The utility of Sentinel-2 MSI to assess wetland vegetation chlorophyll content and leaf area index in wetland areas in Pietermaritzburg, KwaZulu-Natal

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Abstract

Wetland ecosystems are being modified and threatened due to anthropogenic activities and climate change, hence the urgent need for wetland restoration. Wetland rehabilitation is important in the reversal of these dire conditions, through restoring damaged wetland ecosystems and recovering wetland vegetation. Wetland biophysical properties such as leaf area index and chlorophyll content are important indicators of vegetation productivity and stress. Therefore, the overall aim of this study was to assess the variations in wetland vegetation productivity between wetlands under different management regimes in Pietermaritzburg, South Africa using Sentinel-2 MSI data. Chlorophyll and leaf area index were used as proxies of wetland *Cyperus dives* and *Typha capensis* productivity in this study. The first objective was to test the ability of Sentinel-2 MSI data and vegetation indices in estimating leaf area index of wetland vegetation across natural and rehabilitated wetlands. The second objective was to assess the utility of the high-spatial resolution Sentinel-2 MSI data in the estimation of chlorophyll content of *Cyperus dives* and *Typha capensis* species across natural and rehabilitated wetlands. Results showed that vegetation indices derived from red-edge bands produced better LAI estimation accuracies for both wetlands with a root mean square error (RMSE) of 0.32 m^2/m^2 and 0.51 m^2/m^2 as well as R^2 ‘s of 0.61 and 0.75 for the natural and rehabilitated wetlands, respectively. The optimal model for predicting LAI across natural and rehabilitated wetlands was attained based on red-edge bands centered at 705 nm (Band 5), 740 nm (Band 6), 783 nm (Band 7) as well as 865 nm (Band 8a) yielding a RMSE of 0.51 m^2/m^2 and R^2 of 0.75. In addition, the combination of all spectral variables in estimating chlorophyll across different wetland management regimes and species exhibited a relatively low RMSE of 9.11 µg cm^2 (12%) and R^2 value of 0.88 based on red-edge bands centered at 705 nm (Band 5), 740 nm (Band 6), 783 nm (Band 7) as well as 865 nm (Band 8a). The findings of this study indicate that Sentinel-2 MSI data can be optimally used to estimate productivity (chlorophyll content and LAI) of wetland plant species such *Cyperus dives* and *Typha capensis* growing under different management regimes, with the rehabilitated wetland exhibiting improved productivity. Results of this study underscores the unique potential of new generation earth observation sensors in wetland vegetation monitoring and management, this has implications on other ecosystem processes such as wetland water use and carbon sequestration.

Key words: wetland vegetation, productivity, natural wetland, rehabilitated wetland, accuracy

Preface

The research contained in this dissertation was undertaken in the School of Agricultural, Earth and Environmental Sciences of the Collage of Agriculture, Engineering and Science, University of KwaZulu-Natal, Pietermaritzburg, South Africa, under the supervision of Professor Onisimo Mutanga and Dr. Mbulisi Sibanda to fulfill the requirements for the degree of Master of Science.

I, Nonjabulo Neliswa Tshabalala, declare that the current work represents my own ideas and has never been submitted to any other academic institutions and that all the sources cited have been acknowledged.

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Declaration

I, Nonjabulo Neliswa Tshabalala, declare that:

(i) The research reported in this thesis, except where otherwise indicated is my original research.

(ii) This thesis has not been submitted for any degree or examination at any other institution.

(iii) This thesis does not contain other person's data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

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Dedication

This dissertation is dedicated to my father for his endless love, support and encouragement. I hope this achievement will complete the dream that you had for me all those years ago when you chose to give me the best education you could.

To my late mother, you left us beautiful memories, your love is still our guide, although we cannot see you, you're always at our side.

I love you Ma.

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To my family and friends, thank you for your unyielding support and encouragement. Thank you for believing in me and believing in my dreams without judgement. Thank you for keeping me in your prayers and providing a shoulder to lean on. May God keep you until you see the results of your prayers.

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Chapter One

General Introduction

1.1 Study Background

Wetland ecosystems are of utmost importance to the environment, due to their numerous ecological functions and roles. Hence, they need to be well preserved and protected (Zhang et al., 2009). Healthy wetlands freely provide social, economic and environmental benefits. These include preventing or reducing the severe effects of floods, providing unique habitat for flora and fauna, biodiversity and micro-climate stabilisation (Weiguo et al., 2012; Turner et al., 2000 and Kent & Mast, 2005). Wetland systems absorb excess nutrients, sediments and other pollutants before they reach water bodies. They are a natural sponge that absorbs and store water in wet seasons to be released in dry seasons (Teferi et al., 2010). With the impacts of climate change becoming more evident, wetlands play a vital role in reducing these impacts by storing carbon. These ecosystems are also important for their aesthetic value for tourism purposes.

Despite their importance, wetlands are continually deteriorating due to human activities and climate change (Zhao et al., 2010; Tuner et al., 2000 and Meli et al., 2014). Large areas of wetlands are disappearing and those remaining become increasingly vulnerable to anthropogenic impacts such as industrial development, agriculture, aquaculture, urban development and domestic waste (Wu et al., 2017, Akumu et al., 2018 and Moomaw et al., 2018). Wetlands are being drained and converted into agricultural land; while rapid population growth, has resulted in conversion of wetlands into urban landuse. According to Ailstock et al. (2001) and Kotze et al. (2012), 50% of the worlds' wetlands are under threat. In South African alone, an estimate of 65% of wetlands are threatened, with 48% of these wetlands being severely damaged and endangered due to climate change, pollution, increasing population and biological invasion (Nel & Driver, 2012). However, with increasing awareness and research efforts on wetland importance, a large number of wetlands globally are being strictly monitored and many interventions have been made to protect these systems. Governments have enacted legislation that protect and preserve wetlands globally, including South Africa (Cowden et al., 2014). Furthermore, with the awareness of wetland significance, wetland restoration and rehabilitation has become important for proper management of local water resources. Zedler (2000), states that wetland rehabilitation success is measured in comparison to a natural pristine wetland in terms of structure and functionality. This is highly dependent on the wetland component that is being restored, which includes the wetland vegetation and hydrology. In most cases, the sole objective of wetland rehabilitation is to repair and reinstate the structure and core functions of the ecosystem while keeping the whole system fully functional (Cowden et al., 2014).

Wetland condition assessments are generally performed by measuring vegetation properties such as vegetation cover, biomass, plant diversity, and productivity. These provide useful information about the success of the restoration programme. Biochemical and biophysical properties of wetlands such as leaf area index (LAI) and chlorophyll provide information about the condition and productivity of the wetland ecosystem vegetation (Adam et al., 2010 and Ayeni et al., 2012). LAI is a significant vegetation property that aids in assessing vegetation condition in ecosystems. Several studies have highlighted the use of LAI in understanding vegetation productivity across wetlands and various landscapes (Chen et al., 2009; Weiss et al., 2004 and Jonckheere et al., 2004). There are cases where rehabilitated wetlands adhere to the functions of a fully functional wetland (Mitsch & Wilson, 1996; Ruiz-Jaen & Mitchell Aide, 2005). Vegetation types that are valuable to wetland ecosystems include *Typha capensis* and *Cyperus dives*, known as Bulrush and Giant Sedge respectively. *Typha* is not a commonly studied freshwater grass in South Africa (Hall, 1993). Its unbranched, joint less stems grow between 3 to 4m long and the grass-like leaves grow up to 10 to 20m broad. They are commonly found in frequently flooded or fresh water wetlands, growing at or above mean high water. *Typha* are extremely productive, an attribute which enhances the species' invasion in wetlands, therefore regarded as weeds. Furthermore, it is capable of encroaching and crowding out other wetland plant species therefore resulting in the reduction of biodiversity in the affected system. Although *Typha* have a high invasive potential, they play a vital role in water purification and in providing wildlife habitat (Hall, 1993 and BIR, 1980). *Typha* also provides food for humans, feed for animals, medicines to 'cure' various ailments and bioenergy (Saibu, 2017).

Estimating wetland vegetation biophysical properties is essential to wetland monitoring and management. Hence, it is vital to understand the spatial distribution and growth of *Typha Capensis and Cyperus dives* under varying wetland health conditions in both the pristine and rehabilitated wetlands (Adam et al., 2010). Wetland vegetation and their properties are not easily detected and it is often difficult to make a clear distinction between vegetation communities. Therefore, it is important to use techniques that effectively distinguish wetland vegetation spatially and spectrally (Silva et al., 2008). Wetland plant life is characterised by excessive spatial and spectral variability, due to steep environmental gradients and wetland conditions such as varying hydrological properties and soil moisture (Corbane et al., 2015). These conditions may affect the spectral reflectance of wetland vegetation, particularly in the visible, near-infrared and mid-infrared regions of the electromagnetic spectrum due to high water absorption (Adam et al., 2010; Corbane et al., 2013). Therefore, high spatial resolution imagery is considered to be more effective in wetland vegetation mapping and in the estimation of wetland biochemical properties such as chlorophyll (Gitelson et al., 2005; Li et al., 2018 & Haboudane et al., 2002). Changes in chlorophyll over time is related to the vegetation productivity, the different development stages and canopy stresses (Gitelson et al., 2005). Remote sensing techniques offer the ability to observe a large area at a time and that is beneficial in chlorophyll estimation. Changes in leaf chlorophyll results in significant changes in leaf reflectance and transmittance spectra which can be affected by LAI, canopy architecture and soil background. These factors make chlorophyll retrieval at canopy level challenging. Therefore, the use of remote sensing techniques has proven to be more efficient in estimating chlorophyll in leaves and canopies.

Multispectral sensors are commonly used in wetland vegetation mapping. This is largely due to the availability and accessibility of these sensors. Multispectral sensors such as Landsat Thematic Mapper, SPOT XS, Moderate Resolution Imaging Spectroradiometer (MODIS) and Enhanced Thematic Mapper (ETM) are among some of the sensors commonly used in wetland vegetation mapping. They are easily accessible and have been used for ecological monitoring in numerous studies. Landsat TM and SPOT satellites have been proven unsatisfactory to estimate the LAI and in discriminating vegetation species of wetland vegetation. This is due to the lack of high spatial and spectral resolution of optical multispectral imagery, restricting the mapping and detection of vegetation types in densely vegetated wetlands (Adam et al., 2009). The recent launch of new advanced generation sensors such as Sentinel-2 Multi Spectral Instrument (MSI) has provided opportunities for LAI and Chlorophyll estimation. Studies have demonstrated the strength of the additional bands provided by Sentinel-2 MSI for LAI and chlorophyll estimation. For instance, Clevers and Gitelson (2013) successfully estimated chlorophyll in crops and grasslands, which demonstrated the significance of the red-edge bands of the MSI sensor on Sentinel-2. A study by (Delegido et al., 2011 & Herrmann et al., 2011), has also demonstrated the importance of the red-edge band on Sentinel-2 for estimating LAI and chlorophyll in grasslands and crop vegetation. To the best of our knowledge, there has not been studies done on estimating and comparing LAI and chlorophyll content on *Typha capensis* and *Cyperus dives* between natural and rehabilitated wetlands using Sentinel-2 MSI with the red-edge bands. This new advanced multispectral sensor with high spatial, spectral and temporal resolutions is sufficient and inexpensive, therefore, proven attractive for LAI and chlorophyll estimation between natural and pristine wetlands.

1.2. Research objective

The overall aim of this study was to test the utility Sentinel-2 MSI data to assess wetland vegetation productivity in wetlands under different management regimes in Pietermaritzburg, South Africa.

The **specific objectives** are:

- To test the ability of Sentine-2 MSI derived data and vegetation indices in quantifying the variation in leaf area index for vegetation growing in a natural wetland and that growing in a rehabilitated wetland.
- To assess the use of high-resolution Sentinel-2 MSI data for estimating the chlorophyll content of *Typha capensis* and *Cyperus dives* vegetation species growing in a natural wetland and a rehabilitated wetland.

1.3 Outline of dissertation/thesis structure

The dissertation consists of four chapters. The two papers that make up this thesis have been presented as separate chapters. This makes each of them a separate portion of work that contributes to the overarching research question. In this regard, it is imperative to note that there will be inevitable overlaps or repetitions within the dissertation, as each chapter obtains fundamental principles that feed into the overall objective and aim of the research. The chapters of this work are presented in two categories, that is (i) wetland vegetation leaf area index quantification and comparison and (ii) chlorophyll content estimation. Chapter one of this dissertation provides a background of the study, the overall aim and objectives of the study.

Chapter 2 investigates the ability of Sentinel-2 MSI derived data and vegetation indices in quantifying and comparing the variation in wetland vegetation leaf area index between natural and rehabilitated wetlands. Partial Least Squares Regression (PLSR) algorithms were used to predict leaf area index between the two wetlands based on two predictor variables.

Chapter 3 assesses the use of high-resolution Sentinel 2 MSI data in accurately estimating the chlorophyll content of *Typha capensis* and *Cyperus dives* species growing in a natural wetland and a rehabilitated wetland. Partial Least Squares Regression (PLSR) algorithms were used to estimate the chlorophyll content of both *Cyperus dives* and *Typha capensis* leaves and produce estimation models.

The last chapter of the dissertation, chapter 4, presents a synthesis highlighting the key conclusions of the study, conclusions and recommendations for future studies. A list of all the sources used for this research is provided at the end of the dissertation.

Chapter Two

The utility of Sentinel-2 MSI data to estimate wetland vegetation LAI in natural and rehabilitated wetlands

Abstract

Accurate estimation of LAI of wetland vegetation is required by earth-system and ecosystem models to assess wetland conditions and functionality. The present study sought to test the potential of Sentinel-2 MSI derived standard bands, traditional vegetation indices and red-edge derived vegetation indices in estimating wetland vegetation LAI across natural and rehabilitated wetlands. The LAI estimates for each wetland were compared to provide an understanding of how LAI varies between these ecosystems. Partial Least Squares Regression (PLSR) algorithms were used in this study. The results showed that LAI estimates were higher for the natural wetland as compared to the rehabilitated wetland. However, the rehabilitated wetland showed a wider LAI distribution pattern. The optimal models for estimating wetland vegetation LAI were produced based on red- edge bands centered between 705 nm - 783 nm as well as 865 nm (Band 8a) of the electromagnetic spectrum. The results showed that vegetation indices derived from red-edge bands performed better at estimating LAI for both wetlands with a root mean square error of prediction (RMSE) of 0.32 m^2/m^2 and R^2 of 0.61 for the natural wetland, and RMSE of 0.510 m^2/m^2 and R^2 of 0.75 for the rehabilitated wetland. The optimal model for predicting LAI across natural and rehabilitated wetlands was attained based on red-edge bands centered at 705 nm (Band 5), 740 nm (Band 6), 783 nm (Band 7) as well as 865 nm (Band 8a) yielding a RMSE of 0.51 m^2/m^2 and R^2 of 0.54. The rehabilitated wetland exhibited high vegetation productivity compared to the natural wetland. Overall, the results of this study show that vegetation productivity was optimally characterised across wetlands under different management treatments using Sentinel-2 MSI red-edge derived vegetation indices, combined with traditional vegetation indices.

Keywords: natural wetland, rehabilitated wetland, leaf area index, accuracy, ecological functions, ecosystem

2.1. Introduction

Wetlands are important ecosystems and play a significant role in regulating the health of the environment (Jiang, 2012; Janse, 2019). Wetlands are responsible for maintaining environmental quality, micro-climate stabilisation, flood control, water infiltration and biodiversity support (Batzer & Boix, 2018; Dini & Bahadur, 2016; Jiang et al., 2012; Kotze, 2012). They provide an interface for terrestrial and wetland species interaction (Akumu, Pathirana, Baban, & Bucher, 2011; Janse et al., 2019). Furthermore, wetlands have been providing an array of social and economic benefits, which include crafts for centuries (Traynor, Kotze, & McKean, 2010). However, wetlands are continuously being degraded in terms of their ecosystem services, diversity and spatial extent by chiefly anthropogenic activities such as urbanization, agriculture and sand mining, effects of climate change and invasive species (Pan et al., 2018). Invasive alien plant infestation also affects wetland functionality as they reduce the amount of water that is available for the wetland through their voluminous intakes. Alien invasive plants compete with the natural indigenous wetland vegetation for water, therefore decreasing the ability for these plants to perform their function in the wetland ecosystem. Hopkinson, Cai, & Hu, (2012), state that wetland degradation or loss could result in an increase in the net global carbon dioxide in the atmosphere, with an increase of up to 6% per year. This challenge is compounded by the fact that currently there is a dearth of comprehensive frameworks and objective criteria for monitoring the health of these wetlands. In this regard, it is crucial to restore and protect degraded wetland ecosystems. Recent studies on wetland restoration have highlighted the importance of restoring degraded wetlands and the importance of monitoring and maintaining these wetlands.

Wetland functionality and health monitoring has proven to be a complex task due to the complexity of these ecosystems. Specifically, direct assessments of restored wetlands are rare (Zedler & Lindig-Cisneros, 2002). This is a result of limited wetland data that can be used to assess restored wetlands over a period of time. (Eviner, Garbach, Baty, & Hoskinson, 2012; Wortley, Hero, & Howes, 2013). Though, there are other indicators that may be detected shortly after a wetland has been restored (Eviner et al., 2012; Wortely et al., 2013). According to Eviner et al. (2012); Wortley et al. (2013), vegetation characteristics such as LAI, biomass and vegetation height, as well as wetland ecological processes can be used to measure wetland restoration success. In practice, wetland vegetation is the most common indicator of wetland rehabilitation success or failure and therefore can serve as a health index of these ecosystems. This is because wetland degradation is directly reflected in the decreased productivity and even mortality of the wetland vegetation species. Wetland vegetation biophysical and properties such as leaf area index, biomass, chlorophyll and water content can be used as the main indicators of vegetation health and productivity in wetland ecosystems (Eckert & Engesser, 2013; Pan et al., 2018; Stefanik, 2012). Currently there is no standardised method for evaluating the success of wetland restoration, hence the necessity to develop detailed and accurate methods for wetland restoration success assessment.

Remote sensing techniques are frequently used to map and monitor plant species distribution, quality and quantity as a sustainable management method for wetlands (Adam, Mutanga, & Rugege, 2010; Mutanga et al., 2012). This is because, traditional wetland monitoring methods such as manual species discrimination and taxonomical information are highly labour intensive, overpriced and time consuming. Furthermore, some of these methods cannot be applied in lager areas. Meanwhile, remote sensing techniques offer practical and cost-effective means of estimating wetland vegetation biophysical parameters for wetland restoration monitoring (Adam et al. 2010). Leaf area index (LAI) is one of the commonly used vegetation biophysical properties in measuring vegetation health and functionality. It is an indicator of ecological processes, such as photosynthesis, plant and soil respiration, net primary productivity and energy exchange rates between plants and atmosphere (Kamal et al., 2016). It can be used to predict future growth and changes in canopy structure which are fundamental aspects of environmental management (Medeiros, Sampaio, & Nascimento, 2018). Wetland plants and their properties are not easy to detect. Above all, it could be very challenging to identify the boundaries between their plant communities. Therefore, is it important to establish techniques that can effectively distinguish wetland vegetation spatially and spectrally (Silva, Costa, Melack, & Novo, 2008). As a result of varying wetland conditions such as soil moisture and wetland hydrology, wetland vegetation spatial and spectral variance is increased (Corbane et al., 2015).

The launch of the advanced new generation sensor such as Sentinel-2 Multispectral Instrument (MSI) has proven to be of great advantage to LAI estimation (Shoko, 2017). Studies have confirmed the strength of the added red-edge bands provided by Sentinel-2 Multispectral Instrument for LAI estimation (Clevers and Gitelson, 2013). For instance, Clevers & Gitelson (2013) successfully estimated LAI in crops and grasslands, which illustrated the significance of the red-edge bands of the multispectral instrument. A study by Delegido, Verrelst, Alonso, & Moreno (2011), has also demonstrated the importance of the red-edge band on Sentinel-2 MSI for LAI estimation in grasslands and crop vegetation. Furthermore, vegetation indices derived from the red-edge spectrum have proven to have high accuracies when estimating vegetation properties such as biomass, which are extremely associated with LAI (Mutanga & Skidmore, 2004; Sibanda, Mutanga, Dube, Vundla, & L Mafongoya, 2019).

Research on estimating wetland vegetation LAI has often been done on forested wetlands and mangrove wetlands (Turner et al., 2000). According to Adam et al. (2010), the univariate regression analysis inclusive of vegetation indices some of which are normalized difference vegetation index (NDVI) and simple ratio (SR) derived from the visible and NIR wavelengths are the most commonly used empirical models used in estimating LAI. Sibanda et al., (2019) illustrated the error of estimation for LAI was reduced with the inclusion of red-edge vegetation indices. This is because vegetation spectral reflectance is influenced by vegetation biophysical properties such as LAI, chlorophyll content and leaf angle distribution, these properties are known to be highly associated with the red-edge (Delegido et al., 2011; Mutanga & Skidmore, 2004; Verrelst et al., 2012). However, wetlands are characterised by high moisture content, leaf density as well as leaf angle distribution associated with various wetland plant species. These often attenuate the signal of vegetation through the process of saturation making it difficult to characterise physiochemical plant characteristics such as LAI in a wetland setting. Therefore, it is perceived that including red-edge vegetation indices could significantly improve the accuracy of LAI estimation models across the rehabilitated and natural wetlands. In our understanding, there has not been a study undertaken to estimate wetland vegetation LAI across natural and rehabilitated wetlands using Sentinel-2 MSI with the red-edge bands. Therefore, this study aims to test the ability of Sentine-2 MSI derived data and vegetation indices in estimating the variation in leaf area index for vegetation growing in a natural wetland and that growing in a rehabilitated wetland. The ultimate goal is to evaluate whether wetland rehabilitation improves the productivity of wetland vegetation and assess the extent to which this natural capital can be monitored from remote sensing.

2.2. Methods and Material

2.2.1 Study Area Description

The study was conducted in the Greater Edendale Mall wetland (29°38'54.70"S and 30°20'28.03"E) and Wetland Erf 1105 in Willowfontain (29°42'41.51"S and 30°20'49.22"E), both situated in Pietermaritzburg, KwaZulu-Natal (Figure 2.1). The Willowfontain wetland is a natural wetland that is approximately 347.051 m^2, while the Edendale wetland is a rehabilitated wetland that is approximately 502.519 m^2. Currently these wetlands are colonised by common hydrophytes such as *Typha Capensis* and *Cyperus dives* species (Figure 2.2). However, other species such as *Cyperus sphaerospermus, Cyperus textilis, Imperata cylindrical* and *Ischaemum fasciculatum* grow on these wetlands. Degradation of the Edendale wetland was a result of historic and current land use practices, which include encroachment of residential and commercial development as well as grazing pressure which resulted in significant modifications to the catchment. This in turn altered the wetland system's functions such as flood attenuation, sediment trapping and erosion control.

The rehabilitation process on the Greater Edendale wetland started in the year 2010. This was done as part of the development of the Greater Edendale Mall. The rehabilitation was done to ensure that there is no diffuse flow of water through the wetland system. This has allowed for the establishment of a diverse range of wetland species through the transformation from temporary to permanently wet soils (Green Door Environmental, 2016). The wetland was dominated by alien invasive plant species such as *Lantana camara*, *Melia azedarach, Solanum mauritianum* and *Sorghum halepense*. Sewage water was also identified as one of the main disturbances to the wetland ecosystem.

The study site generally experiences summer rainfall, but with some rainfall in winter. Average annual rainfall ranges between 801-1000 mm, while mean annual temperatures range from approximately 4.1^{o}C to 27^{o}C (Green Door Environmental, 2016). The dominant soil types in the study site consists of fill colluvial and residual soils that overlie weathered shale. With the average elevation ranging from 712-721 m.

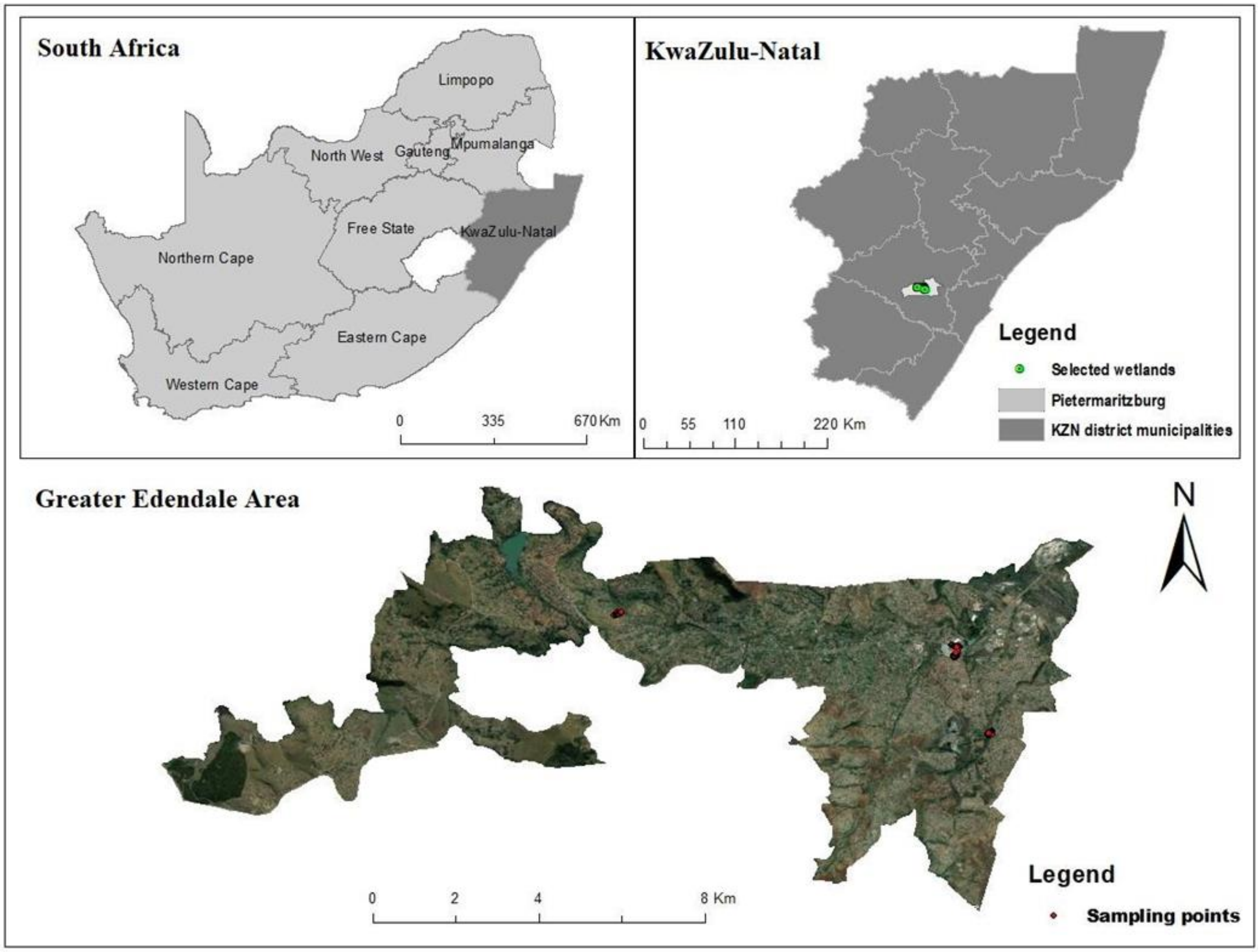

Figure 2. 1: Map showing the location of the study area within KwaZulu-Natal, Pietermaritzburg.

2.2.2. Field Data Collection

Prior to field sampling, Google Earth Pro was used to digitise the wetland areas. Subsequently the digitised polygons were transferred into a Geographic Information System (GIS), where a total of 130 random points were generated for LAI measurement. Specifically, 72 sampling points from the Greater Edendale wetland and 58 from the Willowfontain wetlands were conducted and considered for this research. A handheld global positioning system (GPS), was used for navigation around the wetlands to the point of sampling. At each point, a 10m by 10m quadrat was established and used as a sampling unit. At each quadrat LAI estimate measurements were conducted and recorded against the coordinates of that sampling point using the LAI-2200 Plant Canopy Analyser.

The Plant Canopy Analyser computed the LAI from the canopy, based on incoming radiation measurements from a fisheye optical sensor. In measuring LAI estimates, 5 measurements that were conducted (1 measurement) above and (4 measurements) below the canopy. LAI estimates measurements were conducted in such a way that there were no external objects obstructing the LAI-2200 instrument's optical sensor. The optical sensor was then placed levelled underneath the leaf canopy, with the above canopy measurement focusing in a similar direction. LAI data was thereafter recoded and imported into GIS as a table.

2.2.3. Remotely Sensed Data

A Sentinel-2 Multispectral Instrument satellite image of the area of study was obtained from the ESA Copernicus Open Access Hub (https://scihub.copernicus.eu/) on 3 October 2018, which is the same period that the field sampling was conducted. The image was the pre-processed using Sentinel Application Platform (SNAP) version 2.2, atmospheric correction was thereafter implemented on the image in order to extract accurate wetland vegetation spectra in a GIS system. The spatial resolution on Sentinel-2 MSI ranges between 10 meters to 60 meters with a revisit period of 5 days under clear sky conditions (Frampton et al., 2013). Sentinel-2 MSI consists of 12 spectral bands, where bands 2, 3, 4 and 8 are positioned at 10 meters, bands 5, 6, 7, 8a, 11 and 12 are positioned at 20 meters and bands 1, 9 and 10 are positioned at 60 meters. Sentinel 2 MSI offers unique red-edge bands which are situated at wavelengths between 705nm – 783nm (bands 5, 6 and 7).

However, spectral signatures for wetland vegetation were extracted from all Sentinel-2 MSI bands. Vegetation indices were generated based on simple ratio (sR) and normalised difference vegetation (nDVI) from all conceivable Sentinel-2 MSI band combinations including red-edge bands for estimating LAI. Additionally, traditional vegetation indices such as green normalised difference index (GNDVI), normalised difference water index (NDWI), chlorophyll green (Clgreen), transformed difference vegetation index (TDVI) were also computed using Sentinel-2 MSI bands excluding those with a 60-meter spatial resolution which are atmospheric correction channels (Table 2.1).

Figure 2. 2**:** (a) Greater Edendale Wetland (rehabilitated wetland), (b) Willow fountain wetland (natural wetland) and (c) *Typha Capensis* one of the two dominant wetland vegetation species.

Table 2. 1: List of Sentinel-2 bands and vegetation indices used in this study.

Analysis stage	Variable type	Variable	Formula
1	**All Sentinel 2 bands**	**Standard Bands** Blue, Green, Red, NIR and Red-edge	
		Vegetation Indices	
2	Conventional VI	SR	NIR/Red
		SR.re	NIR/Red-edge
		NDVI	(NIR-Red)/(NIR+Red)
		NDVI.re	(NIR-Red-edge)/(NIR+Red-edge)
		NDWI	(Green-NIR/(Green+NIR)
		GNDVI	(NIR)/(Blue+NIR)
		Chlgreen	(NIR-G)/ (NIR+G)
		TDVI	√(NIR-Red)/(NIR+Red) +0.5
3	Modified Vis *nNDVI & sR*		
4	Combined spectral variables		
5	Pooled data		

2.2.4 Statistical Analysis

Prior to the analysis, a Shapiro-Wilk normality test was completed. This was done to ensure that there are no significant deviations of field measured LAI. The descriptive statistics were also computed on SPSS statistics 24. The Shapiro-Wilk test results illustrated that there were no significant deviations in LAI data from the normal distribution ($P > 0.05$).

2.2.5 Partial Least Squares Regression Method

Partial Least Square Regression (PLSR) is a statistical analysis method that selects optimal spectral features from a large number of variables (Wold et al., 2001). This advanced technique uses a selection of independent variables to predict a selection of dependent variables and is particularly advantageous when prediction is done using a considerable selection of independent variables (Abdi, 2003). This model is desirable for this study because the remotely sensed data (bands) are transformed into new orthogonal factors which aid in avoiding multicollinearity and over fitting issues (Eriksson, Johansson, Kettaneh-Wold, & Wold, 2001; Sibanda et al., 2019). The algorithm imposes sparsity, as it selects the optimal variables for each model that are most suitable for LAI estimation (Sibanda, et al. 2019).

The process of model validation refers to the assessing the performance of a model under realistic conditions using independent data (Richter, Hank, Vuolo, Mauser, & D'Urso, 2012). Leave-one-out cross validation (LOOCV) was therefore completed on a selected measured dataset to evaluate the performance of the PLSR model. Cross validation (CV) has been proven as a useful method in prediction error estimation (Varma, 2006). It is an unbiased and commonly used method to determine the optimal number of components to take into account (Mevik and Wehrens, 2007). CV splits data into training and testing data. Research conducted on plant biophysical data often use LOOCV as a validation method (Richter, 2012). The LOOCV coefficient of determination (R^2), root mean square error (RMSE) and relative root mean square error of prediction (relRMSE) of the regression were used to generate the goodness fit for all the models, and these were computed to assess and compare the LAI estimation models across both wetlands. The models representing the measured and predicted LAI were compared for both wetland types. The most optimal model was represented by the lowest RMSE and relRMSE. This indicated that the model performed better than the other models.

2.3. Results

2.3.1 Measured LAI descriptive statistics

The highest *in-situ* measured LAI value was 5.07 m^2/m^2, which was recorded from the rehabilitated wetland (Figure 2.3). The number of sampled points in the rehabilitated wetland were higher in measured LAI compared to the natural wetland. This is due to the productivity of the rehabilitated wetland as compared to the natural wetland. Field measured LAI mean values of 2 m^2/m^2 and 3 m^2/m^2 were observed for the natural and rehabilitated wetlands, respectively. The standard deviation of LAI data in the natural wetland was 0.60 m^2/m^2 and 1.17 m^2/m^2 for the rehabilitated wetland (Table 2.2). After the outliers were removed, 3.61 m^2/m^2 was the highest recorded LAI measured for natural wetland and 5.07 m^2/m^2 for rehabilitated wetland. The LAI measurements represent a variable distribution across the two types of wetlands, and a wide range of LAI measurements were recorded for the rehabilitated wetland (Figure 2.5). The Shapiro-Wilk test results illustrated that there were no significant deviations in LAI data from the normal distribution ($P > 0.05$).

Table 2. 2: Descriptive statistics of LAI (m^2/m^2) for natural and rehabilitated wetlands.

	Samples	Minimum	Maximum	Mean	Std. Dev
Natural Wetland LAI	46	0.97	3.61	2.051	0.602
Rehabilitated Wetland LAI	52	0.75	5.07	3.042	1.176

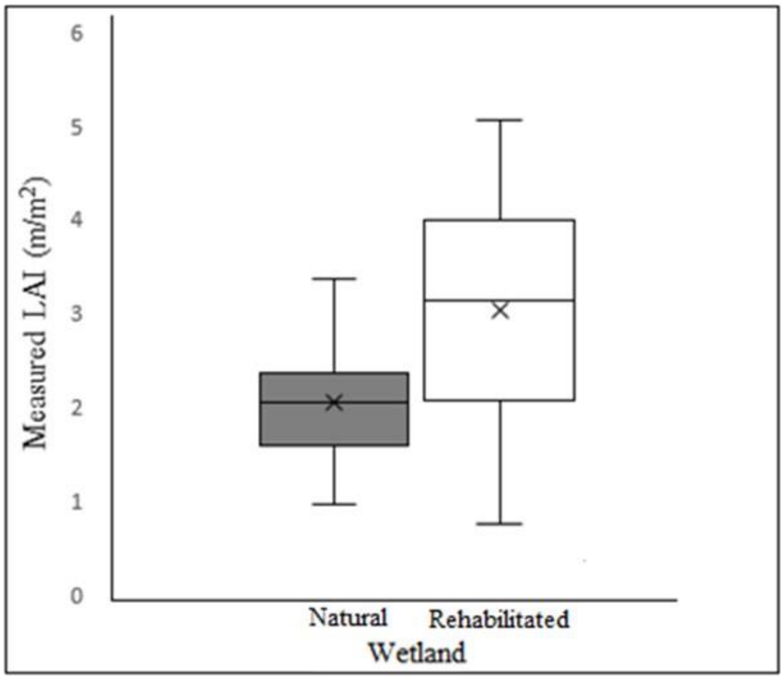

Figure 2. 3**:** Box plots of LAI, where the grey box represents the natural wetland and the white box represents the rehabilitated wetland.

2.3.2 Comparing the influence of standard bands and traditional vegetation indices in estimating LAI of wetland vegetation between natural and rehabilitated wetlands

In comparing the standard bands with traditional vegetation indices in estimating LAI of wetland vegetation, the results exhibited better accuracies when standard bands were used for LAI estimation for the natural wetland, as compared to traditional vegetation indices. A RMSE of 0.72 m^2/m^{-2} and an R^2 of 0.51 was obtained from using standard bands, whereas a RMSE of 0.78 m^2/m^2

and an R^2 of 0.42 was obtained when traditional vegetation indices were used based on the PLSR algorithm. However, for the rehabilitated wetland, results showed that standard bands were outperformed by traditional indices in estimating wetland vegetation LAI. A RMSE of 0.59 m^2/m^2 and R^2 of 0.74 were attained using standard bands, while a RMSE of 0.57 m^2/m^2 and an R^2 of 0.71 was obtained when traditional indices were used. The optimal variables that were selected for this model included red-edge bands, vegetation indices which comprised of red, green and yellow near infrared (NIR) and mid infrared (MIR) for the natural wetland. Whereas, the optimal variables selected for the rehabilitated wetland were from the red section and the red-edge bands.

2.3.3 Comparing the influence of nDVI and sR vegetation indices in estimating LAI of wetland vegetation between natural and rehabilitated wetlands

LAI estimation accuracies improved with the use of nDVI and sR vegetation indices, as compared to the accuracies derived from using standard bands only. A RMSE of 0.32 m^2/m^2 and an R^2 of 0.61 were attained for sR vegetation indices whereas, a RMSE of 0.34 m^2/m^2 and an R^2 of 0.62 were obtained from nDVI (Table 3). Therefore, nDVI vegetation indices were outperformed by sR vegetation indices in the natural wetland. However, for the rehabilitated wetland, results show improved accuracies in LAI estimations for wetland vegetation with the use of nDVI vegetation indices. A RMSE of 0.51 m^2/m^2 and an R^2 of 0.72 were obtained for nDVI vegetation indices and an RMSE of 0.56 m^2/m^2 and an R^2 of 0.74 was attained for sR vegetation indices. The selected optimal variables for the natural wetland were vegetation indices that were a combination of the green, red, red-edge and NIR/SWIR bands. However, for the rehabilitated wetland, some of the optimal vegetation indices included the blue band, red-edge bands and bands from the NIR sections of the electromagnetic spectrum.

Table 2.3: Summary of LAI estimation accuracies for natural and rehabilitated wetlands.

Wetland	**Natural**		**Rehabilitated**	
Variables	R^2	RMSE	R^2	RMSE
Sentinel-2 Bands	0.51	0.72	0.74	0.59
Traditional Indices	0.42	0.78	0.71	0.57
Simple Ratio	0.61	0.32	0.74	0.56
NDVI	0.62	0.34	0.72	0.51
Combined	0.63	0.32	0.75	0.52

2.3.4 Estimating wetland vegetation leaf area index using combined data

When all the Sentinel-2 MSI conventional bands and vegetation indices were collectively used for wetland vegetation LAI prediction, a high estimation accuracy was attained for the natural wetland as compared to the rehabilitated wetland (Figure 2.4 (i & ii) and Table 2.3). A RMSE of 0.32 m^2/m^2 and an R^2 of 0.63 was obtained for combined data (conventional bands and all vegetation indices) for the natural wetland, whereas a RMSE of 0.52 m^2/m^2 and an R^2 of 0.75 was obtained for the rehabilitated wetland. When data from both sites (natural and rehabilitated wetlands) were pooled together a low accuracy was produced for wetland vegetation LAI, with a RMSE of 0.67 m^2/m^2 and an R^2 of 0.51. Figure 2.4 (iii), illustrates the relationship between measured and predicted LAI. Noticeably, the individual predictive models outperformed the pooled predictive model, with the natural wetland model producing high accuracies (Figure 2.4 (i)). The selected optimal variables when natural wetland data was combined comprised of red-edge derived vegetation indices paired with the red, green and yellow NIR bands. The optimal variables that were selected for the rehabilitated wetland included all of the visible section of the electromagnetic spectrum, coupled with red-edge derived vegetation indices and NIR and SWIR section of the electromagnetic spectrum.

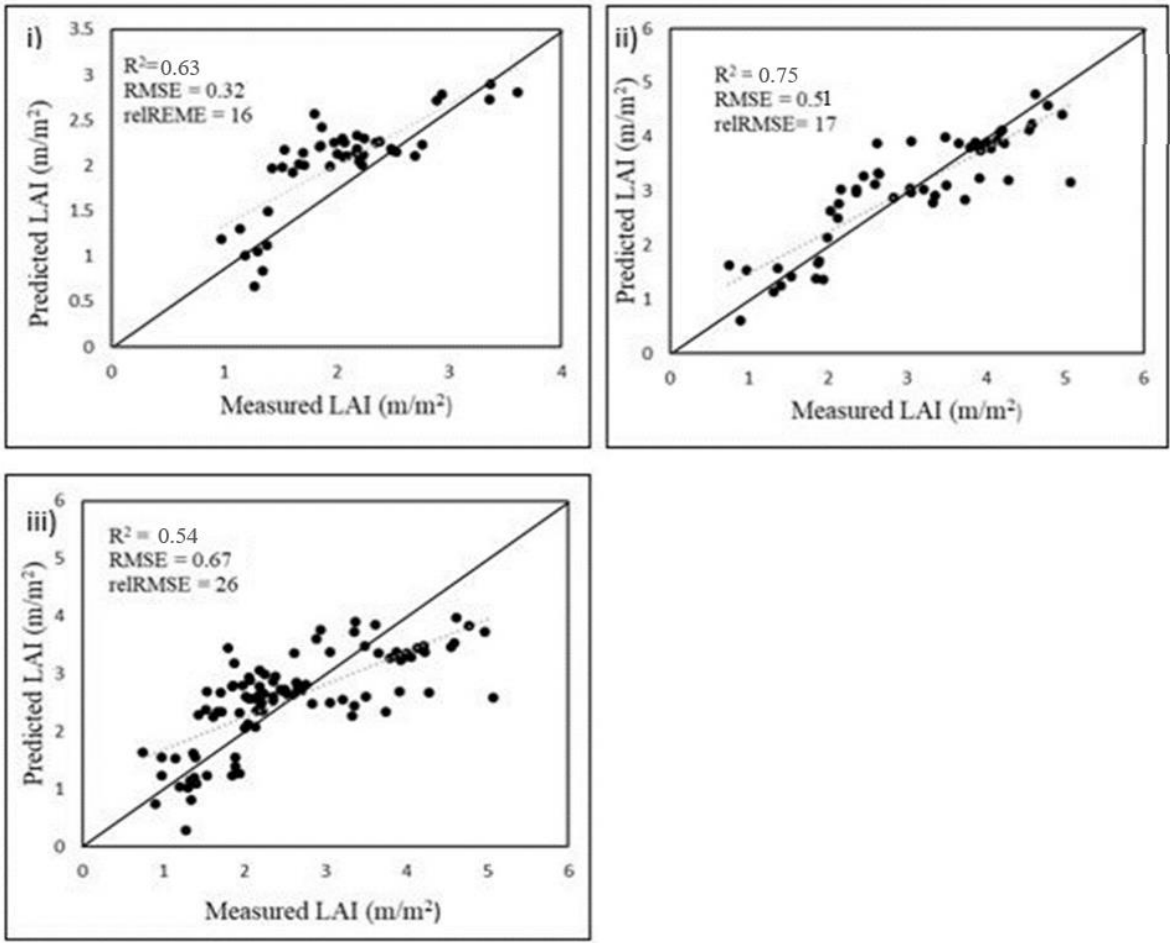

Figure 2. 4**:** The relationship between measured and predicted LAI, i) representing the natural wetland, ii) representing the rehabilitated wetland and iii) pooled dataset.

2.4. Discussion

2.4.1 Variability in measured leaf area index

Results of this study show that wetland vegetation productivity was optimally characterised across wetland systems under different management practices using Sentinel-2 MSI data (Figure 2.4). Specifically, the results illustrated that optimal wetland vegetation LAI estimations were obtained with the use of Sentinel-2 MSI red edge derived vegetation indices in combination with traditional vegetation indices. Particularly, the optimal variables in the model that estimated LAI across the natural and the rehabilitated wetlands were red edge bands 5,6 and 7, as well as NIR band 8a.

The findings of the current study show that the estimation error for the natural wetland was lower when compared to the rehabilitated wetland. This suggests that the estimation model performed better in LAI estimation for the natural wetland. This could be due to high moisture content, leaf density, as well as lack of vegetation diversity in the rehabilitated wetland. These wetland characteristics attenuate the vegetation signal through the process of saturation, making it difficult to characterise physiochemical vegetation properties such as LAI in wetland settings, especially in more managed wetlands as compared to natural wetlands. However, for the natural wetland, these saturation issues were overcome by plant species diversity and representation due to the natural setting of the wetland. The Sentinel-2 MSI red edge region directly influenced the spectral reflectance of wetland vegetation in the natural wetland. Xie et al. (2018) presented similar results, where they illustrated that red and red-edge vegetation indices improved the R^2 of LAI by 10% in a study that highlighted the influence of red and red-edge vegetation indices combinations for LAI estimation. Sibanda et al., (2019), also attained high accuracies with a RMSE of 0.5074 m^2/m^2 and R^2 of 0.91 when Sentinel-2 MSI red edge bands were used to estimate LAI.

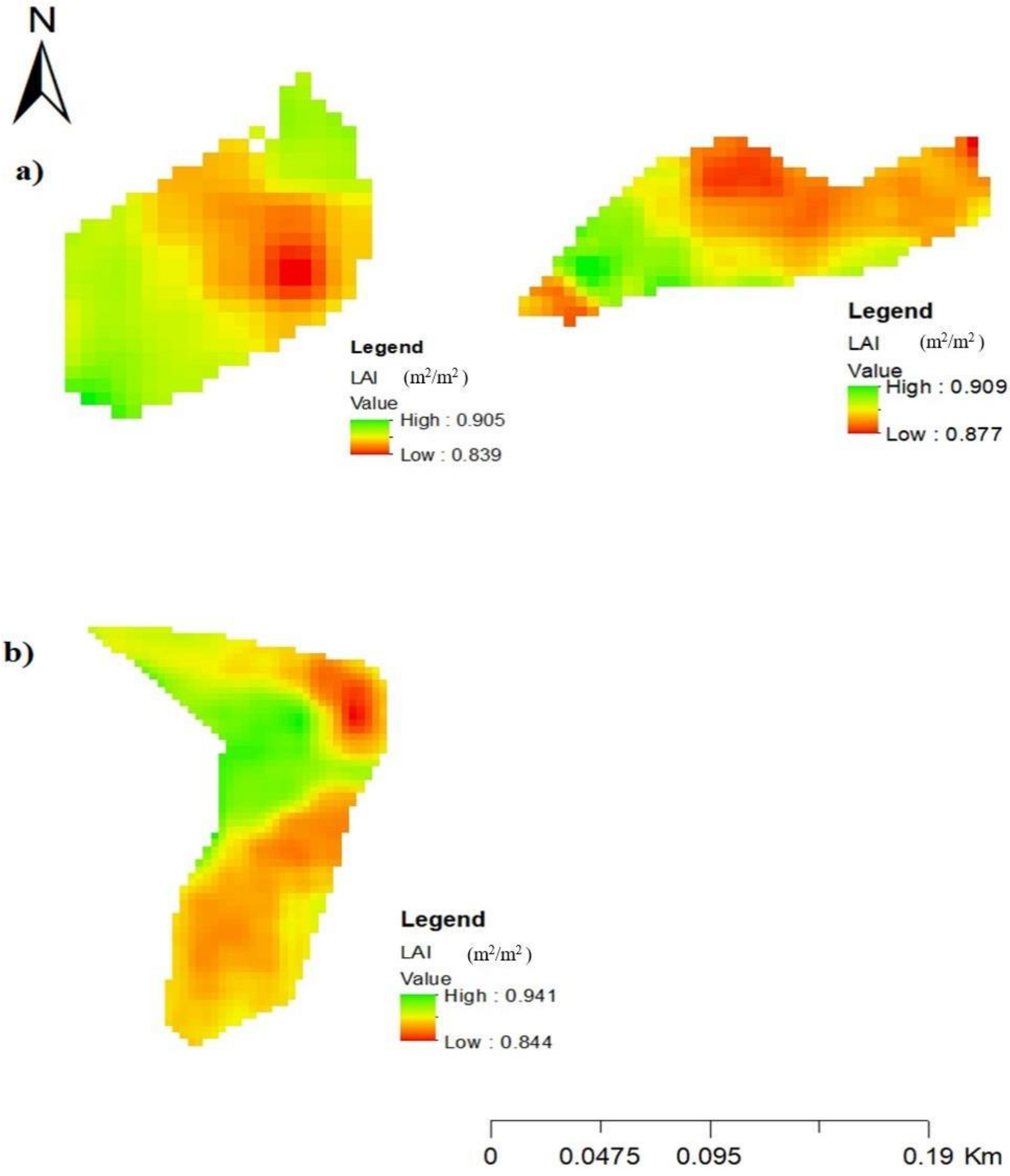

Figure 2. 5: The spatial distribution of LAI for (a) natural wetland and (b) rehabilitated wetland.

2.4.2 Performance of Vegetation indices in estimating wetland vegetation LAI

The findings from this analysis show that vegetation indices significantly improved wetland vegetation LAI estimation for both wetlands by producing a lower error of estimation of 0.32 m^2/m^2 for sR vegetation indices and 0.34 m^2/m^2 for nDVI vegetation indices for the natural wetland. Whereas the error of estimation for the rehabilitated wetland vegetation LAI was reduced to 0.56 m^2/m^2 when using sR vegetation indices and 0.51 m^2/m^2 when using NDVI vegetation indices. Background effects such as soil and litter can affect the model performance, especially with the use of standard bands only. Standard bands are more susceptible to soil background interference and other atmospheric issues that result in the impairment of vegetation reflectance when properties such as LAI are measured (Dong et al., 2019; Du et al., 2016; Mutanga & Skidmore, 2004). The findings of this analysis also indicate that the use of red-edge vegetation indices outperformed standard bands in LAI estimation. This is mainly due to the strong relationship between red-edge bands and LAI, as compared to standard bands. As it has been demonstrated that LAI strongly influences the shape of the red edge reflectance spectra (Xie, 2018).

The results indicate that traditional indices performed poorly in estimating wetland vegetation LAI. Out of the traditional indices that were used in this study, Clgreen was the most optimal in estimating wetland vegetation LAI in the natural wetland. Whereas, for the rehabilitated wetland it was Clgreen and NDWI that proved to be the most optimal variables in estimating wetland vegetation LAI. The reason for this could be these traditional indices were derived from the broadband sections of the electromagnetic spectrum. This makes these vegetation indices (VIs) unstable due to soil moisture, and atmospheric conditions (Taddeo et al., 2019; Maguigan et al., 2018; Mutanga et al., 2012). In a related study, Adam et al. (2010) illustrated that NDVI asymptotically saturates within particular measurement of biomass density and specific ranges of LAI measurements. Therefore, the estimation accuracy drops considerably for both the natural and rehabilitated wetland. Overall the model performed better for wetland vegetation LAI in natural wetland as it provided the least estimation error when compared to the model derived for the rehabilitated wetland. The study adopted a PLSR model to establish the capability of Sentinel-2 MSI derived data in estimating wetland vegetation leaf area index between a natural and rehabilitated wetland. The findings show that the PLSR algorithm can be used to estimate wetland vegetation LAI.

2.5 Conclusion

The current study sought to investigate the ability of Sentinel-2 MSI derived data and vegetation indices to estimate wetland vegetation LAI under different management regimes. The findings show that the new generational Sentinel-2 MSI sensor data can optimally quantify the variability of wetland vegetation LAI across natural and rehabilitated wetlands. The presence of red-edge bands in Sentinel-2 MSI proved to be a great advantage to this study, as most of the optimal variables with the lowest estimation errors for LAI estimation included red-edge bands and red-edge derived vegetation indices. The combination of standard bands, red-edge derived vegetation indices and traditional indices yielded low estimation errors for the natural wetland as compared to the rehabilitated wetland. Overall, the findings confirmed that Sentinel 2 MSI offers a cost effective and less time-consuming data source to accurately estimate LAI in resource scarce environments. The methods used in this study can be used for wetland monitoring by means of LAI estimation and comparison across wetlands under different management regimes.

Chapter Three

Estimating chlorophyll content of *Cyperus Dives* and *Typha Capensis* growing in natural and rehabilitated wetlands

Abstract

Wetland restoration and management has become a pressing issue due to excessive wetland degradation. Vegetation health is a critical component of wetland ecosystem viability and therefore can be used to quantify the impacts of rehabilitation programmes using remote sensing. This study aimed to assess the use of high-resolution Sentinel-2 MSI data for estimating the chlorophyll content, (a proxy for vegetation health) of *Typha capensis* and *Cyperus dives* vegetation species growing in a natural wetland and a rehabilitated wetland. Partial Least Squares Regression (PLSR) algorithms were applied to estimate the chlorophyll content of both *Cyperus dives* and *Typha capensis* leaves. The results indicated that the PLSR model performed better at chlorophyll content estimation for *Cyperus* species from the rehabilitated wetland with a RMSE of 2.54 µg cm^2 (relRMSE = 4%) and R^2 value of 0.86. The final model composed of combined datasets resulted in the accurate estimation of chlorophyll content with a RMSE of 9.11 µg cm^2 (12%) and R^2 value of 0.88 based on red-edge bands centered at 705 nm (Band 5), 740 nm (Band 6), 783 nm (Band 7) as well as 865 nm (Band 8a). The results indicate that wetland rehabilitation improves vegetation productivity. Overall, the results show that Sentinel-2 MSI data can be optimally used for chlorophyll content estimation of plant species growing in wetlands under different management regimes.

Keywords: PLSR, accurate estimation, vegetation health, Sentinel-2 MSI data

3.1 Introduction

There are numerous functions, products and ecosystem services provided by wetlands across different landscapes. These wetland functions include the provision of habitat for various fauna and flora, recreational functions and food products at a local scale (An and Verhoeven, 2019). Moreover, wetland ecosystems are relatively important for regulating the global water cycle functions, as well as productivity and biodiversity (Turner et al., 2000, Jones et al., 2018). Globally, wetlands increase resilience to climate change, as they act as buffers against droughts and floods (Janse et al., 2019). A number of wetland ecosystems are being modified and threatened due to anthropogenic activities and climate change, hence the urgent need for wetland rehabilitation.

Wetland rehabilitation plays a vital role in the reversal of these dire conditions, by restoring damaged wetland ecosystems and recovering important ecosystem services. Studies have reported that wetland restoration focuses on returning the wetland from a disturbed or modified status caused by anthropogenic activities to a pristine condition, through a process of ecological restoration (Zhao et al., 2016). However, it is often a complex task to determine the important variables needed to measure the restoration success (Dou et al., 2018, Hazelton et al., 2019). According to Dou et al. (2018), similar variables should be used to assess the restoration success before and after the restoration process. However, this has proven difficult due to the lack of consistent data that can be used as measures of wetland restoration success (Guo and Guo, 2016, Hazelton et al., 2019). There is a variety of indicators that can be used to measure or assess wetland restoration progress across different wetlands, however, these indicators often differ depending on wetland ecosystem types (Dou et al., 2018, Guo and Guo, 2016). According to Choi (2004), ecological processes such as nutrient cycling, biological exchanges and vegetation structure should be taken into account as indicators when assessing the success of wetland restoration.

Vegetation is a vital component in the ecological functioning of wetlands, and can also be an excellent indicator for wetland ecosystem health, physical and chemical characteristics (Elhadi et al., 2009, Adam et al., 2010). Vegetation properties such as chlorophyll content can provide an overview of the general health of vegetation (Dou et al., 2018). Chlorophyll is also a proxy for plants' physiological status and it is highly related to plant photosynthetic function (Mutanga et al., 2012, Adam et al., 2010). Therefore, measuring leaf chlorophyll content of wetland vegetation such as *Typha capensis* and *Cyperus dives* could help in attaining a complete representation of wetland functionality and restoration progress.

Many African wetlands are characterised by a number of tropical species of the genera T*ypha capensis* and species of *Cyperus* (Ruto et al., 2012). By comparison with other species in the genus, *Typha* is not a commonly studied fresh water plant, and it has only been recognised as widely distributed in freshwater wetlands that have relatively stable hydrological regimes (Masoko et al., 2008). *Typha capensis*, commonly known as Bulrush generally occurs in areas that have permanent fresh water or are frequently flooded. Its unbranched, joint less stems grow between 0.5 to 1.5 m long. Considerable attention has been given to the genus *Typha* in other parts of the world. The main reason for this is its high productivity, which facilitates its invasion and encroachment in wetlands, hence it is often considered as a weed. Since *Typha* is extremely productive, it has a great potential as bio-energy crop which is useful in wastewater purification systems. *Cyperus* provides habitat for wetland fauna in most wetland ecosystems and it plays a critical hydrological, ecological and socio-economic role in wetland ecosystems. For instance, *Cyperus* is a food source for humans and livestock, and it can be used as a building material. However, *Cyperus* species are being endangered due to wetland degradation, agriculture and human encroachment (Elhadi et al., 2009). Subsequently, numerous rehabilitation activities are being conducted to reduce the loss of ecosystem services associated with these wetland species. In this regard, comparing the leaf chlorophyll content of *Typha capensis* and *Cyperus dives* between restored and natural wetlands can offer insight on the variations of these ecosystems after restoration. There is, therefore, a need for effective and timely techniques for mapping and monitoring the productivity and health of such wetland vegetation species as part of their sustainable management (Adam et al., 2010).

Wetlands are delicate ecosystems which are often characterised by thick, dense vegetation which is inaccessible rendering *in-situ* assessments and surveys difficult and tedious especially for relatively large wetlands (Adam et al., 2010). Additionally, field assessments on wetland ecosystems often lack adequate spatial coverage of the entire wetland due to shallow water puddles and high waterlogging conditions which restrict movement. Consequently, information required for that ecosystem monitoring is often scanty and inadequate. Therefore, there is need for more effective timely methods to accurately estimate chlorophyll content of wetland vegetation species such as *Typha* and *Cyperus* as a proxy for wetland health. Meanwhile, remote sensing techniques offer an efficient and timely option for estimating and mapping chlorophyll of wetland vegetation species under different wetland management systems (Wortley et al., 2013).

Wetland vegetation species properties such as chlorophyll (Chl) can be optimally estimated using satellite, airborne or *in-situ* sensors (Mutanga et al., 2012). A number of studies have indicated the successful application of remotely sensed data in Chl estimation at various plant phenological stages and across different landscapes (Gitelson et al., 1997; Chemura et al., 2017; Jay et al., 2017; Lu and He, 2019). Literature suggests space-borne sensors offer a synoptic view that makes remote sensing an ideal technique for estimating Chl at local, regional and global scales. These sensors provide images that are characterised by high spectral and spatial resolution, that are successfully used for vegetation type identification and species discrimination (Gillespie et al., (2015). Hyperspectral, Worldview and Landsat TM data have been successfully used for Chl estimation (Duo et al., 2018; Patra et al., 2017. For example, Dou et al. (2018) used hyperspectral data for chlorophyll content estimation of mangrove vegetation at different stages of restoration. Their results showed that hyperspectral data could be used to estimate biochemical constituents in leaves. Patra et al., (2017), also successfully estimated Chl levels for inland lakes using Landsat 8 Operational Land Imager (OLI) imagery. In a study by Guo and Guo, (2016), hyperspectral data was successfully used to estimate leaf chlorophyll content of emergent plant species in wetlands (RMSE = 0.16 and R^2 = 0.87). The authors concluded that remote sensing methods, particularly hyperspectral data offer an effective and non-destructive technique for monitoring restoration and management of urban wetlands (Guo and Guo, 2016). Although hyperspectral data is effective in chlorophyll estimation due to its high spectral resolution, it is often associated with exorbitant acquisition costs and it is often limited to local scales. Therefore, there is need for cost-effective data sources with similar benefits of high spatial and spectral resolution. Freely available remotely sensed data such as Sentinel offer opportunities to overcome the above limitations.

Recent developments in spaceborne multispectral data provide promising sources of information for assessing wetland vegetation. The European Space Agency's Copernicus programme now provides an opportunity to map wetlands more accurately from space, with the use of its freely accessible Sentinel-2 multispectral imager (MSI) data characterised by high spatial and temporal resolutions (Slagter et al., 2020). Sentinel-2 MSI satellites provide optical multispectral data in resolutions of 10, 20 and 60 meters in the visible, near-infrared (NIR) and short-wave infrared

(SWIR) regions of the electromagnetic spectrum (Slagter et al., 2020, Sibanda et al., 2019). Furthermore, Sentinel-2 MSI has a revisit period of 10 days, which makes it more suitable for assessing wetland health and productivity at a high spatial resolution (Mahdianpari et al., 2019). Unlike its predecessors such as Landsat, Sentinel-2 MSI consists of three narrow red-edge spectral bands which are highly sensitive to vegetation species characteristics such as chlorophyll (Cleveres and Gitelson 2013; Frampton et al., 2013; Vincini et al., 2016). It is, therefore, perceived that it could immensely contribute to the accurate estimation of vegetation biochemical and biophysical properties of wetlands in different management areas. Literature indicates that sensors inclusive of the red edge bands such as Sentinel-2 MSI may produce more accurate and effective results in the estimation vegetation biochemical properties such as chlorophyll. For instance, Pastor-Guzman et al. (2015), presented the potential of estimating chlorophyll content using Sentinel-2 MSI data in large mangrove areas and how this high spatial and temporal data can improve mangrove monitoring. A study by Frampton, Dash, Watmough, & Milton (2013), successfully illustrated how the red-edge section of Sentinel-2 MSI could provide accurate estimations of vegetation chlorophyll content, and it can therefore be used to monitor the health of wetland vegetation. So far, the performance of this sensor has not yet been explored in characterising leaf chlorophyll of wetland plants (*Typha* and *Cyperus)* under different wetland management systems. Therefore, this study will assess the utility of high-resolution Sentinel-2 MSI data in accurately estimating the chlorophyll content of *Typha capensis* and *Cyperus dives* growing in natural wetland and rehabilitated wetlands as proxy of evaluating the success of wetland rehabilitation.

3.2 Methods and Material

3.2.1 Study Area

The study was conducted in the Greater Edendale Mall wetland (29°38'54.70"S and 30°20'28.03"E) and Wetland Erf 1105 in Willowfontain (29°42'41.51"S and 30°20'49.22"E), both situated in Pietermaritzburg, KwaZulu-Natal (figure 3.1). The Willowfontain wetland is in its natural state, while the Edendale wetland was rehabilitated. Common hydrophytes such as *Typha capensis* and *Cyperus dives* are the most dominant species. However, other species such *as Cyperus sphaerospermus*, *Cyperus textilis*, *Imperata cylindrical* and *Ischaemum fasciculatum* are also found in the two wetlands but with negligible population sizes. The cause of degradation for the Edendale wetland was mainly historic and current land use changes such as the encroaching residential and commercial development as well as grazing pressure which resulted in significant modifications to the catchment. This in turn altered the wetland system's functions such as flood attenuation, sediment trapping and erosion control. The rehabilitation process on the Greater Edendale wetland started in the year 2010. This was done as part of the development of the Greater Edendale Mall. The rehabilitation was done to ensure that there is no diffuse flow of water through the wetland system. This has allowed for the establishment of a diverse range of wetland species through its transformation from temporary to permanently wet soils (Green Door Environmental, 2016). The wetland was dominated by alien invasive plant species such as *Lantana camara*, *Melia azedarach*, *Solanum mauritianum* and *Sorghum halepense*. Sewage water was also identified as one of the main disturbances to the wetland ecosystem.

The study site generally experiences summer rainfall, but with some rainfall in winter. Average annual rainfall ranges between 801-1000 mm, while mean annual temperatures range from approximately 4.1^{o}C to 27^{o}C (Green Door Environmental, 2016). The dominant soil types in the study site consists of fill colluvial and residual soils that overlie weathered shale. With the average elevation ranging from 712-721 m.

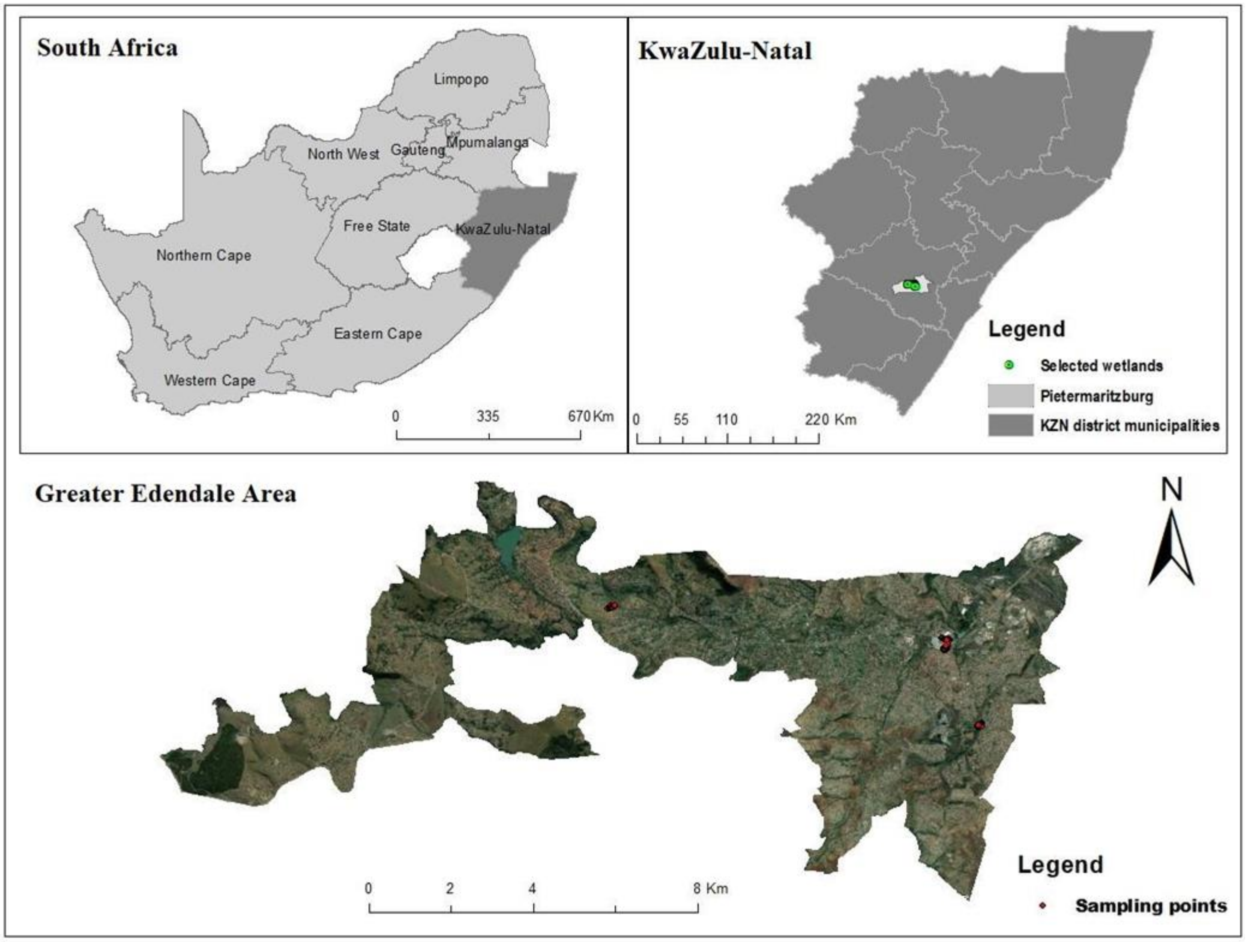

Figure 3. 1**:** Location of the wetlands within Pietermaritzburg in the province of KwaZulu-Natal, in South Africa.

3.2.2 Field Data Collection

Prior to field measurements, Google Earth Pro was used to digitise the wetland areas. Subsequently the digitised polygons were transferred into a Geographic Information System (GIS), where a total of 130 random points were generated for *Cyperus* and *Typha* chlorophyll measurements. Specifically, 72 sampling points from the Greater Edendale wetland and 58 from the Willowfontain wetlands were conducted and considered for this analysis. A handheld global positioning system (GPS), was used for navigation around the wetlands. At each point, a 10m by 10m quadrat was established and used as a sampling unit. Chlorophyll content was measured using the SPAD-502 meter.

The SPAD-502 was used for measuring chlorophyll in the field. The SPAD-502 quantifies leaf absorbance in the red and near-infrared regions where transmittance peaks (Ai et al., 2000). A numerical SPAD value which is relative to the amount chlorophyll that is present in the leaf is calculated by the meter, based on the transmittances of the red and near-infrared regions. SPAD values were measured by inserting a leaf in the measuring head of the SPAD at each of the generated points. Thereafter the SPAD value were recorded as the chlorophyll measurement on the data collection sheet, as well as the coordinates of where the chlorophyll measurements were taken. Since the SPAD values are unit less, a model by Markwell et al. (1995) detailed below was used to convert them into chlorophyll;

$$Chl = 110^{s0.0265}$$

Chlorophyll measured in μmol·m^{-2} is represented by *Chl* and the SPAD readings have no unit of measurement and therefore represented by *S*. With the knowledge of the molecular mass of *Chl a* and *Chl b*, the units were converted from μmol·m^{-2} to μg·cm^{-2}. The SPAD value readings were measured *in situ* at approximately a middle point of a leaf while avoiding the midribs of grass leaves as in Lin et al. (2010).

2.2.3. Remotely Sensed Data

A Sentinel-2 Multispectral Instrument satellite image of the area of study was obtained from the ESA Copernicus Open Access Hub (https://scihub.copernicus.eu/) on 3 October 2018, which is the same period that the field sampling was conducted. The image was the pre-processed using Sentinel Application Platform (SNAP) version 2.2, atmospheric correction was thereafter implemented on the image in order to extract accurate wetland vegetation spectra in a GIS system. The spatial resolution on Sentinel-2 MSI ranges between 10 meters to 60 meters with a revisit period of 5 days under clear sky conditions (Frampton et al., 2013). Sentinel-2 MSI consists of 12 spectral bands, where bands 2, 3, 4 and 8 are positioned at10 meters, bands 5, 6, 7, 8a, 11 and 12 are positioned at 20 meters and bands 1, 9 and 10 are positioned at 60 meters. Sentinel 2 MSI offers unique red-edge bands which are situated at wavelengths between 705nm – 783nm (bands 5, 6 and 7) (Table 3.1).

However, spectral signatures for wetland vegetation were extracted from all Sentinel-2 MSI bands. Vegetation indices were generated based on simple ratio (sR) and normalised difference vegetation (nDVI) from all conceivable Sentinel-2 MSI band combinations including red-edge bands for estimating chlorophyll content. Additionally, traditional vegetation indices such as green normalised difference index (GNDVI), normalised difference water index (NDWI), chlorophyll green (Clgreen), transformed difference vegetation index (TDVI) were also computed using Sentinel-2 MSI bands excluding those with a 60-meter spatial resolution which are atmospheric correction channels. These vegetation indices were chosen and used for this analysis because they were documented in literature to have been successfully used to estimate chlorophyll (Turner et al. 2003, Wu et al. 2007, Frampton et al. 2013, Croft et al. 2017).

Table 3. 1: Spectral and spatial resolution of Sentinel 2 MSI

Bands	Name	Bands (nm)	Resolution
B1	Coastal aerosol	443	60
B2	Blue	490	10
B3	Green	560	10
B4	Red	665	10
B5	Red edge	705	20
B6	Red edge	740	20
B7	Red edge	783	20
B8	NIR	842	10
B8a	Red edge	865	20
B9	Water vapour	945	60
B10	SWIR-Cirrus	1375	60
B11	SWIR	1375	20
B12	SWIR	2190	20

3.4 Statistical Analysis

Prior to the analysis, a Shapiro-Wilk normality test was completed so as to use the parametric regression models for Chl estimation. This was done to ensure that there is no significant deviation in Chl data collected in the field. The descriptive statistics were also computed on SPSS statistics 24. Using the Shapiro-Wilk test results, the Chl data presented no significant deviations from the normal distribution ($P > 0.05$) hence the students t-test and PLSR were used in this study.

3.4.1 Partial Least Squares Regression Method

Partial Least Square Regression (PLSR) is a statistical analysis method that selects optimal spectral features from a large number of variables (Wold et al., 2001). PLSR was employed in this study to estimate Chl content of *Cyperus* and *Typha* species and select optimal modelling spectral features. This advanced technique uses a selection of independent variables to predict a selection of dependent variables and is particularly advantageous when prediction is done using a considerable selection of independent variables (Abdi, 2003). This model is desirable for this study because the remotely sensed data (bands) are transformed into new orthogonal factors which aid in avoiding multicollinearity and over fitting issues (Eriksson, Johansson, Kettaneh-Wold, & Wold, 2001; Sibanda et al., 2019). The algorithm selects the optimal variables for each model that are most suitable for chlorophyll estimation (Sibanda, Mutanga et al. 2019).

The process of model validation refers to the assessing the performance of a model under realistic conditions using independent data (Richter, Hank, Vuolo, Mauser, & D'Urso, 2012). Leave-one-out cross validation (LOOCV) was therefore completed on a selected measured dataset to evaluate the performance of the PLSR model. Cross validation (CV) has been proven as a useful method in prediction error estimation (Varma, 2006). It is an unbiased and commonly used method to determine the optimal number of components to take into account (Mevik and Wehrens, 2007). CV splits data into training and testing data. Research conducted on plant biophysical data often use LOOCV as a validation method (Richter, 2012). The LOOCV coefficient of determination (R^2), root mean square error (RMSE) and relative root mean square error of prediction (relRMSE) of the regression were used to generate the goodness fit for all the models. The accuracies for chlorophyll estimation models across plant species and wetlands were compared based on the RMSE and R^2 they exhibited. Optimal models in this study exhibited a lower relRMSE and RMSE.

3.3 Results

3.3.1. Measured Cyperus and Typha chlorophyll descriptive statistics (µg cm^2)

Using the Shapiro-Wilk test results, the Chl data presented no significant deviations from the normal distribution ($P > 0.05$) hence the students *t*-test and PLSR were used in this study. Measured chlorophyll content was higher for *Typha* species in the rehabilitated wetland with a mean of 73.3 µg cm^2 while *Cyprus* in the natural wetland had a mean of 51.7. The mean Chlorophyll content recorded for *Cyperus* species ranged between 17 µg cm^2 and 58 µg cm^2 in the natural and rehabilitated wetlands respectively. Meanwhile the mean chlorophyll content of *Typha* species ranged between 51.7 µg cm^2 and 73.3 µg cm^2 in the natural and rehabilitated wetlands respectively. Figure 3.2. illustrates significant ($\alpha = 0.05$) differences in Chl content between *Cyperus* species growing in the natural wetland and that growing in the rehabilitated wetland. However, no significant differences ($P > 0.05$) in Chl were observed on *Cyperus* and *Typha* species growing in the rehabilitated wetland, whereas significant differences ($\alpha = 0.05$) were observed between *Cyperus* and *Typha* growing in the natural wetland.

Table 3. 2: Descriptive statistics of *Cyperus* and *Typha* species chlorophyll content in natural and rehabilitated wetlands (µg cm^2).

	Wetland	Mean	Std. Deviation	N
Cyperus	Natural	17.3	21.1	37
	Rehabilitated	58.9	27.6	36
	Total			**73**
Typha	Natural	51.7	11.1	25
	Rehabilitated	73.3	33.2	45
	Total			**83**
Absolute Total				**156**

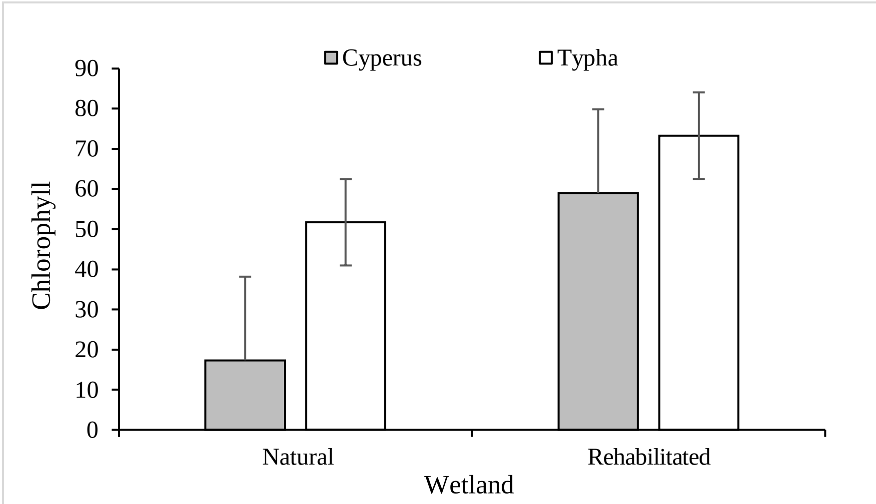

Figure 3. 2: Box plots of Chlorophyll, where grey boxes represent *Cyperus* and white boxes *Typha* between natural and rehabilitated wetland.

3.3.2. Estimating chlorophyll content of Cyperus and Typha plant species in natural and rehabilitated wetlands using Sentinel-2 MSI data

A comparison of chlorophyll content between *Cyperus dives* and *Typha capensis* in a rehabilitated wetland, showed that the estimation model for *Cyperus dives* plant species produced better estimation accuracies with a RMSE of 2.54 µg cm^2 (relRMSE = 4%) and R^2 value of 0.86, whereas, a RMSE of 3.91 µg cm^2 (relRMSE = 8%) and R^2 value of 0.60 was attained for the model for *Typha* plant species (Figure 3.3). However, in comparing these plant species Chl content for the natural wetland, results showed that the model for *Typha* plant species produced better accuracies with a RMSE of 7.70 µg cm^2 (relRMSE =12%) and an R^2 value of 0.75, while a higher RMSE of 8.77 µg cm^2 (relRMSE = 11%) and an R^2 value of 0.78 was attained for *Cyperus* plant species Chl estimation (Figure 3.3). The selected optimal variables for *Cyperus* Chl content estimation included red edge vegetation indices, red-edge bands, yellow and NIR section of the electromagnetic spectrum for the natural wetland. Whereas, the optimal variables that were selected for *Typha* species in the natural wetland included red, NIR and red-edge region. However, the green and red bands as well as red edge derived vegetation indices and NIR sections were selected as the optimal variables for Chl content estimation from *Typha* species in the rehabilitated wetland whereas for *Cyperus*, the red and red-edge sections were selected.

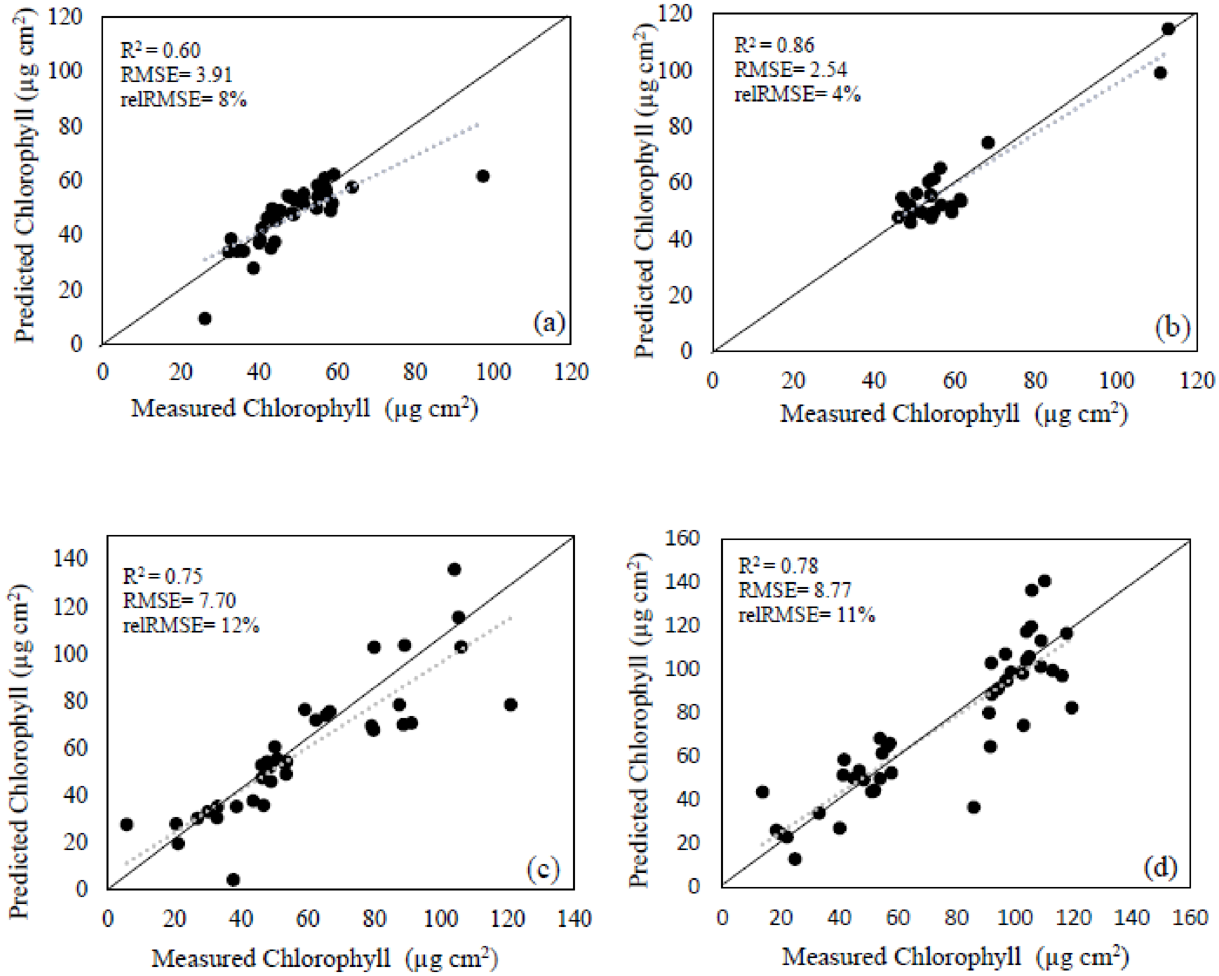

Figure 3. 3**:** Relationship between measured and predicted Chlorophyll, a) *Typha* for rehabilitated wetland and b) *Cyperus* for rehabilitated wetland, c) *Typha* for natural wetland, d) *Cyperus* for natural wetland.

3.3.3. Comparison of wetland plant species chlorophyll content estimation models between natural and rehabilitated wetlands

Figure 3.4. shows that the model for estimating Chl content of wetland vegetation (*Typha and Cyprus* combined) in the rehabilitated wetland outperformed that for the natural wetland. This is illustrated by a lower Chl content estimation RMSE of 3.26 µg cm^2 (relRMSE= 6%) and R^2 of 0.89 for the rehabilitated wetland, whereas a higher RMSE of 7.20 µg cm^2 (relRMSE = 12%) and a R^2 value of 0.86 was obtained for the natural wetland vegetation. The selected optimal variables included red, green, red-edge and NIR sections of the electromagnetic spectrum, as well as red-edge derived indices for both the natural and restored wetlands.

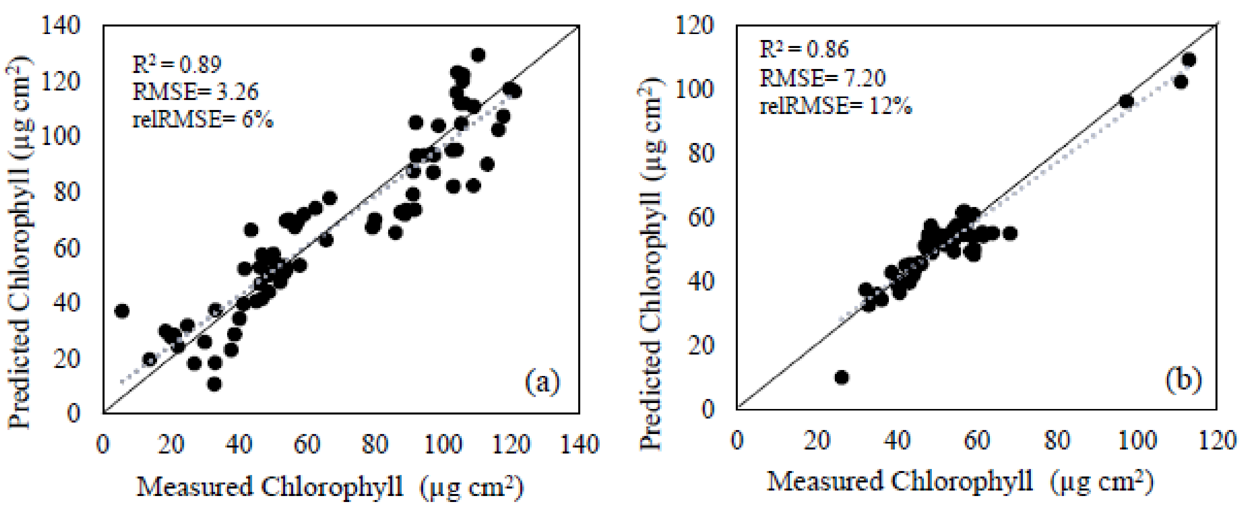

Figure 3. 4**:** Relationship between measured and predicted Chlorophyll, a) vegetation for rehabilitated wetland, b) vegetation for natural wetland.

3.3.4. Estimating wetland vegetation chlorophyll content across different wetland management regimes

Figure 3.5. Illustrates the prediction of Chl content estimates across all the wetland vegetation species data (*Cyperus* and *Typha*) and different wetland management conditions (natural and rehabilitated). When all vegetation species data and the types of wetlands were combined and used to predict Chl, a RMSE of 9.11 µg cm^2 (RelRMSE = 14%) and R^2 of 0.88 were derived using the PLSR algorithm. The overall selected optimal variables for this model included red and red-edge regions and red-edge vegetation indices (Figure 3.6).

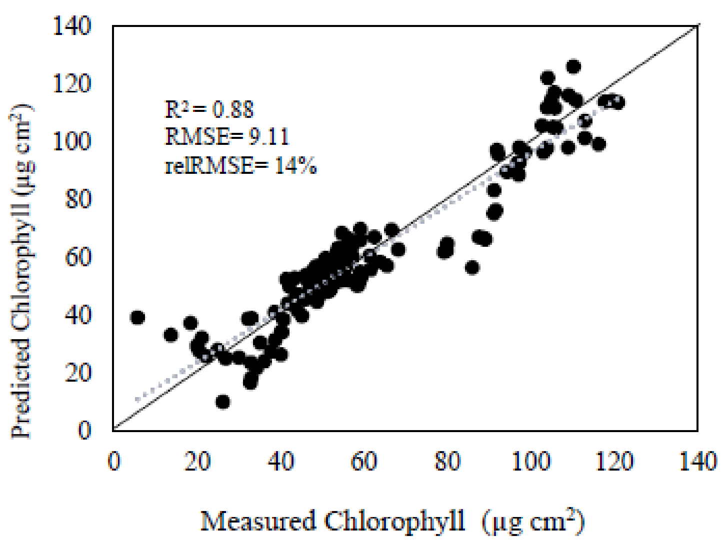

Figure 3. 5: Relationship between measured and predicted Chlorophyll across different wetland management regimes.

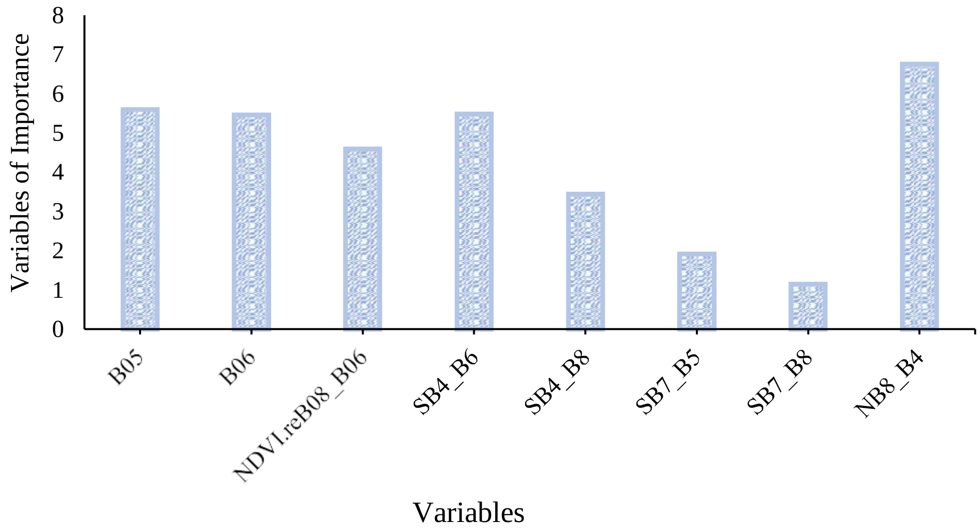

Figure 3. 6**:** Variable of importance scores in Chl estimation based on conventional bands, simple ration and normalised difference vegetation index combinations.

3.4 Discussion

The present study sought to evaluate the use of Sentinel-2 MSI data for estimating the chlorophyll content of *Typha capensis* and *Cyperus dives* vegetation species growing in a natural wetland and a rehabilitated wetland. Chlorophyll content was used as a proxy for vegetation health hence to facilitate a better understanding of the success of wetland restoration programmes.

3.4.1 Performance of Sentinel-2 MSI derived data in estimating chlorophyll content of Cyprus and Typha across different wetland management regimes

The findings of this study indicate that wetland vegetation leaf chlorophyll content can be accurately estimated across wetland ecosystems under varying management conditions with a RMSE of 9.11 µg cm^2 (relRMSE = 14%) and R^2 of 0.88. Particularly, the spectral variables derived from the red-edge bands were the most influential variables. This can be explained by the renowned and proven strong relationship between chlorophyll content and the red-edge region (Curran and Plummer, 1991; Gitelson et al. 2001; Dou et al. 2018). Reflectance in red-edge section of the electromagnetic spectrum (550 nm and 700 nm) are sensitive to leaf chlorophyll content, which results in reflectance peaks in this region when compared to the visible region of the electromagnetic spectrum. Gitelson et al. (2001), illustrated that the reflectance in spectral bands near 700 nm were sensitive to chlorophyll content of crops. Additionally, a study by Gitelson et al. (2002), illustrated a positive correlation between Chl and wavebands positioned further from absorption bands positioned at 550 nm and 700 nm. A study by Curran et al. (1990), identified the red-edge as an optimal variable in estimating chlorophyll content by creating a relationship between the red-edge region and reflectivity at different wavelengths. Subsequently, the red-edge's relationship with plant chlorophyll content of makes it an effective tool for vegetation status assessment using remote sensing.

3.4.2 Comparison of wetland vegetation chlorophyll content between natural and rehabilitated wetlands

The findings of this study also showed that the chlorophyll content of rehabilitated wetlands exhibited more accurate models with a RMSE of 3.26 µg cm^2 (relRMSE= 6%) and R^2 of 0.89 compared to a RMSE of 7.20 µg cm^2 (relRMSE= 12%) and R^2 of 0.86 exhibited by the natural wetland plants. The most influential variables were visible (red and, green) vegetation indices, NIR and red-edge regions. The variations in the accuracies exhibited across the different wetland management regimes could be justified by the variation in chlorophyll content between the wetlands. Vegetation in the rehabilitated wetland is in a healthier state when compared to that from the natural wetland, hence the high spectral reflectance in the rehabilitated wetland. The rehabilitated wetland is in an enclosed environment that is less prone to be affected by external factors such as pollutants, cattle grazing and housing developments, hence there is less impact on vegetation health and foliage density. However, the natural wetland is more susceptible to external influences such as pollution and disturbance due to its lack of fencing and protection. Goats tend to have access and graze the nutritious wetland plants reducing their foliage density. Vegetation in the natural wetland is prone to stress, which affects its productivity and ultimately its spectral reflectance. In a related study, Zhao et al. (2016) indicates how wetland restoration can improve the structure and function of degraded wetland ecosystems, therefore improving vegetation productivity. A plausible explanation could be that the rehabilitated wetland has pure stands of *Typha* which could be accurately recorded by the sensors, whereas there is a lot of background effects in a natural wetland, with undergrowth, mixed species and polluted soils thus affecting reflectance.

3.4.3 Variations in chlorophyll content of Cyperus dives and Typha capensis plant species in wetland settings

Results of this study indicate that the model for estimating *Cyperus* chlorophyll content of the rehabilitated wetland exhibited lower estimation errors with a RMSE of 2.54 µg cm^2 and R^2 of 0.86, based on red-edge region derived vegetation indices and bands when compared to *Typha* species (RMSE = 3.91 µg cm^2 and R^2 = 0.60). *Cyperus* species are predominantly horizontal leaves (planophile). Studies have shown that leaves in planophile position receive a greater total daily radiance, with minimum background effects (Wang et al., 2009). Therefore, the leaves of *Cyperus* species exhibits high reflectances in the visible, near-infrared (NIR) and red-edge positions, hence the better chlorophyll content estimation accuracies. Meanwhile, Typha species are predominantly vertical leaves (erectophile). These leaves have relatively lower interactions with the incoming radiation since part of the light penetrates to the ground and hence affected by background material, therefore exhibit a relatively lower reflectance in the visible, NIR and red-edge regions. As previously mentioned, the red-edge is associated with chlorophyll concentration, which directly affects vegetation spectral reflectance as in the case with *Cyperus* (Sibanda et al., 2019). *Cyperus* species is the dominant cover type in the wetlands and therefore has superior leaf reflectance properties over *Typha* species. A related study by Delegido et al. (2011), highlights the role of Sentinel-2 MSI red-edge bands in significantly improving chlorophyll content estimation, by illustrating a linear positive relationship between chlorophyll content and red-edge bands and indices across various plant types. However, in the natural wetland, the estimation model for *Typha* species produced a low estimation error for chlorophyll content estimation (RMSE = 7.18 µg cm^2 and R^2 = 0.75) compared to *Cyperus*. This can be explained by the high canopy density of *Typha* species in the natural wetland which are characterized by thick leaves in close proximity to each other, which therefore influence the leaf reflectance of *Typha* species. Wang et al. (2009), indicates that where the erectophile canopy is dense, it produces spectral reflectances that are similar to those of a sparse canopy of planophile leaf orientation.

3.5 Conclusion

The present study sought to investigate the ability of Sentinel-2 data to estimate the chlorophyll content of *Cyperus dives* and *Typha capensis* plant species growing in wetlands under different management regimes. Based on the findings of this study the following conclusions were established:

- Wetland vegetation chlorophyll content can be accurately estimated using Sentinel 2 MIS's visible (red and red-edge) spectral variables.
- The stimation model for *Cyperus dives* plant species produced better estimation accuracies when compared to those for *Typha capensis* plant species for the rehabilitated wetland, and estimation model for *Typha* species produced better estimation accuracies for the natural wetland based on the visible red, NIR and red- edge spectral variables.

Results of this study highlight the critical and potential role that could be played by Sentinel 2 MSI's remotely sensed data in monitoring wetland vegetation elements such as chlorophyll content as a wetland health assessment technique. This effective and timely high spatial data could offer means to successfully monitor wetland vegetation productivity and health. Additionally, this study highlighted the ecological benefits of wetland rehabilitation which is clearly represented by healthier and more productive vegetation in the rehabilitated wetland. Furthermore, this study is a pathway towards the monitoring and understanding wetland restoration success, which can assist with future wetland management practices and consequently contribute to preservation and protection of wetland areas in local communities.

CHAPTER FOUR

Synthesis and Conclusions

4.1 Introduction

This research aimed to assess the variation in productivity of plant species in wetland areas under different management regimes in Pietermaritzburg, South Africa using Sentinel-2 MSI data. The objectives of this research were; (i) to test the ability of Sentinel-2 MSI derived data and vegetation indices in estimating the variations in leaf area index for vegetation growing in a natural wetland and that growing in a rehabilitated wetland, and (ii), to assess the use of high-resolution Sentinel-2 MSI data in estimating the chlorophyll content of *Cyperus dives* and *Typha capensis* vegetation species growing in a natural wetland and a rehabilitated wetland. This chapter provides an overview of the aims and objectives of this study and highlight the main conclusions and recommendations for future studies.

4.2 Assessing the utility of Sentinel-2 MSI data in quantifying wetland vegetation leaf area index for natural and rehabilitated wetlands

Findings from this study suggest that the new generational Sentinel-2 MSI sensor data is suitable to optimally quantify the variability of wetland vegetation LAI across natural and rehabilitated wetlands. The combination of standard bands, red-edge derived vegetation indices and traditional indices yielded low estimation errors based on the PLSR estimation algorithm for the natural wetland as compared to the rehabilitated wetland. Based on these findings, we concluded that Sentinel-2 MSI data offers a cost effective and less time-consuming data source for accurate LAI estimation in resource scarce environments and can be used for wetland monitoring by means of LAI estimation and comparison across wetlands under different management regimes.

4.3 Estimating the chlorophyll content of Cyperus dives and *Typha capensis* and *Cyperus dive* species growing in a natural wetland and a rehabilitated wetland using Sentinel-2 MSI data

The findings of this study illustrated the use of Sentinel-2 MSI data to optimally estimate the chlorophyll content of different plant species, characterised by wetland type. The sensors' red-edge region proved to be of significant importance in the accurate estimation of chlorophyll content, as most of the optimal variables with the lowest estimation errors for Chl estimation included the red-edge bands based on PLSR estimation algorithms. In terms of overall performance, the PLSR model proved to be an optimal model for estimating wetland vegetation Chl content by providing a relatively low error of estimation. Furthermore, the study demonstrated that Sentinel- 2 MIS data provides focused and efficient data source for accurate Chl content estimation of different plant species across wetlands under different management regimes.

4.4 Conclusions and Recommendations

This study has confirmed that Sentinel-2 MSI data is an accurate, reliable and timely data source, and can therefore be used to optimally estimate LAI and chlorophyll content of wetland vegetation growing in a natural and a rehabilitated wetland. This conclusion is based on the following observations:

1. When using Sentinel-2 MSI data to estimate wetland vegetation LAI, results show that vegetation indices generated from red-edge bands performed better for both wetlands. Therefore, vegetation productivity was optimally characterised across wetlands under different management treatments using Sentinel 2 MSI red-edge derived vegetation indices, combined with traditional vegetation indices.

2. Sentinel-2 MSI data was successfully used to estimate *Cyperus dives* and *Typha capensis* species chlorophyll content in wetlands under different management regimes with limited errors. The findings show that chlorophyll content was accurately estimated for wetland

vegetation in a rehabilitated wetland when compared to a natural wetland based on the visible red and red-edge spectral variables.

Based on these findings, we conclude that Sentinel-2 MSI data can accurately assess the productivity of wetland vegetation species growing in wetland areas under different regimes. This illustrates the critical role played by new generation remote sensors in wetland vegetation monitoring, especially with the fine spatial and spectral resolutions that provide an added advantage in monitoring essential plant biophysical characteristics such as LAI and chlorophyll content. This provides a pathway towards the monitoring of wetland restoration success, which can assist with future wetland management practices and consequently contribute to the preservation and protection of wetlands in local communities. Furthermore, results of this study highlight the ecological benefits of wetland rehabilitation and preservation in local communities, clearly represented by healthier and more productive vegetation in the rehabilitated wetland. These findings confirm the need to adopt long-term wetland monitoring strategies that are specific to wetland type and vegetation type, especially with the current state of climate change and global warming.

This study focused on some of the key elements of wetland vegetation in wetlands under different management regimes. Future studies should evaluate the role of other critical wetland vegetation indicators such as biomass, vegetation height and also observing the wetland vegetation characteristics in different seasons and growth stages. Furthermore, future studies should observe the role of factors that influence wetland health and functionality such as climate change. It is suggested that wetland ecologists use the methods from this study as a basis for developing a technique that can be used in assessing wetland rehabilitation success in larger wetland ecosystems and future management strategies.

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