect and plot:
for(t in 6:length(transShp$TRANSECT)){
  ggDatSub = ggDat[ggDat$transect==paste0('trans',t),] #Select only data for transect in question
  #Read in map jpeg:
  #library(jpeg)
  #transImage =
readJPEG(paste0('C:/Thesis_2021/Results_Mapwork/R/EcotoneMapping/R_Outputs/transectsmaps
2/Trans1.jpg',t,'.jpg'))

  ##JPEG not working for me###gives unable to open error…used TIFF instead##Daniëlle
  library(tiff)
  transImage<-
readTIFF("C:/Thesis_2021/Results_Mapwork/R/EcotoneMapping/R_Outputs/transectsmaps2/Trans
6.tif", native=TRUE)

  #Transform jpeg to raster image for plotting purposes:
  library(grid)
  g = rasterGrob(transImage, interpolate=FALSE)

#Get probability figure plot:
   ggTransectSub = ggplot(ggDatSub) +
   geom_line(aes(brk, prob, colour=factor(layer), group=factor(layer))) + #Mean probability line for
each veg type
   geom_ribbon(aes(brk, ymin=SElower, ymax=SEupper, group=factor(layer)), alpha=0.1) +
#Standard error shading
   labs(title=paste0('Transect ',t), x='Distance along transect (m)', y="Probability") + #Titles
```

```
   scale_color_manual(values=c("#ff0000","#00FF00","#0000FF","#F28C28"), name = "", labels =
c("Prionium serratum", "Psoralea pinnata","Pter_Restio_Merx","Fynbos")) + #Manual colour
selection
   scale_y_continuous(breaks=seq(0,1,0.2)) + #Manual y-axis tick breaks
   scale_x_continuous(breaks=seq(0,100,20), labels=seq(0,3000,600)) + #Manual x-axis tick breaks
   theme_bw() + #Black and white plot
   theme(strip.background =element_rect(fill=NA), #Remove background colour of plot title
         axis.text.x = element_text(angle = 90, hjust = 1), #Change angle and position of x-axis labels
         axis.text = element_text(size=5), #Change axis label font size
         axis.title = element_text(size=5), #Change axis title font size
         plot.title = element_text(size=6, face='bold', hjust = 0.5), #Change plot title font size
         legend.position="none", #Remove legend
         panel.grid.minor = element_blank(), #Don't show minor grid lines
         panel.grid.major = element_line(size=0.1)) #Change width of major grid lines
#Get map plot:
  ggTransImage = qplot(1:10, 1:10, geom="blank") +
   annotation_custom(g, xmin=-Inf, xmax=Inf, ymin=-Inf, ymax=Inf) +
   theme(line = element_blank(),
         text = element_blank(),
         title = element_blank(),
         panel.background = element_blank())

#Arrange the two plots side by side:
library(gridExtra)
  grid.arrange(ggTransectSub, ggTransImage, nrow=1)
  #Create jpeg image with plots

jpeg(paste0('C:/Thesis_2021/Results_Mapwork/R/EcotoneMapping/R_Outputs/figures2/Transects_
plot',t,'.jpg'), width=11.69, height=4, units='cm', res=600)
  grid.arrange(ggTransectSub, ggTransImage, nrow=1, widths=c(1.8,1))
  dev.off()
}
#####################################End of script############################
```

APPENDIX H

Field vegetation sampling, data collected in October 2020:
*Note: Soil property measurements were recorded in the second round of data collection due to equipment delays.

Time started:	Date:	Co-ordinates X:	Co-ordinates Y:	Elevation:	Quadrat:	Plant id:	Common names	Quadrat Percentage:	Class	Soil: 50cm	Soil: 100cm	Munsell Chart Reading	Comments
09h45	21/10/2020	19.189399	-34.004305	320.528229	Q1	*Merxmuelera cincta*		10%	swv				
		19.189399	-34.004305	320.528229	Q1	*Wachendorfia thyrsiflora*		1%	terrestrial				
		19.189399	-34.004305	320.528229	Q1	*Merxmuelera cincta*		1%	swv				
		19.189399	-34.004305	320.528229	Q1	*Chordifex fastigiatus*		8%	wetland				Australian wetland plant
		19.189399	-34.004305	320.528229	Q1	*Eligia felicae*		50%	wetland	sandy, loam			Restio-native, fynbos
		19.189399	-34.004305	320.528229	Q1	*Restio paniculatus*		5%	swv				
		19.189399	-34.004305	320.528229	Q1	*Helichrysum milfordiae*		15%	terrestrial				Indigenous
		19.189399	-34.004305	320.528229	Q1	*Osteospermum Polygaloides*		10%	terrestrial				
10h05	21/10/2020	19.1895	-34.004194	321.516785	Q2	*Isolepis prolifera*		1%	swv				
		19.1895	-34.004194	321.516785	Q2	unidentified		1%					
		19.1895	-34.004194	321.516785	Q2	unidentified		1%					
		19.1895	-34.004194	321.516785	Q2	*Cliffortia strobilifera*		6%	swv				
		19.1895	-34.004194	321.516785	Q2	*Eligia felicae*		60%	wetland				fynbos restio
		19.1895	-34.004194	321.516785	Q2	*Epischoenis gracilis*		15%	wetland				sedge
		19.1895	-34.004194	321.516785	Q2	*Psoralea pinnata*	fountainbush	8%	wetland				
		19.1895	-34.004194	321.516785	Q2	unidentified		5%					
		19.1895	-34.004194	321.516785	Q2	unidentified		3%					

10h35	21/10/2020	19.189428	-34.004275	318.754395	Q3	*Leucadendron conicum*		98%	fynbos				
		19.189428	-34.004275	318.754395	Q3	unidentified		1%					
		19.189428	-34.004275	318.754395	Q3	unidentified		1%					
11h10	21/10/2020	19.189327	-34.004341	318.820557	Q4	*Elegia filicae*		60%	wetland				Rocky, loose white soil
		19.189327	-34.004341	318.820557	Q4	*Pteridium aquilinium*	bracken fern	10%	wetland				
		19.189327	-34.004341	318.820557	Q4	*Drosera trinervia*		5%	wetland				damp, peaty exposed areas
		19.189327	-34.004341	318.820557	Q4	unidentified		1%	terrestrial				
		19.189327	-34.004341	318.820557	Q4	*Psoralea pinnata L.*	fountain bush (Eng.); fonteinbos, bloukeur, penwortel (Afr.); umHlonishwa (Zulu)	5%	wetland				
		19.189327	-34.004341	318.820557	Q4	*Leucadendron conicum*		10%	wetland				peat
		19.189327	-34.004341	318.820557	Q4	unidentified		5%					
		19.189327	-34.004341	318.820557	Q4	unidentified		3%					
		19.189327	-34.004341	318.820557	Q4	unidentified		1%					
11h55	21/10/2020	19.18921	-34.004425	317.355652	Q5	*Laurembergia repens*		10%	swv				
		19.18921	-34.004425	317.355652	Q5	unidentified		5%					
		19.18921	-34.004425	317.355652	Q5	*Cliffortia strobilifera*		15%	swv				
		19.18921	-34.004425	317.355652	Q5	unidentified		3%					
		19.18921	-34.004425	317.355652	Q5	unidentified		10%					
		19.18921	-34.004425	317.355652	Q5	unidentified		5%					
		19.18921	-34.004425	317.355652	Q5	*Thelypteris confluens*		40%	swv				

		19.18921	-34.004425	317.355652	Q5	unidentified		10%					
		19.18921	-34.004425	317.355652	Q5	unidentified		2%					
12h30	21/10/2020	19.188946	-34.005041	311.366852	Q6	*Thelypteris confluens*		50%	swv				
		19.188946	-34.005041	311.366852	Q6	small swv plants		50%	swv				
12h45	21/10/2020	19.188871	-34.005221	310.508057	Q7	*Isolepis prolifera*		40%	swv				
		19.188871	-34.005221	310.508057	Q7	*Merxmuelera cincta*		5%	swv				
		19.188871	-34.005221	310.508057	Q7	*Merxmuelera cincta*		5%	swv				
		19.188871	-34.005221	310.508057	Q7	*Merxmuelera cincta*		50%	swv				
13h12	21/10/2020	19.181979	-33.986955	332.724548	Q8	*Brabejum stellatifolium*		100%	terrestrial	loose dry white sand			
13h30	21/10/2020	19.181713	-33.986891	332.4888	Q9	*Searsia augustifolia*		10%	terrestrial				
		19.181713	-33.986891	332.4888	Q9	unidentified		5%					
		19.181713	-33.986891	332.4888	Q9	unidentified		20%					
		19.181713	-33.986891	332.4888	Q9	unidentified		10%					
		19.181713	-33.986891	332.4888	Q9	*Dicerothamnus rhinocerotis*		50%	swv				
		19.181713	-33.986891	332.4888	Q9	unidentified		15%					
14h12	21/10/2020	19.181349	-33.987252	330.188507	Q10	*Thelypteris confluens*		60%	wetland				
		19.181349	-33.987252	330.188507	Q10	*Cliffortia strobilifera*		20%	swv				
		19.181349	-33.987252	330.188507	Q10	*Carpobrotus edulis*		5%	terrestrial				
		19.181349	-33.987252	330.188507	Q10	*Epischoenis gracilis*		5%	wetland				
		19.181349	-33.987252	330.188507	Q10	*Pteridium aquilinum*		5%	wetland				
		19.181349	-33.987252	330.188507	Q10	*Cyperus thunbergii*		5%	wetland				

14h35	21/10/2020	19.181158	-33.98734	330.125275	Q11	*Merxmuelera cincta*		90%	wetland				grass
		19.181158	-33.98734	330.125275	Q11	*Elegia filicae*		5%	wetland				
		19.181158	-33.98734	330.125275	Q11	*Elegia capensis*		5%	fynbos				Fynbos
14h50	21/10/2020	19.178657	-33.982652	332.728149	Q12	*Merxmuelera cincta*		80%	wetland				grass
		19.178657	-33.982652	332.728149	Q12	*Elegia filicae*		10%	wetland				
		19.178657	-33.982652	332.728149	Q12	*Juncus spp.*		10%	wetland				
08h45	22/10/2020	19.173443	-33.958172	348.007935	Q13	*Prionium serratum*		30%	wetland				
		19.173541	-33.958126	348.007935	Q13	*Pteridium aquilinum*		30%	swv				
		19.17337	-33.958029	337.292877	Q13	*Psoralea pinnata L.*		20%	wetland				
		19.173289	-33.958003	336.508545	Q13	*Psoralea pinnata L.*		20%	wetland				
09h20	22/10/2020	19.17197	-33.951853	346.822266	Q14	*Pteridium aquilinum*		80%	swv				
		19.17197	-33.951853	346.822266	Q14	*Carpha glomerata*		10%	wetland				
		19.17197	-33.951853	346.822266	Q14	*Psoralea pinnata L.*		5%	wetland				
		19.17197	-33.951853	346.822266	Q14	*Restio paniculatus*		5%	swv				

Field vegetation sampling, data collected in June 2021:

Time started:	Date:	Co-ordinates X:	Co-ordinates Y:	Elevation:	Quadrat:	Plant id:	Common names	Quadrat Percentage:	Soil: 50cm	Soil: 100cm	Munsell Chart Reading	Comments
11h45am	7/06/2021	19.18631	-34.0042	311.0545	Q15	*Prionium serratum*	Palmiet	30%	Sandy loam	Sandy loam	Hue: 5YR, Value: 2.5, Chroma: 1	A lot of organic matter in 50cm, very coarse, very wet. At 100cm completely saturated
		19.18631	-34.0042	311.0545	Q15	*Laurembergia repens*	Water Milfoil	20%	damp	very very wet		Patches of agglomerated palmiet close to smaal tributries
		19.18631	-34.0042	311.0545	Q15	Shrubs		20%				
		19.18631	-34.0042	311.0545	Q15	*Restio paniculatus Rottb.*	calopsis (English); besemgoed (Afrikaans)	20%				
		19.18631	-34.0042	311.0545	Q15	*Berzelia abrotanoides*	redlegs (Eng.); rooibeentjies, vleiknoppiesbos, kolkol, fonteinbos (Afr.)	10%				
	7/6/2021	19.18631	-34.0044	310.2428	Q16	*Pteridium aquilinum*	bracken fern	80%	Sandy loam	Sandy loam	Hue: 5YR, Value: 2.5, Chroma: 1	Very little organic matter, could be seasonally wet zone
	7/06/2021	19.18631	-34.0044	310.2428	Q16	Pink shrub/Herb		20%	low wetness, fairly dry	slightly damp		Light grey
	7/06/2021	19.18593	-34.0046	311.2105	Q17	*Merxmuellera cincta*		90%	Sandy loam	Sandy loam	Hue: 5YR, Value: 2.5, Chroma: 1	Higher & finer organic material, sandy granules closer together and finer
		19.18593	-34.0046	311.2105	Q17	Herbs		5%	very wet	very wet		
		19.18593	-34.0046	311.2105	Q17	*Moss layer on topsoil*		5%				

	7/06/2021	19.18371	-34.0035	310.9797	Q18	*Brabejum stellatifolium*	bitteramandel, wild almond, wilde-amandel, ghoeboontjie, ghoekoffie	90%	Sand	Sand	Hue: 5YR, Value: 2.5, Chroma: 1	Not fine granules but gritty, dry and not very course
		19.18371	-34.0035	310.9797	Q18	*Pteridium aquilinum*	bracken fern	10%	nutrient poor	damp		
	7/06/2021	19.18407	-34.0035	311.996	Q19	*Leucadendron coniferum*	Dune Conebush	90%	Sandy loam	Sandy loam	Hue: 5YR, Value: 2.5, Chroma: 1	Gritty, fine granules
		19.18407	-34.0035	311.996	Q19	*Metalasia muricata/Metalasia densa*	coast metalasia, white bristle bush (Eng.); blombos, witsteekbossie, steekbos (Afr.)	10%	very wet	leached		
14h38 pm	7/06/2021	19.17846	-33.9918	319.4586	Q20	*Pteridium aquilinum*	Bracken fern	100%	Sand	Sand	Hue: 10YR, Value 4, Chroma: 4	More sand than loam failry organic <30% organic carbon
	7/06/2021	19.17867	-33.9919	321.138	Q21	*Restio paniculatus Rottb.*	calopsis (English); besemgoed (Afrikaans)	100%	Sandy loam	Sandy loam	Hue: 10YR, Value 4, Chroma: 4	Fine, reddish sand, little organic matter
	7/06/2021	19.17787	-33.9914	320.4131	Q22	*Merxmuellera cincta*		99%	Loam	Loam	Hue: 7.5YR, Value: 3, Chroma: 3	Fine, brown sand, not very wet & compact
		19.17787	-33.9914	320.4131	Q22	*Thelypteris confluens*	Marsh fern	1%				
	7/06/2021	19.17917	-33.9904	327.0022	Q23	*Leucadendron coniferum*	Dune Conebush	90%	Sandy loam	Sandy loam	Hue: 7.5YR,	Very low wetness

											Value: 3, Chroma: 3	
		19.17917	-33.9904	327.0022	Q23	*Metalasia muricata/Metalasia densa*	coast metalasia, white bristle bush (Eng.); blombos, witsteekbossie, steekbos (Afr.)	10%				
10H21	8/06/2021	19.17845	-33.9827	334.1852	Q24	*Berzelia abrotanoides*	redlegs (Eng.); rooibeentjies, vleiknoppiesbos, kolkol, fonteinbos (Afr.)	80%	Loamy sand	Clay	Hue: 2.5 , Value: 3, Chroma: 1	Course, and gritty chalk white colour at about 70cm
		19.17845	-33.9827	334.1852	Q24	*Restio paniculatus Rottb.*	calopsis (English); besemgoed (Afrikaans)	10%				
		19.17845	-33.9827	334.1852	Q24	*Metalasia muricata/Metalasia densa*	coast metalasia, white bristle bush (Eng.); blombos, witsteekbossie, steekbos (Afr.)	10%				
	8/06/2021	19.17819	-33.9828	330.3489	Q25	*Metalasia muricata/Metalasia densa*		80%	Sand	Sand	N7 Value: 6, Gleyed soil, sand	Little organic matter
		19.17819	-33.9828	330.3489	Q25	*Diospyros glabra*	Blue-berry Bush, Bloubessie	10%				
		19.17819	-33.9828	330.3489	Q25	unidentified		10%				
	8/06/2021	19.178	-33.9831	332.025	Q26	*Brabejum stellatifolium*	bitteramandel, wild almond, wilde-amandel, ghoeboontjie, ghoekoffie	100%	Loamy sand	Loamy sand	Hue: 10YR, Value: 6, Chroma: 2	High organic matter, very dark, fine sand that's almost silty
	8/06/2021	19.17791	-33.9834	332.1571	Q27	*Protea nerifolia*	oleander-leaf protea, narrow-leaf protea (Eng.), baardsuikerbos, baardsuikerkan,	100%	Loamy sand	Loamy sand	Hue: 2.5Y, Value: 4,	Damp, slightly wet and at 100 cm it gets slightly light brown

							blousuikerkan (Afr.)				Chroma: 2	
	8/06/2021	19.17733	-33.9835	329.3565	Q28	*Merxmuellera cincta*		50%	Sandy loam	Sandy loam	Hue: N 2.5, Value: 2.5	Surface water visible, gleyed
		19.17733	-33.9835	329.3565	Q28	*Elegia capensis*	horsetail restio (Eng.); besemriet, fonteinriet, katstert, kanet (Afr.)	50%	very saturated			Very saturated
	8/06/2021	19.16606	-33.9688	321.7184	Q29	*Psoralea pinnata L.*	fountain bush (Eng.); fonteinbos, bloukeur, penwortel (Afr.); umHlonishwa (Zulu)	100%	Sandy loam	Sandy loam, clay	Hue: 10YR, Value: 6, Chroma: 2	Thick organic top 50cm layer, can dominantly mixed with dense clogs of palmiet, ferns and restios as understory
12H35	8/06/2021	19.1664	-33.9689	324.8384	Q30	*Pteridium aquilinum*	bracken fern	90%	Loamy sand	Loamy sand	Hue: 2.5Y, Value: 3, Chroma: 2	Grey & gleyec towards 100cm mark with high organic matter
		19.1664	-33.9689	324.8384	Q30	*Merxmuellera cincta*		10%				
	8/06/2021	19.16666	-33.9689	324.2585	Q31	*Restio paniculatus Rottb.*	calopsis (English); besemgoed (Afrikaans)	80%	Sand	Sand	Hue: 10YR, Value: 6, Chroma: 2	First 15cm is sand, then becomes reddish, then at 50cm its much darker and black
		19.16666	-33.9689	324.2585	Q31	*Merxmuellera cincta*		20%	reddish	darker brown to black		
	8/06/2021	19.17082	-33.9635	335.7029	Q32	*Psoralea pinnata L.*	fountain bush (Eng.); fonteinbos, bloukeur, penwortel (Afr.); umHlonishwa (Zulu)	80%	Clay	Clay	Hue: 10YR, Value: 6, Chroma: 2	Black, then becomes greyish sand further down into 100cm
		19.17082	-33.9635	335.7029	Q32	*Pteridium aquilinum*	bracken fern	10%				

		19.17082	-33.9635	335.7029	Q32	unidentified		10%				
10h24	9/06/2021	19.17063	-33.9634	343	Q33	*Restio paniculatus Rottb.*	calopsis (English); besemgoed (Afrikaans)	45%	Loamy clay	Loamy clay	Gleyed N 2.5	Smooth velvety, very dark, very dense , organic clay
		19.17063	-33.9634	343	Q33	*Psoralea pinnata L.*	fountain bush (Eng.); fonteinbos, bloukeur, penwortel (Afr.); umHlonishwa (Zulu)	45%				
		19.17063	-33.9634	343	Q33	*Zantedeshichia aethiopica*	arum lily	10%				
	9/06/2021	19.17052	-33.9633	334	Q34	*Prionium serratum*	Palmiet	100%	Clayey silt	Sandy loam	Gleyed N 2.5	Smooth velvety, very dark, very dense , organic clay
	9/06/2021	19.1736	-33.9571	344	Q35	*Restio paniculatus Rottb.*	calopsis (English); besemgoed (Afrikaans)	80%	Sandy loam	Loamy, sandy, clay	Gleyed 5 G 5.1	Very wet, surface water
		19.1736	-33.9571	344	Q35	*Deep long leaved green plant*		10%				
		19.1736	-33.9571	344	Q35	*Grass*		10%				
	9/06/2021	19.17374	-33.9571	343	Q36	*Berzelia abrotanoides*	redlegs (Eng.); rooibeentjies, vleiknoppiesbos, kolkol, fonteinbos (Afr.)	20%	Sand	Loamy sand		Light brown, then darker to the core
		19.17374	-33.9571	343	Q36	*Elegia capensis*		20%				
		19.17374	-33.9571	343	Q36	*Restio paniculatus Rottb.*	calopsis (English); besemgoed (Afrikaans)	20%				
		19.17374	-33.9571	343	Q36	*Leucadendron*		20%				
		19.17374	-33.9571	343	Q36	*Pteridium aquilinum*	bracken fern	10%				
	9/06/2021	19.17395	-33.9569	343	Q37	*Berzelia abrotanoides*	redlegs (Eng.); rooibeentjies, vleiknoppiesbos, kolkol, fonteinbos (Afr.)	80%	Sand	Sand	Gleyed sand	fine, lighter, gritty sand
		19.17395	-33.9569	343	Q37	*Leucadendron*		10%				

		19.17395	-33.9569	343	Q37	*Restio paniculatus Rottb.*	calopsis (English); besemgoed (Afrikaans)	10%				
	9/06/2021	19.17345	-33.9546	343	Q38	*Psoralea pinnata L.*	fountain bush (Eng.); fonteinbos, bloukeur, penwortel (Afr.); umHlonishwa (Zulu)	100%	Loamy, fine sand	Sand		high organic matter, fine
	9/06/2021	19.17399	-33.9555	347	Q39	*Pteridium aquilinum*	bracken fern	100%	hard rock	hard rock		
	9/06/2021	19.17301	-33.9555	347	Q40	*Prionium serratum*	Palmiet	100%				