Remote sensing drought impacts on wetland vegetation productivity at the Soetendalsvlei in the Heuningnes Catchment, South Africa

RESPICE PROSPICE

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Abstract

This work aimed at assessing the response of wetland vegetation productivity to the 2014-2017 climate-induced drought at the Soetendalsvlei wetland system in the Western Cape province of South Africa. To achieve this objective, firstly a literature review on the progress of remotely sensed data applications in assessing and monitoring wetland vegetation productivity was conducted. The review elaborates on the role of remote sensing in monitoring and assessing wetland vegetation productivity, with a detailed discussion of the climate change and variability impacts on wetland vegetation productivity. Accurate assessment results are produced when suitable processing techniques are selected as well as appropriate spatial and spectral resolution for extracting spectral information of wetland vegetation productivity. Secondly, wetland vegetation changes and productivity status was assessed using multi-temporal resolution Landsat series imagery and Normalized Difference Vegetation Index (NDVI) during the wet and dry seasons for the period between 2014 and 2018. The results presented that wetland vegetation spatial distribution and productivity status was greatly affected by drought over the years of the study period. The area under vegetation in the Soetendalsvlei wetland drastically declined from 0.13 to 0.07 km^2. The highest derived productivity status value (NDVI = 0.5) for wetland vegetation was observed during the year 2014 but progressively declined over the years. For an in-depth understanding of drought impacts on wetland vegetation productivity, the study also statistically linked the derived productivity status results to the corresponding rainfall and evapotranspiration (ET) observed during the study period. Wetland vegetation productivity status showed a significant (r=0.8-0.92) and positive correlation to the amount of rainfall received over the same period, whereas with ET the relationships showed an opposite trend (r=-0.7 to -0.5). This study indicated a commendable classification model performance because the accuracy assessment methods were ± 80% for all the remotely sensed derived wetland vegetation mapping results. Results of this study highlight the importance of integrating remotely sensed data and climate variability information in assessing wetland vegetation seasonal and long-term variations. Such information can help in decision-making on the conservation of wetlands and effective monitoring of wetland ecosystems.

Keywords: Climate change; climate variability; wetlands; wetland vegetation; wetland monitoring; satellite data; multi-date analysis; wetland condition

Preface

This research study was conducted in the Department of Earth Sciences, Faculty of Natural Sciences, at the University of the Western Cape in South Africa from January 2019 to June 2021 under the supervision of Professor Timothy Dube.

Full name: Noluthando Ndlala Signature: ………… Date: 05.08.2021

As the candidate's supervisor, I certify the aforementioned statement and have approved this thesis for submission.

Full name: Prof. Timothy Dube Signature: Date: 05.08.2021

Declaration

I, Noluthando Conelia Ndlala, hereby declare that this thesis "Remote sensing drought impacts on wetland vegetation productivity at the Soetendalsvlei in the Heuningnes Catchment, Western Cape, South Africa" submitted to the University of the Western Cape for the Degree of Master of Science in Environmental and Water Science, is my own work and has never been previously submitted by me or anyone else at this or any other University. All sources I have used or quoted have been indicated and acknowledged by means of complete references in accordance with departmental requirements. 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.

Full name: Noluthando Conelia Ndlala Date: 5 August 2021 Signature: Ndlala……………

Publications and manuscripts

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The research was presented at the following conferences:

1. The Geo-Information Society of South Africa WC AGM on the 12th of November 2020
2. South African National Space Agency (SANSA) student workshop 2019 on the 9th of October 2019

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Dedications

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Chapter One

Background and context

1.1. Introduction

Wetland vegetation is a major component of South African wetland ecosystems that cover approximately 2.4% of the country's area (Rebelo et al., 2019). Plants in wetlands play an important role in the environmental functioning of these ecosystems through the provision of ecosystem services such as food and critical habitat for organisms that live in or near water resources, such as algae, macro-invertebrates, amphibians, fish, and birds (Clarkson et al., 2013; Palta et al., 2017). Wetland plants help to improve water quality through the uptake of nutrients, metals, and other contaminants (Dhote and Dixit, 2009). In addition, wetland vegetation plays an important role in river catchments both directly and indirectly by contributing to flood control, drought relief, water storage, soil protection, erosion control, sustained stream flow, recreation & tourism, climate change mitigation and adaptation amongst others, and therefore have important conservation value (Erwin, 2009; Russi et al., 2013). However, the ecosystem services provided by wetland vegetation are facing several pressures due to the impacts of climate change and variability induced drought.

Climate-induced drought is commonly recognized as one of the most important drivers of affected wetland vegetation (Garssen et al., 2014). A reduced amount of precipitation entering into a wetland ecosystem usually decreases wetland vegetation productivity (Herbert et al., 2015). Wetland vegetation productivity is largely controlled by the amount and timing of precipitation and corresponding seasonal fluctuations in soil water content (Zhao et al, 2011). With less precipitation, there will be less interception as wetland vegetation becomes stressed, as well as less infiltration and percolation (Love et al., 2010). Water tables will fall (Berland et al., 2017) and increased evapotranspiration (Fan et al., 2014). This, together with the decrease in transpiration, will reduce the valuable functions performed by wetland plants (Watson et al., 2018). Quantifying wetland vegetation productivity and spatial distribution is a crucial technical task essential for understanding the impacts of climate change and variability induced drought on wetland environments (Fang et al., 2017). There is a critical need to understand how drought affects wetland vegetation productivity because drought severity and drought associated wetlands disturbances are expected to increase with climatic change (Abdel-Hamid et al., 2020).

As climate change exerts increasing pressures on wetland ecosystems, improved methods for monitoring wetland vegetation productivity across a range of spatial and temporal scales will be vital for understanding and addressing responses of wetlands to disturbances such as drought (Finlayson et al., 2013). Effective mapping will provide tangible evidence about the condition of wetland vegetation and will be essential in informing evidence-based decision making, assessing progress towards targets, and in environmental reporting (Wegscheidl et al., 2017). Monitoring wetland vegetation productivity requires regular availability of data (Russi et al., 2012). Remote sensing methods offer timely, up-to-date, and relatively accurate information for effective and sustainable management of wetland vegetation (Adam et al., 2010).

Remote sensing has been a popular tool for mapping wetland vegetation (Kaplan and Avdan, 2018). Satellite multispectral imagery can be used to assess wetland vegetation dynamics which in turn can be linked to rainfall variability of a region under investigation (Tiner et al., 2015). Literature shows that Landsat satellite imagery has been used to successfully map wetland vegetation across the planet (Hansen et al., 2013; Chen et al., 2017). Landsat satellites provide freely available and repeat coverage of spatially continuous measurements collected in a systematic, and objective manner (Ahmadian et al. 2016). Several studies produced reasonable results that prove that Landsat imagery enables the mapping of wetland vegetation at both regional and national scale with high temporal, spatial, and improved spectral resolution (Rapinel et al., 2015; Aslan et al., 2016; Gao et al., 2016; Zhou et al., 2016; Balogun et al., 2020; Mao et al., 2020). However, more research is needed to enhance the understanding of wetland vegetation response to climate-induced drought, particularly, in the Southern African region (Kusangaya et al., 2015). Thus, the main objective of this study was to investigate the response of wetland vegetation to the 2015-2017 drought at the Soetendalsvlei wetland system in the Western Cape province of South Africa.

1.2. Problem statement

Drought is reported to have severe adverse effects on wetland vegetation productivity (Moor et al., 2017). One of the main functions of wetland vegetation is water storage, which is slowly released into a catchment system over a period of time (Miguez-Macho and Fan, 2012). This storage ability will be seriously affected by a drought and the period time that it will be able to decant into a catchment system will decrease exponentially (Hrachowitz et al., 2016). During the storage period in a wetland, numerous attributes of the water are changed, led mostly by the purification of the water during the period it is stored in a wetland, including a vast amount of cleaning and purification of the water content (Roa-García et al., 2011). This process is facilitated by wetland vegetation as well as the sequencing of excess heavy metals, which are removed (Thakur et al., 2016). The process is greatly enhanced by the anaerobic condition of the vegetation in the system. With the amount of water released into a catchment system decreasing, the water quality will also diminish in its clarity and quality (Zhang et al., 2020). Certain impurities that would have been changed by wetland vegetation will also start declining and the amount of contaminated water entering the system will increase (Dan et al., 2017). The functionality of the wetland will be overall affected as the drought severity increases, as the amount of water released will diminish and its dilution effect to the catchment will start lessening, affecting the whole catchment (Mani and Kumar, 2014). Since South Africa remains in the grip of a 100-year drought (Bhaga et al., 2020; Bhaga et al., 2020; Sunter et al, 2018), there is a need to investigate the impact this climatic phenomenon had on wetland ecosystems. Wetland science is less than seventy years old, not enough research on a larger scale has been undertaken to provide an exact amount of all the effects a drought will have on wetland vegetation in general (Junk, 2013). Owing to the fact that up to 90% of the wetland research has been focusing on the purification of polluted systems by building biomimicry artificial wetlands using the same plant species that occur in that area or country. So far, information on the impacts of droughts and climate variability on wetland vegetation productivity remains limited. However, for informed management of these ecohydrological systems, understanding wetland vegetation as well as how it responds to these events is therefore imperative.

1.3. Aims and objective of the study

1.3.1. Aim

The aim of this study was to determine how wetland vegetation responds to drought at the Soetendalsvlei wetland system in the Western Cape province of South Africa.

1.3.2. The objectives of the study were therefore to:

I. Provide a critical evaluation of scientific literature on the use of remote sensing techniques in assessing wetland vegetation productivity

II. Characterize and assess vegetation changes in the Soetendalsvlei wetland to understand the impact of the 2014-2018 drought.

III. Examine the relationship between wetland vegetation productivity and rainfall variability.

1.4. Research questions

I. What are the key scientific knowledge gaps and research progress made on the assessment of wetland vegetation productivity using remote sensing techniques?

II. What was the status and distribution of wetland vegetation in the Soetendalsvlei wetland before, during, and after the long-term drought?

III. How did climate change and variability affect wetland vegetation productivity?

IV. Is there a correlation between drought trend results and wetland vegetation productivity?

1.5. Significance of the study

Wetland ecosystems perform valuable ecological functions (Meli et al., 2014). For instance, they act as a water source and regulate runoff, and more importantly, they function as nutrient filters and sinks by filtering suspended solids. They directly support millions of people through the provision of critical ecosystem goods and services (Gunderson et al., 2016). Apart from these important environmental services, wetlands are also valuable in terms of recreation, scientific, educational, and cultural values. Understanding that wetlands are a special type of landscape, that they are widespread, and that they provide both environmental and cultural benefits to society, it is therefore clear that wetlands conservation is essential. As the rate of wetland degradation and losses increases due to drought, it is imperative that tailor made strategies are devised and put in place to conserve these ecosystems from further deterioration. Decision makers, planners, and water resource managers have to understand the impact drought has on wetland productivity.

Remote sensing offers freely available, realistic, and reliable products that can be used for mapping and assessing wetland vegetation productivity over time and space. This study proposes a spatial explicit methodology for mapping and assessing wetland vegetation productivity and their responses to environmental threats such as droughts and climate variability. Such information will provide an in-depth understanding of the relationships between wetland vegetation and rainfall variability, and this can assist in the effective management of wetlands specifically those under threat. Furthermore, the results of the study will provide a baseline for future research on similar or related studies. In addition, spatially explicit information about the response of wetland ecosystems to environmental change will contribute to wetland protection and restoration initiatives. The study will also contribute to the literature on remote sensing wetland vegetation productivity, and impacts of climate change and variability on wetland vegetation productivity.

1.6. Study area

1.6.1. Description of the study area

The study focused on the Soetendalsvlei wetland system found in the Heuningnes Catchment, which occurs in the southernmost region of South Africa (Figure 1). The catchment covers an area of about 1 401 km2 (Hoekstra and Waller 2014) and lies within the Mediterranean climatic zone. The area receives most of its rainfall during the winter season (mid-May to late August). The temperatures in the area vary significantly throughout the year, with an average range of 10ºC in winter and 28ºC in summer and a mean annual rainfall of 500mm (Roberts, 2005). The study site is a natural freshwater lake which is about 8 km long and a width of up to 3 km, it occurs along the Nuwejaars River, between Elim and Soetendalsvlei. It is one of the major lakes in the catchment (~20 km2) and South Africa's second-largest freshwater lake after Lake Chrissie (Hoekstra & Waller 2014).

The area is considered a biodiversity hotspot because of the unique animals, flora, and landscapes found in the region. It is home to a highly threatened lowland fynbos type of vegetation and a prominent area for twitches (Gordon et al. 2012). The indigenous fauna and flora of the region form the basis of the fishing and tourism sectors of the economy (Gordon et al. 2011). Marine resources such as linefish, rock lobster, and abalone as well as the bait species contribute a huge amount to the Western Cape economy, with the industry worth over R1.3 billion per year (Turpie et al. 2003). Both the film industry and tourism are dependent on natural resources with an estimated 24% of foreign visitors to the region being attracted by its scenic beauty. Direct revenue is also generated from the fynbos through harvesting and cultivation of indigenous rooibos tea, wildflowers like proteas, buchu for its aromatic oils, reeds for thatching, and various traditional and commercially marketed medicinal plants (Braschler et al. 2010).

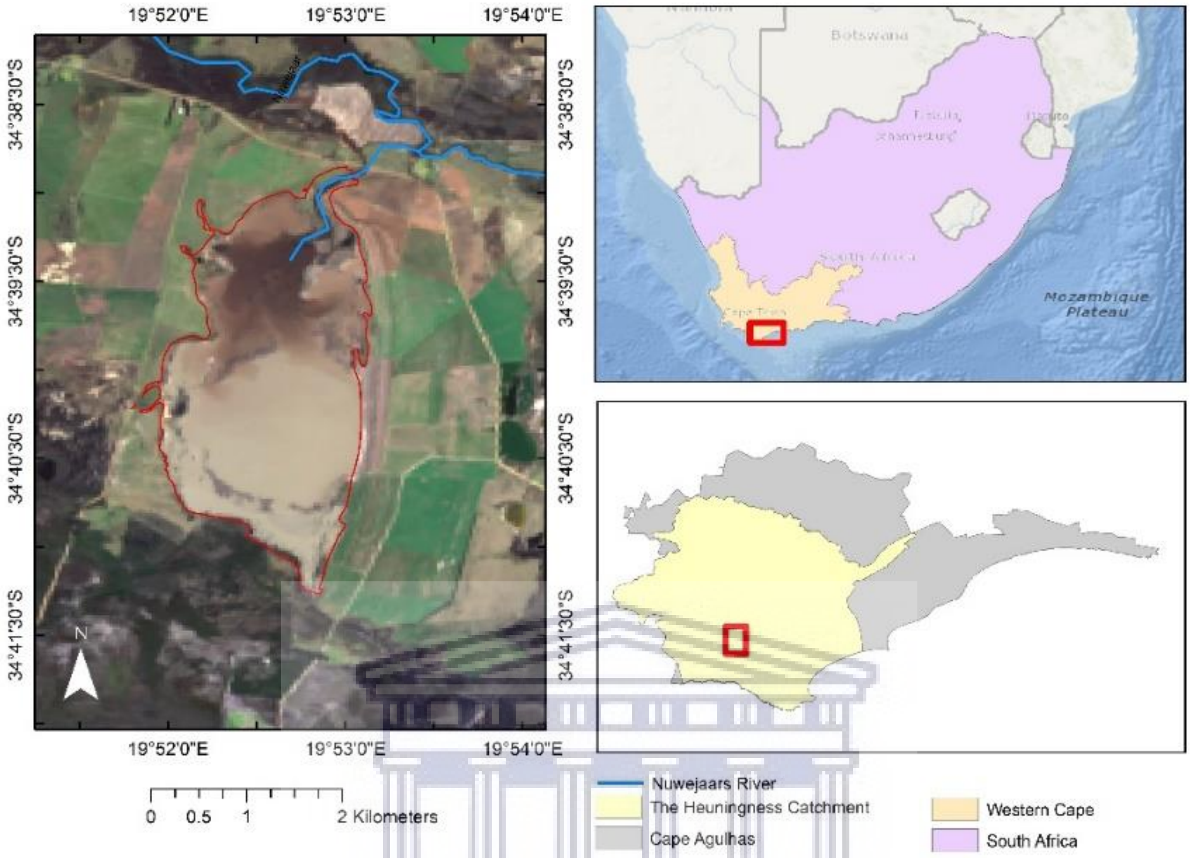

Figure 1: Location of the Soetendalsvlei in the Heuningnes Catchment, South Africa

1.7. Structure of the research

This dissertation consists of four chapters.

1.7.1. Chapter one

This chapter provides the background of the research conducted on the subject. It also presents the main aim and objectives of the study, as well as outlines the problem statement and research questions.

1.7.2. Chapter two

The remote sensing of wetland vegetation is a key requirement for global change research. This chapter provides a detailed review of wetland vegetation productivity using remote sensing methods. Firstly, the review elaborates on the impacts of climate change and climate variability on wetland vegetation productivity. The significance of remote sensing in monitoring and assessing wetland vegetation productivity is explained in detail. The relevance of available remote sensing sensors in determining seasonal and long-term variations of wetland vegetation is also explored. The challenges of remote sensing and progress on wetland vegetation monitoring are provided and the potential of remote sensing vegetation indices for assessing wetland vegetation productivity is also discussed.

1.7.3. Chapter three

Wetland vegetation mapping presents valuable information for understanding the response of ecosystems to global climate change through quantification of vegetation distribution and condition. The chapter is based on the two objectives of the study, which focus on mapping and assessing changes in vegetation health and distribution between the years 2014 to 2018 and examining the relationship between wetland vegetation productivity and rainfall variability. Readily available time series of Landsat 8 OLI images were used to acquire more information about the distribution and extent of vegetation on the site. Estimation of NDVI for the wet and dry seasons was used for extracting wetland vegetation health and cover information. This chapter also comprises detailed comparison information explaining how the amount of rainfall entering into an ecosystem affects the health and distribution of vegetation.

1.7.4. Chapter four

This chapter provides a detailed synthesis of the main findings of the study. Major conclusions and recommendations drawn from the dissertation are also included.

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Chapter Two

Remote sensing of wetland vegetation productivity: A review

Abstract

A literature review on the progress of remotely sensed data applications in assessing and monitoring wetland vegetation productivity was conducted. The review elaborates on the role of remote sensing in monitoring and assessing wetland vegetation productivity, with a detailed discussion of the climate change and variability impacts on wetland vegetation productivity. Firstly, the review highlights the importance of remote sensing in monitoring and assessing wetland vegetation productivity. The relevance of available remote sensing sensors in determining seasonal and long-term variations of wetland vegetation is also discussed in detail. The potential of remote sensing vegetation indices for assessing wetland vegetation productivity is explored and challenges of remote sensing and progress on wetland vegetation monitoring are provided. The review also elaborates on the impacts of climate change and climate variability on wetland vegetation productivity. It can be concluded that the remote sensing of wetland vegetation has some particular challenges that require careful consideration in order to obtain accurate wetland information. These include an in-depth comprehension of factors affecting the relationship between wetland vegetation and electromagnetic radiation in a certain environment, selecting suitable processing techniques as well as appropriate spatial and spectral resolution for extracting spectral information of wetland vegetation.

Keywords: wetlands; wetland vegetation; remote sensing; mapping; vegetation indices; climate change; climate variability.

2.1. Introduction

Wetlands are recognized as one of the richest and most productive ecosystems on earth. Associated with wetlands are a wide range of specially adapted plant species giving food and shelter to a variety of animal life (Desta et al., 2012; Gxokwe et al, 2020). Nearly all of the wetland plants are a valuable food source for wetland wildlife (Cronk and Fennessy, 2016). Animals such as waterfowl, turtles, muskrats, and fish feed on the plants as well as their seeds (Bakker et al., 2016). Wetland vegetation creates habitats for these animals as well as other birds, snails, and insects (van der Valk, 2012). They provide safe breeding and nesting grounds for these and many other creatures (Jedlikowski et al., 2016). Wetland vegetation serves many useful purposes. It not only soaks up water that would otherwise cause flooding but slows the flow as well. It also helps to prevent coastal erosion and also filters out pollutants and sediment

(Malaviya and Singh, 2012). Wetland vegetation productivity is, however, decreasing rapidly, due to increased pressure resulting from human and natural threats such as droughts, flooding, global warming, drainage, overgrazing, pollution, damming to form lakes or ponds, agricultural land management, converting other lands to agriculture, adding pavement, or diverting water flow, which affects the soil's hydrological condition (Bassi et al., 2014; Twilley et al., 2016).

While wetlands act as a buffer against weather occurrences, extreme conditions can diminish vegetation productivity and increase pollution from runoff (Sarkar et al., 2016). Pollution enters the water table through pesticides, sediment, sewage, fertilizers, and many other forms, it degrades wetlands and water quality (Shutes, 2001). Again, wetland vegetation act as a natural filter for polluted water, but it can only absorb so much. Once a wetland is polluted, it is difficult for wetland plants to clean it up. Global warming is also a threat to wetlands (Tiner, 2016). A study by the Pew Center on Global Climate Change found that as air temperatures rise, so do water temperatures (Poff et al., 2002). Because warmer waters are more productive, wetlands may end up overrun by algae, which degrades water quality and poses health problems to humans and animals (Jenny, 2020). The algae bloom known as red tide releases toxins, which have killed thousands of fish (Richlen et al., 2010). Eating affected shellfish can expose humans to these toxins (Marques et al., 2010). Breathing the air near a red tide can also cause respiratory issues in some people (Hoagland et al., 2014). Also, many fish rely on cooler water to survive and can die out when smaller lakes or ponds warm-up (Brönmark and Hansson, 2017). Elevated temperatures also lead to reduced precipitation, which reduces the amount of runoff provided to wetlands (Jeppesen et al., 2009). The functionality of wetland vegetation will be overall affected as the amount of natural and anthropogenic factors combined with global processes increase (Kirwan and Megonigal, 2013). Therefore, monitoring wetland vegetation productivity becomes vital, to ensure their sustainability in maintaining ecosystem services.

Vegetation productivity indicates spatial distribution and change of vegetation cover, throughout this literature review, it is considered as the health of wetland vegetation. Wetland vegetation productivity monitoring is undertaken for forestry plantations around the globe, environment reporting, targeting investment, meeting international obligations, targeting investment, and meeting international obligations, sustainable farming certification, and land management (Kelly and Tuxen, 2009; Taddeo et al., 2019). Monitoring the state of vegetation productivity is a key requirement for wetland ecosystems management research (Lee and Yeh, 2009). It is an important technical task for managing natural resources as vegetation provides a base for all living beings and plays an essential role in affecting global climate change (Canisius et al., 2019). Vegetation mapping also presents valuable information for understanding the natural and man-made environments through quantifying vegetation cover from local to global scales at a given time point or over a continuous period (Mu et al., 2020). It is critical to obtain current states of vegetation cover in order to initiate vegetation protection and restoration programs (Thakur et al., 2012). Better conserving plant communities. Strong preference has been given to acquire updated data on vegetation cover changes regularly or annually to better assess the environment and ecosystem (Xie et al., 2008).

Given the diversity of needs, contexts, and purposes, many different programs have been developed for monitoring wetland vegetation productivity. Traditional methods such as field surveys, literature reviews, map interpretation, collateral, and ancillary data analysis, however, are not effective to acquire vegetation covers because they are time consuming, date lagged, and often too expensive (Gil et al., 2011; Gxokwe et al., 2020). The technology of remote sensing offers a practical and economical means to study vegetation cover changes, especially over large areas (Langley et al. 2001; Nordberg and Evertson 2003). Because of the potential capacity for systematic observations at various scales, remote sensing technology extends possible data archives from the present time to over several decades back (Alonso et al., 2017). For this advantage, enormous efforts have been made by researchers and application specialists to delineate vegetation cover from local scale to global scale by applying remote sensing imagery (Kampe et al., 2010). Increasing demand for information at broader scales has seen the application of spatial modelling (Zerger et al., 2009) as well as many remote sensing studies for mapping and monitoring wetland ecosystems (Slagter and Reiche 2020, Kaplan and Avdan 2019; Long et al 2007). The use of remote sensing for ecological monitoring of wetlands has been reviewed comprehensively (Mahdavi et al 2018; Guo et al 2017; Zhao et al 2015; Kuenzer et al 2011; Henderson and Lewis, 2008; Ozesmi 2002). The reviews focus on wetland classification, biomass estimation, mangrove ecosystems, water quality, sea-level rise, wetland presence, extent, and restoration, but they do not consider the role of remote sensing applications in discriminating and mapping wetland vegetation productivity.

A literature review based on the use of remotely sensed techniques to monitor wetland vegetation productivity is discussed in detail in this study. Initially, the review highlights the importance of remote sensing in monitoring and assessing wetland vegetation productivity. The relevance of available remote sensing sensors in determining seasonal and long-term variations of wetland vegetation is also discussed in detail. The potential of remote sensing vegetation indices for assessing wetland vegetation productivity is explored and challenges of remote sensing and progress on wetland vegetation monitoring are provided. The review also elaborates on the impacts of climate change and climate variability on wetland vegetation productivity.

As climate change place increasing pressures on wetland ecosystems, improved methods for monitoring vegetation across a range of spatial and temporal scales will be vital for understanding and addressing changes to vegetation. Effective mapping will provide tangible evidence about the condition of wetland vegetation and will be essential in informing evidence-based decision making, assessing progress towards targets and in environmental reporting.

2.2. Impacts of climate change and variability on wetland vegetation productivity

Wetland vegetation has the highest carbon density, which makes them play an important role in global climate change and variability, and biogeochemical and carbon cycles (Junk et al., 2013). They are the most valuable part of a wetland providing many beneficial ecosystem services. Among all wetland vegetation services, water purification, flood control, and climate change mitigation are the most important services for human communities (Mitsch and Gosselink, 2007; Mungur et al., 2018). Since the 1950s, global climate systems have shown an unprecedented change (Oleksy et al., 2020). The earth's surface has experienced a warmer climate for each of the past three decades successively. Between 1880 and 2012, the land and ocean surface temperatures have increased by approximately 0.85 °C (range between 0.65 and 1.06 °C) according to Van Ruijven et al. (2014). Wetland plants play an important role in climate change, because of their capacity to modulate atmospheric concentrations of greenhouse gases such as methane, carbon dioxide, and nitrous oxide, which are dominant greenhouse gases contributing to about 60%, 20%, and 6% of the global warming potential, respectively (Bernstein et al., 2007).

Many different factors (biotic and abiotic) influence the function of wetlands. Climate change has been identified as a major threat to wetlands (Osland et al., 2016). It can influence a wetland ecosystem by changing hydrological patterns as well as through increasing temperature, which in turn can alter the biogeochemistry of the ecosystem (Erwin, 2009; Stewart et al., 2013). Wetlands have been identified as one of the most productive ecosystem types; they can actively accumulate and sequester carbon as plant biomass or organic matter in soil through photosynthesis (Alongi, 2012). The waterlogged state of wetlands causes inefficient decomposition that surpasses the rate of production. This anoxic condition brings about an enormous measure of carbon gathering in wetlands, which makes them a sink of carbon (Laiho, 2006).

The hydrological fluctuation of wetlands is inevitable because they are often located in a transition zone between a terrestrial and an aquatic ecosystem (Dronova et al., 2011). Although they have been known to be resilient to change in general, they may still be highly susceptible to hydrological changes, especially when this change is exacerbated by other sources of disturbance such as climate change and variability (Bernstein et al., 2007). Climate change and variability can affect wetland vegetation by direct and indirect effects of rising temperature, changes in rainfall intensity and frequency, extreme climatic events such as drought, flooding, and the frequency of storms (Michener et al., 1997; Leigh et al., 2015). Altered hydrology and rising temperature can change the biogeochemistry and function of wetland vegetation to the degree that some important services might be turned into disservices (Salimi et al., 2021). This means that the plants will no longer provide a water purification service and adversely they may start to decompose and release nutrients to the surface water causing problems such as acidification, brownification, and eutrophication in the water bodies (Roulet and Moore, 2006; Stets and Cotner, 2008; Kritzberg et al., 2018).

Decomposition exceeding wetland vegetation productivity rate because of climate change and variability might result in a shift from a sink to a source of carbon, namely; carbon dioxide and methane emissions to the atmosphere (Laiho, 2006; Flanagan and Syed, 2011). With warmer conditions, more nitrous oxide emissions from wetlands might happen due to higher microbial activity and higher nitrification and denitrification rate as well (Huang et al., 2013; de Klein and van der Werf, 2014). To analyze all of these changes in a wetland, a comprehensive monitoring system is needed to understand how wetland vegetation responds to the stresses and how they can be adapted to future climate change.

The study of climate change and variability impact on wetland vegetation productivity is one of the most critical challenges scientists are facing. According to Stewart et al. (2013), the impact of climate change and variability on wetland vegetation productivity can be assessed by using numerous approaches such as remote sensing tools.

2.3. The importance of remote sensing in monitoring and assessing wetland vegetation productivity

Wetland mapping has been used to determine the spatial extents of vegetation for monitoring and assessment (Hess et al., 2015). Traditionally, it has involved carrying out on-site analysis

(Kusler, 2012) that provided detailed data sets. However, due to the inaccessibility of wetland ecosystems, it has always meant that collected data be extrapolated to describe the conditions in unmapped areas (Ndirima, 2007). Moreover, location, inaccessibility, the variation in sizes, and costs related to additional personnel, time, and equipment has rendered such efforts less valuable (Harvey & Hill, 2001; Garone, 2011).

Increasingly, remotely sensed data is being used for wetland vegetation mapping and monitoring (Hessa et al, 2003; Wu, 2017). This is because remote sensing is cost effective and it provides a synoptic view, multi-temporal and multi-spectral coverage (Bryson et al., 2013). Such remotely sensed data is interpreted visually through automated image classification (Zalazar, 2015) to help understand wetland vegetation productivity dynamics. Using time series data does not only map the spatial distribution of wetland vegetation but also assess its dynamics.

Studies based on optical remote sensing have demonstrated this capability owing to their long period of data acquisition. Such studies have also shown that it is possible to map wetland ecosystems at high accuracy. For example, LaRocque et al. (2020) produced a wetland map for Southern New Brunswick in Canada using a combination of Landsat data, ALOS-1 PALSAR, Sentinel-1, and LiDAR, and achieved an overall accuracy classification of 97.67%. Similarly, Harvey and Hill (2001) using SPOT, and Landsat data in Australia achieved accuracies of over 70% for each. In recent years, ASTER is increasingly recognised as a source of remote sensing data because of its high spatial resolution (Amani et al., 2018). Similarly, high temporal resolution sensors, MODIS and NOAA-AVHRR, have been applied with a preference for MODIS due to high spatial resolution (Huete et al., 2002) and data quality (Pettorelli et al., 2005). Use of Radar in wetland vegetation mapping has been minimal though well demonstrated in literature (Ozesmi and Bauer, 2002; Horrit et al., 2003; Taft et al., 2004; Henderson and Lewis, 2008; Dabboor and Brisco, 2018).

While most of the above data sources are sufficient for single-time mapping, monitoring wetland vegetation productivity requires regular availability of data. Studies (Ozdogan and Gutman, 2008; Hansen et al., 2008; Liu et al., 2010; Huang et al., 2013; Setiawan et al., 2014; Wondrade et al., 2014; Arnous and Green, 2015; Andrew and Warrener, 2017; Monegaglia et al., 2018; Islam et al., 2018) have demonstrated the fundamental importance of multi-temporal remotely sensed data in assessing vegetation dynamics. Nevertheless, the need for multi-temporal data brings into perspective the question of affordability and availability. This drives the consideration of freely available sources like Landsat 8 OLI. Currently, Landsat 8 OLI is preferred for wetland vegetation productivity monitoring due to its narrower NIR band that avoids water absorption regions of the spectrum, and increased chlorophyll sensitivity in the red band (Ke et al, 2015). The derived data is used to calculate vegetation indices (VIs) for monitoring.

Vegetation indices are mathematical combinations that quantify plant vigor for each pixel in a remote sensing image (Xue and Su, 2017). Fang et al. (2014) argue that they help isolate green photosynthetically active signals from the spatially and temporally mixed pixels for meaningful inter-comparisons of vegetation activity. They include the NDVI, Land Surface Water Index (LSWI), Enhanced Vegetation Index (EVI), normalized water vegetation index (NWVI); soil-adjusted, modified soil-adjusted, and transformed soil-adjusted vegetation indices (SAVI, MSAVI, and TSAVI) (Reed, 2006; Zhang and Zhou, 2019). Among these, NDVI is the most commonly used and relies on the absorption of red radiation by chlorophyll and other leaf pigments in the red spectrum, and strong scattering in the infrared spectrum (Dogan et al., 2009). Its application is broad and includes the assessment of biomass, fraction of absorbed photosynthetically active radiation (FAPAR), green cover, and leaf area index (Ndungu et al., 2019; Chidodo et al., 2019).

Time series of vegetation indices have also been used to generate spectral profiles for revealing vegetation health changes (Ozyavus, 2015). This involves the use of algorithms to assess transition dates: green-up, maturity, senescence, and dormancy (Zhang et al., 2010) both in natural and cultivated environments (Rajah et al., 2019; Zhang et al., 2019; Wu et al., 2021). More so, when correlated with environmental variables they help understand the spatial-temporal variations of vegetation that are related to climate change and variability (Wang et al., 2018). Remotely sensed data provide valuable means for monitoring and assessment of wetland vegetation productivity and also helps in understanding its seasonal changes, in addition to revealing its relationship with climate change and variability. Time series of vegetation indices have also been used to generate spectral profiles for revealing vegetation health changes (Ozyavus et al., 2015). This involves the use of algorithms to assess transition dates: green-up, maturity, senescence, and dormancy (Zhang et al., 2010) both in natural and cultivated environments (Rajah et al., 2019; Zhang et al., 2019; Wu et al., 2021). More so, when correlated with environmental variables they help understand the spatial-temporal variations of vegetation that are related to climate change and variability (Wang et al., 2018).

2.4. The relevance of available remote sensing sensors in determining seasonal and long-term variations of wetland vegetation

Historically, aerial photography was the first remote sensing technique to be used for assessing seasonal and long-term variations of wetland vegetation (Cowardin 1974; Shima 1976; Howland 1980, Madison 1981; Pillay 2001; Miyamoto 2004; Mahdavi et al., 2018). According to these studies, aerial photography is the most useful remote sensing method for detailed wetland mapping because of its minimum mapping unit. However, aerial photography is not feasible for determining seasonal and long-term variations of wetland vegetation on a regional scale (Martínez, and Gilabert, 2009). In addition, aerial photography is considered impractical for monitoring that requires continual validation of information because it is time-consuming to process and costly (Mlambo et al., 2017).

Presently, a range of remote sensing images are available for mapping and assessing seasonal and long-term variations at different levels (Zheng et al., 2015). Numerous space-borne and airborne sensors from multi-spectral to hyperspectral sensors function within the different optical spectrum, with different spatial resolutions ranging from sub-metre to kilometers and with different temporal frequencies alternating from 30 minutes to weeks or months have been developed (Nagendra et al., 2013). Among them, aerial photography, Landsat TM, and SPOT images were ordinarily researched in mapping wetland vegetation seasonal changes. Image analysis methods commonly used include digital image classification such as supervised and unsupervised classification (Lee et al., 2011; Sghair and Goma, 2013; Lane et al., 2014; Amani et al., 2019), and vegetation index clustering (Yang, 2007; Mtshali, 2015; Walter and Mondal, 2019; Eid et al., 2020).

Mosime and Tesfamichael (2017) did a comparison of SPOT and Landsat TM data in classifying wetland vegetation in the Klipsriersberg Nature Reserve of South Africa. Their results showed that the overall accuracy of SPOT images was higher than Landsat images. They concluded that SPOT imagery is recommended to map wetland vegetation diversity in a localized area. But neither Landsat TM nor SPOT data were effective to determine seasonal and long-term variations of wetland vegetation. McCarthy et al. (2005) in Botswana found that the high spatial and temporal variation in vegetation in the Okavango Delta makes eco-region classification from Landsat TM data unsatisfactory for achieving land cover classification. In Australian heterogeneous floodplain wetlands, Landsat TM has proven to be a potential source of defining vegetation density, vigor, and moisture status, but not efficient for assessing subtle changes of wetland vegetation (Thomas et al., 2015).

SPOT and Landsat TM satellite images have proven deficient for determining seasonal and long-term changes of vegetation in detailed wetland environments (Sirin et al., 2018). This is due to the broad nature of the spectral wavebands with respect to the sharp ecological gradient with narrow vegetation units in wetland ecosystems, and the lack of high spectral and spatial resolution of optical multispectral imagery, which restricts the detection and mapping of vegetation seasonal variations in densely vegetated wetlands (Fensham and Fairfax, 2002). Although these studies produced reasonable results on mapping wetland vegetation at a regional scale and vegetation communities, more research is needed to explore the benefits of incorporating bathymetric and other auxiliary data to improve the accuracy of assessing wetland vegetation seasonal and long-term variations.

Hyperspectral imagery proved to be useful in determining wetland vegetation seasonal and long-term variations with higher accuracy. For example, Judd et al. (2007) used hyperspectral image data for mapping wetland vegetation. They examined the utility of airborne hyperspectral imagery in mapping salt marsh vegetation in Humboldt Bay, California, USA. Overall accuracy among salt marsh vegetation was assessed at 85.1%. Zhang (2014) also explored a combination of hyperspectral and LIDAR systems for vegetation mapping in the Florida Everglades. A synergy of hyperspectral imagery with all LIDAR-derived features achieved the best result with an overall accuracy of 86 percent and a Kappa value of 0.82 based on an ensemble analysis of three machine-learning classifiers. The study shows the promise of the synergy of hyperspectral and LIDAR systems for mapping complex wetlands. These studies prove that hyperspectral images produce accurate information for wetland vegetation monitoring. However, hyperspectral imagery is time-consuming to process, expensive to acquire, even when small areas are covered (Adam et al., 2010). Innovative methods that take advantage of the relatively large coverage and high spatial resolution of the fine sensors and the high spectral resolution of hyperspectral sensors could result in more accurate assessment models of wetland vegetation at a reasonable cost.

Determining wetland vegetation seasonal and long-term modifications requires regular the availability of data, improved spatial and spectral resolution. With availability of free images acquired by Landsat-8 OLI and Sentinel-2 remote sensing satellites, it becomes possible to enable temporal resolution of an image every 3-5 days, and therefore, to develop next-generation wetland vegetation products at higher spatial resolution (30 m). Bhatnagar et al. (2020) mapped wetland vegetation communities' ecological condition inside Ireland wetlands using Sentinel-2 data. 10 bands of Sentinel-2 Level-2 data and 3 indices, Normalised

Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Normalised Difference Water Index (NDWI) were used to create vegetation maps of each wetland using Bagged Tree (BT) ensemble classifier and graph cut segmentation also known as MAP (maximum a posteriori) estimation. An overall classification accuracy up to 87% depending on the size of the vegetation community within each wetland has been achieved which suggests that the proposed method is appropriate for wetland health monitoring. Tieng et al. (2019) mapped the spatial distribution of Cambodia's mangrove forest derived from 30 m x 30 m spatial resolution and polygon spatial extent from Landsat 8 (L8) image. Random Forest (RF) Classifier, a supervised classification technique, was applied to three L8 images Archive Pre-Collection Level-1 (L8 OLI/TIRS) collected in December 2014, February 2015, and April 2015. Statistical analysis indicates the total area of mangrove forest cover reached 73,240ha with an overall classification accuracy of 98.2%, 97.9%, and 99.5% for three periods and the validation overall accuracy were 91.5%, 89.1%, and 97.6%, respectively. Their findings suggest that L8 imagery can be used to estimate long-term changes in mangrove forests in Cambodia with higher accuracy. The results of this study may be useful to assist decision-making in planning for mangrove ecosystem restoration initiatives, evaluation of ecological services, and in better estimation of carbon stock in a mangrove forest. These studies produced reasonable results that prove that Landsat 8 and Sentinel 2 enable the mapping of wetland vegetation at both regional and national scales with a high temporal, spatial and improved spectral resolution, which is a fundamental requirement for assessing wetland vegetation seasonal and long-term dynamics. Table 1 provides a detailed summary of remote sensing studies on mapping wetland vegetation productivity.

Table 1: Summary of remote sensing applications in assessing and mapping wetland vegetation

Sensor	**Image Analysis Technique**	**Results**	**References**
Sentinel 2	Bagged Tree (BT) ensemble classifier	Overall classification accuracy=87%	Bhatnagar et al. (2020)
Landsat 8	Random Forest (RF) Classifier	Overall classification accuracy of 98.2%, 97.9% and 99.5% for three periods and the validation overall accuracy were 91.5%, 89.1% and 97.6%, respectively.	Tieng et al. (2019)

SPOT 5, SPOT 6, Landsat 7, Landsat 8 and Sentinel 2	Object-oriented, trees, minimum distance, and neural networks classification methods	Overall accuracies for minimum distance and object-oriented method=95.00% and 94.58% better than neural network and trees methods= 88.96% and 80.83%	Sirin et al. (2018)
Landsat 8 OLI SPOT 7	Unsupervised classification	SPOT accuracy assessment (Overall accuracy=71%; kappa=0.58) Landsat 8 OLI accuracy assessment (Overall accuracy=53%; kappa=0.35)	Mosime and Tesfamichael (2017)
Landsat 7 ETM+ and Landsat 5 TM	Unsupervised classification, NDVI, NDI, and Normalised Difference Water Index (NDWI)	Landsat imagery overall accuracies were 93% and 95% for a small and large inundated area. Producer's and user's accuracies=94–99%	Thomas et al. (2015)
Hyperspectral and lidar	Machine learning classifier	overall accuracy=86%; Kappa=0.82	Zhang (2014)
Airborne hyperspectral imagery	Linear spectral unmixing (LSU)	Overall accuracy=85.1%, r^2 = 0.32 to r^2 = 0.53	Judd et al. (2007)

2.5. The potential of remote sensing vegetation indices for assessing wetland vegetation productivity

Remotely sensed data of growth, vigor, and their dynamics from wetland vegetation can provide extremely useful insights for applications in environmental monitoring, biodiversity conservation, and other related fields (Chiloane et al. 2020; Chiloane et al., 2021; Kuenzer et al., 2014). Wetland vegetation productivity can be assessed through Vegetation Indices (VIs) obtained from remote sensing-based canopies (Adam et al., 2010). VIs are quite simple and effective algorithms for quantitative and qualitative evaluations of vegetation cover, vigor, and growth dynamics, among other applications (Muraoka et al., 2013). They are generated by combining data from multiple spectral bands into a single value (Vila et al., 2014). SVIs are also designed to enhance the vegetation signal in remotely sensed data and provide an approximate measure of live, green vegetation amount (Gonsamo Gosa, 2009). The rationale for VIs is to exploit the unique spectral signature of green vegetation as compared to the spectral signatures of other earth materials. Green leaves have a distinct spectral reflectance pattern in the Near-Infrared (NIR) and visible (VIS) wavelengths (Svotwa, et al., 2012). Reflectance in the red and blue regions is very low, with a slightly higher bump in the green (Dana et al., 1999). This is why leaves appear green to human eyes. In the NIR, the spectral response of green leaves is much greater than in any portion of the visible (Hunt et al., 2011). Other materials such as bare soil, sand, exposed rock, concrete, or asphalt, generally show a steady rise in reflectance as wavelength increases from the visible to the near-infrared (Heiden et al., 2007).

VIs integrate spectral information from the red and NIR reflectance (Zhao et al., 2005). Red reflectance is sensitive to chlorophyll content and the NIR reflectance is sensitive to the mesophyll structure of leaves (Houborg and Boegh, 2008). In a given image scene, the greater the difference between the red and NIR reflectance, the greater the amount of green vegetation present (Miura et al., 2006). Small differences between the red and near-infrared reflectance indicate a pixel containing mostly bare soil or other non-vegetated classes (Ganguly et al., 2012). Spectral vegetation indices are related to several biophysical variables of interest to many researchers, including Leaf Area Index (LAI), percent vegetation cover, green leaf biomass, fraction of absorbed photosynthetically active radiation (fAPAR), photosynthetic capacity, and carbon dioxide fluxes (Xie et al., 2018). VIs have the ability to discriminate wetland vegetation from other landcover classes, assess its condition, and map percent vegetation cover, a fundamental method to analyze wetland vegetation productivity.

The most common vegetation index is the NDVI. The adoption of VI including the most widely used NDVI is another method to assessing wetland vegetation productivity using optical remote sensing devices (Xie et al., 2008). The principle of applying NDVI in the assessment of wetland vegetation productivity is that wetland vegetation is highly reflective in the near-infrared and highly absorptive in the visible red (Jensen et al., 2019). The contrast between these channels can be used as an indicator of the status of the vegetation found in wetland ecosystems (Stratoulias et al., 2018). In other words, NDVI is a biophysical parameter that correlates with the photosynthetic activity of vegetation. In addition to providing an indication of the greenness of the vegetation (Wang and Tenhunen 2004), NDVI is also able to offer valuable information on the dynamic changes of wetland vegetation given that multiple-time images are analyzed.

NDVI is a good indicator to reflect periodically dynamic changes of wetland vegetation (Geerken et al. 2005). Wetland vegetation productivity can be assessed through dynamic signals of NDVI (Lenney et al. 1996). For example, Wilson and Norman (2018) did an Analysis of vegetation recovery surrounding a restored wetland using the normalized difference infrared index (NDII) and NDVI at Cienega San Bernardino, an important wetland in southeastern Arizona and northern Sonora, Mexico. In the study, NDVI was used analyze spatial and temporal trends in vegetation greenness. NDVI was better able to track changes in vegetation in the study area. Eid et al 2020 also carried out a study to evaluate the dynamics of land cover change using three change scenes of recent and past satellite data from 1990 to 2019 at El-Burullus wetland, in Egypt. NDVI was employed to assess the changing scenario of the area. Results indicated that vegetated land has increased significantly with a concomitant shrinkage in the water body and open soil during the study period. Narumalani et al 2009 characterized the patterns and trends of wetland vegetation for an area around Island Lake in the Sandhills of Nebraska, in the USA. In this study, NDVI was used to examine the variation of wetland vegetation across different terrain features within the landscape. NDVI trends over the 11-year period were determined and average NDVI values along with standard deviation were computed for each year. The highest mean NDVI was recorded for the marsh, while the lowest occurred on the dune top. Results also showed that the marsh was prone to higher variation in NDVI from year to year than any of the other terrain types. Ju and Bohrer 2020 classified wetland vegetation based on NDVI time series generated from NASA's Classification of wetland vegetation based on NDVI time series generated from HLS dataset Yang Ju a, b, Gil Bohrera, ba Environmental Science Graduate Program b Department of Civil, Environmental and Geodetic Engineering Abstract Harmonized Landsat Sentinel-2 (HLS) dataset at Lake Erie in Ohio. Miranda et al 2018 studied the changes of vegetation cover of the Pantanal wetland detected by vegetation index: a strategy for conservation. The objective of this study was to analyze the vegetation cover of the Pantanal in the period of 2000, 2008 and 2015, and to make a projection for 2030. Therefore, NDVI from the sensor MODIS was analyzed and the transition matrix was calculated by the DINAMICA EGO. The results of the study indicated alterations of the vegetation cover of the Pantanal, with an increase of short vegetation in the evaluated period. The projection pointed out that in 2030 the Brazilian Pantanal wetland area will be covered by 78% of short vegetation and only 14% of dense (arboreal-shrubby) vegetation.

All the above studies prove that NDVI can be used to assess spatial-temporal variations of wetland vegetation, and this makes NDVI the most valuable VI for monitoring the growth condition of wetland plants. Although these studies produced reasonable results on assessing wetland vegetation productivity through NDVI, more research is needed to explore the benefits of incorporating bathymetric and other auxiliary data to improve the accuracy of mapping wetland vegetation variations.

2.6. Challenges of remote sensing and progress on wetland vegetation monitoring

Wetland vegetation is not as easily as terrestrial vegetation, which occurs in enormous stratification. This is because of the steep environmental gradients that produce short ecotones and sharp demarcation between the vegetation units that make wetland vegetation exhibit high spatial and spectral variability (Adam and Mutanga 2009). Furthermore, the reflectance spectra of wetland vegetation canopies are often combined with reflectance spectra of the underlying soil, hydrologic regime, and atmospheric vapor (Lin and Liquan 2006). When wetland classes' reflectance spectra combine, image classification becomes complicated and result in a reduction in the spectral reflectance, especially in the near to mid-infrared regions where water absorption is stronger (Adam et al., 2012). Thus, the current methods used to map terrestrial plants using optical remote sensing, may not be able, either spectrally or spatially, to successfully assess wetland vegetation because the performance of near to mid-infrared bands are decreased by the occurrences of underlying wet soil and water (Klemas, 2013). However, hyperspectral narrow spectral sensors offer the potential to assess wetland vegetation of wetland vegetation (Ouyang et al., 2013).

Significant progress has been made in applying remote sensing sensor data and methods in the mapping of wetland vegetation. However, there are still challenges to be addressed in many aspects. First, traditional digital imagery from multi-spectral scanners is subject to limitations of spatial and spectral resolution compared to narrow vegetation units that depict wetland ecosystems (Lu et al., 2018). Second, despite the fact that hyperspectral sensors are able to effectively map wetland vegetation, the reflectance of wetland vegetation is influenced by its biochemical and biophysical properties (Guo et al., 2017). Additionally, these properties are directly influenced by environmental factors and therefore the unique spectral signature of wetland vegetation has become questionable. In addition, spectral variations can also occur because of soil and water background, precipitation, and topography.

A third research challenge is that in most African countries such as South Africa there are only a handful of studies that have used hyperspectral data to map wetland vegetation variations due to high cost and poor accessibility (Mutanga and Kumar, 2007). Despite these shortcomings, there is no doubt that remote sensing techniques could play a vital role in the assessment and monitoring of wetland vegetation effectively by selecting appropriate spatial and spectral resolution as well as suitable processing techniques for extracting vegetation productivity information. From a research perspective, however, there are a number of most important challenges in the application of remote sensing in wetland species that need to be addressed.

First, the most current remote sensing techniques in mapping vegetation have been undertaken in arid and semi-arid regions with low vegetation cover and less complexity within the vegetation unit. These techniques are therefore of little use for narrow vegetation units that characterize wetland ecosystems. The additional research effort is needed to adopt more classification techniques to improve the accuracy of the spatial resolution of the current sensors, which varies from 20 to 30 m (Adam et al, 2010; Seaton et al., 2020; Seaton et al., 2021). Second, in the southern African region, more research is needed to enhance the ability in assessing the response of wetland vegetation productivity to climate change and climate variability, which have been overlooked in scientific research. A third research prospect is the availability of hyperspectral sensors that could allow the mapping of both variations and the health of wetland vegetation. This will enhance a fundamental understanding of the spatial distribution of wetland vegetation and its productivity, which could lead to the development of early warning systems to detect any subtle changes in wetland systems such as signs of stress and to develop techniques to classify wetland ecosystem conditions based on vegetation quality and quantity.

2.7. Conclusion

Given the state of decline of wetland vegetation productivity due to climate change and variability, improved monitoring over a range of temporal and spatial scales is immediately required. The assessment of wetland vegetation productivity necessitates cost-effective methods because monitoring wetland vegetation productivity requires systematic obtainability of data. In addition, more research is needed to develop the ability in assessing the response of wetland vegetation productivity to climate change and variability in the Southern African region. Remote sensing methods have proven very valuable in advancing the field of wetland vegetation monitoring at their relative scales of application. However, to produce precise and reliable wetland vegetation assessment and monitoring results, you need to effectively select appropriate spatial and spectral resolution as well as suitable processing techniques for extracting vegetation productivity information. This review has assessed the role of mapping and assessing wetland vegetation productivity using remote sensing techniques in detail, including impacts of climate change and variability on wetland vegetation productivity. It can be concluded that climate change and variability will severely affect wetland vegetation productivity. There is a need for a comprehensive monitoring system to understand how wetland vegetation responds to the disturbances and how they can be adapted to future climate change. Current technological advancements such as the increasing free availability of satellite image time series, will likely enable further research in mapping and monitoring wetland vegetation productivity across a range of scales. Remote sensing may provide an improved understanding of complex spatial processes and patterns of wetland vegetation, which is important for natural resource management and quantifying vegetation productivity status across a range of scales.

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Chapter Three

Use of remotely sensed derived metrics to assess wetland vegetation responses to climate variability induced drought at the Soetendalsvlei wetland system in the Western Cape province of South Africa

Abstract

Wetland areas are the most vital ecosystems and they provide important functions towards stabilizing the environment. Hydrological processes in these wetland systems directly affect the productivity of plants. Therefore, assessing vegetation response to climate variability induced drought is vital in wetlands. In this study, the subtle changes in vegetation distribution were used as a proxy to examine and quantify the extent of drought impacts on wetland ecosystems within the Heuningnes catchment, South Africa. First, vegetation health information was extracted by calculating the normalized difference vegetation index (NDVI) during the wet and dry seasons for the period between 2014 and 2018. The derived NDVI results were further statistically linked to the corresponding rainfall and evapotranspiration (ET) observed during the study period. An analysis of NDVI results revealed that gradual vegetation health change occurred across the study area. The highest derived NDVI (0.5) for wetland vegetation was observed during the year 2014 but progressively declined over the years. Change in vegetation health indicated a significant ($\alpha = 0.05$) and positive correlation to the amount of rainfall received over the same period. The results of this study showed that healthy vegetation deteriorated between the study periods due to the 2015-2017 Western Cape drought.

Keywords: drought; evapotranspiration; Heuningnes catchment; NDVI; wetland extent; vegetation health.

3.1. Introduction

Wetlands are amongst the Earth's most productive ecosystems. Although they merely occupy 6.2 to 7.6% of the land surface, wetlands are a valuable natural resource of considerable scientific value because they are associated with high biological diversity (Ndirima 2007; Sghair and Goma 2013; Kuria et al. 2014). Wetlands within the Heuningnes catchment are important as natural ecosystem remnants facilitating nutrient cycling, cleaning, and the purification process of water, as well as provide scenic attractions for tourists and wildlife habitats (Melendez-Pastor et al. 2010; Chen et al. 2014). Long-term threats to these wetlands include agricultural development, droughts, urban development, climate change, and variability as well as other impacts associated with it, such as alien invasion species (Orimoloye et al. 2019; Rebelo et al. 2019). Wetlands are vulnerable and particularly sensitive to fluctuations in the quantity of water supply. In this respect, changes in precipitation due to climate change also pose great challenges to wetland conservation (Erwin 2009).

Inadequate rainfall can induce significant declines in overall plant productivity and even lead to high rates of plant mortality (Touchette et al. 2007; Yu et al.2019). Plants are excellent indicators of wetland conditions for many reasons including their relatively high levels of species richness, rapid growth rates, and direct response to environmental change (Cronk and Fennessy 2009; Chatanga and Sieben 2019). Many alterations to the environment that act to degrade wetland ecosystems cause shifts in plant community composition that can be quantified easily (Ehrenfeld 2000). Insufficient water supply may lead to the depletion of soil moisture (Bordi and Sutera 2007), which will further have adverse effects on the growth and health of plants. Increases in temperature also affect wetland systems by accelerating the rate of evaporation and transpiration (Abtew and Melesse 2013). Therefore, the ability to map and assess wetland vegetation productivity in detail, especially in response to climate change, will always be an objective in the management of wetland ecosystems.

Monitoring the response of vegetation to drought is important for the sustainable conservation of wetland ecosystems as it is related to the condition of the water supply. However, continuous observation and investigation based on physical methods remains restricted to small geographic coverage, for a specific period and it focuses mainly on individual species (Hooper et al. 2005; Guo et al. 2017). In addition, research done physically can be resource-intensive and problematic when the study area is remote and hazardous (Daryadel and Talaei 2014). Similarly, developing models for monitoring wetland vegetation at individual levels remains impractical, especially in light of the global effects of climate change (Xie 2008). Drought indices such as Palmer Drought Severity Index (PDSI) and Standardized Precipitation Index (SPI) become unreliable because of their dependence on accuracy of ground observed meteorological inputs that provide sparsely (Zhao et al. 2017) and possess poor spatial resolution at a regional scale, especially, in areas where a few of ground observations are available.

Recent advancements in satellite remote sensing, as powerful means of Earth's surface assessment, have provided efficient, reliable, and affordable monitoring tools for identifying, describing, and mapping the distribution of wetland vegetation with various spatial, temporal, and spectral resolutions at wide scales from local to global (Jones et al. 2009; Kaplan et al. 2019). In particular, the normalized difference vegetation index (NDVI), precipitation, and evapotranspiration (ET) products may provide valuable information to understand the wetland ecosystems response to drought because meteorological data obtained from ground observation stations often have poor spatial resolutions (Wan et al. 2004). The NDVI picks up the frequency that the plant leaf releases in order to measure its vigor of the plant's health (Xue and Su 2017; Onyia et al. 2018). Sensors typically capture some combination of visible and near-infrared light using narrow filters to increase the sensitivity and specificity of the measurements (Lapray et al. 2014). When a plant becomes dehydrated or stressed, the spongy layer of the plant collapses, and its leaves reflect less NIR light, yet they still reflect the same amount of light in the visible range (Jacquemoud and Ustin 2019). Thus, vegetation health is one of the most crucial factors to look at when studying the response of wetland ecosystems to drought.

Investigating the relationship between NDVI and ET or precipitation can infer water stress from different plants. This is because sufficient water promotes efficient transpiration and cool plant, while water deficiency promotes closing plant stomata and intense transpiration rate, thus, lower ET represents the stronger evaporative cooling for pixels with the same NDVI (Petropoulos et al. 2009; Yu et al. 2019). As an approach towards assessing wetland vegetation response to climate variability induced drought at the Soetendalsvlei in the Heuningnes Catchment, South Africa, this study mapped and assessed changes in vegetation health and distribution between the years 2014 to 2018, and also examined the relationship between wetland vegetation productivity and rainfall variability.

3.2. Materials and Methods

In this study, time series of Landsat images were used to acquire more information about the extent and distribution of vegetation in the site. Landsat 8 (L8) Operational Land Imagery (OLI) Level 1 data acquired for the period of January 2014 to December 2018 were used, freely available from https://earthexplorer.usgs.gov/. The data are available every 16 days with a spatial resolution of 30m, different bands of the sensor and its specifications are available in Table 2. Cloud-free images and images with less than 10% cloud cover were selected. Two images representing wet and dry seasons for each year were obtained and details of these data are provided in Dube and Mutanga (2014). Band 4 (Red) and 5 (NIR) were used for the estimation of NDVI for the wet and dry seasons of each selected year (Tucker 1979). The L8 images were atmospherically corrected using FLAASH atmospheric correction method. The selection of the drought monitoring period was informed by the documented literature and information on the onset of drought (Botai et al. 2017; Leslie and Richman 2018; Otto et al. 2018).

Evapotranspiration (ET), and Precipitation data were acquired from https://wapor.apps.fao.org/catalog/1. The ET data was delivered on a dekad (10-days basis) and is mainly the sum of soil evaporation, canopy transpiration, and evaporation from rainfall intercepted by leaves. The value of each pixel represents the average daily ET in a given dekad (Sazib et al. 2018). Precipitation dataset was obtained from CHIRPS (Climate Hazards Group InfraRed Precipitation with Station), a quasi-global rainfall dataset, starting from 1981 up to the near present. For CHIRPS, the value of each pixel represents the average of daily precipitation in the dekad expressed in mm (Funk et al. 2015).

Table 2: Specifications of the satellite images used for spatial assessment of vegetation

Year	Date of Acquisition	Image Scene Detail	Path/ Row	Land Cloud Cover (%)
2014	June 21	LC81740842014172LGN01	174/84	0.36
	24 December	LC81740842014348LGN01	174/84	0.02
2015	8 June	LC81740842015159LGN01	174/84	0.76
	17 December	LC81740842015351LGN01	174/84	0.09
2016	25 May	LC81740842016146LGN01	174/84	0.3
	3 December	LC81740842016338LGN01	174/84	0.01
2017	29 June	LC81740842017180LGN01	174/84	0.63
	6 December	LC81740842017340LGN00	174/84	3.04
2018	18 July	LC81740842018199LGN00	174/84	1.97
	25 December	LC8174082018359L	174/84	0.64

		GN00		

3.2.1. Extraction of Vegetation Cover

Since there is great variation in vegetation distribution within a given year, in order to obtain abundant cover information about vegetation productivity, wet and dry season vegetation cover in each year was considered for this particular study. In this study, the wet season stretches from May to October and November to April for the dry season. To map and extract the wetland vegetated area and other land cover features that are water and non-vegetated areas within the Soetendalsvlei wetland, the Normalized Difference Vegetation Index: NDVI (Nir - Red/Nir + Red) was calculated. The red and NIR electromagnetic signals (bands) help to differentiate a plant from a non-plant and healthy plants from the stressed plants as well as water from other surface features (Lima et al. 2020). The computed NDVI values ranged from -1 through 0 to 1, where -ve values approaching -1 correspond to water, values close to zero (-0.1 to 0.1) depict barren areas e.g. rockoutcrops, sand, bare surfaces, and +ve indicate plant health (Bhandari 2012; Wang et al. 2018). Since the derived water and vegetation exhibited unique and distinct NDVI values, we then reclassified the derived NDVI images into three classes (non-vegetated water, and vegetation) using the common geographic information tools as detailed in remote sensing literature (Wang et al. 2018; Wilson and Norman 2018; El-Gammal et al. 2014).

NDVI thresholds were defined and set for each class and these thresholds were somehow informed by literature (Wilson and Norman 2018; Wang et al. 2018). In the study, thus thresholds were set as following non-vegetated (NDVI range between -0.21 and 0.19), vegetated (NDVI ≥ 0.2), and water (NDVI≤-02). We then conducted an accuracy assessment for the derived classes by computing the user, producer, and the overall accuracies, validation was done using ground control points, and Google Earth digitized sample points. Further, the derived results were compared to climate data for the areas to determine trends and relationships between derived vegetation metrics and climate data. Specifically, correlation analysis was used to assess the response of wetland vegetation to drought by evaluating the relationship between NDVI results and rainfall variability. The Pearson product-moment correlation coefficient, better known as the r was performed to derive the statistical analysis results. The coefficient was calculated for the 12 months data for each year from May to April. The correlation coefficient was computed as:

$$r = \frac{\sum\left(NDVI_i - \overline{NDVI}\right)(Y_i - \overline{Y})}{\sqrt{\sum(NDVI_i - \overline{NDVI})^2}\,(Y_i - \overline{Y})^2}$$

Where Y is the precipitation or ET and NDVI is the normalized difference vegetation index and average monthly total precipitation or ET for the years 2014, 2015, 2016, 2017, and 2018 adopted in this study. Possible values of r range from -1 to +1, with values close to 0 signifying the little relationship between the two variables. When r is above 0.5, there is a positive relationship between the two variables but there is no significant association. The value ranges from 0.8 to 1 represent a positive significant relationship between the two variables. A detailed description of the methodology is summarized in figure 2.

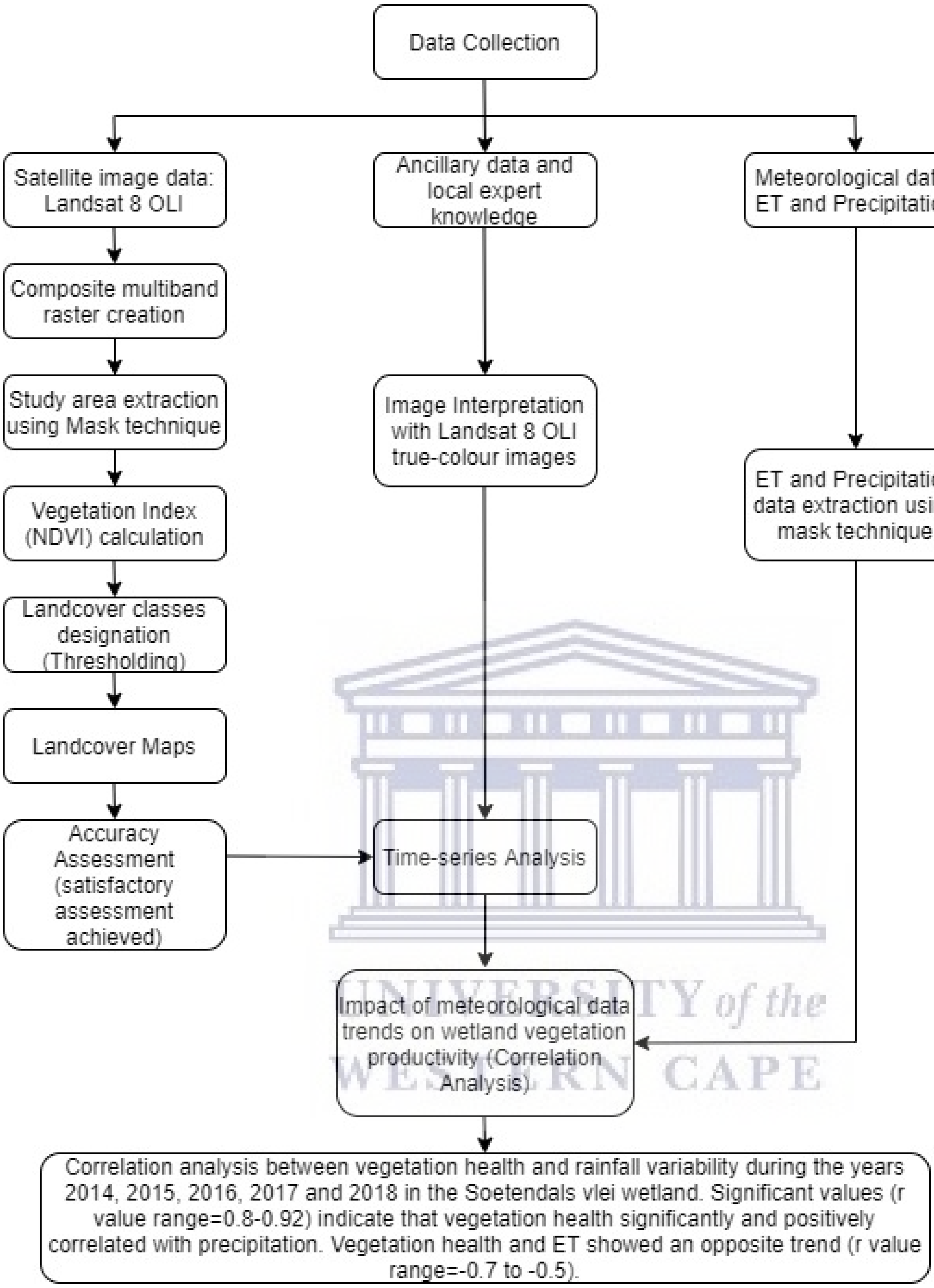

Figure 2: Methodological workflow used for wetland vegetation mapping and assessment of 2014-2018 drought impact

3.3. Results

3.3.1. Remotely sensed mapping of wetland vegetation

The results of the study demonstrated that wetland vegetation was greatly affected by drought between the years 2014 and 2018 (Figure 3, 4, and 5). For instance, the area under vegetation drastically declined in the wetland from 0.13 to 0.07 km^2, whereas the area under water declined by 0.85km^2. The year 2016 had the highest wetland vegetation cover during the dry season and the lowest coverage was observed in the year 2018. Further, the wetland vegetation cover varied from 0.13 to 0.07 km^2. On the other hand, a similar trend was observed for non-vegetated areas as they increased by about 97% during the study period. Exceptions were only observed between 2014 and 2016 dry seasons where non-vegetated surface area shrank by nearly half from only 0.46km^2 in 2016. The highest water surface area in the wetland was observed during the wet season in 2014. However, from 2014 to 2018, the water surface area shrank from 1.34 to 0.49km^2 (63%). Comparatively, from 2014 to 2018, the minimum water surface area in the wetland was observed during the 2014 dry season period, which coincided with the onset of drought that took place during the same year.

Derived classification results showed that wetland vegetation can be mapped with very high accuracies. High classification accuracies in terms of producer, user, and overall accuracies were observed (Table 3). For all the remotely sensed derived wetland mapping results, all the accuracy assessment methods were ± 80%, demonstrating a commendable classification model performance.

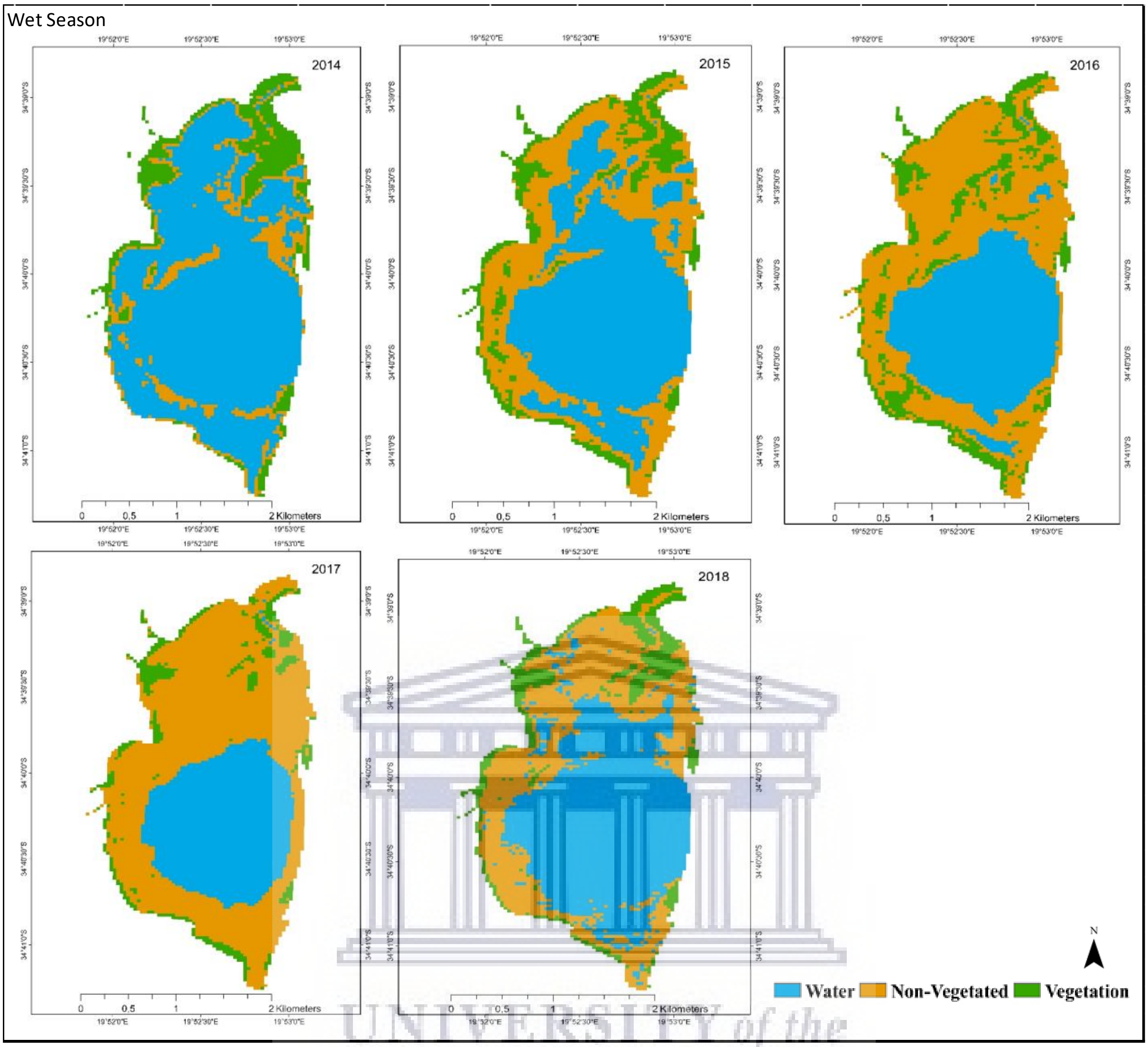

Figure 3: Remotely sensed derived wetland vegetation for the Sondentalsvlei in the Heuningnes catchment, South Africa

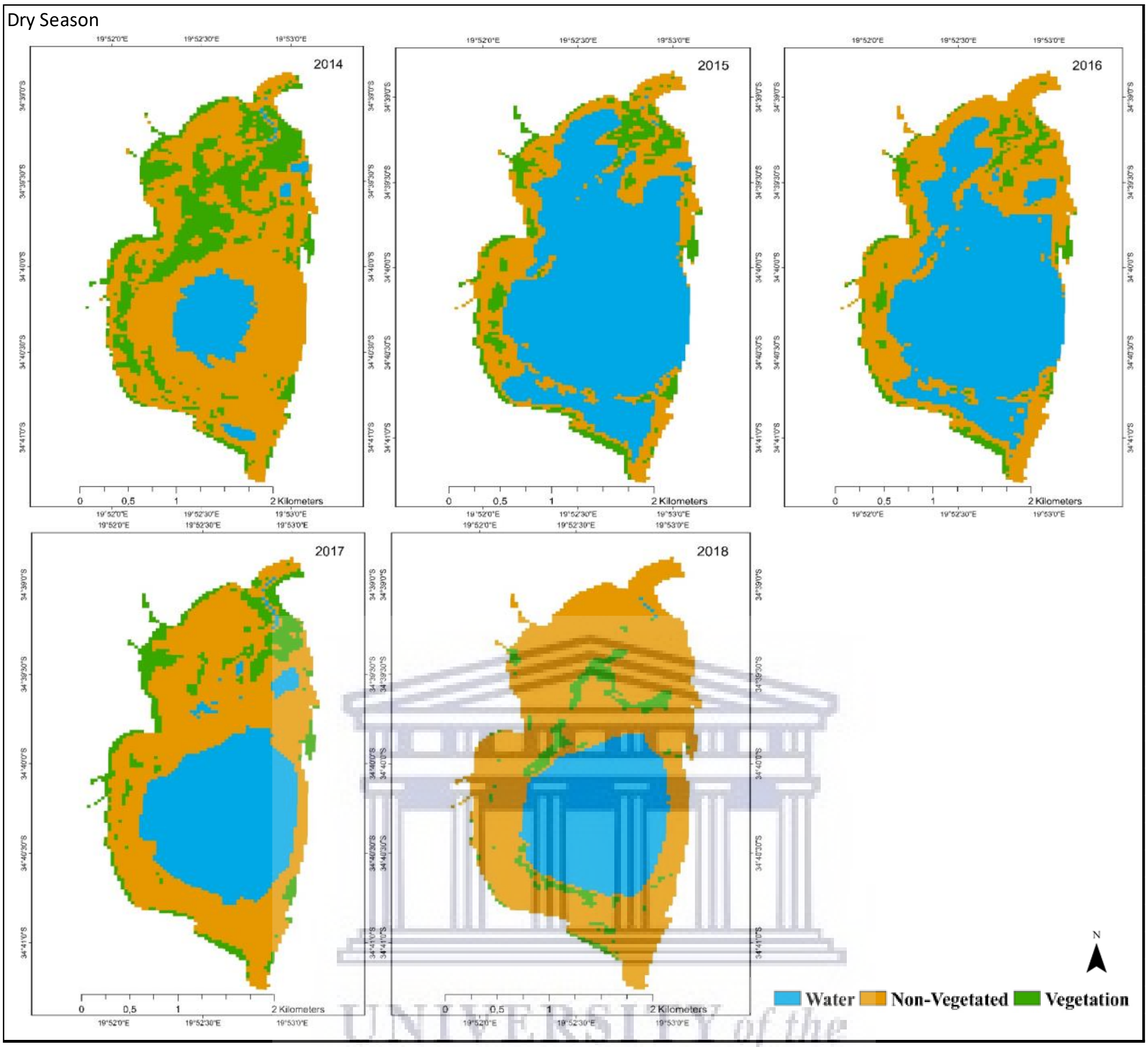

Figure 4: Remotely sensed derived wetland vegetation for the Sondentalsvlei in the Heuningnes catchment, South Africa

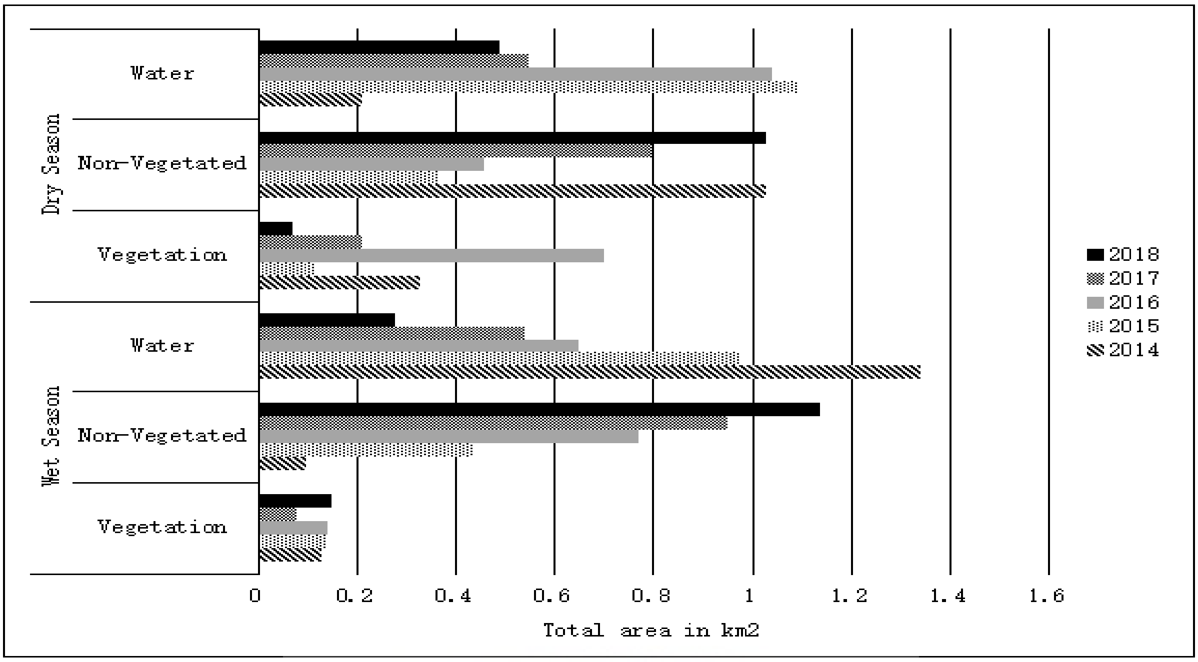

Figure 5: Detailed statistics on the areal extents and observed changes in wetland vegetation between the wet and dry season for the entire monitoring period

Table 3: Accuracy assessment of Landsat 8 images captured in the years 2014 to 2018 in Soetendalsvlei

	Class	**PA (%)**	**UA (%)**	**OA (%)**	**Kappa**
2014	Water	92.4	90.7	90.5	0.89
	Vegetation	79.3	88.5		
	Non-vegetated	100	100		
2015	Water	97	94.1	91.0	0.9
	Vegetation	95.9	85.5		
	Non-vegetated	93.5	95.6		
2016	Water	93.8	93.8	88.4	0.82
	Vegetation	89.8	90.1		
	Non-vegetated	81.3	100		
2017	Water	79.5	90.6	87.5	0.8
	Vegetation	99.2	77.7		

	Non-vegetated	83.6	98.3		
2018	Water	68.7	100	89.5	0.83
	Vegetation	77.1	100		
	Non-vegetated	95.8	86.5		

PA: Producer's Accuracy; UA: User's Accuracy; OA: Overall Accuracy

3.3.2. NDVI seasonal and inter-annual variations of wetland vegetation

Seasonal and inter-annual comparisons of wetland vegetation productivity was assessed, using the NDVI to determine the impact of drought on wetland vegetation conditions (Figure 6). The results showed that NDVI varied significantly between seasons and between the years. Overall, the highest NDVI was observed in the year 2014, whereas the years 2015 and 2017 exhibited a similar trend. It is, however, important to note that during the same years NDVI from wetland vegetation was very low around 0.20 in the wet season. Only the 2017 dry season exhibited a bit of recovery with NDVI increasing to around 0.25. However, between 2014 and 2018, the impact was largely observed during the 2018 dry season period where NDVI values were below 0.05. Inter-annual comparisons demonstrated a sharp decline in wetland vegetation productivity since the onset of drought in 2014 to 2018 with slight recoveries in between the years and seasons.

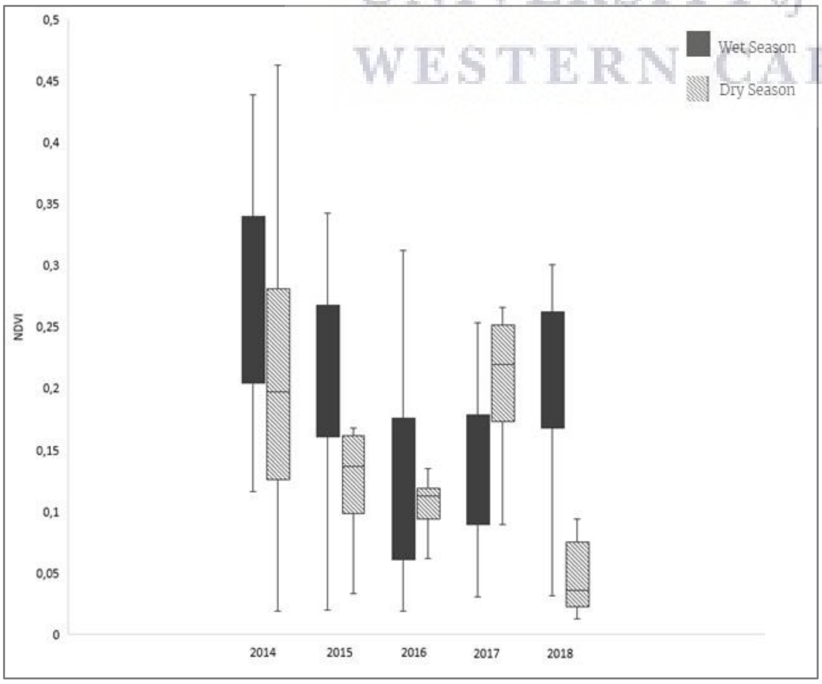

Figure 6: Seasonal and inter-annual variations and trends in wetland vegetation productivity

3.3.3. Relationships between derived NDVI and climate data

The results indicated that wetland vegetation productivity was largely controlled by rainfall availability and evapotranspiration rates. The results from table 4 showed high correlations between wetland vegetation derived NDVI and rainfall as well as evapotranspiration. For example, for all the years NDVI and rainfall correlations coefficients were high and positive, on average above 0.80 whereas for NDVI and evapotranspiration the relationships were significantly but above -0.50. Figure 7 further details the observed monthly NDVI, precipitation, and evapotranspiration trends for the entire study period. It can be observed that evapotranspiration and precipitation controlled or had a bearing on NDVI or wetland vegetation productivity.

Table 4: NDVI vs. Climate data statistical relationships

Year	NDVI vs. Precipitation	NDVI vs. ET
2014	0.8*	-0.70
2015	0.9*	-0.50
2016	0.92*	-0.70
2017	0.8*	-0.60
2018	0.8*	Insignificant association at r = 0.06

*** represents significant positive relationships**

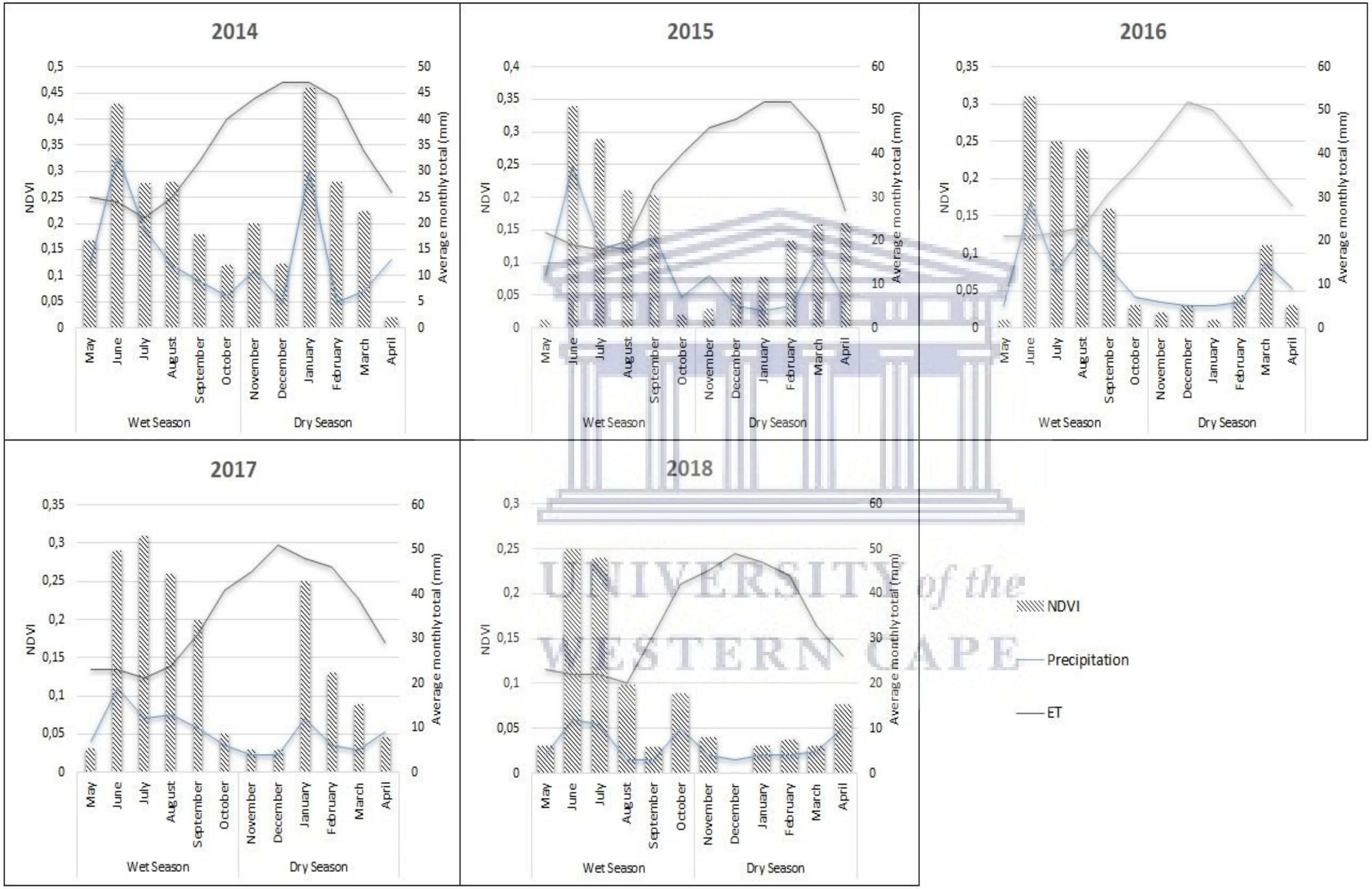

Figure 7: Monthly NDVI, precipitation, and evapotranspiration relationships for the entire period under study 2014-2018

3.4. Discussion

3.4.1. Wetland vegetation growth dynamics between the years 2014, 2015, 2016, 2017 and 2018

Wetlands comprise notable attributes of species diversity, richness, abundance, and succession, and they are therefore considered to be the most dominant and important ecosystems, globally (Mitsch et al. 2015). This study examined changes in wetland cover to determine the ecosystem's response to drought by using remote sensing techniques. Work done in this study has relevance to the maintenance of ecological processes and quantification of natural disasters impacts because it explores: 1) spatial, temporal, and seasonal variations of wetland cover; 2) seasonal variability of wetland vegetation health; 3) the link between wetland vegetation growth dynamics and rainfall variability to assess the response of wetland ecosystems to drought.

An analysis of classified maps revealed that gradual ecosystem change occurred across the study area. Other studies such as that by Middleton and Kleinebecker (2012) done to assess the effects of climate change-induced drought on freshwater wetlands, and that of Belle et al. (2018) in the eastern Free State, South Africa, confirms that vital wetland productivity processes that sustain biodiversity in the ecosystem may be critically affected by the occurrence of drought. Climate change-induced drought, especially in arid regions, drives change in hydrology and vegetation health, thus affecting ecological processes within the wetland ecosystem.

This study suggests that the decline in vegetation extent and water, and increase non-vegetated area in the wetland as a result of rainfall variability. Furthermore, climate change is predicted to increase drought, the number of high heat days, and the frequency of severe storms, all of which affected wetland ecosystems. Results for wetland transition shown in this study are comparable to Ridolfi et al. (2006), who observed that wetland ecosystems are vulnerable to disturbances such as a severe drought and may respond to biomass losses with highly irreversible catastrophic shifts to unvegetated conditions. Similarly, Nhamo et al. (2017), using the Landsat satellite data to delineate wetland extent and assess seasonal variations in South Africa from 2000 to 2015, found a continuous decline in wetland area and the minimum value was observed in 2015 which coincided with an El Nino associated drought in the study area (Rembold et al. 2016; FAO 2016).

3.4.2. Impact of meteorological data trends on wetland vegetation productivity

Based on long-term (5 years) data, this study examined the influence of rainfall variability on the productivity of wetland vegetation in the Soetendalsvlei wetland system. The relationship between wetland vegetation health and quantity as well as the temporal patterns of rainfall variability were assessed and yielded two key results. Firstly, over the past 5 years, NDVI (Vegetation health) significantly and positively correlated with precipitation; and secondly, the NDVI and ET showed an opposite trend, ET exceeds the amount of precipitation during the period of this study.

The results of this study highlight the importance of rainfall variability on wetland vegetation productivity. One explanation is that rain events provide sufficient soil moisture and maintain high water availability (Merolla 2012). In arid and semiarid ecosystems, water is typically a limiting factor for plant health, and available moisture generally increases plant biomass (Twisa and Buchroithner 2019). The photosynthesis of plants depends on water availability, therefore, insufficient water availability can minimize the assimilation of carbon, thereby decreasing wetland vegetation productivity (Pinheiro and Chaves 2011).

For instance, the results of the study by Barros and Albernaza (2014) found that an elevation in water availability leads to a reduction in wetland vegetation growth rates or the reproductive success of many species. Wetland vegetation has highly developed root systems that hold the soil in place and filter pollutants, naturally improving water quality (Finlayson et al. 2015). Therefore, a drought will likely cause the loss of, or reduction in wetlands and will challenge the adaptability, composition, and distribution of wetland plants. Moreover, if wetland vegetation productivity is challenged, pollutants could become more concentrated in wetlands and this will affect water quality.

3.4.3. Remote sensing spatial and seasonal variations of wetland vegetation

Similar to other arid lands, vegetation, precipitation, and ET in the study area is both spatial and temporally heterogeneous, making ground-based measurements invaluable. However, the study area is remote and the use of in-situ methods can be resource-intensive and problematic when the study area is remote and hazardous (Adam et al. 2010). Remote sensing, therefore, provides invaluable means of monitoring vegetation to assess environmental conditions in wetland ecosystems (Amler et al. 2015). The tool has been popular for collecting meteorological data, and offers spatially explicit data as well as repeated observations and covers large geographic locations (Boisvenue and White. 2019).

Remote sensing images are key data sources for earth monitoring programs considering the great advantages that they have (Makapela et al. 2015). For instance, it is more easily obtainable to produce and update vegetation inventories over large regions if aided by satellite imagery and appropriate imagery analysis. A growing number of studies have examined the response of wetland vegetation productivity to drought by using remotely sensed data (Santos et al. 2019; Easterday et al. 2019; Adamu et al. 2018; Wilson and Norman 2018; Nhamo et al. 2017). However, although remote sensing technology has tremendous advantages over traditional methods in vegetation mapping, we should have a clear understanding of its limitations. It is important to understand how well will the chosen vegetation index/ drought proxy represents actual vegetation community composition. Also, it is critical to determine how effectively images from remote sensing capture the distinguishing features of each mapping unit within the classification and how well these mapping units are delineated by photo interpreters. A well-fit vegetation classification system should be carefully designed according to the objective of the study in order to better represent actual vegetation community compositions.

The capacity to accurately detect wetlands in moderate resolution data from Landsat is desired to facilitate understanding of spatial and temporal dynamics of wetlands. Landsat provides the highest spatial resolution and longest systematically sampled historical remote sensing record dating back to approximately 1984 (Pouliot et al. 2019). Thus, Landsat offers the greatest opportunity for understanding wetland change and drivers of these changes. There are only a few wetland studies reporting accuracy for small extent applications for similar ecosystems and sensors. At the reduced three-class thematic level. Hird et al. (2017) reported an overall accuracy of 85% within the Central Canadian Boreal Forest Region, whereas Filatow and Carswel (2018) achieved a satisfactory accuracy of 91% in northern British Columbia.

Vegetation index NDVI was used to detect any significant differences in vegetation cover between the years 2014 to 2018. The results indicated that NDVI was able to discriminate wetland vegetation from other classes within the study area. Results required for drought impacts assessment showed the change in landcover distribution and vegetation productivity between 2014, 2015, 2016, 2017, and 2018. These results revealed that the wetland was negatively affected by the long-term drought. Temporal remotely sensed data enabled the assessment of wetland vegetation health conditions as far as back as 2014, therefore remote sensing provided an effective tool in analyzing and determining vegetation changes in wetlands under different management regimes. Frequent wetland monitoring is important for timely intervention in the case of an identified negative change. Remote sensing has shown its strength in wetland mapping and for monitoring wetland dynamics over time and is thus an important tool for wetland management.

3.5. Conclusion

Temporal and spatial distribution of wetland cover classes and vegetation cover was assessed using NDVI to examine the impact of rainfall variability (drought) on wetland vegetation. Results showed a significant variation in the wetland surface area from 2014 to 2018. Specifically, vegetation and water decreased significantly over the monitoring period, while the extent of the bare surface increased rapidly. Wetland extent mapping was achieved with average overall accuracy (85–90%) in this study. Further, Vegetation productivity significantly and positively correlated with precipitation over the past five years, while ET showed a negative significant relationship, ET exceeds the amount of precipitation during the period of this study. From the observation of the whole study period, healthy vegetation has deteriorated due to drought that occurred in the study area between the monitoring periods. The amount of rainfall entering into an ecosystem is typically a limiting factor for plant health; the results of this study highlight the importance of rainfall variability on wetland vegetation productivity.

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Chapter Four

Remote sensing the response of wetland vegetation productivity to drought: A synthesis

4.1. Introduction

Wetland vegetation provides food and critical habitat for organisms that live in or near water resources, such as algae, macroinvertebrates, amphibians, fish, and birds (Schofield et al., 2018). It improves water quality by taking up nutrients, metals, and other contaminants (Masters, 2012). The vegetation strongly influences water chemistry, acting as both nutrient sinks through uptake, and as nutrient pumps, moving compounds from the sediment to the water column (Bouwman et al., 2013). Plants in wetlands influence the hydrology and sediments of wetlands by stabilizing shorelines, modifying currents, and abating the effects of flooding (Junk et al., 2013). They also control hydrologic conditions in many ways including peat accumulation, water shading, and transpiration (Watson and Adams, 2010). Wetland vegetation is the most important component of wetland ecosystems; however, the ecosystem services provided by wetland vegetation are facing several pressures due to climate change and variability impacts (Erwin, 2009; Arias et al., 2014). Climate change is commonly recognized as one of the most important drivers affecting vegetation (Piras et al., 2016). Drying and warming climate decreases wetland vegetation productivity is largely influenced by the timing and amount of precipitation entering into a wetland ecosystem (Parton et al., 2012; Li et al., 2013). Mapping distribution, quality, and quantity of wetland vegetation is important for wetland protection, management, and restoration (Fu et al., 2017). Remote sensing is valuable for assessing wetland vegetation information because it provides repeat coverage of spatially continuous measurements collected in a systematic and objective manner (Abdel-Hamid et al., 2020). Therefore, the objectives of this study were to:

I. Provide a critical evaluation of scientific literature on the use of remote sensing techniques in assessing wetland vegetation productivity
II. Characterize and assess vegetation changes in the Soetendalsvlei wetland to understand the impact of the 2014-2018 drought.
III. Examine the relationship between wetland vegetation productivity and rainfall variability.

4.2. Remote sensing literature of wetland vegetation productivity

The impact of climate change and variability on wetland vegetation productivity can be assessed by using remote sensing tools. Remote sensing is cost-effective and it provides a synoptic view, multi-temporal and multi-spectral coverage. Monitoring wetland vegetation productivity requires the regular availability of data. Multi-temporal remotely sensed data such as Landsat 8 OLI plays a fundamental role in assessing wetland vegetation productivity information. Landsat 8 OLI is freely available and can help to derive metrics critical for wetland vegetation monitoring. Vegetation indices such as NDVI help isolate green photosynthetically active signals from the spatially and temporally mixed pixels for meaningful inter-comparisons of vegetation characteristics. Time series of vegetation indices are also used to generate spectral profiles for revealing vegetation productivity changes. Remote sensing techniques provide valuable means for monitoring and assessment of wetland vegetation productivity and also helps in understanding its seasonal changes, in addition to revealing the relationship with climate change and variability. More research is however required to further determine and understand how wetland vegetation responds to climate change and variability in South Africa.

4.3. Mapping and assessing wetland vegetation changes between the years 2014 to 2018 in the Soetendalsvlei wetland

The study aimed at assessing wetland vegetation changes at the Soetendalsvlei wetland before, during, and after the climate-induced drought that occurred in the Western Cape Province. The study quantified wetland vegetation extent and health in order to analyze the impacts of climate-induced drought on wetland vegetation productivity. The results revealed that wetland vegetation was greatly affected by drought between the years 2014 and 2018. For example, the area under vegetation drastically declined in the wetland from 0.13 to 0.07 km^2. Derived classification results showed that wetland vegetation can be mapped with very high accuracies (± 80%). Inter-annual comparisons of wetland vegetation productivity demonstrated a sharp decline in wetland vegetation productivity since the onset of drought in 2014 to 2018 with slight recoveries in between the years and seasons.

4.4. Examining the relationship between wetland vegetation productivity and rainfall variability

Changes in rainfall pose a significant threat to wetlands, causing them to dry out. A low amount of rainfall entering into a wetland have an effect on wetland vegetation productivity. Thus, it is important to investigate the relationship between wetland vegetation productivity and changes in rainfall entering into a wetland ecosystem. Based on the results of the study, high correlations between wetland vegetation productivity and rainfall variability have been observed. For example, for all the years' wetland vegetation productivity and rainfall correlations coefficients were high and positive, on average above 0.80 whereas for vegetation productivity and evapotranspiration the relationships were significantly but above -0.50. Thus, rainfall and evapotranspiration control a bearing on wetland vegetation productivity.

4.4. Conclusions

- Remote sensing tools have the ability to assess and understand seasonal and long-term changes in wetland vegetation productivity
- NDVI can accurately be used to assess spatial-temporal variations of wetland vegetation, making the satellite-derived metric to be one of the most valuable models for monitoring the growth condition of wetland plants.
- The accuracy assessment methods were ± 80% for all the remotely sensed derived wetland mapping results, indicating a commendable classification model performance.
- The results of the study showed a significant variation in the wetland surface area from 2014 to 2018. Thus, the extent of the non-vegetated surface increased rapidly while vegetation and water decreased significantly over the monitoring period.
- Results showed a positive significant relationship between wetland vegetation productivity and rainfall during the period of this study, while ET showed a negative significant correlation.
- Healthy vegetation has deteriorated due to drought that occurred in the study area
- Further, the amount of rainfall entering into a wetland ecosystem is typically a limiting factor for wetland vegetation productivity

4.5. Recommendation

Although the findings of this study demonstrate the relevance of multispectral broadband in wetlands characterization and productivity assessment and monitoring over time and space, their performance remains a challenge particularly for smaller wetlands, especially if predominantly characterized with mixed plant species (Adam et al., 2010; Dronova, 2015; Tshabalala, 2020). There is, therefore, a need to consider hyperspectral and new generation of multispectral satellites e.g. Sentinel 2 and Worldview 2 images for mapping wetland vegetation productivity given its unique sensing characteristics, which include hundreds of narrow bands (Li et al., 2017; Transon et al., 2018; Lu et al., 2020). These bands are reported to be sensitive to subtle plant biochemical and biophysical properties, which is key for mapping-related studies (Turpie et al., 2015; Aneece and Thenkabail, 2018). Further research advancing wetland vegetation productivity and associated responses to climate change and variability in South Africa are needed. It is important to keep up with the present developments and incorporate the latest data which include biophysical aspects e.g. soils, hydrology, and ecological information.

Future research on wetland vegetation productivity will also help in keeping track of the influence of climate change on South Africa's scarce water resources and help raise awareness for a wide range of environmental issues affecting the nation's water resources.

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