Environmental modelling of wetland distribution in the Western Cape, South Africa: A climate change perspective

by

Shanice Mohanlal

Student number: 3879544

A thesis submitted in fulfilment of the academic requirements for the degree Magister Scientiae in Environmental and Water Science, Department of Earth Sciences, University of the Western Cape

Supervisors: Dr Nicholas A. Rivers-Moore

Prof Michael C. Grenfell

2021

Abstract

Wetlands have been recognised as one of the most intrinsically valuable and threatened ecosystems in the world. Global estimates indicate that wetlands are being lost or transformed at a rapid rate, exacerbated by projected climate change impacts. This has prompted the need to improve wetland mapping to address the conservation and management of these ecosystems effectively. However, this remains a challenge. Current mapping approaches estimates of wetland extent vastly underestimate the true extent. Ancillary data has been acknowledged to improve the accuracy of mapping the distribution of wetlands. This study adds to the growing body of knowledge on wetland mapping while incorporating present and projected climate change scenarios. The purpose of the study was to model the current and potential future wetland distribution for the different climate change scenarios in the Western Cape, South Africa. The study combines Geographic Information Systems (GIS), field survey, environmental modelling, and spatial statistical analyses. The overall wetland density for the study area is seven wetlands/10 km^2; however, the distribution is uneven. There is an increase in overall wetland density from east to west and north to south, and follows a similar pattern as the aridity gradient. A Principal Component Analysis (PCA) was used to remove redundant and highly correlated environmental variables. The wetland dataset was divided into a training and verification dataset, 70% and 30%, respectively. The outcomes of the logistic regression model was used to create raster layers to map the probabilities of wetland occurrence in the study area. Model validation included two datasets; a digital verification dataset and a field verification dataset. The final model output predicted wetland presence distribution well, with area under receiver operating characteristic curve (AUC ROC) values of 0.687 (SE± 0.006) and 0.643 (SE± 0.021) for the digital and field verification datasets, respectively. The potential change in the distribution of wetlands was modelled under the climate change scenarios based on the Representative Concentration Pathways (RCP) 4.5 and RCP 8.5 for the near- (2050) and far- (2070) future to determine the spatial differences between the current and future distributions. The change analysis indicated a potential loss in wetland distribution for 2050 is between 62-90 % and 71-98% for 2070 under

RCP 4.5 and RCP 8.5 climate change scenarios, respectively. The findings of this study demonstrate the potential of using predictive modelling techniques with readily available environmental variables as an important reference for future studies to improve the mapping of wetland distribution at a regional scale.

Keywords: GIS, logistic regression, predictive modelling, principal component analysis, RCP 4.5, RCP 8.5, wetland mapping.

Declaration

I, Shanice Mohanlal, declare that the thesis entitled, “Environmental modelling of wetland distribution in the Western Cape, South Africa: A climate change perspective” is my own work, that it has not been submitted for any degree or examination in any other university, and that all the sources I have used or quoted have been indicated and acknowledged by complete references.

Full name: Shanice Mohanlal

Date: 6 August 2021

Signed:

Acknowledgments

First and foremost, I thank God for the opportunities presented to me.

Several people and organisations have contributed to the completion of this research. I would like to begin by expressing my appreciation to the South African National Biodiversity Institute - Freshwater Unit and the Water Research Commission for funding this work and providing me with the opportunity to learn.

I extend my deepest gratitude to my supervisors, Dr Nick Rivers-Moore and Professor Michael Grenfell. Thank you so much for your guidance, assistance, knowledge and particularly your patience throughout this journey. Thank you, Dr Rivers-Moore, for your assistance with fieldwork. My gratitude goes to Ms Nancy Job for your kindness and support and for developing my critical thinking skills. A sincere thank you to Dr Donovan Kotze for verifying my fieldwork. To my colleagues Shae-Lynn Sampson, Faith Mamphoka and Faeeza Fortune, who have been a part of this academic journey alongside me. I would like to thank Bhavna Ramdhani for her support and encouragement.

I would like to extend a special thank you to my family - Dad, Mum, Shivan, Reshlyn and Onyx, for your constant love and support that have made my possibilities endless. I am deeply thankful to have you all as a pillar of strength in my life.

To my brother, Shivan, your continuous support and banter is truly appreciated. I would like to thank my partner, Reshlyn Bridglall, for your enthusiasm and always believing in me. Your immense support and encouragement in times when I was ready to give up has spurred me on. Lastly, to my parents, thank you for all the sacrifices you have made and for supporting me in every way possible; without you I would not have made it this far.

I dedicate this thesis to my parents, Suren and Ronica Mohanlal.

If there is no struggle, there is no progress - Fredrick Douglass 1857

Abbreviations

AI	Aridity Index
AIC	Akaike Information Criterion
ARZ	Aseasonal Rainfall Zone
AUC ROC	Area under receiver operating characteristic curve
BN	Bayesian Network
CMIP5	Coupled Model Intercomparison Project Phase 5
CVB	Channelled valley bottom
DEM	Digital Elevation Model
FN	False negative
FP	False positive
GCM	Global Climate Models
GHG	Greenhouse gas
GIS	Geographic Information System
GLM	Generalised linear model
GPS	Global Position System
GRA2	Groundwater Resource Assessment Phase 2
HGM	Hydrogeomorphic
IPCC	Intergovernmental Panel on Climate Change
IPCC AR5	Intergovernmental Panel on Climate Change Fifth Assessment Report
KMO	Kasier-Meyer-Olkin
LR	Logistic regression
MAE	Mean annual potential evapotranspiration
MAP	Mean annual precipitation
MARS	Multivariate Adaptive Regression Splines
Mbgl	Metres below ground level
MIROC-ESM	Model for Interdisciplinary Research on Climate - Earth System Model
NWA	National Water Act
NWM	National Wetland Map

PCA	Principal Component Analysis
PET	Potential evapotranspiration
RCP	Representative Concentration Pathway
SAIIAE	South African Inventory of Inland Aquatic Ecosystems
SDG	Sustainable Development Goals
SRTM	Shuttle Radar Topography Mission
SRZ	Summer Rainfall Zone
SUDEM	Stellenbosch University’s Digital Elevation Model
TMG	Table Mountain Group
TN	True negative
TP	True positive
TPI	Topographic Position Index
UNFCCC	United Nations Framework Convention on Climate Change
UVB	Unchannelled valley bottom
WRZ	Winter Rainfall Zone

Table of contents

List of Figures

List of Tables

Chapter One: General introduction and theoretical background

1.1 Introduction

Wetlands are valuable natural ecosystems that occupy about 6% of the world's land cover (Maltby and Acreman, 2011; Mitsch et al. 2015). Wetlands are areas that experience periodic or continuous inundation to a shallow depth and have saturated soils where plants and other biological activities are adapted to wet conditions (Tooth et al. 2015). They provide a series of ecosystems services that benefit the environment, biota and humans, such as flood attenuation, water purification, wildlife habitat, climate change mitigation, tourism and recreation and provision of resources for human consumption (Kotze et al. 2009). The development and survival of human society depend on wetlands due to their rich natural resources (Turner et al. 2000). Despite this, there has been rapid degradation and loss of wetlands throughout the world due to climate change and anthropogenic activities (Davidson, 2016; Mitsch and Hernandez, 2013; Schuyt, 2005). The combined and cumulative effects of wetland fragmentation and loss, the disruption to the ecosystems, and the effects of climate change have contributed to their degradation. Recognition of the value and importance of wetlands and their interdependence with surrounding ecosystems have emphasised the proper management and conservation practices of these systems (Hiestermann and Rivers-Moore, 2015).

The risk of threat and loss of a wetland is primarily attributed to insufficient understanding of the complexity and spatial relations between surface water, groundwater and wetland vegetation (Murphy et al. 2007). Climate change is projected to impact the hydrological regime, precipitation patterns, local changes in temperature and consequently changes in evapotranspiration patterns, as well as the frequency and intensity of extreme events (Engelbrecht and Engelbrecht, 2016; Junk et al. 2013).

Aridity is a complex variable related to changes in climate parameters. It states the ratio between the mean annual precipitation and the average annual potential evapotranspiration to determine the long-term state of dryness or average water stress of the environment (Chevalier and Chase, 2016; UNEP, 1997). Furthermore, spatial and temporal regional aridity gradients influence the distribution and extent of wetlands in a landscape (Fay et al. 2016; Metz and Tielbörger, 2015).

The effective management of wetlands necessitates the development of knowledge inventories that include location, size, type, ecological condition, which are integrative of scientific wetland information and socio-economic concerns (Murphy et al. 2007). Wetland inventories provide baseline wetland data that can be built upon and serve several purposes such as guiding policy-making and prioritising the response of wetlands to guide the management, assessment and monitoring of specific wetlands. (Davidson et al. 2018; Hiestermann and Rivers-Moore, 2015; Rebelo et al. 2009).

Comprehensive spatial wetland inventories, which include information on the distribution, size, classification and connectivity in the landscape, are the way forward for best wetland management practice (Fay et al. 2016; Murphy et al. 2007). Mapping wetlands in their current distribution, type, and size has proven difficult due to the many factors that influence their presence in the landscape. The mapping and classification of wetlands is an abstract of the actual on-ground wetland distribution. In actuality, these environments form a portion of the continuum of soil hydrological condition that traverses a landscape (Murphy et al. 2007).

Environmental modelling is an important tool for developing research and understanding and a tool for simulation and predictions. Modelling allows for the integration of different components, and it provides an abstraction of reality. The abstraction is a simple representation of those complex reality components considered important for modelling (Wainwright and Mulligan, 2004). Modelling helps improve wetland inventory through predicting wetland distribution and extent. Furthermore, predicting the effects of climate change on wetlands can benefit from environmental modelling by providing an understanding and subsequent design of management techniques to increase wetland resilience to climate change (Erwin, 2009).

1.2 Rationale for the study

In South Africa, there is high variability and the mean annual rainfall and evaporation rates across the country. There is less than 100 mm to 1 500 mm of rainfall per annum in the west and east, respectively. The mean annual evaporation varies geographically from 800 mm to 2 000 mm (DWS, 2015; Kohler, 2016). The mean annual rainfall is 450 mm, which is substantially lower than the global average rainfall of 860 mm per annum and classifies the country as semi-arid and the freshwater resources under immense pressure. Wetlands in South Africa are a particularly important resource for their regulatory and provisioning benefits (Schuyt, 2005; Sinchembe and Ellery, 2010). Despite South African being one of the signatories of the Ramsar Convention, which provide the framework for the protection of wetlands, historically, there has been poor monitoring and conservation of wetlands. This finding is consistent with Driver et al. (2012) and Sinchembe and Ellery (2010), as more than half of the country's wetlands have undergone severe degradation or destruction.

Currently, wetlands constitute only 2.2% of South African land cover (van Deventer et al. 2020). This small area of wetland coverage provides high-value ecosystem services (Driver et al. 2012). The loss and degradation of wetlands are likely to encumber future socio-economic development, and poor and rural communities are more vulnerable because people's livelihoods and survival are intrinsically linked to the resource (MEA, 2005).

Gaps in data to accurately quantify wetlands' spatial and temporal distribution at different scales and their response to the effects of projected climate change is a major challenge for environmental managers and decision-makers. This information is critical in informing decision-makers where wetlands are in the landscape and prioritising conservation efforts based on the wetland type and ecological condition of these ecosystems. The inventory will serve as a fundamental baseline study for more comprehensive plans for planning and decision-making with regard to policies and development. The inventory of wetlands is dependent on several factors that influence the occurrence and status of the wetland in the landscape (Hiestermann and Rivers-Moore, 2015). Wetlands coverage is vast and often located in inaccessible areas, resulting in difficulty using conventional site-specific methods as they are time-consuming, labour intensive, expensive and spatially restrictive (Tallis and Polasky, 2009). Additionally, dynamic climate-related data are less common for wetland modelling to determine water availability and the net local water availability (Nyandwi et al. 2016). Therefore there is a need to improve inventory in terms of current and projected future wetlands distribution.

Recent Intergovernmental Panel on Climate Change (IPCC) models for climate change depict a decrease in rainfall and an increase in temperature for South Africa (IPCC, 2014). The temperatures in the Western Cape are projected to drastically increase by 4-6°C and a reduction in winter rainfall of about 20% by 2100 (Engelbrecht and Engelbrecht, 2016; Engelbrecht et al. 2009). The aridity gradient across the Western Cape is of spatial and temporal importance for the current climate and projected climate change scenarios. The Western Cape is expected to incur the following impacts under climate change projections: significant reductions in the supply of water and associated effects on wetlands; rising sea-level; loss of species in the biodiversity hotspots; increase in evapotranspiration; increases in the frequency of wildfires; as well as several effects on livelihood in the province (Dallas and Rivers-Moore, 2014; Driver et al. 2012; Pasquini et al. 2013).

The focus of this study is to determine the distribution of wetlands across the aridity gradient in the Western Cape in its current distribution and predicted future distribution under various climate change scenarios. The findings of the study will be a valuable resource to inform future research and planning of conservation efforts.

1.3 Aim and objectives

The aim of this study was to model the probability of current and future geographical wetland distributions under present climate conditions and predicted climate change scenarios in the Western Cape, South Africa using logistic regression.

The objectives of the study are as follows:

1. To determine the variation in the density of wetlands along the aridity gradient in the Western Cape.
2. To identify mutually independent environmental variables associated with the presence of wetlands in the Western Cape.
3. To develop probability maps of current and future wetland distribution under the current climate conditions and predicted climate change scenarios Representative Concentration Pathways (RCP) 4.5 and RCP 8.5 using a logistic regression model.
4. To determine the predicted loss/gain of wetland distribution extent for the current climate change scenarios.

1.4 Research questions

The study addresses the following questions:

1. What is the change in wetland density along the aridity gradient in the Western Cape?
2. What is the effect of each independent environmental variable in determining the presence of wetlands?
3. What is the current potential geographical distribution of wetlands in the Western Cape?
4. What are the suitable areas for wetland distribution under the climate change scenarios for the near- (2050) and far- future (2070)?
5. What will the change be from the current potential wetland distribution according to the RCP 4.5 and RCP 8.5 climate scenarios in 2050 and 2070?

1.5 Thesis structure

Chapter One (this chapter) provides a brief introduction to the research project and provides an overview of the importance of wetlands in a global and South African context regarding the current and projected wetland distribution under climate change scenarios. It further explains the need for accurate mapping of the distribution of wetlands. The aims and objectives of the study are outlined.

Chapter Two reviews the literature and key concepts upon which the study is based. Key areas reviewed in this chapter include wetland formation, environmental modelling techniques used to model wetlands, a status quo of wetlands in the Western Cape, and the impact of climate change on wetland distribution.

Chapter Three describes the regional setting and study area in the Western Cape Province.

Chapter Four describes the research design and methodology implemented to achieve the aim and objectives of the study.

Chapter Five presents the findings of the wetland distribution probability maps for current and future climate change scenarios in the study area. Furthermore, the chapter includes the results of model evaluation and wetland distribution change analysis.

Chapter Six discusses the results acquired from the study and the accuracy of the resultant probability layers using the logistic regression model. The relevance of the results was discussed and how it pertains to current research and relation to previous research undertaken in South Africa and internationally. Lastly, the chapter summarises the concluding remarks of the study and recommendations for future research.

Chapter Two: Literature review

2.1 Introduction

The distribution of wetlands varies both spatially and temporally. An inventory of wetland distribution and characteristics is fundamental for informed planning, decision-making and management of these resources. Identification of the presence of wetlands is important. This chapter presents a review of relevant literature, key concepts and principles which form the foundation of the research project. The purpose of the review is to introduce important literature on wetlands, to determine the findings of current knowledge on a global, national and local scale in terms of wetland inventory, planning for climate change and the environmental modelling thereof. Several studies have focused on the wetland inventory in its current distribution however, there is a limited number of published works related to the potential change in the distribution of wetlands in terms of climate change. Particularly, in relation to a decrease in rainfall and an increase in temperature conditions as projected for the Western Cape Province of South Africa. The methods of using logistic regression model in wetland distribution modelling in the study aims to further explore its application.

2.2 Definition of wetlands

The definition used in this thesis follows the South African National Water Act (NWA) No. 36 of 1998: 18, wherein a wetlands is described 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" (NWA 36 of 1998). The NWA received international attention as it was the first piece of legislation in South Africa that made it mandatory for planning and developing of water resources to consider its impact on wetlands and rivers (de Moor and Day, 2013). Despite this, the NWA focuses more on the need to maintain wetlands and rivers in a 'sustainably usable' state rather than the explicit conservation of wetlands and as a result it is not as successful as anticipated (de Moor and Day, 2013).

2.3 Classification of wetlands

Wetland classification systems categorise wetlands that have a set of similar general characteristics into groups and subgroups. These characteristics include chemical, ecological, geomorphological and hydrological (Cowardin et al. 1979). Wetland classification provides a starting point for wetland inventory (Finlayson and van der Valk, 1995).

South Africa uses the hydrogeomorphic (HGM) classification system developed by Ollis et al. (2013) that catalogues wetlands by their position in the landscape such as on a crest, slope or valley and according to the way in which water moves in, through and out of a wetland system. These include floodplains, channelled valley bottoms, unchannelled valley bottoms, wetland flats, depression (including lakes), hillslope seep and seepage wetlands (Figure 2.1). For detailed description of HGM wetland types refer to Ollis et al. (2013).

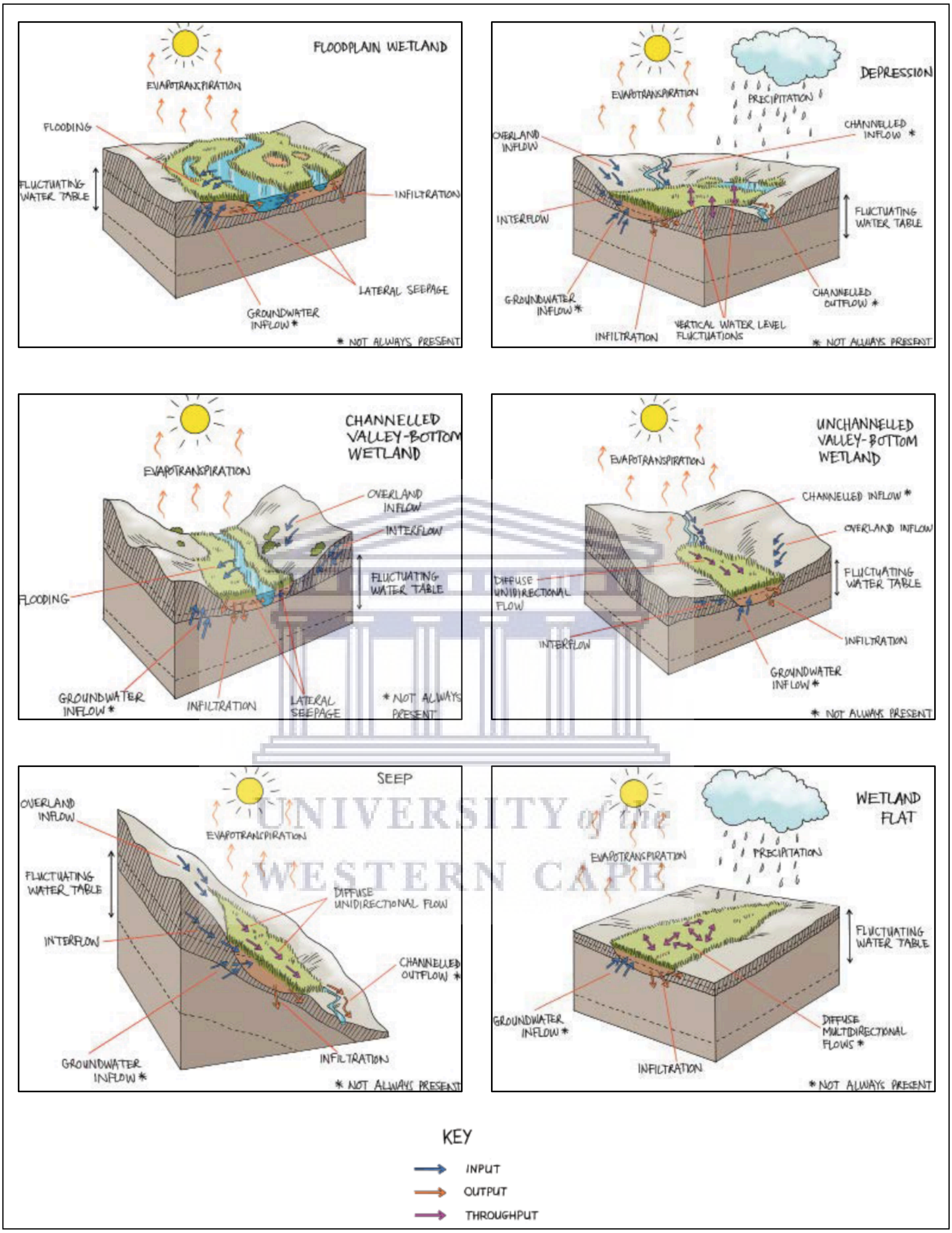


Figure 2.1: The different hydrogeomorphic types (Ollis et al. 2013).

2.4 Wetland formation

The formation of wetlands can be determined by natural and/or anthropogenic factors. Both factors play an important role in the formation mechanism of wetlands. For the purposes of the study, we will focus on the natural factors. Wetland formation occurs as a result of many abiotic and biotic factors. There are three main components that are often included in wetland definitions either by themselves or in conjunction and can be considered diagnostic (Maltby and Acreman, 2011; Mitsch, 2005): 1) the predominant presence and dynamics of water either at or above the surface or within the root zone; 2) unique soil or sediment conditions that differ from adjacent non-wetland (terrestrial or fully aquatic) areas; and 3) vegetation (and generally animals) are specifically adapted to permanently or seasonally wet conditions (Figure 2.2).

These components are as a result of the interaction between the physical factors, which in turn influence the distribution of wetlands in a landscape. The interaction between the physical factors occurs at various spatio-temporal scales ranging from the regional setting which is influenced by the climate, the water catchment which is influenced by the hydrology and topography, and the site specific environment of the wetland that is dependent on the geomorphology and soil properties. Hydrology is the primary factor that determine the degree to which wetlands exist. The wetland structure, processes and functions is determined by different hydrological regimes and results in several different HGM wetland types (Maltby and Acreman, 2011). The hydrology affects the physicochemical environment including soils. Consequently, the interaction between hydrology and the physiochemical environment determine the type and quantity of biota, including vegetation is found in a wetland. The biota, in turn, cause feedbacks that modify the hydrology and physicochemical environment (Mitsch, 2005). The inundation of water into the system for a prolonged or significant duration of the hydrological regime characterises and is the dependent variable in the formation and development of wetlands (Turner et al. 2000). Generally, wetlands are more abundant in cool, wet climates than in hot, drier climates. This is because the water balance in cool, wet climates tend to be more favourable to wetland formation and persistance i.e. experience less evapotranspiration and more rainfall resulting is less water loss than from the land than hot, drier climates (Mitsch and Gosselink, 2007).

The geomorphology of a landscape determines where wetlands are likely to be present as it influences how water moves in, through and out of the soil (Kolka and Thompson, 2007; Ollis et al. 2013). Depressions and flat gently sloping terrains are likely to have a higher abundance of wetlands than steep sloping landscapes. The geomorphic setting is important as it is a product of the water source and hydrodynamics (such as unidirectional flow, reversing flow) although it also constrains the water source and hydrodynamics (National Research Council, 1995).

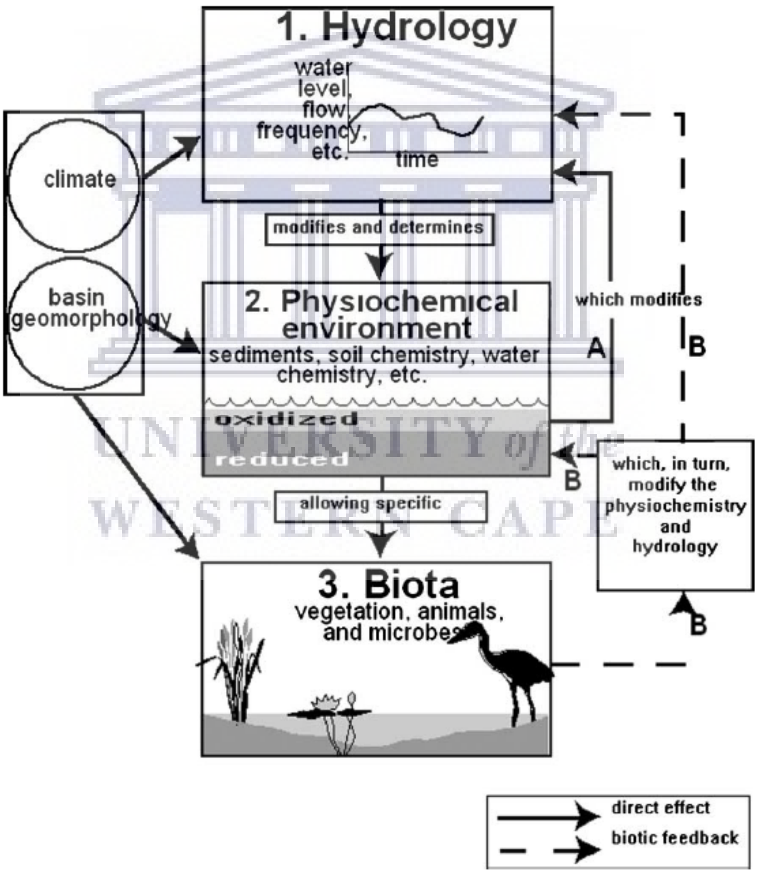


Figure 2.2: The three main components of wetlands and their principal cause of wetlands – climate and landscape geomorphology commonly used in wetland definitions (Mitsch and Gosselink, 2000).

2.5 South African wetland distribution

South Africa is predominantly classified as a semi-arid, water stressed country. Approximately 70% of the countries falls in the arid to semi-arid climatic region of South Africa (Schulze, 1997). The country lies in the temperate region of the globe and the climate is influenced by variations caused by factors such as elevation, proximity to the ocean and relief features such as mountain ranges (Mabaya et al. 2011). Consequently, approximately 65% of the country characterised by an average rainfall of 450 mm per year almost half of the global average of approximately 860 mm per year. While the driest areas located to the west, make up 21% of the country receives less than 200 mm (Lakhraj-Govender and Grab, 2019; Otieno and Ochieng, 2004). The average potential evapotranspiration is relatively high as a result of high average annual temperatures, and far exceeds the rainfall over most of the country (Schulze, 1997).

In a global context, the country's water resources are limited and scarce. This is attributed to the uneven distribution of natural availability of water combined with strong seasonal rainfall. The mountainous regions of South Africa off the southern and eastern coastal plains create a rain shadow across the interior regions. This results in a mostly dry interior and the leeward side of the escarpment that creates high water yield areas (Bradshaw and Cowling, 2014; DEA, 2016).

As previously discussed in Section 2.2 wetlands are more abundant in regions that have a positive water balance, where rainfall exceeds atmospheric water demands than in regions with a negative water balance, where the converse is true. The atmospheric demand for water can be quantified using potential evapotranspiration as an indicator, where solar radiation provides the energy that drives evapotranspiration. Global wetland distribution is generally favoured towards regions that have a positive water balance and topographic impact of the recent glaciation event (approximately 8000 years ago) (Ellery et al. 2009; Mitsch and Gosselink, 2000). Despite this, wetlands do occur in regions with a negative water balance as a result of other factors. The southern African landscape is situated at an unusually high mean elevation despite the landscape being ancient, with relatively no tectonic activity in recent years and has not been significantly shaped by the recent glaciation event which affected the landscape of most other regions. Further to this, the interior and western margin of the country is classified as dryland (MAP:PET < 0.65; UNEP, 1997). as there is a negative water balance experienced resulting from low rainfall combined with high potential evapotranspiration due to high temperatures and southern and eastern margins of the country have a narrow humid zone. Thus, these conditions vastly differ from those experienced in the northern temperate regions (Ellery et al. 2009; Schulze, 1997).

The presence of wetlands in South Africa is considered unlikely due to the country's position in a long–term cycle of incision from the Miocene uplift with the development of a well-integrated drainage network in addition to a combination of factors previously mentioned. Despite this, South Africa has diverse range of perennial, seasonal and ephemeral wetlands in diverse settings. The diversity of wetlands in the country occurs due to differences in climate, drainage, geology, and anthropogenic activity to a lesser extent (Ellery et al. 2009; Tooth and McCarthy, 2007).

According to Midgley et al. (2005) there is an aridity gradient following an east to west trajectory in South Africa that extends from sub-humid to semi-arid in the eastern interior, and an increase in aridity from arid to hyper arid in the west. Many of South African wetlands are not sustained by rainfall alone, and their water source is generally supplemented to an extent with either surface input and/or groundwater discharge. Rainfall remains an important factor in sustaining inland wetlands as the rainfall becomes runoff (surface or river flow) when it falls in different parts of the catchment, and/or adds to groundwater recharge that enters into the wetland via subsurface flow, and rainfall may fall directly into the wetland. The inputs into the wetland from rainfall and its contribution to runoff and the atmospheric water demand is used to determine the water balance of a wetland. Despite the climate constraints, the majority of the wetlands in South Africa exist where a local positive near-surface or surface water balance that persists throughout the year or for a portion of the year generally occur as part of the river drainage network (Ellery et al. 2009; Grenfell et al. 2019; Tooth and McCarthy, 2007).

The South African landscape like other dryland landscapes are shaped by the long-term geomorphological processes and changes in the earth's surface material and the concentration of flow accumulation at or near the surface creates suitable conditions for wetland formation (Grenfell et al. 2019; Tooth et al. 2015). The formation and dynamics of wetlands in South Africa are as a result of geological controls and geomorphic processes of erosion and deposition on the landscape (Ellery et al. 2009).

The deposition process is the movement of mass, for instance downslope sediment movement, and is predominantly gravity-driven, moves from a higher to lower elevations however, tectonic uplift can result in the upward movement of sediment from lower to higher elevations. When there is mass accumulation in the landscape that contains the wetland to create features such as rivers channel levees it is classified as primarily depositional, conversely, it is classified as erosional when the sediment mass is being removed to create features such as gullies. Generally, wetlands act as sediment sinks accumulating sediment over a long period resulting in large amounts of sediments that may store significant amounts of carbon, rather than sediment sources (Tooth et al. 2015). Steep slopes indicate higher energy flow and lower rates of deposition, while gentle slopes have reduced energy flow allowing for higher rates of deposition, therefore wetlands are more likely to be found in latter conditions. While erosion is a natural process of a wetland, when exacerbated by some disruption such as human activity may threaten the health and existence of the wetland (Ellery et al. 2009).

Erosion-resistant lithologies (e.g. basalt, dolerite, quartzite) are important for the formation of wetlands, as it erodes at a slower rate than the surrounding lithologies that may weather more readily (e.g. sandstones and mudstones). This impedes the movement of water away from the site, which subsequently reduces the slope gradient and the energy of water flow, allowing for conditions suitable for wetland formation (Ellery et al. 2009; Grenfell et al. 2019).

Tooth and McCarthy (2007) acknowledges there are other types of wetlands that are not linked to river drainage network. These wetlands are primarily fed by local rainfall or groundwater discharge as a result segregation from the riverine inputs or the wetland formation and functions are not associated with the drainage network such as depression and seep wetlands, however, the extent of these wetlands are generally smaller and are localised landscape features. The variations in the key components (i.e. climate, geomorphology and hydrology) responsible for wetland formation result in wide distribution of wetlands across South Africa.

The importance of wetlands in semi-arid regions such as South Africa is emphasised for several reasons including: their ability to retain large amounts of water during the dry season, thus resulting in the a moderately high and stable water table and an oasis for wildlife during these periods; they provide a crucial habitat, foraging and/or breeding grounds for wildlife and are particularly important from a migratory bird species perspective as the wetlands provide the southern terminals; further more wetlands play a significant role for flood retention and climate regulation (MEA, 2005; Orimoloye et al. 2020). Wetlands provide an array of other ecosystem goods and services, however it is beyond the scope of the study to provide a detailed overview, refer to Kotze et al. (2009) for a more comprehensive explanation. The ecosystem goods and services further emphasise the importance of wetlands, and the need for accurate inventory and mapping of wetlands.

2.6 Climate change and impacts

The Intergovernmental Panel on Climate Change (IPCC) (2014) defines climate change as an identifiable change in the state of climate using the mean and variability of the climates properties to statistically quantify the change, and usually persist for an extended amount of time. Climate change is both attributed to the natural climate variability and influenced by anthropogenic activities that either directly or indirectly causes changes in the composition of the atmosphere observed over a long period, thus climate change refers to both natural and anthropogenically induced changes. Global climate change has become an imminent reality in today's world where widespread impact is already being experienced by humans and natural systems.

The global mean surface temperature is expected to rise over the 21st century and is primarily attributed to cumulative carbon dioxide emissions warming is largely attributed to the cumulative carbon dioxide emissions (IPCC, 2014). There are four RCPs based on the Coupled Model Intercomparison Project Phase 5 (CMIP5) models of the IPCC Fifth Assessment Report 5 (IPCC AR5) describe the pathways of greenhouse gas (GHG) emissions and atmospheric concentrations, air pollutant emissions and land use and are used to make projections (IPCC, 2014).

The RCP scenarios include: a mitigation scenario RCP 2.6, slowly declining emissions scenario RCP 4.5, a stabilising emissions scenario RCP 6.0, and a high emissions, business as usual scenario RCP 8.5. Global mean surface temperature is likely to increase by 1.1-2.6 ℃ under RCP 4.5 and 2.6-4.8 ℃ under RCP 8.5 between 2050 and 2100 (IPCC, 2014). The Paris Agreement under the United Nations Framework Convention on Climate Change (UNFCCC), referred to as the Paris Agreement, is an international treaty adopted in 2015 and aimed to reduce the global emissions that contribute to climate change to prevent global temperatures from exceeding 2℃, which has been further revised to 1.5 ℃ (UNFCCC, 2015). Increases in global mean temperature up to 1.5℃ by 2100 will result in several climate related changes regionally these include an increase in extreme temperatures, increase in the frequency, intensity and magnitude of heavy precipitation, and an increase in the frequency and/or intensity of drought in some regions (IPCC, 2014). The current year, 2020 marks a pivotal year in terms of climate change to limit the trajectory to remain at below a 1.5℃ pre-industrial levels as countries will be updating their Nationally Determined Contributions which states their mandate to reduce their emissions (Ourbak and Tubiana, 2017).

2.6.1 Climate change in South Africa

Climate change is of significant concern in South Africa. Global Climate Models (GCMs) and downscaled models predictions for South Africa suggest that climate change is not uniform and is more likely to impact strongly on the western regions of the country, than on the eastern regions (Engelbrecht et al. 2015; Engelbrecht and Engelbrecht, 2016). Climate change is anticipated to result in increased in mean annual temperatures, an increase in extreme precipitation events and droughts as well as a change in the rainfall patterns in both the direction and the magnitude, many of which South Africa is already experiencing (Ziervogel et al. 2014).

2.6.2 Climate change in the Western Cape Province

The Western Cape Province of South Africa is expected to experience a change in the rainfall pattern with an anticipated decrease in the overall rainfall, an increase in rainfall variability and an increase in temperature. This further results in an increase in the divide between mean annual precipitation and potential evapotranspiration, which will in turn result in a changes to the current aridity of the landscape, likely to drive changes in the distribution of species, increased wildfire as well as exacerbate pest outbreak (Blamey et al. 2014; Davis-Reddy and Vincent, 2017; Engelbrecht et al. 2009). The is a projected overall rise in surface temperature by 0.3-0.7°C, and an increase in summer maximum temperature and minimum temperature by 1.5-2.25°C and 1-2°C, respectively based on the RCP 8.5 scenario. The trajectory of rainfall is harder to model than temperature, however there is consensus that there will be a decrease in total winter rainfall of the region (Blamey et al. 2014). This is further confirmed by studies conducted by Engelbrecht et al. (2013) and MacKellar et al. (2014) that detected an increase in the inter-annual rainfall variability since the late 1960s and an increase in the intensity and magnitude of drought, and a decrease in rainfall and the number of rainfall days over parts of the South Africa, respectively.

2.6.3 Climate change and wetlands

According to the IPCC (2014) climate change poses an increased risk to the composition, structure and function of marine, terrestrial and freshwater ecosystems including wetlands. Song and Zhang (2018) argues that the climate change and anthropogenic activities are the driving factors causing changes to wetlands. Climate change is likely to cause changes to the multiple drivers of wetland formation and function increasing the likelihood of abrupt changes to the wetland that are of a large magnitude and difficult or expensive to reverse or irreversible entirely. It is anticipated in lieu of strong conservation and management approaches to wetlands, their continued loss and degradation is projected. This will reduce the capacity of wetlands to provide climate regulation services such as buffer the effects of climate change and contribute climate adaptation as well as the regelation of the microclimate of an area thus providing a natural buffer of resilience (Kelvin et al. 2017; Kotze et al. 2009; Kuşçu Şimşek and Ödül, 2018). Wetlands are vulnerable to the effects of climate change as their ability to adapt to changing environmental conditions is slow (Erwin, 2009). Currently, a limited number of studies have focused on projecting the potential distribution of wetlands to inform effective planning (Xue et al. 2018). The need for proper wetland management and conservation is highlighted in light of climate change, which in turn emphasises the need for improved the mapping and inventory.

2.7 Wetland mapping

The misuse and poor management of wetlands persist throughout the world despite the governance of international agreements, national policies and strategies aimed the wise use and conservation of these ecosystems. The continued degradation and loss of wetlands are related to information failures in mapping and inventory which provides the baseline on which more comprehensive wetland studies are based (Turner et al. 2000). Wetland maps provide information on the location, size and type of wetlands. These maps are an essential starting point to developing knowledge inventories used to inform the effective wetland management and policy targets, best practice guidelines in addition to the integration of wetland knowledge socio-economic considerations for planning (Begg, 1986; Finlayson and van der Valk, 1995). Finlayson et al. (1999: 132) defines wetland inventory as a "collection and/or collation of core information for wetland management, including the provision of an information base for specific assessment and monitoring activities." Mapping of wetlands and their subsequent inventory started in the late 1970s when land uses were being assigned various categories and wetlands were being integrated into legislation for their conservation and management (Mitsch and Gosselink, 2007). Planners use wetland inventories that are spatially explicit as an instructive source of information.

The importance the wise use, conservation and restoration of wetlands and their protection and restoration have been included in the Sustainable Development Goals (SDGs) Goal 6 – ensuring availability and sustainable management of water and sanitation for all. In addition, the role of wetland mapping and subsequent inventory are important to indicator 6.6.1 of the SDGs which relates to the long-term monitoring of the changes in the extent of water-related ecosystems (Ramsar Convention on Wetlands, 2018). The Ramsar Convention on Wetlands promotes all Contracting Parties to create national inventories of wetlands. Mapping wetlands is complex, due to the different types of wetlands, the various landscapes they are found in, and variability in their spatial extent due to their hydroperiod as perennial, seasonal or ephemeral (Nhamo et al. 2017).

Wetland mapping has utilised several different techniques. The most suited technique or combination of techniques are selected based on trial and the degree of detail of the map (Hiestermann, 2014). The mapping techniques include: field verification survey, aerial photography, satellite remote sensing and environmental modelling, although to a limited extent. These techniques have been used both internationally as well as locally in South Africa.

Field verification

The commonly used traditional technique that yields the highest accuracy is the field verification technique with reference to an aerial photograph, where wetlands are physically ground-truthed by the researcher or consultant by traversing the perimeter of the wetland using a Global Positioning System (GPS) device or a map of the study area to record the boundary and other important elements of the wetland that should be noted for example, a weir, furthermore, soil samples were collected using a soil auger at various points to verify the boundary of the wetland. However, despite the high accuracy of this technique, it is laborious, time consuming, expensive and requires accessibility to the site which is difficult due to remote, uneven and unstable terrain sometimes resulting large portions of the landscape left under-mapped (Rivers-Moore et al. 2020). The constraints of field verification mapping make it an unfeasible option when mapping vast expanses and inaccessibility to many of the wetlands.

Aerial photography and satellite imagery techniques

Over the past century stride have been made in the field of remote sensing, particularly in the last twenty years including the new remote sensors, increased data handling capabilities and image processing and analysis techniques which has rapidly advanced wetland mapping and inventory (Cracknell, 2018; Klemas, 2013). The use of remote sensing products such as aerial photography, Light Detection and Ranging, satellite hyperspectral imagery, and satellite multispectral scanners such as Landsat, provide a viable option to wetland mapping as it reduces the amount of fieldwork required, ability to cover large areas resulting in less costly data collection, it is less time consuming and is relatively accurate (Adam et al. 2010; Nhamo et al. 2017). The technique of using remote sensing applications is advantageous as it can map areas that are difficult to access on foot and the most comparative advantage lies with change detection in near real-time manner as the sensors record imagery of vast expanses of land within defined time frames (Nhamo et al. 2017).

Aerial photography

The application of aerial photography in wetlands mapping has been vast and based primarily on manual visual interpretation of the imagery including or excluding visual enhancements (Scarpace et al. 1981). This technique is often time-consuming and requires an expert to visually detect where wetlands are and either physically draw in the boundaries onto a hardcopy map resulting in constraints to knowledge sharing or using heads-up digitising which can also be done using satellite imagery.

Manual heads-up digitising

Manual heads-up digitising is the method of scanning an image or map onto a geographic information system (GIS) using a mouse as a digitiser to trace the features in the image, and are stored as coordinates in either point, line or polygon format (Longley et al. 2015). Another challenge with heads-up digitising is comparably lower levels of detail regarding the wetland boundary and confidence in data, furthermore, the technique is strenuous and time-consuming, and may contain source map errors and operational errors (Job et al. 2018; Tsoulos and Skopeliti, 2000).

Satellite remote sensing

The wide application of satellite remote sensing has been extensively viewed and is the most common technique used map wetlands at a regional scale (Guo et al. 2017; Mahdianpari et al. 2020; Rebelo et al. 2009). Wetlands can be delineated using various classification methods such as supervised, unsupervised and semi-automated classification using hyperspectral imagery and various multispectral imagery. Examples of multispectral imagery used in wetland mapping include Landsat, Quickbird, System Pour l'Observation de la Terre, aerial photographs (Guo et al. 2017). Furthermore, LiDAR data has been used in conjunction with multispectral imagery to map wetlands. LiDAR is used to detect inundation in wetlands during the dry season when the vegetation is less by producing high level inundation maps. However, the frequent use of LiDAR data is not feasible due to limited data availability and high costs (Huang et al. 2014). The accuracy of remote sensing is greatly improved when used together with ancillary data (Hiestermann and Rivers-Moore, 2015). Ancillary data is used to assist the analysis and classification process and is data from sources other than remote sensing (ESRI, 2017). A combination of these techniques are used in determining the global wetland inventory. According to Finlayson et al. (1999) the global estimate derived from national sources of a total 1,280 million hectares of wetlands is inaccurate and an underestimation of reality despite being much higher than previous estimations.

2.7.1 Wetland mapping in South Africa

The wetland classification system developed by Ollis et al. (2013) provided the basis to national wetland inventory (NWI) and mapping. The South African Inventory of Inland Aquatic Ecosystems (SAIIAE) is the NWI of South Africa and is repository of the country's national wetland information. The SAIIAE forms part of the National Biodiversity Assessment (NBA) and is updated at regular intervals using a combination of datasets that were derived using different techniques, at various resolutions, extents and from different sources (Job et al. 2018). A wetland inventory requires a continuous process to identify new wetlands, and improve the extent and resolution of those already identified. There have been five iterations of the SAIIAE National Wetland Map with the most recent revision referred to as National Wetland Map 5 (NWM5) in 2018 (van Deventer et al. 2020).

The NVM5 contains information about the location, size as well as the ecosystem types. The ecosystem types includes estuarine and inland aquatic ecosystems. Furthermore, inland aquatic ecosystems is made up of rivers and inland wetlands. For the purposes of the study, only inland wetlands will be considered. Significant measures were taken to improve the representation of inland wetlands in the NWM5 and the percentage of inland wetlands that make up the landcover in South Africa increased to 2.2% and have been mapped as part of the SAIIAE. The findings of the NWM5 indicated that spatial extent and representation of estuarine and aquatic ecosystem, inland wetlands in particular was improved. Although, significant steps need to be made towards improving the confidence level of the inland wetland representation in the next update of the NWM (van Deventer et al. 2020).

2.8 Environmental modelling

Environmental modelling is a representation of real world space and time processes and is becoming increasingly more relevant for scientist and environmental engineers (Chaulya and Prasad, 2016; Scholz, 2016). A GIS is primarily used to manage the spatial interactions and topographic rules as well as provide input variables that is often environmental ancillary data which is required for the models. Further to this, GIS provides visualisation and analyses of the of the output data (Chaulya and Prasad, 2016). Scholz (2016) demonstrates the use of an environmental modelled solution that can be applied to solve real world solutions. Machine learning is one of the techniques used in environmental modelling and will be employed in the study, it is an application of artificial intelligence that provides the model with the ability to learn and improve automatically without being programmed explicitly for this reason (Dietterich et al. 2010).

The machine learning techniques such as logistic regression models can be used to spatially interpolate environmental variables (Gibert and Sànchez-Marrè, 2011). The model uses ancillary data which takes the form of probability maps as an outcome that is easily interpretable as values ranging between 0 and 1, and their accuracy can be tested using verification data (Hiestermann and Rivers-Moore, 2015). The logistic regression models are binary in nature with discrete outcomes. However, Rivers-Moore et al. (2020) suggests that conditional probabilities would be more informative to mapped wetlands rather than discrete classifications. Thus, the probability maps will provide of probability values for each cell expressed as a percentage for the occurrence of wetlands. These predictive models are anticipated to be used in conjunction with traditional approaches to wetland mapping.

According to Schuwirth et al. (2019) it has become increasingly important to have a succinct understanding of the various predicted ecological consequences to support environmental management decisions, this can be achieved by the use of environmental models. Examples of the use of environmental models are the spatial planning for species conservation, wetland conservation and management, biodiversity protection, habitat restoration and management of ecosystem services.

2.8.1 Logistic regression

Logistic regression models is a type of multivariate analysis used to solve problems of binary classification by forecasting the probability of the binary event (presence or absence) occurrence that this based on the coefficients of a number of explanatory variables (independent variables) (Hoffman, 2015). The purpose of the logistic regression model is to provide a model of best fit to draw correlations between the presence and absence of the dependent variable, in the case of the study, wetland occurrence and a suite of explanatory variables that can be a combination of continuous and discrete data (Pal and Talukdar, 2018). The model requires an equal number of presence and absence points to obtain a more comprehensive sampling pattern. The model is developed using the logistic regression equation and translated into spatially explicit layers that represents the probability of occurrence in a given study area. There have been two studies in South Africa using logistic regression models in the subtropical region of KwaZulu-Natal and in the all-year round rainfall region of Port Elizabeth to determine the occurrence of wetlands at different scales (Hiestermann and Rivers-Moore, 2015; Melly et al. 2017). The findings of both studies are in agreement regarding the prediction accuracy of the wetland occurrence differs between different HGM wetland types.

2.8.2 Other environmental modelling techniques used

There have been a number of environmental modelling techniques have been used to map wetlands such as Bayesian network models (BN), multivariate adaptive regression splines (MARS) and MaxEnt models are machine learning techniques. The technique of using BN models in environmental research is still in its infancy as it has not been extensively used however, it is becoming increasingly popular (Hiestermann, 2014). The Bayesian network uses Bayes theorem to predict and describe the classification, additionally, conditional probabilities are characteristic of BN models allowing for readily interpretable classifiers using logic that is important to decision making (Friedman et al. 1997; Park et al. 2018). In South Africa, two studies based on the BN model of wetland occurrence were conducted in the KwaZulu-Natal (Hiestermann and Rivers-Moore, 2015), and wetland occurrence and HGM wetland types in City of Cape Town and Drakenstein local municipality (Rivers-Moore et al. 2020). Both studies had good predictive capacity.

The MARS has the capability to model the complex relationship between the predictor and explanatory variables without the need for strong model assumptions. Furthermore, MARS uses build tree and basic functions to determine important independent variables when several predictor variables are under consideration, and is not a time consuming modelling process which is useful for modelling large datasets (Friedman, 1991; Lee et al. 2006). A study across based on the National Resource Inventory of southern United States was develop a probability map indicating the risk of wetland loss as a function of wetland features and landscape context using MARS, the finding were that the model had substantial predictive ability across the study area (Gutzwiller and Flather, 2011).

The MaxEnt model a popular species distribution model that has been used to model wetland distribution. The model is based on the principle of maximum entropy, where the selected model is the one with the most widespread distribution with regards to uncertainty (Harremoës and Topsøe, 2001). Chignell et al. (2018) used MaxEnt to create a probability map to the occurrence of wetland and riparian distribution across the Colorado watershed, with the results for MaxEnt indicating a high accuracy. Additionally, a study related to the small, valley-bottom palmiet wetlands used MaxEnt to predict the potential distribution of this wetland community (Rebelo et al. 2017).

A study by Collins (2018) was conducted to improve on the findings of the NWM4 using a country-wide digital elevation model (DEM) and 2013 SPOT 5 imagery to model the extent of wetlands to determine the wetland probable extent, using a combination of the percentile filter tool from the Whitebox GIS and flow accumulation maps from ArcGIS and the mapping process was facilitated using several python scripts. The wetland probability map outcome of the study showed a significant accuracy in wetland presence, improved coverage as compared to the NWM4. However, there was low agreement with reference dataset and did not account for 70.4% of the reference dataset was not mapped in the prediction resulting in concerns over the models ability to predict the true presence of wetlands. The study recommends the inclusion of a wetland probability map determined by either Bayesian statistics or logistic regression will make important contributions to mapping (Collins, 2018).

2.9 Conclusion

Chapter two which encompasses the literature review of the study has illustrated the complexities in wetlands that range from definition, formation, classification and the subsequent mapping and knowledge inventorying of these systems. Numerous techniques have been used to map wetlands and their performance in accuracy, time, complexity and expense factor of each of the techniques were reviewed. Often techniques are used in conjunction with one another. Increased recognition about the importance of wetlands and their role in buffering the effects of climate change have highlighted the need for more robust inventory, starting with accuracy of the spatial location, extent and type of wetland. The importance of improved mapping subsequently leads to improved inventory, and allows for better informed decision-making regarding effective and strongly relevant conservation and management and the drafting of wetland related policies. The starting point to achieve the aforementioned items, remains as more accurate and comprehensive wetland mapping.

Currently, global estimates of wetland inventory have been severely underestimated, however this may be due to highly heterogenous environmental factors as well as different regions and countries following different definitions. The latest NWM5 repository of wetland information in South Africa estimates that inland wetlands cover only 2.2%, and has seen improvement in the representation and spatial extent. However, van Deventer et al. (2020) notes that the confidence level of the representation of inland wetlands needs to be significantly improved in the next update of the NWM. The approach of using environmental modelling to map wetlands and as ancillary data to complement the more traditional approaches to mapping has been widely recognised and is gaining more attention as a baseline tool. Several environmental modelling techniques were reviewed and the merits and disadvantages of each were presented. The review highlighted the need for ancillary data derived from environmental modelling techniques to complement traditional approaches in mapping wetlands. Additionally, it emphasised the need for mapping wetland distribution with respect to the future projected climate change scenarios to effectively inform decision making. The study focuses on the research gap of using the environmental modelling machine learning techniques, logistic regression to map the probability of wetland distribution in the current climate as well as the potential wetland distribution in future climate change scenarios for three municipalities in the Western Cape.

Chapter Three: Study area

3.1 Introduction

This chapter presents a description of the Western Cape Province of South Africa and the study area, which includes the City of Cape Town, Breede Valley and Drakenstein Municipalities. The selection of the study area was based on the climate and its vulnerability to climate change. The prominent physiographic characteristics of the study area were described in terms of location, topology, climate, hydrology and geology.

3.2 Location

The Western Cape province is located on the south-western tip of South Africa between coordinates 30 to 35° South and 15 to 25° East. The Western Cape is one of nine provinces, neighbouring the Northern Cape and Eastern Cape provinces to the north and east, respectively and bordered seaward by the warm Indian Ocean in the south and the cold Atlantic Ocean in the west. The province is divided into one metropolitan municipality and five district municipalities which are further subdivided into 24 local municipalities. The study area encompasses the City of Cape Town metropolitan municipality and Breede Valley and Drakenstein local municipalities (Figure 3.1). The Cape Winelands District Municipality governs the latter two municipalities. The climate and geology of the province are typically distinct due to vast differences in topography (DEA, 2011).

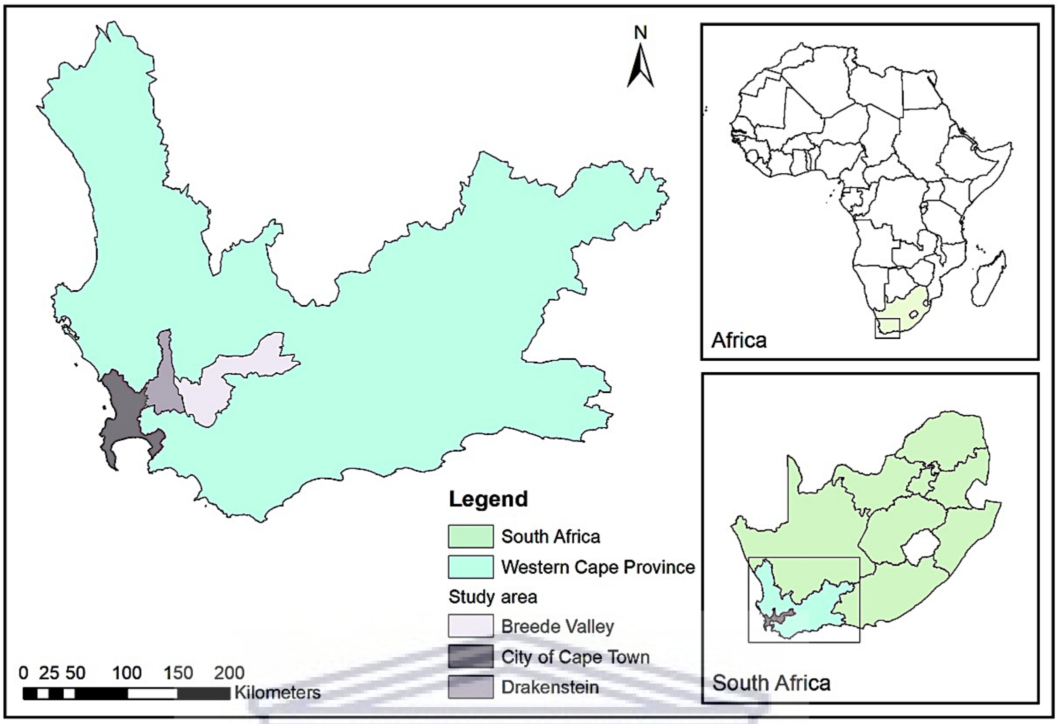


Figure 3.1: The location of the study area in the Western Cape province of South Africa.

3.3 Topography

The Western Cape province has high topographic heterogeneity, with the Cape Fold Belt an L-shaped mountain range that extends along the length of the province and dominates the topography of the region (Figure 3.2). The Cape Fold Belt comprises two distinct belts: a north-south trending Atlantic belt and an east-west trending southern belt. The belts converge in the southwest, inland of Cape Town (Partridge et al. 2010). The lower-lying coastal areas are separated from the inland plateau by an escarpment that lies along the boundary of the Western Cape province and the Northern Cape province. Thus, the Cape Fold Belt act as geographic barriers to create an orographic effect that contributes to the distinct climate zones and forms important water catchments. This high climatic variation is due to several factors, including noticeable differences in altitude and distinct geology and soil types over short distances (Midgley et al. 2005; van Niekerk and Joubert, 2011).

3.4 Climate

The majority of the extent of South Africa is considered a semi-arid country and has a complex climate (Schulze, 1997). The main factors that determine the climate include the latitudinal location of the country (~ 22-34°S) at the interface of the tropical, subtropical and temperate atmospheric circulation systems; the migration of the Intertropical Convergence Zone; the altitude of the interior plateau; and influence of the ocean circulation systems which creates three distinct rainfall zones (Nicholson, 2000; Tyson and Preston-White, 2000). The majority of South Africa, with the exception of the southwest of the country, lies within the summer rainfall zone (SRZ). The Western Cape province lies predominantly within the winter rainfall zone (WRZ) and a relatively small aseasonal rainfall zone (ARZ) (Chase and Quick, 2018; Tyson and Preston-White, 2000). The study area lies mainly in the WRZ, with a small portion to the east that extends into the ARZ (Figure 3.2). The climate, particularly the rainfall of the Western Cape province, is influenced by the diverse oceanic and atmospheric circulation systems brought by the intersection of the cold Atlantic Ocean and the warm Indian Ocean at the coastal landmass of the province (Chase and Thomas, 2007).

The WRZ is characterised by warm, dry summers and mild, wet winters and extends over the southwestern and west coast of the province (Ziervogel et al. 2014). The WRZ receives predominantly frontal induced rainfall between the austral winter months of May and September. The northward displacement of the South Atlantic high-pressure system (called South Atlantic Anticyclone) carries cold fronts and, combined with the persistent westerly winds over the cold Benguela current, produces eighty percent of the rainfall in the region. Conversely, dry conditions are experienced in the WRZ in the austral summer months. This is a result of the southward shift of the well-developed South Atlantic anticyclone, which blocks the westward movement of easterly waves that bring summer rainfall to the SRZ and the polar frontal systems that bring rainfall to the WRZ (Du Plessis and Schloms, 2017; Matthews et al. 2016). There is a marked increase in aridity and decrease in rainfall as the influence of the polar frontal systems decreases as one moves northwards (Matthews et al. 2016).

The ARZ is a narrow transitional zone of approximately 400 km, which receives winter and summer rainfall and lies between WRZ and SRZ along the southern coast (Chase and Thomas, 2007; Engelbrecht et al. 2015). The zone has a high variation in the frequency, intensity and amount of rainfall and consists of both the South Coast region and the Karoo region, as described by van Niekerk and Joubert (2011). The South Coast region extends eastward from Cape Agulhas and experiences all-year rainfall, most frequently occurring as bimodal rainfall during the transitional seasons of autumn and spring. Rainfall occurs due to the movement of warm, moist air from the Indian Ocean, which creates ridging high-pressure cells and cut-off lows (Bradshaw and Cowling, 2014; van Niekerk and Joubert, 2011). The Karoo region is confined to the inland plateau of South Africa, separated by the Cape Fold Belt that forms a natural barrier between the two regions that lie within the ARZ. Rainfall in the Karoo region is relatively evenly distributed throughout the seasons, with a late summer maximum in the form of erratic thundershowers (van Niekerk and Joubert, 2011).

There is substantial variation in the amount and intensity of rainfall both spatially and temporally in the Western Cape province. Rainfall decreases towards the interior of the province, and the Cape Fold Belt Mountains, like many mountainous areas, create a localised orographic effect along the entire belt. This phenomenon results in an exception to the general trends. There is most notably an increase in annual rainfall with an increase in elevation. The mean annual rainfall is approximately 400 mm/year. However, rainfall can range from a high of 3 000 mm/year in the mountainous regions to a low of less than 200 mm/year in low-lying regions and the interior (Lakhraj-Govender and Grab, 2019). There is a range of climatic gradients in the province including, aridity and rainfall gradients (Figure 3.2). The aridity gradient exists with a steep transition from the south to north, with areas to the north being considerably drier. The rainfall seasonality gradient is found from the east to west, with an increase in summer rainfall in areas east of the province. Furthermore, the rainfall seasonality with altitude gradient (0-2 325 m above mean sea level) is a less well-known trend. The higher altitude of mountainous areas experiences substantially higher amounts of summer rainfall and are often classified as all-year rainfall zones than the adjacent lower altitude plains (Meadows, 2003; Midgley et al. 2005).

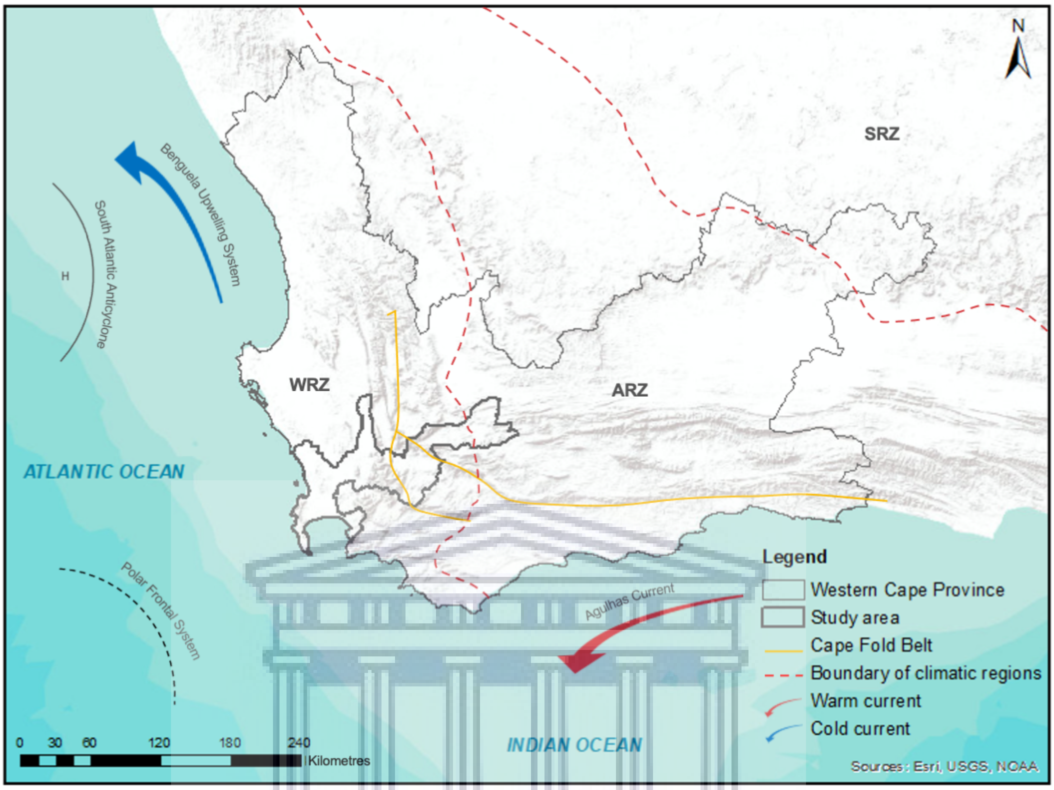


Figure 3.2: Topographic map of the Western Cape province, which represents the Cape Fold Belt mountains (indicated by the solid yellow line), the climatic regions (indicated by red dash line – winter rainfall zone (WRZ), aseasonal rainfall zone (ARZ) and summer rainfall zone (SRZ)), the pressure systems and ocean currents that influence climate in the province (adapted from Chase and Quick, 2018).

3.5 Hydrology

There is high variability and availability in the number of water resources in the Western Cape province. According to Midgley et al. (2005), hydrology in the province is largely influenced by the interplay between the topography and geology, the location and orientation of the Cape Fold Belt, and to some extent, regional sea-surface temperatures that create the WRZ climate. The natural barrier of the Cape Fold Belt creates interior rain shadows due to the orographic effect. These physiographic characteristics control the complex groundwater-surface water interactions that result in the differences in hydrology across the province. Two main drainage patterns traverse the province; in the east, the Breede River, also known as Breë River, and Gouritz River flows south into the Cape Fold Belt and drains into the Indian Ocean. Conversely, in the west, the Berg River and Olifants River drains into the Atlantic Ocean. The province’s characteristic trellis drainage patterns are influenced by the geological structure (Partridge et al. 2010).

The study area presents the administrative boundary of the Breede Valley, City of Cape Town, and Drakenstein municipalities. The quaternary catchments found within and which intersect the study area boundary were taken into consideration to account for the hydrological boundaries (Figure 3.3).

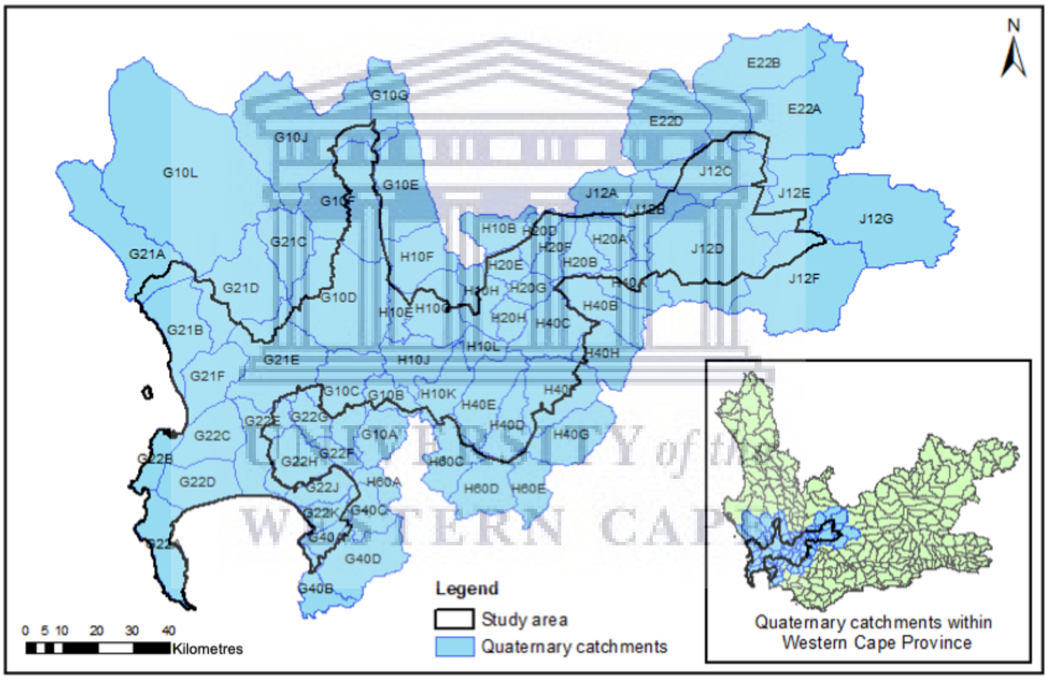


Figure 3.3: The quaternary catchments that lie within the study area (Middleton and Bailey, 2011).

3.6 Geology and soils

The geology of the Western Cape province is diverse and complex. The rock types in the province consist mostly of sedimentary rock such as sandstone, limestone and shale. Although to a smaller extent, igneous rock such as granite, basalt and andesite make up the mountain ranges from Paarl to Piketberg. The

Cape Fold Belt mountains are a prominent feature in the geology of the Western Cape Province, which has been formed due to the collision of the ancient Falklands Plateau and the African plate, creating a convergence boundary. The Paleozoic Cape Supergroup outcrops dominate the Cape Fold Belt. The predominant geological associations in the province consist of the Adelaide Subgroup, Ecca Group, Cape Supergroup, including the sandstones of the Table Mountain Group (TMG) and the Bokkeveld Group, Malmesbury Group, Vanrhynsdorp Group, Namaqua Metamorphic Complex, Enon Malmesbury Group, and several types of alluvial and coastal deposits (Figure 3.4) (Blewett and Phillips, 2016; SACS, 1980).

The weathering, folding and faulting in the Cape Fold Belt create fractured rock aquifers and fractured and intergranular aquifers in the TMG sandstones and quartzites, and the varying metamorphic group of the Malmesbury Group and in primary aquifers on sandy plains. In contrast, shale and silestone have limited groundwater discharge. Groundwater is stored in the fractures, joints and cavities of the rock mass, and the availability of water is dependent on the interconnection and nature of the fractures (Colvin et al. 2007). The availability of groundwater is important for the formation of most wetlands - where groundwater and surface water flow are concentrated or drainage inhibited due to impermeable rock mass (Tooth et al. 2015).

The high variation in lithology and climatic gradients within the region creates a rugged, uneven topography with highly diverse soil characteristics. Soil types are dependent on the parent material of an area. The dominant soil type is substrates derived from the Malmesbury Group (Western Cape Provincial Spatial Development Framework, 2005). The combination of these environmental variables supports the diversity of vegetation types found in the Western Cape.

The vegetation distribution of the Western Cape is strongly determined by soil type, which indicates the underlying geology (Bradshaw and Cowling, 2014). Change in the type of vegetation distribution passing from one geologic formation to another is typically distinct. Fynbos distribution is associated with granite, ferricrete and highly leached, nutrient-poor sandstone substrates of the Cape Fold

Belt and adjacent sand plains. The distribution of renosterveld relates closely to shales and sandstones, and succulent karoo vegetation is determined by shales from Bokkeveld and Cape Supergroup (Mucina and Rutherford, 2006; Rebelo et al. 2006).

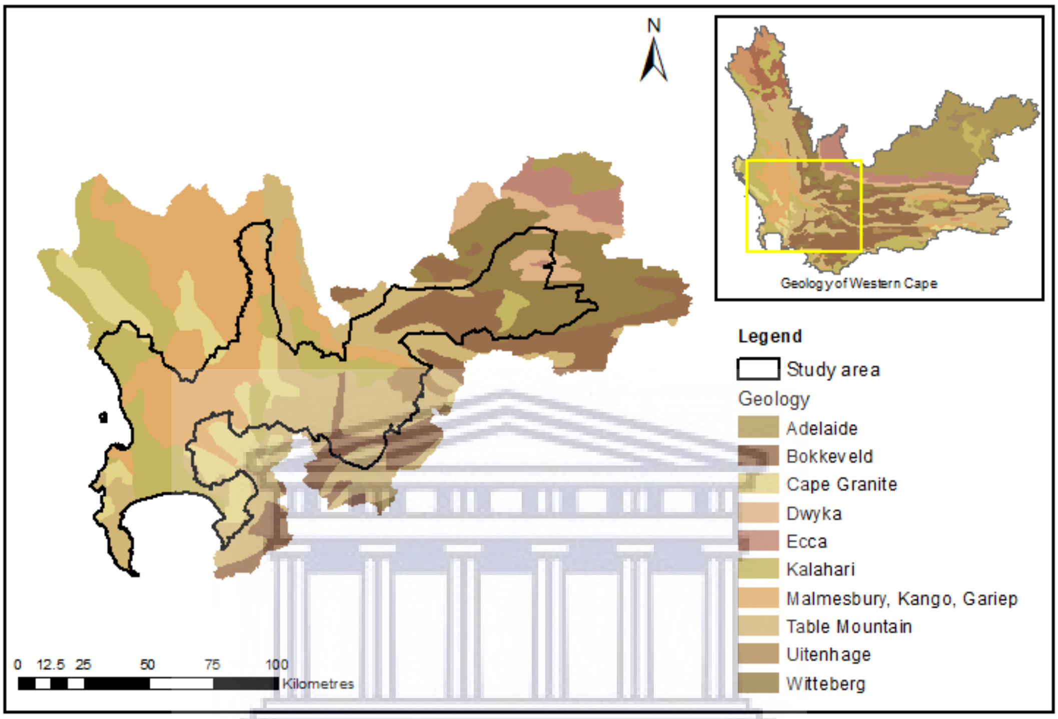


Figure 3.4: Geology of the hydrological boundary of the study area (CGS, 2019).

Chapter Four: Methodology

4.1 Introduction

This chapter presents an outline of the research design, approach and methods used to achieve the objectives of this study. The methods of data collection, variable selection, and analysis of variables are described, followed by the methods used to build, and evaluate the wetland prediction models. Lastly, the predicted change in wetland distribution was investigated.

4.2 Research design

The study followed a quantitative empirical research method that uses a quasi-experimental research design. A combination of descriptive and explanatory research was used to address the study aim and objectives described in Chapter 1 (Leedy et al. 2015). The first objective of the study was to determine the current distribution of wetlands in relation to aridity and required an analysis of the density of wetlands along the aridity gradient. Analyses to achieve the second objective of the study required the elimination of redundant variables to identify mutually independent environmental variables associated with wetlands. The third and fourth objectives required environmental modelling techniques to map the current and predicted future wetland distribution and evaluate the potential wetland loss and/or gain under the climate change scenarios RCP 4.5 and RCP 8.5. The study excluded rivers as their characteristics, functionality and ecosystem services differ from those of the other HGM wetland types. The remaining HGM wetland types defined as Level 4 of the Classification System in Ollis et al. (2013) were included in this study (Figure 2.1).

4.3 Aridity index and wetlands

The status quo of wetland distribution along the aridity gradient was assessed using the National Wetland Map 5 (NWM5) dataset (Van Deventer et al. 2020) for the City of Cape Town metropolitan municipality, Drakenstein municipality and Breede Valley municipality. The NWM5 shapefile was clipped using the clip tool in ArcGIS 10.6 (ESRI, 2017) to the extent of the study area. The north-south aridity gradient that traverses the study area was used to map the current distribution of wetlands. Aridity is a complex concept and represents an interplay of atmospheric and land surface processes (Greve et al. 2019). According to the classification proposed by UNEP (1997), the aridity index (AI) is defined as the ratio of mean annual precipitation (MAP) to mean annual potential evapotranspiration (MAE). Furthermore, the AI provides a measure of the dryness of a region.

$$\text{Aridity Index (AI)} = \frac{\text{MAP}}{\text{MAE}}$$

The wetland dataset was superimposed onto the global aridity index (Trabucco and Zomer, 2019) raster layer to extract the AI values in ArcGIS 10.6 (ESRI, 2017) to determine the number of wetlands and HGM wetland types found in each aridity class. The global aridity dataset was calculated using MAP from the WorldClim dataset (Hijmans et al. 2005) and the MAE was evaluated based on the Global-PET database (Trabucco and Zomer, 2019). The aridity index has been categorised into a generalised climate classification scheme that defines dryland and non-dryland regions and further subdivided into climate classes (Table 4.1).

Table 4.1: The climate classification scheme of the aridity index values (UNEP, 1997).

AI value	Climate class
Dryland subtypes	
< 0.03	Hyper arid
0.03 – 0.2	Arid
0.2 – 0.5	Semi-arid
0.5 – 0.65	Dry sub-humid
Non-drylands	
> 0.65	Humid

The purpose was to provide a descriptive overview of the current distribution of wetlands in relation to aridity in the study area. Following this initial overview, environmental modelling techniques were used to model the current and projected wetland distribution under the climate change scenarios.

4.4 Environmental modelling

4.4.1 Research approach

The flow chart summarises the methods and approaches followed to achieve objectives 2-4 (Figure 4.1).

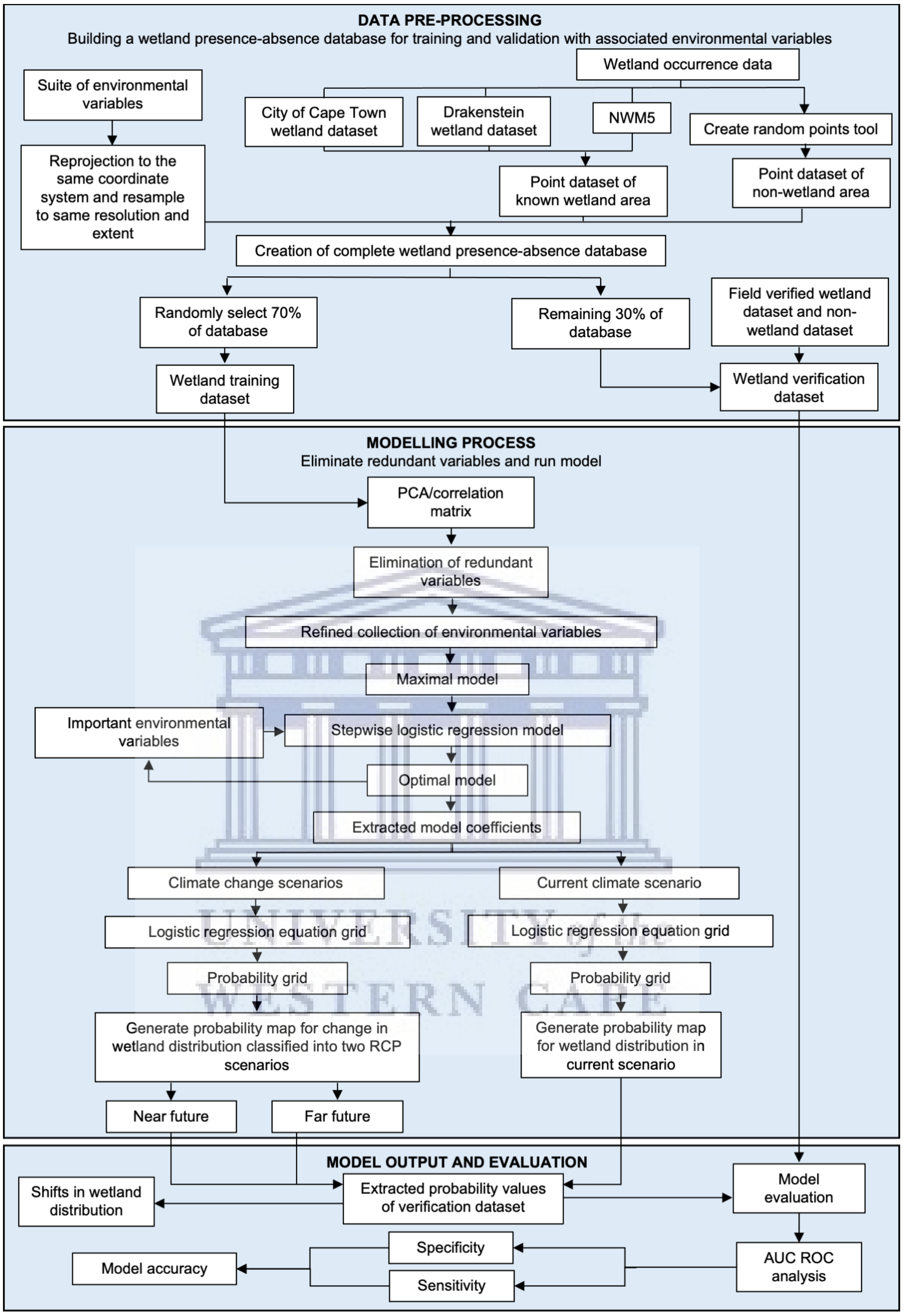


Figure 4.1: A flow chart illustrating the methodology for the logistic regression model used to generate the probability layers of wetland distribution in the study area. (PCA = Principal Component Analysis, RCP = Representative Concentration Pathways, AUC ROC = Area under receiver operating characteristic curve).

4.4.2 Variable selection

The dependent variable (response variable) for the study is the probability of wetland presence in the landscape. The independent variables (predictor variables) are represented by an array of environmental variables outlined in Table 4.2 and comprised of variables that were identified to contribute directly or indirectly to wetland formation and persistence as reviewed in Chapter 2: Literature Review. Mitsch and Gosselink (2000) describes the main components of hydrology, physiochemical environment, biota, climate and geomorphology that affect the formation and function of wetlands. The datasets used in the study are described below.

4.4.2.1 Field verification dataset

A field verification survey was conducted between February - May 2019 and used as a verification dataset to test the performance of the model. The survey provides a representation of wetland types in the study area. A set of criteria was met prior to the selection of sites, this included the location (representing the different regions), avoidance of wetland systems that were artificially created or significantly altered or disturbed, and accessibility to the site. A desktop exercise was conducted to select sampling sites prior to the field survey. The create random points tool in data management toolbox in ArcGIS 10.6 (ESRI, 2017), which automatically generates a specified number of random points within the constraining extent provided was used to determine wetland presence and absence sites. The absence points generated was in proportion to the number of wetlands found in the study area. The NWM5 layer was used as a baseline to identify wetland presence points and the random points that intersected the layer were considered for selection. Thereafter the NWM5 layer was added to Google Earth Pro (Google Earth Pro, 2021) satellite imagery and sampling sites were selected. To prevent the detection of the same wetland twice, absence points did not overlap with identified potential wetland presence points, and points were a minimum of 150 m apart.

The GPS location of each point were identified in the field using the desktop exercise as a reference using a Garmin GPSMAP 65S handheld device with an accuracy of 3m. Other information was recorded on field data sheets included the observed HGM wetland type, time, photograph and additional notes that were considered important. A total of 730 sites, of which 398 sites were known wetland areas (wetland presence) and 332 were non-wetland areas (wetland absence), were assessed across the study area. Lastly, the limitations associated with the sampling design and data collection were that in some cases, sample sites were excluded due to inaccessibility and alternative sampling sites were assessed.

4.4.2.2 Collation of the wetland and environmental variables dataset

Collation of wetland dataset

The wetland dataset consists of three existing datasets which included coverage for the City of Cape Town metropolitan municipality (n = 7,272; City of Cape Town, 2017), Drakenstein municipality (n = 4,238; Day et al. 2009) and the National Wetland Map 5 (NWM5) shapefile was clipped using the clip tool in ArcGIS 10.6 (ESRI, 2017) for wetland presence in the Breede Valley municipality (n =357; Van Deventer et al. 2020). The City of Cape Town and Drakenstein wetland datasets were used for modelling in their respective municipalities as they have a high confidence and spatial resolution due to extensive ground-truthing exercises.

The model used the wetland dataset (wetland presence) (n = 11,867) referred to above, and a non-wetland (wetland absence) point dataset was created for the study area using the random point generator in ArcGIS 10.6 (ESRI, 2017).

A total of 12,000 wetland absence points were generated and was done in proportion to the number of wetlands found with the study area. Similar to what was done for the field verification dataset, the points were a minimum of 150 m apart to mitigate counting the same wetland twice. This dataset was used to train and test the model.

Environmental variables

The environmental variables necessary for determining wetland presence in a landscape consisted of four broad themes climate, hydrology, geology and soil variables, and DEM-derived topographic variables were selected as the maximal dataset (Table 4.2). A brief description of the variables are provided in Section 4.4.2.3. A list of assumptions and limitations related to environmental variables is presented below:

- Several of the datasets were extrapolated and model-derived. Therefore, it is possible that the errors of these datasets were compounded when constructing the model.
- Some of the datasets lacked substantial information or metadata on how the variable was derived thus the strengths and weaknesses of the input variables could not be determined.
- The datasets were collated from several institutions and organisations resulting in layers with different data formats at various projections, extents and resolutions.
- Therefore, standardisation of all the datasets was required. The standardisation process used map algebra for computation which potentially resulted in the original errors of the datasets being compounded.
- Lastly, there are several uncertainties related to the projection of climate change scenarios.

Table 4.2: List of input environmental variables used in maximal and optimal modelling process.

	Environmental variable	Abbreviation	Units	Data type	Source	Cell size
Climate	Annual mean temperature	bio1	°C	Continuous Raster	Hijmans et al. 2005	0.8 km
	Mean diurnal range (Mean of monthly (T_{max} – T_{min})	bio2	°C	Continuous Raster	Hijmans et al. 2005	0.8 km
	Isothermality (bio2 / bio7) (×100)	bio3	°C	Continuous Raster	Hijmans et al. 2005	0.8 km
	Temperature seasonality (standard deviation ×100)	bio4	°C	Continuous Raster	Hijmans et al. 2005	0.8 km
	Maximum temperature of warmest month	bio5	°C	Continuous Raster	Hijmans et al. 2005	0.8 km
	Minimum temperature of coldest month	bio6	°C	Continuous Raster	Hijmans et al. 2005	0.8 km
	Temperature annual range (bio5 – bio6)	bio7	°C	Continuous Raster	Hijmans et al. 2005	0.8 km
	Mean temperature of wettest quarter	bio8	°C	Continuous Raster	Hijmans et al. 2005	0.8 km
	Mean temperature of driest quarter	bio9	°C	Continuous Raster	Hijmans et al. 2005	0.8 km
	Mean temperature of warmest quarter	bio10	°C	Continuous Raster	Hijmans et al. 2005	0.8 km
	Mean temperature of coldest quarter	bio11	°C	Continuous Raster	Hijmans et al. 2005	0.8 km
	Potential evapotranspiration	ET0	mm	Continuous Raster	Trabucco & Zomer, 2019	0.8 km
Hydrology	Annual precipitation	bio12	mm	Continuous Raster	Hijmans et al. 2005	0.8 km
	Precipitation of wettest month	bio13	mm	Continuous Raster	Hijmans et al. 2005	0.8 km
	Precipitation of driest month	bio14	mm	Continuous Raster	Hijmans et al. 2005	0.8 km
	Precipitation seasonality (Coefficient of variation)	bio15	mm	Continuous Raster	Hijmans et al. 2005	0.8 km
	Precipitation of wettest quarter	bio16	mm	Continuous Raster	Hijmans et al. 2005	0.8 km
	Precipitation of driest quarter	bio17	mm	Continuous Raster	Hijmans et al. 2005	0.8 km
	Precipitation of warmest month	bio18	mm	Continuous Raster	Hijmans et al. 2005	0.8 km
	Precipitation of coldest month	bio19	mm	Continuous Raster	Hijmans et al. 2005	0.8 km
	Depth to groundwater	gw_depth	m	Continuous Raster	Murray, 2005	1.0 km
Geology and soils	Geology group	geology_group	n/a	Nominal Vector	CGS, 2019	2.5 km
	Geology formation	geology_form	n/a	Nominal Vector	CGS, 2019	2.5 km
	Soils	soil_type	n/a	Nominal Vector	Land Type Survey Staff, 2006	2.5 km
	Soil depth	soil_depth	m	Ordinal Vector	Land Type Survey Staff, 2006	2.5 km
	Clay content	clay_content	%	Ordinal Vector	Land Type Survey Staff, 2006	2.5 km
DEM-derived	Elevation	elevation	m	Continuous Raster	CGA, 2019	5 m
	Slope (degrees)	slope	degree	Continuous Raster	DEM-derived, 2019	20 m
	Aspect	aspect	degree	Continuous Raster	DEM-derived, 2019	20 m
	Flow accumulation	flowacc	n/a	Continuous Raster	DEM-derived, 2019	20 m
	Flow direction	flowdir	degree	Continuous Raster	DEM-derived, 2019	20 m
	Landform	landform	n/a	Nominal Raster	DEM-derived, 2019	20 m

4.4.2.3 Description of environmental variables

Climate variables

Nineteen biologically-meaningful climate (bioclimatic) variables were downloaded from the WorldClim version 1.4 dataset at a resolution of approximately 1 km (Hijmans et al. 2005). The bioclimatic variables were derived from interpolation of monthly averages of rainfall and temperature recorded at weather stations throughout the world and can be used to better understand distribution responses to climate change (Fick and Hijmans, 2017). Please refer to Fick and Hijmans (2017), Hijmans *et al.* (2005), and O'Donnell and Ignizio (2012) for a full description of the bioclimatic variables.

The bioclimatic variables for 2050 and 2070 were derived from the commonly used general circulation model (GCM), the Model for Interdisciplinary Research on Climate-Earth System Model (MIROC-ESM) (Watanabe et al. 2011). The MIROC-ESM is based on the Coupled Model Intercomparison Project Phase 5 (CMIP5) model and it was selected because it is one of the major models has contributed to the IPCC AR5. The climate change modelling data for the RCP 4.5 and RCP 8.5 emission scenarios were selected to model the future wetland distribution under the MIROC-ESM.

Hydrology variables

Interactions between climate and hydrology are related to the atmospheric demand and as a result influences the water availability in a wetland. The *depth to groundwater* variable was derived from the water level data collected as part of the Groundwater Resource Assessment Phase 2 (GRA2) national scale project (Murray, 2005). The aim of GRA2 was to quantify South Africa's groundwater resources. The variable is presented as a continuous raster dataset with a 1×1 km resolution of mean depth to ground water expressed as metres below ground level (mbgl) (Allwright et al. 2013). The depth to groundwater determines the local water table, and the interaction between groundwater and surface water plays a vital role in wetland formation and persistence (Tooth and McCarthy, 2007).

Potential evapotranspiration (PET) variable was derived from the global reference evapotranspiration dataset. Trabucco and Zomer (2019) describes PET as a measure of the atmospheres ability to remove water through the evapotranspiration process. The Penman-Monteith equation was used to estimate PET using evapotranspiration for reference crop, net radiation at the crop surface, soil heat flux density, mean daily air temperature, the wind speed, the saturation vapour pressure and the actual vapour pressure.

Geology and soil variables

The geology and soil are important factors in the formation of wetlands (refer to Section 2.2.1: Wetland formation and Section 3.6). The geology group and geology formation variables were extracted from the digital 1:250 000 geological series of maps for South Africa from the Council of Geosciences (formerly Geological Survey of South Africa) (CGS, 2019). The soil type, soil depth and clay class variables were derived from the digital 1:250 000 land types of South Africa map and soil inventory datasets. The datasets formed part of the national Land Type Survey and were obtained from the Agricultural Research Council-Institute for Soil, Climate and Water (Land Type Survey Staff, 2006). The Land Type Survey was compiled based on approximately 400 000 soil observations, 2500 modal soil profiles and 10 000 series identification samples, which provided quantitative data about the range of soil properties across South Africa. The soils variables were based on the broad soil patterns in the area and soil depth variable provides an estimation of the depth to which plant roots are active. The clay content variable was based on the average clay content expressed as a percentage of clay in the topsoil and classified into distinct classes. Clay content is an important component contributing to the role of wetlands as sediment sinks and it is an ideal substrate for wetland vegetation to develop (Lambrechts and MacVicar, 2004; Paterson et al. 2015).

Digital elevation model (DEM) derived variables

The *DEM* obtained was Stellenbosch University's digital elevation model (SUDEM) model at a 5 m spatial resolution (CGA, 2019). The SUDEM was generated by a combination of two DEMs. The first DEM was derived from interpolated 20m (vertical interval) contours and spot height data shown on the South African 1:50 000 topographical map series. The interpolated surface was used to fill the sinks in the 30 m resolution Shuttle Radar Topography Mission (SRTM) DEM; thereafter a patented weighting scheme was used to fuse the two DEMs. The resultant SUDEM maximises accuracy (CGA, 2019). DEMs are described by Pakoksung and Takagi (2016) as important tools that provide a digital representation of terrain and topographic parameterisation for widespread application. Furthermore, the DEM was used to derive several other topographic variables such as aspect, flow accumulation, flow direction, landform and slope to conduct the terrain analyses.

The flow direction is important to understand the hydrological characteristics of a landscape. The variable was calculated using the D8 single-flow algorithm to determine the direction of flow out of each cell. Thereafter, the flow direction was used to determine the *flow accumulation* into each cell, by accumulating the weight of all the cells that flow into the downslope neighbouring cells in the raster output. The flow direction and flow accumulation variables were derived using the hydrology toolbox in ArcGIS 10.6 (ESRI, 2017).

The *aspect* variable is measured in clockwise degrees from north, where flat areas are allocated a value of -1 as there is no downslope direction and identifies the maximum rate of change in value from each cell to its neighbours. Aspect can be considered to be the slope orientation and was calculated using the flow accumulation and flow direction variables. The *slope* variable identifies the steepness of each cell of the input surface. The slope was derived using the DEM as the input variable to the slope tool in the Spatial Analyst toolbox in ArcGIS 10.6. The resultant output raster layer was calculated as the rise divided by the run, multiplied by 100 to express the slope as percent rise. Flatter terrain has lower slope values whereas, steeper terrain has higher slope values (ESRI, 2017).

The topography of the earth comprises a complexity of various geomorphic features. These specific geomorphic features are defined as *landforms.* The landform variable was derived using the topography toolbox in ArcGIS 10.6 (ESRI, 2017). Landform classification provides important information about a complex landscape. The first step was to calculate the topographic position index (TPI) based on the Jenness algorithm to identify different features (Jenness, 2006; Weiss, 2001). The TPI presents the change in elevation at a cell and the mean elevation of the neighbouring cells that surround it. A positive TPI value denotes that the cell is higher than the neighbouring cell e.g. ridges, the converse applies to cells with negative TPI values e.g. valleys, and TPI values near zero indicate flat areas or areas that have a constant slope (Nair et al. 2018). The TPI grid value were determined from two different neighbourhood sizes. A 50 m and 200 m neighbourhood were used to classify small features like streams and drainage, as well as large mountains and canyons, respectively. Thereafter, the landform classification tool was used to classify the various landforms using the TPI grids (Tagil and Jenness, 2008). The landforms of the earth's landscape provides valuable information in detecting where wetlands can be found (Ellery et al. 2009; Tooth et al. 2015).

4.4.3 Building a wetland database with associated environmental variables

The wetland database prepared for the logistic regression model was a collation of wetland (wetland presence) and non-wetland (wetland absence) point datasets and extracted statistical values from the associated environmental variables. The first step to building the wetland database was to standardise the layers to the same spatial projection, extent, data format and resolution. The spatial projection of all layers was standardised into the projected coordinate system World Geodetic System 84 Universal Transverse Mercator Zone 34 South (WGS 84 UTM Zone 34S) and the study area extent. The data format of the layers were standardised by converting the vector data (polygons, polylines or point features to raster using the conversion toolbox and feature to raster tool. Lastly, the spatial resolution of the layers was resampled to 20 m using two resampling techniques to interpolate the raster layers. The cubic convolution resampling technique was best suited to address continuous data by fitting a smooth curve through the centres of the nearest 16 cells to the output cell to determine its value. Whereas, the nearest neighbour resampling technique was used to interpolate categorical data as it preserves the original values of the input raster (ESRI, 2017). Environmental variables that contain categorical data were allocated numerical values to understand the analytical differences between wetland presence and absence points.

The wetland database was randomly split into a training and verification dataset to mitigate overfitting of the model (Aguilera et al. 2011; Hiestermann and Rivers-Moore, 2015). Splitting of the wetland database was achieved by using the field calculator in ArcGIS 10.6 to generate random values in a new field of the attributes table. Next, the ‘select by attributes tool’ was used to select 70% of the database as the wetland training dataset and the remaining 30% of the database as the digital verification dataset to test the models (ESRI, 2017). The ratio of wetland presence and wetland absence points for the datasets were roughly equal. The training dataset was used to calibrate the models, and the verification dataset was used to validate the accuracy of the models (Hao et al. 2020). The statistical values of each environmental variable were extracted to the wetland presence and absence points of the training dataset using ArcGIS 10.6 (ESRI, 2017; Hiestermann and Rivers-Moore, 2015). The training dataset was exported as excel spreadsheets for further editing and compilation. Building the wetland database was the foundation for the successive steps to develop the model.

4.4.4 Model development

4.4.4.1 Elimination of redundant variables

This step aimed to systematically eliminate redundant variables to derive a maximal dataset for input into the model. Redundant variables have high collinearity and multicollinearity levels that hinders statistical analysis as it is challenging to understand the effect of a particular independent variable on a dependent variable (Booth et al. 1994). Thirty-two environmental variables were identified and sourced for the modelling of wetland distribution. A Principal component analysis (PCA) and correlation matrix were used refine the suite of environmental variables.

The Kasier-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett’s test of sphericity were used to determine the usefulness of a PCA. The purpose of these tests were to verify that PCA can reduce the dataset in a meaningful way.

The Bartlett's sphericity test was used to determine if the correlation matrix is an identity matrix (this means that each variable correlate only with itself) at $p <$ 0.05 and indicates whether there are relationships among variables (Hair et al. 2010). The KMO values ranges from 0 to 1. A threshold value of >0.5 mean that the variables are sufficiently interdependent for PCA to be applied (Field, 2013). The PCA was conducted on the Multivariate Statistical Package version 3.2 (MVSP 3.2) to refined suite environmental variables had the greatest predictive power to determine the likelihood of wetland distribution.

The PCA technique is used to increase the interpretability of large datasets by reducing the size and complexity of the dataset while maintaining majority of the information (Jolliffe and Cadima, 2016). PCA creates a set of orthogonal variables called principal components which are linear functions of the original variables in the dataset such that it successively maximizes variance. The principal components represent the important information extracted from the dataset and provides a visual representation of the similarity of observations and variables as points in Euclidean biplot maps (Abdi and Williams, 2010).

PCA is a multivariate statistical technique commonly used in exploratory data analysis and predictive modelling using ordinal data (Hess and Hess, 2018). The five nominal variables were excluded from this step and later added to the maximal model, these variables included *geology groups, geology formation, soil type, clay content* and *landform*.

The dataset was centred and standardised before the PCA was run because the variables in the dataset were measured on different scales and orders of magnitude. The optimal number of principal components that account for the most variation in the dataset was selected based on Jolliffe's rule (Jolliffe, 1972). The rule is a modification of Kaiser-Guttman's rule (Kaiser, 1960) which is to retain principal components whose eigenvalues are greater than 0.7 instead of greater than 1 in order to better incorporate the effects of sample variance (Jolliffe and Cadima, 2016). The elimination of variables was an iterative process that analysed the biplots for the similarity of observation and the variable loading of each variable. Variable loadings were used to determine collinearities between variables. Higher variable loadings have the least unexplained variability while lower variable loadings are associated with high levels collinearity and small changes in the data values may lead to large changes in the estimates of the coefficients. The magnitude of the effect of a variable on the presence of wetlands are represented as the vector length in the biplot. The angle-based measure, cosine similarity measure determines the similarity between two vectors from the orientation between them by calculating the cosine angle between two non-zero vectors (Booth et al. 1994). Consequently, in cases where there is a no or a small angle between two or more vectors, the variable with the lowest variable loading would be considered redundant and removed. This was conducted with due consideration to the potential importance of variables to wetland distribution, and its interaction with other variables.

After the elimination of variables, the PCA was rerun to test the collinearity of the dataset. This was cross referenced with the correlation matrix by eliminating variables that exceed the collinearity threshold of $r > 0.85$. The techniques provided rigorous testing and elimination of redundant variables. The resultant set of refined variables was then combined with the previously excluded categorical variables to provide the maximal model for input into the logistic regression model.

4.4.4.2 Logistic regression model

Logistic regression is a type of Generalised linear model (GLM) suitable to analyse binary response data. The model was run using a binomial distribution and logit-link function, for the selection of variables to be included in the final model to estimate the probability of wetland distribution (Meyer and Laud, 2002). A logistic regression model was used to determine the relationship between the probability of wetland presence in the landscape and environmental variables. The maximal dataset (complete wetland locations with associated environmental variables) was saved as a text file. The statistical software package R version 4.0.0 (R Core Team, 2020) was used to compute the model.

The modelling process involved two steps, namely running a GLM and performing stepwise selection of the models. The GLM was formulated by Nelder and Wedderburn (1972) and it is an extension of the classic linear regression model to wider class of response types.

The GLM consists of three components: 1) the random component which refers to the probability distribution of the dependent variable, y, 2) the systematic component specifies parameter η which assumes magnification of the variance of each independent variable $(x_1, \dots, x_p)$ as a function of its linear predictors $(\beta_1, \beta_2, \dots, \beta_i)$, and 3) the link function (*η(.)*) of the independent variables, which links the random and systematic component, $g(\mu) = \eta$ (McCullagh and Nelder, 1989; Neuhaus and McCulloch, 2011).

The GLM is expressed using the following equation, where β_0 is the y intercept (constant value) in the linear predictor:

$$\eta(y) = \mu = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$$

The logistic regression is based on the logit-link function ($g(\mu)$), which is described as:

$$g(\mu) = \log \frac{\mu}{1 - \mu}$$

The optimal and most parsimonious GLM was identified using the Akaike Information Criterion (AIC) (Akaike, 1973) as a measure of goodness-of-fit of each model relative to each of the other models, using a stepwise logistic regression. The model with the lowest AIC was the most parsimonious and best-fit model within the collection of models considered. The parsimonious model explained the most variance with the minimum number of parameters.

The stepwise LR model used the binary dependent variable (wetland presence/absence) and the significant continuous and categorical independent variables (environmental variables) from the GLM and fit the model using the maximum likelihood estimation (Crawley, 2012; Rawlings et al. 1998). A stepwise logistic regression allows for simplification of a more complex model. The stepwise selection is a combination of both backward elimination and forward selection procedures (Crawley, 2012; Quinn and Keough, 2002). The logistic regression model is expressed as the following equation:

$$Y_i = \frac{e^{\beta_0+\beta_1 x_1}}{1+e^{\beta_0+\beta_1 x_1}}$$

where Y_i is the probability of outcome for the binary dependent variable where the estimated probability is one binary outcome category rather than a continuous outcome, in this case it represents the probability of a wetland is present; e is the exponential function; and β_0 and β_1 are the environmental variables to be estimated and x_1 is the value of each independent variable weighted by its respective beta coefficient (β). β_0 is the y intercept (constant value) and β_1 is the regression coefficient (Hosmer and Lemeshow, 2000; Quinn and Keough, 2002). The regression coefficients β_1 provide important information about the relationship between the independent variables and the dependent variable. The logit-link function transforms the binary dependent variable, wetland presence/absence from discrete outcomes of 0 or 1 into a continuous probability that varies between 0 to 1.

4.4.4.3 Developing the probability maps

The aim of the final step of the model development process was to create probability maps of wetland distribution using ArcGIS 10.6 (ESRI, 2017). Spatial modelling of the final logistic regression model used the Raster Calculator Tool in the Spatial Analyst toolbox. Building the model followed four steps: 1) multiplication of independent variables raster layers and related coefficients, 2) the linear predictor equation grid, 3) the exponent grid, and 4) probability grid. The raster layers of environmental variables identified as significant in the LR model were multiplied by their corresponding regression coefficient, to create new raster layers. The resultant raster layers and the modelled constant value (intercept) were used to scale the linear predictor in accordance with the LR equation above to create an equation grid. The exponential grid was calculated using the sum of the equation grid and the base 10 exponential function. This was followed by the calculation of the probability grid (P) using the inverse logistic transformation to obtain probability values for each of the cells in the grid between 0 and 1, according to the equation below, which is effectively based on the logistic regression equation:

$$P = \frac{e^{equation\ grid}}{1 + e^{equation\ grid}}$$

Values closer to 1 indicate a high likelihood of a wetland being present, conversely values that are closer to 0 indicate a high likelihood of a wetland being absent (Quinn and Keough, 2002). The probability maps were reclassified into discrete binary values of 0 and 1 for the current distribution of wetlands, by implementing different thresholds. The probability values above this threshold were indicated by wetland presence. Conversely, probabilities below the threshold represented wetland absence.

The climate change component of the study involved modelling wetland distribution for four future climate change scenarios (RCP 4.5-2050, RCP 4.5-2070, RCP 8.5-2050, and RCP 8.5-2070). The environmental variables in the final LR model, which represents the equation for the current wetland distribution were substituted with the raster layers corresponding to the projected environmental variables for the future climate change scenarios. Future wetland distributions were predicted using the future environmental variables following the same GIS LR steps used in the predict the current distribution to create the spatial grid to calculate the predicted future wetland distribution. The probability maps for future predictions of wetland distribution was modelled using the binary coding 1 for wetland presence and 0 for wetland absence. The probability layers were then extracted to the study area extent using the extract by mask tool in the Spatial Analyst toolbox of ArcGIS 10.6 (ESRI, 2017).

4.4.5 Model evaluation and validation

The final step of the environmental modelling process was to evaluate the robustness of the model by conducting an accuracy assessment. Two independent verification datasets were used in the evaluation of the model namely, the digital verification dataset which is the remaining 30% of the wetland database (n = 7,041) and the field verification dataset (n = 730). The wetland verification datasets were used to extract values from the probability raster layer that was created for the current distribution of wetlands in ArcGIS 10.6. These datasets were then exported as a text file and inputted into statistical software package R (R Core Team, 2020).

The performance of the model was determined using the quantitative, threshold independent evaluation metric, area under the Receiver Operating Characteristic curve (AUC ROC). AUC ROC analysis is widely used to determine the overall accuracy of prediction models with meaningful interpretations (Fielding and Bell, 1997; Hanley and McNeil, 1982). It is a measure of discrimination that reflects the model's ability to correctly discriminate between presence and absence. The ROC curve was generated by plotting the sensitivity against the 1 – specificity for all possible thresholds (Fielding and Bell, 1997; Phillips et al. 2006). The AUC ROC values range from 0 to 1 and follows the evaluation criteria: poor (0.5-0.6), fair (0.6-0.7), good (0.7-0.8), very good (0.8-0.9) and excellent (0.90-1.00). The AUC ROC values below 0.5 represents a model with random discrimination, and a value of one represents perfect discrimination (Hosmer and Lemeshow, 2000).

Sensitivity is the true positive (TP) rate of predictions refers to the percentage of correctly identified wetland presence correctly identified by the model and represents the absence of omission error. Specificity, known as the true negative (TN) rate of predictions, refers to the percentage of wetland absence correctly identified by the model as non-wetland area. Thus 1-specificity refers to the false positive (FP) rate and represents commission error (Phillips et al. 2006). The accuracy was calculated as the overall success of the probability layer. The measures were defined using the following equations:

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$Accurracy = \frac{TN + TP}{TN + TP + FN + FP}$$

Where, TP are the true positives and TN are true negatives, and FP are false positives and FN are false negatives. The evaluation techniques were used to determine the model performance and accuracy. The model with the highest levels of sensitivity, specificity, accuracy, and AUC ROC was selected as the final probability layer (Hiestermann and Rivers-Moore, 2015).

4.4.6 Changes in wetland distribution

The trends in the change of wetland distribution were calculated and compared using the Raster Calculator Tool in the Spatial Analyst toolbox. The binary raster layers for the current and future of wetland distributions were added together to calculate the overall wetland distribution. The distribution change was calculated from the from the current distribution for RCP 4.5 and RCP 8.5 for 2050 and 2070 time periods. The resultant raster layer represents areas that would remain suitable for wetland distribution received a value of two; a loss of wetland distribution had a value of one, and a value of zero indicates areas not suitable for wetland distribution (Zhang et al. 2018). The potential loss of wetland distribution was expressed as a percentage (%). Percentage loss of wetland distribution was calculated based on the number of cells (each cell is $20m^2$ spatial resolution) for each value, multiplied by the spatial resolution of the layer, and multiplied by 100 (Çoban et al. 2020; Zhang et al. 2018).

Chapter Five: Results

5.1 Introduction

This chapter aims to present the results used to address the objectives of this study. The chapter starts with a description of the wetland density variation across the aridity gradient of the study area. Detailed analysis of the correlated environmental variables is performed. This is followed by a presentation of the logistic regression model, probability layer output and model performance and verification. Lastly, the chapter concludes with the change analysis results of wetland distribution for the different time periods under two climate change scenarios.

5.2 Wetland density and the aridity gradient

The variation in wetland density in the study area was based on the NWM5 (Figure 5.1). The resultant map and data must be analysed taking into consideration that the NWM5 dataset is an assemblage of datasets collected from various sources at different spatial and temporal scales using different mapping techniques. General trends on wetland density along the aridity gradient were deduced from observations. There is an overall wetland density of 7.00 wetlands per 10 km^2 in the study area; however, the distribution is uneven. This is evidenced by the increase in overall wetland density from east to west and north to south and follows a similar pattern as the aridity gradient (Figure 5.1/Figure 5.2). Wetland density hotspots coincide with the dry sub-humid and semi-arid conditions found in the City of Cape Town and Drakenstein municipalities. The Breede Valley Municipality had the lowest wetland density and the highest aridity.

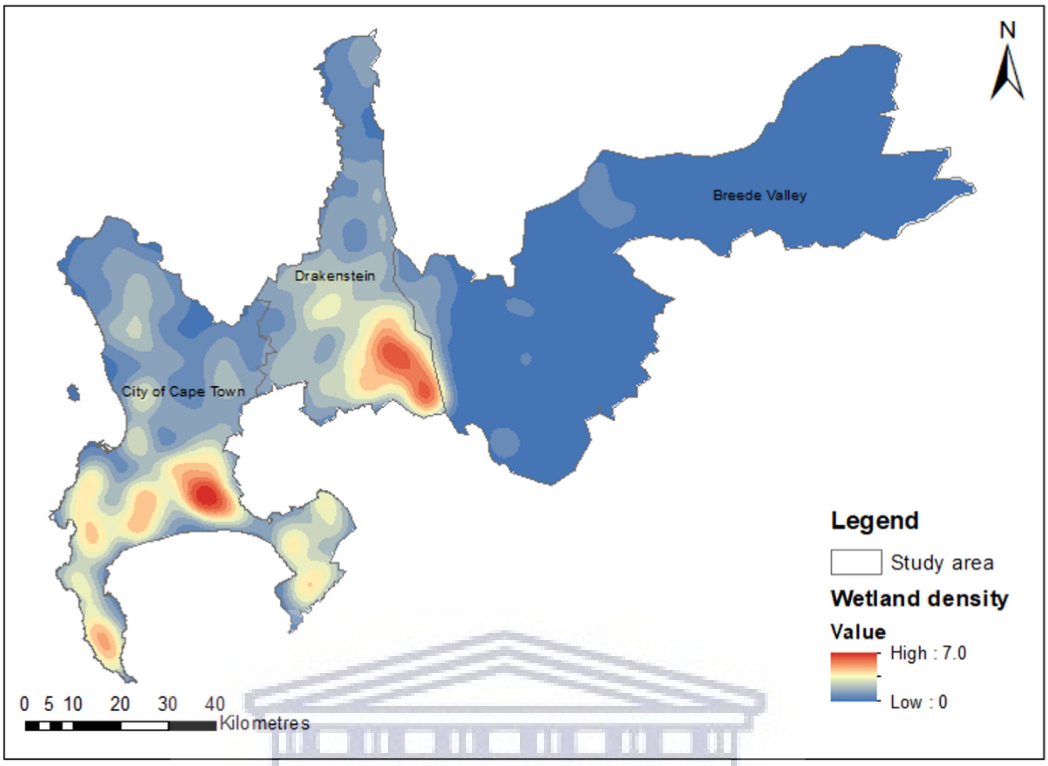


Figure 5.1: Wetland density across the study area.

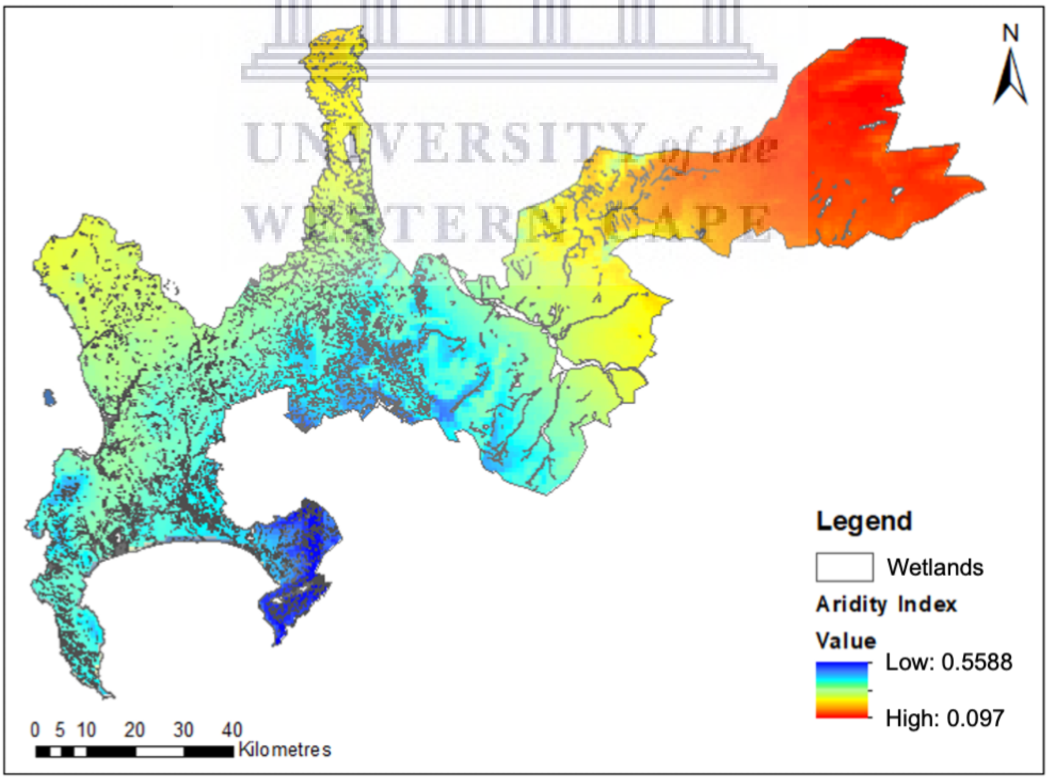


Figure 5.2: An aridity index map showing wetlands in the study area.

The total coverage of wetlands in the study area is 376.59 km^2 (37,659 ha), which accounts for less than 1% of the total extent of the study area. The number and size of the wetlands varied within the aridity class and among other aridity classes. The majority of the wetlands were found in the semi-arid region (Figure 5.3). The dominant HGM wetland types in the study area were seeps, depressions, and channelled bottom wetlands, respectively, contributing to approximately 43% of the total wetland coverage. The number of seeps contributed to roughly 50% of the total density of wetlands. Despite the significant abundance of seep wetlands, this type covers a small extent (22%) of the total wetland area. The least frequently occurring HGM wetland type was wetland flats that contributed to less than 1% of the total wetland area. There were no wetlands flats found in the dry sub-humid region and a limited number in the arid region. Wetland flats were most abundant in the semi-arid regions.

Table 5.1: The number of HGM wetland types within the aridity classes.

	HGM wetland type						
AI classes	**CVB**	**Depression**	**Wetland flat**	**Floodplain**	**Seep**	**UVB**	**Total**
Arid	11	6	3	0	19	5	44
Semi-arid	586	1703	49	290	3383	535	6546
Dry sub-humid	33	5	0	1	337	12	388
Total	630	1714	52	291	3739	552	6978

Floodplain wetlands covered the largest extent across the study area, approximately 12,930 ha. The HGM wetland type was not found in the arid regions and contributed to a limited extent (1.78 ha) to wetland area in the dry sub-humid region. The unchanneled valley bottom wetland density was the highest in the semi-arid region and contributed to approximately 19% of the total extent. Lastly, depression wetlands were the second most abundant HGM wetland type across the study area and semi-arid regions but had a relatively small contribution of 4% to the total wetland area. The results of the variance in wetland density across the study areas is explained in further detail in Chapter 6.

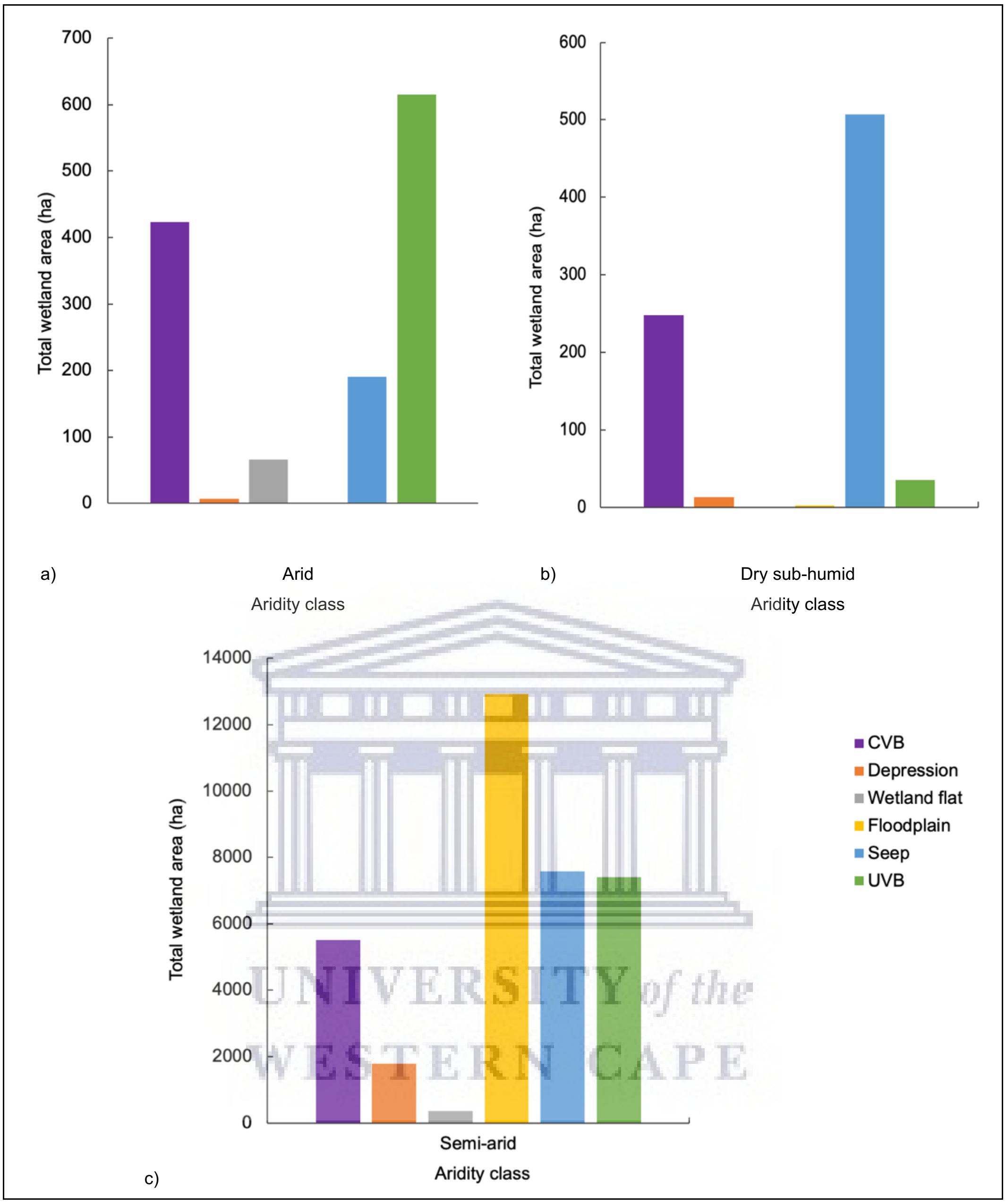


Figure 5.3: The overall wetland area (ha) per hydrogeomorphic wetland type (CVB – channelled valley bottom wetland, UVB – unchanneled valley bottom wetland) for the aridity classes, a) arid, b) dry sub-humid, and c) semi-arid.

5.3 Statistical analysis of environmental variables

Twenty-seven ordinal environmental variables from the original dataset were extracted as the dataset for this component of the study. Bartlett's Test of Sphericity was significant, $p < 0.001$, which indicates that it is appropriate to apply PCA. This was cross-referenced with the KMO statistic of 0.88, which is higher than the threshold value (KMO test > 0.5) and suggests that the maximal ordinal dataset had high correlations among variables (Table 5.2).

Table 5.2 The Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity results.

Kaiser-Meyer-Olkin measure of sampling adequacy		0.881
Bartlett's test of sphericity	Chi-Square	719,329.993
	Degrees of freedom	378
	Significance	<0.001

The application of the PCA reduced the number of environmental variables from 27 to six through an iterative elimination process. The maximal PCA was explained by the cumulative variance of 76.24% and an eigenvalue of 4.12 (Figure 5.4).

Following the first iteration of PCA, six variables were eliminated due to their short vector length, which is indicative of their low contribution towards determining the effect of wetland presence or absence. Variables included *aspect, flow accumulation, flow direction, bio3, bio15* and *groundwater depth*.

In the second run of the PCA, the rainfall variables *bio16, bio18* and *bio19* were removed due to the high correlation (r < 0.86) between the variables and *bio17*. Variable *bio17* was retained as it had a longer vector length, indicating that the variables contribution to determining the model's outcome was better than the others.

The third PCA found a high correlation (r>0.85) between *bio12, bio13, bio14* and *bio17* and their vectors lie at the same angle. Variables *bio12, bio13,* and *bio14* was removed due to the shorter vector lengths, and the lower variable loadings reinforced the elimination.

The outcome of the fourth iteration of the PCA indicated a strong correlation (r>0.94) between *bio2, bio4, bio7* and *PET* and their vectors lie along a similar angle. The PCA retained *bio7* as it had a longer vector length and had a higher variable loading of 0.17.

In the fifth PCA rerun, the temperature variables *bio1, bio5, bio9* and *bio10* had high levels of correlation (r > 0.92), and *bio10* was retained as it had the highest variable loading.

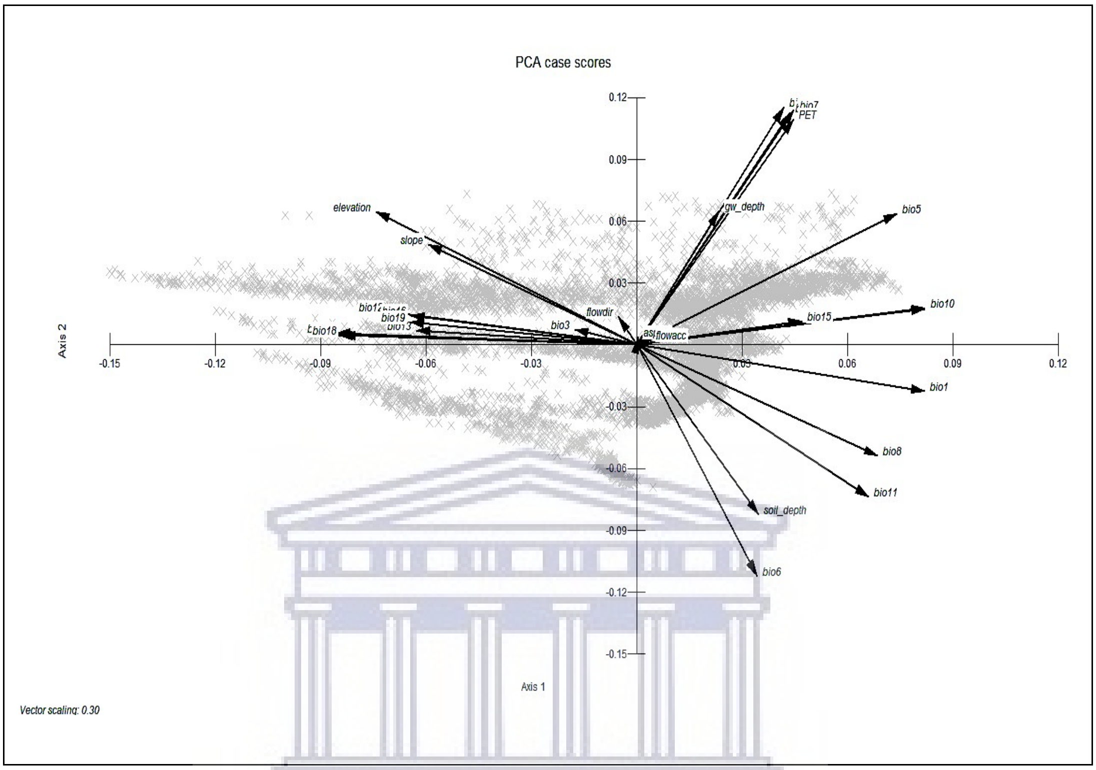


Figure 5.4: An Euclidean biplot of the maximal dataset (refer to Table 4.2 for the description of variables) of the Principal Component Analysis.

The final iteration of the PCA eliminated *soil depth* because the variable was the shorter vector length when compared to *bio6*. Lastly, a strong negative correlation (r > -0.93) between *elevation* and *bio8* and *bio11* resulted in the elimination of *bio11* and *elevation* variables. The optimal PCA accounted for 83.05% of the cumulative variance of the dataset in the first two axes (Figure 5.5). The objective to remove the interdependency of variables from the dataset was satisfied.

The final PCA was presented in Table 5.3. Axis one accounted for 54.30% of the variance. The variable loadings that contributed the most to determining wetland presence were *bio8, bio10* and *bio17* with -0.509, -0.485 and 0.424, respectively. The highest variable loadings in axis two were attributed to *bio7* and *bio6*, with 0.729 and -0.547, respectively.

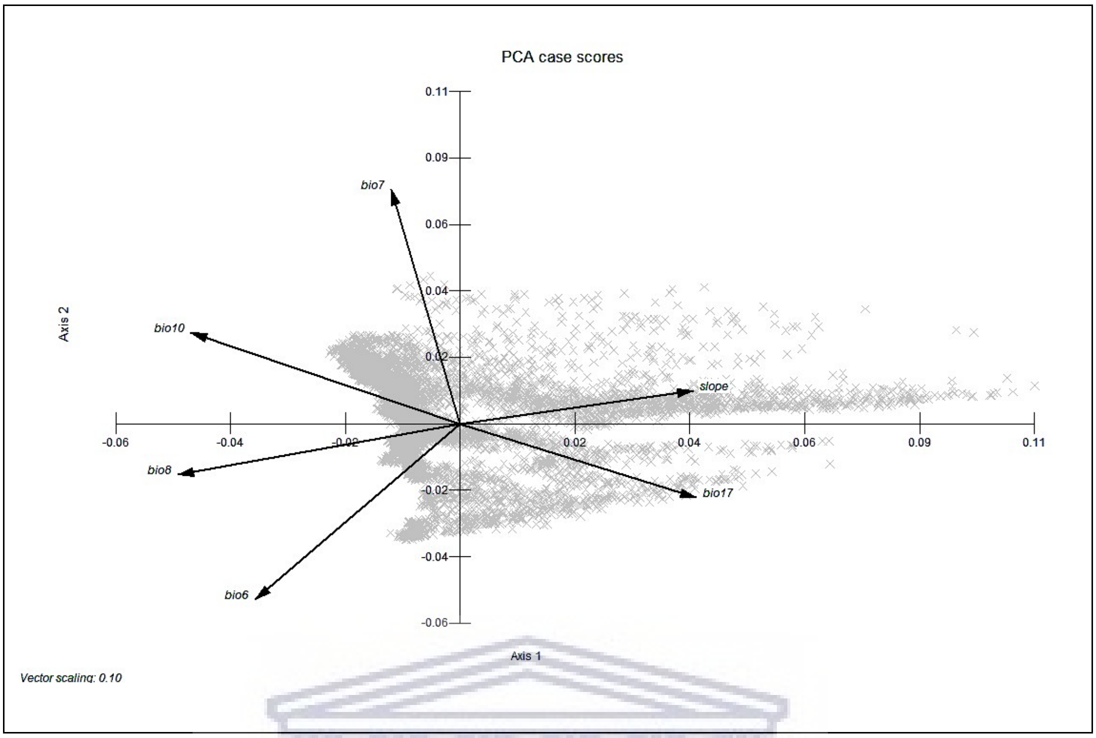


Figure 5.5: The final PCA illustrated as an Euclidean biplot showing the refined suite of ordinal variables (refer to Table 4.2 for the description of variables).

Table 5.3: The variable loadings for the refined suite of variables for Axis 1 and Axis 2.

PCA variable loadings	Axis 1	Axis 2
bio6	-0.369	-0.547
bio7	-0.124	0.729
bio8	-0.509	-0.159
bio10	-0.485	0.284
bio17	0.424	-0.23
slope	0.419	0.102

Following the elimination of redundant variables, the nominal variables were added to the refined dataset to make the complete maximal dataset that will be used to model the distribution of wetlands.

5.4 Logistic regression model

The LR model was fitted using the maximal dataset, which consisted of 11 environmental variables that were used to generate the wetland distribution model (Table 5.4). The variables in the maximal LR model that were found to make a significant contribution to building the model were *bio6, bio8, bio10, bio17, slope, soil type* and *clay content*. Based on the coefficients of the model, *bio10* followed by *bio6* had the largest contribution to determining the presence of wetlands; however, the variables were also associated with high standard errors. The *bio7, geology group,* and *geology form* variables were not significant (p>0.05) to contribute to the generation of the model.

Table 5.4: The coefficients and standard errors for variables used in the logistic regression model. The *p*-values are highly significant at 0.001.

	Coefficient	**Standard error**	***p*-value**
Intercept	2.7689628	0.4294954	< 0.0001
bio6	0.4863637	0.1531111	0.00149
bio7	-0.1089010	0.0798126	0.17242
bio8	-1.2544117	0.0691687	< 0.0001
bio10	0.6047105	0.0972870	< 0.0001
bio17	0.0214296	0.0016100	< 0.0001
slope	-0.0427102	0.0026598	< 0.0001
landform	-0.1423172	0.0057177	< 0.0001
geology group	0.0128833	0.0103282	0.21225
geology formation	-0.0004304	0.0006013	0.47415
soil type	-0.0301904	0.0030565	< 0.0001
clay content	-0.2258114	0.0263599	< 0.0001
AIC		20603	

Note: The result is significant at $p \leq 0.05$.

Variables that did not contribute to building the model were removed, and the stepwise LR model was run. Four models iterations were conducted as part of the stepwise selection process (Table 5.5).

Table 5.5: Comparison of the logistic regression models generated in the stepwise selection process.

	LR 1	**LR 2**	**LR 3**	**LR 4**
No. of variables	11	10	9	8
AIC value	20,602.74	20,601.25	20,600.57	20,600.1

The selection of all the environmental variables identified in the model was necessary for the formation and persistence of wetlands. The most parsimonious model was LR 4, with an AIC value of 20,600.1 and included eight variables that were all statistically significant, $p < 0.001$ (Table 5.5 and Table 5.6). The coefficients from the final LR model reiterated the findings of the optimal model indicate that *bio6* and *bio10* were the most important environmental variables to predict wetland distribution.

Table 5.6: The coefficients and standard errors for variables used in final logistic regression model. The *p*-values are highly significant at 0.001.

	Coefficient	**Standard error**	***p*-value**
Intercept	2.477413	0.386722	< 0.0001
bio6	0.677977	0.035404	< 0.0001
bio8	-1.292794	0.054859	< 0.0001
bio10	0.475064	0.025278	< 0.0001
bio17	0.021465	0.001603	< 0.0001
slope	-0.043278	0.002626	< 0.0001
landform	-0.141929	0.005710	< 0.0001
soil type	-0.029772	0.003024	< 0.0001
clay content	-0.224008	0.026011	< 0.0001

Note: The result is significant at $p \leq 0.05$.

A LR equation was fit in ArcGIS 10.6 using the coefficients from the model to spatialise the probability of wetland distribution in a final raster layer. Each cell value in the raster indicates the probability of wetland distribution as a continuous probability from 0 to 1, where values approaching 1 indicate a higher chance of predicting wetland presence. The probability values were expressed as a percentage in the results. The probability of wetland distribution in the study area is represented in Figure 5.6.

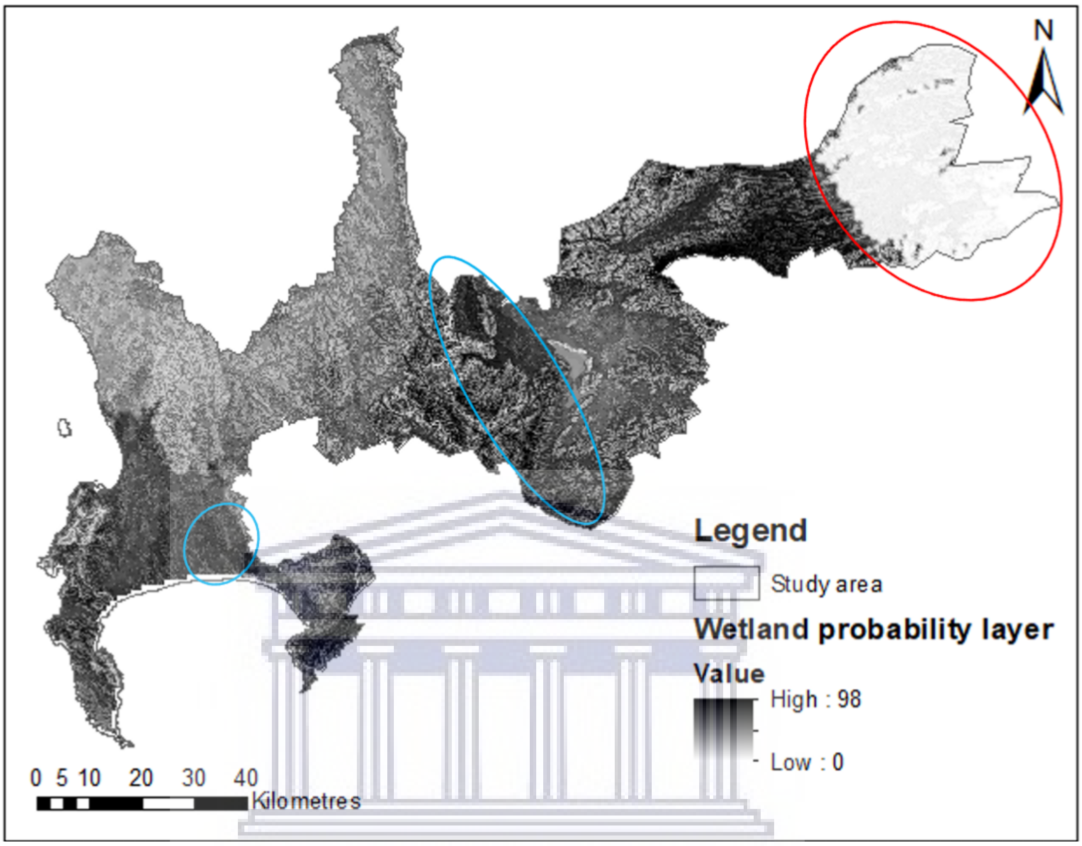
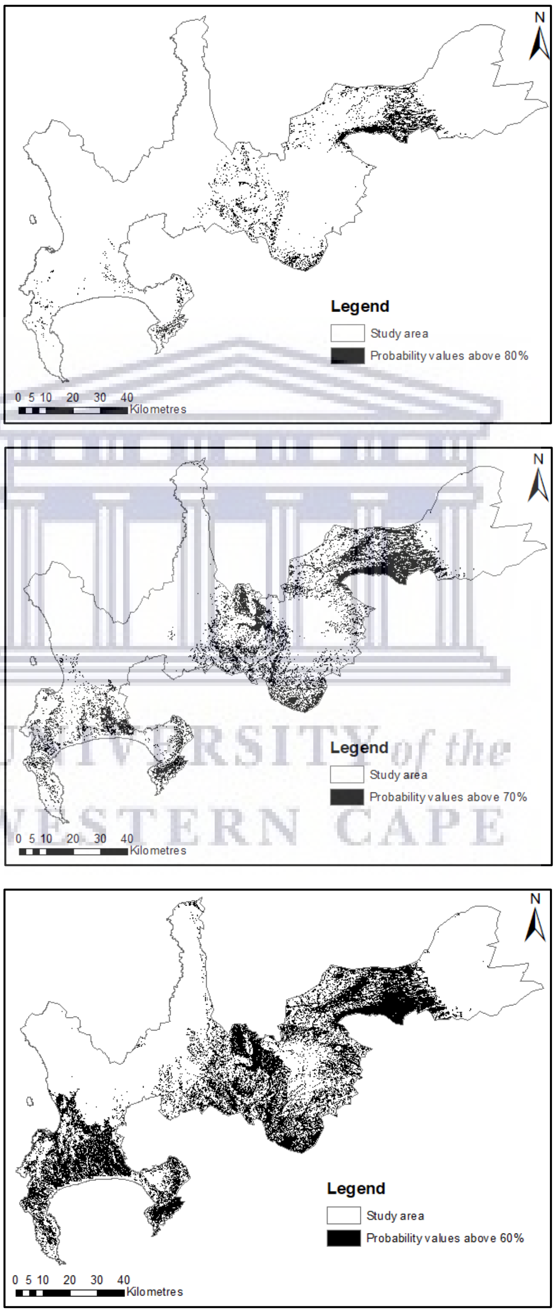


Figure 5.6: The wetland probability layer for the current wetland distribution in the study area. Blue circles represented dense wetland areas, and a red circle represented low wetland density areas.

From visual inspection, the wetland probability layer distinctly identified the arid region of the Breede Valley Municipality (33°3’S 20°2’E) as low wetland density is represented by a red circle and the two areas that indicate dense wetland regions is indicated by the blue circles in Figure 5.6. The two areas that represent a high density of wetlands are the wetland system associated with the Eerste River (34°0’S 18°9’E) and seep wetlands that litter the Cape Fold Belt Mountains on Du Toits Kloof (33°7’S 19°1’E). Both dense wetland areas coincide with the transitional zone between semi-arid and dry sub-humid regions.

Three thresholds values were applied to reclassify the probability layer for probabilities ranging from above 60%, 70% and 80% to represent the study area

(Figure 5.7). The probability layer at a 90% threshold was not illustrated because the number of wetlands represented above the threshold was severely underestimated. By contrast, the binary probability layer created for above 60% of probability values indicates an overestimation of wetland presence in the study area (Figure 5.7, c).



a) b) c)

Figure 5.7: The probability maps of wetland distribution at different thresholds, a) above 80%, b) above 70%, and c) above 60%.

5.5 Model performance and evaluation

In this study, the field verification dataset and the digital verification dataset (the remaining 30% of the total wetland dataset) were used to evaluate the models. The AUC ROC evaluation metric was used to assess the accuracy of the model. The AUC ROC was calculated with a score of 0.643 (SE ± 0.021) and 0.687 (SE± 0.0063) for the field verification and digital verification datasets, respectively (Figure 5.8). The sensitivity, specificity and overall accuracy was calculated for the verification datasets. Both datasets had sensitivity below 0.5 which indicates the model had challenges correctly identifying true positive rate resulting in an absence of omission error. Based on the AUC ROC values, the models ability to detect the true negative rate and the overall accuracy values indicates that the model performed better than a random model and had a fair performance. However the predictions were more accurate for the digital verification dataset than the field verification dataset (Table 5.7).

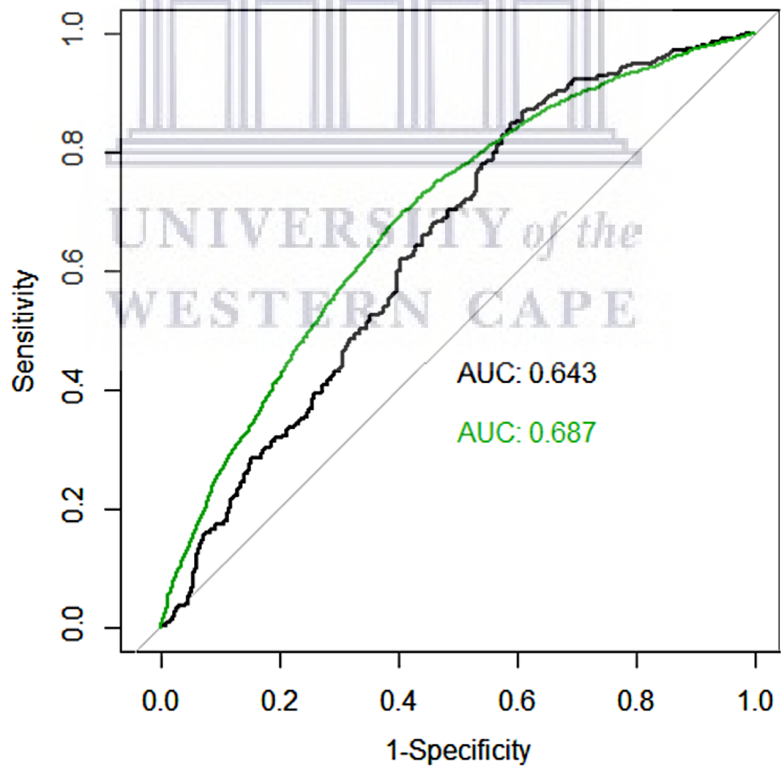


Figure 5.8: The area under receiver operating characteristic curve analysis of the model on the field verification dataset indicated in black and the green line represents the digital verification dataset.

Table 5.7: The model performance statistics for the LR model at a probability of 60%.

	Field verification dataset	Digital verification dataset
Sensitivity	0.435	0.446
Specificity	0.699	0.785
Overall accuracy	0.555	0.645

5.6 Changes in wetland distribution

The current and predicted wetland distribution was compared for the 2050 and 2070 time periods under the RCP 4.5 and RCP 8.5 climate change scenarios (Figure 5.9/Table 5.8). The modelled current wetland distribution is approximately 394.17 km^2 (39416 Ha). Overall, the predicted wetland distribution decreased substantially for the future scenarios and time periods. According to the RCP 4.5 climate change scenario, there is a 62-71% loss between the 2050 and 2070. In the RCP 8.5 scenario there is predicted to be a large loss of wetlands between 90-98%. The impact of the RCP 8.5 scenarios on the change in wetland distribution was evident when compared to the RCP 4.5 scenarios. Approximately only 9-49% of the current wetland distribution will remain suitable.

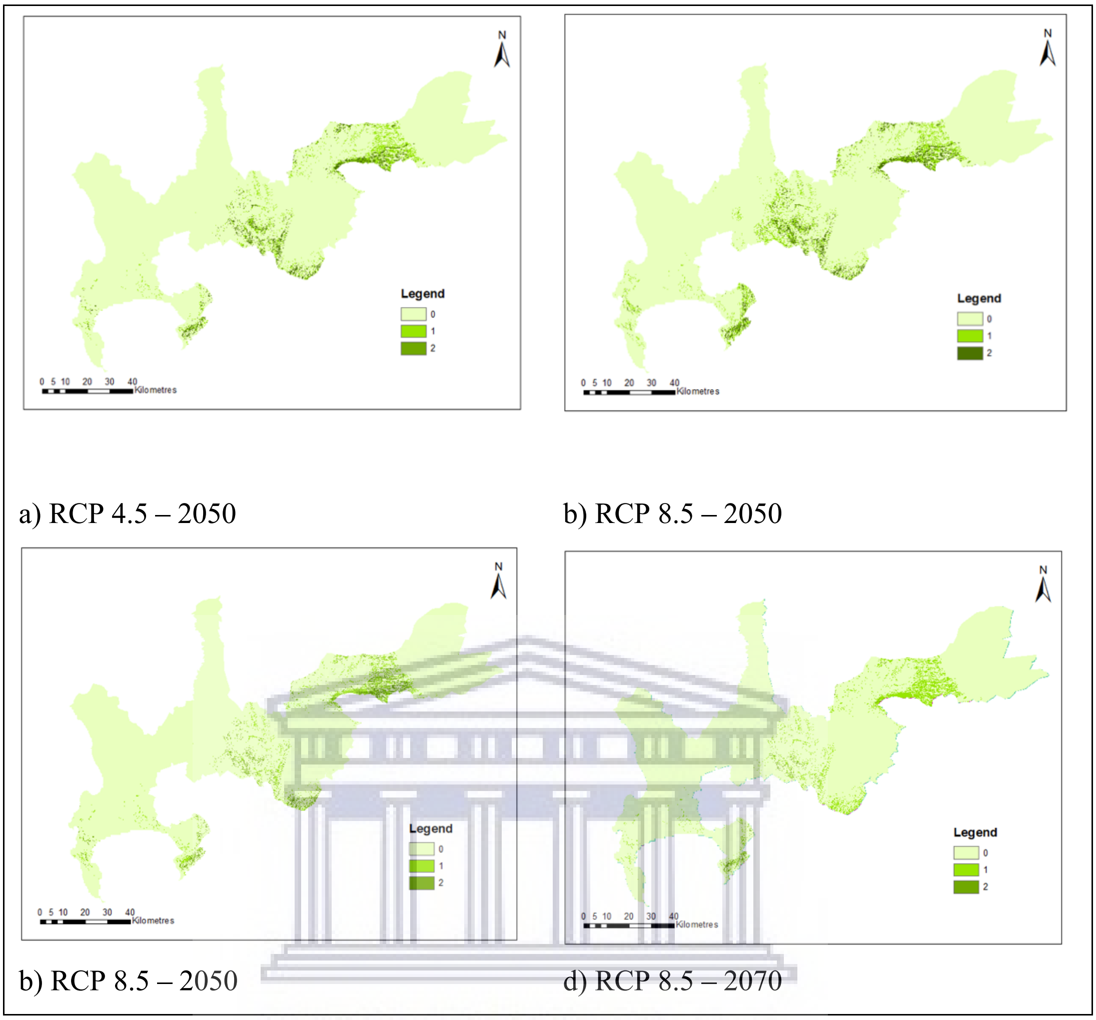


Figure 5.9: Wetland distribution and change in wetland distribution for the 2050 and 2070 and the RCP 4.5 and RCP 8.5 climate change scenarios. The code for suitability change is given by 0 - not suitable, 1 - loss of wetland distribution, 2 - remains the suitable for current and future scenarios.

Table 5.8: Spatial analysis of the change in wetland distributions from current distribution to its future potential distributions in 2050 and 2070.

	2050		2070	
	RCP 4.5	**RCP 8.5**	**RCP 4.5**	**RCP 8.5**
Loss of Wetlands (%)	62.34	90.27	71.36	98.43
Loss of habitat (km^2)	245.73	355.81	281.29	388
Not suitable (km^2)	7330.55	7341.12	7300.65	7152
Remain suitable (km^2)	159.19	38.53	153.53	195

Chapter Six: Discussion and Conclusions

The discussion chapter provides a comprehensive explanation of the results of the current and predicted wetland distribution. In addition to the description of the current wetland distribution variation along the aridity gradient of the study area, the study aimed to firstly determine the current predicted wetland distribution using logistic regression and evaluate the findings, and secondly determine the change in predicted wetland distribution under climate change. These two modelling objectives are evaluated in relation to the risks of wetland loss due to climate change and its implications.

6.1 Wetland distribution across the aridity gradient

The study assessed the variation of wetland density along the aridity gradient to understand the distribution of wetlands in the study area. The results indicate that the study area has a high density of wetlands and the distribution is relatively uneven. This is a result of the change in aridity classes over a short distance and high topographic heterogeneity. The steep north-south aridity gradient in the Western Cape is enforced by the rainfall seasonality gradient that extends from east to west and a temperature gradient that increases from the pole to the equator (Midgley et al. 2005; Tyson, 1999). Tooth et al. (2015) and Mitsch and Gosselink (2007) highlight the role of geomorphology, hydrology and long-term climate factors that control wetland formation and development. The diverse topography of the Cape Fold Belt mountains creates local climate conditions, such as the orographic effect that creates a band of humid conditions over the mountain range (DEA, 2011).

Seep wetlands were the dominant HGM wetland type found primarily in dry sub-humid conditions that persist over the Cape Fold Belt mountains, although their extent is limited. This finding supports the suggestion of Ellery et al. (2009) that these wetlands are likely to be found in areas with relatively higher rainfall and lower rates of potential evaporation than is the case in drier areas with fewer wetlands. A similar pattern was noted for wetland density across the study area. The abundance of depression wetlands similarly had a small total wetland extent.

The small extent of depression wetlands is often a result of the wetland being isolated on a closed or near-closed elevation contour that is not connected to an outlet drainage network (Ellery et al. 2009; Ollis et al. 2013). Wetland flats were the least frequently occurring wetlands and can be attributed to the rugged topography of the landscape. This HGM wetland type was found in semi-arid conditions as one moves from the Drakenstein Municipality to the Breede Valley Municipality, where the topography is relatively level. The distribution of valley bottom wetlands was linked to the trellis drainage patterns and influenced by the geology of the study area (Partridge et al. 2010). Floodplain wetlands (*sensu* Ollis et al. 2013) were distinctly absent from the arid region and contributed to a limited extent to the dry sub-humid region. The absence or near absence of floodplains from these regions indicates the importance of topography and lithology controls on the formation of the HGM wetland type (Tooth et al. 2004). Ollis et al. (2013) explain that floodplain wetlands are generally found in broad valleys with a gentle slope. These landscape features are mostly uncommon in the dry sub-humid region of the study area due to the Cape Fold Belt mountains and associated narrow coastal plains relative to the east of South Africa.

In conclusion, Tooth (2013) argues that geology is an important control on some HGM wetland types and overrides the effects of climate in some cases. Findings from Chase and Quick (2018) and Engelbrecht and Engelbrecht (2016) predict that climate conditions will become warmer and drier across the Western Cape; this suggests that the aridity gradient will likely shift southwards due to displacement of the polar frontal systems that brings rainfall to the WRZ.

6.2 Verification of the probability layer for current and future wetland distribution

A logistic regression model was used to map the predicted current wetland distribution, and the future wetland distribution for 2050 and 2070 under the RCP 4.5 and RCP 8.5 climate change scenarios. The technique has previously been used to map wetland distribution in South Africa and internationally at different spatial scales and resolutions (Grant, 2005; Hiestermann and Rivers-Moore, 2015; Melly et al. 2017). The probability layer of the current wetland distribution consisted of continuous probability values ranging from 0-98%. The AUC ROC value provided a measure of the overall accuracy that is comparable among different models (Ling et al. 2003). The AUC ROC of the probability layer was between 0.643-0.687, and overall accuracy of 64.5% indicated that the model had a fair performance and was compared to the findings of other studies (Table 6.1). The threshold values of the probability layer above 80% and 70% underestimated wetland distribution, while a value of 60% overestimated wetland distribution. Overestimation of wetland distribution could be a result of spatial autocorrelation among the wetland presence and absence dataset used in the model (Ishihama et al. 2010).

Table 6.1: The area under receiver operating characteristic curve (AUC ROC) values and overall accuracy of other wetland distribution models. (LR = logistic regression; BN = Bayesian Network)

Study	Description	AUC ROC value	Overall accuracy (%)
Melly et al. (2017)	LR model for Nelson Mandela Bay Metropolitan (NMBM) Municipality in Gqeberha	0.69	66
Rivers-Moore et al. (2020)	BN model for predicting HGM wetland type in the Western Cape	-	68
Grant (2005)	LR model for assessing the occurrence of vernal pools in Massachusetts, USA	-	64.8
Zhong et al. (2021)	MaxEnt model to predict wetland distribution in Northeast China	0.85	-
Rebelo et al. (2017)	MaxEnt model to predict palmiet wetlands in the Cape Floristic Region (CFR) of South Africa	0.81	-
Hiestermann and Rivers-Moore (2015)	LR wetland distribution model for KwaZulu-Natal (KZN)	0.84	-
Hiestermann and Rivers-Moore (2015)	BN model for KZN	0.85	-

The poor performance of the LR model compared to other studies in KZN and NMBM Municipality is possibly due to the physical characteristics of the region. The Hiestermann and Rivers-Moore (2015) LR model was based on a study area in the SRZ with relatively low evapotranspiration rates, where the climate and topography are more or less consistent for most of the study area. Similarly, the LR model for the Nelson Mandela Bay Municipality (NMBM) took place in the ARZ with relatively consistent climatic conditions and topography throughout the study area (Melly et al. 2017). Whereas the LR model performed for this study had steep changes in climate as evidenced by the aridity gradient that traverses the study area and high topographic heterogeneity, making it difficult to predict the distribution of wetlands.

Other important factors that influenced model performance was the quality of the environmental variables dataset used to build the models. For example, most of the data used in this study were international and national datasets at a low spatial resolution (~ 0.8 – 2.5 km for environmental variables) which contributed to the low model performance. Local datasets are beneficial, such as the hydrogeomorphic soils dataset used in the LR and BN models (Hiestermann and Rivers-Moore, 2015). The bioclimatic variables had a low spatial resolution, and there were high levels of correlation among some of the variables (refer to Section 5.3: Statistical analysis of environmental variables). This was further emphasised by the high standard errors of the bioclimatic variables that are evident in the final LR model. Despite this, the optimal dataset retained these variables alongside other variables in the model to account for the complex interactions necessary for wetland formation and persistence (Melly et al. 2017).

Similar to the studies conducted by Melly et al. (2017) and Rebelo et al. (2017), prediction success increased for wetlands above a size threshold of 1 hectare. Several small wetlands (< 1 ha) occurred throughout the study area and accounted for the difficulty in estimating wetland presence through the modelling process. The fair model performance can further be attributed to the fact that only one data location point at the centroid of the wetland was used to train and test the model, which may result in the location point lying cell with a low probability value. Furthermore, the climatic regions, slope and input datasets vary among the studies and may not be comparable. These observations are consistent with those of Hiestermann and Rivers-Moore (2015) and Melly et al. (2017), indicating that a buffer of an appropriate size must be used when extracting the probability values to test the performance of the model (Valavi et al. 2018).

Lastly, the model performed poorly compared to Rebelo et al. (2017) study on palmiet wetland distribution using the MaxEnt approach and could result from the study focusing on a specific HGM wetland type. In contrast, this study looked at determining the distribution of wetlands for all HGM wetland types. Rivers-Moore et al. (2020) had a similar result when looking specifically at different HGM wetland types. The accuracy may improve if the LR model was run per HGM type or by removing an HGM wetland type from the current model (Melly et al. 2017). Overall the model performance in terms of accuracy and the AUC ROC evaluation metric was above the threshold of 0.5 and used a field verification dataset to validate the model.

6.3 Changes in predicted wetland distribution under climate change and implications

In this study, the current and future wetland distribution was modelled for the 2050 and 2070 time periods under the RCP 4.5 and RCP 8.5 climate change scenarios using the final LR model. The LR model revealed the optimal dataset of environmental variables were all statistically significant ($p < 0.05$) and contained the following variables *bio6, bio8, bio10, bio17, slope, landform, soil type* and *clay content*. The *slope, landform, soil type* and *clay content* variables are geomorphic variables that change over centennial to millennial timescales and, therefore, will not significantly change over the time period considered for modelling of future wetland distribution (Tooth et al. 2015). They do however, determine the structure of the wetland setting, and will determine the resilience of wetlands to other process changes (Tooth, 2018), although this is beyond the scope of the present study to consider. Variables *bio6, bio8, bio10, bio17* are bioclimatic variables, and projections indicate that these variables will change according to the climate change scenarios over relatively short timescales (Hijmans et al. 2005). The temperature variables *bio6, bio8* and *bio10* are expected to increase overall, and the hydrology variable *bio17,* which is precipitation in the driest quarter of the year, is anticipated decrease based on projections of a warmer and drier climate over the Western Cape (Engelbrecht and Engelbrecht, 2016). Temperature variables contributed the most in determining wetland presence in the model (Table 5.6). The position within the topography (*landforms*) is also important to predict wetland distribution in connection with its effects on the microclimate (Çoban et al. 2020; Dobrowski, 2011). According to Zhong et al. (2021), models that include climate variables and relevant non-climate variables are able to provide a more holistic representation of distribution.

The current wetland distribution was compared to the predicted future wetland distributions under RCP 4.5 and RCP 8.5. The results confirmed that there would be a significant change in wetland distribution, although the nature of the change depends on the respective climate change scenario. Considering that many wetlands are dependent on a positive water balance, the future climate conditions will become less suitable for wetland distribution and will result in a severe loss of wetlands. This is consistent with the climate projections for the region (Engelbrecht et al. 2015; Engelbrecht and Engelbrecht, 2016). Shifts towards a drier and warmer climate will result in a reduction in inundation of some wetlands and drying up of others, particularly those that are rainwater dependent (Ellery et al. 2009; Sandi et al. 2020). Climate change is an important factor that will influence the loss and fragmentation of wetlands (Çoban et al. 2020; Pearson and Dawson, 2003). Areas that remained suitable for wetland distribution coincided with the mountain ranges found in the study area and suggest that the mountain's complex topography provides a buffer to the effects of climate change (Albrich et al. 2020). In summary, the results presented for this study provide quantifiable spatial projections of wetland distribution and analysis of change and wetland resilience under different climate change scenarios to support decision-making (Figure 5.6 and Table 5.8). The study recommends that wetlands with low probabilities in the future climate change scenarios are prioritised for wetland conservation planning (Xu and Chen, 2019). Although it may not be possible to provide more water to these wetlands, all efforts should be made to prevent increases in anthropogenic hydrological stressors in their surface and subsurface catchment areas.

6.4 Conclusion and Recommendations

The study aimed to develop a logistic regression model of current and future wetland distribution using environmental variables. Based on the findings of the study, the following conclusions were drawn. The wetland density increases with a decrease in aridity gradient in the study area. The most abundant HGM wetland type was seep wetlands found predominantly in the dry sub-humid region. Redundant ordinal environmental variables were eliminated using a PCA. The LR had a fair performance in predicting wetland distributions, with an AUC ROC value greater than 0.64. The bioclimatic variables, specifically the climate variables, had a higher contribution to predicting wetland distribution than the geomorphic variables, possibly due to the generally steep and well-dissected terrain of the region which does not typically favour wetland persistence. Modelling the current and future wetland distribution and predicting the potential loss of wetlands and change in suitable wetland distribution indicated an overall decline in distribution for 2050 and 2070 under the RCP 4.5 and RCP 8.5 climate change scenarios. In conclusion, the model and approach used in this study provide a valuable reference for future studies , and a point of departure for the refinement of approaches to modelling the effects of climate change on wetland distribution. The results will help improve the conservation of wetlands and protect rare and endangered wildlife dependent on wetlands for survival.

The limitations and recommendations of the study were addressed. Limitations to the study were to increase the number of wetlands sampled during the wetland verification exercise, particularly towards the arid spectrum of the aridity gradient. In addition, the availability of high-resolution bioclimatic variables for current and future climate change scenarios was limiting in the study. The limitations identified in this study can be improved through future research. It is recommended that research improve the ground-truthing exercises of wetland sites on the inland arid landscape of the ARZ and improve the availability of high-resolution input layers (Hiestermann and Rivers-Moore, 2015).

Further development of environmental modelling using additional environmental parameters and remote sensing techniques could be investigated. Finally, it is recommended that the LR model for the potential current and future wetland distributions be extended to model the distributions according to HGM wetland type (Hiestermann and Rivers-Moore, 2015; Melly et al. 2017; Rivers-Moore et al. 2020). The new probability layers would provide specific information on each HGM wetland type and shifts in distribution due to climate change.

References

Abdi, H., and Williams, L. J. (2010) Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics* 2(4): 433–459.

Adam, E., Mutanga, O., and Rugege, D. (2010) Multispectral and hyperspectral remote sensing for identification and mapping of wetland vegetation: A review. *Wetlands Ecology and Management* 18(3): 281–296.

Aguilera, P. A., Fernández, A., Fernández, R., Rumí, R., and Salmerón, A. (2011) Bayesian networks in environmental modelling. *Environmental Modelling and Software* 26(12): 1376–1388.

Akaike, H. (1973) Information theory and an extension of maximum likelihood principle. In Petrov, B. N. and Csaki, F. (Eds.), *Second International Symposium on Information Theory*. Budapest: Akademiai Kiado.

Albrich, K., Rammer, W., and Seidl, R. (2020) Climate change causes critical transitions and irreversible alterations of mountain forests. *Global Change Biology* 26(7): 4013–4027.

Allwright, A., Witthueser, K., Cobbing, J., Mallory, S., and Sawunyama, T. (2013) *Development of a Groundwater Resource Assessment Methodology for South Africa: Towards a Holistic Approach Report to the Water Research Commission*.

Begg, G. (1986) *The wetlands of Natal (Part 1): an overview of their extent, role and present status*. Pietermaritzburg: The Natal Town and Regional Planning Commission.

Blamey, R., Jack, C., Steynor, A., Sutherland, K., and Taukoor, S. (2014) *Climate science input into municipal climate adaptation plans*. Cape Town, South Africa: Climate System Analysis Group (CSAG) at the University of Cape Town.

Blewett, S. C. J., and Phillips, D. (2016) An Overview of Cape Fold Belt Geochronology: Implications for Sediment Provenance and the Timing of Orogenesis. In *Origin and Evolution of the Cape Mountains and Karoo Basin*, 45-55.

Booth, G. D., Niccolucci, M. J., and Schuster, E. G. (1994) *Identifying proxy sets in multiple linear regression: an aid to better coefficient interpretation*. Department of Agriculture, Forest Service, Intermountain Research Station, Ogden, Utah.

Bradshaw, P. L., and Cowling, R. M. (2014) Landscapes, rock types, and climate of the Greater Cape Floristic Region. In *Fynbos: Ecology, Evolution, and Conservation of a Megadiverse Region*. Oxford University Press.

Centre for Geographical Analysis (CGA) (2019) *5 m Stellenbosch University Digital Elevation Model (SUDEM)*.

Chase, B. M., and Thomas, D. S. G. (2007) Multiphase late Quaternary aeolian sediment accumulation in western South Africa: Timing and relationship to palaeoclimatic changes inferred from the marine record. *Quaternary International* 166(1): 29–41.

Chase, B., and Quick, L. (2018) Influence of Agulhas forcing of Holocene climate change in South Africa's southern Cape. *Quaternary Research* 90: 1–7.

Chaulya, S. K., and Prasad, G. M. (2016) Application of Cloud Computing Technology in Mining Industry. In *Sensing and Monitoring Technologies for Mines and Hazardous Areas*. Elsevier, Amsterdam.

Chevalier, M., and Chase, B. M. (2016) Determining the drivers of long-term aridity variability: A southern African case study. *Journal of Quaternary Science* 31(2): 143–151.

Chignell, S. M., Luizza, M. W., Skach, S., Young, N. E., and Evangelista, P. H. (2018) An integrative modeling approach to mapping wetlands and riparian areas in a heterogeneous Rocky Mountain watershed. *Remote Sensing in Ecology and Conservation* 4(2): 150–165.

City of Cape Town (2017) Wetlands of Cape Town - Aquatic Features of the Biodiversity Network. Accessed: 21st July 2020: https://web1.capetown.gov.za/web1/OpenDataPortal/DatasetDetail?DatasetName=Wetlands.

Çoban, H. O., Örücü, Ö. K., and Arslan, E. S. (2020) MaxEnt Modeling for Predicting the Current and Future Potential Geographical Distribution of Quercus libani Olivier. *Sustainability* 12(7): 2671.

Collins, N. B. (2018) *Chapter 5: Modelling of probable wetland extent. South African Inventory of Inland Aquatic Ecosystems (SAIIAE): Technical Report.* FSDESTEA internal report.

Colvin, C., Le Maitre, D. C., Saayman, I. C., Hughes, S., South Africa, Water Research Commission, and CSIR Natural Resources and the Environment (Organization) (2007) *Aquifer dependent ecosystems in key hydrogeological typesettings in South Africa: report to the Water Research Commission*.

Council for Geoscience (CGS) (2019) *Geology shapefile data at a scale of 1:250 000*. Pretoria, South Africa: Council for Geoscience.

Cowardin, L. M., Carter, V., Golet, F. C., and LaRoe, E. T. (1979) *Classification of wetlands and deepwater habitats of the United States*. US Department of the Interior, US Fish and Wildlife Service.

Cracknell, A. P. (2018) The development of remote sensing in the last 40 years. *International Journal of Remote Sensing* 39(23): 8387–8427.

Crawley, M. J. (2012) *The R Book*. Sussex, England: John Wiley & Sons.

Dallas, H. F., and Rivers-Moore, N. (2014) Ecological consequences of global climate change for freshwater ecosystems in South Africa. *South African Journal of Science* 110(5–6): 1–11.

Davidson, N. C., Fluet-Chouinard, E., and Finlayson, C. M. (2018) Global extent and distribution of wetlands: Trends and issues. *Marine and Freshwater Research* 69(4): 620–627.

Davidson, N. C. (2016) Wetland Losses and the Status of Wetland-Dependent Species. In *The Wetland Book: II: Distribution, Description and Conservation*. Dordrecht: Springer Netherlands.

Davis-Reddy, C. L., and Vincent, K. (2017) *Climate Risk and Vulnerability: A Handbook for Southern Africa*. (Second Edition). Pretoria, South Africa: CSIR.

Day, E., Snaddon, K., Ractliffe, S. G., Ollis, D. J., and Murray, I. (2009) *Provision of a Wetland GIS Cover for the Drakenstein Municipal Area*. Prepared for the Department of Environmental Affairs and Development Planning Provincial Government of the Western Cape, Cape Town.

de Moor, F. C., and Day, J. A. (2013) Aquatic biodiversity in the mediterranean region of South Africa. *Hydrobiologia* 719(1): 237–268.

Department of Environmental Affairs (DEA) (2016) *South Africa's Third National Communication under the United Nations Framework Convention on Climate Change*.

Department of Environmental Affairs (DEA) (2011) *South Africa's Second National Communication under the United Nations Framework Convention on Climate Change*. Republic of South Africa, Pretoria: Department of Environmental Affairs.

Department of Water and Sanitation (DWS) (2015) *Strategic overview of the water services sector in South Africa*. Pretoria.

Dietterich, T., Bishop, C., Heckerman, D., Jordan, M., and Kearns, M. (2010) Introduction to Machine Learning. *Second Edition Adaptive Computation and Machine Learning*.

Dobrowski, S. Z. (2011) A climatic basis for microrefugia: the influence of terrain on climate: A Climatic Basis for Microrefugia. *Global Change Biology* 17(2): 1022–1035.

Driver, A., Sink, K. J., Nel, J. L., Holness, S., Van Niekerk, L., Daniels, F., Jonas, Z., Majiedt, P. A., Harris, L., and Maze, K. (2012) *National Biodiversity Assessment 2011: An assessment of South Africa's biodiversity and ecosystems. Synthesis Report*. Pretoria: South African National Biodiversity Institute and Department of Environmental Affairs.

Du Plessis, J. A., and Schloms, B. (2017) An investigation into the evidence of seasonal rainfall pattern shifts in the Western Cape, South Africa. *Journal of the South African Institution of Civil Engineering* 59(4): 47–55.

Ellery, W., Grenfell, M., Grenfell, S., Kotze, D., McCarthy, T., Tooth, S., Grundling, P., Beckedahl, H., le Maitre, D., and Ramsay, L. (2009) *WET-Origins: Controls on the distribution and dynamics of wetlands in South Africa*. Pretoria: Water Research Commission.

Engelbrecht, C. J., Engelbrecht, F. A., and Dyson, L. L. (2013) High-resolution model-projected changes in mid-tropospheric closed-lows and extreme rainfall events over southern Africa. *International Journal of Climatology* 33(1): 173–187.

Engelbrecht, C. J., and Engelbrecht, F. A. (2016) Shifts in Köppen-Geiger climate zones over southern Africa in relation to key global temperature goals. *Theoretical and Applied Climatology* 123(1–2): 247–261.

Engelbrecht, C. J., Landman, W. A., Engelbrecht, F. A., and Malherbe, J. (2015) A synoptic decomposition of rainfall over the Cape south coast of South Africa. *Climate Dynamics* 44(9–10): 2589–2607.

Engelbrecht, F. A., McGregor, J. L., and Engelbrecht, C. J. (2009) Dynamics of the Conformal-Cubic Atmospheric Model projected climate-change signal over southern Africa. *International Journal of Climatology* 29(7): 1013–1033.

Environmental Systems Research Institute (ESRI) (2017) *ArcMap 10.6 for Desktop (Advanced)*. Distributed by ESRI, Redlands, California.

Erwin, K. L. (2009) Wetlands and global climate change: the role of wetland restoration in a changing world. *Wetlands Ecology and Management* 17(1): 71–84.

Fay, P. A., Guntenspergen, G. R., Olker, J. H., and Johnson, W. C. (2016) Climate change impacts on freshwater wetland hydrology and vegetation cover cycling along a regional aridity gradient. *Ecosphere* 7(10).

Fick, S. E., and Hijmans, R. J. (2017) WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology* 37(12): 4302–4315.

Field, A. (2013) *Discovering Statistics Using IBM SPSS Statistics*. Thousand Oaks, CA, USA: Sage.

Fielding, A. H., and Bell, J. F. (1997) A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation* 24(1): 38–49.

Finlayson, C. M., Davidson, N. C., Spiers, A. G., and Stevenson, N. J. (1999) Global wetland inventory - Current status and future priorities. *Marine and Freshwater Research* 50(8): 717–727.

Finlayson, C. M., and van der Valk, A. G. (1995) Wetland classification and inventory: A summary. *Vegetatio* 118(1–2): 185–192.

Friedman, J. H. (1991) Multivariate adaptive regression splines. *The Annals of Statistics* 19(1): 1–141.

Friedman, N., Geiger, D., Provan, G., Langley, P., and Smyth, P. (1997) Bayesian Network Classifiers. *Machine Learning* 29: 131–163.

Gibert, K., and Sànchez-Marrè, M. (2011) Outcomes from the iEMSs Data Mining in the Environmental Sciences Workshop Series. *Environmental Modelling and Software* 27(6): 983–985.

Google Earth Pro (2021) Google Earth Pro version 7.3.4.8248.

Grant, E. (2005) Correlates of vernal pool occurrence in the Massachusetts, USA landscape. *Wetlands* 25: 480–487.

Grenfell, S., Grenfell, M., Ellery, W., Job, N., and Walters, D. (2019) A Genetic Geomorphic Classification System for Southern African Palustrine Wetlands: Global Implications for the Management of Wetlands in Drylands. *Frontiers in Environmental Science* 7: 174.

Greve, P., Roderick, M. L., Ukkola, A. M., and Wada, Y. (2019) The aridity Index under global warming. *Environmental Research Letters* 14(12): 124006.

Guo, M., Li, J., Sheng, C., Xu, J., and Wu, L. (2017) A Review of Wetland Remote Sensing. *Sensors* 17(777): 1–36.

Gutzwiller, K. J., and Flather, C. H. (2011) Wetland features and landscape context predict the risk of wetland habitat loss. *Ecological Applications* 21(3): 968–982.

Hair, J., Anderson, R., Tathan, R., and Black, W. (2010) *Multivariate Data Analysis*. (Seventh.). New Jersey: Prentice Hall.

Hanley, J. A., and McNeil, B. J. (1982) The meaning and use of the area under a receiver operating characteristic (ROC) curve. *Radiology* 143(1): 29–36.

Hao, T., Elith, J., Lahoz-Monfort, J. J., and Guillera-Arroita, G. (2020) Testing whether ensemble modelling is advantageous for maximising predictive performance of species distribution models. *Ecography* 43(4): 549–558.

Harremoës, P., and Topsøe, F. (2001) Maximum entropy fundamentals. *Entropy* 3(3): 191–226.

Hess, A. S., and Hess, J. R. (2018) Principal component analysis. *Transfusion* 58(7): 1580–1582.

Hiestermann, J. (2014) *Modelling the likelihood of wetland occurrence in KwaZulu-Natal, South Africa: a Bayesian approach*. University of KwaZulu-Natal.

Hiestermann, J. and Rivers-Moore, N. (2015) Predictive modelling of wetland occurrence in KwaZulu-Natal, South Africa. *South African Journal of Science* 111(7–8).

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., and Jarvis, A. (2005) Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* 25(15): 1965–1978.

Hoffman, J. I. E. (2015) Logistic Regression. In *Basic Biostatistics for Medical and Biomedical Practitioners*. Elsevier.

Hosmer, D. W., and Lemeshow, S. (2000) *Applied Logistic Regression*. *Applied Logistic Regression* (Second Edition). Hoboken, New Jersey: John Wiley & Sons.

Huang, C., Peng, Y., Lang, M., Yeo, I. Y., and McCarty, G. (2014) Wetland inundation mapping and change monitoring using Landsat and airborne LiDAR data. *Remote Sensing of Environment* 141: 231–242.

Intergovernmental Panel on Climate Change (IPCC) (2014) *Climate Change 2014: Synthesis Report Contribution of Working Groups I, II and III to the Fifth*

Assessment Report of the Intergovernmental Panel on Climate Change. (Core Writing Team, Pachauri, R. K., and Meyer, L. A., Eds.). Geneva, Switzerland: IPCC.

Ishihama, F., Takeda, T., Oguma, H., and Takenaka, A. (2010) Comparison of effects of spatial autocorrelation on distribution predictions of four rare plant species in the Watarase wetland. *Ecological Research* 25(6): 1057–1069.

Jenness, J. (2006) Topographic Position Index (tpi_jen.avx) extension for ArcView 3.c, v1.2. Jenness Enterprises. Retrieved from http://www.jennessent.com/downloads/TPI_Documentation_online.pdf.

Job, N., Mbona, N., Dayaram, A., and Kotze, D. (2018) *Guidelines for mapping wetlands in South Africa. SANBI Biodiversity Series 28*. Pretoria: South African National Biodiversity Institute.

Jolliffe, I. T. (1972) Discarding Variables in a Principal Component Analysis. I: Artificial Data. *Applied Statistics* 21(2): 160.

Jolliffe, I. T., and Cadima, J. (2016) Principal component analysis: a review and recent developments. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 374(2065): 20150202.

Junk, W. J., An, S., Finlayson, C. M., Gopal, B., Květ, J., Mitchell, S. A., Mitsch, W. J., and Robarts, R. D. (2013) Current state of knowledge regarding the world's wetlands and their future under global climate change: A synthesis. *Aquatic Sciences* 75(1): 151–167.

Kaiser, H. F. (1960) The Application of Electronic Computers to Factor Analysis. *Educational and Psychological Measurement* 20(1): 141–151.

Kelvin, J., Acreman, M. C., Harding, R. J., and Hess, T. M. (2017) Micro-climate influence on reference evapotranspiration estimates in wetlands. *Hydrological Sciences Journal* 62(3): 378–388.

Klemas, V. (2013) Using Remote Sensing to Select and Monitor Wetland Restoration Sites: An Overview. *Journal of Coastal Research* 29(4): 958–970.

Kohler, M. (2016) Confronting South Africa's water challenge: A decomposition analysis of water intensity. *South African Journal of Economic and Management Sciences* 19(5): 831–847.

Kolka, R. K., and Thompson, J. A. (2007) Wetland geomorphology, soils, and formative processes. In Batzer, D. and Sharitz, R. (Eds.), *Ecology of Freshwater and Estuarine Wetlands*. University of California Press.

Kotze, D., Marneweck, G., Batchelor, A., Lindley, D., Breen, C., Dini, J., Ellery, W., Mitchell, S., and Uys, M. (2009) *A technique for rapidly assessing ecosystem services supplied by wetlands Wetland Management Series WET-EcoServices WET-EcoServices*. Pretoria: Water Research Commission.

Kuşçu Şimşek, Ç., and Ödül, H. (2018) Investigation of the effects of wetlands on micro-climate. *Applied Geography* 97: 48–60.

Lakhraj-Govender, R., and Grab, S. W. (2019) Rainfall and river flow trends for the Western Cape Province, South Africa. *South African Journal of Science* 115(9–10).

Lambrechts, J. J. N., and MacVicar, C. N. (2004) Soil genesis and classification and soil resources databases. *South African Journal of Plant and Soil* 21(5): 288–300.

Land Type Survey Staff (2006) *Land types of South Africa: digital map (1:250 000 scale) and soil inventory databases*, PhD Thesis. ARC-Institute for Soil, Climate and Water, Pretoria.

Lee, T.S., Chiu, C.C., Chou, Y.C., and Lu, C.J. (2006) Mining the customer credit using classification and regression tree and multivariate adaptive regression splines. *Computational Statistics & Data Analysis* 50: 1113–1130.

Leedy, P. D., and Ormrod, J. E. (2015) *Practical Research: Planning and Design*. Pearson.

Ling, C. X., Huang, J., and Zhang, H. (2003) AUC: A Better Measure than Accuracy in Comparing Learning Algorithms. In Conference of the Canadian society for computational studies of intelligence. Springer, Berlin, Heidelberg.

Longley, P. A., Goodchild, M. F., Maguire, D. J., and Rhind, D. W. (2015) *Geographic Information Science and Systems*. (Fourth Edition). Wiley.

Mabaya, E., Tihanyi, K., Karaan, M., and van Rooyen, J. (2011) *Case Studies of Emerging Farmers and Agribusinesses in South Africa*. *Case Studies of Emerging Farmers and Agribusinesses in South Africa*. Stellenbosch: Sun Press.

MacKellar, N., New, M., and Jack, C. (2014) Observed and modelled trends in rainfall and temperature for South Africa: 1960-2010. *South African Journal of Science* 110(7–8): 1–13.

Mahdianpari, M., Granger, J. E., Mohammadi-Manesh, F., Salehi, B., Brisco, B., Homayouni, S., Gill, E., Huberty, B., and Lang, M. (2020) Meta-analysis of wetland classification using remote sensing: A systematic review of a 40-year trend in North America. *Remote Sensing* 12(11).

Maltby, E., and Acreman, M. C. (2011) Ecosystem services of wetlands: pathfinder for a new paradigm. *Hydrological Sciences Journal* 56(8): 1341–1359.

Matthews, T., Measey, G. J., and Roberts, D. L. (2016) Implications of summer breeding frogs from Langebaanweg, South Africa: Regional climate evolution at 5.1 mya. *South African Journal of Science* 112(9–10): 5.

McCullagh, P., and Nelder, J. A. (1989) *Generalized Linear Models*. *Applied Statistics* (Second Edition). Florida, USA: CRC Press.

Meadows, M. E. (2003) Soil erosion in the Swartland, Western Cape Province, South Africa: implications of past and present policy and practice. *Environmental Science & Policy* 6(1): 17–28.

Melly, B. L., Schael, D. M., Rivers-Moore, N., and Gama, P. T. (2017) Mapping ephemeral wetlands: manual digitisation and logistic regression modelling in Nelson Mandela Bay Municipality, South Africa. *Wetlands Ecology and Management* 25(3): 313–330.

Metz, J., and Tielbörger, K. (2015) Spatial and temporal aridity gradients provide poor proxies for plant–plant interactions under climate change: a large-scale experiment. *Functional Ecology* 30(1): 20–29.

Meyer, M. C., and Laud, P. W. (2002) Predictive Variable Selection in Generalized Linear Models. *Source: Journal of the American Statistical Association* 97(459): 859–871.

Middleton, B. J., and Bailey, A. K. (2011) *Water Resources of South Africa, 2005 Study (WR2005)*. WRC Report No. TT 513/11. Water Research Commission, Pretoria, South Africa.

Midgley, G. F., Chapman, R. A., Hewitson, B., Johnston, P., de Wit, M., Ziervogel, G., Mukheibir, P., van Niekerk, L., Tadross, M., van Wilgen, B. W., Kgope, B., Morant, P. D., Theron, A., Scholes, R. J., and Forsyth, G. G. (2005) *A Status Quo, Vulnerability and Adaptation Assessment of the Physical and Socio-economic Effects of Climate Change in the Western Cape. Report to the Western Cape Government, Cape Town, South Africa*. University of Cape Town.

Millennium Ecosystem Assessment (MEA) (2005) *Ecosystem and human well-being: Wetlands and water synthesis*. Washington, D.C.: World Resource Institute.

Mitsch, W., and Gosselink, J. G. (2000) *Wetlands*. (Third Edition). New York: John Wiley & Sons.

Mitsch, W. J. (2005) Applying science to conservation and restoration of the world's wetlands. *Water Science and Technology* 51(8): 13–26.

Mitsch, W. and Hernandez, M. E. (2013) Landscape and climate change threats to wetlands of North and Central America. *Aquatic Sciences* 75.

Mitsch, W. J., Bernal, B., and Hernandez, M. E. (2015) Ecosystem services of wetlands. *International Journal of Biodiversity Science, Ecosystem Services & Management* 11(1): 1–4.

Mitsch, W.J., and Gosselink, J. G. (2007) *Wetlands*. (Fourth Edition). Hoboken, New Jersey: Wiley.

Mucina, L. and Rutherford, M. C. (2006) *The vegetation of South Africa, Lesotho and Swaziland.* (Mucina, Lasislav and Rutherford, M. C., Eds.) *Strelitzia 19*. Pretoria: South African National Biodiversity Institute.

Murphy, P. N. C., Ogilvie, J., Connor, K., and Arp, P. A. (2007) Mapping wetlands: A comparison of two different approaches for New Brunswick, Canada. *Wetlands* 27(4): 846–854.

Murray, R. (2005) *GRA2: Depth to groundwater (mbgl)*. Department of Water and Sanitation.

Nair, H. C., Joseph, A., and Gopinathan, V. P. (2018) GIS Based landform classification using digital elevation model: a case study from two river basins of Southern Western Ghats, Kerala, India. *Modeling Earth Systems and Environment* 4(4): 1355–1363.

National Research Council (1995) *Wetlands: Characteristics and Boundaries*. Washington, D.C.: National Academies Press.

National Water Act (NWA) 36 of 1998: 18.

Nelder, J. A., and Wedderburn, R. W. M. (1972) Generalized Linear Models. *Journal of the Royal Statistical Society. Series A (General)* 135(3): 370–384.

Neuhaus, J., and McCulloch, C. (2011) Generalized linear models. *Wiley Interdisciplinary Reviews: Computational Statistics* 3(5): 407–413.

Nhamo, L., Magidi, J., and Dickens, C. (2017) Determining wetland spatial extent and seasonal variations of the inundated area using multispectral remote sensing. *Water SA* 43(4): 543–552.

Nicholson, S. (2000) The nature of rainfall variability over Africa on time scales of decades to millenia. *Global and Planetary Change* 26(1–3): 137–158.

Nyandwi, E., Veldkamp, T., and Amer, S. (2016) Regional climate sensitivity of wetland environments in Rwanda: the need for a location-specific approach. *Regional Environmental Change* 16(6): 1635–1647.

O'Donnell, M. S., and Ignizio, D. A. (2012) Bioclimatic Predictors for Supporting Ecological Applications in the Conterminous United States. *U.S Geological Survey Data Series 691* : 10.

Ollis, D., Snaddon, K., Job, N., Mbona, N., Day, J., Ewart-Smith, J., Grobler, R., Kotze, D., and Macfarlane, D. (2013) *Classification System for Wetlands and* *other Aquatic Ecosystems in South Africa. User Manual: Inland Systems. SANBI Biodiversity Series 22*. Pretoria: South African National Biodiversity Institute.

Orimoloye, I. R., Kalumba, A. M., Mazinyo, S. P., and Nel, W. (2020) Geospatial analysis of wetland dynamics: Wetland depletion and biodiversity conservation of Isimangaliso Wetland, South Africa. *Journal of King Saud University - Science* 32(1): 90–96.

Otieno, F. A. O., and Ochieng, G. M. M. (2004) Water management tools as a means of averting a possible water scarcity in South Africa by the year 2025. *Water SA* 30(5): 668–672.

Ourbak, T., and Tubiana, L. (2017) Changing the game: the Paris Agreement and the role of scientific communities. *Climate Policy* 17(7): 819–824.

Pakoksung, K., and Takagi, M. (2016) Digital elevation models on accuracy validation and bias correction in vertical. *Modeling Earth Systems and Environment* 2(1): 1–13.

Pal, S., and Talukdar, S. (2018) Application of frequency ratio and logistic regression models for assessing physical wetland vulnerability in Punarbhaba river basin of Indo-Bangladesh. *Human and Ecological Risk Assessment* 24(5): 1291–1311.

Park, E., Chang, H., and Nam, H. S. (2018) A Bayesian Network Model for Predicting Post-stroke Outcomes With Available Risk Factors. *Frontiers in Neurology* 9: 699.

Partridge, T. C., Dollar, E. S. J., Dollar, L. H., and Moolman, J. (2010) The geomorphic provinces of South Africa, Lesotho and Swaziland: A physiographic subdivision for earth and environmental scientists. *Transactions of the Royal Society of South Africa* 65(1): 1–47.

Pasquini, L., Cowling, R. M., and Ziervogel, G. (2013) Facing the heat: Barriers to mainstreaming climate change adaptation in local government in the Western Cape Province, South Africa. *Habitat International* 40: 225–232.

Paterson, G., Turner, D., Wiese, L., van Zijl, G., Clarke, C., and van Tol, J. (2015) Spatial soil information in South Africa: Situational analysis, limitations and challenges. *South African Journal of Science* 111(5/6): 1–7.

Pearson, R. G., and Dawson, T. P. (2003) Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful? *Global Ecology and Biogeography* 12(5): 361–371.

Phillips, S. J., Anderson, R. P., and Schapire, R. E. (2006) Maximum entropy modeling of species geographic distributions. *Ecological Modelling* 190: 231–259.

Quinn, G. P., and Keough, M. J. (2002) *Experimental Design and Data Analysis for Biologists*. Cambridge: Cambridge University Press.

R Core Team (2020) *R: A language and environment for statistical computing.* Vienna, Austria: R Foundation for Statistical Computing.

Ramsar Convention on Wetlands (2018) *Scaling up wetland conservation, wise use and restoration to achieve the Sustainable Development Goals*.

Rawlings, J. O., Pantula, S. G., and Dickey, D. A. (1998) *Applied Regression Analysis: A Research Tool*. *Applied Regression Analysis* (Second Edition). New York: Springer.

Rebelo, A. G., Boucher, C., Helme, N., Mucina, L., and Rutherford, M. C. (2006) Fynbos Biome. In Mucina, L. and Rutherford, M. C. (Eds.), *The Vegetation of South Africa, Lesotho and Swaziland. Strelitzia 19.* South African National Biodiversity Institute.

Rebelo, A. J., Scheunders, P., Elser, K. J., and Meire, P. (2017) Detecting, mapping and classifying wetland fragments at a landscape scale. *Remote Sensing Applications: Society and Environment* 8: 212–223.

Rebelo, L. M., Finlayson, C. M., and Nagabhatla, N. (2009) Remote sensing and GIS for wetland inventory, mapping and change analysis. *Journal of Environmental Management* 90: 2144–2153.

Rivers-Moore, N. A., Kotze, D. C., Job, N., and Mohanlal, S. (2020) Prediction of Wetland Hydrogeomorphic Type Using Morphometrics and Landscape Characteristics. *Frontiers in Environmental Science* 8: 58.

Sandi, S. G., Rodriguez, J. F., Saintilan, N., Wen, L., Kuczera, G., Riccardi, G., and Saco, P. M. (2020) Resilience to drought of dryland wetlands threatened by climate change. *Scientific Reports* 10(1): 13232.

Scarpace, F. L., Quirk, B. K., Kiefer, R. W., and Wynn, S. L. (1981) Wetland mapping from digitized aerial photography. *Photogrammetric Engineering and Remote Sensing* 47(6): 829–838.

Scholz, M. (2016) Classification of Sustainable Flood Retention Basins. In *Wetlands for Water Pollution Control*. Elsevier.

Schulze, R. E. (1997) *South African Atlas of Agrohydrology & Climatology*, No. 3. (Vol. 1). Pretoria: Water Resource Commission Report No TT82/96, Water Research Commission.

Schuwirth, N., Borgwardt, F., Domisch, S., Friedrichs, M., Kattwinkel, M., Kneis, D., Kuemmerlen, M., Langhans, S. D., Martínez-López, J., and Vermeiren, P. (2019) How to make ecological models useful for environmental management. *Ecological Modelling* 411: 108784.

Schuyt, K. D. (2005) Economic consequences of wetland degradation for local populations in Africa. *Ecological Economics* 53(2): 177–190.

Sinchembe, M., and Ellery, W. N. (2010) Human impacts on hydrological health and the provision of ecosystem services: a case study of the eMthonjeni–Fairview Spring Wetland, Grahamstown, South Africa. African Journal of Aquatic Science. *African Journal of Aquatic Science* 35(3).

Song, N., and Zhang, J. (2018) Modelling the abundance of an endangered medicinal species, Phellodendron amurense: Generalised linear model vs. generalised additive model. *Botanica Serbica* 42(2): 199–208.

South African Committee for Stratigraphy (SACS) (1980) *Stratigraphy of South Africa. Part I*. Pretoria: Lithostratigraphy of the Republic of South Africa.

Tagil, S., and Jenness, J. (2008) GIS-based automated landform classification and topographic, landcover and geologic attributes of landforms around the Yazoren Polje, Turkey. *Journal of Applied Sciences* 8(6): 910–921.

Tallis, H., and Polasky, S. (2009) Mapping and Valuing Ecosystem Services as an Approach for Conservation and Natural-Resource Management. *The Year in Ecology and Conservation Biology* 1162: 265–283.

Tooth, S. (2013) Dryland Fluvial Environments: Assessing Distinctiveness and Diversity from a Global Perspective. In, *Treatise on Geomorphology*: 612-644.

Tooth, S., Brandt, D., Hancox, P. J., and McCarthy, T. S. (2004) Geological controls on alluvial river behaviour: a comparative study of three rivers on the South African Highveld. *Journal of African Earth Sciences* 38(1): 79–97.

Tooth, S. (2018) The geomorphology of wetlands in drylands: Resilience, nonresilience, or …? *Geomorphology* 305: 33–48.

Tooth, S., Ellery, F., Grenfell, M., Thomas, A., Kotze, D., and Ralph, T. (2015) 10 Reasons Why the Geomorphology of Wetlands is Important. *Wetlands in Drylands Research Network* (August 2015): 1–18.

Tooth, S. and McCarthy, T. S. (2007) Wetlands in drylands: geomorphological and sedimentological characteristics, with emphasis on examples from southern Africa. *Progress in Physical Geography: Earth and Environment* 31(1): 3–41.

Trabucco, A., and Zomer, R. J. (2019) Global aridity index and potential evapotranspiration (ET0) climate database v2. figshare. Fileset. doi:https://doi.org/10.6084/m9.figshare.7504448.v3.

Tsoulos, L., and Skopeliti, A. (2000) Assessment of data acquisition error for linear features. *International Archives of Photogrammetry and Remote Sensing* 33(B4): 1087–1091.

Turner, R. K., van den Bergh, J. C. J. M., Söderqvist, T., Barendregt, A., van der Straaten, J., Maltby, E., and van Ierland, E. C. (2000) Ecological-economic analysis of wetlands: Scientific integration for management and policy. *Ecological Economics* 35(1): 7–23.

Tyson, P. D. (1999) Atmospheric circulation changes and palaeoclimates of southern Africa. *South African Journal of Science* 95: 195–201.

Tyson, P. D., and Preston-White, R. A. (2000) *The weather and climate of southern Africa*. Oxford University Press.

United Nations Environment Programme (UNEP) (1997) *World atlas of desertification*.

United Nations Framework Convention on Climate Change (UNFCCC) (2015) Paris agreement. FCCC/CP/2015/L.9/Rev1.

Valavi, R., Elith, J., Lahoz-Monfort, J., and Guillera-Arroita, G. (2018) blockCV: an R package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models. *Methods in Ecology and Evolution* 10: 1–8.

van Deventer, H., van Niekerk, L., Adams, J., Dinala, M. K., Gangat, R., Lamberth, S. J., Lötter, M., Mbona, N., Mackay, F., Nel, J. L., Ramjukadh, C. L., Skowno, A., and Weerts, S. P. (2020) National wetland map 5: An improved spatial extent and representation of inland aquatic and estuarine ecosystems in South Africa. *Water SA* 46(1): 66–79.

van Niekerk, A., and Joubert, S. J. (2011) Input variable selection for interpolating high-resolution climate surfaces for the western cape. *Water SA* 37(3): 271–280.

Wainwright, J., and Mulligan, M. eds. (2004) *Environmental Modelling Finding Simplicity in Complexity Editors*. Chichester: John Wiley & Sons.

Watanabe, S., Hajima, T., Sudo, K., Nagashima, T., Takemura, T., Okajima, H., Nozawa, T., Kawase, H., Abe, M., Yokohata, T., Ise, T., Sato, H., Kato, E., Takata, K., Emori, S., and Kawamiya, M. (2011) MIROC-ESM 2010: Model description and basic results of CMIP5-20c3m experiments. *Geoscientific Model Development* 4(4): 845–872.

Weiss, A. D. (2001) Topographic position and landforms analysis. Poster Presentation at the ESRI User Conference, San Diego, CA, USA.

Western Cape Provincial Spatial Development Framework (2005) *The Western Cape Province today*. Cape Town: Environmental planning, landscape architecture, urban design.

Xu, E., and Chen, Y. (2019) Modeling Intersecting Processes of Wetland Shrinkage and Urban Expansion by a Time-Varying Methodology. *Sustainability* 11: 4953.

Xue, Z., Zou, Y., Zhang, Z., Lyu, X., Jiang, M., Wu, H., Liu, X., and Tong, S. (2018) Reconstruction and Future Prediction of the Distribution of Wetlands in China. *Earth's Future* 6(11): 1508–1517.

Zhang, K., Yao, L., Meng, J., and Tao, J. (2018) Maxent modeling for predicting the potential geographical distribution of two peony species under climate change. *Science of The Total Environment* 634: 1326–1334.

Zhong, Y., Xue, Z., Jiang, M., Liu, B., and Wang, G. (2021) The application of species distribution modeling in wetland restoration: A case study in the Songnen Plain, Northeast China. *Ecological Indicators* 121: 107137.

Ziervogel, G., New, M., Archer van Garderen, E., Midgley, G., Taylor, A., Hamann, R., Stuart-Hill, S., Myers, J., and Warburton, M. (2014) Climate change impacts and adaptation in South Africa. *Wiley Interdisciplinary Reviews: Climate Change* 5(5): 605–620.