THE IMPACT OF LAND USE AND LAND COVER CHANGES ON WETLAND PRODUCTIVITY AND HYDROLOGICAL SYSTEMS IN THE LIMPOPO TRANSBOUNDARY RIVER BASIN, SOUTH AFRICA

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A thesis submitted to the Department of Earth Sciences, Faculty of Natural Sciences at the University of the Western Cape in fulfilment of the academic requirements for the degree of Doctor of Philosophy in Environmental and Water Science

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ABSTRACT

Wetlands are highly productive systems that act as habitats for a variety of flora and fauna. Despite their ecohydrological significance, wetland ecosystems are under severe threat as a result of environmental changes (e.g. the changing temperature and rainfall), as well as pressure from anthropogenic land use activities (e.g. agriculture, rural-urban development and dam construction). Such changes result in severe disturbances in the hydrology, plant species composition, spatial distribution, productivity and diversity of wetlands, as well as their ability to offer critical ecosystem goods and services. However, wetland degradation varies considerably from place to place, with severe degradation occurring particularly in developing regions, such as sub-Saharan Africa, where Land Use and Land Cover changes impact on wetland ecosystems by affecting the diversity of plant species, productivity, as well as the wetland hydrology. These impacts are further exacerbated by poor management practices, which lead to their under-utilisation and an over-reliance on them for people's livelihoods. Although wetlands threats are well-documented, the focus has only been directed on larger wetland ecosystems, under the Ramsar Convention, rather than on the over-utilised and isolated small wetlands. Currently, the distribution and status of small wetlands remains poorly understood, particularly unprotected wetlands that support human livelihoods. This has been largely due to the lack of accurate spatial resolution and robust techniques, as well as reliable data sources, which are necessary for wetland estimation and continuous monitoring on a small and large scale. The crop of new-generation satellite sensors i.e. Landsat 8 Operational Land Imager (OLI) and Sentinel-2 Multi-Spectral Imager (MSI) data, which have a unique sensor design and improved sensing characteristics, is perceived to provide new prospects for the mapping and monitoring of the extent and condition of wetlands. The accurate monitoring of changes in the spatial extent, hydrological dynamics, vegetation species diversity and productivity patterns of wetland ecosystems provides critical information on the factors that are causing their deterioration. Therefore, this study aimed at assessing the impacts of land use and land cover change on wetland productivity and the hydrological processes, using remotely-sensed dataset. The study was conducted in Maungani wetland located in Limpopo Province of South Africa. To achieve this, historical Landsat data were used to assess the wetland changes over a period of 36 years (1983-2019). During the study period, the Maungani wetland lost 728 400 ha, mainly due to built-up areas and agricultural fields. The changes within the wetland were mapped with a high Overall classification Accuracy (OA), ranging from 77.55% to 92.69%. Furthermore, Sentinel-2 MSI was used to model the diversity and productivity of the wetland vegetation species, by using diversity indices. The findings showed that the diversity and biomass of the wetland vegetation species can be estimated with a high accuracy by using Sentinel-2 MSI data. For instance, the model performances ranged from a r^2 of 0.54 (54.72%) (RMSEP = 0.572 gm^{-2}) to r^2 of 0.84 (84%) (RMSEP = 0.067 gm^{-2}), respectively. Furthermore, the red-edge bands, centered at 750 nm (B5), 740 nm (B6), 783 nm (B7) and 863 nm (B8a), were identified as the most influential variables in estimating wetland vegetation biomass and species diversity. The capabilities of Sentinel-2 MSI and the derived spectral indices were also used to assess the hydrological dynamics of wetlands and the extent of inundation. The results revealed that monthly meteorological data have influenced the status of the water presence and inundation in the Maungani Area. In addition, the vegetation configurations and moisture content demonstrated that the wetland inundation declined during the dry months (May, June and July). The presence of water was also associated with increased rainfall during the wet season. The extent of wetlands declined during the drier period, due to less rainfall (0.20-0.60 mm) and a decreased actual evapotranspiration (9.90 mm-10.43 mm). The findings of this study underscore the relevance of new-generation Sentinel-2 MSI data for estimating and mapping the presence of wetland water, vegetation diversity and biomass, particularly in small wetlands that are non-Ramsar sites. The spatially-explicit and periodic information offered by satellite remote sensing demonstrated a unique opportunity for documenting and understanding the ecohydrological dynamics of small and neglected wetlands. This information is beneficial for the development of tailor-made wetland management strategies and for a possible rehabilitation framework for unprotected wetland ecosystems, which was previously a challenging task, when using broadband multispectral sensors.

Keywords: Anthropogenic activities; change detection; ecohydrological modelling; livelihoods; satellite data; wetland agriculture; wetland status

PREFACE

This research study was conducted in the Department of Earth Sciences (ESD) at the University of the Western Cape, South Africa, from January 2019 to September 2021, under the supervision of Prof. Timothy Dube (Earth Sciences, University of the Western Cape) and Dr. Cletah Shoko (Archaeology and Environmental Studies (AES), University of the Witwatersrand).

I declare that the work presented in this thesis has never been submitted, in any form, to any other institution. This work represents my original work, except where due acknowledgements are made.

Kgabo Humphrey Thamaga
November 2021

We certify that the above statement is correct and, as the candidate's Supervisor, I have approved this thesis for submission.

Shoko

Professor Timothy Dube
Supervisor (UWC)
November 2021

Dr. Cletah Shoko
Co-supervisor (Wits)
November 2021

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DECLARATION 2 – PLAGIARISM

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1. I understand what plagiarism is and I am aware of the University of the Western Cape’s policy in this regard.
2. I declare that this dissertation is my own original work. Where other people’s work has been used (either from a printed source, the Internet or any other source), this has been properly acknowledged and referenced in accordance with departmental requirements.
3. I have not used work previously produced by another student or any other person, to hand in as my own.
4. I have not allowed and will not allow anyone to copy my work with the intention of passing it off as his or her own work.

Signed

Kgabo Humphrey Thamaga
November 2021

DECLARATION 3 – PUBLICATIONS AND MANUSCRIPTS

Published papers and manuscripts form part of this thesis. The contribution (the conceptualisation, experimental work, data analysis and preparation) of the published articles and manuscripts were completed by the author (Kgabo Humphrey Thamaga), under the supervision of Prof. Timothy Dube and Dr. Cletah Shoko. Below is the list of published and manuscript papers:

Publication 1:

Thamaga K.H., Dube, T. & Shoko, C., 2021. Advances in satellite remote sensing of the wetland ecosystems in sub-Saharan Africa. *Geocarto International*, 1-19. https://doi.org/10.1080/10106049.2021.1926552.

Manuscript 1 (under review)

Thamaga, K.H., Dube, T. & Shoko, C., 2021. Evaluating the impacts of land use and land cover change on unprotected wetland ecosystems in the arid tropical areas of South Africa, using the Landsat dataset and Support Vector Machine. *Geocarto International*, TLUS-2021-0103 (Manuscript accepted).

Manuscript 2 (under review)

Thamaga, K.H., Dube, T. & Shoko, C., 2021. Modelling wetland vegetation by using integrated Sentinel-2 MSI and diversity indices in the semi-arid regions located in the Limpopo Transboundary Basin, South Africa. *International Journal of Remote Sensing*, (Manuscript under-review).

Manuscript 3 (under review)

Thamaga, K.H., Dube T. & Shoko C., 2021. An assessment of small wetland eco-hydrological dynamics, using Sentinel-2 MSI derived spectral indices in semi-arid environments of South Africa. *Wetland Ecology and Management*, WETL-D-21-00141 (Manuscript under-review).

DEDICATION

To the late Kwena Frans Thamaga.

Papa, you left us early, before you could witness this journey. Your presence will always and forever be sorely missed.

To my mother, Mosima Glady Thamaga, and my daughter, Rebabaletswe.

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Glory be to God, for His strength, guidance and protection
in the process of completing this PhD thesis

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CHAPTER ONE

GENERAL INTRODUCTION

1.1. Importance of Small Wetland Ecosystems in the African Context

Wetlands are described as areas with low water levels that are often near the ground surface and that are characterised by hydrophytic plants during the growing season (Barducci *et al*., 2009; Liu *et al*., 2020). They exist where the soil is either saturated or inundated with available water for varying durations (seasonal, inter-annual and decal) and frequencies (Reis *et al*., 2017; Chatanga, 2019; Zhang *et al*., 2020). Wetlands experience periodic flood inundation, which exhibits changes in the spatial distribution and temporal duration (Zhao *et al*., 2015). They occur in different landscapes across the globe and occupy approximately 9.2 million km^2, with 1.3 million km^2 being found in Africa (Melendez-Pastor *et al*., 2010; Rebelo *et al*., 2010; Kabiri *et al*., 2020). Only 146 wetlands in Africa have been recognised by the Ramsar Convention as having international importance (Gardner *et al*. 2018; Xu *et al*. 2019); however, unprotected (small) wetlands that support neighbouring and predominantly rural communities are continuously being ignored. Small wetlands are productive ecosystems that serve the impoverished communities in developing regions, especially in sub-Saharan Africa (Rebelo *et al*., 2010; Marambanyika *et al*., 2017). Because of their ecological complexity, wetlands contribute in a diverse way (socially, economically, aesthetically and ecologically) to the livelihoods of millions of people by providing several benefits (grazing, irrigation, agricultural practices and a water supply) (Rabelo *et al*., 2010). Small wetlands support the livelihoods of many more rural and poor households than the large wetlands under the Ramsar Convention.

Despite their vast expanse and benefits for sustaining human well-being, many wetlands remain threatened by anthropogenic activities and environmental change. Anthropogenic land use activities complicate the functionality of ecosystems and reduce the spatial extent of the existing small wetlands. Anthropogenic land use change, such as rural-urban expansion and rapid population growth, put more pressure on these systems, which results in their deterioration, in terms of their spatial extent (Brody, 2013). Farmers in developing regions depend extensively on unprotected wetlands for subsistence agricultural purposes which, in turn, have a cumulative impact on the catchment hydrology. Verhoeven and Setter (2010) demonstrated that farmers degrade wetland ecosystems by converting large portions of wetland into agricultural fields, due to their fertile and rich soil, the extent of inundation, as well as their water availability. The over-extraction of water for irrigation purposes drains the spatial extent of wetlands and hampers the hydrological regime, which results in a shift of dominant vegetation, by reducing the species frequency, their richness and evenness, as well as the loss of sensitive species (Elton *et al*., 2011). In addition, the changing climatic conditions, such as the rising temperatures, changes in the rainfall patterns and evaporation, further influence the disruption of the wetland processes (a reduced inundation area and a loss of water through evapotranspiration). The rate of wetland degradation is further exacerbated by the lack of conservation skills and a lack of knowledge by wetlands users, on a local scale. However, where information is available, it is often geared towards the relatively large wetlands and there is less focus on understanding the value of smaller wetlands, probably because they are considered to be insignificant. A lack of up-to-date and reliable spatial information on wetland loss, degradation and fragmentation threatens the biodiversity and functioning of the ecosystem, which further complicates the management of wetland ecosystems. Therefore, the detection, mapping and monitoring of small wetlands provides the required baseline information for ecological restoration and conservation efforts.

Traditionally, wetland management efforts rely on non-periodic surveys that are costly and laborious, and consequently, their application lacks spatial representation; it therefore becomes challenging for continuous monitoring, particularly in relatively small areas. To alleviate these limitations, remotely-sensed data have since emerged as the most suitable primary data source for mapping and monitoring wetlands conditions at varying spatial scales. By using remotely-sensed data, the LULC changes and their associated impacts on small wetland ecosystems can be traced and quantified. Given the scarcity of ground data or the lack of data access, due to institutional restrictions, remotely-sensed data therefore provide unique opportunities for wetland monitoring, particularly in data-scarce environments.

1.2. The Remote Sensing of Small Wetland Ecosystems

Remote sensing has been a valuable tool for evaluating land use and land cover (LULC) change since the 1960's (Taramelli *et al*., 2010; Tiner, 2015). Several satellite sensors, with varying spatial and temporal resolutions, have been widely used for the modeling and monitoring of LULC changes (Wang *et al*., 2012; Sun *et al*., 2014; Watson *et al*., 2014), wetland areas (Dronova *et al*., 2015; Mizuochi *et al*., 2017; Dzurume *et al*., 2021), invasive aquatic plant species (Thamaga and Dube, 2019), hydrological dynamics (Hiyama *et al*., 2017; Xie *et al*., 2015; Mondal and Pal, 2018), vegetation abundance and productivity (Lumbierres *et al*., 2017), as well as the carbon cycle and climate warming in wetland environments (Raymond *et al*., 2013; Kreplin *et al*., 2021). Other studies have reviewed remote sensing applications on wetland ecosystems and addressed issues of wetland degradation, classification, change detection, as well as vegetation abundance and productivity (Gxokwe *et al*., 2020; Thamaga *et al*., 2021). The use of remotely-sensed data and modelling techniques is critical for assessing the effects of LULC transformation on freshwater resources in data-scarce watersheds. Long-term hydrological monitoring is essential for evaluating the human and environmental impacts and wetland health, which are critical for their management and restoration. The spatial extent and temporal value of wetlands need to be understood well, since they determine their usage and contribute to human livelihood profiles and conservation. This knowledge is critical in decision-making and can reduce the unsustainable use of wetland ecosystems (Turpie, 2010). Although studies have shown the capabilities of remote sensing in the monitoring and mapping of wetlands, the focus has been directed mostly on larger wetlands that have been designated by the Ramsar Convention, while neglecting the small wetland ecosystems, despite them playing a critical role in developing regions. Using newly-developed satellite sensors, such as Landsat and Sentinel data, for the monitoring and assessment of small wetland ecosystems provides new opportunities for understanding their ecohydrological dynamics. Several studies have demonstrated the strength of newly-launched satellite images in the characterisation, mapping and monitoring of various species (Dube and Mutanga, 2015a; Thamaga and Dube, 2019). For example, Thamaga *et al*. (2019) observed the capabilities of Sentinel-2 MSI data in mapping and monitoring seasonal aquatic invasive alien plant species, with a high classification accuracy. Due to improvements in the new satellite sensors, they are perceived to provide avenues for the monitoring and mapping of small wetland ecosystems (ecosystem change, vegetation diversity and productivity, hydrological dynamics), which was previously difficult to accomplish with broadband satellite sensors.

1.3. Aims and Objectives

The main aim of this study is to assess and monitor the impacts of Land Use and Land Cover (LULC) change on the productivity and hydrological condition of wetlands, using remote sensing and geospatial analytics.

The objectives of this study are as follows:

(i) to provide an overview of remote sensing application in wetland ecosystems and to assess the impacts of LULC change on wetlands;

(ii) to evaluate the state of the environment of small wetland ecosystems and to estimate the remaining percentage of wetlands in the Limpopo Transboundary River Basin;

(iii) to quantify the species diversity in wetlands in the Limpopo Transboundary River Basin as a proxy of the wetland conditions, using a remotely-sensed dataset; and

(iv) to monitor the impacts of LULC on the wetland hydrological dynamics of the Limpopo Transboundary River Basin.

1.4. Structure of the Research

This thesis consists of seven chapters. Apart from the first chapter, which focuses on the general introduction, and the last chapter, which contains a synthesis of the research work, this thesis consists of four stand-alone papers (Chapter 2, 3, 4 and 5). The review paper (Chapter 2) published, two (Chapter 3 and 4) manuscript are accepted and one manuscript under review in different journals and they answer each objective in this study. Therefore, each paper is comprised of an individual Introduction, Materials and Methods, Results and Discussion section. The published chapters have their own style, according to the publishing journal. Although attempts were made to conform to a general style in the thesis, there may be some overlapping and repetition in some of the sections.

Chapter One: This chapter provides a general overview of the research background and it outlines the objectives and structure of the thesis.

Chapter Two: Information on the state-of-the-art methods in optical imagery for the successful detection of surface water are combined and presented in this chapter.

Chapter Three: This chapter evaluates the capability of Landsat datasets in detecting and mapping the state of the Maungani wetland ecosystem. The information of the wetlands has changed over time (1983-2019) and was extracted by using Landsat datasets and the Support Vector Machine (SVM).

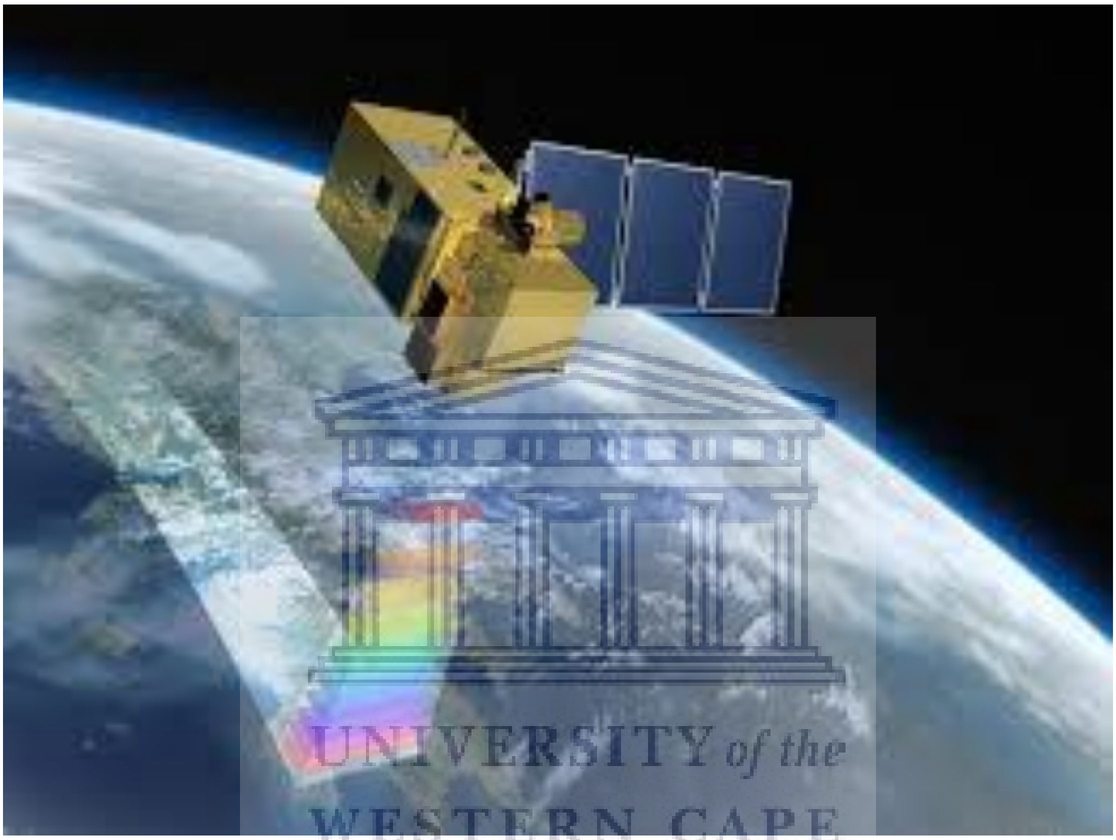
Chapter Four: Integrated Sentinel-2 MSI datasets and species diversity indices i.e. Margalef, Pielou, Shannon-Wiener and Simpson, are used to model the wetland vegetation species diversity and productivity in this chapter.

Chapter Five: This chapter assessed the wetland ecohydrological dynamics using monthly (July 2020-June 2021) Sentinel-2 MSI datasets and spectral indices i.e. the Normalised Differences Moisture Index (NDMI), the Normalised Difference Phenology Index (NDPI) and the Modified Normalised Difference Water Index (MNDWI). Climate data i.e. rainfall, temperature and evapotranspiration were used to assess the extent of water coverage and inundation.

Chapter Six: This chapter synthesises and consolidates the findings, the discussions and the overall conclusions of the four preceding chapters. Based on the limitations pointed out in the study, this chapter also makes recommendations (perspectives) for future research. Lastly, the Reference List is provided to acknowledge the work of other authors that was used in this thesis.

CHAPTER TWO

ADVANCES IN SATELLITE REMOTE SENSING OF THE WETLAND ECOSYSTEMS IN SUB-SAHARAN AFRICA



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Abstract

Wetlands are highly-productive systems that act as habitats for a variety of fauna and flora. Despite their ecohydrological significance, wetland ecosystems are under severe threat from the global environmental changes, as well as from the pressure of anthropogenic activities. Such changes result in severe disturbances in the composition of plant species, their spatial distribution, productivity and diversity, as well as their ability to offer critical ecosystem goods and services. However, wetland degradation varies considerably from place to place, with severe degradation occurring in developing regions, especially in sub-Saharan Africa. This is due to poor management practices, which lead to their under-utilization and the over-reliance on them for livelihoods. The lack of monitoring and assessment in this region has therefore led to the lack of a consolidated and detailed understanding of the rate of wetland loss. For example, the lack of up-to-date and reliable spatially-explicit information further complicates the management of wetland ecosystems in semi-arid tropical environments. To monitor, understand and document the wetland degradation rate, it remains imperative that remote sensing is used for the accurate estimation and precise mapping of present and historical information. Similarly, there is a need to develop robust methodologies to precisely assess and monitor wetland degradation, the ecohydrological processes and the condition of wetlands over space and time. This work, therefore, provides a comprehensive overview of the remote sensing applications that are used for the monitoring and mapping of wetland ecosystems. It also highlights the strengths and challenges associated with the use of satellite data for the purpose of wetland monitoring. The spatially-explicit and periodic information offered by satellite remote sensing provides a unique opportunity for documenting and understanding wetlands, the ecohydrological processes and the environmental conditions.

Keywords: Human influence; remote sensing; satellite data; spatial resolution; species diversity; wetland degradation; wetland productivity

2.1 Introduction

Wetlands are distinctive, complex ecohydrological systems that occur within a wide range of climatic and topographical environments. They constitute one of the world's most productive and important natural resources. Wetlands fall under central public management and they are recognized as an integral part of a productive ecosystem that is capable of supporting the 2030 UN Agenda on Sustainable Development Goals (SDGs) (Kakuba and Kanyamurwa, 2021). The wetland hydrophytic vegetation species, hydromorphic soil and hydrology are a critical part of wetland ecosystems, and they contribute towards the provision of fundamental goods and services. For instance, wetlands offer food and a habitat for species, they maintain the water quality, they recharge the aquifers and control soil erosion, climate regulation and carbon storage (McCartney *et al.*, 2010; Adam *et al.*, 2012; Wood *et al.*, 2013; Meli *et al.*, 2014; Scott *et al.*, 2014; Sieben *et al.*, 2016). They also provide a wide variety of goods for local communities, including reeds for weaving, grazing for domestic stock and services to downstream consumer facilities, such as flood attenuation and nutrient retention (Mutanga *et al.*, 2012; Dadson *et al.*, 2017; Mahdavi *et al.*, 2017). In sub-Saharan Africa, wetlands are predominantly significant sources of forage for livestock, which support the livelihoods for most rural communities, as well as for the vast wildlife populations (Marambanyika and Beckedahl, 2016). Despite covering 6% of the earth's surface, wetlands offer about 40% of the regulatory services (Marambanyika and Beckedahl, 2016; Reis *et al.*, 2017). However, not all wetland ecosystems provide regulatory services; their unique wetland services depend on the type of wetland and their location and positioning within a catchment (Hu *et al.*, 2017; Slagter *et al.*, 2020). Due to their response to climate variability, precipitation, evapotranspiration and anthropogenic activities, the surface water level and groundwater recharge in wetland ecosystems vary seasonally.

Despite their associated ecohydrological benefits, the quantity and quality of wetlands are vulnerable to changes, as a result of the intensified anthropogenic and natural global changes (Sieben *et al.*, 2016; Sutton *et al.*, 2016; Xie *et al.*, 2017; Bhaga *et al.*, 2020; Novoa *et al.*, 2020). The ongoing transformation and alterations in the landscape, due to global warming, urban development and agricultural expansion, significantly affect their ecological attributes. For example, the Ngiri-Tumba-Maindombe in the western Congo Basin, in the Democratic Republic of the Congo, is apparently under threat due to pressure from the rapid population growth and illegal activities that have led to the over-exploitation of wetland resources (Xu *et al.*, 2019). On the other hand, land use and land cover changes alter the hydrological processes, thus influencing the flow regime, aquifer recharge and water storage within the catchment (de Medeiros *et al.,* 2019). The remaining portions of the wetland are exposed to a wide range of stress-inducing changes i.e. infrastructure development, hydrological changes, excess nutrient inputs and invasive species (Oliver-Cabrera and Wdowinski, 2016; Hu *et al.,* 2017). These cause a dramatic reduction and deterioration of the natural landscape, which, in turn, complicate the functionality of wetlands and have significant repercussions that are amplified in their ecological, socioeconomic and cultural benefits (Hu *et al.,* 2017). Therefore, in order to safeguard their ecohydrological systems, it is critical to understand the threats to wetland ecosystems, their characteristics, their species diversity (richness and evenness), as well as their productivity, soil and hydrology.

There is a growing interest in developing new operational frameworks, as well as spatially-explicit and sound tools, to assess the wetland health conditions. Having accurate information, by monitoring the wetland status, is therefore the first step in determining the ecological integrity of a wetland. Dennison *et al.* (1993) highlighted that wetland vegetation remains an exceptional indicator for the first signs of any biophysical or chemical degradation in a wetland environment. However, the characterization of the spatial patterns and the extent of wetlands is often challenging, due to their heterogeneous nature (Szantoi *et al.,* 2013). Previous studies used traditional methodologies, based on ground-based measurements, to assess and monitor wetland ecosystems, for example, the wetland hydrology, the soil, the species richness and evenness, the species composition and the aboveground biomass (Luo *et al.,* 2017). These measurements were recognized as the most direct and accurate method of assessing and monitoring wetland ecosystems and their diversity. Although the traditional approaches provide the most accurate results, these methods are generally not effective, due to their limited spatial representation. Similarly, the inherent distribution and composition of heterogeneous species (Szantoi *et al.,* 2013) are very difficult to capture. In addition, these techniques are time-consuming, labour-intensive and costly, besides being difficult to carry out effectively to assess the spatial extent of wetlands, especially across large areas over time (Psomas *et al.,* 2011; Adam *et al.,* 2012; Han *et al.,* 2015; Orimoloye *et al.,* 2018). Therefore, the derived wetland information lacks the required spatial and temporal representation, and hence there is a limited understanding of the dynamics of soil, water and wetland vegetation within these ecosystems. It is important to track wetland ecosystems on a spatial and periodic basis, as this offers comprehensive information that can lead to the sustainable conservation of ecosystem services.

The availability of automated, reliable and near-real-time remotely-sensed data has emerged as the most critical data source for gathering spatially-explicit information on the condition, distribution and spatial configuration of wetland ecosystems, both on a local and a global scale. The spatial distribution of wetlands varies at different times and can be analysed with the aid of multi-spectral and hyperspectral remote sensing satellite images, such as Landsat, MODIS, SPOT and RapidEye. Some of these images have high spectral and spatial characteristics, which enable the enhanced monitoring and mapping of wetland ecosystem characteristics. When compared to conventional labour-intensive field investigations, remote sensing information not only saves time, but it also enhances the prospect of characterizing wetland species through spectral and texture analytics (Vasconcelos *et al.,* 2002; Kokaly *et al.,* 2003; Roberts *et al.,* 2003). Recent advances in remote sensing data have shown their high potential for examining land use and land cover changes that threaten the functioning and services provided by wetland ecosystems (Pettorelli *et al.*, 2017). In addition, advances in sensor technology have contributed to the acquisition of freely-available satellite imagery, such as the Sentinel dataset. For example, Sentinel-2 MSI is characterized by a finer spatial resolution (10 m) and a higher spectral resolution (13 spectral bands including red edge strategic bands), which are essential for the extraction of wetland ecosystem characteristics, with varying geographical coverage (285 km) for the evaluation of wetland dynamics (Truus, 2011; Adelabu *et al.*, 2014; Orimoloye *et al.*, 2018). Remote sensing technology allows for repetitive image acquisitions over the same area that are required for the detection of temporal changes and patterns in wetland ecosystems. For instance, Sentinel-2 offers remotely-sensed data at a high revisit frequency of between five and nineteen days.

In the light of the advantages associated with the use of remotely-sensed data, researchers in sub-Saharan Africa have used both passive optical sensors and active sensors to map and delineate the spatial distribution of wetlands, in order to understand their status under the changing environmental and anthropogenic pressures. Knowing the past and current distribution of small wetlands in sub-Saharan Africa could help to understand their development, or the trends and improvements, as well as their contribution to ecosystem goods and services. In addition, it is critical for obtaining the status of degradation, vegetation cover, species diversity, water level, erosivity, and the rate of sedimentation, in order to ensure informed decision-making for proper wetland protection and restoration programs (Davidson *et al.,* 2018; Gxokwe *et al.,* 2020). However, major attempts are now being made to integrate geospatial data products (i.e. water, soil moisture and vegetation) into various land surface models to enhance the monitoring and evaluation of wetland ecosystems.

This work provides a comprehensive overview of remote sensing applications for the monitoring and mapping of wetland ecosystems (wetland vegetation, species diversity, productivity, hydrology, soil), and it highlights the strengths and challenges associated with the use of satellite data. To meet the above-mentioned aim, related literature information was acquired from wetland, ecology, water and remote sensing journals. Numerous keywords and expressions are used, including the following: ‘wetland’, ‘water-level monitoring’, ‘wetland hydrological processes’, ‘wetland-catchment linkage’, ‘hydrological modelling’, ‘hydrophytic vegetation’, ‘vegetation diversity’, ‘biodiversity’, ‘species richness and evenness’, ‘wetland productivity’, ‘wetland plant species’, ‘aboveground biomass (AGB)’, ‘remote sensing’, ‘satellite data’ and ‘Synthetic Aperture Radar’ (SAR).

In order to retrieve information during literature search, articles published in international peer-reviewed journals were selected via the relevant search engines. These included the following: the ‘ISI Web of Science’, ‘Google Scholar’, ‘Photogrammetric Engineering and Remote Sensing’, ‘GIScience and Remote Sensing’, ‘Applied Earth Observation and Geoinformation’, ‘IEEE Applied Earth Observations and Remote Sensing’, ‘SCOPUS’, ‘Wetland Ecology’, ‘Hydrology’, ‘Ecology’, ‘Ecohydrology and Hydrobiology’, ‘African Ecology’ and other internationally-recognized remote sensing and wetland science journals. Due to a limited number of studies on remote sensing applications, particularly in the sub-Saharan region, the review was not limited to a specific criterion. Consequently, all studies that utilized remote sensing for wetland monitoring and assessment were considered.

2.2 Geographical Distribution of Wetland Ecosystems

Globally, wetlands occupy an area of nearly 9.2 million km^2, with 1.3 million km^2 of these are found in Africa (Melendez-Pastor *et al.,* 2010; Rebelo *et al.,* 2010; Kabiri *et al.,* 2020). Finlayson *et al.* (2011) also showed that estimates of the spatial extent of wetlands across the world, including Africa, differ across various studies, due to the different definitions of wetlands and the approaches that are used to delineate them. The common types of wetland found in sub-Saharan Africa include dambos, lakes, reservoirs, freshwater marshes, floodplains, swampy forests, flooded forests, coastal wetlands, pans, brackish/saline wetlands and intermittent wetlands (Gxokwe *et al.,* 2020). These wetlands vary according to the topography or landscape characteristics and climatic regimes, and they support diverse and unique wetland habitats (Space Applications Centre (SAC) 2011; Rebelo *et al.,* 2017). Xu *et al.* (2019) highlighted that about 2 303 of global wetlands are designated under the Ramsar Convention. They are referred to as wetlands of international importance (Ramsar Secretariat, 2013) and are unevenly distributed in different parts of the world (Figure 2.1). As shown in Figure 2.1, Europe has the largest number of sites, with a total of 1 004 occupying 44% of the Ramsar sites, 397 (17%) are in Africa, 146 (6%) in South America, 368 (16%) in Asia, 309 (13%) in North America and 79 (4%) in the Oceania region (Rebelo *et al.,* 2010; Ramsar Secretariat, 2013; Davidson *et al.,* 2018; Gardner *et al.,* 2018; Xu *et al.,* 2019). Despite the number of wetlands designated under the Ramsar Convention, there are many other small and unprotected wetlands that potentially perform an incredible function for their neighbouring communities, but they are continuously ignored in the policy process. As a result, some of these wetlands have already been threatened, degraded and lost, due to uncontrolled activities, both natural and anthropogenic. According to the National Biodiversity Assessment for South Africa (NBASA), which was carried out in 2011, wetlands occupy only 2.4% of the country's total area. However, 48% of these ecosystems are critically endangered, 12% are endangered, 5% are vulnerable, while 35% are the least affected (MacFarlane *et al.,* 2014).

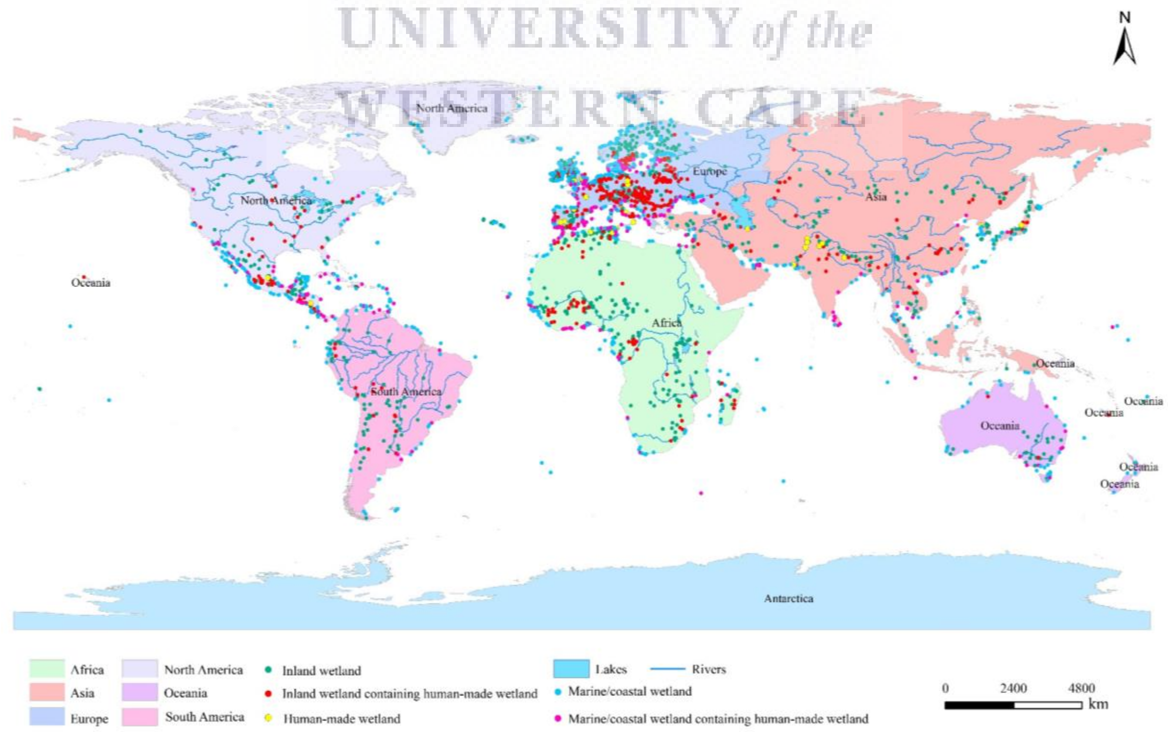


Figure 2.1 Global wetland distribution designated under Ramsar (Xu *et al*., 2019)

2.3 Factors influencing Wetland Degradation

Wetlands have a long history of transformation, destruction and degradation. Estimates suggest that about 50% of the global wetland areas have been degraded in the 20th century (Jogo and Hassan, 2010; van Dam *et al.,* 2013). The remaining wetlands are under threat from anthropogenic activities and the impact of climate change, despite robust regulations for their protection and conservation or restoration (TEEB, 2013). Literature demonstrates that there are multiple factors that degrade wetland ecosystems and maintain their survival. The anthropogenic factors include agriculture, reclamation, water use, infrastructure development, environmental pollution and the unsustainable use of wetland resources (Ramsar Convention Secretariat (RCS), 2010; Vörösmarty *et al*., 2010; van Asselen *et al*., 2013; Gardner *et al*., 2018; Xu *et al.,* 2019). Such factors affect the hydrology, soil, species diversity, productivity and composition of wetlands (Klemas, 2013). Gardner *et al.* (2018) stated that pollution caused by population growth and socio-economic development is a major factor leading to their degradation and loss. Rebelo *et al.* (2010) showed that a gradual cause of wetland destruction is primarily the need for flat, fertile land with a water supply, to be used for agricultural purposes (both for cultivation and livestock production). These studies concur with the work conducted by Slagter *et al.* (2020), who found that South Africa has lost, and continues to lose, wetlands due to dam construction, overgrazing, pollution, crop production, urbanization, erosion, development and the poor management of land resources. The loss of connective rivers also contributes to the rate of wetland degradation (IPCC, 2013; Tiner *et al.,* 2015; Oliver-Cabrera and Wdowinski, 2016).

Climate change is also a major threat to wetlands, particularly changes in the rainfall patterns and global warming (Boon *et al.,* 2016). These changes result in significant biodiversity configurations and wetland biochemical processes, which are quite variable over space and time, both on a local and a global scale (Dawson *et al.,* 2011; Bellard *et al.,* 2012). The rising temperatures may aid the invasion of warmer-water species into older zones and these species out-compete the dominant species. Climate change is also considered to be a cause for habitat destruction, a shift in species composition and habitat degradation in the existing wetlands (Titus *et al.,* 2009). Moreover, acute pollution and siltation have exaggerated these sensitive systems in recent times (van Asselen *et al.,* 2013; Li *et al.,* 2014).

It has been estimated that much wetland acreage from the existing inland and coastal marshes has been lost since the early 1900s, with about 56% to 65% having been lost through the conversion to agricultural production in Europe and North America, 27% in Asia and 6% in South America (Prigent *et al.,* 2012), while China has lost about 23% of its freshwater swamps, 16.1% of its lakes, 15.3% of its rivers and 51.2% of its coastal wetlands (Niu *et al.,* 2012). In Africa, a notable decrease in wetland areas has also been observed. For example, in Tanzania, the extent of wetlands has shrunk by 18% (Nguyen *et al.,* 2017). In other parts of the African continent, estimates of the degraded wetland acreage are a challenge and still rudimentary, due to the lack of historical documentation and monitoring of these ecosystems (Marambanyika and Beckedahl, 2016; Grenfell *et al.,* 2019; Xu *et al.,* 2019; Stephenson *et al.,* 2020). The decrease in the extent and quality of wetlands has caused many populations of wetland-dependent species to decline (Zhang *et al.,* 2020). Although other strategies are in place to protect them, many wetland ecosystems still suffer from degradation through eutrophication, reduced water availability, as well as the impacts of weeds and pests (Gopal, 2016). Other major causes of wetland destruction, more specifically in sub-Saharan Africa, are mainly due to the lack of awareness of planners, natural resource managers and wetland users (Ellery *et al.,* 2003). A lack of conformity between government policies in the areas of economics, environment, biodiversity conservation and development planning are one of the reasons for the continued degradation of these systems (Turner *et al.,* 2000), while a lack of action taken to conserve wetlands, as well as poor governance and management, further complicate the management strategies (Kumar *et al.,* 2013). The monitoring of wetland hydrology, soil and vegetation is becoming a major concern, due to the rise in anthropogenic activities in wetlands.

2.4 The Role of Remote Sensing Applications in Wetland Ecosystem Mapping

Since the 1960s, remote sensing observations, in particular satellite imagery, have served as the most useful tool for gathering information on land cover change or mapping features in wetland regions, on climate warming in wetland ecosystems, on species diversity and productivity and on hydrological processes in wetlands (O'Grady and Leblanc, 2014; Prospere *et al.,* 2014; Brisco *et al.,* 2015; Tiner *et al.,* 2015; Guo *et al.,* 2017). Remotely-sensed datasets and approaches provide frequent data with varying footprints and resolutions, which are more a practical and economical means for addressing the issues of wetland identification, delineation, classification, hydrophytic vegetation or biomass, hydromorphic soil, hydrology and vegetation characteristics, productivity and density (Mansour *et al.,* 2013). Literature gathered from peer-reviewed remote sensing journals shows that remote sensing applications have progressed remarkably over the years, due to technological advances that have led to efficient data processing (Figure 2.2) in the mapping and quantification of wetland ecosystems (i.e. forested wetlands or swamps, marshes) in sub-Saharan Africa. Most of these studies have focused mainly on wetland ecosystems that are designated under the Ramsar Convention, but they have neglected the small or unprotected wetlands, which serve their neighbouring communities. There has been an increase in the application of remote sensing for wetlands under Ramsar (r^2 = 0.88), compared to those that are non-Ramsar sites (r^2 = 0.66). This highlights the fact that limited studies use remote sensing for small wetland ecosystems, which provide a lifeline for rural communities, particularly in sub-Saharan Africa (Guo *et al.,* 2017; Osorio *et al.,* 2020; White *et al.,* 2020). The reason for this is because, in most cases, the smaller wetlands, when compared to image spatial resolutions, largely result in spectral mixing, and hence, there is a failure to derive accurate and highly-informative information, particularly from coarse resolution or broadband satellite images, like MODIS. Progress in remote sensing data usage (from aerial photography to multispectral scanners) in the mapping and monitoring of wetlands ecosystems is thus linked to the availability of freely-accessible satellite images (i.e. Landsat, Sentinel), as well as the recent technological capabilities (improved spatial, spectral and temporal resolution) that can rapidly detect and map wetlands on a large scale. Most of the studies conducted in Africa have used the multispectral remote sensing datasets. These new cutting-edge technologies substitute the use of aerial photographs, which are not practically possible for acquiring information from large areas (Thamaga and Dube, 2019). Therefore, based on the literature that was examined, most of the wetland studies used aerial photographs and the Landsat and MODIS datasets (Landmann *et al.,* 2010; Adam *et al.,* 2012; Hladik and Alber, 2012; Mutanga *et al.,* 2012; Tiner *et al.,* 2015; Guo and Guo, 2016; Gxokwe *et al.,* 2020). These sensors (Figures 2.3 and 2.4) were mainly applied in mapping and monitoring the extent of wetlands, the impacts of LULC, as well as for wetland classification. However, the use of remote sensing for determining wetland vegetation, soil and hydrology, remains understudied.

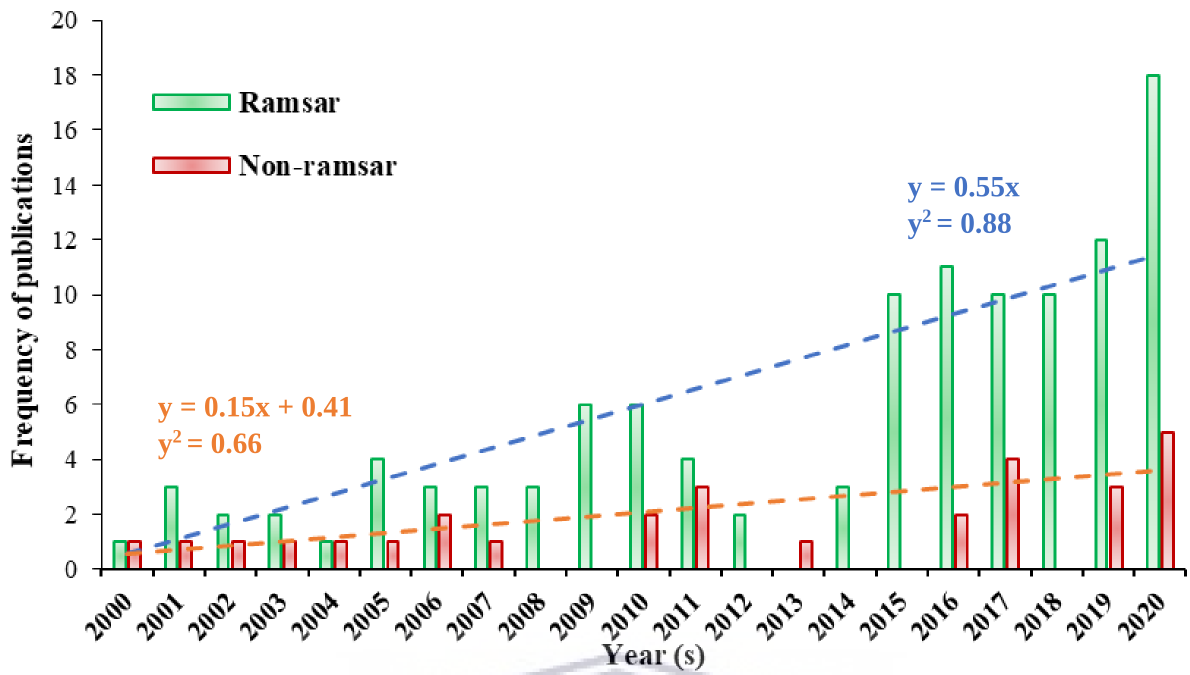


Figure 2.2 Progress of remote sensing publications in mapping wetland ecosystems in Africa

Previous studies have confirmed the effectiveness of satellite remote sensing tools for wetland monitoring and classification (Berlanga-Robles *et al.*, 2011; Rapinel *et al.*, 2015; Mahdianpari *et al.*, 2018). These approaches have effectively addressed the large-scale historical challenges for managing and mapping wetlands synoptically, compared to conventional approaches (e.g. accessibility and repeatability), which are time-consuming and labour-intensive. Given the capability of the sensors to collect synoptic observations more often, remote sensing techniques have become effective in studying, identifying and quantifying wetland ecosystems (i.e. plant species, diversity and productivity, as well as hydrological estimation) (Li *et al.*, 2013; Han *et al.*, 2015; Lou *et al.*, 2016; Pande-Chhetri *et al.*, 2017; Chen *et al.*, 2018), from small- to large-scale projects with spatially-continuous coverage, from several satellite datasets (Kuenzer *et al.*, 2011; Tiner *et al.*, 2015). Nevertheless, remotely-sensed satellite datasets (Table 2.1) with varying spatial resolutions of less than 10 m to several kilometres have been used globally to detect wetland ecosystems (Laba *et al.*, 2010; Betbeder *et al.*, 2015; Liu and Abd-Elrahman, 2018).

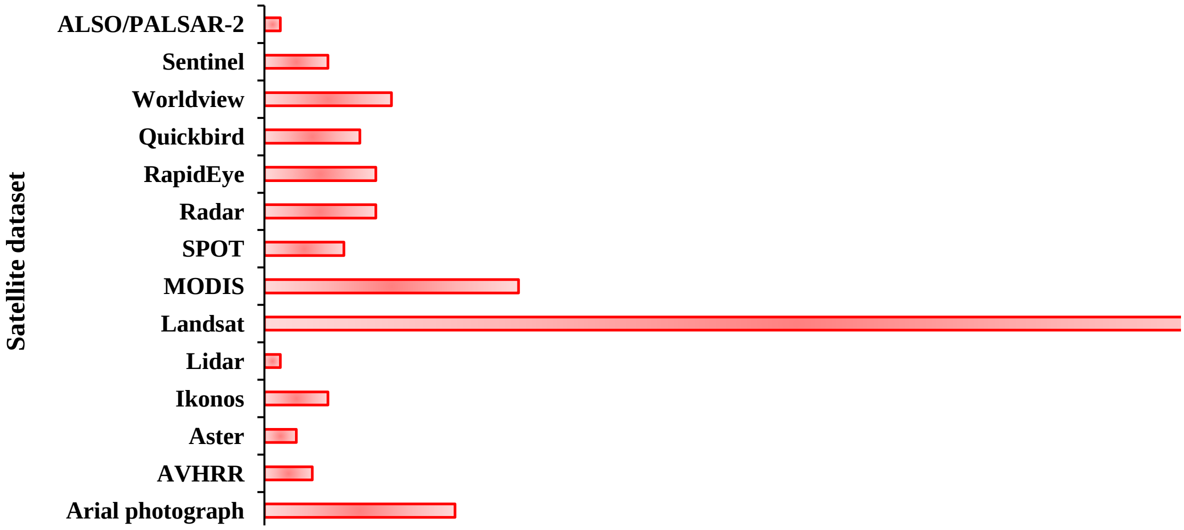


Figure 2.3 The number of satellite images used to the study wetland ecosystem

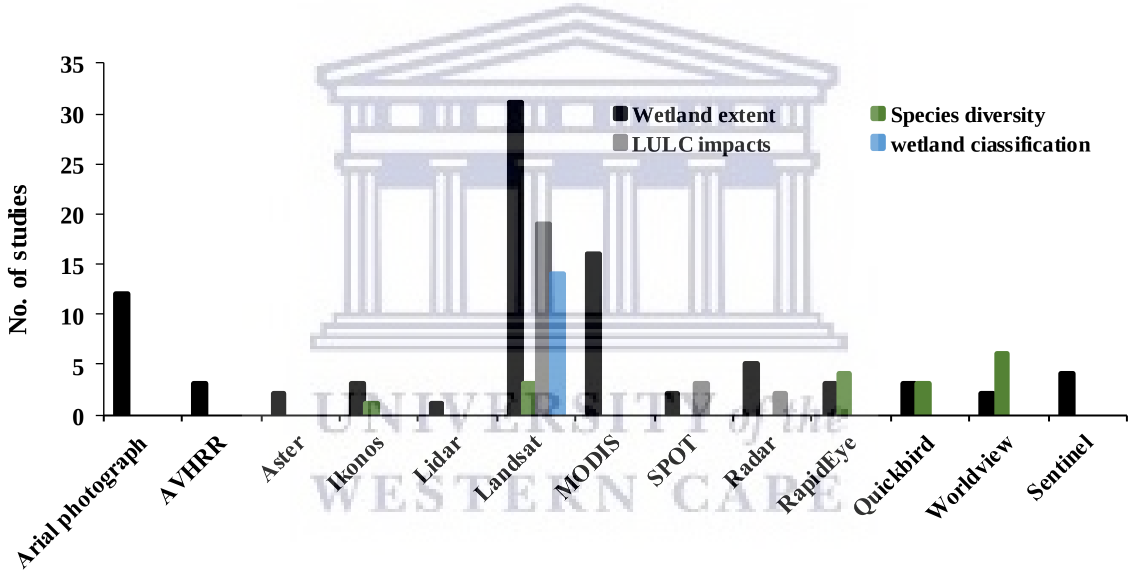


Figure 2.4 Monitoring and mapping wetlands using remotely sensed data

Table 2.1 Remote sensing sensor specifications and associated acquisition cost per square meter

Sensor	Spectral bands	GSD (m)	Description	Swath-width (km)	Frequency (days)	Cost of image acquisition (US $/km^2)
Landsat Thematic Mapper (TM)	7	30 120	Band (1-5 & 7) Band 6	185	26	Free
Landsat Enhanced Thematic Mapper plus (ETM+)	8	30 15	Band (1-7) Band 8	185	18	Free
MODIS	36	250 500 1000	Band (1-2) Band (3-7) Band (8-36)	2330	1-2	Free
Sentinel-2	13	10 20 60	Band (2,3,4 & 8) Band (5, 6, 7, 8a, 11 and 12) Band (1,9 & 10)	290	5	free
RapidEye	5	5	All bands	77	1 (off nadir) / 5.5 (nadir)	US $1.28
Système Pour I'Observation de la Terre 5 (SPOT 5) High-Resolution Stereoscopic (HRS) High Resolution Geometric (HRG) Vegetation (VGT)	5	10	Band (1-3)	60	2.5	US $5.15
Quickbird	5	20 2.40	Band 4 All multi-spectral bands	16.8	1-3.5	US $24
World View-2	8	2 0.48	All multi-spectral bands Panchromatic band	16.4	1.1	US $28.5
World View-3	8	1.24 0.31	All multi-spectral bands Panchromatic	13.1	1	US $29

Broadband multispectral and hyperspectral images can be acquired with different characteristics that provide new insights or approaches for assessing wetlands. The availability of affordable and freely-accessible remote sensing data has marked a new beginning for the continuous mapping and comprehensive monitoring of wetland ecosystems. For instance, Landsat, which has a long history of spatial data archival, has been used in a variety of wetland studies, including wetland classification, mapping and change detection (Guo *et al.*, 2017). Long-term change detection enables researchers to better understand the trends and gradual changes of wetlands, to analyse the changing dynamics, and to protect the wetlands. Rebelo *et al.* (2010), Adam *et al.* (2012) and Gxokwe *et al.* (2020) have provided comprehensive reviews of remote sensing datasets and methods for wetland characterization. Overall, previous studies have also shown that the probability of satellite remote sensing is critical for detecting information on permanently flooded, or intermittently exposed and open water surfaces; however, a knowledge gap still exists, particularly on the mapping and monitoring of small wetlands (unprotected wetlands).

2.5 Remotely-sensed Applications on Wetland Hydrology and Soil

Hydrology and hydromorphic soils sustain wetland ecosystems, but wetlands are being drained for irrigation purposes and dams have been constructed for drinking water. On the other hand, pollution in wetland ecosystems has affected the fertility of the soil, soil moisture and carbon sequestration, as well as the water quality, thereby exerting pressure on these systems (van Asselen *et al.,* 2013; de Klein and van der Werf, 2014; Xiaolong *et al.,* 2014; Zhang *et al.,* 2015; Were *et al.,* 2019). Remote sensing data provide an effective and efficient tool for detecting the extent of the water bodies and the quality of the soil. MODIS, with its high temporal resolution, has shown its significant advantages in mapping the extent and changes in wetlands over time (Ordoyne and Friedl, 2008). In North-Central Namibia, Mizuochi *et al.* (2017) identified the surface water distribution by using the Modified Normalised Difference Water Index (MNDWI) of the MODIS image and the Normalized Difference Polarization Index (NDPI) of the Advanced Microwave Scanning Radiometer Observing System (AMSR-E). On the other hand, Zoffoli *et al.* (2008) used AVHRR NDVI to analyse the seasonal and annual wetland changes over time and showed that NDVI can provide useful information on the wetland surface water. Klein *et al.* (2015) mapped open water bodies daily, by using the MODIS time series data and the threshold technique, which depicts the annual water changes. Frazier *et al.* (2003) used Landsat images to assess and describe the relationship between flow regulation and the inundation of flood plain wetlands before and after flood occurrence. The results of their study highlighted that river regulation could reduce the duration and frequency of inundation. Other sensors, such as Sentinel and SPOT, have been employed to examine wetland hydrological regimes and to map the extent of wetlands at various scales, with satisfactory results (Davranche *et al.,* 2010, 2013; Muro *et al.,* 2016; Xing *et al.,* 2018; Bhatnagar *et al.,* 2020; Slagter *et al.,* 2020). Indices, such as the Land Surface Water Index (LSWI) and the NDWI, have been extensively used to improve accuracies. For instance, the LSWI is known to be sensitive to the total amount of liquid water in the vegetation and the associated soil background. Using hydrological models, such as the Soil Water Assessment Tool (SWAT), HECRAS and Geo-rus, together with satellite data, the soil and climatic information seems to be promising for assessing the wetland hydrology, as well as the soil quality and quantity.

2.6 Wetland Plant Species Characterization

Remote sensing has the ability to analyse, map and monitor wetland plant species at all scales, using various satellite datasets. Ecologically-based studies have demonstrated the benefits of using multi-remote sensing sensors (both active and passive) include providing a wide range of data at varying resolutions and having the ability to extract various physiological, chemical and phenological characteristics of a species, in order to determine wetland plant species (Ustin and Gamon, 2010; Pau *et al.*, 2013). The retrieved information, using remotely-sensed data, provides spatially-explicit data on the dynamics, structure, annual precipitation, hydrological pathways and local physiological cycle of wetland species (Gallant, 2015). In addition, remote sensing techniques provide information on inaccessible areas, which cannot be accessed during field surveys, and this contributes to the enhanced estimation of the wetland plant species and to understanding and identifying the key factors that have an impact on wetland biodiversity and biomass. The method of remote sensing for estimating the vegetation in wetland ecosystems has not been used in much detail, especially in developing regions. The detection, delineation and mapping of wetland plant species remains a challenge with multispectral satellite imagery, due to the lack of spatial resolution of most satellites, with respect to the small and sharp vegetation units that are present within wetland ecosystems (Brisco *et al.*, 2017). Therefore, the spectral mixing of several vegetation species in various proportions, using multispectral imagery, remains a challenge (Zomer *et al.*, 2009). Moreover, the use of wide spectral bands from coarse multispectral imagery for mapping wetland species remains difficult, due to the spectral overlap among species, since healthy vegetation species typically show similar spectral responses in the visible and near-infrared region, due to the similarities and limited basic components that contribute to their spectral reflection.

2.6.1 The mapping of wetland vegetation using remote sensing data

Wetland vegetation can be used to reflect the status of wetland ecosystems, and biomass estimates can provide basic information about a particular wetland. Having a knowledge of the wetland plant species types, productivity and diversity is key, in terms of the planning, conservation and protection of the ecosystem functions. Spatially-explicit information on wetland vegetation is retrieved from satellite imagery and serves as the baseline evidence that is needed for the monitoring and assessment of the status and health of wetlands. Wilen *et al.* (2002) noted that satellite remote sensing images offer much better results of the wetland plant species. Hence, these could be critically used for the prioritization of different purposes, including planning, environmental impact assessments, wetland assessment and monitoring, the detection of alien plant species, the water flow and level, rehabilitation, and the analysis of trends in the wetland status, in order to enhance the conservation of wetland ecosystems

(Wilen *et al.*, 2002; Zheng *et al.*, 2014). Mutanga and Skidmore (2004), Zheng *et al.* (2014) and Wu *et al.* (2018) highlighted the fact that the estimation, monitoring and mapping of wetland species biomass (aboveground biomass) is required for studying nutrient allocation, species diversity, productivity and the carbon cycle. Furthermore, Mutanga and Skidmore (2004) and Adam *et al.,* (2012) emphasized that, despite the wetlands exhibiting discrete light-reflectance characteristics centred in the visible or infrared region of the Electromagnetic Spectrum Radiation (EMR), achievements in estimating the biochemical and biophysical parameters in some ecosystems have revealed that the remaining challenges are strongly affected by water, atmospheric conditions and soil. The use of vegetation indices, such as NDVI, EVI and NDWI, offers opportunities that can supersede the effects of the soil background, the atmospheric composition and the zenith angle effects, while improving the vegetation signal, when estimating wetland plant species (Mutanga *et al.,* 2012; Ramoelo *et al.,* 2015; Sibanda *et al.*, 2015). The high-resolution vegetation mapping of wetland complexes, with accurate distribution and population estimates for different functional plant species, can be used to analyse the vegetation dynamics, to quantify the spatial patterns of vegetation evolution, to analyse the effects of environmental changes on vegetation and to predict the spatial configuration of species diversity.

2.6.2 Mapping species diversity in wetland environments

Many predominantly upland regions encompass small patches of wetland habitats, which hold great potential for the conservation of biological diversity; however, these areas have received little recognition (Nicolet, 2003; de Meester *et al.*, 2005). These wetlands can contribute disproportionately to the landscape-level diversity, since they often have high levels of species richness (alpha diversity) and spatial variations in community composition (beta diversity) (Tiner, 2003; de Meester *et al.*, 2005). Wet habitation patches that are surrounded by uplands, support unique species assemblages, which are different from those of large-scale wetlands (Nicolet, 2003; de Meester *et al.,* 2005). These communities often include rare regional species, and they can serve wetland specialists in landscapes where major wetlands are being destroyed, degraded or absent (Nicolet, 2003). Few studies on the species diversity of small wetlands have focused on a single wetland category, such as seasonal pools with mineral soils, riparian areas in headwater streams (Hagan *et al.,* 2006) or groundwater seepage. The snapshots from a single image lack details. However, these wetlands often defy simple classification and the distinctions among wetland types remain largely arbitrary and inconsistent, with inherent differences in the wetland vegetation species often resulting in spectral overlaps. To understand how small wetlands contribute to the plant diversity of regional species, we need to consider all the wet areas within a landscape and identify them, based on their vegetation composition. Different indices for determining species diversity have been developed. These include the widely-used Shannon-Wiener Index (H'), the Simpson diversity index (1-D), Fisher's alpha - a diversity index (a), the Menhinink richness index (DMn), the Margalef richness index (DMg) and the Sheldon (Buzas and Gibson) evenness index (E_3) (Kent and Cocker, 1992; Barajas-Gea, 2005; Mitchell *et al.*, 2006; Janisova *et al.*, 2014; Caranqui *et al.*, 2016; Yaranga *et al.*, 2018). These indices can thus be used to quantify diversity of species within a wetland. Integrating the diversity indices with remotely-sensed data i.e. Landsat, Sentinel, Worldview, provides a better understanding of the condition of wetlands and their functioning, in general.

2.6.3 Wetland productivity and assessment

Wetland productivity is the positive increase in the vegetation species biomass per unit. This not only reflects the condition of the vegetation, but it is a central variable for carbon cycling (Luyssaert *et al.*, 2007). It was revealed in different studies (Cramer *et al.*, 2001; Klemas, 2013; Yin *et al.*, 2017) that wetland productivity changes in the volume and measure of prospective resource products have received attention from a rising number of researchers in the context of global change. Wetland productivity is also a function of climate variability and hydrological fluctuations. For example, fluctuations in the water table provide a better understanding of wetland conditions and their functioning, in general, with increased climate variability strongly affecting wetland vegetation productivity. Work by Rivera-Monroy *et al.* (2019) highlighted the fact that the Louisiana Wetland in the Gulf of Mexico has lost 4 900 km^2 of wetland area since the early 1930s. Furthermore, the study showed that, despite the relevance of wetland biomass and the net primary productivity procedures in wetland ecosystems assessment, there is a lack of vegetation simulation models for forecasting the trends of biomass and productivity. A long-term overview of the wetland simulation models with remote sensing datasets can provide a better understanding of wetland plant productivity.

2.7 Analytical Algorithms for evaluating Wetland Ecosystems and Conditions, using Remote Sensing

Several algorithms and remotely-sensed datasets offer opportunities for classifying and quantifying wetland ecosystems. These algorithms can be broadly categorized into the threshold method, an unsupervised and supervised classification, an object-based classification, a principal component analysis and a hybrid classification (Dronova *et al.,* 2015; Villa *et al.,* 2015; Liu and Abd-Elrahman, 2018). The Artificial Neural Network (ANN) (Kumar *et al.,* 2013), Decision Tree (DT) (Khosravi *et al.*, 2017), Random Forest (RF), CART and Support Vector Machine (SVM) (Xie *et al.,* 2017) are also non-parametric supervised machine-learning techniques that are commonly used for land cover classification. In addition, digital data from satellite imagery enable efficient and rapid classifications by using automated methods that have been shown to improve the accuracy, rather than simple aerial photo interpretations (Tiner *et al.,* 2015). The use of remote sensing techniques has been explored over large wetland regions. For instance, it has been applied in species and cover type assessments, canopy density or Leaf Area Index (LAI) estimations (Wang *et al.,* 2012), biomass monitoring (Mutanga *et al.,* 2012; Byrd *et al.*, 2014) or on quantities related to plant productivity and stress (Amani *et al.*, 2017). The newly-advanced methodologies, such as drones, the Google Earth Engine cloud-based platform and Artificial Intelligence (AI) have been adopted to understand wetland ecosystems around the world (Alonso *et al.,* 2016; Xie *et al.*, 2019). Wu *et al.* (2019) stated that moderate resolution satellite imagery cannot be used as a stand-alone method for wetland delineation; however, they integrated an automated approach to delineate the extent of wetland inundation at a watershed scale, using the Google Earth Engine. The outcomes of the algorithm not only delineated the current state of the wetland, but it also demonstrated critical information on the hydrological dynamics. Other studies used drone technology to assess the ecological integrity of wetlands. Dıaz-Delgado *et al.* (2019) showed that derived thematic maps from drone data are a very valuable input for assessing the wetland hydrology, soil, habitat diversity, wetland health, dynamics and wetland productivity by wetland-related managers or researchers, as frequently as desired. These advanced algorithms are scalable for mapping and quantifying wetland inundation on a small and larger geographical scale. The integration of multispectral remote sensing imagery, together with automated algorithms, enhances image classification and also provides a practical, frequent and required framework, which plays a critical role in delineating the inundation dynamics of wetlands.

The increase in the use of remote sensing data in mapping wetland ecosystems is linked to their ability to offer a variety of new applications that can quickly and synoptically monitor and manage large areas. Table 2.2 shows the recent studies that have indicated that the use of satellite imagery provides the most reliable primary data for the detection, monitoring and mapping of wetland ecosystems. For example, Nhamo *et al.* (2017) mapped wetlands in Mpumalanga by using Landsat 8 and the MODIS-based NDVI and found that the extent of the wetlands had declined by 19%. Nineteen percent of the degraded land has been mainly replaced by urban and agricultural development, which has affected the ecohydrological processes and functions. In a different study, Orimoloye *et al. (*2018) assessed the potential of Landsat data for understanding the status of the Isimangaliso Wetland in South Africa. The results obtained from the study showed that the extent of the wetland had shrunk from 655.416 km^2 (1987) to 429.489 km^2 (2017), and that an overall classification accuracy of 97.55% and a kappa coefficient of 0.941 were achieved. Berhane *et al.* (2019) showed that the integration of the machine-learning techniques, Landsat and Pleiade-1B, improved the mapping of wetland ecosystems, by obtaining an overall classification accuracy of 93%, with a Kappa coefficient of 0.92.

2.8 The Implications of the Remote Sensing of Wetland Vegetation and Productivity Mapping

Despite the robust and advanced remote sensing techniques and modelling algorithms, the spatial assessment of wetland ecosystems at various spatial scales remains a challenging task. This is primarily due to the heterogeneous nature of wetland ecosystems that are difficult to capture, especially when using broadband and coarse spatial resolution sensors. In addition, a high similarity of vegetation spectral characteristics has been noted, due to wetland fragmentation, which contributes to the confusion in species mapping (Corcoran *et al.,* 2013; Peimer *et al.,* 2017; Wu *et al.,* 2018). A major reason for this difficulty is that although each of the wetland species has several distinctive characteristics, they share some ecological and phenological similarities (Boon *et al.,* 2016) with non-wetland plant species (Henderson & Lewis, 2008). Therefore, this makes it difficult to spectrally distinguish some of the wetland plants from non-wetland plant species, when using remote sensing imagery (Amani *et al.,* 2017). Furthermore, the accuracy of monitoring and assessing the impacts of LULC changes on wetland ecosystems is mainly limited by the imaging characteristics of remotely-sensed data, as well as the algorithms that have been developed by different studies or for a specific application scale.

Previous studies treated all vegetation communities as one single type, or they focused only on a short period (Dronova *et al.,* 2012; Chen *et al.,* 2014; Han *et al.,* 2015). Vegetation species vary and these variations influence their functions within a wetland. In this regard, they generally view these species as a single type, which then masks considerable information that is critical for understanding the dynamics of wetland ecosystems. Wetland vegetation varies over time; hence, focusing on a particular period is inadequate for the implementation of sustainable regulations and policies for its conservation. Nevertheless, other researchers have attempted to adopt the long-term monitoring of wetland species. For example, Ballanti *et al.* (2017) used Landsat imagery to identify the changes within the watershed and wetland ecosystems in the Nisqually River Delta over a period of 58 years. Their findings revealed that the emergent marsh wetlands increased by 79% (188.4 ha) as a result of the rehabilitation strategies implemented in 2009. Furthermore, it was highlighted that, despite the wetland gains in 2009, 35% of the marsh wetland was lost between 1957 and 2015, due to the river shifting and the erosion patterns. A study by Son *et al.* (2015) used the Landsat dataset to identify the changes between 1979 and 2013 (a period of 34 years) in Vietnam. The results indicated that 16% of the wetland ecosystems were lost because of anthropogenic activities. In assessing the vegetation characteristics of the wetland, the study found that alien plant species dominated the wetland areas and demonstrated the critical role of remote sensing in wetland change detection, as well as for future monitoring. Although long-term data have been used in some studies to identify different vegetation communities, the phenological disparities between the different years that are associated with inter-annual water level changes were not considered (Chen *et al.*, 2014; Gallant, 2015; Hu *et al.*, 2017; Wu *et al.*, 2018). The transition of different vegetation communities within a wetland over the years, remains largely unknown. Similarly, the processes or causes of these drastic changes are poorly documented, and consequently, high vegetation fragmentation is observed when classifying these wetland ecosystems (Henderson and Lewis, 2008).

In summary, wetlands have high intra-class and low inter-class variability, which makes their classification challenging. The use of advanced remote sensing images with an improved resolution, coupled with modelling techniques, can enhance the classification of wetland ecosystems. Furthermore, wetlands lack a defined boundary, and their borders are almost fuzzy, since they transition gradually from a wetland to other land cover classes, such as upland or open water, or even other types of wetlands (Dronova, 2015). In addition, the proximity of the ecotone to the wetlands is sometimes very narrow, which makes its detection or discrimination from wetlands difficult (Gallant, 2015). Therefore, the quality of the image interpretation and feature extraction methodologies in assessing wetlands should be considered (Dronova, 2015). Remote sensing satellite images are also restricted to a specific spatial resolution, which might limit the detection of small wetlands (Ozesmi and Bauer, 2002). Despite these limitations, some notable research efforts have investigated applications of remote sensing data for regular wetland monitoring. There is a need to use freely-available sensors, such as Landsat and Sentinel, which have a high revisit time, that cover a large swath-width, that have an improved resolution and that are authoritative in solving the noted limitations relating to the monitoring, estimation and mapping of wetland ecosystems.

Table 2.2 Summary of recent remote sensing applications in mapping wetland ecosystems

Sensor(s)	Study	Image analysis technique(s)	Major findings	Reference
Pléiade-1B, Landsat-8	Wetlands along the Etrix River in North Xinjiang, China	Random forest (RF) Normalized Difference Vegetation Index (NDVI)	RF classifier achieved an overall accuracy of 93% with a Kappa coefficient of 0.92.	Tian *et al*. (2016)
Landsat TM, Landsat 8 OLI, Landsat 8 TIRS,	Isimangaliso Wetland – KwaZulu-Natal, South Africa	Normalized Difference Water Index (NDWI)	Wetland extent shrunk from 655.416 Km^2 (1987) to 429.489 Km^2 (2017) during the study period. The study revealed that other land cover features increased from 2149.911 Km^2 to 2375.838 Km^2 in 1987 and 2017. The classified imagery managed to achieve an overall classification accuracy of 97.55% and a Kappa coefficient of 0.94. NDWI revealed that there is a depletion of water in the study area mainly due to environmental and human interferences.	Orimoloye *et al*. (2018)
RADARSAT-2, TerraSAR-x ALOS-1 & 2 Sentinel-1	Newfoundland and Labrador (NL) Wetlands of Canada	Random Forest classifier	RADARSAT-2 was superior to the other sensors used in terms of accuracies except for TerraSAR-x for which the user accuracy was higher than that of RADARSAT-2.	Mahdavi *et al.* (2017)
MODIS Landsat 8	Witbank Dam Catchment in Mpumalanga Province	NDWI	The delineated wetlands show a declining extent from 2000 to 2015, which could worsen in the coming few years if no remedial action is taken. Current efforts to demarcate wetland extent varied time-series trend analysis. The wetland area declined by 19% during the period of study.	Nhamo *et al*. (2017)
WorldView-2	South American	Object-based Image Analysis approach,	Overall classification accuracy was 81%, and the Kappa index was 78.10%.	Gonzalez *et al*., 2019
WorldView-2	Selenga River Delta of Lake Baikal, Russia	Nonparametric machine-learning algorithms (DT, RB, and RF)	RF classification outperformed both the DT and RB methods, achieving overall classification accuracy of more than 81%.	Berhane *et al*., (2019)
RapidEye	Peninsula, Newfoundland and Labrador, Canada.	Random Forest and Support Vector Machine	The top three convnets (ResNetV2, ResNet50, and Xception), provide high classification accuracies of 96.17%, 94.81%, and 93.57%, respectively. The classification accuracies obtained using Support Vector Machine (SVM) and Random Forest (RF) is 74.89% and 76.08%. InceptionResNetV2 found to be superior to all other convnets. It can be suggested that the integration of Inception and ResNet are efficient for classifying complex remote sensing scenes such as wetlands.	Mahdianpari *et al*. (2018)

2.9 Future Investigations into Improved Wetland Ecosystem Conservation

Significant progress has been made in the application of remote sensing techniques in wetland ecosystems research. Remote sensing techniques play a critical role in detecting and mapping areas that are impacted by different forms of anthropogenic and natural activities. Hence, the use of remote sensing to detect and map wetland ecosystems across sub-Saharan Africa has gained attention over the past decade. While several studies have successfully utilized remotely-sensed data in wetland research, there are still challenges that need to be addressed. Spatial studies on these ecosystems require versatile and robust computational methods to help deal with non-linear relationships, high-order interactions and missing data. Despite these difficulties, the methods used for mapping the distribution of wetlands should be clear to understand and easy to interpret. Wetland ecosystems are important to society and there is a need to establish digital efforts for wetland conservation. Furthermore, the wetland resource surveys, legislation, management and research need to be revised, since there is still much work to be done to protect wetlands in the future.

2.10 Conclusion

Several scholars have studied various characteristics and functions of wetland ecosystems, the impacts of land use and land cover changes, as well as the delineation and degradation of these ecosystems. Most studies have focused on estimating and mapping the biophysical and biochemical parameters of vegetation in those wetlands that are recognized under the Ramsar Convention; however, little emphasis has been placed on small and unprotected wetlands, which also play a critical role for their adjacent communities. Little attention has therefore been focused on the wetland hydrology, soil, vegetation quantification, species characteristics, species diversity and productivity of these smaller wetlands. The quantification and frequent mapping and monitoring of these wetlands across diverse landscapes is required for sustainable and effective wetland management control and for the formulation of governmental policies that promote their ecological preservation under increased pressure from human interference and climate change. However, long-term ecological studies have revealed that human activities continue to affect the wetland water levels and vegetation composition, as well as the structure, productivity, diversity and functioning of the ecosystems, for decades after these activities have ceased. A new crop of robust satellite sensors, e.g. Landsat, which have an improved spatial resolution and a high record of archival data, provides the most needed spatial tool for detecting, monitoring and understanding the status of wetlands at a low cost. There is a data gap, or undocumented information, on the state of wetlands in developing regions, which further complicates the management strategies and policy development. Therefore, this review provides insights for wetland-related managers and it emphasizes the urgent need to shift towards the use of cheap and readily-available techniques for assessing and controlling wetland degradation, especially the small wetlands dotted across under-resourced regions. Furthermore, there is a need for future studies to utilize new and advanced satellite imagery, coupled with the use of robust machine-learning algorithms, such as the Google Earth Engine (GEE), a principal component analysis, to improve modelling for well-informed management decisions on wetland ecosystems.

CHAPTER THREE

EVALUATING THE IMPACTS OF LAND USE AND LAND COVER CHANGE ON UNPROTECTED WETLAND ECOSYSTEMS IN THE ARID TROPICAL AREAS OF SOUTH AFRICA, USING THE LANDSAT DATASET AND SUPPORT VECTOR MACHINE

The manuscript is entitled:

Thamaga, K.H., Dube, T., Shoko, C., 2021. Evaluating the impacts of land use and land cover change on unprotected wetland ecosystems in the arid tropical areas of South Africa, using the Landsat dataset and Support Vector Machine. *Geocarto International*, TGEI-2021-0407. (Accepted manuscript).

Abstract

We explored the impacts of the Land Use and Land Cover (LULC) change dynamics on the condition and status of the unprotected Maungani wetland, which is located in the arid, tropical parts of the Limpopo Province, South Africa. The long-term Landsat archival data series was used to map and quantify the impacts of LULC changes on the wetland, on a nine-year basis, over a period of 36 years (1983-2019). A multi-source satellite image analysis was performed, using the Support Vector Machine (SVM) algorithm and advanced spatially-explicit geographic information system tools. In addition, post-classification maps for the Maungani wetland area were analysed to provide a quantitative assessment and a detailed overview of the rate of change. The study findings showed that the spatial extent of the wetland area declined severely during the period under study. The introduction of settlements and agricultural activities was the major driver of change in the area. By the year 2019, the wetland had an estimated spatial extent of 3 450 800 ha, which had increased from 1 073 500 ha in the year 1983. The built-up area increased by 934 300 ha (37.51%), other vegetation also increased by 375 400 ha (15.07%) and agriculture increased by 373 700 ha (15%), resulting in a 728 300 ha decrease in the wetland area between 1983 and 2019. The changes within the wetland were mapped with a high Overall classification Accuracy (OA), ranging from 77.55% to 92.69%. The findings of this work provide critical insights and baseline information about the state of unprotected wetlands in the rural parts of the Limpopo Province, South Africa. This information is useful for the development of tailor-made wetland management strategies and a possible rehabilitation framework for unprotected wetland ecosystems.

Keywords: Drivers of wetland conversion; rural development; support vector machine; temporal change; wetland degradation.

3.1 Introduction

Most wetlands are located adjacent to fresh or salt water and are characterised by hydric soil that experiences wet saturation conditions, either periodically during the rainy season, or permanently all year round (Tiner *et al*., 2015; Adeli *et al*., 2020). Although wetlands occupy approximately 6% of the earth's surface, they are among the most productive and ecologically-diverse ecosystems globally. In their natural condition, wetlands support many environmental and socio-economic services to neighbouring communities, which are, to some extent, primarily largely controlled by the variations in inundation and soil saturation patterns (Dubeau *et al*., 2017; Thamaga *et al*., 2021). These ecosystems are irreplaceable and play a critical role by controlling floods, moderating the micro-climatic, maintaining and improving the water quality and protecting against erosion and carbon sequestration (Chandler *et al*., 2017; Calhoun *et al*., 2017; Materua *et al*., 2018). For instance, in sub-Saharan Africa, wetlands provide a basis for the human livelihoods of many communities living around these ecosystems (Rabelo *et al*., 2010; Horwitz and Finlayson, 2011). For example, communities around the Yala Swamp in Western Kenya were found to depend on it for drinking, cooking and washing, while 86% of the population relies on it for the building materials that are gathered from the wetland, such as clay, sand, wood and papyrus (Schuyt, 2005). It was noted that in areas with a strong seasonal and interannual hydro-climatic variability, wetland inundation provides suitable conditions for perennial crop production in arid tropical environments. Most arid tropical regions experience erratic rainfall patterns, which lead to crop failure, and hence, there has been a shift towards the utilisation of wetlands, which are characterised by fertile soils and optimal moisture conditions for the sustenance of rural livelihoods.

Despite these benefits, wetlands in the arid tropical regions remain the most fragile and frequently-threatened ecosystems, by both natural and anthropogenic processes. Natural processes, such as global warming, discharge patterns, precipitation changes and extreme weather conditions expedite wetland degradation (Singh *et al*., 2016; Malak and Hilarides, 2016; Mohammadimanesh *et al*., 2018). In sub-Saharan Africa, for example, the rising water scarcity, as well as prolonged and severe droughts, are major threats to wetland ecosystems. Many wetlands are increasingly vulnerable to changes in the population patterns and are frequently affected by the Land Use and Land Cover (LULC) processes. The conversion of wetlands to agricultural land threatens the ecohydrological functions of wetlands, particularly when large-scale drainage alterations occur (Mohammadimanesh *et al*., 2018; Chen *et al*., 2020). According to Symeonakis and Drake (2010) and Sakane *et al*. (2011), the degradation of upland fields and the increasing rainfall variability due to climate change, push farmers to cultivate crops in wetland areas, where water is readily-available for crop irrigation. The conversion of wetlands, particularly small wetlands, into agricultural land and settlements, is expected to occur on flat terrains or in areas with a gentle slope, as they are largely suitable for crop cultivation and the construction of infrastructure. When land is transformed, small patches of wetland in the converted area are likely to be lost or to disappear, depending on the rate of conversion. On the other hand, the factors associated with anthropogenic disturbances and improvements in unprotected wetland ecosystems include eutrophication, direct pollution through agrochemicals, sewage waste pollution from the neighbouring peri-urban settlements and hydrological changes that are caused by excessive abstraction for industrial or domestic purposes (Malak and Hilarides, 2016; Russi *et al*., 2016; Dlamini *et al*., 2021). Siachalou *et al*. (2014) highlighted that the conversion of land to agricultural fields and settlement spaces for development, limits the geographical scale of wetland areas, while complicating their ecological functions. A study conducted by van Asselen *et al*. (2013) revealed that agricultural development, economic growth and population density are the main causes of wetland transformation and the most frequently-observed factors that perpetuate the degradation process. This is consistent with studies by Lambin and Meyfroidt (2010), Nkonya *et al*. (2016) who noted that the overexploitation of natural resources and unregulated infrastructure development placed much pressure on wetland ecosystems, due to the unsustainable utilisation of wetland ecosystems, which leads to a great loss of their ecological functions. These threats disrupt the ecohydrological stability of wetlands and have major consequences, such as an increase in wetland degradation, changes in the wetland's hydrological system, ecological diversity and ecosystem services, all of which contribute to the destruction of wetlands (McCarthy *et al*., 2018, Jaramillo *et al*., 2018). The observed land degradation trends in arid tropical areas therefore require accurate, continuous and up-to-date information about the extent and status of the condition of wetlands, particularly unprotected wetland systems, to help comprehend the spatio-temporal pattern of the existing land use and land cover activities in the proximity of wetland systems.

Details on the spatio-temporal extent of unprotected wetlands, as well as their status, remain scanty, especially on a localised scale in Sub-Saharan Africa (Lee *et al*., 2001). As a result, quantifying wetland transition patterns and land cover classification, over a smaller to a larger spatial scale, is critical for understanding their distribution and health status. Due to the remoteness, vastness and the highly-dynamic nature of wetlands, field-based measurements for the continuous monitoring of wetlands remain impractical, especially in data-scarce environments. These methods are costly, time-consuming, labour-intensive and they lack spatial representation, given the size of the wetlands (Gao *et al*., 2010; Adeli *et al*., 2020). Furthermore, Lin *et al*. (2018) have indicated that sampling errors have proved to be a major drawback when collecting wetland data, due to their inaccessible location. Therefore, given the inaccessibility of in situ wetland data, there is a pressing need to establish suitable and reliable tools that have the appropriate spatial and temporal scales and monitoring capabilities.

Remote sensing remains the critical alternative tool for addressing the challenging task involved with ground-based methods. It renders an operational, repeatable and integrated mapping framework that screens the spatial degree and condition of wetlands across small to larger landscapes (Lin *et al*., 2018). Remote sensing satellite imagery enables access to the historical and up-to-date information that is needed to characterize wetland ecosystems; it provides an inventory for monitoring and evaluating the impacts of LULC changes on unprotected wetlands, and it is also a practical and cost-effective means of doing so (Robertson *et al*., 2015). Satellite mapping helps to identify baseline information on ecosystem health of wetlands, to diagnose the threats and pressures to wetlands, to monitor any changes in their magnitude and state and to inform enhanced decision-making and management strategies.

Thus far, several studies have used various satellite datasets for wetland characterization, as well as for monitoring, mapping and assessing the associated LULC changes over time, at varying spatial and temporal resolutions (Lin *et al*., 2018; Munishi and Jewitt, 2019). Satellite imagery, such as Landsat, ASTER, SPOT, AVHRR and MODIS, provide long-term spatial data archives for ecological assessment, monitoring and management purposes (Nagendra *et al*., 2013; Robinson *et al*., 2016; Muavhi and Mavhungu, 2020). These images have been used in various studies, for example, on LULC change, wetland monitoring and extent mapping, biomass estimation and mapping, soil moisture applications, inundation mapping and water level monitoring (Chatziantoniou *et al*., 2017; Yirsaw *et al*., 2017; Connolly, 2018; Ligate *et al*., 2018; Munishi and Jewitt, 2019; Mudereri *et al.*, 2019; Slagter *et al*., 2020; Basu *et al*., 2021), amongst others. Davranche *et al*. (2010) used SPOT-5 and Landsat TM datasets to detect and classify wetlands by using the Decision Tree technique, and their findings revealed that the combination of different knowledge bases and techniques provides an effective and promising method for the identification and classification of wetlands. In addition, Hettiarachchi *et al*. (2015) used Landsat images to map wetland degradation, and the findings revealed that urbanization, industrialization and the expansion of agriculture were the major threats influencing wetland degradation. In contrast, Bassi *et al*. (2014) found that the loss of the spatial extent of wetlands in India was due to the rapid population growth in the remote areas. Jiang *et al.* (2015) stated that agricultural expansion and urban development in China resulted in extensive wetland degradation. Due to their large spatial extents, they remain the spatial data of choice for capturing accurate information in heterogeneous environments.

In this study, we therefore hypothesize that determining the past and present status of unprotected wetlands could help and guide environmental managers in their efforts to conserve wetland areas in a sustainable manner. Previous studies related to wetland monitoring, mapping and assessment have only focused on large wetlands that are designated under the Ramsar Convention, and they neglect unprotected wetlands (non-Ramsar), which are also of global importance (Hu *et al*., 2018; Munguía and Heinen, 2021; Xi *et al*., 2021). Thus, this study aims to map the impacts of land use and land cover change dynamics on the condition and status of the unprotected Maungani wetland, using the Landsat data series, as well as geospatial techniques, such as statistical analysis and Support Vector Machines (SVM), and to measure the LULC changes that affected the Maungani wetland during the 1983 to 2019 period (36 years). We therefore assume that the findings of this study will enhance the capacity and knowledge of environmental managers, policymakers, and local governments, in order to minimize the human footprint on unprotected wetlands in semi-arid tropical areas, particularly in sub-Saharan Africa.

3.2 Materials and Methods

3.2.1 Description of the Study Area

This research was carried-out in Maungani wetland, which lies adjacent to the Dzindzi River, a tributary of Levuvhu River within the Luvumbu quaternary, in the Limpopo Transboundary River Basin (LTRB) of the Limpopo Province, South Africa. The study area is located within a longitude of 30°26'30" E, 22°59'05" S and a latitude of 30°25'45" E, 22°58'45" S and (Figure 3.1). The Maungani wetland occupies a geographical area of approximately 2 490 700 ha. The rainfall and temperature are influenced by the Soutpansberg Mountains. The temperature of the region ranges between 18°C and 37°C, with the mean annual rainfall being between 7 mm and 642 mm each year. The annual average relative humidity is 75%. The distribution of wetland vegetation is strongly influenced by the environmental gradients, with mixed vegetation types appearing at high altitudes and Acacia-Themeda bush growing on the plains. Various seasonal storms exist; however, these quickly dry up as the dry season sets in. The wetland is characterised by stamp lands, as well as marshy vegetation. In addition, it is dominated by the *Thelypteris interrupta, Phragmites australis and Eichinochloa pyramidalis* plant species, amongst others. Agriculture, the rearing of livestock and subsistence farming are the primary economic activities in the area. The Maungani wetland is home to approximately 142 000 people who live in the surrounding communities (StatsSA, 2011). The major land cover types in the selected study site include wetland vegetation, water, other vegetation, built-up areas, agricultural land and bare land.

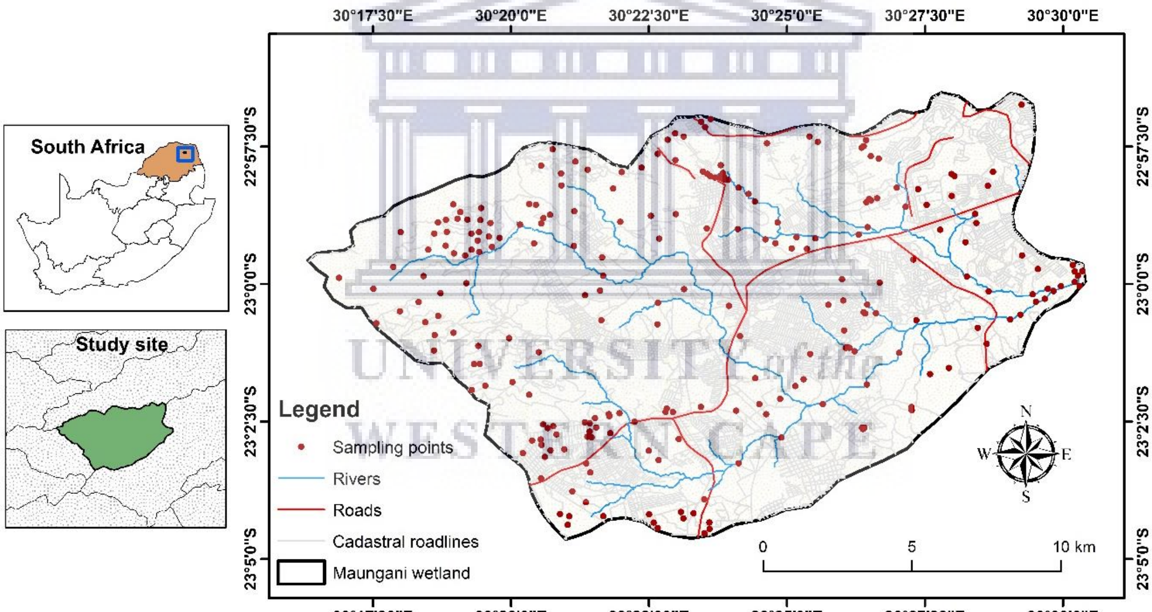


Figure 3.1 Map of the Maungani Wetland in the Limpopo Province of South Africa

3.2.2 Field data collection

The data used in this study were collected from the 03rd – 10th of October 2019 (Figure 3.2). This period was selected because of its suitability to detect, to discriminate, and thereafter to distinguish, the wetland from other vegetation species in the area. During the field data collection, the Trimble hand-held Global Position Systems (GPS) at submeter accuracy were used to record LULC feature coordinates within the Maungani wetland. The collected ground-based data are detailed in Table 3.1. In addition, these data were used to validate the

LULC classification and evaluate the precision of classified images. The sample locations of LULC were created, using Hwath's analysis in a GIS environment and they were then imported into the Trimble GPS, in order to navigate us to the specified spots. A total of 350 sample points (50 per land cover class) were collected for each class.

Figure 3.2 An illustration of the Maungani wetland landscape (photo by K.H. Thamaga)

Table 3.1 Description of land use land cover classes used in the study

LULC class	**Description of land use land cover classes**
Agriculture	Agricultural or cultivated lands and farmlands.
Built-up	Built-up comprises all developed land, including residential, commercial and socio-economic infrastructure.
Bare land	This is the area without or with little vegetation cover.
Forest	Land covered with relatively tall trees with at least a 20% canopy, mainly dominated by shrub lands and forest nursery.
Other vegetation	Mixed grassland, vegetation lands, vegetation on customary land. This class also consist of unmanaged land areas that are not characterised in any of the above classes.
Water	River, streams and waterbodies.
Wetland	Area is covered with by water and hydrophytic vegetation in either rivers, streams, lakes or catchments.

3.2.3 Satellite image acquisition and pre-processing

Field data that coincide with remote sensing satellite data (Landsat 5 TM and 8 OLI) were attained and used to investigate the LULC, as well as change dynamics of the Maungani wetland. Landsat satellite images were selected because they have sufficient archival data, they are freely accessible and because of their reported performance in other land cover classifications and wetland analysis studies (Jin *et al*., 2017; Fashae *et al*., 2020). For this study, five scenes of cloudless Landsat 5 TM and one Landsat 8 OLI satellite imagery time-series data, dating from 1983 to 2019, with 9-year intervals, covered the study area, and they were acquired from the United States Geological Survey (USGS) data portal (*http://glovis.usgs.gov*).

Preceding to the classification process, Landsat images were imported into the ENVI software (Harris Geospatial Solutions, Herndon, VA, USA, version 5.3). The Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube (FLAASH) radiative transfer model was used for atmospheric corrections made to images during the study period (Mushore *et al*., 2016). Images were orthorectified and geometrically corrected by using randomly selected ground control points (GCPs) (350). Selected bands from Landsat images (Table 3.2 and Table 3.4) were also used. Bands 1 (coastal aerosol), 6 and 7 (thermal band), 9 (water vapour), 8 (panchromatic), 9 (SWIR – cirrus), 10 (LWIR-1) and 11 (LWIR-2) were excluded from the analysis, due to their spatial resolution (60 and 120 m) and their relevance relating to the detection of atmospheric features (Drusch *et al*., 2012; Hagolle *et al*., 2015). The spectral bands have been considered to be inapplicable in vegetation monitoring (Immitzer *et al*., 2016). The Blue, Green, Red, NIR and SWIR 1 and 2 bands were used in this study.

Table 3.2 2015-2019 Landsat 8 Operational Land Imager (OLI) band specifications used for 2019

Band name	Centre of electromagnetic region (µ)	GSD(m)
1. Coastal/Aerosol	0.433 – 0.453	30
2. Blue	**0.452 – 0.512**	**30**
3. Green	**0.533 – 0.590**	**30**
4. Red	**0.636 – 0.673**	**30**
5. NIR	**0.851 – 1.879**	**30**
6. SWIR – 1	**1.566 – 1.651**	**30**
7. SWIR – 2	**2.107 – 2.294**	**30**
8. Panchromatic	0.500 – 0.680	15
9. Cirrus	1.360 – 1.390	30
10. LWIR-1	10.6 – 11.2	100
11. LWIR-2	11.5 – 12.5	100

*NIR –Near Infra-red, SWIR – Shorter Wave Infrared, LWIR – Lower Wave Infrared. The six bands highlighted in bold were used in the study for the analysis

Table 3.3 Landsat 5 TM band specifications used for the year 1983 and 2010

Band name	Centre of electromagnetic region (µ)	GSD (m)
1. Blue	**0.45 – 0.52**	**30**
2. Green	**0.52 – 0.60**	**30**
3. Red	**0.63 – 0.69**	**30**
4. NIR	**0.76 – 0.90**	**30**
5. SWIR – 1	**1.55 – 1.75**	**30**
6. SWIR – 2	**2.03 – 2.35**	**30**
7. Thermal	10.40 – 12.50	120

*NIR – Near Infrared, SWIR – Shorter Wave Infrared. The bolded bands are used in the study and the band not written in bold was not used for the analysis

3.2.4 Image classification

The Support Vector Machine (SVM) classifier embedded in ENVI 5.3 was used to assess the impacts of LULC changes affecting the Maungani wetland for the years 1983, 1992, 2001, 2010 and 2019. The SVM is a supervised, non-parametric statistical machine learning technique that used to classify high-dimensional data. It is suitable for image classification when a limited number of training data is available. Comparative studies assessed the performance of supervised classifiers and found that SVM classifier produced higher accuracy results than other supervised classifiers such as Maximum Likelihood, Mahalanobis Distance, Minimum Distance, Spectral Angle mapper, Random Forest (Jia *et al.*, 2014;

Muavhi, 2020). The SVM Classifier appear to be advantageous in the presence of heterogeneous classes for which only few training data are used than other machine learning classifiers which require additional training dataset as the input dimensionality increases (Yu *et al.,* 2013; Muavhi, 2020). It locates the optimal hyper-plane between two classes to separate them in a new high-dimensional feature space by taking into account only the training samples that lie on the margin of the class distributions known as support vectors. The SVM, is a method produced to solve pattern recognition and nonlinear function estimating problem (Sahu *et al.*, 2015). SVM was implemented using the Radial Basis Function (RBF) kernel characterised by default gamma of 0.33, penalty parameter of 100.00, pyramid level was set at 0 and classification probability threshold was also 0. Although its performance was tested on large scale mapping, using SVM in this study will provide a clear view on the rate of small wetland status.

3.2.5 Classification accuracy assessment

The derived LULC change maps for the years 1983, 1992, 2001, 2010 and 2019 were assessed for accuracy. The field data samples were divided into those for training (70%) and testing (30%). The field data samples were divided into 70% training (245 points) and 30% testing (105 points). The principle behind separating data into 70/30 is because they represented a large training data set, while the remaining data were preserved to compute accuracy statistics (Adjorlolo *et al*., 2013; Adelabu *et al*., 2014). An error matrix was used to assess the accuracy of the classification process (the overall, user and producer accuracy) relative to the reference data. Further, the error matrix provided a comprehensive evaluation of the agreement, omission and commission amongst the classification results and training data, with evidence on how the classification errors occurred (Pontius and Millones, 2011). We then computed the statistical analysis (a one-way Analysis of Variance: ANOVA test) to check for any significant differences ($\alpha = 0.05$) among the derived spectral reflectance for each of the different land covers.

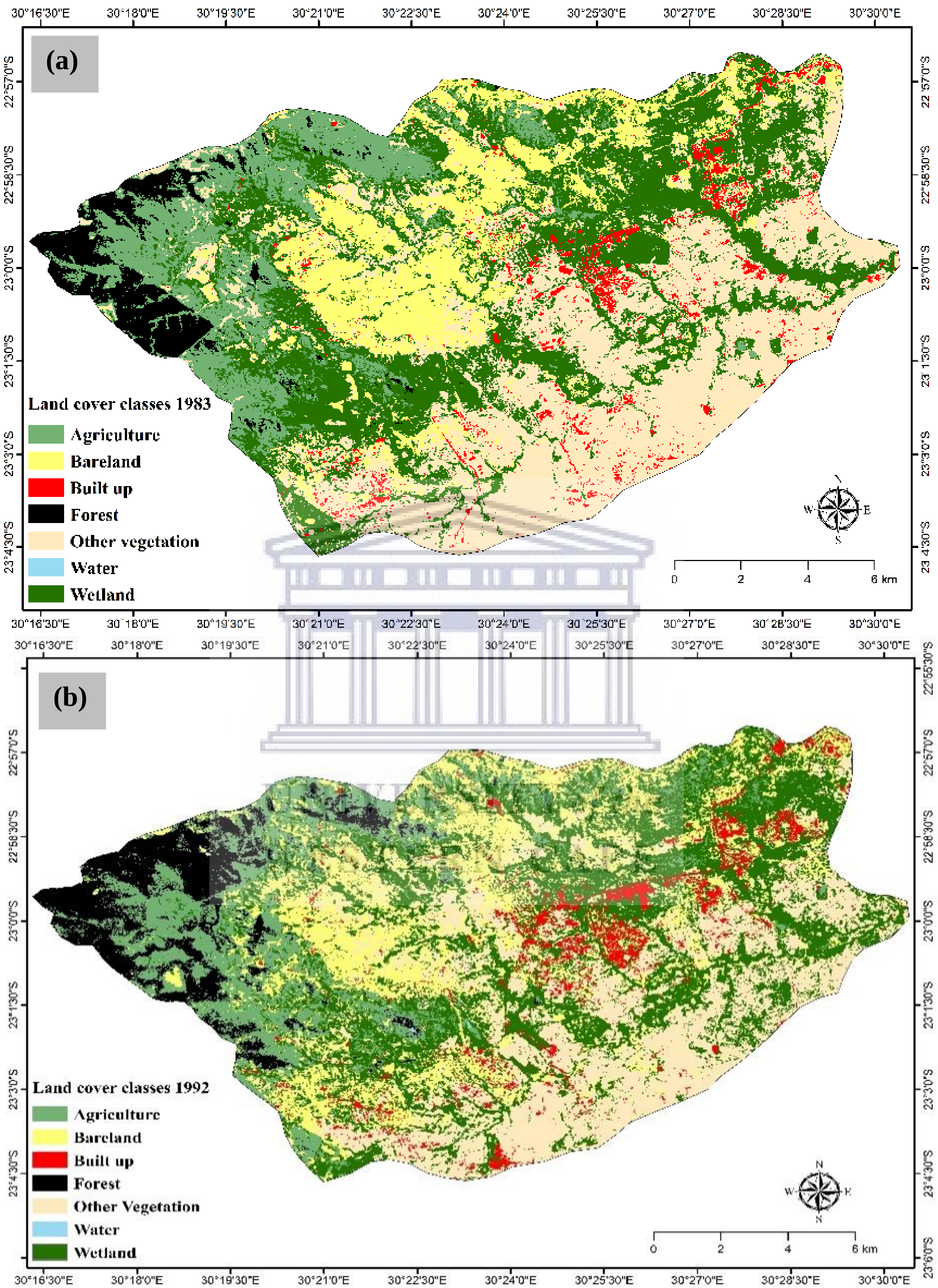
3.2.6 Change detection analysis and post-classification

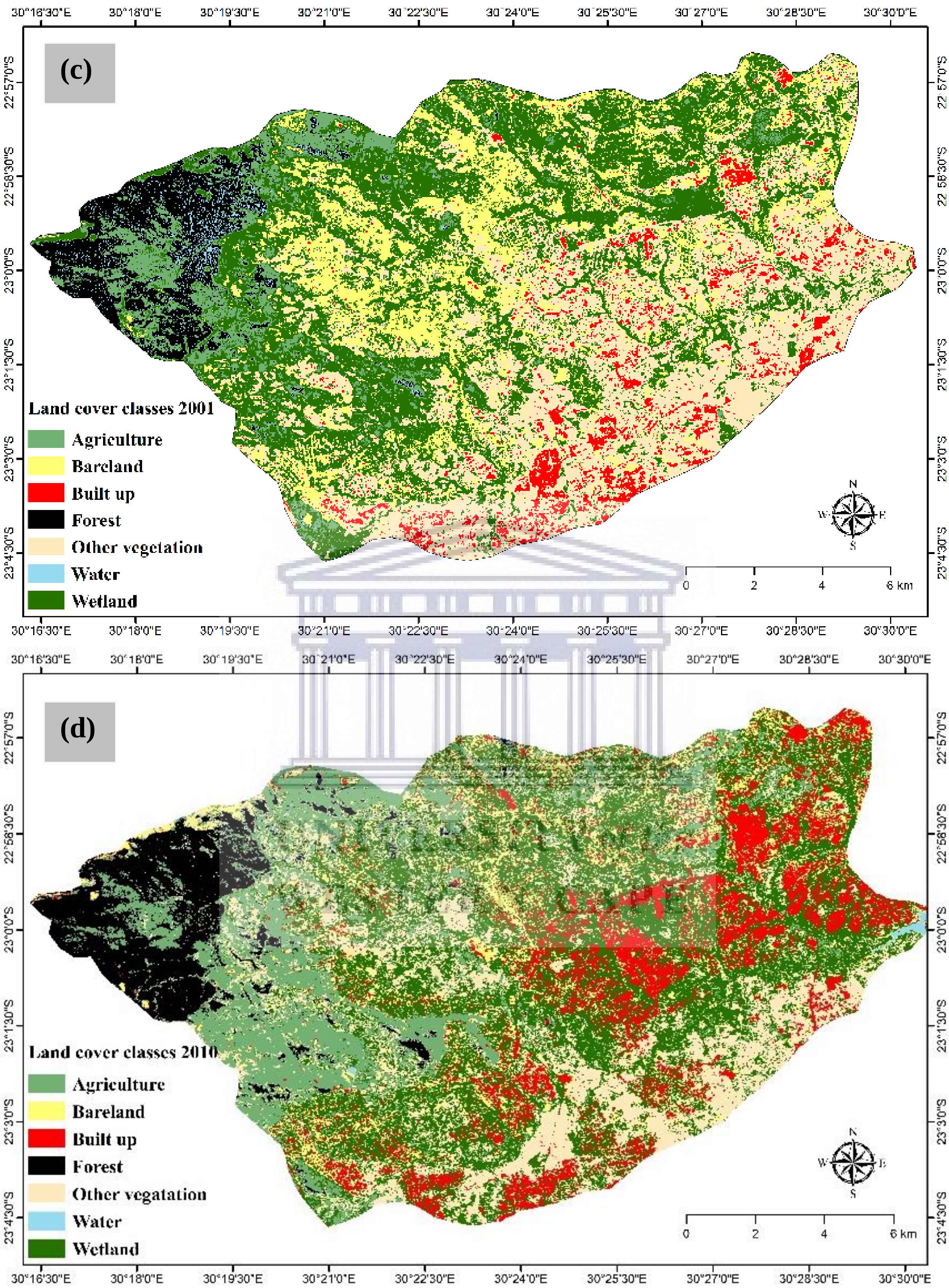
The existing LULC types occupying the Maungani wetland were evaluated for the time-frame of the study and expressed as the amount for the entire study area. This allowed for the assessment and estimation of the LULC changes within the 1983-1992, 1992-2001, 2001-2010, 2010-2019 and 1983-2019 time periods. The post classification comparison was used as the change detection techniques. This approach is a comparative analysis of satellite images belonging to different times classified as independently from each other. Advantage of this method is that it gives information about the magnitude and direction of change. Although both images come from the same sensor, spectral differences are expected to occur in the same land use/cover classes due to changes in atmospheric conditions, sun angle. even if the time interval is very small in multi-time data (Munyati, 2000). Based on the post classification comparison technique, the change is identified based on pixel-by-pixel basis by overlapping LULC maps belong to different dates obtained by the classification technique. At the end of the process, the number of areas which have undergone change and which class has changed can be identified. An overall change detection map, from 1983-2019, was produced to show the LULC conversion. This type of analysis was very useful in identifying the various changes in the LULC classes, such as the increase in built-up areas and the high decrease in the extent of the wetland.

3.3 Results

3.3.1 Satellite-derived wetland land use land cover change (1983-2019)

Derived maps were produced, using SVM, in order to understand the rate of conversion for the period between 1983 and 2019 (see Figure 3.3). It was observed that in 1983 the wetland, other vegetation, bare land and agriculture dominated the entire study area. Wetland areas were found in all directions, other vegetation occupied the larger part in the south, and agriculture occupied the western parts of the wetland. In 1992, a considerable portion of agriculture had been converted to forest. Although the wetland covered a larger area in 2001, part of its areal extent was replaced mainly by vegetation or bush encroachment. During 2010 and 2019, there was a sharp increase in the built-up area, which replaced a large portion of the wetland area. In 2010, the area under agriculture increased, when compared to the year 2002, particularly on the western side of the study area. Overall, the maps showed a decline in wetland coverage, which was replaced by built-up areas.


(a)
Land cover classes 1983
Agriculture
Bareland
Built up
Forest
Other vegetation
Water
Wetland
0 2 4 6 km
(b)
Land cover classes 1992
Agriculture
Bareland
Built up
Forest
Other Vegetation
Water
Wetland
0 2 4 6 km


(c)
Land cover classes 2001
Agriculture
Bareland
Built up
Forest
Other vegetation
Water
Wetland
0 2 4 6 km
(d)
Land cover classes 2010
Agriculture
Bareland
Built up
Forest
Other vegatation
Water
Wetland
0 2 4 6 km

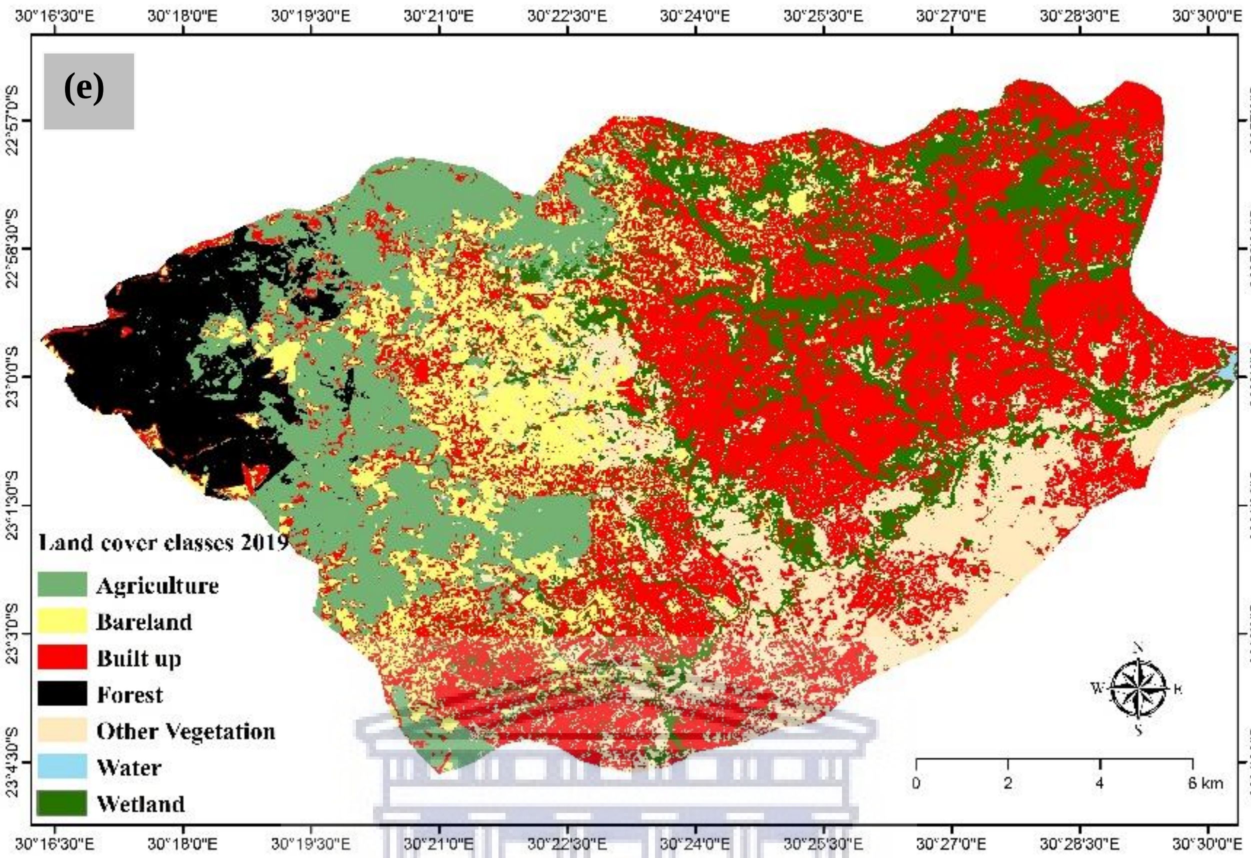


Figure 3.3 Spatial distributional pattern of identified land use land cover change maps for the period between (a) 1983, (b) 1992, (c) 2001, (d) 2010 and (e) 2019

Table 3.4 Summary of the land use land cover area coverage between 1983 and 2019 (area in ha)

LULC types	Total change in area									
	1983		1992		2001		2010		2019	
	Area	%	Area	%	Area	%	Area	%	Area	%
Agriculture	201 900	8.11	286 800	11.51	175 100	7.03	406 400	16.32	373 700	15
Bareland	352 100	14.13	348 100	13.98	389 300	15.63	207 000	8.31	289 000	11.60
Built up	79 100	3.17	901 00	3.62	121 400	8.87	402 000	16.14	934 300	37.51
Forest	115 800	4.65	115 000	4.62	153 700	6.17	208 800	8.38	171 400	6.89
Other vegetation	668 400	26.84	680 400	27.32	685 100	27.51	511 700	20.54	375 400	15.07
Water	100	0.0004	5 000	0.20	22 100	0.89	40 400	0.16	18 900	0.08
Wetland	1 073 500	43.10	965 300	38.75	944 100	37.90	750 900	30.15	345 100	13.85

3.3.2 Spatio-temporal change analysis of wetland area over time

The spatio-temporal change analysis of the wetland area has been presented in Figure 3.4 and Table 3.4. During the study period, five (5) thematic maps were derived by using the SVM classifier to assess the change dynamics of the Maungani wetland area for the years 1983, 1992, 2001, 2010 and 2019. This wetland experienced significant change due to anthropogenic activities. In the year 1983, the wetland was the dominant land feature type, covering 43.10% (10 734 900 ha) of the total area, followed by other vegetation that covered 668 400 ha (26.84%). It was also observed that in the western part of the study site, agricultural land occupied an area of about 201 900 ha (8.11%), and in the eastern part, the concentration of built-up areas was 79 100 ha (3.17%), respectively. It can be observed from the map that the wetland area decreased by 108 200 ha, to 965 300 ha (38.76%), in 1992, when compared with areal coverage in 1983. Overall, there was an increase in areas with vegetation, in bare land and built-up areas, which covered an area of 680 400 ha (27.32%), 286 800 ha (11.52%) and 90 100 ha (3.62%), respectively. On average, the wetland shrunk greatly, with much of the area being replaced by bushy vegetation (27.32%) in the south towards the eastern part of the study site and bare land (13.97%). It was observed that more than 50% of wetland area was lost to other land cover classes from 2001, with 944 100 ha (37.90%) of the wetland remaining. Other vegetation covered 685 100 ha, mainly in the east and south of the study site ha (27.51%), with bare land covering 389 300 ha (15.63%) and a consistent increase in built-up areas, which occupied approximately 8.87% of the wetland. In the year 2010, the wetland area remained at 750 900 ha (30.15%), with an increase in the vegetation and built-up areas occupying major parts of the wetland, with an aerial extent of 511 700 ha (20.54%) and 402 000 ha (16.14%), respectively. In addition, during the year 2019, the results revealed that the wetland was impacted by other LULC changes. Only 345 100 ha (13.85%) of the wetland remained unaffected. When compared to the year 1983, the Maungani wetland lost approximately 728 300 ha in 2019. This observation was further confirmed by the results in Figure 3.6, which show the trends of the wetland change and other LULC changes that occurred within the study area. The overall classification during the study period (1983-2019) showed that the wetland area lost 728 300 ha of its spatial extent to vegetation covered areas with 375 400 ha (15.07%), and built-up areas with 934 300 ha (37.51%), respectively.

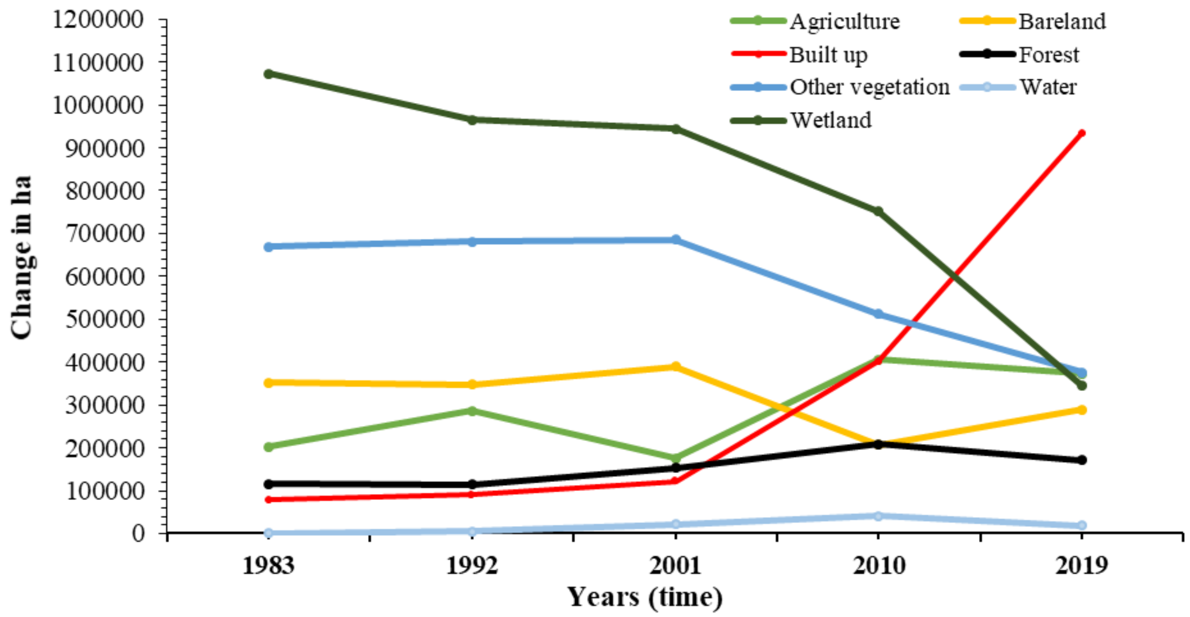


Figure 3.4 Time series variation of land use land cover change and wetland dynamics from 1983 to 2019

3.3.3 Accuracy assessment derived from thematic maps

Based on ground-truth data and Google Earth imagery, the derived satellite images of the wetland area were validated (Figure 3.6). Between 1983 and 2019, the SVM classifier achieved higher overall classification accuracies, ranging from 77.55% to 92.24% (see Table 3.5). During the years 1983, 1992, 2001, 2010 and 2019, the overall classification accuracies achieved were 87.76%, 77.55%, 92.24%, 91.43% and 83.67%, respectively, which indicate that there was agreement between the reality on the ground and the satellite-derived images. However, in this study, the accuracies of the producers and users generating LULC maps were satisfactory and ranged from 42.86% to 100%. The commission, agreement, and omission errors (see Figure 3.5) were found to be the lowest for the year 2001 and ranged between 0% and 3%.

Table 3.5 Derived land use land cover classification accuracies: Overall Accuracy (OA), Producer Accuracy (PA) and User Accuracy (UA) between the years (a) 1983, (b) 1992, (c) 2001, (d) 2010 and (e) 2019

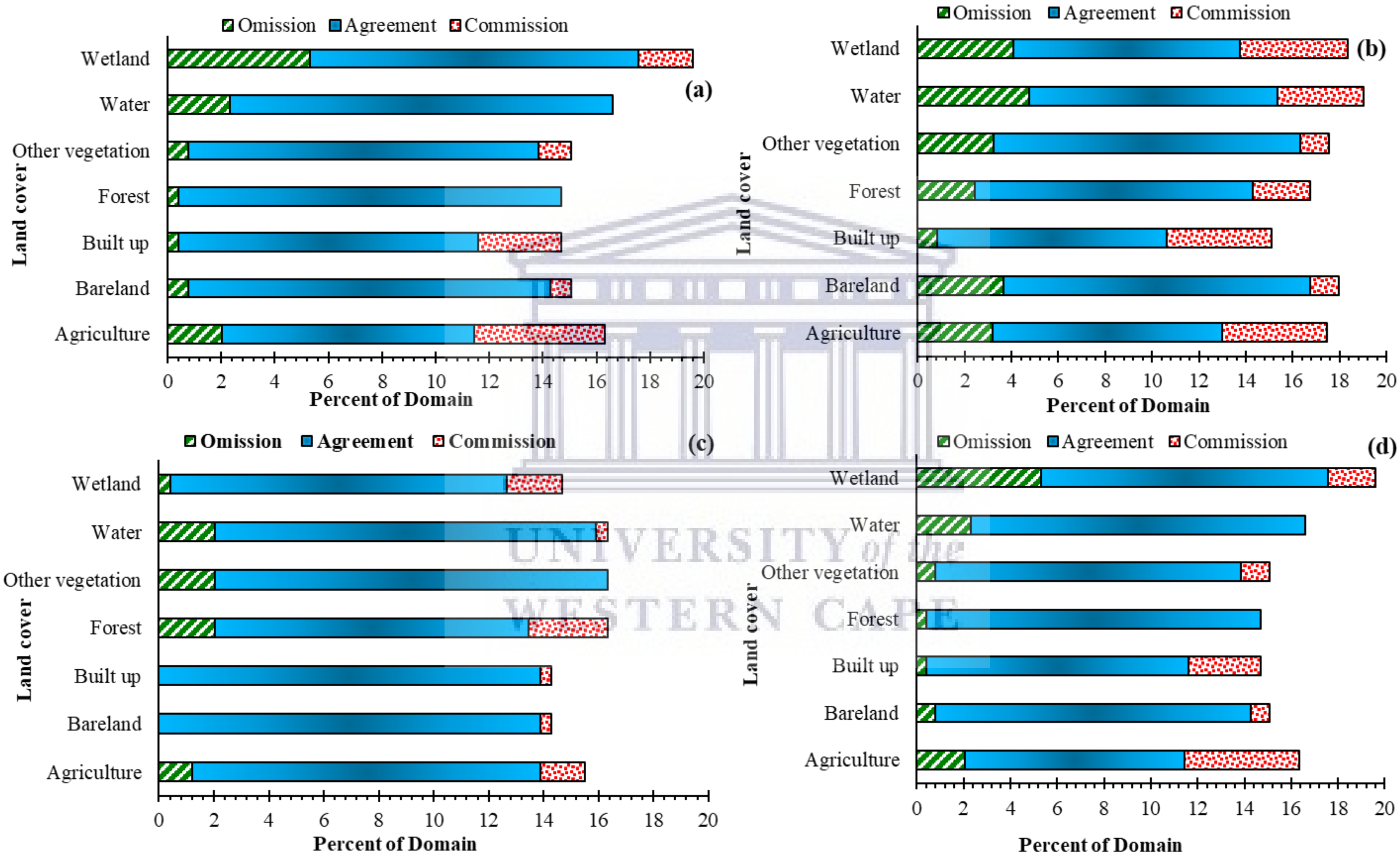
1983 [a]	Agriculture	Bare land	Forest	Other vegetation	Water	Wetland	Built up	Total	**UA (%)**
Agriculture	23	0	1	0	0	11	0	35	**65.71**
Bare land	0	35	0	0	0	0	0	35	**100**
Forest	0	0	31	0	4	0	0	35	**88.57**
Other vegetation	0	0	0	32	0	2	1	35	**91.43**
Water	0	0	0	0	35	0	0	35	**100**
Wetland	5	0	0	0	0	30	0	35	**85.71**
Built up	0	2	0	2	2	0	29	35	**82.86**
Total	28	37	32	34	41	43	30	245	**87.76**
PA (%)	**82.14**	**94.59**	**96.88**	**94.12**	**85.37**	**69.77**	**96.67**		

1992 [b]	Agriculture	Bare land	Built up	Forest	Other vegetation	Water	Wetland	Total	**UA (%)**
Agriculture	24	0	0	2	1	3	5	35	**68.57**
Bare land	0	32	0	0	3	0	0	35	**91.43**
Built up	0	8	24	0	3	0	0	35	**68.57**
Forest	4	0	0	29	0	2	0	35	**82.86**
Other vegetation	0	0	2	0	32	0	1	35	**91.43**
Water	0	1	0	4	0	26	4	35	**74.29**
Wetland	4	0	0	0	1	7	23	35	**65.71**
Total	32	41	26	35	40	38	33	245	**77.55**
PA (%)	**75**	**78.05**	**92.31**	**82.86**	**80**	**68.42**	**69.79**		

2001 [c]	Agriculture	Bare land	Built up	Forest	Other vegetation	Water	Wetland	Total	**UA (%)**
Agriculture	31	0	0	4	0	0	0	35	**88.57**
Bare land	0	34	0	0	0	0	1	35	**97.14**
Built up	0	0	34	0	1	0	0	35	**97.14**
Forest	2	0	0	28	0	5	0	35	**80**
Other vegetation	0	0	0	0	35	0	0	35	**100**
Water	0	0	0	1	0	34	0	35	**97.14**
Wetland	1	0	0	0	4	0	30	35	**85.71**
Total	34	34	34	33	40	39	31	245	**92.24**
PA (%)	**91.18**	**100**	**100**	**84.85**	**87.50**	**87.18**	**96.77**		

2010 [d]	Agriculture	Bare land	Built up	Forest	Water	Wetland	Other vegetation	Total	UA (%)
Agriculture	34	0	0	0	0	1	0	35	**97.14**
Bare land	0	31	0	1	1	0	2	35	**88.57**
Built up	0	3	32	0	0	0	0	35	**91.43**
Forest	0	0	0	35	0	0	0	35	**100**
Water	0	0	0	1	34	0	0	35	**97.14**
Wetland	1	1	0	0	0	30	3	35	**85.71**
Other vegetation	0	0	0	0	0	7	28	35	**80**
Total	35	35	32	37	35	38	33	245	**91.43**
PA (%)	**97.14**	**88.57**	**100**	**94.59**	**97.14**	**78.95**	**84.85**		

2019 [e]	Agriculture	Bare land	Built up	Forest	Other Vegetation	Water	Wetland	Total	UA (%)
Agriculture	15	0	0	0	0	20	0	35	**42.86**
Bare land	0	32	0	0	3	0	0	35	**91.43**
Built up	0	2	30	1	1	1	0	35	**85.71**
Forest	0	0	0	32	0	3	0	35	**91.43**
Other Vegetation	0	0	0	0	35	0	0	35	**100**
Water	9	0	0	0	0	26	0	35	**74.29**
Wetland	0	0	0	0	0	0	35	35	**100**
Total	24	34	30	33	39	50	35	245	**83.67**
PA (%)	**62.50**	**94.12**	**100**	**96.97**	**89.74**	**52**	**100**		


Omission
Agreement
Commission
(a)
(b)
(c)
(d)
Wetland
Water
Other vegetation
Forest
Built up
Bareland
Agriculture
Land cover
Percent of Domain
0
2
4
6
8
10
12
14
16
18
20

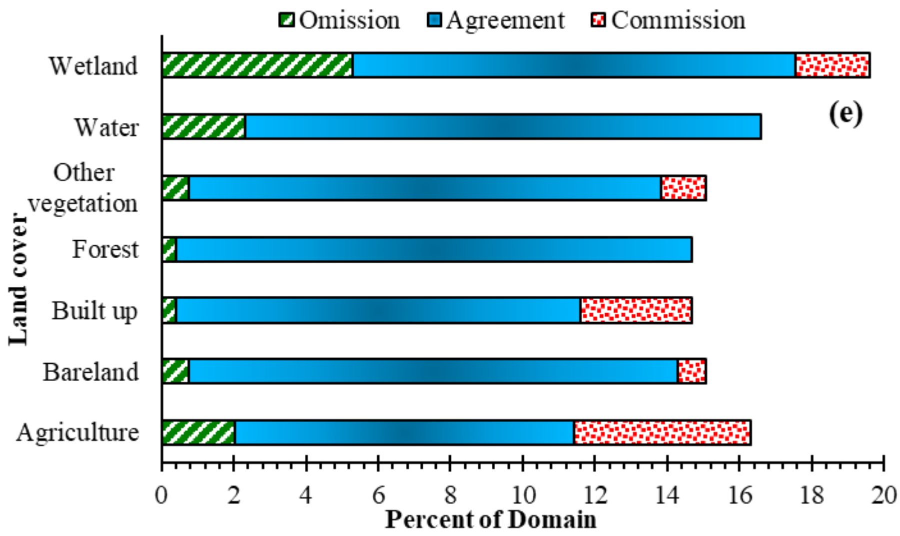


Figure 3.5 Commission, omission error depicted in (a) 1983, (b) 1992, (c) 2001, (d) 2010 and (e) 2019

3.3.4 Increase and loss of land use land cover (net-change)

The spatial information in Figure 3.6 and Table 3.6 for the period under study revealed that both gains and losses occurred within the boundary of Maungani wetland boundary. The net-changes, as a result of gains or losses for each LULC type between 1983-1992, 1992-2001, 2001-2010 and 2010-2019, are depicted in Figure 3.5. We realised that much of the wetland was lost (108 200 ha) between 1983 and 1991, while the agriculture and built-up areas increased by 78 000 ha and 11 100 ha, respectively. Between 1991 and 2001, the agriculture and wetland areas lost 118 200 ha and 71 900 ha, respectively, while the built-up areas (31 300 ha) and bare lands (41 200 ha) gained in their spatial extent. Between 2001 and 2010, the wetland (193 200 ha), bare lands (173 400 ha) and other vegetation (182 300 ha) lost the most spatial extent, whereas between 2001 and 2010, the built-up areas (280 600 ha) and agriculture (231 300 ha) gained a larger proportion. Furthermore, the wetland (405 800 ha) and other vegetation (136 300 ha) suffered the greatest declines between 2010 and 2019. The built-up and agricultural areas covered an aerial extent of 532 400 ha and 82 000 ha, respectively. The wetland lost an aerial extent of about 728 400 ha between 1983 and 2019. The built-up area was found to be the most dominant feature class, occupying 855 300 ha of the total area. In the same period, other vegetation (393 000 ha) lost its spatial coverage over the same time-frame, while agriculture gained coverage by 171 800 ha and 855 300 ha, respectively.

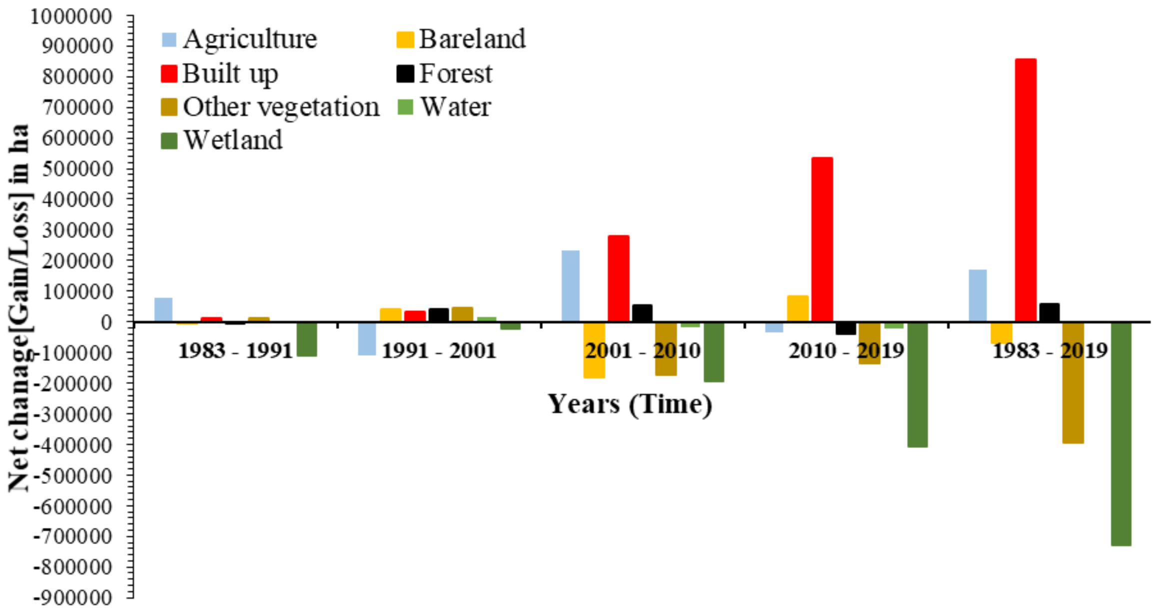


Figure 3.6 Total area and amount of land use land cover changes (Net change: gains/losses) on wetland area between 1983 and 2019

Table 3.6 demonstrates the percentage loss of wetlands to other LULC types between 1983 and 2019. The spatial extent of wetlands has experienced a massive modification, compared to other LULC types, during the period of study. Over the period of 36 years, 728 300 ha of the wetland area was lost. The majority of the wetland was lost to 784 500 ha of built-up areas and 22.97% of agricultural land.

Table 3.6 Land use land cover change transition between land cover classes 1983 to 2019

Initial state (1983)/Final state (2019)	**Transition of change between LULC classes**						
	Agriculture	**Bare lands**	**Built up**	**Forest**	**Other vegetation**	**Water**	**Wetland**
Agriculture	171 800	21 700	296 700	257 900	-294 700	373 700	-699 700
Bare land	87 100	-63 100	209 900	173 200	-379 500	288 900	-784 500
Built up	732 500	582 300	855 300	818 500	265 900	934 300	-139 100
Forest	-30 500	-180 700	92 300	55 600	-497 100	171 400	-902 000
Other vegetation	173 500	23 300	296 300	259 600	-293 000	375 400	-698 000
Water	-2 000	-350 200	-77 200	-113 900	-666 500	11 900	-1 071 500
Wetland	143 200	-69 800	266 000	229 300	-323 300	345 100	-728 300

3.3.5 Change detection measurements that occurred over a 36-year period

The spatial extent of the Maungani wetland has declined over the years, compared to other LULC types. In Figure 3.7, it can be observed that there has been a major transformation in the wetland between 1983 and 2019, due to the rapid population growth and anthropogenic activities. In Figure 3.8, it can be observed that the wetland (2550.19 ha), other vegetation (4190.47 ha) and bare land (1949.67 ha) were largely converted to built-up areas. The LULC cover transition replaced the wetland area, particularly in the low-lying areas. Pockets of wetland were also converted into other LULC classes.

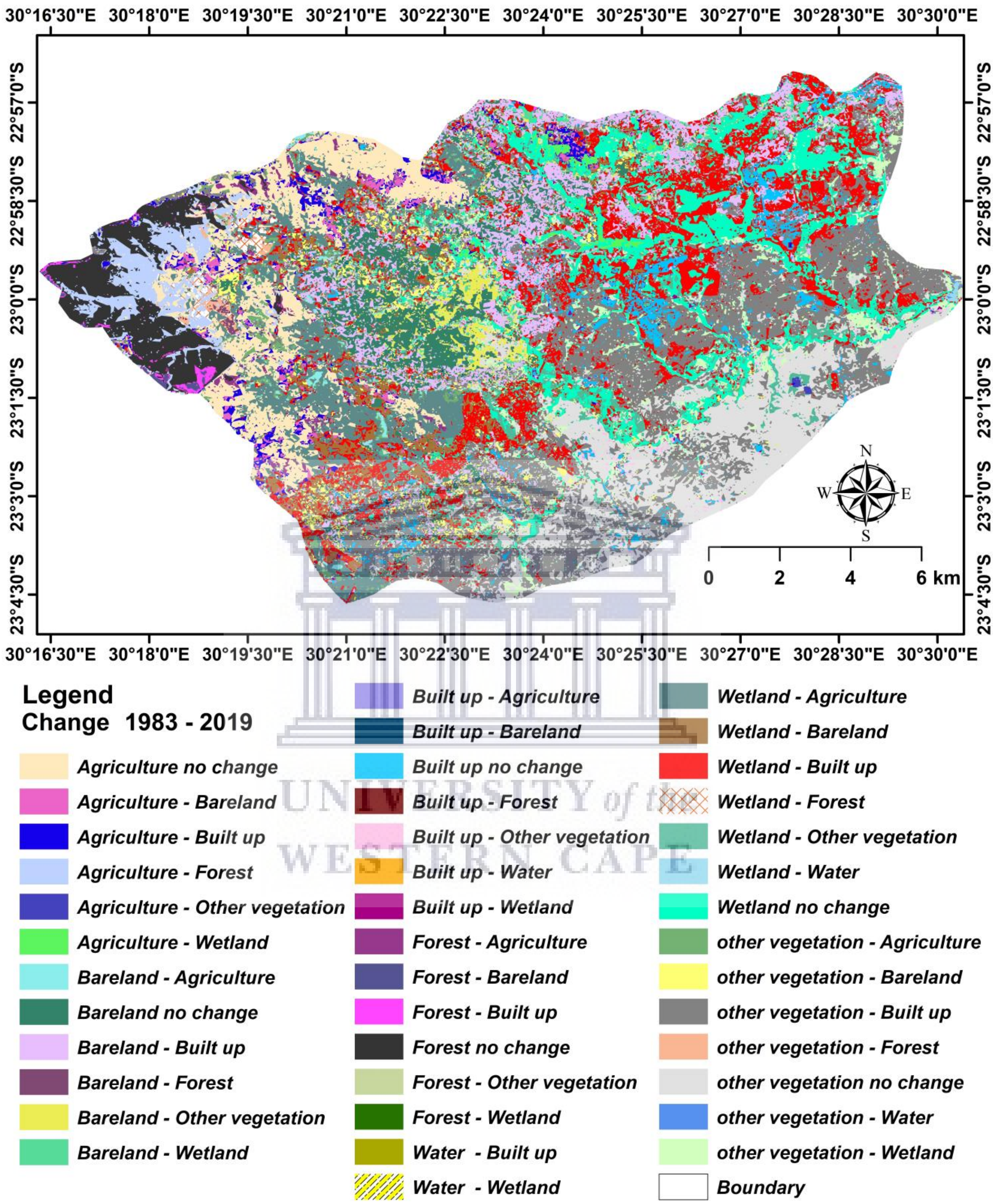


Figure 3.7 Overall land use and land cover conversion during the monitoring period (between 1983 to 2019)

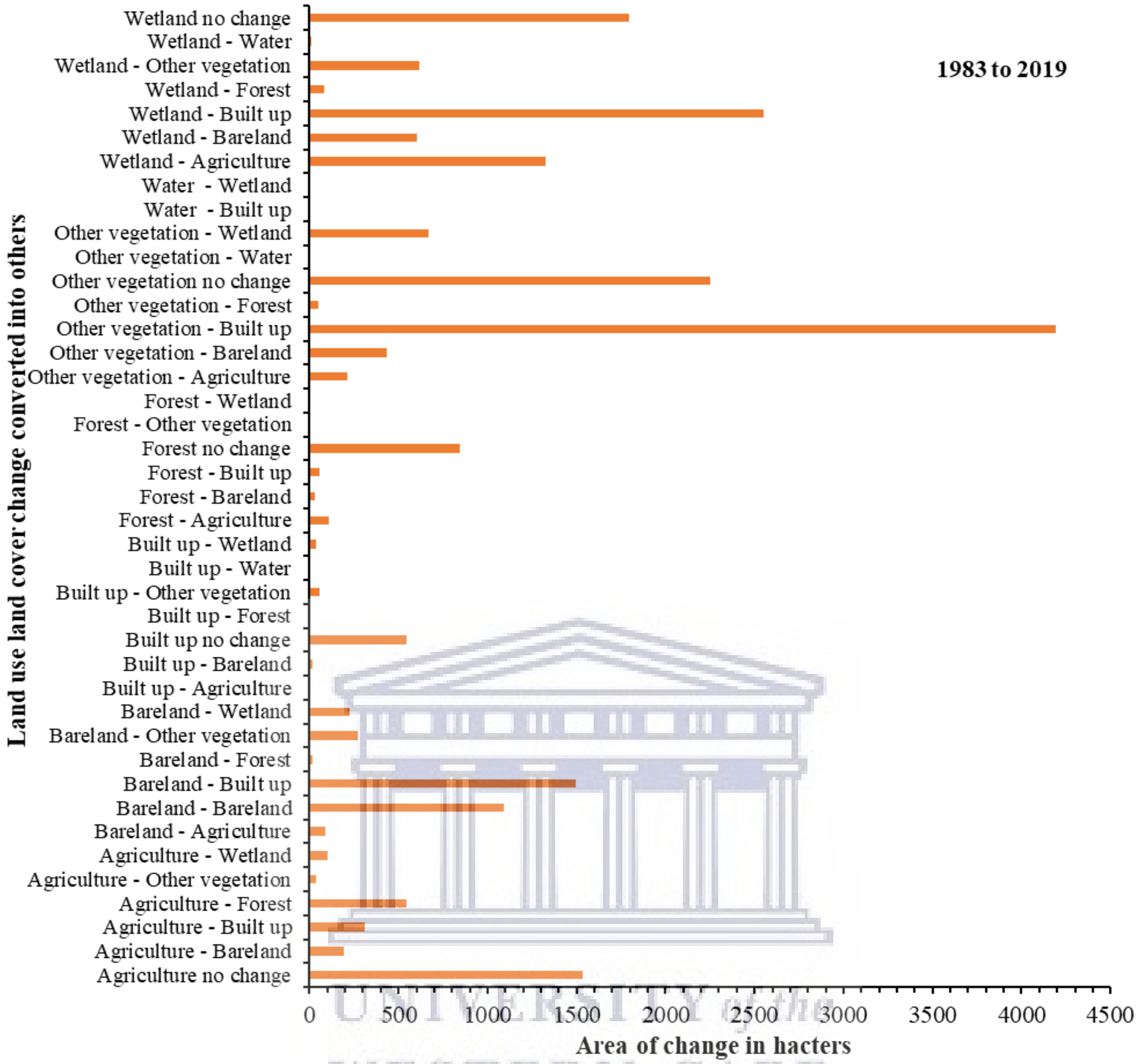


Figure 3.8 Area of the Maungani wetland ecosystem converted into other land use and land cover classes

3.4 Discussion

The present study investigated the impacts of LULC change dynamics on the unprotected Maungani wetland, which is located in the semi-arid tropical regions of the Limpopo Province, South Africa. The freely-available Landsat satellite data and Support Vector Machine enabled the study of the wetlands and LULC changes between 1983-2019 (a 36-year period).

3.4.1 Wetland dynamics in relation to other land use and land cover changes between 1983 and 2019

The findings obtained from the study showed that the Maungani wetland has been subjected to continuous decline over the last 36 years (1983-2019). The wetland shrunk by 74.94% between 1983 and 2019. On the other hand, the built-up areas continuously expanded into the wetland area and it was confirmed that 10.40% of wetland was lost to these areas. The loss of wetland to built-up areas is mainly attributed to population growth in the area. The population growth raised from 53 376 in 1996, 58 149 in 2001 and 618 462 in 2011 which increased demand for land for residential purposes or economic development in the vicinity of Maungani (STATSSA, 2011). In agreement with the 2011 census data, the national population, which includes the Maungani local community, was reported to have increased to 51.8 million in 2011 (STATSSA, 2011). Other studies have also shown that the built-up areas are one of the major threats to unprotected wetland ecosystems. Wang *et al*. (2012), for example, revealed that urbanisation and the influx of migrants have resulted in a sharp decline in regional ecological land in China. The ecological value of wetland ecosystems that occur in areas with a rapid population growth and economic development is lower, as in the Maungani area; however, a similar effect has been observed in other areas e.g. in Ethiopia and Zimbabwe (Dubeau *et al*., 2017; Marambanyika *et al*., 2017). As depicted by the 1983 image, the population growth rate was low to the south and to the east of the wetland, when compared to high influx in the built-up areas in 2019, which shows the influence of the rapid population growth.

On the other hand, the least areal coverage of wetland was converted to forest (3.41%), bare land (8.60%) and other vegetation (9.24%) between the year 2000 and 2019. During the study period, it was also observed that there was a gradual increase in the deterioration of the wetland near the built-up area south-east of it, when compared to other areas of the study. The increase in infrastructural development in the built-up area fuelled the loss of the spatial extent of the wetland. These is due to the flat terrain, because when the wetland gets dry, people occupy and develop the land. The drying of the land is associated with the decreased precipitation pattern and increased climatic conditions, as a result of climate change, which puts pressure on the extent of the wetland. Furthermore, human interference worsens the ecological condition of the Maungani wetland. Despite the high loss of its spatial extent, the wetland gained 2.37% from other vegetation and 0.92% from water. The wetland lost its major cover and other land cover types, such as water (37.08%), forest (33.99%), cultivated land (25.16%), as well as bare land (26.15%). In 2015, it was observed that there was an increase in the development of settlements to the south-east of the wetland, when compared to other portion of the study. Bare land dominated the north-east of the study area and, in 2019, a large portion of this area was converted to a built-up area. Urban development has a major influence on wetland shrinkage. Similar trends were observed in other parts of the continent. Studies by Mhlanga *et al*. (2014) and Chikodzi and Mufori (2018) showed that human activities transformed the wetland hydrology in parts of the Harare metropolitan district in Zimbabwe, reducing their spatial extent, as these ecosystems were replaced by buildings or developments that affected the wetland retention, and eventually led to a loss of habitat for the aquatic species. In South Africa, Phethi and Gumbo (2019) found that poverty and population growth were the driving forces behind wetland mismanagement. They revealed that the cultivation of crops, road construction and built-up development, during the period from 1978 to 2004, were the main activities that contributed to the deterioration of the Makhitha wetland, located in the Limpopo Province. On the other hand, Orimoloye *et al*. (2020) conducted a spatial pattern of the Isimangaliso Wetland by using Landsat data between 1987 and 2017 and witnessed a significant change in the extent of the wetland during the study period (from 655.42 km^2 to 429.49 km^2). Climate change, built-up areas and agricultural activities were found to be the major factors that replace the extent of wetlands.

3.4.2 Long-term wetland monitoring, using Landsat data

Mapping the spatial patterns of wetland areas over time is critical for detecting and monitoring the LULC changes and for understanding their effects on the integrity and ecological functioning of wetland. The use of a freely-accessible, accurate and reliable remote sensing dataset i.e. Landsat, with a 30-m spatial resolution, has enabled the mapping of the spatial extent of LULC in unprotected wetlands that are surrounded by rural communities. This will enable researchers and other wetland managers to investigate the spatial transformation of wetland over particular time periods (i.e. 1983-2019). Our approach supplements the wetland characterization systems that have demonstrated the use of multi-temporal mapping of wetland areas for understanding the pattern of LULC changes degrading wetland ecosystems (Gómez-Rodríguez *et al*., 2010; Rover *et al*., 2011; Knight *et al*., 2013). Gabrielsen *et al.* (2006) employed a time-series approach in their analysis, which resulted in temporal wetland predictions regarding the probability of wetland inundation, and it is more successfully characterises wetlands as ephemeral inclines. Their strategy effectively uses high- and moderate-resolution data to measure the likelihood of wetland inundation and the prospect that wetlands may be wet over time. Multi-temporal approaches derived by Gabrielsen *et al.* (2006) produced lower prediction errors of Rapid Eye 3.1–15% and Landsat 0.3–1.5% in the Northern Great Plains of the USA.

The Landsat data series has shown its capabilities for depicting and accurately mapping complex wetland areas and the surrounding LULC dynamics. The information depicted by Landsat images is critical for aquatic and wetland management and decision-making, especially in regions that have a restricted network system of field observation frameworks in place (Thamaga and Dube, 2019). The findings of this study are consistent with previous investigations and they underscore the precision and strength of using Landsat data for long-term mapping in wetland-related studies, LULC quantification, biomass estimation, crop and fire mapping, aquatic plant species and urban development (Dube and Mutanga, 2015; Robinson *et al*., 2016; Dube *et al.*, 2018; Rampheri *et al*., 2020). Jin *et al*. (2017) demonstrated the unique strength and superiority of Landsat missions, as well as their practical viability in accurately mapping, detecting and monitoring the spatio-temporal changes for wetland assessment over-time. Although the imagery has been used in larger areas, particularly the wetlands recognised by the Ramsar Convention (Mozumder and Tripathi, 2014), its application in small and unprotected wetlands serving the surrounding communities remains limited and under-studied. This demonstrated the ability of Landsat to map wetland conditions, using publicly-available data, especially in data-scarce regions, such as in the semi-arid tropical regions of the sub-Saharan Africa, and it would greatly assist in accurately deriving, monitoring and reporting on the health condition and rate of degradation of wetlands.

Although the study provides an insightful overview of the state of unprotected wetlands in the arid tropical regions of sub-Saharan Africa, the understanding of these ecosystems could be better depicted through the integration of multi-source data, including the perceptions of indigenous communities as well as seasonal dynamics. In addition, considering that wetland LULC characterisation was done by using broadband and spatial resolution satellite data, some inherent changes could have been missed. The 30-m spatial resolution of Landsat is associated with spectral mixing, which results in its poor discrimination ability. In this regard, spatially-explicit methodologies must be explored that focus on analysing changes in the soil moisture, different types of vegetation or indices, as well high-resolution data. More so, there is need to include climate and soil data, so as to determine whether these changes are solely linked to anthropogenic activities. For example, the study showed that there was also an increase in vegetation (bush encroachment) in the wetland and that this may be due to climate variability and climate change (Bhaga *et al*., 2020). A review study by Bhaga *et al*. (2020) demonstrated that climate variability and recurrent droughts have caused remarkable strain on water resources in most regions across the globe, with the arid and semi-arid areas being the hardest hit and that this is likely to have an effect on the wetland conditions. This assertion is further strengthened by the work of Gxokwe *et al*. (2020), who noted that wetlands are degrading at a rapid rate globally, due to the environmental changes. Lastly, we assume that the provision of information on the accuracy of individual maps is likely to be insufficient, and hence there is a need for further studies to consider accuracy assessment of land use change, by using stratified estimation (Olofsson *et al*., 2013; Olofsson, *et al*., 2014). Robust and transparent statistical approaches for assessing accuracy and estimating the areas of change are critical for ensuring the integrity of land change information. It is therefore imperative to adopt the holistic monitoring of wetlands, as well as an assessment framework that includes climate and environmental data in the long-term mapping and modelling of wetland changes and their possible degradation.

3.4.3 Implications for wetland conservation and land use and land cover management

The complexities of wetland ecohydrological processes necessitate a profound interpretation of LULC transition, as these changes influence the spatial extent of wetlands, the diversity, the waterflow, and ultimately, the proliferation of alien plant species. According to the findings of this study, the extent of the wetland ecosystem area is diminishing rapidly. This information provides the requisite baseline information required by environmental and wetland managers to devise sustainable intervention measures and strategies to curb the further deterioration of ecohydrological systems from the possible threats emanating from both anthropogenic and natural causes. These necessitate responsive management strategies to stop or reverse the rate of degradation or loss of wetlands, especially unprotected wetlands that have been overlooked in policy formulation. Increased management strategies, with an emphasis on wetland rehabilitation and restoration, are not backed up by adequate integrated data collection, reliable information and reviews. Uncertainty over the previous policy outcomes for LULC change and wetlands, as well as recent attempts to strengthen their protection, pose critical concerns about their ecological significance. Ecosystem managers need to strengthen their implementation policies to conserve wetland ecosystems, and to minimise the rate of their shrinkage, the extension of urban landscape patterns must be regulated.

3.5 Conclusions

This work explored the impacts of LULC change on wetland ecosystems in the Maungani wetland, which is located in the semi-arid tropical regions of South Africa. The integrated time-series Landsat data and Support Vector Machine algorithms were used to depict and model the historical LULC and wetland change for a period of 36 years (1983-2019) to overcome the degradation and to contribute towards the sustainable management of these wetland ecosystems. There has been a widespread conversion of wetlands during the period of study. Based on our findings, the following conclusions were drawn.

- The Maungani wetland has undergone significant changes in terms of the LULC change dynamics over the years (1983 to 2019).
- Derived thematic maps show that the degraded wetland size has been largely replaced by built-up areas.
- The Maungani wetland has shrunk dramatically from 1 073 500 ha (43.10%) in 1983 to 345 100 ha (13.85%) in 2019.

Overall, the findings of this study demonstrated the use of historical and archival Landsat data series for understanding the effects of LULC change on the spatial extent of wetlands located in semi-arid tropical regions of sub-Saharan Africa. The Landsat data-series offers the novel, accessible and up-to-date information that is required for the accurate monitoring of LULC change dynamics. The rate of degradation and encroachment by other LULC changes, especially on unprotected wetlands, plays a critical role in the surrounding communities. Furthermore, this work shows that there has been a steady deterioration of the Maungani wetland over the past 36 years. As a result, in order to combat the challenges of LULC change for the sustainability of the catchment areas, this work recommends a holistic framework approach in the management of wetland resources. This comprehensive information can be used as a guideline for future LULC assessments, monitoring and planning.

CHAPTER 4

MODELLING WETLAND VEGETATION USING INTEGRATED SENTINEL-2 MSI AND DIVERSITY INDICES IN SEMI-ARID REGIONS

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Abstract

Wetland vegetation is a key indicator of the health status of vegetation in small wetland ecosystems. The accurate estimation of wetland species diversity is therefore critical for monitoring the ecosystem behaviour, in order to understand the changes in vegetation distribution and productivity patterns. Monitoring wetlands, given their vulnerability to anthropogenic pressures, including those associated with climate change, hydrodynamics and sewage waste disposal, will improve the management of these wetland systems. In this study, the plant species diversity and biomass were estimated, using the new generation Sentinel-2 MSI data. The study was conducted in the Maungani wetland, which is situated in the Limpopo Province of South Africa. Four species diversity indices (e.g. the Margalef, Pielou, Shannon-Wiener and Simpson indices), Sentinel-2 derived spectral bands and vegetation indices were used to estimate the wetland vegetation diversity and biomass across the study area. The findings of this study showed that the diversity and biomass of vegetation species can be estimated with a high accuracy by using Sentinel-2 data. For instance, the model performances ranged from a r^2 of 0.54 (54.72%) (RMSEP = 0.572 gm^{-2}) to r^2 of 0.84 (84%) (RMSEP = 0.067 gm^{-2}), respectively. Further, the red-edge bands centered at 750 nm (B5), 740 nm (B6), 783 nm (B7), as well as 863 nm (B8a), were identified as the most influential variables in the estimation of wetland vegetation biomass and species diversity. The Margalef index (least) and Simpson index (highest) were identified as the most important diversity indices in estimating the diversity of wetland vegetation species across the Maungani wetland. Using Sentinel-2 derived thematic maps, the Simpson diversity index map showed a higher distribution of species diversity. Overall, the findings of this study underscore the relevance of new generation Sentinel-2 MSI data in estimating and mapping wetland vegetation diversity and biomass, particularly in small wetlands that are non-Ramsar sites.

Keywords: Biomass estimation; Maungani wetland; Red-edge region; Sensor resolution; diversity index; Species richness

4.1 Introduction

Wetland vegetation is an excellent indicator that ascertains the vegetation health condition of small (unprotected) wetland ecosystems, and it characterises the stages of species diversity and productivity (Adam *et al*., 2010; Allan *et al*., 2013). Wetland vegetation is dependent on the presence of water and climate change, particularly rainfall variability, is expected to have a substantial influence on these ecosystems and their associated species. While wetlands account for a comparatively limited proportion of the total productivity, their contribution is nonetheless irreplaceable. The ecological value of wetlands varies, but they are of great importance to the surrounding communities. For example, these wetlands maintain groundwater storage, biodiversity conservation, weather patterns, human health and livelihoods, as well as the nutrient cycle (Mudd *et al*., 2009; Marambanyika *et al*., 2017; Thamaga *et al*., 2021). For instance, sub-Saharan Africa is predominantly rural, and the majority of communities in these areas rely on wetlands for their livelihoods, which puts pressure on these systems. The distribution of wetland vegetation influences the pattern of grazing and wildlife/livestock, especially during the dry season (Zomer *et al*., 2009). However, the species diversity and productivity within a wetland reflects the complexities of their physical, chemical and human habitats (Moss, 2008). According to Gichuki *et al.* (2001), there is a substantial relationship between the quality of the environment, the species diversity and the productivity of wetland vegetation, with large coupling effects occurring in regions that are vulnerable to anthropogenic alterations within a wetland. As a result, wetland vegetation is one of the most significant biophysical features that distinguishes wetland species, and it is required for research on wetland species diversity, productivity and ecohydrological stress.

Unprotected wetlands, particularly those found in developing regions, are largely affected due to the poor regulations and land use management systems that are in place. The species diversity of wetland vegetation can be impacted by environmental disturbances to the extent that the ecosystem is dominated by few native plant species or other competing species (van de la Chenelière *et al*., 2014). Several studies (van de la Chaneliere *et al*., 2014; Bhatnagar *et al*., 2020; Thamaga *et al*., 2021) have demonstrated that the composition of wetland vegetation species diversity is primarily influenced by the slope, aspect, altitude, hydrodynamics and anthropogenic activities. Precipitation, drought and increased temperature variability have impacted the species abundance, dominance, richness and evenness in wetland ecosystems. Thus, the emergence of vascular and nonvascular plant species within demarcated wetlands exemplifies the occurrence of anthropogenic disruptions in catchment areas (Asef *et al.*, 2016). The growing population continues to put great pressure on wetlands and the rate of degradation is increasing over time, particularly in developing regions (Tariku and Abebayehu, 2011; Hagos *et al*., 2014; Marambanyika *et al*., 2017). It is recognised that wetland areas and water systems are at a substantial risk of eutrophication, extensive siltation, resulting in the elimination of native plant species and the encroachment of invasive alien plant species, which has a major effect on species diversity in freshwater environments (Dube *et al*., 2017, Thamaga and Dube, 2018a), and it reduces the ecological value of wetland ecosystems. On the other hand, Burns and Schallenberg (2001) highlighted the fact that agriculture, livestock grazing and wildfires may lower the species diversity in wetland environments, and Marambanyika *et al*. (2021) pointed out that, drought and increased population growth in Zimbabwe has forced people to migrate to, or expand, their agricultural fields in wetland areas. This has a devastating effect and results in the deterioration of spatial extent of wetlands, which could lead to the extinction of biodiversity, thereby decreasing the species diversity. Lastly, the changing climate alters the normative trends and processes by amplifying the environmental stresses, and it can have a cascading effect on the ecological response, wetland vegetation diversity and productivity, and, ultimately, its resilience. Understanding the distribution and characteristics of wetland vegetation will therefore help in their preservation and in the sustainable management of species diversity, under observed environmental changes. Thus, rapid and efficient estimation of wetland vegetation species diversity is required, particularly in small wetland ecosystems.

Traditionally, the methods of estimating wetland vegetation diversity were based on field measurements. However, these methods lack spatial representation, and they are often time-consuming, labour-intensive in large-scale areas, expensive and inefficient (Adam *et al*., 2010; Lumbierres *et al*., 2017; Thamaga *et al*., 2021). Since field measurements are challenging when it comes to the detection and mapping of wetland ecological information over larger areas (Klemas, 2013), remote sensing technologies emerged as an alternative method for solving these limitations. The integration of remote sensing datasets and plot data can provide the continuous local- to regional-scale monitoring and mapping of wetland vegetation diversity, in order to understand its health status and the dynamic changes. A study by Meng *et al*. (2016) demonstrated that remote sensing satellite datasets have drawn significant attention in the derivation of information on species diversity by enabling convenient data acquisition, while retaining an acceptable accuracy. Recent satellite remote sensing techniques for estimating wetland vegetation include optical remote sensing sensors, radio detection and ranging (Radar), light detection and ranging (Lidar), as well as hyperspectral data. Predicting species diversity, from a small to a large geographical scale, remote sensing data has become feasible in the current scientific community, as a result of the expanding spectrum of publicly- and easily-accessible remote sensing products (Kassahun *et al*., 2014).

Satellite images have the advantage of covering wider areas, which provides an opportunity to derive landscape-scale biomass and other related species data. Hyperspectral and multispectral satellite images have been applied in mapping species diversity. Despite the performance of hyperspectral data, their numerous narrow bands make them sensitive in detecting and mapping species diversity characteristics (Adam *et al*., 2010). However, the costs attached to hyperspectral data acquisition and their larger areal coverage make it unsuitable for the estimation of wetland vegetation species diversity in financially-constrained regions (Kassahun *et al*., 2014). Cheap and freely-available multispectral satellite data have demonstrated their potential in mapping and the detection of vegetation distribution (Mutanga *et al*., 2015; Shoko and Mutanga, 2017; Fatoyinbo *et al*., 2018). Several sensors from different platforms, such as RapidEye, IKONOS, Landsat series, MODIS, and SPOT, with varying spatial resolutions, were used for the estimation of species diversity, primary productivity, leaf area index and biomass, and their capabilities in retrieving information on wetland species diversity have been observed (Chen *et al*., 2018; Schug, *et al*., 2020).

As newer sensors, with finer spatial and temporal resolutions and increased spectral information have become available, optical sensors remain one of the most interesting options for vegetation estimation. Advancements in broadband multispectral satellite sensors have increased their potential to improve the efficiency of retrieving vegetation attributes (Thamaga and Dube, 2019). The recent launch of Sentinel-2 MSI offers new avenues for investigating the capabilities of remote sensing for fine-scale diversity classifications and supporting complex wetland vegetation monitoring. Sentinel-2 MSI is freely accessible, which makes it simple for researchers with limited resources to utilise the data and to supplement it with other freely-available datasets, such as the Landsat data series. In many developing regions, like Africa, which lack the financial means to secure commercially-based remote sensing satellite images, Sentinel-2 provides a suitable alternative, with an excellent spatial resolution. The presence of strategically-positioned spectral bands, such as the red edge, which were previously a feature of high-resolution commercial sensors, such as Worldview 2, IKONOS, and others, has its own set of advantages that might enable the delicate detection of species diversity. Its enhanced sensing capabilities have shown significant potential in vegetation detection, mapping and monitoring (Shoko and Mutanga, 2017). Studies have advocated that enhanced spatial resolution from the Sentinel data series have helped to reduce the uncertainty and improved the accuracy of vegetation mapping and species diversity at a finer scale (Chen *et al*., 2018). Pandit *et al.* (2018) explored the potential of Sentinel-2 data in predicting forest biomass, and the biomass estimation model scored an $r^2 = 0.81$, as well as an RMSE = 25.57 t ha^{-1}. Shoko *et al*. (2018) performed a comparative study using the Landsat 8 OLI, Sentinel-2 MSI and Worldview 2, to measure C3 and C4 grasses Above Ground Biomass (AGB). The spatial information derived and performance of Sentinel-2 MSI from different studies need to be tested in wetland ecosystems in order to understand their vegetation dynamics and diversity. Sentinel-2 data have the potential to make a substantial contribution to wetland species diversity and AGB monitoring, mapping and estimation. Therefore, this study seeks to estimate the wetland vegetation species diversity and map wetland vegetation AGB in the Maungani wetland, which is located in the Limpopo River Transfrontier Basin. The study sought to estimate the species diversity using different satellite derivatives and in-situ data.

4.2 Materials and Methods

4.2.1 Field sampling and wetland vegetation species data collection

Field data collection was carried out between the 12^{th} and 16^{th} of February 2020 (Figure 4.1). The data collection time-frame was during the maximum growth or peak productivity of wetland vegetation interaction effects, and it was characterised by moderate and high precipitation. At each sampling location, a square quadrant (1 m by 1 m) made up of wire was randomly placed and the spatial coordinates at the centre of each quadrant were recorded, using a Trimble hand-held Global Positioning System (GPS) receiver at a sub-metre accuracy. The field campaign visited 40 plots distributed across the study area. The quadrant was separated by an interval of at least 10 m along transects (ensuring that the corners of each plot correspond to Sentinel-2 MSI pixels), to measure the species abundance and to minimise auto-correction. The herbaceous species in the quadrants have been identified and their percentage of groundcover was determined. Within each quadrant, the vegetation was harvested and sealed in a plastic bag in the field, and the raw vegetation was then measured and recorded immediately in the laboratory, using a digital scale. After replacing the plastic bags with brown bags, the sample vegetation was initially dried in an oven at 80°C for 36 hours, or until a constant weight was achieved, and then the dry biomass weight was determined. The following species were identified during the field surveys (see Table 4.1):

Table 4.1 List of wetland vegetation classes identified in sampling plots using taxonomic keys

Family	**Names**	**No. of Species**
Amaryllidaceae	*Crinum macowani*	1
Cyperaceae	*Carex austroafricana, Cyperus difformis, Cyperus dive, Cyperus latifidius, Cyperus sexangularis, Schoenoplectus brachyceras*	6
Lamiaceae	*Mentha longifolia*	1
Nymphaeaceae	*Nymphaea nouchalia var.coerulea,*	1
Poaceae	*Phragmites australis, Short mixed C3 and C4 grass, Setaria megaphylla*	3
Thelypteridaceae	*Cyclosorus intteruptus*	1
Typhaceae	*Typha capensis*	1
Xyridaceae	*Xyris capensis*	1
	Total	**15**

Figure 4.1 (a) Cutting of wetland vegetation species within a 1 m by 1 m quadrant (represented by red box), (b) raw vegetation carried in a plastic bag, and (c) species productivity and diversity in the Maungani wetland

4.2.2 Satellite image acquisition and pre-processing

Sentinel-2 MSI, which is a sun-synchronous and polar-orbiting satellite image that covers the study area, was used. The level 1C product, single scene of the Sentinel-2 image was retrieved from the European Space Agency (ESA) Copernicus Open Access Hub (*https://scihub.copernicus.eu/*). The image was delivered orthorectified at a Top of Atmosphere (TOA) reflectance in Universal Transverse Mercator (UTM) projection with the World Geodetic System (WGS). Sentinel-2 MSI imagery has a swath width of 290 km^2 and provides 13 spectral bands at varying spatial resolutions, ranging from 10 m (visible and narrow NIR bands), 20 m (red edge, NIR and SWIR bands) and 60 m (costal aerosol, water vapour and cirrus bands) (see Table 4.2). For this study, we utilised 10 spectral bands (2, 3, 4, 5, 6, 7, 8, 8A, 11 and 12) for analysis. Costal aerosol, water vapour and cirrus bands were excluded from the analysis, due to their relevance in the detection of atmospheric features, and they were considered to be inappropriate for vegetation mapping and monitoring (Thamaga and Dube, 2019). The raw satellite image was pre-processed in the Sentinel Application Platform (SNAP) tool for atmospheric correction, using the Sen2cor module in SNAP software. The spectral bands (red edge, NNIR and SWIR) were resampled to 10 m, based on the nearest neighbourhood technique using sen2cor module, to ensure that all bands had a comparable spatial resolution and to determine the advantage of a higher resolution, for compatibility purposes and for further analysis. Ten (10) spectral bands were stacked, using composite bands under raster processing, and randomly generated sample points (using Hwath tool) were employed to extract multi-values in the ArcGIS 10.6 environment.

4.2.3 Vegetation indices and species diversity estimation models

Traditionally, field observations have been directly linked to wall-to-wall remote sensing data, using statistical models for the estimation of wetland vegetation species diversity. In this present study, spectral reflectance (10 spectral bands) derived from Sentinel-2 MSI for each quadrant were used to calculate 13 selected vegetation indices (Table 4.3), in order to estimate diversity and productivity of the wetland vegetation species. The spectral reflectance is critical for classifying wetland vegetation species because it can be applied to record the biophysical and biochemical attributes of vegetation, such as biomass. The spectral band and derived vegetation indices were reported to have been extensively applied by previous studies to predict and capture vegetation attributes over larger areas (Shoko and Mutanga, 2017; Ramperi *et al*., 2020). These indices capture the sensitivity of vegetation features, while maximising the influence of confounding factors, such as soil background and atmospheric effects or illumination (Xue and Su, 2017). For instance, EVI is sensitive to high biomass regions, due to its correction factor that eliminates the influence of aerosols and canopy backgrounds, while GNDVI is sensitive to variations in chlorophyll. Vegetation indices are based on the capacity of plants to significantly reflect incident electromagnetic signals in the NIR band, when compared to optical bands. These proxies have been applied in wetland vegetation-related studies (Rokni *et al*., 2014; Mahdavhi *et al*., 2017; Eid *et al*., 2020).

Table 4.2 Sentinel-2 Multi-Spectral Imager satellite characteristics. The spectral bands utilised in this study for analysis are shown in bold letters

Band No. and name	**Central wavelength (nm)**	**Bandwidth (nm)**	**Spatial resolution (m)**
1 – Costal aerosol	443	20	60
2 – Blue	**490**	**65**	**10**
3 – Green	**560**	35	**10**
4 – Red	**665**	**30**	**10**
5 – VRE 1	**705**	**15**	**20**
6 – VRE 2	**740**	**15**	**20**
7 – VRE 3	**783**	**20**	**20**
8 – NIR	**842**	**115**	**10**
8a – NNIR	**865**	**20**	**20**
9 – Water vapor	945	20	60
10 – SWIR – Cirrus	1380	30	60
11 – SWIR 1	**1610**	**90**	**20**
12 – SWIR 2	**2190**	**180**	**20**

***VRE**: Vegetation Red Edge, **NIR**: Near Infra-Red, **NNIR**: Narrow Near Infra-Red, **SWIR**: Short Wave Infra-Red

Table 4.3 Vegetation indices that were utilised in the present study with their respective formulae, as well as references

Vegetation index	Formula	Reference
EVI	2.5 * ((NIR – Red)/(1 + NIR + 6Red – 7.5Blue))	(Huete *et al.* 1997; Gao *et al*., 2000)
SAVI	((NIR – Red) * (1 + L))/(NIR + Red + L)	(Huete 1988)
NDVI	(NIR – Red)/(NIR + Red)	(Liu and Huete, 1995)
VARIg	(Green – Red)/green + Red – Blue	Gitelson *et al*., 2002
ARVI	(NIR – (2*(Red – Blue)))/(NIR + (2*(NIR – Blue)))	(Kaufman and Tanré 1992)
PVI	NIR/NIR + R	(Richardson and Weigand, 1977)
GNDVI	(NIR – Green)/(NIR + Green)	(Gitelson *et al*., 1996)
OSAVI	(NIR – Red)/(NIR + Red + 0.16)	(Rondeaux *et al*., 1996)
DVI	NIR – Green	(Tucker, 1979)
CIgreen	(NIR/Red) – 1	(Gitelson *et al*. 2005)
MSR	((NIR/Red) -1)/((NIR /Red)$^{1/2}$ + 1)	(Chen, 1996)
NDVI45	(Red edge1 – Red)/(Red edge 1 + Red)	Delegido *et al*., 2011
S2REP	705 + 35 *((((NIR + R)/2) - RE1)/(RE2 - RE1))	Frampton *et al*., 2013

*Enhanced Vegetation Index **(EVI)**, Simple Adjusted Vegetation Index **(SAVI),** Normalised Different Vegetation Index **(NDVI),** Visible Atmospherically Resistant Index green (**VARIg**), Atmospherically Resistant Vegetation Index **(ARVI),** Perpendicular Vegetation Index **(PVI),** Green Normalized Difference Vegetation Index **(GNDVI),** Atmospherically Resistant Vegetation Index **(ARVI),** Renormalized Difference Vegetation Index **(RDVI),** Difference Vegetation Index **(DVI),** Greenness Index **(GI),** Visible Atmospherically-Resistant Index, **Green chlorophyll index, (NDI45),** Sentinel-2 Red-edge Position **(S2REP),** Modified Simple Ratio (**MSR**)

4.2.4 Wetland species diversity estimation indices

To quantify the wetland vegetation species diversity indices, the Shannon-Wiener, Simpson, Margalef and Pielou presented in Table 4.4 were used for the evaluation process. For each plot placed in this study, the species diversity, richness and evenness were determined by calculating the selected indices and the list of species available. The diversity indices were chosen because of their frequent use in vegetation species modelling. According to the suggestions of Brown *et al*. (2013), the richness, variety and evenness of species were determined. These were determined for each plot by computing the Shannon-Wiener index and identifying the species. The percentage of the plot filled by species *i* is denoted as *pi*, and this value indicates the relative abundance of species *i*. The *pi* was used to compute *H'*, which is a proxy for species diversity, as shown in the following formulae*:*

Table 4.4 The diversity indices used to quantify the wetland vegetation species

Diversity Index	Equation	Description	Reference
Shannon-Wiener index	H' = $-\sum_{i=1}^{s} pi\ln(pi)$	The Shannon-Wiener index articulates the existence of the ith species in a community, its values typically range from 0 to 3.5, with the values correlating to more species diversity. Lower numbers imply a lower degree of species diversity found in the region, and it occurs when all species are present in equal numbers.	Shannon and Wiener (1949)
Simpson index	$D_2 = 1/\sum_{i=1}^{s} pi^2$	The Simpson index estimate the likelihood that two individuals chosen randomly from a sample will belong to the same species. The index has a value between 0 and 1, and the higher value, the greater the sample variety. The index indicates the likelihood that two individuals drawn at random from a sample will be of different species.	Simpson (1949)
Margalef index	$R_1 = \frac{(s-1)}{Inn}$	The Margalef index estimates the variety of species present within a certain area. It is also determined by the amount of vegetation present in the defined region.	Margalef (1958)
Pielou index	J' = $\frac{H'}{H'_{max}}$	The Pielou index is used to measure the relative frequency of species groups. The index can have a quantity of 1 (all species are equally abundant) and 0 (only one type of species). The higher value, the greater the species diversity, and the lower the value, the lower the species abundance.	Pielou (1975)

4.2.5 Regression algorithm used for wetland vegetation prediction

In this study, the Multiple Linear Regression (MLR) method, which is statistical method that uses the spatial distribution of dependent variables, by means of linear combination, to predict the outcomes of the independent variables. The technique was utilised to determine the factors, and the contribution of these components were determined by a repeated iterative regression analysis and significance testing. The MLR is a widely-used method that is used to construct regression models for various prediction applications i.e. grasslands, forests and wetland estimation (Hu *et al*., 2020).

4.2.6 Model assessment for wetland vegetation species diversity

In order to assess the effectiveness of the model in estimating the accuracy of the diversity and productivity of wetland vegetation species, the following three criteria were chosen: determination of coefficient (r^2) (Equation 1), the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE) (Equation 2). R^2 is utilized to determine the collinearity between the predicted and observed vegetation values (the measure of the proportion of variance of a predicted outcome) (Husch *et al.*, 2003). RMSE (Equation 3) is a standard metric for measuring the differences between the estimated value by the model and the actual biomass values; however, it is easily influenced by outliers (Chai and Draxler, 2014). It is suggested that the MAE be used with RMSE for determining the variations of errors in the model (Bui *et al*., 2016). The RMSE and MAE values close to 0 and an R^2 value close to 1 indicate that the model is an accurate predictor. The most accurate model yields a high value of the r^2 and a low RMSE. The Akaike Information Criterion (AIC) was also used to assess the model complexity i.e. a low AIC highlights the most parsimonious model. From each analysis, using the field-based measurement, a better model was identified, and the selected model and its associated variables were then used to produce wetland vegetation diversity maps for the study area.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_{is}-y_{it})^2}{\sum_{i=1}^{n}(y_{is}-\gamma_{it})^2} \qquad \text{Equation 1}$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(y_{is}-y_{it})^2}{n}} \qquad \text{Equation 2}$$

$$MAE = \frac{\sum_{i=1}^{n}|y_{is}-y_{it}|}{n} \qquad \text{Equation 3}$$

Where y_{is} is the i^{th} simulated wetland vegetation value, y_{it} is the real wetland vegetation value among the tested sample points, γ_{it} is the average simulated wetland vegetation for all the tested points, and n is the size of the tested samples.

4.3 Results

4.3.1 Wetland vegetation species diversity estimation models, based on all spectral bands and vegetation indices

Considering the potential of the MLR algorithm for predicting the wetland vegetation species diversity, the model with all input variables provided satisfactory results. The prediction of the diversity of wetland vegetation species is dependent on the combination of selected vegetation indices and spectral bands derived from Sentinel-2 MSI. In this study, 13 vegetation indices, along with ten spectral bands, were required in this analysis to extract the values against the species diversity indices. The wetland vegetation species diversity and abundance estimation (Figure 4.2) were derived from the vegetation indices, using Sentinel-2 image yield coefficient of determination (r^2) value of 0.66 (65.69%), RMSE = 37.78 m g^{-2}, and an AIC of 302.361 for dry biomass. The Shannon-winner index yielded an r^2 value of 0.64 (63.78%), an RMSE of 0.246 m g^{-2} and an AIC of 99.824. The Simpson index achieved the best relationship for predicting and estimating species diversity with r^2 of 0.84 (84.36%), an RMSE = 0.067 m g^{-2} and an AIC of 204.497. The Margalef index yielded an r^2 value of 0.53 (52.72%), an RMSE of 0.572 m g^{-2} and an AIC of 11.662. The Pielou index yielded an r^2 value of 0.70 (69.19%), an RMSE of 0.159 m g^{-2} and an AIC of 134.913. The variable performance of the wetland species diversity indices that are presented in Figure 4.2, illustrated that the Simpson index has the strongest MLR in estimating wetland vegetation species, with the Margalef index having a lower r^2, respectively.

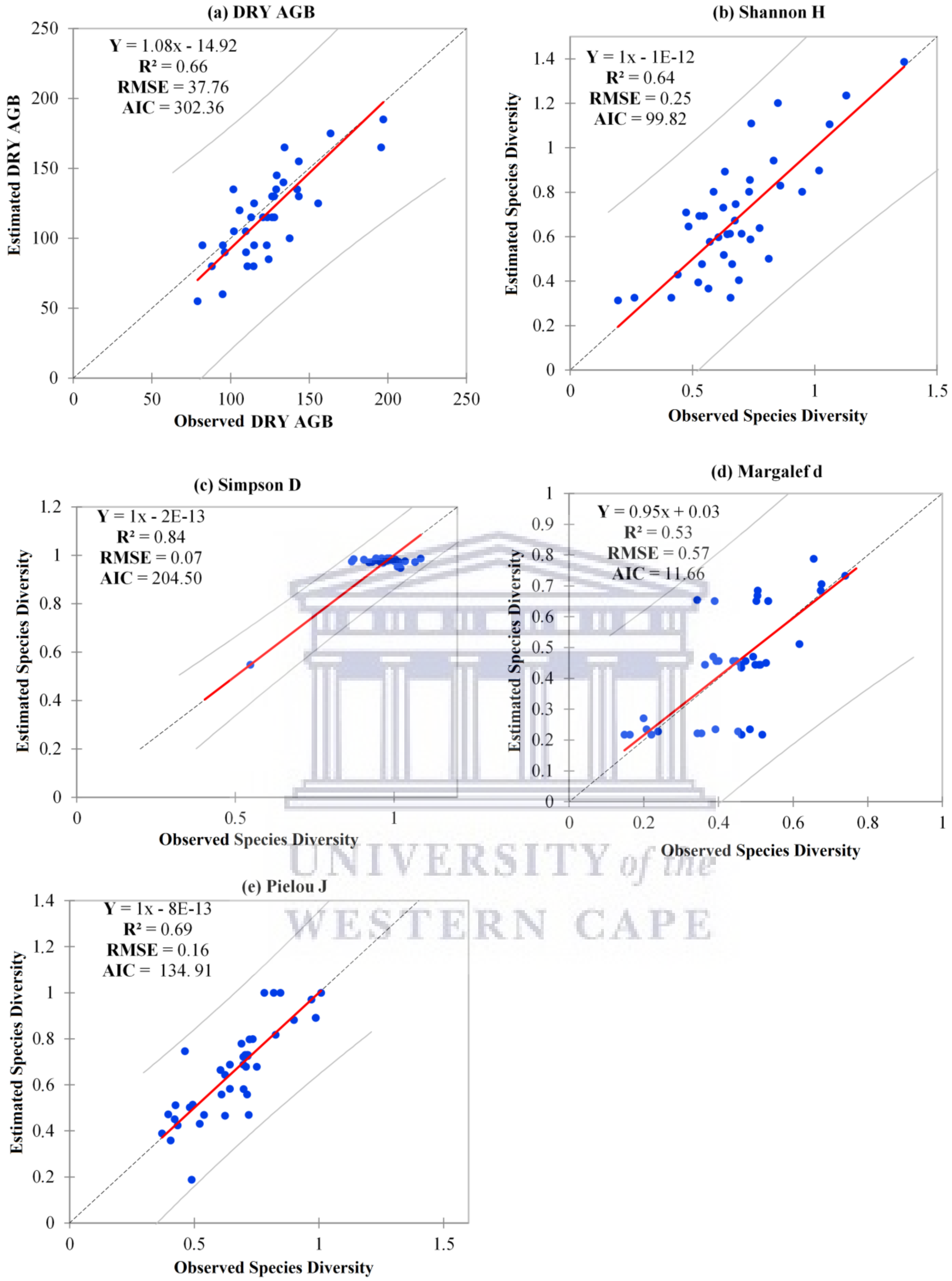


Figure 4.2 Predicted results for: (a) Above Ground Biomass (AGB), (b) Shannon-Wiener Diversity Index, (c) Simpson Diversity Index, (d) Pielou Evenness Index and (e) Margalef Richness Index based on selected variables from remotely sensed dataset, using MLR

4.3.2 Variable of importance measures

The Variable of Importance (VIP) of the individual predictor variables for species diversity estimation models, combined with the remote sensing dataset and vegetation indices, as presented in Figure 4.3, had VIP magnitude of change ranging between 0.3 and 4.6, respectively. It can be observed in Figure 4.3 (a) that PVI, Red-Edge 2, OSAVI and NDVI were the top four largest contributors with Red, NDVI45, Blue and Red-Edge 2 in Figure 4.3 (b). On the other hand, AVIR, NIR, Green and near NIR were identified as the best variables using the Simpson index, MSr, Red, SWIR-1 and S2REP were the best with the Pielou index, and lastly, in the Margalef index, NDVI45, MSR, S4REP and red-edge 2 were ranked the major top-five contributors. Following the VIP results, Red-Edge 2 band was found to be the most variable in improving the estimation of wetland vegetation diversity.

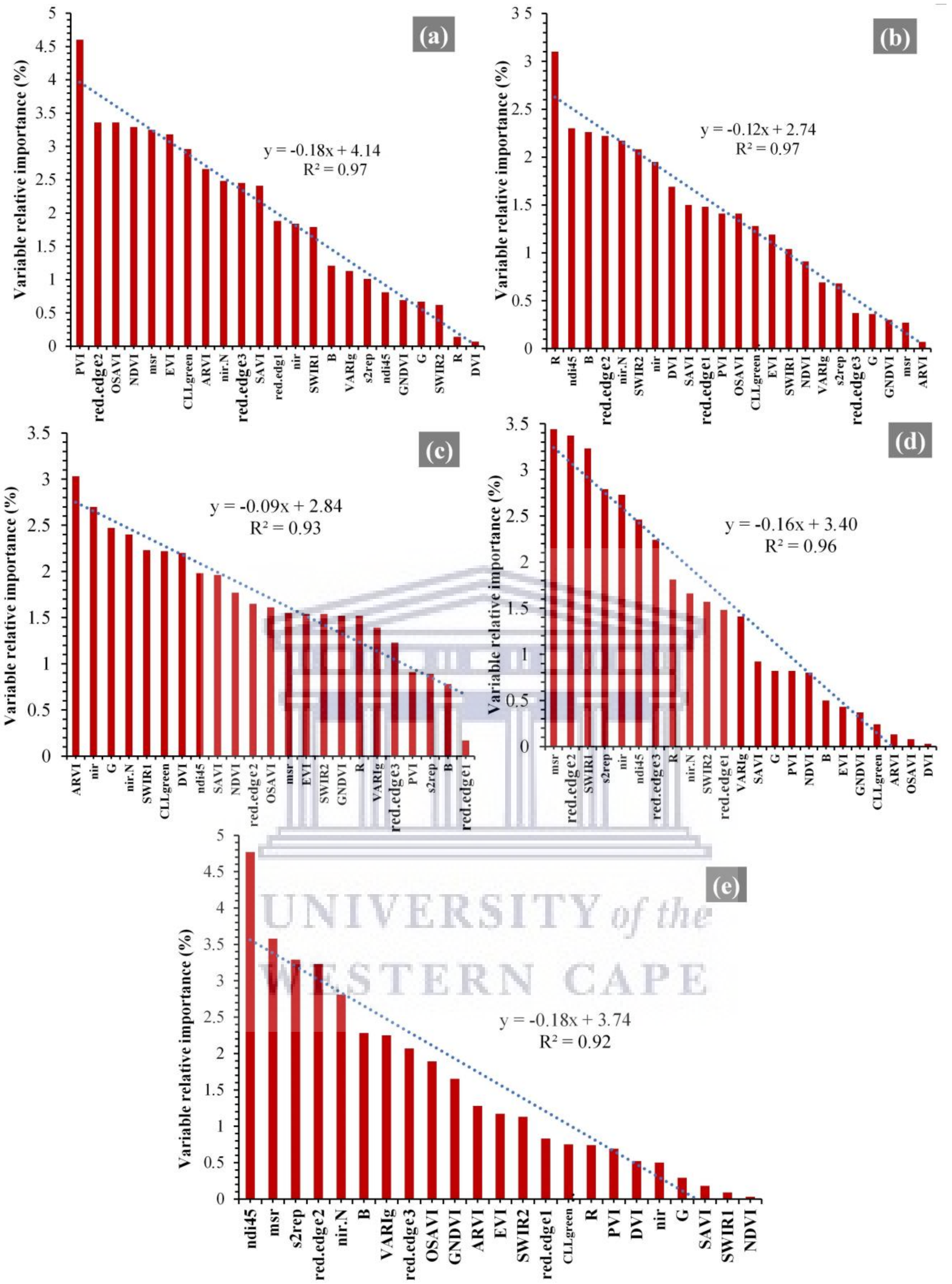
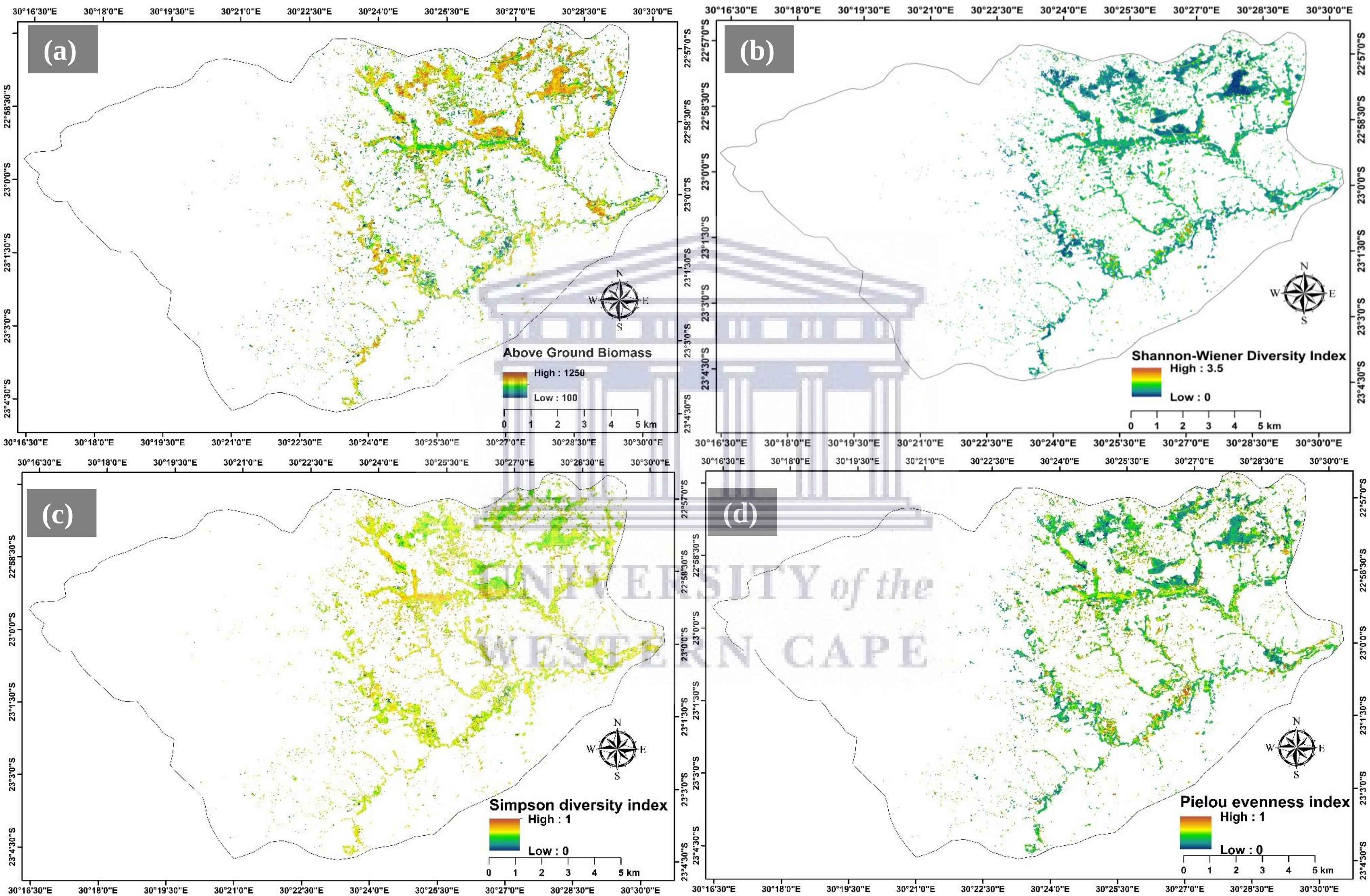


Figure 4.3 Variable importance derived from: (a) Above Ground Biomass (AGB), (b) Shannon-Wiener Diversity Index, (c) Simpson Diversity Index, (d) Pielou Evenness Index and (e) Margalef Richness Index. The relative importance of variables in the multisource dataset. The variables are ranked based on their contribution to the MLR model

4.3.3 Mapping wetland vegetation using Sentinel-2 MSI and diversity index

The wetland vegetation species diversity derived maps in Figure 6a-e demonstrate that the diversity pattern (evenness and richness) is consistent within the area of study. It can be observed from Figure 4.4a that there is a high concentration of AGB in the northern and western parts of the Maungani wetland. The concentration of AGB can also be observed in the centre towards the southern site of the Maungani wetland. The Shannon-Wiener thematic map (Figure 4.4b) illustrates a low distribution of vegetation diversity, with a medium concentration at the centre of the wetland. The Simpson Index (Figure 4.4c) managed to depict a higher vegetation species diversity in the entire Maungani wetland area. A lower distribution of species diversity can be observed in the northern portion. The Pielou Evenness Index (Figure 4.4d) illustrates a lower, medium and higher species diversity distribution. A lower concertation can be observed in the northern side, with a medium diversity concentration in the southern site and a higher species concentration at the centre of the study. Figure 4.4e shows how the Margalef Index managed to depict a higher species diversity in the northern portion and a medium concentration at the centre of the study area, towards southern side.



(a)
(b)
(c)
(d)
30°16'30"E
30°18'0"E
30°19'30"E
30°21'0"E
30°22'30"E
30°24'0"E
30°25'30"E
30°27'0"E
30°28'30"E
30°30'0"E
22°57'0"S
22°58'30"S
23°0'0"S
23°1'30"S
23°3'0"S
23°4'30"S
N
W
E
S
Above Ground Biomass
High : 1250
Low : 100
Shannon-Wiener Diversity Index
High : 3.5
Low : 0
Simpson diversity index
High : 1
Low : 0
Pielou evenness index
High : 1
Low : 0
0 1 2 3 4 5 km

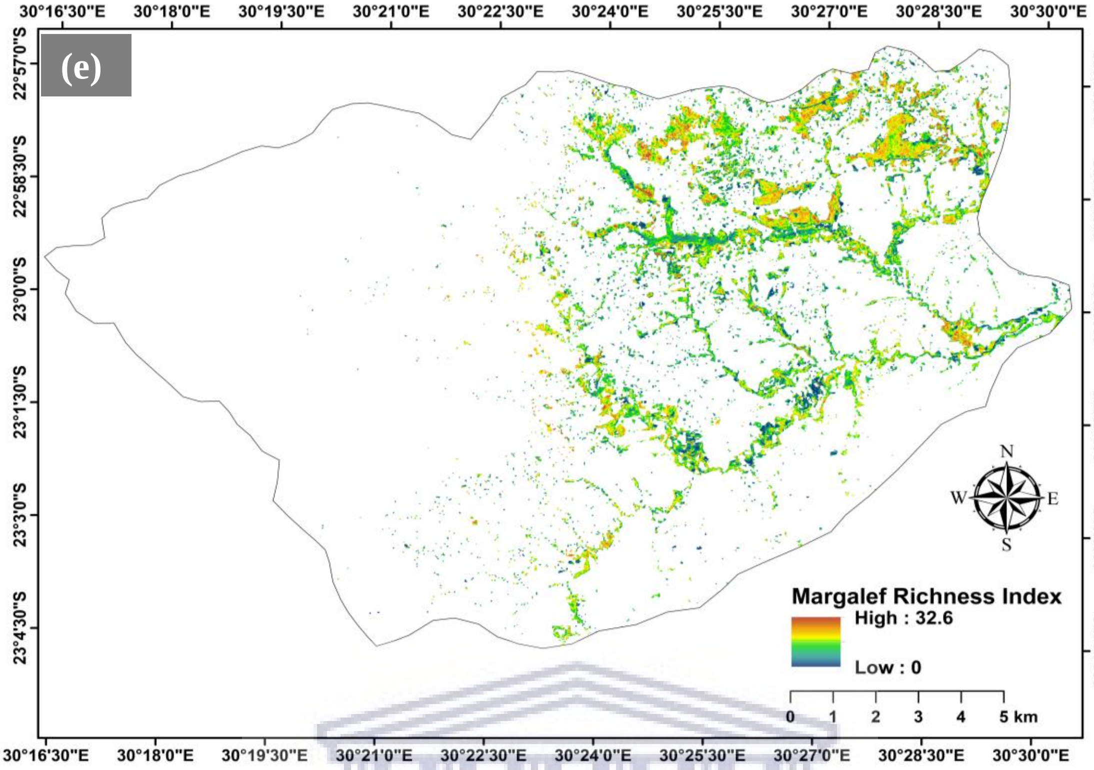


Figure 4.4 Remotely sensed derived wetland species diversity distribution maps for the Maungani wetland ecosystem: (a) Above Ground Biomass (AGB), (b) Shannon-Wiener Diversity Index, (c) Simpson Diversity Index, (d) Pielou Evenness Index and (e) Margalef Richness Index

4.4 Discussion

Small unprotected wetland ecosystems serve the surrounding communities and have multiple functions; however, their ecological and environmental conditions are not yet fully understood. Therefore, accurate and reliable information on the diversity of vegetation species in unprotected wetlands is essential for catchment managers, land use planners and conservation managers, in order to ensure sustainable wetland management (policy-making, strategic planning, rehabilitation). The estimation of wetland vegetation species by using satellite images remains challenging because of a number of factors that impact the relationship between the field data and remote sensing variables. The use of the recently-launched remote sensing data is very critical in detection, monitoring and mapping of vegetation species diversity. In this study, Sentinel-2 MSI and MLR were explored to estimate the diversity of wetland vegetation species in the Maungani wetland of Limpopo Province, South Africa.

4.4.1 Wetland vegetation species diversity estimation

Fifteen vegetation species were identified in the Maungani wetland and these belonged to eight (8) families, namely, Cyperaceae and Poaceae. The presence of these species indicate that the wetland is rich in species diversity. A number of factors influence the diversity (i.e. abundance, richness and evenness) of vegetation species, particularly in small wetlands; they include the hydrodynamics, elevation, grazing, and anthropogenic activities. Hosieni *et al*. (2016) showed that the destruction and degradation of wetlands leads to a reduction in species richness and evenness. Therefore, in order to understand the wetland landscape, it is imperative to assess the species diversity by using various biodiversity indices such as a diversity index (Shannon-Wiener index and Simpson index), a species richness index (Margalef index) and a species evenness index (Pielou index).

The results of the Simpson index showed that the vegetation species diversity was high in the wetland. In the northern and western parts of the study area, the Shannon-Wiener Index demonstrated a lower diversity of vegetation species, while at the centre of the study there is a moderate to high species diversity. This is because the Shannon-Wiener Index describes the uncertainty of individual species. A higher uncertainty of a species represents a high diversity, while a lower uncertainty represents a lower diversity. This index is widely used in the biodiversity field to measure the diversity of ecosystems. Simpson's diversity index is more sensitive to dominant species, while the Shannon-Wiener's diversity index is more sensitive to rare species (Boyle *et al*. 1990). Generally, the Simpson Index ranges between 0 and 1. However, the higher diversity values that range between 0.6 and 0.9 demonstrate a mature and stable wetland community, while the lower values, closer to zero, show that the wetland community is under stress conditions, exhibiting low diversity (Dash, 2017). This diversity index always exhibits higher values where a smaller number of vegetation species dominate the community and when the dominance is mainly by large number of species (Whittaker, 2014). Based on species diversity indicators, it can be concluded that the Simpson index is associated with an increase in the number of individuals and the number of species. In addition to its relative simplicity, the use of this indicator can also give a good understanding of species diversity within an ecosystem. The diversity of the study area supports mainly the distribution of *Typha capensis, Phragmites australis*, *Cyperus sexangularis* and *Cyperus dive*, which dominate the whole area. Based on our results, the dominance of a single species was mainly a result of disturbance. For instance, the use of fertilisers by small-scale farmers and the anthropogenic activities around the Maungani wetland contributed to the dominance of a single species.

The Margalef and Pielou Indices displayed an evenness and richness in the vegetation species. The results derived from the Margalef Index map showed that the wetland vegetation species is rich. This index depends on a number of vegetation species being present within the demarcated area under study and it has no limited value for representing species richness. It takes only one component of diversity (species richness) into consideration, which reflects its sensitivity to the identified sample size. Our results are therefore consistent with the field observations. On the other hand, the Pielou Index showed a low to medium distribution of species richness in the northern part of the study area. However, a low to moderate mean annual precipitation reduces or lowers the diversity of the wetland vegetation species. The geology, hydrodynamics and drought periods in the northern parts of the wetland are likely to have influenced species diversity in the area. Our results concur with a study by Shackleton (2000), who highlighted that an increase in species richness and evenness is influenced by the increased average to high precipitation in the area. It has been reported that the diversity of vegetation and its spatial distribution have a significant impact on the functioning of wetland ecosystems.

4.4.2 Performance of Sentinel-2 MSI-derived data in estimating wetland vegetation species diversity and productivity

Sentinel-2 images played a critical role in estimating and mapping the diversity of wetland vegetation species and helped to understand the state of species richness and abundance in the unprotected wetland in the Maungani area. The results showed the capability of strategically-positioned bands in strengthening the sensor for estimating and modelling wetland species diversity. These results concur with other vegetation and diversity estimation studies that have used the Sentinel dataset (Thamaga and Dube, 2019; Pandit *et al.*, 2019). The presence of Red-edge bands in Sentinel-2 benefited the detecting, mapping and estimation of the diversity of wetland vegetation. For this purpose, the performance of Sentinel-2 and Landsat 8 in estimating wetland vegetation species was investigated. The derived results showed that Sentinel-2 performed better than Landsat 8. Thamaga and Dube (2018b) observed similar observations where Sentinel-2 outcompeted Landsat 8 in detecting and mapping water hyacinth in a narrow river system. Red-edge bands were the most sensitive to vegetation estimation and this can be attributed to the physiochemical properties of wetland vegetation species. The results also imply that Sentinel-2 spectral bands that are integrated with the vegetation indices, mapped out vegetation species diversity for the entire study area. This study supports Asner and Martin’s (2016) findings that species biochemical and biophysical characteristics might aid in the mapping of the distribution of invasive species. The maps derived from the study show that there are lows and highs in the dominance and evenness patterns of species diversity in the Maungani wetland area. Based on our ecological knowledge, climate change scenarios, land use activities and invasive plant species altered the dominant structure of wetland ecosystem (Kardol *et al*., 2010; Forrestel *et al*., 2015). Furthermore, climate change patterns resulting from droughts, increased the temperatures and influenced the dominance and evenness of the species distribution, rather than its richness.

4.4.3 Implications for wetland species conservation

The rapid population growth, agricultural activities, water level fluctuation changes, livestock grazing, as well as climate change, remain a challenge in developing regions, particularly in areas near unprotected wetlands. For instance, increasing droughts have led to the risk of wetland vegetation degeneration and shrinkage at lower elevations. Furthermore, Li *et al*. (2018) highlighted that the increasing nutrient concentrations during the dry season because of the reduced water levels, leading to eutrophication, which affects the wetland diversity. However, in managing the vegetation diversity of unprotected wetland species, an in-depth understanding is required of the water quality and complexity of the ecohydrological environment. Furthermore, in data-scarce locations like sub-Saharan Africa, obtaining precise and reliable information on the geographic distribution, configuration, and propagation rates remains a problem. Therefore, a better understanding of wetland biodiversity may benefit from the spatial environmental factors that affect the ecosystem.

4.5 Conclusion

The study aimed at modelling vegetation species diversity by integrating the Sentinel-2 MSI dataset and diversity indices in the unprotected Maungani wetland. Based on our findings, we conclude that:

- Variable predictors, such as the Simpson index, had the strongest relationship in estimating wetland vegetation, compared to the Margalef Index, which had a lower r^2.
- The presence of red-edge bands was also found to be the most reliable for enhancing the estimation, mapping, monitoring and management of wetland vegetation in

unprotected wetlands that are still lacking in data scarce regions i.e. African regions, in the face of climate change.

- Furthermore, the results highlighted the relevance of Sentinel-2 data, which have the potential to contribute to more robust and evidence-based information that can assist in policy-making in conservation and the sustainable use of wetland ecosystems.

Overall, the mapping and monitoring of species diversity, using the Sentinel-2 dataset and biodiversity indices, are critical because they can provide benefits for the planning, conservation and rehabilitation of wetlands. The link between remotely-sensed variables and vegetation diversity confirms the capabilities of Sentinel-2 MSI for the conservation process, particularly for screening, in order to locate the biodiversity hotspots.

CHAPTER FIVE

AN ASSESSMENT OF SMALL WETLAND ECOHYDROLOGICAL DYNAMICS USING SENTINEL-2 MSI-DERIVED SPECTRAL INDICES IN SEMI-ARID ENVIRONMENTS OF SOUTH AFRICA

Thamaga, K.H., Dube T., Shoko C., 2021. An assessment of small wetland ecohydrological dynamics using Sentinel-2 MSI derived spectral indices in semi-arid environments of South Africa. *Wetland Ecology and Management*, WETL-D-21-00141, (Manuscript under-review)

Abstract

The presence of water within small wetlands serves as a determining factor that influences their biodiversity, productivity and functionality. Small wetlands remain largely unprotected; hence, they are more sensitive to frequent exposure to environmental modifications, and are less resilient to the changing rainfall patterns, climate change and variability, droughts and changing land use practices. Accurate and up-to-date spatial and temporal information on changes in the surface water and the extent of inundation becomes imperative for the proper management of these wetlands. Therefore, this study sought to extract and monitor ecohydrological dynamics (surface water and inundation extent) of wetlands, using monthly Sentinel-2 MSI remotely-sensed datasets. These dynamics were assessed for the period between July 2020 and June 2021, using the Modified Normalised Difference Water Index (MNDWI), the Normalised Difference Moisture Index (NDMI) and the Normalised Difference Phenology Index (NDPI) derived from Sentinel-2 MSI data. The results showed that the rainy season (Dec 2020-Feb 2021) had a larger water coverage extent (10948 m^2 (0.05%) to 31594 m^2 (0.13%)), when compared to the dry season (July 2020: 19157 m^2 (0.04%) and June 2021:14429 m^2 (0.03%)). The extent of the surface area declined during the dry period, due to less rainfall (0.20 mm) and the decreased actual evapotranspiration (9.90 mm-10.43 mm). Furthermore, the NDPI showed a high concentration of wetland vegetation between October 2020 and April 2021. On the contrary, a higher moisture content was observed between December 2020 and April 2021. The increase in vegetation concentration and moisture content reflects the spatial extent of the inundation. The extent of the wetland water, soil moisture and vegetation condition were assessed with a high overall accuracy that ranged between 70.83% and 97.36%. Overall, the results indicated that small wetlands are characterised by significant variations in the levels of inundation and productivity throughout the year.

Keywords: Agricultural practices; Climate variability; High resolution satellite data; Inundation extent; Moisture variation; Surface water presence; Wetland productivity

5.1 Introduction

Wetlands are distinctive and complex ecohydrological systems that occur within a wide range of climatic and topographic environments (Olefeldt *et al*., 2017; Thamaga *et al*., 2021). They are defined as areas that have a low water level, frequently near the ground-surface, and that are characterised by the presence of hydrophytic vegetation during the growing period (Barducci *et al*., 2009). Wetlands arise when the soil is flooded or inundated with water for various time periods (seasonal, inter-annual and decal) and at different frequencies (Li *et al*., 2015; Zhang *et al*., 2020). Their ecological processes are impacted by water-related processes that regulate the surface water and groundwater recharge, as well as dissolved water and inputs and outputs of material. Despite covering a smaller proportion of land (3%--8%), unprotected wetlands distributed across sub-Saharan Africa offer several ecohydrological and socio-economic benefits (Tiner *et al*., 2015; Marambanyika & Beckedahl, 2016; Gxokwe *et al*., 2020; Dzurume *et al*., 2021). These wetlands, for example, support the livelihoods of neighbouring rural communities, and often-poor households, with water, particularly in water-scarce areas. Small wetlands play a critical role in rural economics, as they sustain thousands of smallholder farmers more than larger protected wetlands (Azumi, 2010; Tanko, 2013). In Southern and Central Africa, 'dambos' continue to support water provision, seasonal agriculture, grazing and fishing (Wood and Thaw, 2013). In areas where access to water is scarce or limited during dry season, such as in the highlands of Ethiopia, wetlands regulate the hydrological cycle and enhance water availability in the region (Finlayson *et al*., 2005). Water availability within wetlands serves as a baseline factor that influences the biodiversity hotspots of wetland ecosystems. The water presence and spatial extent of a wetland reflect its hydroperiod, which is the period of water level fluctuations that take place in a wetland over time (temporary, seasonal or permanent) (Jackson *et al*., 2014). Small wetlands, on the other hand, are under tremendous pressure and are being radically transformed to non-wetland habitats, which may lead to expansion, owing to both anthropogenic activities (water diversion, intensive agricultural and industrial development, as well as water abstraction) and natural processes (rainfall variability, evapotranspiration, drought and climate change).

Despite their vast expanse and benefits, small wetland ecosystems are highly vulnerable, they undergo immense pressure from natural and anthropogenic activities and their survival is being threatened. For instance, Marambanyika and Sibanda (2020) demonstrated that the spatial extent of wetlands in Zimbabwe decreased by 3.6% in the 1980s, when compared with

1.8% in 2015. On the other hand, Thamaga *et al*. (2021) illustrated that the Maungani wetland in South Africa lost 43.10% (728 400 ha) of its spatial extent between 1983 and 2019. These studies highlighted that a decline in wetland areas has been mainly attributed to an increase in the built-up areas. Other studies have revealed that unprotected wetlands are extremely sensitive to natural and anthropogenic land-use changes, due to changes in the hydrological regime, which directly threatens the ecosystem and the animals that rely on them (Bhanga *et al*., 2020; Wanjala *et al*., 2020). Natural processes, including a change in temperature, rainfall patterns, evapotranspiration, the drought rate and erosion have fast-tracked wetland water losses (Xia *et al*., 2017; Chen *et al*., 2018). It was noted that river channels and the associated floodplain wetlands signify spatial and temporal hydrological changes, because flooding and the drought rates affect the area of inundation (Lambs, 2020). A decrease in the water table alters the interaction between the surface and groundwater and frequently shrinks the hydrological regimes of flood plain wetlands (Li *et al*., 2018). On the other hand, anthropogenic modifications resulting from dam construction and increased rural-urban development because of the increased population growth, alter the hydrological regimes in stream channels and riparian wetlands, which causes changes in ecohydrological dynamics of wetlands (Millennium Ecosystem Assessment (MEA), 2005). Gordon *et al*. (2010) reported that wetlands are being drained and approximately 27% of them are being lost, due to intensive agricultural practices. Furthermore, processes, such as desiccation, salinization, eutrophication, contamination and the emergence of alien plant species, disrupt biodiversity, spatial extent, water quality and availability of wetlands (Thamaga and Dube, 2018b; 2019). With the changing climate expected to dramatically affect South Africa's precipitation patterns, wetlands will be more critical than ever in mitigating the adverse effects of severe events, such as floods and the drought rate (Knoesen *et al*. 2009). To date, the hydrological dynamics of small wetlands serving nearby communities remains poorly quantified and managed, due to the lack of management prioritization. Therefore, there is a need to accurately and frequently monitor small wetlands, to put proper management practices in place and to support the sustainable management of wetland water resources.

The accurate extraction of wetland water and the extent of inundation is of great significance for the planning, monitoring and protection of these systems. Monitoring wetland ecohydrological dynamics by using traditional techniques has proven to be ineffective, owing to problems in capturing the spatio-temporal variability and sampling mistakes. In addition, these methods are expensive, laborious and restricted in their geographical coverage

(Thamaga and Dube, 2019; Thamaga *et al*., 2021). The use of satellite-based remote sensing as an alternative can accurately detect and monitor small to larger wetlands in real-time, providing hydrological information, inundation spatial extent over time, especially in areas where in-situ datasets are limited (Tanko, 2013). Some sensors, such as Landsat datasets, Sentinel-2 and MODIS, have proved themselves to be promising in studies on wetland inundation, surface water estimation, water quality and the hydrological cycle (Chiloane *et al*., 2020; Dzurume *et al.*, 2021).

Previous studies utilised various methods to distinguish, map and monitor the distribution of wetlands, surface waterbodies, inundation, and non-water areas (Niemuth *et al*., 2010; Wright, 2010). Some of the water delineation methods used include the thresholding, Decision Tree, classification and inter spectral relation methods (Mondal and Pal, 2018). Furthermore, appropriate spectral bands were combined, using various algebraic operations, to enhance their capabilities to differentiate water coverage areas from non-water bodies. Water indexing techniques to extract surface water bodies include the Water Ration Index (WRI), Tasselled Cap Wetness (TCW), the Automated Water Extraction Index (AWEI), the Normalised Difference Water Index (NDWI), the Land Surface Water Index (LSWI), the Modified NDWI (MNDWI), and the Water Index (WI) (Chiloane *et al*., 2020). The efficiency of indices for the extraction of water bodies was assessed, using the overall accuracy and kappa coefficient (Poulin *et al*. 2010). These indices perform differently in extracting surface water or in inundation areas. For instance, the study by Chiloane *et al*. (2020) tested multiple indices in the Kgalagadi Transfrontier Park of Southern Africa to pan inundation and the associated seasonal changes within the park. The results of the study showed that the MNDWI outperformed other indices in extracting pan inundation. In this study, we sought to extract and monitor the surface water and inundation area of small wetlands, using monthly Sentinel-2 MSI datasets for the period between July 2020 and June 2021. We further assessed the variability in wetland productivity by using the newly developed normalised difference phenology index (NDPI) as a proxy for vegetation condition.

5.2 Materials and Methods

5.2.1 Ancillary data

In this study, the field data was collected between 2nd and 5th June 2021 and (60) points for non-water areas and open water surfaces were recorded. For other months between July 2020 to May 2021 the high spatial resolution of Google Earth Images was used to generate feature points. Meteorological datasets, mainly the monthly average rainfall data and mean temperature, were acquired from the South African Weather Services (SAWS) (*https://www.weathersa.co.za/*) for the Thohoyandou AWS station from July 2020 to June 2021. In addition, the monthly actual evapotranspiration (ET) was obtained from the MODIS data. The ET data was extracted on a monthly basis, between July 2020 and June 2021, and ET was used to assess the amount of evaporation and transpiration lost in the Maungani wetland. Meteorological and ET data were used to infer on the observed satellite-derived wetland ecohydrological dynamics i.e. the inundation extent, surface water variability and vegetation condition. The characteristics of wetland inundation and surface water are presented in Table 5.1. Vegetation cover within the wetland shows areas where it is temporarily or permanently inundated.

5.2.2 Satellite image acquisition and pre-processing

Dry and wet seasonal monthly Sentinel-2 MSI images for the period between July 2020 and June 2021, were retrieved from the European Space Agency (ESA) Copernicus Open Access Hub (*https://scihub.copernicus.eu/*). The raw satellite images were pre-processed using the Sentinel Application Platform (SNAP) tool for atmospheric, geometric and radiometric corrections, by using the Sen2Cor module in SNAP software, before being used for the computation spectral metrics. All the Sentinel-2 MSI data were converted to the Top of Atmosphere (TOA) reflectance value and to correct the Bottom of Atmosphere (BOA) value. Subsequently, Bands 1, 9 and 10 were excluded from the datasets. Lastly, the images were then resampled at 10 m, using a bilinear technique, and they were sub-set to the extent of the study site.

Table 5.1 Wetland characterisations considered in studying wetland inundation and surface water

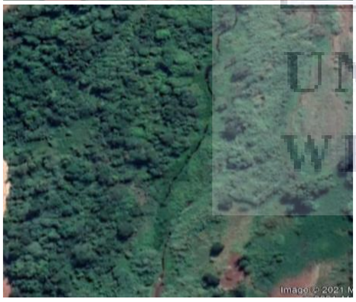
	Permanently moist	**Temporarily flooded**	**Permanently flooded**
Non-vegetated	**NONE**	**NONE**	**NONE**
Low-vegetated			
Medium-vegetated			
Highly vegetated			

Table 5.2 Characteristics of Sentinel-2 used in the study

#	Bands	Wavelength (µm)	Resolution (m)
1	Coastal/	0.43 – 0.46	60
2	Blue	0.44 – 0.54	10
3	Green	0.55 – 0.58	10
4	Red	0.65 – 0.68	10
5	RE1	0.70 – 0.73	20
6	RE2	0.73 – 0.75	20
7	RE3	0.77 – 0.79	20
8	NIR	0.76 – 0.90	10
8A	NIR narrow	0.86 – 0.88	20
9	Water vapor	0.94 – 0.96	60
10	Cirrus	1.36 – 1.39	60
11	SWIR – 1	1.54 – 1.68	20
12	SWIR – 2	2.08 – 2.32	20

5.2.3 Topographic position

The topographic position in this study was utilised as an additional indication of the presence of wetlands. The Digital Elevation Model (DEM) is frequently utilised to generate topographic metrics, such as elevation, slope, aspect and curvature. In this study, the DEM downloaded from *https://dwtkns.com/srtm30m/* was used to derive the Topographic Wetness Index (TWI), which is a hydrological measure that is determined by the flow speed and concentration of water flow at a watershed point (Buchanan *et al*., 2014). The TWI is also an index for soil moisture, which affects the growth and composition of vegetation (Gábor *et al*., 2020). The value of TWI specifies the amount of water held in slope component materials, which might affect and influence the slope instability. The aspect is given in degrees (0 and 360) pointing north, and it is calculated in radians and then sine converted to range, from -1 to 1. The slope stability factor has a significant impact on the flash flood process. This is influenced by the drainage system and the amount of rain that falls. TWI quantifies the inclination of grid cells for the collection and accrual of water (Sörensen *et al*., 2006). This index has been successfully used for studying vegetation patterns and predicting the spatial distribution of plants (Sørensen *et al*., 2006). Soil type data were retrieved from the ISRIC data hub (*http://data.isric.org/*), and the TWI equation (Equation 1) is defined as:

$$\mathrm{TWI} = \ln\left(\frac{A}{\tan(\beta)}\right) \qquad \text{Equation (1)}$$

Where A is the upslope contributing area and β is the local slope angle. The higher the TWI of a cell, the higher is the tendency to accumulate water and/or to inundate an area.

5.2.4 Measuring wetland hydrology and inundation dynamics, using derived spectral indices

In order to assess the wetland hydrological dynamics for a twelve-month period (from July 2020-June 2021), the MNDWI (Equation 1) (after Xu, 2006) was applied to identify, discriminate and measure the surface water from the non-water pixels within the study area. The MNDWI is dimensionless and ranges from -1 and 1, with a greater MNDWI value indicating a high-water content. These indices provide the accurate extraction of open water features, compared to the standard NDWI. According to Ji *et al*. (2009), detecting variations in the water surface is a tough task, when using a single threshold value, owing to the dynamic nature of the land cover component that alters, based on the sub-pixels. The bands were chosen to enhance the reflectance of the water features, by using a green light wavelength, and to reduce the poor reflection of SWIR by water features by taking advantage of the high reflectance of the vegetation and soil features in the SWIR band (Du, 2016). MNDWI value is calculated by using the following equation (Equation 2):

$$\boldsymbol{MNDWI} = \frac{Green - SWIR\ 1}{Green + SWIR\ 1} \qquad \text{(Equation 2)}$$

The Normalised Difference Moisture Index (NDMI) shows the moisture variations of the land surface; it is highly correlated with the water content of the vegetation and is a good indicator of vegetation change (Rouse *et al*., 1974). The NDMI (Bernstein 2012) values range between -1 and 1. The positive value represents a high moisture content, while the negative value represents a lower moisture level. NDMI uses NIR and SWIR-1 bands (see Equation 3) below:

$$\boldsymbol{NDMI} = \frac{NIR - SWIR\ 1}{NIR + SWIR\ 1} \qquad \text{(Equation 3)}$$

The wetland vegetation was assessed by using the Normalised Difference Phenology Index (NDPI) (Wang *et al*., 2017). The NDPI is reliable and outperforms NDVI in distinguishing plants from the background, which theoretically enables it to be used for spring phenology monitoring. The NDPI (Equation 4) integrates the NIR, red and SWIR bands to extract vegetation information. It ranges between -1 and 1, where a value closer to -1 represents a low vegetation concentration, while a value closer to +1 represents a high vegetation concentration.

$$\boldsymbol{NDPI} = \frac{NIR-(0.74\times Red+0.26\times SWIR\ 1)}{NIR+(0.74\times Red+0.26\times SWIR\ 1)} \qquad \text{(Equation 4)}$$

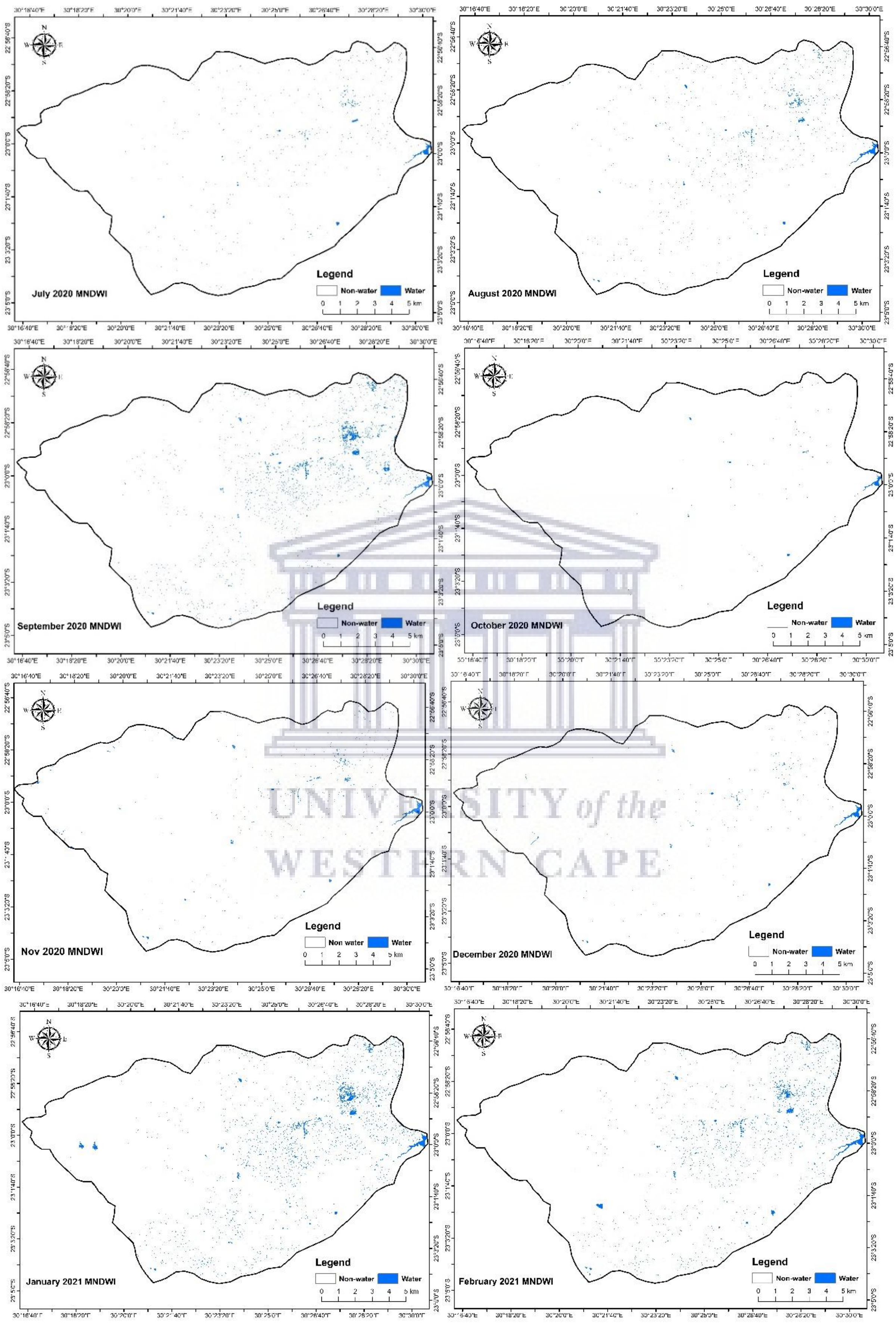
5.2.5 Accuracy analysis

The field data points (60) for non-water areas and open water surfaces were derived by using the high spatial resolution of Google Earth Images. For the duration of this study, sample points were used to validate the water presence within the Maungani wetland. The extracted multi-values for MNDWI, NMDI and NDPI were then used to derive classification accuracies. The derived ecohydrological dynamics were then compared with the climatological and ET data to establish the trends and to infer on the observed wetland conditions.

5.3 Results

5.3.1 Monthly extraction of surface water derived by using MNDWI

The water presence and inundation extent of the wetland were extracted from Sentinel-2 derived indices. The satellite-derived wetland water availability varies significantly across the area under study (Figure 5.1 and 5.2). A high-water presence was recorded in the summer season (December 2020 to February 2021) with an area of 10 948 m^2 (0.05%), 29 772 m^2 (0.12%) and 31 594 m^2 (0.13%), followed by August 2020 and September 2020, which covered an area of 12 711 m^2 (0.05%) and 19 157 m^2 (0.08%), respectively. In July 2020, water covered an area of 10 312 m^2 (0.04%), in August 2020 it covered 12 711 m^2 (0.05%) and in September the area increased to 19 157 m^2 (0.08%). During the study period, less water coverage was observed during dry period, which had experienced less precipitation and an increased temperature variability. The least water presence was observed in November 2020, when it covered 5 295 m^2 (0.02%).


July 2020 MNDWI
August 2020 MNDWI
September 2020 MNDWI
October 2020 MNDWI
Nov 2020 MNDWI
December 2020 MNDWI
January 2021 MNDWI
February 2021 MNDWI
Legend
Non-water
Water
0 1 2 3 4 5 km

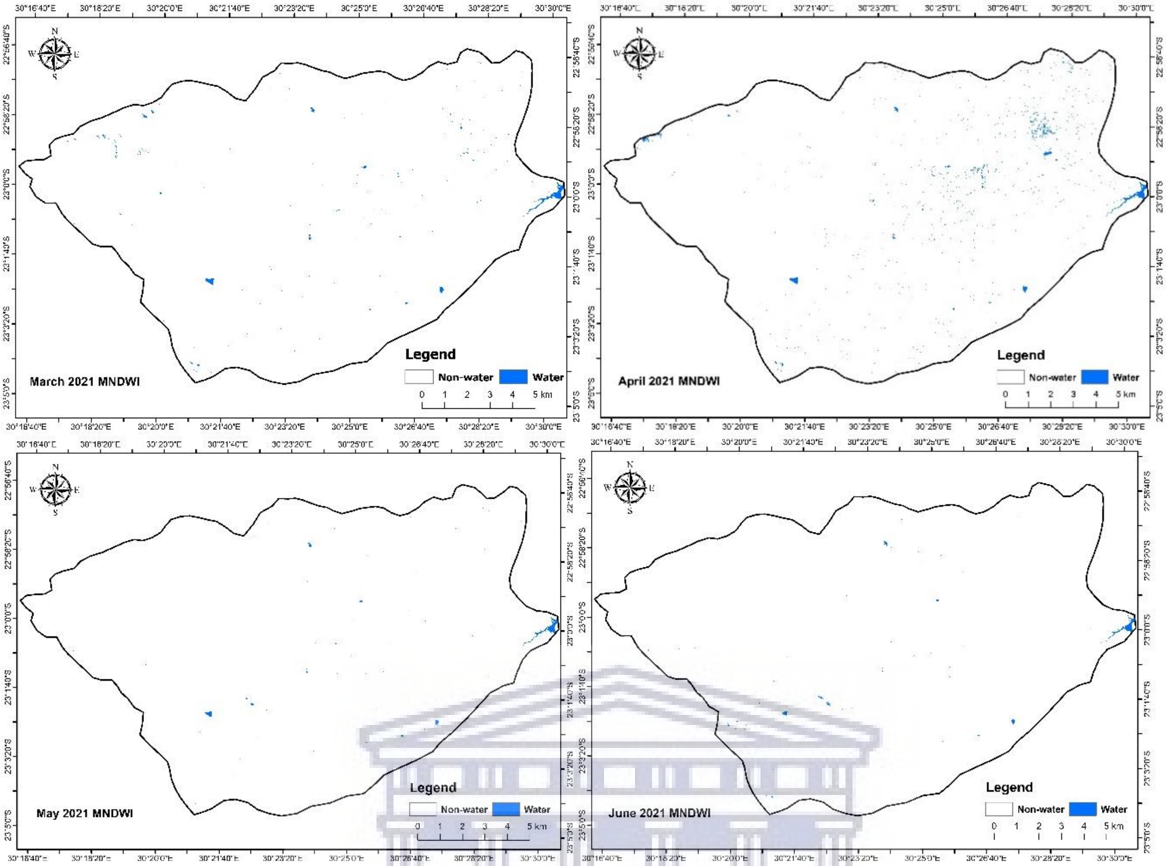


Figure 5.1 Monthly surface water coverage depicted from July 2020 to June 2020

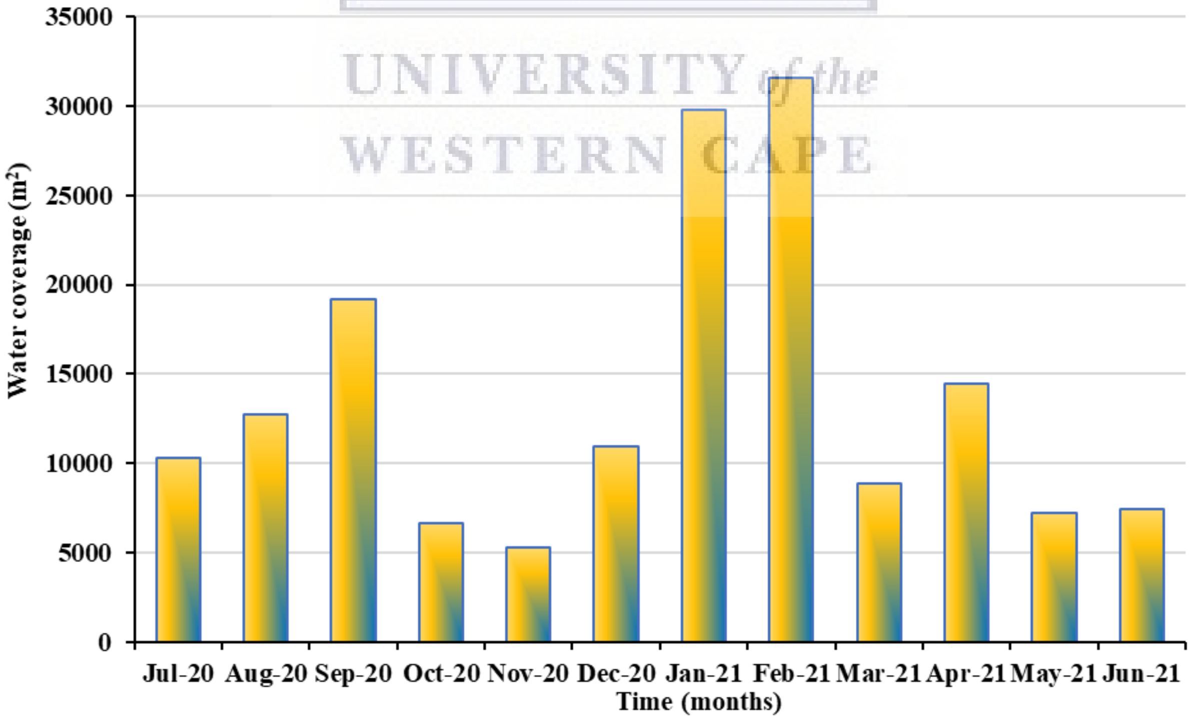
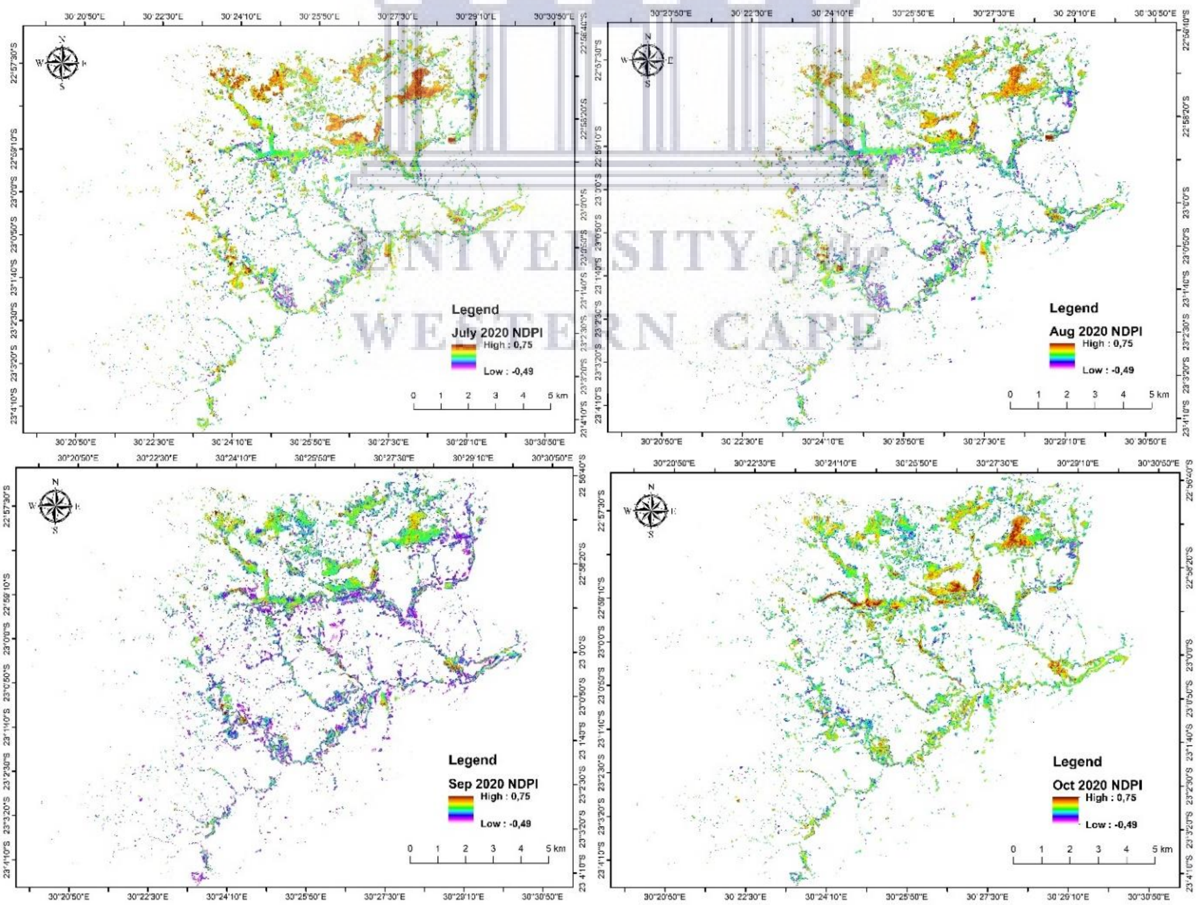


Figure 5.2 Seasonal variation in wetland water coverage derived using modified normalised difference water index

5.3.2 Monthly variation of wetland vegetation distribution in relation to the inundation periods, using NDPI

The monthly variations in the wetland vegetation condition results varied from 0.75 (higher) to -0.49 (low). Figure 5.3 shows that there was a higher concentration of wetland vegetation in the northern part of the wetland, with a medium to low configuration in the centre to southern parts in July and August 2020, respectively. In September 2020, the larger dominating part of the wetland area had less cover than the northern part, which had a medium cover. Wetland vegetation with medium cover was observed from the centre to southern parts of the Maungani wetland in October 2020. In November 2020, a gradual rise was observed. Furthermore, the months of December 2020 to April 2021 had a higher vegetation configuration than the other months selected in this study. In May and June 2020, there was a reduction in vegetation from the centre of the study towards the southern part of the wetland. The monthly variation, rainfall, temperature and evapotranspiration trends have an influence on the reduction of vegetation productivity in the wetland.



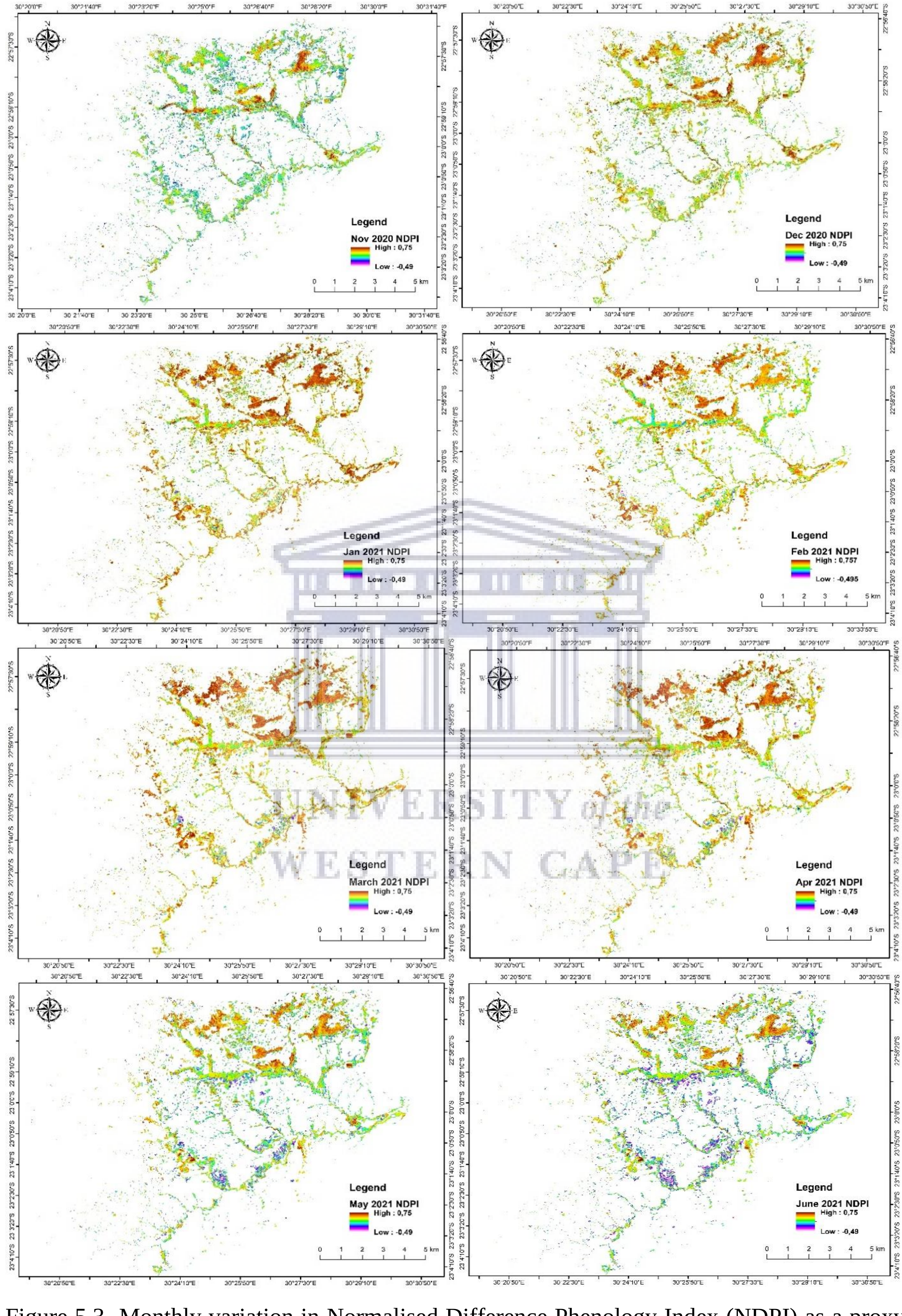
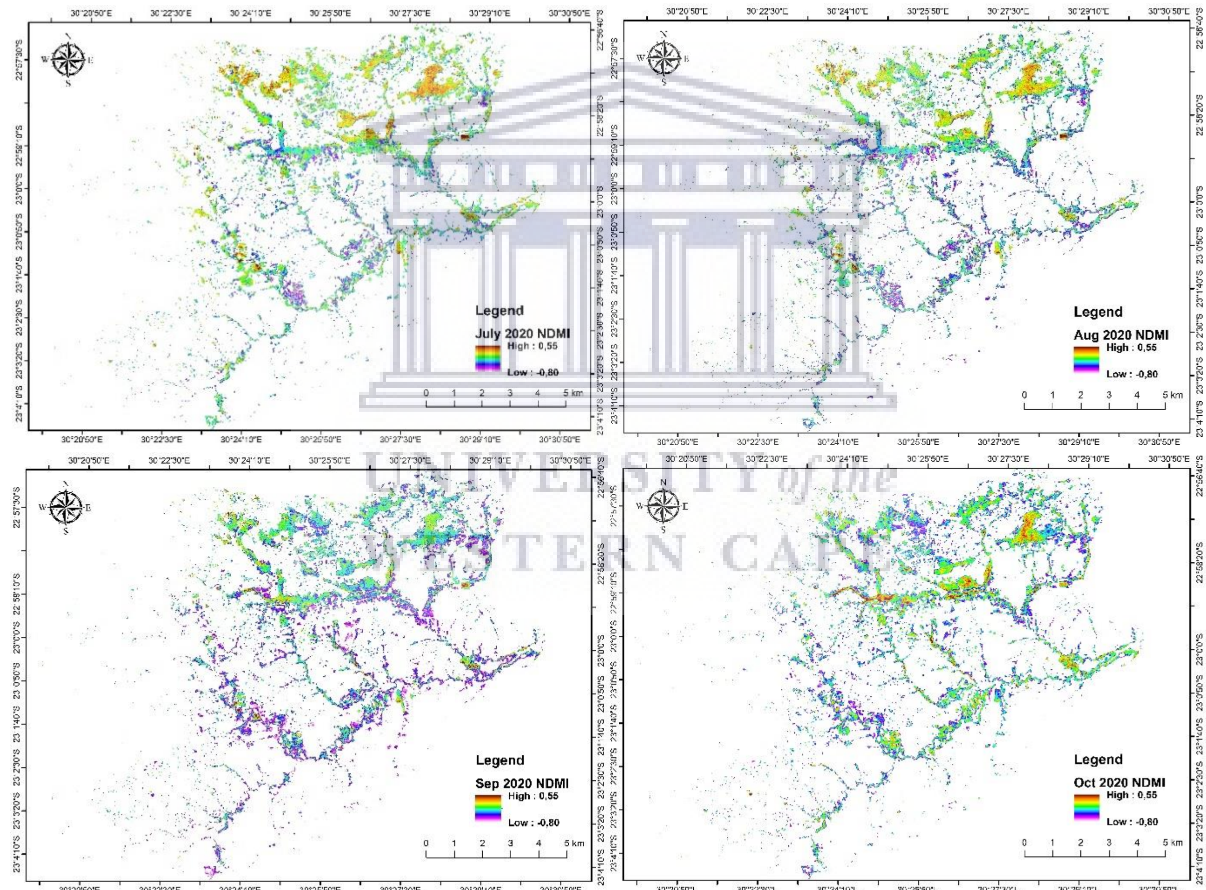


Figure 5.3 Monthly variation in Normalised Difference Phenology Index (NDPI) as a proxy for wetland vegetation condition

5.3.3 Monthly variation of moisture within the Maungani wetland area

Figure 5.4 shows the monthly distribution of the moisture content in the Maungani wetland area, using NDMI. The retrieved findings varied from as low as -0.80 to 0.55. There was evidence that the months between December 2020 and April 2021 experienced medium to high amounts of moisture. In July and August 2020, a high, moderate and low moisture content was observed in the northern, middle and southern parts of the study, while in October 2020, November 2020 and June 2021, a reduction in the moisture content was observed in the northern part of the study area. The findings showed that the month of September had the lowest moisture content, compared to the other months.



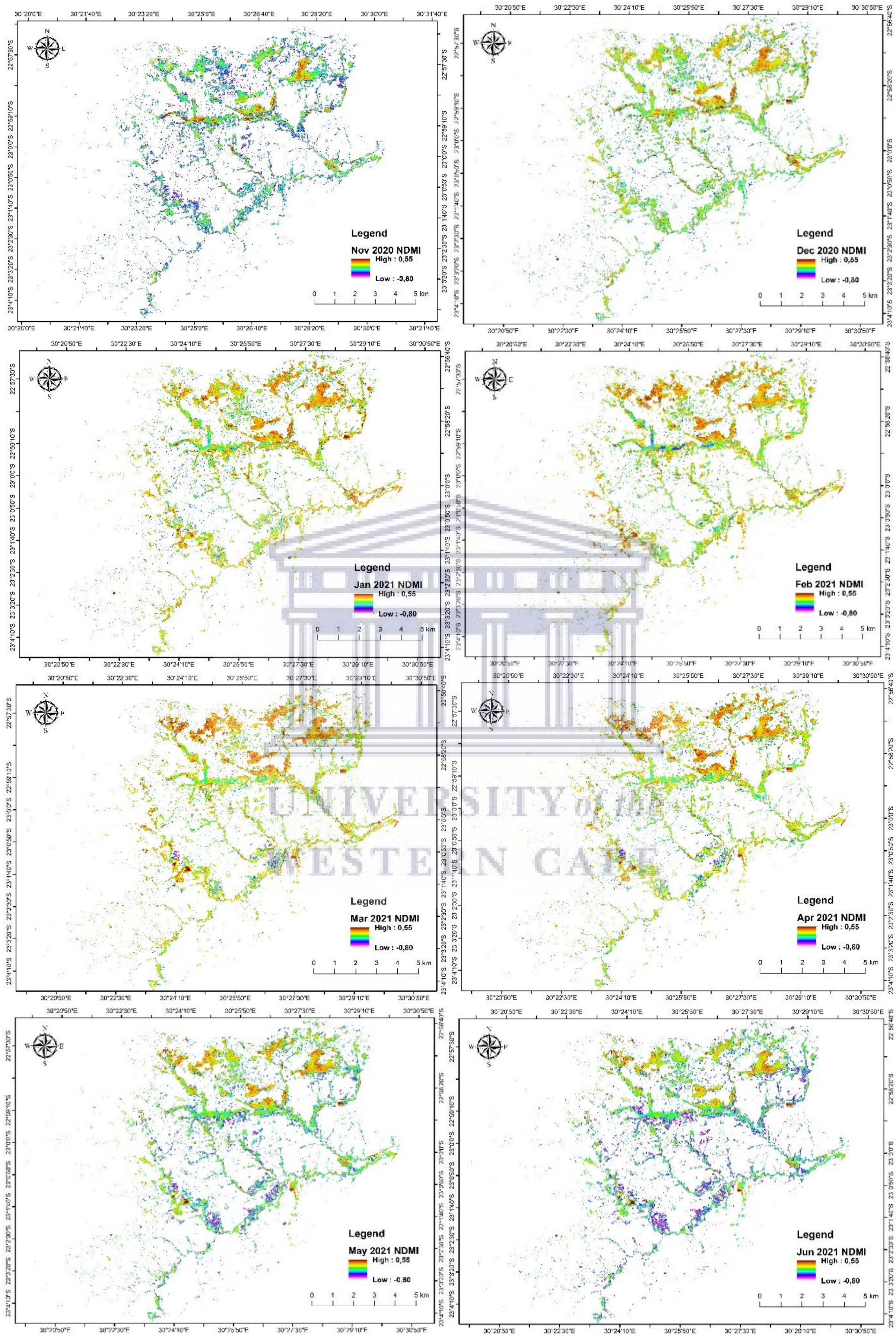


Figure 5.4 Monthly moisture variation depicted between July 2020 and June 2021

5.3.4 Accuracy assessment derived to extract surface water coverage, moisture and vegetation distribution

During the study period, overall classification accuracy (Figure 5.5) was used to assess the extraction capabilities of the NDMI, NDPI and MNDWI. The NDPI achieved an overall accuracy that ranged from 70.83% to 91.65%, respectively, while the NDMI extracted the moisture within the wetland with a high overall accuracy of 95.63% and 73.47%. Lastly, MNDWI achieved an overall accuracy of 78.31% and 97.36%.

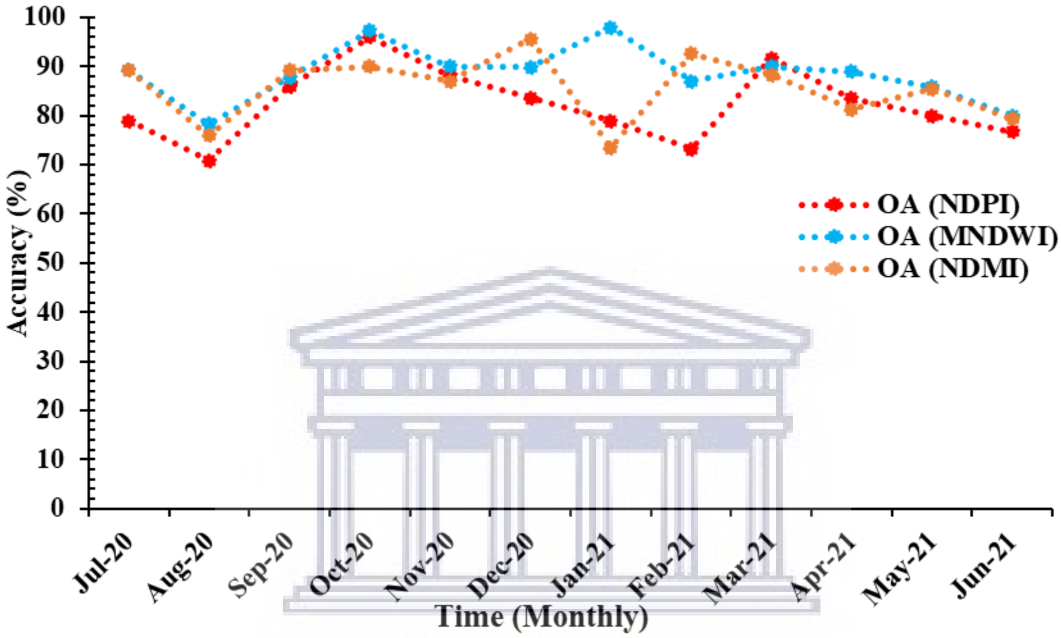


Figure 5.5 Overall classification accuracies achieved from the different combination of the three algorithms (NDPI, NDMI and MNDWI) and Sentinel-2 sensors

5.3.5 Relationship between rainfall pattern, temperature and evapotranspiration

Figure 5.6 shows a monthly rainfall and mean temperature trend within the Maungani wetland. The results shows that the wetland area experiences both low and high rainfall and temperatures. The rainfall was found to be higher during the wet period in December 2020, January 2021 and February 2021, with 18.44 mm, 20.45 mm and 12.85 mm, respectively. During the drier periods, the rainfall was lower, ranging from 0.20 mm in May 2021 to 0.60 mm in July 2020. On the other hand, it can be observed that mean monthly temperature ranged between 16.15°C in July and 25.65°C in December.

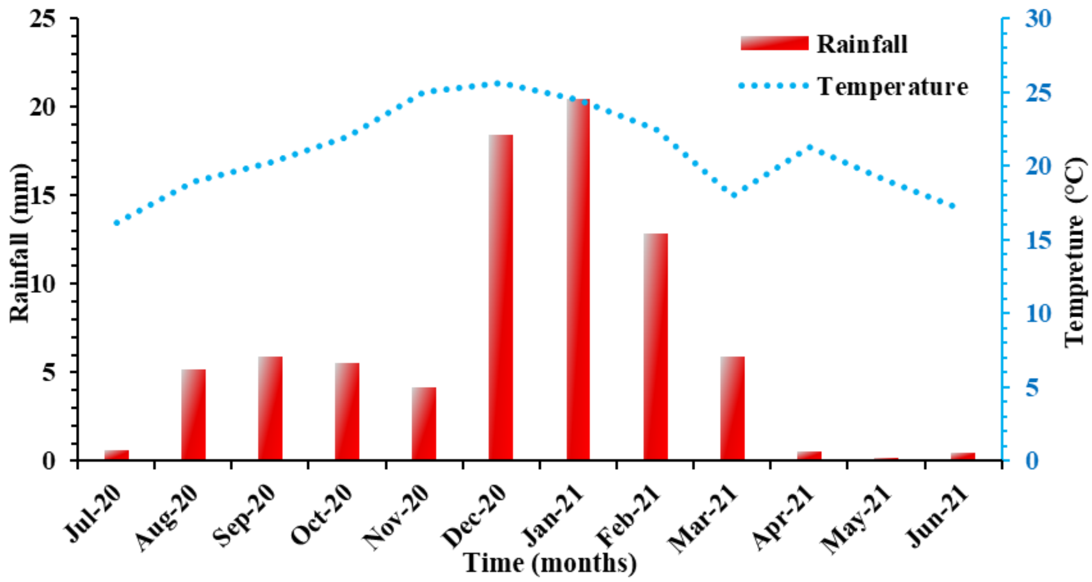


Figure 5.6 Monthly mean rainfall and temperature for the period between July 2020 and June 2021

Figure 5.7 shows the relationship between the monthly (July 2020-June 2021) water extent and the actual evapotranspiration (ET). It can be observed that the seasonal variation influences the actual ET trends within the wetland, where wet periods experience a higher ET than in the drier periods. Meanwhile, a maximum ET value (139.16 mm) was observed in December 2020 and a minimum ET value of 9.90 mm in June 2021. During the first six months (July-December 2020), a gradual increase in the actual ET trend was observed from 10.43 mm in August 2020 to a maximum peak of 139.16 mm in December 2020. Furthermore, a decline in ET was observed between January and June 2021, from 132.39 mm to 9.90 mm. The results also confirmed that the water availability or coverage had a high ET estimate between November 2020 and February 2021, compared to the other months.

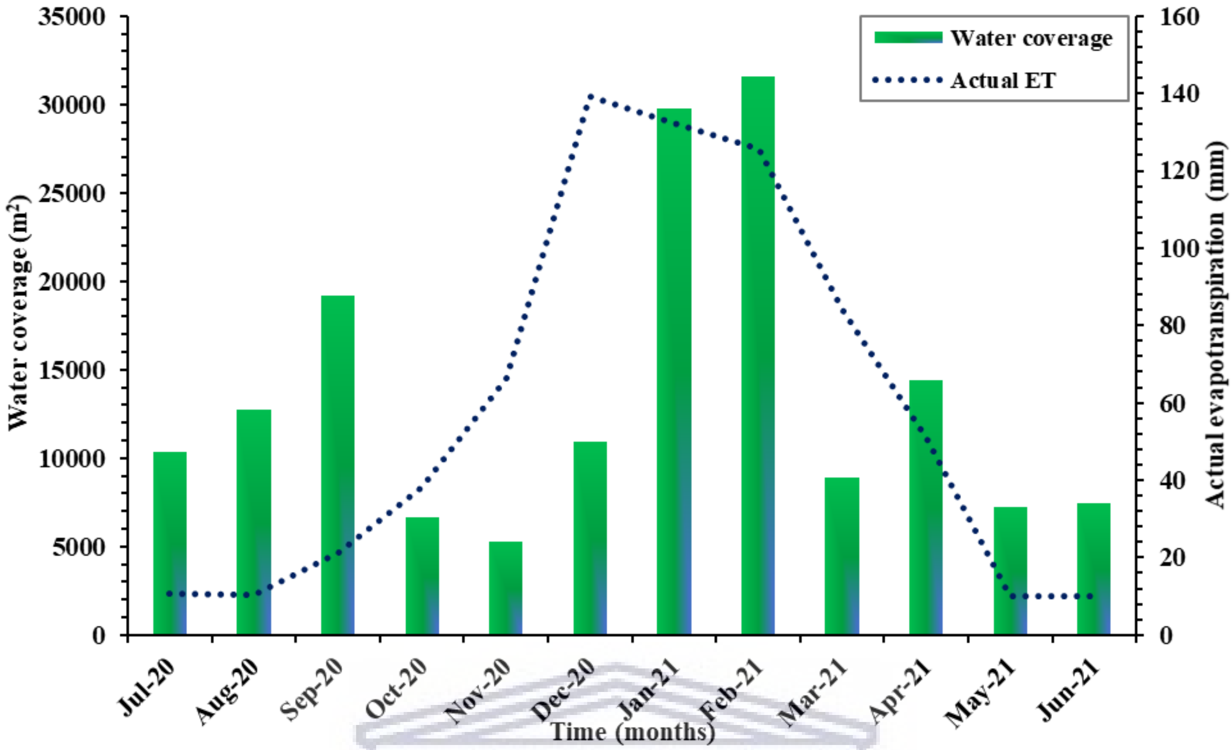


Figure 5.7 Relationship between the extracted water extent and actual evapotranspiration from July 2020 to June 2021

5.4 Discussion

The increasing number of remotely-sensed datasets provide new opportunities for the monitoring of surface water and inundation in small wetland ecosystems in water-stressed environments. As a result, this study sought to map and assess the monthly wetland water and inundation variations (July 2020-June 2021), using the Sentinel-2 MSI derived Modified Normalised Difference Water Index (MNDWI), the Normalised Difference Moisture Index (NDMI) and the Normalised Difference Phenology Index (NDPI) in the Maungani wetland of the Limpopo Transboundary Basin. Sentinel-2 MSI, with its improved spatial (up to 10 m on certain bands) and temporal (a 5-day revisit) resolution, is freely available and provides detailed and timely information that is critical to wetland ecologists and water resources managers. This information will strengthen the policies, management systems, monitoring and quantification of neglected small wetland ecosystems serving neighbouring communities and it will improve the rural economy.

5.4.1 Small wetland response due to monthly precipitation and evaporation variability

Water presence is the main factor controlling ecohydrological dynamics and functionality of wetlands. Wetlands respond differently to variations in rainfall, increased evapotranspiration and temperature. The findings of the study revealed that rainfall, evapotranspiration, temperature and water coverage trends were higher during the summer months (December 2020, January 2021 and February 2021), compared to the dry months (July 2020, August 2020, May 2021 and June 2021). The period facilitated wetland water losses and the reduced extent of inundation through evapotranspiration. A study by Zou *et al*. (2017) showed that rainfall increases the soil moisture content, inundation and water availability within wetland ecosystems. A clear picture of monthly wetland water fluctuation and inundation area is provided during the period of study. The increase in the evapotranspiration rate far exceeds the rainfall, hence it has a significant effect on the presence of wetland water (Dini and Everard, 2016). The evapotranspiration rates increased during the dry periods, resulting in significant wetland water losses and the condition of wetland vegetation (Evenson *et al*. 2016). Mathews *et al*. (2019) highlighted that the spatial extent of wetland inundation is dependent on upstream rainfall and on the ambient trends of evapotranspiration and infiltration, or groundwater recharge. Furthermore, the impacts of evapotranspiration, due to the increased net radiation energy, reduces the vaporised inundation area as well as the moisture availability in small wetlands. Wetland water availability and soil moisture during the summer months reflects the extent of inundation, which is strongly related to the configuration of the vegetation community.

The NDPI results demonstrated similar trends with regard to the inundation extent and moisture variability. In cases where the Maungani wetland area experiences less rainfall and a reduced inundation extent, it resulted in the disruption of vegetation productivity. When dramatic hydrological changes were observed in Poyang Lake in China, it greatly influenced the wetland vegetation (Petus *et al*., 2013). Similar observations were observed by Smith *et al*. (2011) who stated that disconnected streams reduced the water presence and inundation extent, which affected the wetland species diversity and productivity. Water shortages during low rainfall periods and rising temperatures resulted in prolonged droughts, which led to the drying up of small wetland ecosystems. A reduction in the extent of monthly inundation and water presence has a significant influence on vegetation productivity of wetlands. The encroachment of drought conditions within the wetland areas increases the susceptibility of wetland vegetation productivity and complicates the functionality of wetlands.

Water deficits in the wetlands represent a severe threat to ecohydrological systems (Lesk *et al*., 2016). In addition to the climatic factors, anthropogenic land-use activities alter the water flow, water availability and extent of inundation. Furthermore, the modifications of the underlying surface characteristics, such as soil moisture, vegetation community, surface roughness and temperature, changes water and heat balance at the surface. This has long-term implications for the surrounding communities that rely on wetland ecosystems. Excessive wetland water withdrawal for irrigation purposes drains the water table beyond its depth and it disrupts the vegetation that is dependent on the inundation area, which then deteriorates and irreversibly complicates the ecohydrological system (Nevill *et al*., 2020). Smith *et al.* (2011) highlighted that wetland linked to aquifers undergo diminished inundation because the aquifers are drying up, or excessive withdrawals of water are made for agricultural purposes. Agricultural malpractices are putting additional strain on the wetlands, which results in the ecosystem drying up, and the impacts are being exacerbated by the increasing temperatures, with less precipitation (Martin *et al*., 2020).

Our results showed the applicability of Sentinel-2 MSI and metrics (MNDWI, NDPI and NDMI) in assessing the availability of wetland water and the extent of inundation in the Maungani wetland. The results were obtained by using MNDWI, NDPI and NDMI, which managed to retrieve the water, vegetation, and moisture information with high classification accuracies during the study period. Satellite-extracted ecohydrological data provide baseline information for creating an early warning of impending transitions. With the information gathered from the study, management strategies and decisions can be drawn to protect small wetland ecosystems from further degradation. Although developing regions depend heavily on the ecohydrological systems, policies that monitor the withdrawal of wetland water need to be enforced, in order to regulate the agriculture-related activities in these wetlands.

5.4.2 Implications of using a remotely-sensed dataset to study wetland ecohydrological systems

Existing small wetland ecohydrological systems have deteriorated and/or disappeared, yet there is little information available on the extent of wetland water and inundation. Furthermore, the hydrological dynamics of unprotected wetlands are influenced by drought or erosion, climatic conditions and anthropogenic activities, which contribute to the deterioration of wetland ecosystems and make rehabilitation difficult and expensive (Grenfell *et al*., 2019). Monitoring these ecosystems by using Sentinel-2 MSI contributes to a better understanding of ecohydrological systems. However, these images have limitations, for example, cloud cover during the rainy season, which limit the capability for extracting the monthly water presence and the inundation extent (Whitcraft *et al*., 2015). A five-day overpass period, the frequent cloud cover during the rainy season, as well as shadows, make the accurate monitoring and mapping of wetland water and inundation areas difficult.

5.5 Conclusion

This study assessed the monthly variations of the water presence and inundation areas in wetlands, by using the monthly Sentinel-2 MSI dataset. Monthly images, dating from July 2020 to June 2021, were used to extract the water and inundation areas by using MNDWI, NDPI and NDMI. The following conclusions were drawn from the results:

- During the period of study, MNDWI, NDMI and NDPI achieved overall classification accuracies ranging from 70.83% to 98%.
- The findings revealed that there was a high moisture and phenological coverage between October 2020 and April 2021, which indicates the wetness within the Maungani wetland area.
- The results that were derived by using MNDWI showed that the water covering the Maungani area varies during the winter (July and August 2020), spring (September) and summer seasons (December 2020, January 2021 and February 2021).

The findings derived from this study provide new insights into small wetland ecosystems. Moisture and phenological information provide a better understanding of the wetland inundation area, which is critical for devising sustainable management strategies. Adopting the use of digital technologies at a local level will be critical for safeguarding small wetlands, which remain understudied.

CHAPTER SIX

SYNTHESIS, CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

Wetlands provide distinctive productive ecosystems that offer a wide range of goods and services and that influence the functioning of these ecosystems (Martin *et al*., 2016; Singh *et al*., 2017). The mapping of wetland conditions, ecohydrological dynamics and vegetation diversity and productivity, offers valuable information that is required for understanding the status of wetlands in the face of climate change and variability in the face of the rising LULC changes (Gxokwe *et al*., 2020; Thamaga *et al*., 2021). Wetland vegetation is an excellent indicator of vegetation health for small (unprotected) wetland ecosystems and characterises the stages of species diversity and productivity (Janse, 2019). However, efficient, accurate and robust tools are urgently needed for the frequent and timely wetland delineation and monitoring of wetlands. The emergence of remotely-sensed data with improved sensing characteristics provides new opportunities for capturing vegetation diversity, productivity and hydrological dynamics of wetlands, which could be difficult when using the traditional approaches. Traditional approaches for the continuous mapping and monitoring of wetlands lack spatial representation and are challenging. Remote sensing approaches offer a great opportunity to detect and investigate land use change, vegetation patterns and wetland change in a spatially-explicit manner. Satellite remote sensing can monitor on a small to large spatial scale in near real time, and it can provide observations on change in the wetland ecosystem, especially in regions where in situ networks are scarce.

The use of newly-launched satellite images (Sentinel-2 and Landsat 8), with improved spectral bands, a revisit cycle and spatial resolution has produced satisfactory results in mapping wetland ecosystems. The capabilities of these sensors were tested in different studies (Thamaga and Dube, 2018, 2019; Muavhi, 2020) and were perceived to provide critical information when applied in wetlands. However, their performance in mapping of wetland conditions, ecohydrological dynamics and vegetation diversity and productivity is less understood. These sensors opened opportunities for the accurate delineation, mapping and monitoring of wetland ecosystems (vegetation diversity and productivity, hydrological dynamics and wetland degradation), particularly in small wetlands. Hence, the objectives of the study were as follows:

(i) to provide an overview of remote sensing application in wetland ecosystems and to assess the impacts of LULC changes on wetlands;

(ii) to evaluate the state of the environment of small wetland ecosystems and to estimate the remaining percentage of wetlands in the Limpopo Transboundary River Basin;

(iii) to quantify the species diversity in wetlands in the Limpopo Transboundary River Basin, using remotely-sensed datasets, as a proxy of wetland conditions, and

(iv) to monitor impacts of LULC on the wetland hydrological dynamics of the Limpopo Transboundary River Basin.

6.1.1 An overview of remote sensing application on wetland ecosystem, together with the impacts of land use and land cover change that affect the water quality and degradation of wetlands

Several studies have investigated various characteristics and functions of the wetland ecosystem, the impacts of LULC changes, delineation, as well as the degradation of these ecosystems (Mansour *et al*., 2013; Marambanyika and Beckedahl, 2016; Gxokwe *et al*., 2020). Most studies have focused on estimating and mapping the biophysical and biochemical parameters of vegetation in wetlands that are recognized under the Ramsar Convention (Kandus *et al*., 2018; Orimoloye *et al*., 2018); however, small and unprotected wetlands, which also play a critical role in sustaining local communities, have received little attention. Very little attention has been directed towards the hydrology, soil, vegetation quantification, species characteristics, species diversity and productivity status of these small wetlands (literature outlined in Chapter 2). In the face of increased pressure from human interference and climate change, estimation, frequent mapping, monitoring of these wetlands across diverse landscapes is required for sustainable and effective wetland management control, as well as the formulation of governmental policies that promote ecological preservation. Long-term ecological studies (Peter *et al*., 2020; Valdez *et al*., 2011) have found that anthropogenic activities continue to have an impact the water levels, vegetation composition, structure, productivity, diversity and functioning of wetland ecosystems, for decades after the activities have ceased. A new crop of robust satellite sensors, such as Landsat, with improved spatial resolutions and a high record of archival data, provides the most needed spatial tool for detecting, monitoring and understanding status of wetlands, at a low cost. There is a data gap, or undocumented information, on the state of wetlands in developing regions, which further complicates the management strategies and policy development. This review, therefore, provides the insights for wetland-related managers and it emphasizes the urgent need to shift towards the use of cheap and readily-available techniques for assessing and controlling wetland degradation, especially in small wetlands dotted across under-resourced regions.

6.1.2 Evaluation of the state of the environment for wetland ecosystems and the estimation of the remaining percentage of wetlands in the Limpopo River Basin

Studies conducted across African regions that assessed the impacts of LULC change on wetlands, demonstrated the potential of using remote sensing datasets (Wang *et al*., 2011; Mwita, 2013). However, these studies applied remote sensing primarily for wetlands designated under Ramsar (r^2 = 0.88) than non-Ramsar sites (r^2 = 0.65) (Thamaga *et al*., 2021). These findings highlight that there are limited studies that uses remote sensing to monitor small wetland ecosystems that support rural communities (Guo *et al*., 2017; Osorio *et al*., 2020; White *et al*., 2020). To retrieve historical information, we need accurate LULC mapping to track changes overtime, especially in small wetlands were previously undocumented. Satellite data enables efficient and rapid classification of small wetlands with improved accuracies. This study took advantage of Landsat satellite images with high archival data, which plays a critical role for understanding the status of small wetlands by cost-effective monitoring and mapping (demonstrated in Chapter three). Hence, the goal of this study was to explore the effects of LULC change on wetland ecosystems in the Maungani wetland, which is situated in the Limpopo Transboundary Basin. In this study, the integrated time-series Landsat data and Support Vector machine algorithm were used to detect and model the LULC changes that occurred between 1983 and 2019, in order to overcome the degradation of small wetland ecosystems and contribute towards their sustainable management.

During the period of study, there has been widespread conversion of the wetland to built-up areas and agricultural fields. Based on the findings, the Maungani wetland has undergone significant changes in terms of LULC change dynamics during study period (1983 to 2019). Derived LULC change maps showed that the degraded wetland was largely converted into built-up areas. The Maungani wetland shrunk dramatically, from 1 073 500 ha (43.10%) in 1983 to 345 100 ha (13.85%) in 2019. Overall, the findings of this study demonstrated the use of historical and archival Landsat data series for understanding the effects of LULC changes on the spatial extent of wetlands located in semi-arid tropical regions of sub-Saharan Africa. The Landsat data series offers novel, accessible and up-to-date information that is required for the accurate monitoring of the land use and land cover change dynamics. The rate of degradation and encroachment by other LULC changes, especially with respect to unprotected wetlands, play a critical role in surrounding communities. Furthermore, this work showed that there has been a steady deterioration of the Maungani wetland over time. Therefore, this work recommends a holistic framework approach in the management of wetland resources, in order to combat the land use and land cover change challenges, for the sustainability of the catchment areas. This comprehensive information can be used as a guideline for future LULC assessments, for monitoring and for planning.

6.1.3 Quantification of species diversity in wetlands in the Limpopo River Basin, using remotely-sensed data

The use of multispectral remotely sensed datasets in modelling wetland vegetation species diversity and productivity has faced difficulties, resulting in estimation errors due to saturation issues and spatial resolution which led to pixel mixing. The emergence of new crop of satellite images with more spectral bands and spatial resolution such as Sentinel-2 MSI, improved the estimation of wetland vegetation species diversity and productivity. This study showed the potential of integrating Sentinel-2 MSI with in-situ data, vegetation indices and diversity indices (the Simpson, Shannon-Wiener, Margalef and Pielou indices) to accurately estimate wetland species diversity and productivity in the Maungani wetland, is demonstrated in Chapter four. The findings showed that variable predictors, such as the Simpson Index ($r^2 = 0.84$ (84%)), had the strongest relationship in estimating wetland vegetation, with the Margalef Index having a lower $r^2 = 0.54$ (54.72%). The presence of red-edge bands was also found to be the most variable for enhancing estimation, mapping, monitoring, and management of wetland vegetation in data-scarce regions like unprotected wetlands i.e. in African regions in the face of climate change and rapid land use change. Moreover, the results highlight the relevance of Sentinel-2 data in that they have the potential to contribute to a more robust and evidence-based information that can assist in policymaking in conservation and in the sustainable use of wetland ecosystems. Overall, species diversity mapping and monitoring, using Sentinel-2 dataset and biodiversity indices, are critical because they provide benefits for the planning, conservation and rehabilitation of wetland ecosystems. The significant relationship observed between remotely-sensed variables and the diversity of vegetation species confirms the use of Sentinel-2 MSI for practical application in conservation, particularly as a screening tool for identifying biodiversity hotspots.

6.1.4 Assessing wetland ecohydrological dynamics in the Limpopo River Basin, using remotely-sensed data

To better understand how monthly climatic conditions, evapotranspiration and precipitation influences ecohydrological dynamics in small wetlands, Sentinel-2 MSI and indices were used to investigated water availability in relation to vegetation distribution (Chapter Five). The use of these indices (MNDWI, NDPI and NDMI) assessed water availability, moisture content and phenology. The study assessed the monthly variation of wetland water availability and inundation areas, using the Sentinel-2 MSI dataset. The methods used to retrieve information include thresholding on individual pixels ignoring the correlation amongst neighbouring pixels. Considering that, the individual pixels are not independent random variables but a random field, the potential to improve the accuracy of inundation extent. The findings showed that monthly satellite images, dating from July 2020 to June 2021, were used to extract the areas of water availability and inundation, using the Modified Normalised Difference Water Indices (MNDWI), the Normalised Difference Phenology Index (NDPI) and the Normalised Difference Moisture Index (NDMI). Based on the results, the following conclusions were drawn: During the period of study, MNDWI, NDMI and NDPI used the achieved overall classification accuracies ranging from 70.83% to 98%, respectively. Between October 2020 and April 2021, the findings revealed that there is a high moisture and phenological coverage that indicates the wetness within the Maungani wetland area. On the other hand, the MNDWI showed that water coverage varies during winter (July and August 2020), spring (September) and the summer season (December 2020, January 2021 and February 2021). These findings provide new insights into small wetland ecosystems. The moisture and phenological information retrieved from the study gave a better understanding of the wetland inundation area, which is critical for devising sustainable management strategies. Adopting the use of digital technologies at a local level will be critical in safeguarding small wetlands that have, thus far, remained understudied.

6.2 Conclusion

Land use and land cover changes influence the spatial, temporal extent and functionality of unprotected wetland ecosystems. The main aim of this study was to assess the impacts of land use land and cover change on wetland productivity and hydrological processes, by using remotely-sensed datasets in Limpopo River Transboundary Basin. The data used in this study played a critical role, with the selected and appropriate approaches for wetland change, vegetation species diversity and productivity estimation, as well as hydrological dynamics, being based on remotely-sensed data. Furthermore, the findings retrieved during the period of study presented the capabilities of remotely-sensed datasets in the detection, mapping and monitoring of small wetland status, vegetation species diversity and productivity, surface water change and inundation periods. Based on the findings of this study, it can be concluded that:

- Landsat data-series provided critical information for the monitoring of land use and land cover change in the unprotected wetland in the Maungani area. Within the period of study (1983-2019) that proportion of wetland spatial extent was largely reduced by being converted into built-up areas;
- Landsat satellite images have achieved a higher data in the study of long-time changes that occur within wetland ecosystems, and hence, they remain the most used dataset;
- Sentinel-2 MSI, with its increased resolution, managed to detect and map water availability, moisture, and inundation area of wetlands with a high overall classification accuracy;
- The findings further revealed that there is a high moisture and phenological coverage, which indicates that there was the wetness within the Maungani wetland area, between October 2020 and April 2021;
- The results that were derived using MNDWI showed that water covering the Maungani area varies during the winter (July and August 2020), spring (September) and summer seasons (December 2020, January 2021 and February 2021). The period facilitated wetland water losses and a reduced extent of inundation through evapotranspiration; and
- Lastly, the results showed that the monthly variation in water coverage, moisture and inundation area were influenced by the changing climate data i.e. the rainfall pattern and temperature.

Overall, the findings of this study revealed that newly-launched satellite images have the potential in the monitoring, delineating and mapping of small wetland ecosystems. The findings also provide insights for wetland-related managers, which stresses the urgent need to shift towards the use of cheap and readily-available techniques for assessing and controlling wetland degradation, especially in small wetlands that are dotted across under-resourced regions. The long-term monitoring of wetland ecosystems over space and time has provided knowledge that influences the spatial extent of wetlands. The study of wetland vegetation has provided a clear view of the status of vegetation species diversity and productivity, while the hydrological dynamics, vegetation distribution and moisture content demonstrated monthly changes, due to the climatic conditions. This information contributes to the development of well-informed decisions, conservation strategies that can lead to the sustainable utilization of wetland ecosystems, particularly anthropogenic land use and climate variability.

6.3 Recommendations

The present study results contribute to a better understanding of the land use and land cover changes in small wetland ecosystems. The retrieval of information on valuable small wetlands by using remotely-sensed datasets will assist wetland-related scientists and managers in conservation, in the prioritization of policies and in the sustainable use of wetlands. These findings offer new opportunities for remote sensing advancements and their prospective uses in small wetland ecosystems, which was previously a difficult task, but which has been made easier by a new crop of remotely-sensed datasets. The study illustrated the capability of Landsat data series in detecting changes in small wetland ecosystems over time and space (1983-2019). Furthermore, Sentinel-2 showed its strength in detecting and estimating wetland vegetation species productivity, water availability and the inundation areas. This study suggests the following recommendations for future research:

- There is a need for future studies to utilize the new and advanced satellite imagery, coupled with the use of robust machine learning algorithms, such as GEE, and the principal component analysis, to improve modelling for well-informed management decisions on wetland ecosystems.
- In this study, vegetation species diversity and productivity of wetlands were assessed; therefore, there is a need for future research to detect and eliminate alien plant species that are present.
- Future studies need to estimate water loss and how it affects the aquifers.
- Although this study showed the capabilities of remotely-sensed datasets, it is advisable for future studies to integrate climate data, in order to assess the ecohydrological behaviour.
- There is a need for future studies to assess the effects of fertilizers that are being applied to agricultural fields on the water quality and vegetation diversity of wetlands.
- It is advisable for future studies to research the impacts of changing climate on the wetland water budget, particularly in smaller wetlands that serve nearby communities, by using remotely-sensed datasets.

- Future studies need to evaluate all wetland components and land use and land cover changed, in order to draw up proper policies and protection strategies.

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