Assessment and mapping of wetland vegetation as an indicator of ecological productivity in Maungani wetland in Limpopo, South Africa

by

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DISSERTATION

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DECLARATION

I declare that the Assessment and mapping of wetland vegetation as an indicator of ecological productivity in Maungani wetland in Limpopo, South Africa hereby submitted to the University of Limpopo, for the degree of Master of Science in Geography has not previously been submitted by me for a degree at this or any other university; that it is my work in design and in execution, and that all material contained herein has been duly acknowledged.

Mashala, MJ **Date**

Abstract

Wetland vegetation provides a variety of goods and services such as carbon sequestration, flood control, climate regulation, filtering contamination, improve and maintain water quality, ecological functioning. However, changes in land cover and uses, overgrazing and environmental changes have resulted in the transformation of the wetland ecosystem. So far, a lot of focus has been biased towards large wetlands neglecting wetlands at a local scale. Smaller wetlands continue to receive massive degradation by the surrounding communities. Therefore, this study seeks to assess and map wetland vegetation as an indicator of ecological productivity on a small scale. The Sentinel-2 MSI image was used to map wetland plant species diversity and above-ground biomass (AGB). Four key diversity indices; the Shannon Wiener (H), Simpson (D), Pielou (J), and Species richness (S) were used to measure species diversity. A multilinear regression technique was applied to establish the relationship between remotely sensed data and diversity indices and AGB. The results indicated that Simpson (D) has a high relationship with combined vegetation indices and spectral band, yielding the highest accuracy when compared to other diversity indices. For example, an R^2 of 0.75, and the RMSE of 0.08 and AIC of -191.6 were observed. Further, vegetation AGB was estimated with high accuracy of an R^2 of 0.65, the RMSE 29.02, and AIC of 280.21. These results indicate that Maungani wetland has high species abundance largely dominated by one species (*Cyperus latifidius*) and highly productive. The findings of this work underscore the relevance of remotely sensed to estimate and monitor wetland plant species diversity with high accuracy.

Keywords: Aboveground biomass; mapping; remote sensing; Sentinel 2; species diversity,

Preface

This research study was conducted in the Department of Geography and Environmental Studies, University of Limpopo, South Africa, from February 2018 to 0ctober 2019, under the supervision of Dr. Timothy Dube and Dr. Inos Dhau.

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

Makgabo Johanna Mashala signature ________________ Date: _________________

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

Dr. Timothy Dube signature

Dr. Inos Dhau signature

Publication and manuscripts

The following published papers and manuscripts include my Supervisor. My contribution was greatest and appropriate to be the first author in all cases and in the order that they are presented.

Mashala, M.J., Dube, T. and Dhau, I, 2019. Estimating and mapping wetland vegetation species diversity using sentinel-2 satellite data. *African Journal of Ecology*, *AFJE-19-28*. (Manuscript under review)

Mashala, M.J., Dube, T. and Dhau, I, 2019. Assessing and mapping species aboveground biomass as an indicator of ecological productivity. *African Journal of Ecology,AFJJE-19-305.* (Manuscript under review)

Mashala, M.J., Dube, T. and Dhau, I, 2019. Remote sensing of wetland vegetation species diversity and productivity: A review. *South African Geographical Journal, RSAG-2019-0036.* (Manuscript under review)

Dedication

This thesis is dedicated to my late father Selati Michael Mashala you passed too early to witness such endeavours you are dearly missed, and to my mother Violet Malehu Mashala and the rest of the family.

Acknowledgments

I would like to express my deep gratitude to Dr. Dube and Dr. Dhau my research supervisors, for their patient guidance, enthusiastic encouragement and useful reviews of this research work and sacrificing a lot of their time to make sure that I complete this research. I would also like to thank Dr. Browyn Egan, for assistance in identifying wetland species. My grateful thanks are also extended to the Risk and Vulnerability Science Centre (RSVC) University of Limpopo for their support with transport arrangements. To Frederick Mashao, Phumlani Zwane, Kabisheng Mabitsela and Humphrey Thamaga for assisting with field data collection.

I would also like to extend my thanks to the University of Limpopo, more especially the Geography and Environmental Studies department for their help in offering me the resources. I wish to thank my mother Violet Mashala, my brothers Tshepo Mashala, Mphihla Mashala, Choene Mashala, and my sister Makoena Mashala for the support, patience, and encouragement throughout my study.

Above all, I would like to thank the all mighty God for the blessing and for giving me wisdom and strength day by day to be able to finish this work.

Table of Contents

List of tables

List of figures

1. CHAPTER ONE:

GENERAL INTRODUCTION

1.1. Introduction

Wetlands are an area that periodically inundated, where the water table is either at or near and sometimes above the surface and supports vegetation within the system (Banner and MacKenzie, 2000; EPA, 2002). As such, wetlands are highly productive ecosystems (Mitsch et al., 2015; Kayastha et al., 2012) that provide a wide variety of goods and services such as carbon sequestration, flood and erosion control, food provision, regulate regional climate and sustaining human livelihoods (Davis et al., 2008). In addition, these systems are the most valuable ecosystem on the earth as they play a significant role in water cycle, ecological functions, improvement, and maintenance of water quality and purification hence they are largely recognized as biodiversity hotspots (Mitsch et al., 2015; Singh et al., 2017; Clarkson et al., 2004). Wetland vegetation is thus regarded as a good indicator of wetland condition (DWAF, 2008; Du et al., 2017; Sieben et al., 2014). However, human activities such as pollution, habitat alteration for agriculture and settlement development and the introduction of alien invasive species have impacts on the wetland (Davis et al., 2008).

Previous work done on wetlands indicate continued degradation of wetlands ecosystems (Ren et al, 2007; Moreno-Mateos et al, 2012; Jogo and Hassan, 2010). This has increased the need for spatial explicit detailed information on wetland conditions and health especially on wetlands of the global relevance (Ren et al, 2007; Junk et al, 2012). The lack of critical information for smaller wetlands and proper management strategies in place can also be associated with the sustained research bias towards large wetlands ignoring smaller ones. The smaller wetlands, in fact, are the ones that continue to experience massive degradation and overharvesting by the surrounding communities (Davis et al., 2008) as they are scattered all over areas. The lack of detailed research on these wetlands has made their protection, rehabilitation, and conservation difficult. Therefore, there is a need to assess and map wetland vegetation to provide a baseline information for assessing their ecological status and condition. So far, numerous methods have been applied in assessing wetland condition and these include field surveys and spatial techniques and most of have numerous shortcomings (Fuller et al., 1998; Galatowitsch et al., 2000; Lee and Yeh, 2009). The traditional method or field surveys for monitoring wetland vegetation relied on biological assessment techniques which are time-consuming and field intensive and costly and spatial limited (EPA, 2002; Cao et al., 2005; Chiarucci et al., 2011; Rocchini et al., 2015).

Thus, quick cost and time effective methods are required for monitoring wetland vegetation. Literature shows that remote sensing provides the most proven and powerful platform used for mapping and classifying wetlands over the years (Rundquist et al., 2001). The recently launched 10m Sentinel 2 satellite data provides high prospects for mapping and monitoring wetland vegetation at different scales regardless of wetland size, a previously challenging task with the broadband sensors, such as MODIS, and Landsat (Dube et al., 2016; Lee and Yeh, 2009). Besides, the sensor has a 5-day revisit making it relevant for timely monitoring assessment. The 5-day revisit time permits continuous mapping of wetland vegetation over time and this is critical if sustainable wetland vegetation assessment is to be achieved. Thus, this study seeks to assess and map wetland vegetation as an indicator of ecological productivity at a local scale using remotely sensed data and biodiversity indices.

1.2. Aim and Objectives

1.2.1. Aim

The aim of the study was to assess and map wetland vegetation as an indicator of ecological productivity in Maungani wetland in Limpopo, South Africa.

1.2.2. Objectives

i. To identify and assess vegetation species diversity using in situ data and Sentinel 2 data in Maungani wetland.
ii. To map wetland vegetation species biomass as an indicator of ecological productivity in Maungani wetland in Limpopo, South Africa.

1.3. Description of the study area

The study was conducted in Maungani wetland, which is a riverine wetland that forms part of the Levubu/Levuhu river catchment located in the northeast of Limpopo province, South Africa (figure 1.1). It is found within 22° 59′ 1.44″ S, 30°26′ 41.67″ E. The area receives an annual rainfall of 2000 mm which is influenced by Soutpansberg Mountains (Jewitt et al., 2004) and an average temperature of 21°C in the upper catchments, and 85% of the rainfall occurs in summer (Nkuna and Odiyo, 2016). About 60% of the evaporation occurs during the 6 months from October to March. The area is mostly dominated by Cyperaceae family and the dominating species is the Cyperus Latifidius. The community member in Maungani village practice crop farming and they use water for irrigation and residential use. They also harvest wetland plants to create craft and sell them to generate income and some use them for medicinal purpose

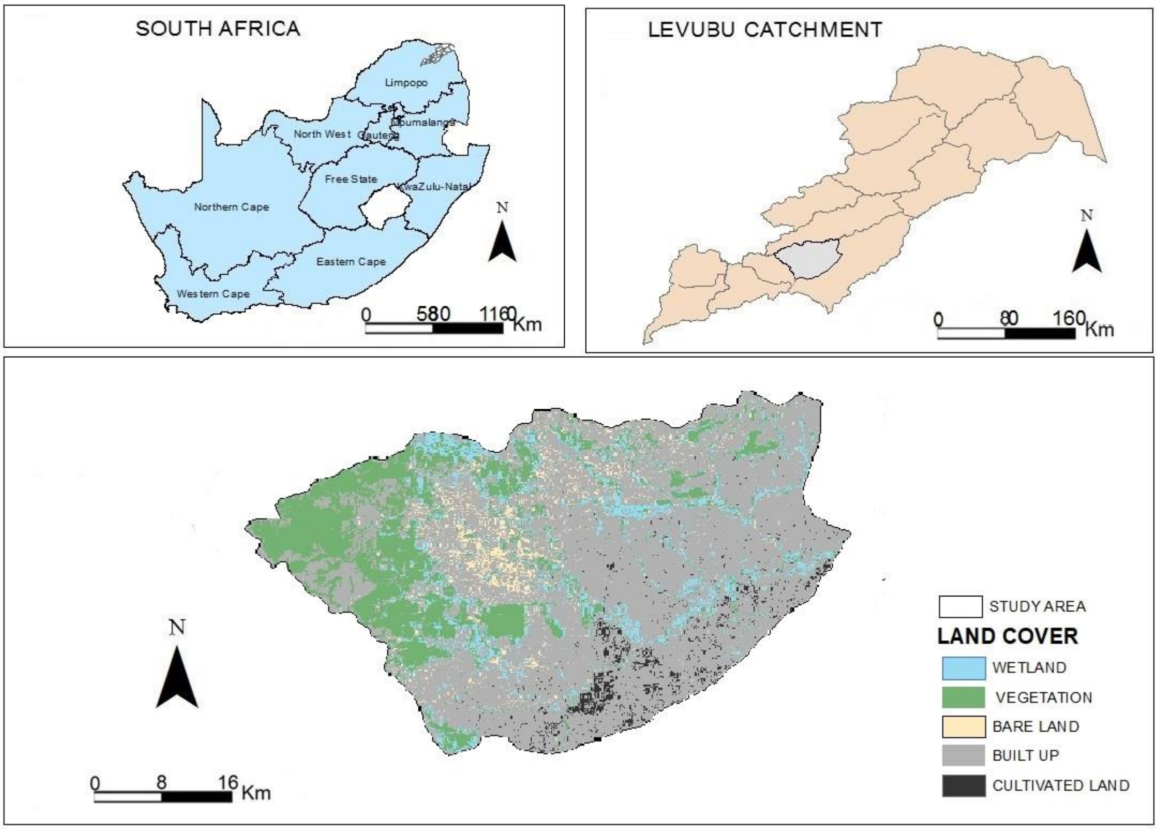

Figure 1.1: Location of the study area

1.4. Structure of the Research

This dissertation consists of five chapters excluding the first chapter which is focused on the general introduction:

Chapter one

This chapter provides an overview of the research background and outlines the objectives and the structure of the dissertation.

Chapter two: This chapter introduces the study in the form of existing literature about wetland vegetation species diversity and productivity. The chapter elaborates more on the methods and how remote sensing has been used to identify, estimate and map wetland vegetation species diversity and productivity. Moreover, the chapter provides progress and as well as future research gaps as well as ways that remotely sensed data can be harnessed to help improve and understand wetland vegetation species diversity and productivity. This enabled the identification of key knowledge gaps, which further inform the study objectives.

Chapter three: This chapter examined the strength of sentinel 2 variables in predicting and mapping species diversity using four widely used diversity indices.

Chapter four: In this chapter, the potential of Sentinel 2 variables in predicting wetland vegetation species aboveground biomass is assessed.

Chapter five:

This chapter provides the findings of the research, discussion, and the general conclusion

2. CHAPTER TWO

Remote sensing of wetland vegetation species diversity and productivity: A review

Abstract

This work provides an overview of remote sensing applications in estimating wetland vegetation species diversity and productivity. The review focuses on remote sensing techniques for identifying wetland vegetation, monitoring species diversity and biomass, mapping, progress, and future studies. Research needs for successful applications of remote sensing in wetland vegetation mapping and the major challenges are also discussed. The results showed that remote sensing of wetland vegetation species diversity is still a challenge that requires the involvement of ecologists and remote sensing specialists for a comprehensive and dynamic ecological productivity and species diversity monitoring assessment. This includes selecting the best spatial and spectral resolution and suitable techniques for extracting spectral information of wetland vegetation and well-experienced ecologist and botanist for identification of wetland vegetation species and selecting appropriate techniques for mapping and measuring wetland plant species diversity and aboveground biomass.

Keywords: Aboveground biomass; Mapping; Species diversity; wetland vegetation.

2.1. Introduction

Wetland vegetation plays the most critical role in the wetland ecosystems it harbors biodiversity by contributing to primary productivity and provides food and habitats to numerous species such as wildlife animals (Mitsch and Gosselink, 2000; Catterall et al., 2007; Kansiime, 2007, Mitsch et al., 2015). Moreover, wetland vegetation removes toxic substances and trap sediments in an anoxic environment where anaerobic bacteria reduce many nutrients to a gaseous form, these processes have a positive impact on water quality (Cronk and Fennessy, 2001). Further, wetland vegetation detoxifies chemicals that flow into waterways from roads and developed areas. A traditional herbalist uses wetland vegetation such as Cyperus to cure fever and some of the South Africa people eat the rhizome of the papyrus plants (Dahlberg, 2005). Communities also use wetland vegetation such as reeds to create craft and sell them to gain income (Pereira et al., 2006; Dahlberg and Burlando, 2009).

Nevertheless, wetlands vegetation is regarded as a good indicator of wetland ecological condition because of the high level of species richness, rapid growth rates, and they respond quickly to environmental changes (Cronk and Fennessy, 2001; DWAF, 2008; Sieben et al., 2014). Despite their importance, wetlands ecosystems are exploited and degraded by overharvesting, overgrazing, and the introduction of alien invasive species (Sanchez et al., 2015). These impacts result in a direct loss or extinction of the wetland ecosystem, and fragmentation reduces the quality of wetland and increases wetland stress (Torbick et al., 2006).

Therefore, finding the most appropriate method for monitoring wetland vegetation species diversity and productivity is very important for effective management strategies and conservation plans. The monitoring of species diversity has relied on biological assessments such as species count and field survey. This technique requires experienced taxonomists to identify genus and species at the community level. Patience and Klemas (1993) added that the taxonomist should be able to identify species list vertical structure (lifeform), and a horizontal arrangement (coverage percentage and density). Prior to sampling species issues needs to be solve includes number of sampling units to be investigated, the choice of the sampling design, the need to clearly define the statistical population, the need for an operational definition of a species community (U.S. EPA, 2002; Chiarucci, 2007; Rocchini, et al., 2010). The method is accurate for measuring species as well as productivity, however, they are field intensive, time-consuming, and costly.

Estimating wetland vegetation aboveground biomass (AGB) is very important for studying productivity, carbon cycle and nutrients allocation, and to understand dynamic changes of the wetland ecosystem (Adam et al., 2010; Du et al., 2010). The direct method of AGB involves cutting, weighing and drying this method is accurate but it is also field intensive, time-consuming and not environmentally-friendly (Zheng et al., 2004; Lu 2006; Vashum and Jayakumar, 2012; Li et al., 2014). Thus, quick and strong methods are needed to minimize time and cost, and remote sensing provides cost and effective data, and to understand the spatial distribution of species diversity and biomass is critical.

Remote sensing technology has the capability of covering a large area and offers spatial and temporal data, as well as having a large spectral resolution that enables the differentiation of different vegetation types (Shaikh et al., 2001; Ozesmi and Bauer, 2002; Muldavin et al. 2001, Duro et al., 2007). This gives ecologists the opportunity to gain critical knowledge about the drivers of the spatial and temporal distribution of wetland plants and to move beyond traditional methods of ecology (Rocchini et al., 2005). Remote sensing data provides more opportunities especially on spatial and temporal properties by providing a spatially explicit assessment and monitoring system of wetland plant species and AGB.

There is a success in remote sensing studies of wetland vegetation species diversity (Fuller et al., 1998; Rocchini et al., 2004; Rocchini, 2007) and wetland vegetation biomass (Mutanga et al., 2012; Adam et al., 2012; Adam et al., 2014). The progress has been made from the simple univariate models (Gould, 2000; Peng, 2018), to multivariate statistics such as Principal Component Analysis (Madonsela et al., 2017) and neural networks (Foody and Cutler 2003).

There are many shortfalls and gaps in a monitoring capacity, but the findings of existing data on wetland species are not readily accessible in a way that they could be used to inform management decisions. The majority of wetland species diversity studies are focused on fishes (Fernandes et al., 2004; April et al., 2011) and birds (Aynalem and Bekele, 2008; Green and Figuerola, 2005), whereas wetland vegetation is not assessed in most regions (Geller et al., 2017). Adam et al (2010) reviewed the multispectral and hyperspectral sensors that are used to identify and map wetland vegetation. Patience and Klemas (1993) reviewed the biomass and productivity of wetlands. Sieben et al (2014) classified and analyzed wetland vegetation type for conservation, planning, and monitoring. The limitation of the mentioned studies is that most of them focus on the use of remote sensing in identification and mapping productivity of wetland plants and neglecting the species diversity of wetland plants. The study provides a review of the application of remote sensing on wetland vegetation species diversity and productivity.

2.2. Remote sensing classification techniques for identifying wetland vegetation

Vegetation indices are the mathematical combination or transformation of spectral bands in the visible and near-infrared that emphasizes the spectral properties of green plants so that they appear distinct from other image features and reduces atmospheric and topographic effects where possible (Bannari et al., 1995; Rondeaux et al., 1996; Xue and Su, 2017). Vegetation indices are widely used to assess wetland ecological condition, and they provide sensitive and specific detection of an environmental change (Deimekea, et al., 2013). They help isolate the green photosynthetically active from spatially and temporally mixed pixels for meaningful inter-comparison between vegetation. They indicate the amount of vegetation and distinguish vegetation from other land cover types such as soil, water, etc., through spectral reflectance in individual wavelength (Bannari et al., 1995; Rondeaux et al., 1996; Xue and Su, 2017). Vegetation indices are formulated to suppress spectral reflectance from non-vegetative features while enhancing the spectral content from vegetation (Viña et al., 2006; Madonsela et al. 2017).

Normalized Difference Vegetation Index (NDVI) is the commonly used to detect the health of the vegetation and do not eliminate atmospheric effects but minimize the topographic effects (Bannari et al., 1995; Rondeaux et al., 1996; Xue and Su, 2017). Although, it is limited to an area with high saturation vegetation and when canopy cover reaches 100%, the amount of red light that can be absorbed by vegetation reaches a peak while NIR reflectance continues to increase due to multiple scattering effects (Mutanga et al., 2012). The Difference Vegetation Index (DVI) is applied for monitoring the vegetation's ecological environment (Xue and Su, 2017). It can differentiate vegetation from the soil, but it is very sensitive to soil background.

Ratio Vegetation Index (RVI) is widely used for green biomass estimations and monitoring, specifically, at high density vegetation coverage, since this index is very sensitive to vegetation and has a good correlation with plant biomass and eliminates one mathematical operation per image pixel that is important for the rapid processing of large amounts of data. However, it is limited to sparse vegetation cover and is sensitive to atmospheric effects. Soil fudge factor is considered in the calculation of the Soil Adjusted Vegetation Index (SAVI) for wetlands monitoring. The soil fudge which is presented by L factor out the soil background that has no effect on the extraction of vegetation information. However, it is more sensitive to atmospheric differences. Adjusting for the influence of soils comes at a cost to the sensitivity of the vegetation index (Qi et al., 1994). Enhanced Vegetation Index (EVI) was developed to improve NDVI and it was specifically for areas with a high density of vegetation, but it is limited to the blue band since it needs a blue band in order to be calculated.

A variety of image classification algorithm has been used widely to map wetland plant species using satellite images (Mahdianpari et al., 2018), such as spectral reflectance technique, supervised technique, unsupervised technique, hybrid classification algorithms, and rule-based classification. The unsupervised classification does not require human knowledge of classes, it uses a clustering algorithm to classify the image and they determine the numbers and location of unimodal spectral class (Richards, 1993; Liu, 2002). Migrate means clustering is one of the methods of unsupervised classification, which labels each pixel to unknown cluster centers and moving from one cluster to another (Richards, 1993; Liu, 2002).

Many classification techniques use different spectral responses of wetland vegetation type for classification and are very useful for determining which wetland plant species type is spectrally separated and which bands and time are best for wetland discrimination (Ozesmi and Bauer, 2002). Most spectral reflectance studies have been done on the tidal marshes that have shown that biomass could be estimated from reflectance value (Osemzi and Bauer, 2002). The spectral reflectance method cannot distinguish deep marshes with mixed vegetation and water and classifying similar characteristics such as boundaries of vegetation community types as one thing. Supervised classification supports the process of separating soil and vegetation related to water bodies or wetlands from and other land covers (Sanchez et al., 2015). The advantage of using a supervised classification method is that it can train a classifier that has a perfect boundary to differentiate classes accurately and specify number of classes required by the user (Liu, 2002).

Visual interpretation is the most effective technique to identify wetlands, especially wetlands at a local scale. Garg, (2013) emphasized how valuable visual analysis of hardcopy can be for mapping wetlands, especially for those not trained in remote sensing. Visual interpretation method used to assign qualitative turbidity levels and indicate the presence of vegetation in inland wetlands (Garg, 2013). Visual interpretation does not necessarily provide an easily interpretable picture of a waterbody's ecological condition and it uses the visual estimation of percentage, which is difficult to interpret. However, it is scale limiting, because it covers small areas, time-consuming and needs trained personnel to interpret features of the wetlands. Therefore, recent work has emphasized the use of 153 of computerized classification methods, because of the reduction in analyst time.

2.3. Conventional methods for monitoring species diversity

Monitoring biodiversity has traditionally relied on both local diversity (alpha diversity) and species turnover (beta diversity), while the combination of both measures of diversity was used to estimate the whole diversity (gamma diversity) of an area (Rocchini et al., 2015). Different diversity indices were used to estimate the species diversity but, the widely used local diversity indices are Simpson, Shannon wiener, Pielou and Species richness (table 2.1)

Table 2.1: Alpha diversity indices and their formulas

Alpha diversity indices	formula	reference
Shannon Wiener (H)	$H = -\sum_{i-1}^{n}[(ni/N)ln(ni/N)]$	Shannon and Wiener (1948)

Simpson index (D)	$D = 1 - [\sum_{i-1}^{n} ni(n-1) \ /N(N-1)]$	Simpson (1948)
Pielou index (J)	$J = lnS$	Pielou (1966)
Species richness(S)	S	Coldwell (2009)

Where *ni* is the individual species, *N* is the total number of species, *S* species count, and *ln* is a natural algorithm.

These local diversity indices are reliable, and feasible for measuring species diversity accurately in a small area (Rocchini et al., 2015). However, species monitoring in a large area it is still a challenge since it requires an evaluation of complete enumeration of species and quantifying sampling effort (Palmer, 2005; Rocchini et al., 2015). It is also difficult to survey or inspect large areas by the fact that field ecologists or biologists cannot examine every individual species while accounting for changes in species composition over time (Palmer et al., 2002; Rocchini et al., 2015).

In addition, the issues such as the sampling method should be considered and be well developed when assessing the vegetation, for instance, looking at the number and length of transect or quadrats and this depends on the shape, orientation, hydrologic gradient and interspersion of plant community and the sampling techniques such as stratified or random (EPA, 2002). These methods are time-consuming, field intensive and lack spatial data. Remote sensing data have provided a better alternative for monitoring species diversity in terms of accessibility, cost, and effective data. The use conventional method for monitoring species are not totally rejected by the authors of this review, integrating them with modern remote sensing data would considerably help in quantifying, monitoring, and understanding species diversity at various scale (Fuller et al., 1998; Lucas and Carter, 2008; Silva et al., 2008).

2.4. Remote sensing techniques for estimating diversity

Remote sensing of species diversity is very essential for the management of the ecosystem at a large spatial extent. The methods of remote sensing are usually divided into direct and indirect approaches (Nagendra, 2001; Turner et al., 2003; Duro et al., 2007). Direct approaches use space-borne sensors to identify either species, such as the identification of wetland plant species, or land cover types and directly map the distribution of species assemblages (Gillespie et al., 2008). Indirect approaches use space-borne sensors to model species diversity distribution, functional diversity, and habitat mapping along with climate or primary productivity estimates (Nagendra, 2001, Turner et al., 2003). Both approaches have significant applications for species and ecosystem conservation that have still not been completely developed to their full utility.

2.4.1. Direct estimation of diversity

The Spectral Variation Hypothesis is the most commonly used direct method to estimate species diversity using multi-sensors (Herkul et al., 2013; Rocchini et al., 2004). The SVH relates spectral heterogeneity or variation to environmental heterogeneity as a proxy to species diversity (Gould 2000; Palmer et al., 2002; Rocchini, 2007). Rocchini et al., 2010 mentioned that the performance of this approach depends on instrument characteristics, target vegetation types, and metrics derived from remote sensing data. The spectral hypothesis links ecological resource theory to fundamental physical principles to provide a rapid and accurate approach to measure biodiversity via optical patterns (Ustin and Gamon, 2010). Spectral diversity or optical diversity shows the variation in spectral patterns detected by optical remote sensing, which can itself be related to species diversity, functional diversity, and genetic diversity (Wang et al., 2016; Wang and Gamon, 2019). Optical type is regarded not only as an indicator of plant physiological and biochemical properties but also as a fundamental vegetation property, resulting from ecological rules driven by strategies of resource allocation (Wang and Gamon, 2019). Instead of, mapping species individually the spectral diversity typically detect spectral patterns related to the functional and structural properties which differ among species functional group (optical type) (Gamon et al., 1997; Ustin and Gamon, 2010; Wang and Gamon, 2019).

The remote sense data uses vegetation indices based on spectral patterns to assess biodiversity. A widely used vegetation index is the Normalised Difference Vegetation Index (NDVI) is often related to species richness due to the link between productivity and biodiversity by using statistics (Nagendra, 2001; Gould, 2000). Spectral diversity mostly categorises spectra according to different set types of spectral species by the use of classification technique either supervised or unsupervised classification (Féret and Asner, 2014; Schäfer et al., 2016; Wang et al., 2018). Therefore, the remotely sensed images estimate biodiversity using spectral types than actual species. In this regard, spectral species are considered proxies or analogs for biological species, and spatial variation in spectral species can be used to infer species richness alpha diversity and beta diversity. The species based spectral diversity may be less sensitive to soil background and can be accurately classified given high spatial resolution (Roth et al., 2015; Wang and Gamon, 2019).

Nonetheless, the challenge with the species-based metric is limited value characterizing canopy with a mixture of several species when the pixel size data cannot support the identification of individual species. Thus, the coarse pixels are not suitable for this technique (Schmidtlein and Sassin, 2004; Fassnacht et al., 2016) and can be sensitive to vegetative community composition (evenness and richness), specifically sampling method and spectral diversity metrics. Species with large intraspecific variation in spectral reflectance can also influence spectral diversity relationships, which may complicate the estimation of true diversity (Dahlin et al., 2013; Roth et al., 2015; Wang et al., 2018).

2.4.2. Indirect estimation diversity

The indirect method of species diversity is estimated by deriving models of the relationship between diversity indices and remote sensing data and verification has been carried out using statistics (Nagendra, 2001). Species diversity is indirectly estimated using habitat mapping (Cogan et al., 2009; Held and Schneider von Deimling, 2019; Guisan and Zimmermann, 2000), distribution of species or functional types (Austin, 2007; Kelly and Goulden, 2008; Franklin, 2010) and functional traits (McGill et al., 2006; Swenson and Weiser, 2010).

Habitat heterogeneity is one of the methods indirectly used to assess biodiversity. Habitat mapping applies remote sensing indices with environmental parameters related to geodiversity such as climate and habitat structure, geology, and topography, or heterogeneity or regional models or local model to estimate biodiversity. Habitat mapping using remote sensing is applied at a coarse scale (Wulder et al., 2004; Corbane et al., 2015; Tuanmu and Jetz, 2015). In this regard, Detailed information on landscape complexity is lost when using such relatively coarse resolution satellite products (Wang and Gamon, 2019). Although, the limited spectral information contained in those products limits the accuracy of habitat mapping and prohibits widespread usage or direct linkage to functional vegetation biophysical and biochemical properties (e.g., pigment levels, nitrogen content, leaf or canopy structure, etc.) that are often related to patterns of biodiversity.

Moreover, a few studies dealing specifically with estimating species diversity of wetland plants using remote sensing have been conducted by Kindscher et al., 1997; Schmidt and Skidmore, 2003; Rocchini et al., 2004; Lucas and Carter, 2008; Hu et al., 2010. The studies that estimate local species richness or abundance by spectral heterogeneity have relied on simple univariate regression models incorporating as explanatory variable the variation of single bands or vegetation indices, with generally low but significant determination coefficients (Palmer et al., 2002; Rocchini et al., 2004; Oldeland et al., 2010; Rocchini et al., 2010). Remotely sensed of spectral heterogeneity when using additional spectral information with univariate analysis produced reasonable results.

Nonetheless, it is difficult to achieve a strong relationship between single predictors and species diversity in a univariate regression in this regard there is no single method produces great results. Therefore, Feilhauer and Schmidtlein (2009), suggested the use of multivariate analysis for the production of better and greater results. Studies such as (Madonsela et al., 2017; Mutowo and Murwira, 2012) demonstrated an increase in the strength of the relationship between species alpha-diversity and remotely sensed spectral heterogeneity when using additional spectral information such as medium resolution (Landsat TM) and high spatial resolution.

The challenge of using remote sensing to map species diversity in a large area is infeasible, thus new methods, techniques, and approaches for mapping a large area are required for future use. The major problem is also relating spatial scale to species diversity data. It is difficult to match remote sensing images and species diversity sampling units (Rocchini et al., 2015). Clearly, pixels should ideally be smaller than the sampling units, at least when calculating local spectral heterogeneity for local species diversity estimates. An inappropriate match of satellite spatial resolution and the grain size of field data could hide actual spatial heterogeneity with subpixel variability remaining undetected (Rocchini et al., 2015). Matching the scale of the image with species diversity data perfectly is still a constraint, thus the theory needs a test and thus requires trained personnel for the development of models and interpretation of the results.

2.5. Wetland vegetation species productivity assessment and monitoring

Primary productivity is the rate of plant growth during a certain period and is regularly measured by harvesting and weighing dried plants and it is measured in grams' dry weight per square meter per year (g/m^2 year) (Cronk and Fennesy, 2009). Early ecosystem health research assessed ecosystem health using keystone species, which lacks the ability to show the presence of the energy flux, nutrient cycle, productivity, diversity or response capacity to disturbance. Although, it was indirectly showing the presence of the interaction among keystone species, other species, and the physical environment in the ecosystem (Li et al., 2014). Estimating wetland vegetation biomass is very essential for studying productivity, carbon cycle and nutrients allocation (Adam et al., 2010), and to understand the dynamic changes of the wetland ecosystem (Du et al., 2017). Wetland vegetation biomass can be estimated through field measurement, GIS, and remote sensing techniques (Vashum and Jayakumar, 2012).

2.5.1. The direct method of aboveground biomass

The direct method used to estimate aboveground biomass (AGB) is to clip plant species and harvest them within a series of quadrats or plots (Lu, 2006). Then the harvested plant species are taken to the lab to be dried in an oven to convert it to dry biomass. It is the most accurate measure to estimate the aboveground biomass of vegetation and productivity (Lu, 2006). The challenges of using direct method is limited to a small area and small sample of trees, and is not feasible for large-scale analysis because it is time-consuming and expensive in terms of resource availability and destructive to the ecosystem since it involves cutting down of trees and grasses (Li and Liu, 2001; Lu, 2006; Vashum and Jayakumar, 2012; Li et al., 2014).

2.5.2. The indirect method of aboveground biomass

According to Vashum and Jaykumar (2012), the indirect method is a non-destructive method of biomass estimation that is applicable for ecosystems with protected tree species where harvesting of such species is not very possible. This method uses the allometric regression equation, which is the measurement of height and diameter at breast height (DBH) volume of the tree and wood density of wetland trees and shrubs to determine wet AGB. The estimated wet biomass is multiplied by live tree density to determine dry biomass. The limitation of using indirect method is that allometric equations developed for aboveground biomass need to be validated by cutting down and weighing of trees components.

2.5.3. Remote sensing of the aboveground biomass

Remote sensing of aboveground biomass is the most accurate method and uses multiple regression techniques to estimate aboveground biomass. One of the instruments commonly used is a hand-held radiometer, which is very easy to work with and saves a lot of time compared to a typical harvest study (Patience and Klemas, 1993). According to Lu (2006), remote sensing uses multiple regressions, K nearest neighbouring and neural network to estimate biomass, for analysis and interpretation, this method requires a thorough knowledge of the techniques. The challenges of these methods require trained personnel with knowledge of using the software and it is applicable for a small sample of trees on a small scale.

2.6. Remote sensing for mapping wetland vegetation species

Remote sensing offers critical methods for digital data capturing and mapping transformation and it uses the dynamics range of temporal and spatial information contained in data (Mwita et al., 2013). The repetitive practice of using multispectral and multi-sensors image system to capture information and provide valuable data for managing land base resource and it also offer the standardized data collection procedure, data integration, and analysis within a geographic information system (Mwita et al., 2013; Ozesmi and Bauer, 2002). Therefore, it is very important to apply remote sensing and GIS tools on wetland vegetation mapping because satellites data has repeatable coverage for wetlands to be monitored (Ozesmi and Bauer, 2002) and assess the ecological productivity.

Remote Sensing offers information on surrounding land uses and their changes over time and it is less costly and less time-consuming for larger geographic areas (Price et al., 2002). Different types of sensors that are useful for mapping and monitoring wetland plants are aerial photography, multispectral, hyperspectral, light detection and ranging (LIDAR), and synthetic aperture radar (SAR), interferometric SAR (InSAR), and other microwave systems (Ozesmi and Bauer, 2002; Gallant, 2015). Remotely sensed satellite that is mainly used for mapping and monitoring wetland vegetation are Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS), SPOT, Advanced Very High-Resolution Radiometer (AVHRR), radar systems (Mwita et al., 2013; Ozesmi and Bauer, 2002).

Aerial photography is regarded to be useful and the scale of the image is important as well and offers the high spatial resolution and is very good at detecting many wetland features, such as vegetation, more especially wetland plants at a smaller scale (Ritchie and Das, 2015; Ozesmi and Bauer, 2002). Aerial photograph collects a large amount of unique information of an area and it is the principal remote sensing technology used to analyze ground surface events (Guo et al., 2017). However, it is typically time-consuming and experiences intensive manual interpretation or manipulation, and repeat acquisitions have historically been limited (Gallant, 2015).

Landsat TM images are very helpful in identifying wetland vegetation as well as other land cover types. The most important band for mapping wetland vegetation is Near Infrared (band 5) because of its capabilities to differentiate vegetation and soil moisture levels (Ozesmi and Bauer, 2002). In 2013, Landsat 8 Operational Land Imager and Thermal Infrared Sensor launched with improved spectral and radiometric characteristics (Xie et.al, 2017). Landsat 8

OLI sensor produces a refined spectral range for certain bands that are important in improving the vegetation reflectance in the near-infrared (NIR) and panchromatic bands. Most research has concluded that Landsat MSS data are useful for spectral discrimination of large vegetated wetlands (Jensen et al. 1984; Ozesmi and Bauer, 2002) Although it is limited to spatial resolution and is very challenging to map wetland vegetation at the species level in the heterogeneous community (Xie et al 2008) because of the pixel size of 30m. The 16 days revisit makes it difficult to map wetland vegetation at the interest time period and it is limited to weather conditions especially during the rainy season they produce poor quality images (Xie et al., 2008).

MODIS instruments involved NASA Aqua and Terra satellite thus provide nearly daily repeated coverage of the Earth’s surface with 36 spectral bands and a swath width of approximately 2330 km (Guo et al., 2017). MODIS plays a significant role in mapping the wetland vegetation extent and dynamics at a coarse spatial resolution (Guo et al., 2017). MODIS is suitable for mapping vegetation at large area and its revisit time makes more suitable for monitoring vegetation on a larger scale (Xie et al., 2008). The combination of spectral, spatial and temporal resolution when compared to other sensors MODIS produces good results and found in different studies of water resources mapping and monitoring (Guo et al., 2017). However, wetland vegetation mapping at a local scale or regional scale is not an option to use MODIS due to the coarse spatial resolution.

LiDAR is a survey technology that measures distance using laser 3-D scanning when applied over large areas, which is aircraft based (Drake et al. 2003). LiDAR data is useful for creating high-resolution topography data and vegetation classification. LiDAR is very good for estimating biomass especially for areas with a high saturation of biomass (Næsset and Okland, 2002; Drake et al., 2003, Hernandez-Stefanoni et al., 2015). LiDAR data is limited to a large geographic region and weather conditions such as rainy season and cloudy days. The French government in 1986 launched SPOT and it was the first earth resource satellite that had a pointable optic with high resolution, which increases the high opportunity of the imaging area (Ozesmi and Bauer, 2002). SPOT image has capabilities of obtaining information every day at any time due to frequency revisit time and can map wetland vegetation ranging from regional scale to global scale (Xie et al., 2008). SPOT imagery is useful and effective in monitoring the distribution and growth of particular plants (Xie et al., 2008).

The Advanced Very High-Resolution Radiometer (AVHRR) Pathfinder dataset includes daily and 10-day composites of 12 data layers at a spatial resolution of 8 km (Defries et al., 1995). AVHRR is affordable and it has a high probability of obtaining a cloud-free view of the land surface (Xie et al, 2008). According to Xie et al (2008), AVHRR is very useful to study long-term and short-term changes in wetland vegetation. AVHRR was infrequently used for monitoring wetlands, but it was used to estimate wetlands forest and the alluvial plain of the Mississippi River (Ozesmi and Bauer, 2002). AVHRR estimation was accurate for a total percentage of gross land cover within the 5% of the ground truth of 3 states area and within 1% of Louisiana, however, it was not able to detect small forest because of coarse resolution (Ozesmi and Bauer, 2002). However, it has limited spectral coverage and variations and it tends to introduce errors at various stages of processing and analysis (Xie et al., 2008).

2.7. Progress and future direction

The traditional methods of identifying and monitoring species diversity relied on simple indices and species count. Simple indices were only focusing on species richness, and no single factor drives the biodiversity pattern. The species count method followed the direct count of species in a sample and this method is considered to be the most effective technique to measure the species diversity (Peet, 2003). However, the direct count method lacks theoretical elegance, provides one of the simplest, and most practical and most objective measures of species richness and is time-consuming, field intensive, and lacks spatial data (Peet, 2003). Moreover, surveying large area techniques tend to miss rare species since a complete enumeration of the species within an area is required, and is logistically infeasible to completely survey a large area (Chiarucci et al., 2011).

The early applications of remote sensing in biodiversity estimation mostly focused on mapping landscape or habitat through land cover classification mainly using optical remote sensing products without providing detailed proof of the habitat diversity or biodiversity relationship (Stoms and Estes, 1993; Wang and Gamon, 2019). The progress was constrained by limited ecological information and understanding of the effects of biodiversity on ecosystem function. The information provided by early remote sensors was limited with insufficient image processing techniques such as simple classification methods with no indices designed for biodiversity assessment and a lack of understanding of interpreting ecological information from remote sensing products (Stoms and Estes, 1993).

Recent advances in biodiversity mapping are based on the processing of high spatial resolution imaging spectroscopy and Light Detection and Ranging (LiDAR) systems have greatly enriched the dimensionality of remotely sensed data (Asner et al., 2012; Thompson et al., 2017) and have expanded the range of detectable plant biochemical, physiological and structural properties that can contribute to an assessment of diversity (Ustin and Gamon, 2010; Asner et al., 2012). Moreover, the use of an original approach to testing the validity of SVH for the estimation of alpha diversity in marine (Herkul et al 2013). Further, the freely available and affordability of these technologies have been improving, making it easier for more people to use remote sensing for diversity monitoring.

The diversity indices (table1.1) are able to measure both the species richness and evenness which are necessary to capture the full complexity of diversity. However, the methods failed to show the variation, Chiarucci et al (2011) suggested that phylogenetic relationships among the species should be included in diversity measures which can capture trait and functional variation. The phylogenetic tree is more diverse because species are likely to have a different ecological function or similar function achieved through different phylogenetic pattern, thus, further research is needed on phylogenetic diversity when assessing and monitoring species diversity. Monitoring wetland plant species of the larger area has been a challenging task that requires the development of the new method, sampling techniques, and cost for success in evaluating the complete species lists and quantifying sampling effort. Field survey and biological assessment techniques are time-consuming, costly and risky due to environmental and social-political condition and they lack spatial and temporal data.

Remote sensing data provides more opportunities especially on spatial and temporal properties by developing a spatial explicit of the wetland plant species productivity assessment and monitoring system. The use of multi-sensors data may reduce the uncertain health indicators and minimize the scale issues. Remote sensing technology has the capability of covering a large area and offers spatial and temporal data. This gives ecologists an opportunity to gain critical knowledge about the drivers of the spatial and temporal distribution of wetland vegetation (Rocchini et al., 2005).

Early ecologists have been mapping wetlands ecosystems based on in-situ observation using aerial photography. The challenge of using aerial photographs require intensive manual interpretation and analyses, which is time-consuming and limited to a small scale. Therefore, remote sensing has improved the quality of wetland plants assessments for large areas, the quality of an assessment is still heavily dependent on the availability and quality of field data. Prediction of models is usually developed for mapping wetland vegetation. Mapping wetland plants at the regional scale is still a challenge that requires the ecologist and remote sensing specialist for developing new methods, sampling techniques, and cost.

Regardless of progress in remote sensing and its application on wetland species diversity and productivity they are still challenges. The researcher uses one vegetation index to relate remote sensing with field example (Gould, 2000; He et al, 2009; Peng, 2018). Estimating alpha diversity from empirical relative abundance distribution depends only on a total of species and a total number of individuals, this requires substantial computation because of iterative methods must be used. Wetland vegetation species is the main ecological drivers of wetland productivity, yet anthropogenic and natural changes activities impact the ecosystem. Thus, both involvements of ecologists and remote sensing specialists are required for a comprehensive and dynamic ecological productivity assessment and monitoring.

The use of multi-sensors data may reduce the uncertain health indicators and minimize the scale issues. The use of high-resolution sensors data produces good results with high accuracy when compared to other medium resolution sensors. Issues related to remote sensing ecosystem productivity assessment are based on single indicators, yet comprehensive assessment and dynamic measurements such as vigor, organization, and resilience are not assessed (Li et al., 2014). Improved new freely available sensors and data analysis techniques have become available that make remote sensing techniques attractive for monitoring natural ecosystem changes, including wetland vegetation species. Satellites with high-resolution multispectral such as sentinel images have improved the mapping of the extent, species composition, and biomass of upstream wetlands, salt marshes, and mangroves, therefore, the use of this satellite should be effective in future for better results.

2.8. Conclusions

The review showed progress in remote sensing species diversity and productivity studies, but the majority of the studies use hyperspectral sensors which is costly, thus high-resolution satellites such sentinel are freely available for use. This review has shown the high potential of remote sensing in ecological research as well as the challenges underpinning the development of this interdisciplinary field of research. Further studies on a phylogenetic need to be undertaken to understand the drawback of sampling techniques, data collection processes, and models for continuous ecological analysis and an improved understanding of current challenges. Free accessibility of information on methods, techniques and on monitoring wetland species will help in filling the gaps and challenges on currently used techniques and methods. Assessment and monitoring wetland plants using remotely sensed based techniques will require increasingly complex data analyses for great results. The remote sensing satellite sensors are available, and they provide high prospects for mapping and monitoring wetland vegetation species at different scales regardless.

3. CHAPTER THREE

Estimating and mapping wetland vegetation species diversity using sentinel-2 satellite data

Abstract

In this study, we sought to estimate and map wetland vegetation species diversity at a wetland level using four key diversity indices; the Shannon Wiener (H), Simpson (D), Pielou (J), and Species richness (S). A multiple linear regression technique was applied to establish the relationship between remotely sensed data and diversity indices. The results indicated that Simpson (D) has a high relationship with combined vegetation indices and spectral band, yielding the highest accuracy when compared to other diversity indices. For example, an R^2 of 0.75, and the RMSE of 0.08(8%) and AIC of -191.6 were observed. Further, the results indicate that Maungani wetland has high species abundance largely dominated by one species (*Cyperus latifidius*). The findings of this study underscore the relevance of Sentinel 2 to estimate and map wetland plants species diversity with high accuracy.

Keywords: Mapping; Wetland vegetation; Remote sensing; Species diversity.

3.1. Introduction

Wetland vegetation is the most important component of the ecosystem that harbour biodiversity by contributing to primary productivity and providing food and habitat to numerous species such as animals and insects. In addition, Wetland vegetation is regarded as a good indicator of wetland ecological condition because of the high level of species richness, rapid growth rates, and they respond quickly to environmental changes (DWAF, 2008; Sieben et al., 2014). Wetlands are, however, impacted by overharvesting, overgrazing and the introduction of alien invasive species pose a serious threat to wetlands ecosystems (Sanchez et al., 2015). These impacts result in a direct loss or extinction of the wetland ecosystem, degradation, and fragmentation reduces the quality of wetland and increases wetland stress (Torbick et al., 2006).

Therefore, mapping and monitoring wetland plant species diversity, distribution and quality, extent are essential techniques for sustainable management (Adam et al., 2010) and to ensure that disturbance is within the resilience capacity of the ecosystem (Druce et al., 2008). The most common methods used for identifying and monitoring species diversity relied on species count, intensive ground surveys or inventories of species in the field (Peet, 2003). The disadvantage of using these methods is that they are time-consuming, field intensive, it is difficult to survey large areas, and rare species are missed and results in false absences. In this regard, different field data sources can lead to dissimilar maps of species distributions and diversity, even in relatively well-studied areas (Graham and Hijmans 2006; Mutowo and Murwira, 2012). Thus, the implementation of quick and strong methods to understand the spatial distribution of species diversity is critical.

Remote sensing technology has the capability of covering a large area and offers spatial and temporal data, as well as having a large spectral resolution that enables the differentiation of different vegetation types (Muldavin et al., 2001, Duro et al., 2007). This gives ecologists the opportunity to gain critical knowledge about the drivers of the spatial and temporal distribution of wetland plants and to move beyond traditional methods of ecology (Rocchini et al., 2005). Remote sensing data provides more opportunities especially on spatial and temporal properties by providing a spatially explicit assessment and monitoring system of wetland plant species.

Lately, there has been an escalation in the research of biodiversity leading to advances in sensor technology or focusing on broad patterns in variables related to biodiversity (Kerr et al., 2001; Turner et al., 2003; Rocchini et al., 2007). These advances in remote sensing are usually divided into direct and indirect approaches (Nagendra, 2001; Turner et al., 2003; Duro et al., 2007). Direct approaches use space-borne sensors to identify either species, such as the identification of wetland plant species, or land cover types and directly map the distribution of species assemblages (Gillespie et al., 2008). Indirect approaches use space-borne sensors to model species distribution and the distribution of diversity. Both approaches have significant applications for species and ecosystem conservation that have still not been completely developed to their full utility. The use of multi-sensors data may reduce the uncertain health indicators and minimize the scale issues.

The level of success on monitoring systems using remotely sensed data depends on the availability of spatially detailed and updated information on the distribution patterns and abundance of species (Turner et al., 2003), understanding ecological patterns such as wetland vegetation species diversity, and appropriate remotely sensed indices used to relate the ground measurement of the biological diversity indicators. The application of remote sensing in biodiversity research has relied on the relationship between the derived spectral data from the image and local scale. The success of remote sensing applications in biodiversity research pivots more on the spectral resolution of data than spatial resolution (Rocchini et al., 2007; Nagendra et al., 2010).

Literature, have shown the success of remote sensing application in biodiversity estimation depends highly on the spectral resolution of the data (Rocchini et al., 2007; Nagendra et al., 2010; Cho et al., 2012; Gillespie et al., 2008). Remotely sensed measures such as the standard deviation or the coefficient of variation in the normalized difference vegetation index (NDVI) have been related to underlying species diversity in the landscape (Nagendra 2001; Oindo and Skidmore, 2002; Levin et al., 2007; Gillespie et al., 2008; Mutowo and Murwira, 2012). However, the challenge in the application of remote sensing indices has been unclear hypothetical frameworks (Mutowo and Murwira, 2012).

Thus, it provided fewer prospects for the wider adoption of this method in vegetation species diversity studies. In addition, studies such as Gould, (2000); Parviainen et al., (2010); Wood et al., (2013) tested Landsat data for estimating tree species diversity have focused only on the red and near-infrared bands present in most remote sensing. Frequently, NDVI is derived from these two bands and often showed a positive relationship with species diversity in different biomes (Gould, 2000; He et al., 2009; Parviainen et al., 2010; Madonsela et al. 2017). However, the NDVI is sensitive to areas with high vegetation. Vegetation indices are formulated to suppress spectral reflectance from non-vegetative features while enhancing the spectral content from vegetation (Viña et al., 2006; Madonsela et al., 2017).

Shannon, Pielou, and Simpson diversity indices measures both richness and evenness and important for biodiversity measures, thus far their application with remote sensing data have only been limited to African savannah tree species studies by (Oldeland et al., 2010; Mutowo and Murwira, 2012; Madonsela et al. 2017). In this regard wetland plant species, diversity was performed in the wetland within the upland forest (Flinn et al., 2008), arid and semi-arid wetland region (Li et al., 2007) but these studies neglect the use of remote sensing data.

Therefore, this study aims to estimate and map wetland plant species diversity in Maungani wetland using Sentinel 2 data. The sensor was chosen based on the technological advancement, such as an improved revisit interval (5days) and improved spectral bands, and refined spatial resolution, as well as its performance, was reported in the research by Sibanda et al (2015) in quantifying above-ground biomass across different fertilizer treatments; Shoko and Mutanga, (2017) in discriminating differences between C3 and C4 grass species.

3.2. Material and methods

3.2.1. Field data collection

During field data collection a 1m x 1m quadrat was randomly placed at a distance of 50 m where all wetland plant species within the subplot were identified, individual and overall cover percentage of wetland plants were estimated. Garmin global positioning system (GPS) was used to record the coordinates of each plot and a tape measure was used to measure a distance. Field data collection was conducted from the 11th to the 14th of December 2018. Wetland plant species were identified in the field and the unknown plant was taken to the University of Limpopo herbarium for identification by the qualified botanist.

3.2.2. Species diversity analysis

The field measurement of wetland plant species diversity within each subplot was calculated using four local measures of diversity indices which are Shannon Wiener (H), Simpson index (D), Pielou (J), and species richness (S) (see table 3.1). These indices measure both species richness and evenness. In addition, these indices are widely, and frequently used measures of diversity based on the information theory of ecological literature (Coldwell, 2009; Morris et al., 2014; Madonsela et al., 2017) and were selected to ensure that the results are comparable with other studies. The Shannon Wiener Index determines the species diversity using the formula in table 3.1 (Maurer and McGiII, 2011), and it ranges from 0 to infinity (Nagendra, 2002). The higher value of H that ranges from 0.5 to infinity indicates high species richness and signifying that different species in the quadrat or a community are nearly equally abundant and values that range from 0.4 to 0 signify lower species richness.

The Simpson diversity index was derived by Simpson in 1949 (Mandaville, 2002), which is referred to as the evenness diversity index and its formula is expressed in table 1. It ranges from zero to 1 (Maurer and McGiII, 2011; Morris et al., 2014) and values closer to 0 signify more species richness and closer to 1 indicates more evenness. Pielou index diversity was derived from the Shannon index by Pielou in 1966. The ratio of the observed value of the Shannon index to the maximum value gives the Pielou Evenness Index result. The values range from 0 to 1. The values closer 0 designate more evenness and closer to 1 designate more richness and the formula is articulated in table 3.1. Species richness is measured of the variety of species and is based simply on a count of the number of species in a particular sample (Morris et al., 2014).

Table 3.1: Local diversity indices

Alpha diversity indices	formula	reference
Shannon Wiener (*H*)	$H = -\sum_{i-1}^{n} [(ni/N) ln(ni/N)]$	Shannon and Wiener (1948)
Simpson index (*D*)	$D = 1 - [\sum_{i-1}^{n} ni(n-1)\ /N(N-1)]$	Simpson (1948)
Pielou index *(J*)	$J = lnS$	Pielou (1966)
Species richness(*S*)	S	Coldwell (2009)

Where *ni* is the individual species, *N* is the total number of species, *S* species count, and *ln* is a natural algorithm.

3.2.3. Remote sensing data acquisition and pre-processing

Sentinel-2 MSI is a high spatial resolution multispectral image with a full mission of twin satellite 2A and 2B, each of the satellite carries a single payload of Multispectral Instrument (MSI) flying in the same orbit with a high revisit frequency of 5 days (ESA, 2018). The optical (MSI) consists of 13 spectral bands ranging from visible to shortwave infrared (SWIR) bands (Drusch et al., 2012). The spatial resolution of the bands at 10 m, 20 m and 60 where, four bands are at 10 m, six bands at 20 m and three bands at 60 m (ESA, 2015). Sentinel 2 MSI images have a dynamic range of 12-bits (0-4095 levels) and the orbital swath width of 290 km. The sensor is very good for monitoring coastal land, and vegetation. The sensor employs the push-broom technology which enables the data acquisition with much better signal-to-noise (SNR) performance and higher radiometric resolution.

It represents better spectral properties of vegetation and enhances the detection of temporal and spatial heterogeneity of vegetation. Sentinel 2 MSI imagery covering the study area was acquired during the time that corresponded with field data collection dates. The image was acquired during a sunny and clear sky day condition with a cloud cover of 0%. The image covering the study area was acquired on 13 December 2018. The image was accessed from the USGS Earth Resources Observation and Science (EROS) Centre archive (http://earthexplorer.usgs.gov/) on 13 December 2018. The image was orthorectified and geometrically corrected using Dark Object Subtraction (DOS1) model under the Semi-Automated Classification (SCP) embedded in Quantum GIS 3.0. Prior to any analysis, the Sentinel-2 MSI satellite image was pre-processed using a geospatial tool to convert all the image bands into reflectance. The extracted reflectance values per spectral band were then exported as a table in Microsoft excel. The data was then used to calculate spectral vegetation indices (Table 2.2)

3.2.4. Regression algorithm for predicting species diversity

This study used multiple linear regression (MLR) to estimate the species diversity of wetland vegetation species using the Sentinel 2 multispectral dataset. MLR is one of the robust and powerful models with reported potential in predicting vegetation biophysical properties using remote sensing data (Shoko et al., 2018). MLR analysis is known to perform well in the prediction model (Fox, 1997), thus using this method with different remote sensing datasets, including hyperspectral and multispectral imagery will provide accurate measures. This enabled the recent studies in species diversity estimation to shift towards its adoption. The model builds estimation functions and associated variables using remote sensing datasets were achieved through the transformation of the remote sensing variables to a set of components and variables, which show their ability in estimating species diversity.

3.2.5. Model accuracy assessment

The prediction error encountered when estimating the alpha diversity indices were reported, using the determination of coefficient (R^2), and Root Mean Square Error (RMSE%) shows the high accuracy of the model. Akaike information criterion (AIC) was used to evaluate the relative quality of the statistical models. The component and associated variables with the highest R^2, lowest RMSE% and lowest AIC estimation errors were then considered for further analysis and the species diversity estimation. This was performed to produce integrated species diversity models for mapping. All the computations of the MLR model were run using XLSTAT software.

3.2.6. Remote sensing data for estimating species diversity

Variables derived from sentinel 2 images were used to predict species diversity using the MLR. The vegetation indices (VIs) (table 3.2) were chosen based on their performance and have been confirmed to improve the performance in predicting local species diversity and had shown great potential using different datasets (Madonsela et al., 2017). In analysis (i) and (ii), individual variables were used in separation to predict species diversity. Hence, analysis (i) include the use of spectral bands and their field and calculated diversity indices were used to run the model. For analysis ii derived vegetation indices (Table 2.2) were used to estimate species diversity, whereas the combination of spectral bands and derived vegetation indices relate were used in the analysis (iii). Moreover, sensor data synthesis was done, where all the variables from the sensor were fused and used in the model. This was performed using the three variables which included all sensors (i) spectral bands, (ii) vegetation indices, and (iii) combined spectral bands and vegetation indices (Table 3.3). This provides a more comprehensive insight into the capability of Sentinel 2 variables in estimating species diversity and the data synthesis provides the most essential spectral bands or vegetation indices across multispectral sensors.

Table 3.2: Vegetation indices

Vegetation index	Equation	Reference
Difference Vegetation Index (DVI)	NIR - Red	Tucker (1980)
Enhance vegetation index (EVI)	2.5*((NIR -Red)/(1 + NIR + (6*Red) - 7.5*Blue)	Huete et al.,1997
Normalized Difference Vegetation Index (NDVI)	(NIR – Red) / (NIR + Red)	Rouse et al. (1973)
Perpendicular Vegetation Index (PVI)	NIR/ NIR+ Red	Crippen (1990)
Soil Adjusted Vegetation Index (SAVI)	((NIR – Red) / (NIR + Red + 1)) * (1+ L)	Huete (1988)
Chlorophyll Green Leaf (Cl green)	(NIR/Green) –1	Gitelson et al., 2002
Advanced Ratio vegetation Index (ARVI)	(NIR– (2*(Red –Blue)))/(NIR + (2*(NIR –Blue)))	Kaufman and Tanré, 1992
Simple Ratio Index (SRI)	(NIR/Red)	Jordan (1969)

Table 3.3: Remote sensing variables used to predict species diversity

Data Type	Details	Analysis
Spectral band (SB)	1-8A (Coastal, blue, green, red, Red-Edge1-3, Near - infrared, Red-edge4)	i
Vegetation Indices (VIs)	DVI, EVI, NDVI, PVI, SAVI, SRI, ARVI, Clgreen.	ii
SB+ VIs	(1-8A) + (DVI, EVI, NDVI, PVI, SAVI, SRI, ARVI,	iii

	Clgreen)

3.3. Results

3.3.1. **Identification of wetland plant species found within the Maunagani wetland**

A total of 14 individual wetland plant species were sampled in 40 subplots and recorded which belongs to 8 families (table 3.4). Cyperaceae was found to be the most dominant family in the Maungani wetland represented by six types of vegetation species and followed by the Poaceae family with three types of species. However, the most dominating species was the Cyperus latifidius which was identified in 33 plots out of 40 subplots with the cover percentage of 82.5%.

Table 3.4: Types of species identified

Family	Name of species	No of species
Amaryllidaceae	*Crinum macowani*	1
Cyperaceae	*Carex austroafricana, Cyperus difformis, Cyperus dive, Cyperus latifidius, Cyperus sexangularis, Schoenoplectus brachyceras*	6
Lamiaceae	*Mentha longifolia*	1
Nymphaeaceae	*Nymphaea nouchalia var.coerulea*	1
Poaceae	*phragmites australis, Setaria megaphylla*	2
Thelypteridaceae	*Cyclosorus intteruptus*	1
Typhaceae	*Typha capensis*	1
Xyridaceae	*Xyris capensis*	1
	Total	15

3.3.2. Measured local species diversity indices

Table 3.5 shows the descriptive statistics of measured species diversity indices, where the minimum value of Shannon was found in plot 35 and the maximum values were found in plot 7 with an overall average of 0.68. Simpson diversity minimum value was found in plot 2, while the maximum value was found in plot 15, 16, 21, 34, 36 and plot 40 with an average of 0.95. For the Pielou diversity index, the minimum value was found in plot 34 and the maximum value was found in plot 7, 11, 32 and 35 with an average of 0.66. Species richness minimum value was found in plot 35 and the maximum was found in plot 30 with an average of 2.93. However, Simpson outperformed all the indices with an average of 0.95 which concluded, thus the wetland vegetation within the Maungani is more abundances dominated by only one type of species meaning is less diverse.

Table 3.5: Descriptive statistics of measured diversity indices

	N	Min	Max	Mean/Avg	Stdev
Shannon (H)	40	0	1.39	0.68	0.29
Simpson (D)	40	0.27	0.99	0.95	0.13
Pielou (J)	40	0.19	1	0.66	0.20
S	40	1	5	2.93	0.89

3.3.3. Remote sensing variable for predicting species diversity

3.3.3.1. Analysis I: The relationship between measured and predicted species diversity using spectral bands

The results in Table 3.6 indicates the performance of variables derivatives from Sentinel 2 for estimating species diversity. Overall, all the variables showed a considerable perspective in predicting species diversity. The results obtained from the image spectral bands (Table 3.6) and diversity indices slightly improved estimating species diversity when compared to the use of vegetation indices. However, Simpson diversity performed better when compared with the three diversity indices. The scatter plot graph figure 3.1 (b) indicates the relationship between the measured and predicted diversity indices using spectral bands and the model equations that can be used for the mapping of species diversity.

Table 3.6: Species diversity model estimation using sentinel 2 variables

	Species diversity indices	**R^2**	**RMSE**	**AIC**
(i) Spectral Bands (SB)	H	0.24	0.28 (28.%)	-92.2
	D	0.72	0.08 (8%)	-195.8
	J	0.18	0.21 (21%)	-117.7
	S	0.31	0.85 (85%)	-5.3
(ii) Vegetation indices (VIs)	H	0.13	0.30 (30%)	-90.6
	D	0.40	0.11 (11%)	-168.9

	J	0.17	0.20 (20%)	-121.2
	S	0.14	0.91 (91%)	-0.4
(iii) SB+ VIs	H	0.36	0.29 (29%)	-89.3
	D	0.75	0.08 (8%)	-190.4
	J	0.21	0.22 (22%)	-109.3
	S	0.39	0.86 (86%)	-0.5

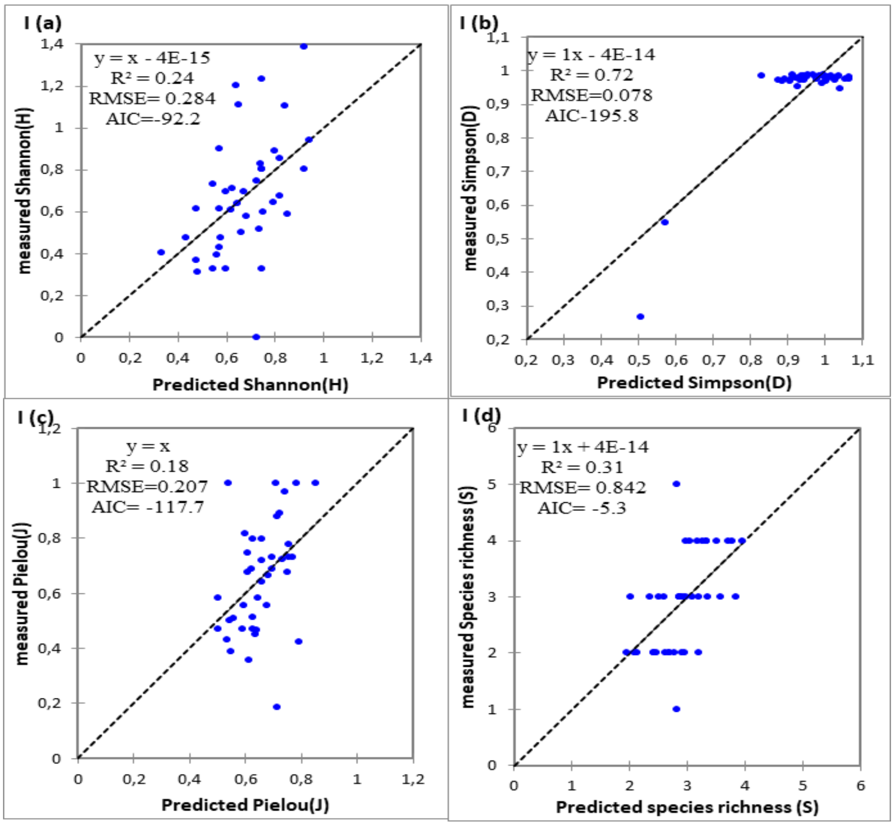

Figure 3.1: The relationship between measured and predicted diversity indices (a) Shannon wiener, (b) Simpson, (c) Pielou, and (d) Species richness using spectral bands

3.3.3.2. Analysis II: the relationship between measured and predicted diversity indices using vegetation indices

The results obtained when estimating species diversity using vegetation indices and diversity indices were poor. The scatter plot graph figure 3.2 (a, b, c, d) indicates the relationship between the measured and predicted diversity indices using vegetation indices.

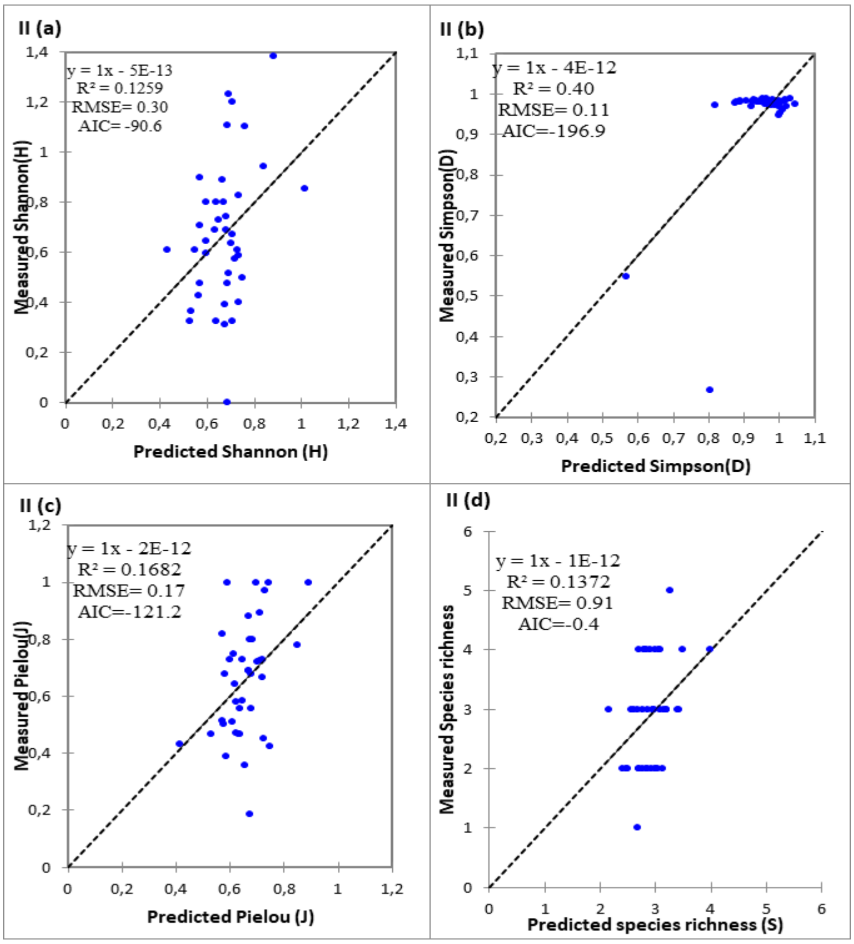

Figure 3.2: the relationship between measured and predicted diversity indices (a) Shannon wiener (b) Simpson (c) Pielou (d) Species richness using vegetation indices

3.3.3.3. Analysis III: the relationship between measured and predicted diversity indices using combined derived spectral bands and spectral vegetation indices

The use of combined spectral bands and vegetation indices produced satisfactory results for estimating species diversity when compared to the use in separation of spectral bands and vegetation indices. The results yielded from the combination of spectral bands and vegetation indices produced the best results for all diversity indices. The scatter plot graph figure 3.3 (b) indicates the relationship between the measured and predicted diversity indices using spectral bands and vegetation indices, and the model equations that can be used for the mapping of species diversity. However, Simpson provided overall the best relationship for predicting species diversity with the highest R^2 value of 0.75, lowest RMSE of 0.081(8%) and lowest AIC of -189.9 when compared to other indices and was selected as the best model to plot the relationship. Thus the equation acquired from the scatter plot graph Figure 3.3 (b) was used to produce a species diversity map as it has the best relationship.

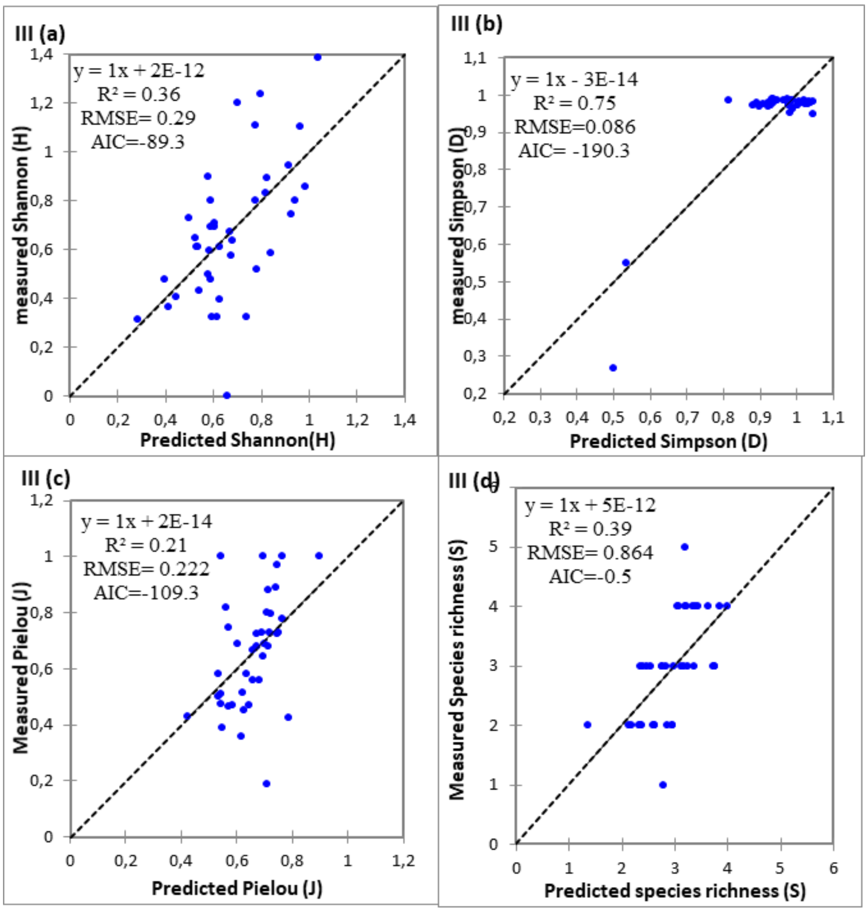

Figure 3.3: the relationship between measured and predicted diversity indices (a) Shannon wiener, (b) Simpson, (c) Pielou, (d) using combined SB and VIs

3.4. Predicting and mapping species diversity using Sentinel-2 MSI

The integrated variables and derived Simpson index was the most critical in estimating species diversity and was selected as the best model to plot the relationship. Thus, the model equation was applied in the raster calculator in the geospatial tool for mapping species diversity (Figure 3.4) of the study area. The species diversity map obtained indicates the variation of species diversity across the study area (Figure 3.4), where the high values of species diversity range from 0.5 to 1 signify high species diversity and low values range from 0 to 0.4 represent low species diversity.

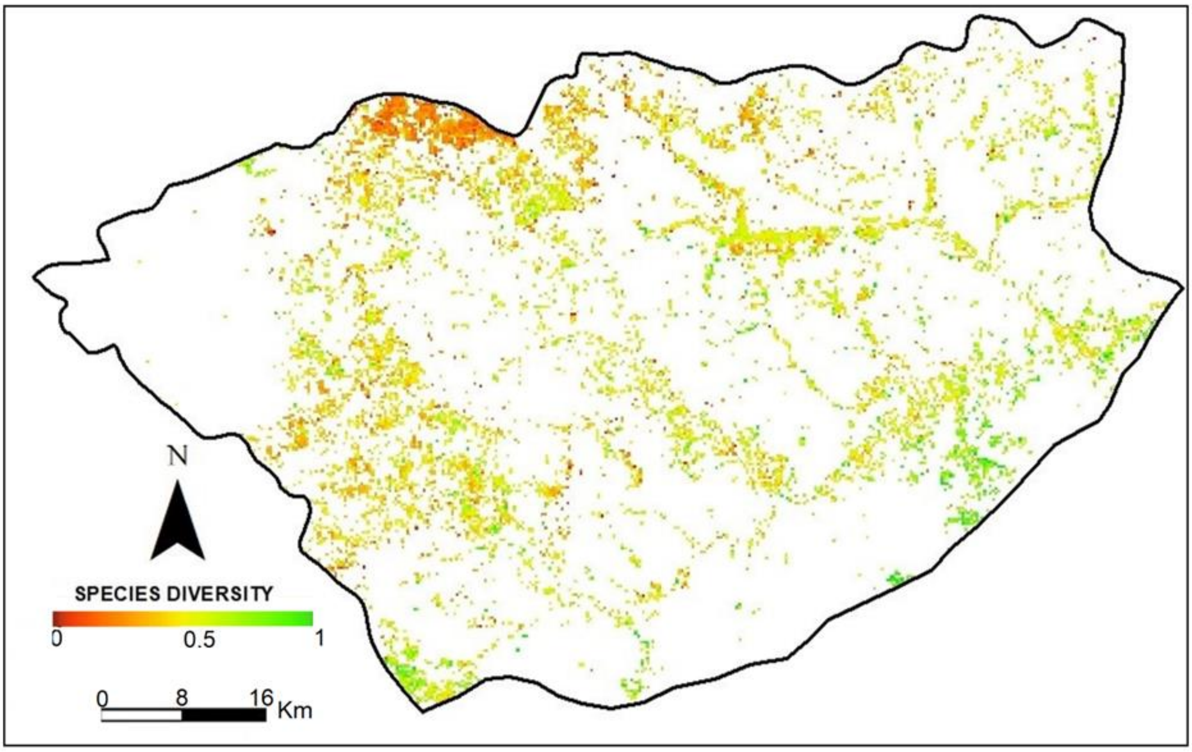

Figure 3.4: species diversity variation within the study area

3.5. Discussion

The complexity of species composition and dense vegetation in tropical wetland areas introduces a challenge for remote sensing (Adam et al., 2010; Mutanga et al., 2012). Remotely sensed data has shown great success in estimating species diversity, potential and challenges have been discussed by studies such as Chiarucci et al., (2011) and Rocchini et al, (2015). The relationship between remotely sensed measures of wetland plant species and local species diversity indices is primarily useful in terms of biodiversity assessments of wetland plants and was initially used as a valuable tool in integrated approaches to biodiversity assessment and conservation (Gould, 2000). This study aims to evaluate whether the unique sentinel 2 MSI has the capability in estimating and mapping wetland plant species diversity of Maungani wetland.

Accurate estimation of species diversity measured information is necessary for obtaining reliable results for estimating and mapping local species diversity using remotely sensed data from the Sentinel-2 MSI sensor. When estimating and mapping species diversity, one must consider important issues of relating spatial scale to local species diversity data (Rocchini et al, 2015), and the power of representation of the sample species (Moreno and Halffter 2002). It is also important for remote sensing community to shift towards the use of freely-available sensors, which have emerged with better capabilities for better species diversity estimation. Although multispectral sensor provides an attractive alternative for monitoring species diversity at local scale especially in areas with limited access to high-resolution data and the necessary technical expertise, one of their primary challenges is the inability to reduce the error of estimation (Dube and Mutanga, 2015).

Analysis of the results acquired was performed using multilinear regression to estimate species diversity of wetland vegetation species in Maungani wetland. The relationship between vegetation indices and species diversity indices (analysis ii) produces poor results. This is due to the maximum absorption of NDVI which resulted in a high reflection of the saturation level reached on dense vegetation (Chen et al., 2009; Mutanga and Skidmore, 2004; Mutanga et al., 2010). Nevertheless, Mandosela et al (2017) observed that species diversity measures relate better with vegetation indices and Principle Components and poor relationship with spectral bands. Meanwhile, these results show a poor relationship with vegetation indices using MLR and slightly improved the results with spectral bands which raise an ecological question. The poor relationship might be caused by saturation level or the chlorophyll and water content that is found within the vegetation which shows the positive relationship with spectral bands in the visible blue light of electromagnetic spectrum and EVI. Moreover, the slight improvement of estimating species diversity using spectral bands of Sentinel allows the computation of new vegetation indices, which offers additional information for vegetation analysis (Shoko et al., 2018).

Furthermore, slightly improved results of estimating species diversity using spectral bands might be due to the vegetation Red-Edge (RE) which is one of the Sentinel 2 bands. This band provides a sensitive measurement of the red-edge reflectance. Therefore, it strengthens the performance of sentinel 2 in measuring vegetation parameters (Mutanga et al., 2010; Shoko et al, 2017). In contrast to other bands, the blue, red, RE and Short Wave Infrared (SWIR) spectral regions played a critical role in enhancing spectral separability of wetland from other land cover types. The selection of these bands can be attributed to the improved and unique sensitivity to plant biophysical and chemical properties (Dube and Mutanga 2015) and this relates to studying of Shoko et al., (2018).

Despite, the use of integrated dataset derivatives (analysis iii) provides better estimation and mapping results of species diversity. Moreover, the combined dataset from the 10 m Sentinel-2 spatial resolution enhanced the sensor’s potential to estimate wetland vegetation species diversity. In this regard, results achieved in this study coincide with the finding of studies by Sibanda et al. (2015); Shoko and Mutanga, (2017); Thamaga and Dube, (2018). This might be attributed to more or an increase in variation of wetland vegetation species diversity.

Furthermore, these results demonstrated that Sentinel-2 MSI has the ability to predict and map species diversity of wetland plants in freshwater systems. Outcomes of this study coincide with previous studies highlighting the capability of using Sentinel-2 MSI in aquatic or vegetation mapping related studies (Dube et al., 2017; Shoko and Mutanga, 2017). The results indicated that sentinel 2 improved spatial and spectral resolution in mapping wetland plant species diversity provides critical information or input to ecologists, botanists, and water resource managers, especially on rare and threatened wetland plant species; an area where there is a shortage of freshwater. In addition, this information gives a better understanding of wetland plant extent, and configuration required for frequent monitoring, assessment level, sustainability, and management practices.

3.6. Conclusions

The result designated that Maungani wetland is less diverse since it is dominated by only one type of species that was proved by Simpson's diversity index with high average values of evenness. Moreover, Sentinel-2 MSI showed the capability to estimate and map vegetation species diversity in Maungani wetland which has been a challenge with other broadband multispectral sensors. The application of multilinear regression of combined spectral bands and vegetation indices was able to provide a subset of variables and improved prediction for mapping species diversity, better than the frequent use of individual vegetation indices and spectral bands. Hence, remotely sensed data and derived diversity indices can be used to model and predict wetland plant species diversity. Thus, the development and implementation of local-scale conservation strategies are recommended to protect the threatened wetland and plant species of Maungani wetland. The study of spatial and temporal changes within the area is recommended in future studies.

4. CHAPTER FOUR

Assessing and mapping species aboveground biomass as an indicator of ecological productivity

Abstract

The study aims to assess the potential of Sentinel 2 image in estimating wetland vegetation species aboveground biomass. Multiple-linear regression technique was applied to establish the relationship between remotely sensed data and measured species biomass. The combination of the derived spectral bands and vegetation indices yielded high predictive accuracies. For example, an R^2 of 0.65, the RMSE 29.02, and AIC of 280.21. Whereas, the Sentinel 2 vegetation indices variables yielded weaker predictive accuracies and spectral bands slightly improved predictive accuracies with an R^2 of 0.23, RMSE of 38.33, AIC of 298.02, and R^2 of 0.46, RMSE of 33.63, AIC of 289.72, respectively. The findings of this study indicated a considerable potential of Sentinel 2 in estimating wetland vegetation species AGB. Moreover, Maungani wetland is highly productive.

Keywords: Aboveground biomass; productivity; Sentinel 2; wetland vegetation**.**

4.1. Introduction

Wetland vegetation plays the most critical role in the wetland ecosystem, they harbour biodiversity by contributing to primary productivity, providing food and habitat to numerous species such as animals and insects (Mitsch, W.J. and Gosselink, J.G., 2000; Catterall et al., 2007; Kansiime, 2007, Mitsch et al., 2015). Besides, wetland vegetation is regarded as a good indicator of wetland ecological condition because of the high level of species richness, rapid growth rates, and they respond quickly to environmental changes (DWAF, 2008; Sieben et al., 2014). Despite, wetland plants are impacted by overharvesting, overgrazing and the introduction of alien invasive species pose a serious threat to wetlands ecosystems (Sanchez et al., 2015). These impacts result in a direct loss or extinction of the wetland ecosystem, degradation, and fragmentation reduces the quality of wetland and increases wetland stress (Torbick et al., 2006).

Hence, estimating aboveground biomass is very essential for studying productivity, carbon cycles, nutrient allocation and understanding the dynamic changes of the wetland ecosystem (Zheng, 2004; Du et al., 2010; Adam et al., 2010). The AGB governs the potential carbon emission that could be released to the atmosphere due to degradation and change of regional

AGB is associated with changes in climate and ecosystem (Lu, 2005). Wetland biomass is a key index to the health of the wetland ecosystem and provides quantitative information for understanding its ecological and environmental functions (Liao et al., 2013). Moreover, accurate and repeated monitoring of wetland ecosystem status can also help in introducing appropriate planning and monitoring conservation efforts (Dube and Mutanga, 2015) The most frequently used method of *in suti* estimation involves harvesting, weighing and drying of wetland vegetation species. The drawback of using this method is time-consuming, labour intensive, destructive to the ecosystem and it is limited to a small area (Lu, 2006; Vashum and Jayakumar, 2012; Li et al., 2014).

Nevertheless, remote sensing provides the most proven and powerful platform for accurately estimating the aboveground biomass of wetland vegetation (Muldavin et al. 2001, Duro et al. 2007). Likewise, remote sensing also provides the repetitive practice of using multispectral and multi-sensors image system to capture information that enables consistent data collection procedure, data integration, and analysis within a geographic information system (Liao et al., 2013; Mwita et al., 2013; Ozesmi and Bauer, 2002). Improved new sensors and data analysis techniques are available that make remote sensing attractive for monitoring wetland ecosystem changes and make it an efficient source for large-area biomass estimation, especially in areas of difficult access (Klemas, 2013; Liao et al., 2013). Satellite sensors such as multispectral, hyperspectral, light detection and ranger, and radar are available for mapping changes of wetland extent, species composition and biomass (Salis et al., 2006; Klemas, 2013).

Recently, remote sensing-based biomass estimation has increasingly attracted scientific attention leading to advances in sensor technology or focusing on the broad patterns in variables related to wetland vegetation biomass (Salis et al., 2006; Lu, 2006; Fatoyinbo et al., 2008; Mutanga et al., 2010; Aslan et al., 2016). However, the level of success on monitoring systems using remotely sensed data depends on the availability of spatially detailed and updated information on the distribution patterns and abundance of species (Turner et al., 2003), understanding ecological patterns such as wetland vegetation productivity, and appropriate remotely sensed indices used to relate the ground measurement of the aboveground biomass.

Literature has shown the success of remote sensing application in aboveground biomass estimation depends highly on the spectral resolution of the data (Mutanga et al., 2010; Adam et al., 2010; Adam et al., 2009; Liao et al., 2013, Adam and Mutanga, 2009). AGB can be directly estimated using remotely sensed data with different approaches, such as multiple regression analysis, K nearest neighbour, and neural network (Steininger 2000; Foody et al., 2003; Zheng et al., 2004), and indirectly estimated from canopy parameters such as height, diameter, and allometric equation which is first derived from remotely sensed data using multiple regression analysis or different canopy reflectance models (Popescu et al. 2003).

The majority of the study on remote sensing aboveground biomass of wetland vegetation has relied on the use of hyperspectral data which has been found to be costly (Rocchini et al., 2004; Mutanga et al., 2012; Liao et., 2013; Byrd et al., 2014; Adam et al., 2014). Whereas multispectral sensors such as Landsat often persist with saturation problem (Lu and Batistella, 2005; Pandit et al., 2019), due to lack of strategic red edge bands. Therefore, sentinel 2 sensor with more spectral bands and improved spatial resolution and the presence of red edge bands and is perceived to offer more opportunities for estimating AGB in tropical and subtropical regions (Pandit et al., 2019). Thus, this study aims to test the performance of freely available sentinel 2 sensors in estimating and mapping wetland vegetation AGB as an indicator of ecological productivity. The sensor was chosen based on technological advancements, such as an improved revisit interval (5days), improved spectral bands and refined spatial resolution, which was reported to be useful and successfully proved the potential for estimating and mapping AGB of vegetation. Sibanda et al., (2015) demonstrated the use of sentinel 2 in quantifying above-ground biomass across different fertilizer treatments; Shoko and Mutanga, (2017) in discriminating differences between C3 and C4 grass species, Pandit et al (2018) in predicting sub-tropical forest AGB.

4.2. Materials and methods

4.2.1. Field data collection

Field data was conducted from the 11th to the 14th of December 2018, where 1m x 1m quadrat was randomly placed at a distance of 50 m. Within the 40-sub plot, wetland plant species were clipped, weighed using a portable scale and recorded wet biomass(g/m^2). Then stored clipped stored in a paper bag taken to laboratory and oven-dried at 65°C for 24 hours to obtain dry biomass. The dry biomass was also recorded in excel for analysis.

4.2.2. Remote sensing data acquisition and pre-processing

Sentinel-2 MSI is a high-resolution multispectral image with a full mission of twin satellite 2A and 2B, each of the satellite carries a single payload of Multispectral Instrument (MSI) flying in the same orbit with a high revisit frequency of 5 days (ESA, 2018). The optical (MSI) consists of 13 spectral bands ranging from visible to shortwave infrared (SWIR) bands (Drusch et al., 2012). The spatial resolution of the bands at 10 m, 20 m and 60 where, four bands are at 10 m, six bands at 20 m and three bands at 60 m (ESA, 2015). Sentinel 2 MSI images have a dynamic range of 12-bits (0-4095 levels) and the orbital swath width of 290 km. The sensor is very good for monitoring coastal land, and vegetation. The sensor employs the push-broom technology that enables the data acquisition with much better signal-to-noise (SNR) performance and higher radiometric resolution.

It represents better spectral properties of vegetation and enhances the detection of temporal and spatial heterogeneity of vegetation. Sentinel 2 MSI imagery covering the study area was acquired during the time that corresponded with field data collection dates. The image was acquired during a sunny and clear sky day condition with a cloud cover of 0%. The image covering the study area was acquired on 13 December 2018. The image was accessed from the USGS Earth Resources Observation and Science (EROS) Centre archive (http://earthexplorer.usgs.gov/) on 13 December 2018. The image was orthorectified and geometrically corrected using Dark Object Subtraction (DOS1) model under the Semi-Automated Classification (SCP) embedded in Quantum GIS 3.0. Prior to any analysis, the Sentinel-2 MSI satellite image was pre-processed using a geospatial tool to convert all the image bands into reflectance. The extracted reflectance values per spectral band were then exported as a table in Microsoft excel. The data was then used to calculate spectral vegetation indices (Table 4.1)

4.2.3. Regression algorithm for predicting species above-ground biomass (AGB)

This study used multiple linear regression (MLR) to estimate the AGB of wetland vegetation species using the Sentinel 2 multispectral dataset. MLR is one of the robust and powerful models with reported potential in predicting vegetation biophysical properties using remote sensing data (Shoko et al., 2018). MLR analysis is known to perform well in the prediction model (Fox, 1997), thus using this method with different remote sensing datasets, including hyperspectral and multispectral imagery will provide accurate measures. This enabled the recent studies in AGB estimation to shift towards its adoption. The model builds estimation functions and associated variables using remote sensing datasets are achieved through the transformation of the remote sensing variables to a set of components and variables, which show their ability in estimating AGB.

4.2.4. Model accuracy assessment

The prediction error encountered when estimating the alpha diversity indices were reported, using the determination of coefficient (R^2), and Root Mean Square Error (RMSE) shows the high accuracy of the model. Akaike information criterion (AIC) was used to evaluate the relative quality of the statistical models. The component and associated variables with the highest R^2, lowest RMSE, and AIC estimation errors were then considered for further analysis. This was performed to produce integrated species AGB models for mapping. All the computations of the MLR model were run using XLSTAT software.

4.2.5. Remote sensing data for estimating aboveground biomass

Three sets of variables derived from the Sentinel 2 image were used to predict aboveground biomass using the MLR. The vegetation indices (VIs) in table 4.1 were chosen based on their performance and have been confirmed to improve the performance in predicting species aboveground biomass and had shown great potential using different datasets (Mutanga et al., 2012). In analysis (i) and (ii) individual variables were used in separation to predict species aboveground biomass. Hence, analysis (i) include the use of spectral bands and their field and calculated species aboveground biomass was used to run the model. For analysis ii derived vegetation indices (Table 3.1) were used to estimate aboveground biomass, whereas the combination of spectral bands and derived vegetation indices were used in analysis iii. Moreover, sensor data synthesis was done, where all the variables from the sensor were fused and used in the model. This was performed using the three variables, which included (i) spectral bands, (ii) vegetation indices, and (iii) combined spectral bands and vegetation indices (Table 4.2). This provides a more comprehensive insight into the capability of Sentinel 2 variables in estimating species AGB and the data synthesis provide the most essential spectral bands or vegetation indices across multispectral sensors.

Table 4.1: Vegetation Indices used in biomass estimation as a proxy for wetland productivity

Vegetation index	Equation	Reference
Difference Vegetation Index (DVI)	NIR - Red	Tucker (1980)
Enhance vegetation index (EVI)	2.5*((NIR -Red)/(1 + NIR + (6*Red) - 7.5*Blue)	Huete et al.,1997
Normalized Difference Vegetation	(NIR – Red) / (NIR + Red)	Rouse et al.

Index (NDVI)		(1973)
Perpendicular Vegetation Index (PVI)	NIR/ NIR+ Red	Crippen (1990)
Soil Adjusted Vegetation Index (SAVI)	((NIR – Red) / (NIR + Red + 1)) * (1+ L)	Huete (1988)
Chlorophyll Green Leaf (Cl green)	(NIR/Green) –1	Gitelson et al., 2002
Advanced Ratio vegetation Index (ARVI)	(NIR– (2*(Red –Blue)))/(NIR + (2*(NIR –Blue)))	Kaufman and Tanré, 1992
Simple Ratio Index (SRI)	(NIR/Red)	Jordan (1969)

Table 4.2: Remote sensing variables to predict aboveground biomass

Data Type	Details	Analysis
Spectral band (SB)	1-8A (Coastal, blue, green, red, Red-Edge1-3, Near - infrared, Red-edge4)	i
Vegetation Indices (VIs)	DVI, EVI, NDVI, PVI, SAVI, SRI, ARVI, Clgreen.	ii
SB+ VIs	(1-8A) + (DVI, EVI, NDVI, PVI, SAVI, SRI, ARVI, Clgreen)	iii

4.3. Results

4.3.1. Types of wetland plant species

The results in table 4.3 indicate types of species that were recorded within 40 sample plots, with their overall cover percentage, dry aboveground biomass. Generally, it can be observed *cyperus latifidius* was the most predominant species and followed by *Cyperus difformis*

Table 4.3: types of wetland vegetation species

Name of species	Family	Number of plots	Species cover percentage (%)	Species dry AGB biomass g/m²

Carex austroafricana	Cyperaceae	4	10	45
Crinum macowani	Amaryllidaceae	2	5	55
Cyclosorus interruptus	Thelypteridaceae	15	37.5	696
Cyperus difformis	Cyperaceae	19	47.5	917
Cyperus dive	Cyperaceae	2	5	90
Cyperus latifidius	Cyperaceae	33	82.5	1614
Cyperus sexangularis	Cyperaceae	3	7.5	115
Mentha longifolia	Lamiaceae	2	5	5
Nymphaea nouchalia var.coerulea	Nymaphaceae	4	10	7
Phragmites australis	Poaceae	4	10	85
Setaria megaphyla	Poaceae	16	40	532
Schoenoplectus brachyceras	Cyperaceae	3	7.5	22
Typha capensis	Thypaceae	6	15	275
Xyris capensis	Xyridaceae	8	20	18

4.3.2. Measured species aboveground biomass

The results in table 4.4 indicate the descriptive statistics of measured aboveground biomass where the lowest value of AGB g/m² was found in plot 20 and the maximum value was found in plot 18. The area has an average of 124.86 g/m² and a standard deviation of 40.26 g/m² deviating close to the mean.

Table 4.4: Descriptive statistics of species aboveground biomass

	N	Min	Max	Avg/Mean	Std dev
Dry AGB g/m²	40	55	245	124.86	40.26

4.3.3. The performance of sentinel variables in estimating species AGB

The results in table 4.5 indicate the performance of variables derivatives from Sentinel 2 for estimating species AGB. Overall, all the variables showed considerable prospective in predicting AGB. The results obtained when estimating species AGB using vegetation indices (Table 4.1) (ii) were poor and slightly improved when using the image spectral bands. The use of combined spectral bands and vegetation indices (iii) produced satisfactory results for estimating species AGB when compared to the use in separation of spectral bands and vegetation indices. The scatter plot graphs figure 4.1 (a, b, c) indicates the relationship between the measured and predicted AGB using sentinel 2 variables (table 3.5), and the model equations that can be used for mapping of species AGB. The equation used for mapping species diversity was selected based on the overall prediction model. Combined variables (iii) provided overall the best relationship for predicting aboveground biomass with the highest R^2 of 0.65, the lowest RMSE of 28.02, and the lowest AIC of 280.21 when compared to the use of individual variable and was selected as the best model to plot the relationship. Thus the equation acquired from the scatter plot graph figure 4.1 (c) was used to produce species aboveground biomass.

Table 4.5: Species aboveground biomass model estimation using sentinel 2 variables

	R^2	RMSE	AIC
(i). Spectral bands (SB)	0.46	33.63	289.72
(ii).Vegetation indices(VIs)	0.23	38.33	298.01
(iii). SB + Vis	0.65	29.02	280.21

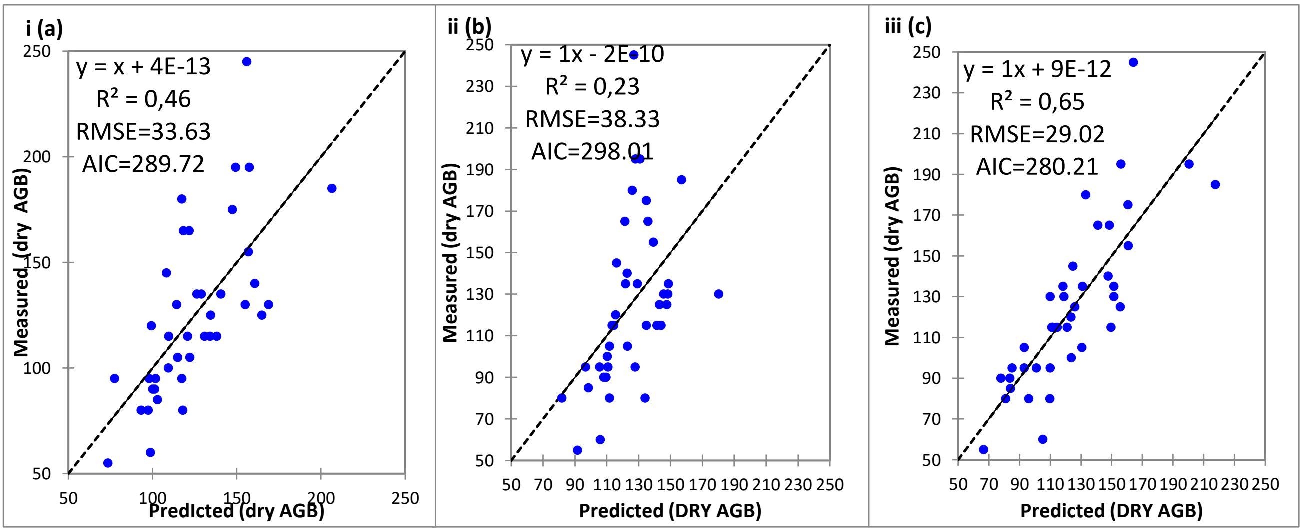

Figure 4.1. (a), (b) and (c) shows the relationship between measured and estimated AGB using sentinel 2 variables and AGB

4.3.4. Predicting and mapping species aboveground biomass using Sentinel-2 MSI

The integrated variables were the most substantial in estimating aboveground biomass using MLR. The model was applied in the raster calculator in a geospatial tool to produce the map showing the species aboveground biomass across the study area (figure 3.2.)

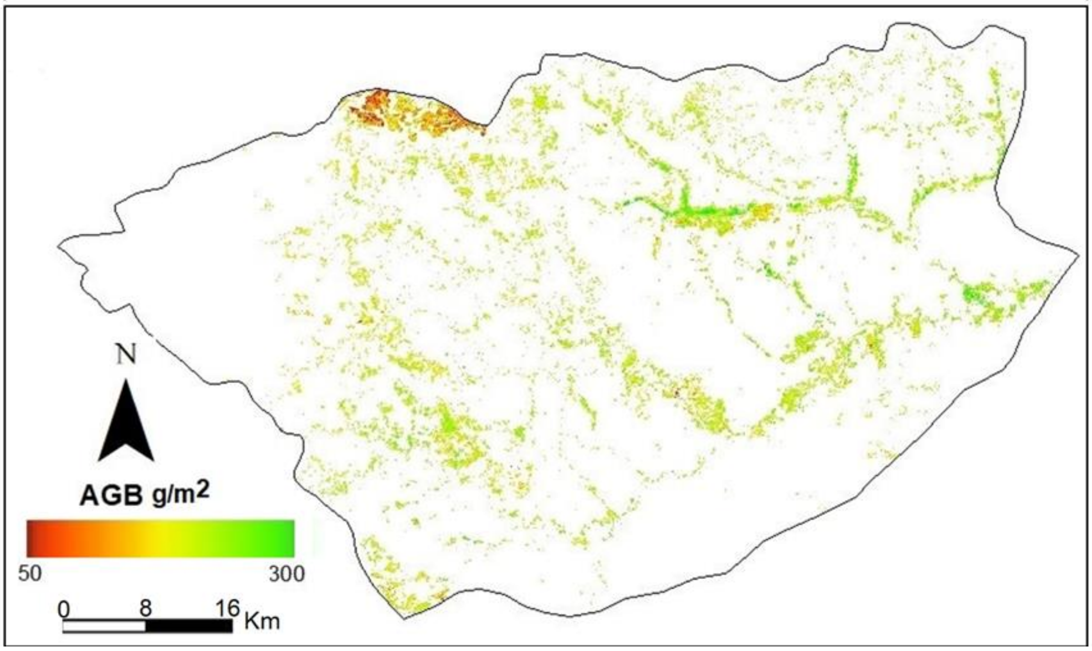

Figure 4.2: Derived aboveground biomass for Maungani wetland as a proxy for productivity

4.4. Discussion

The major challenges in predicting the complexity of species composition and dense vegetation in wetland areas using medium spatial resolution multispectral data sets are the inability to overcome the problem of saturation in areas with high canopy cover. Accurate estimation of aboveground biomass provides an important input dataset required for ecological modelling and carbon quantification. However, the cost, volume, and availability of high spatial and spectral resolution sensors, such as hyperspectral, Worldview-2, RapidEye, lidar and radar data sets, remain one of the major setbacks in resource-limited environments. Therefore, the study aims to examine whether the sentinel 2 image has the capability to improve the quantification of wetland vegetation aboveground biomass and provide better alternatives for hyperspectral resource constraints.

Analysis of the results acquired was performed using MLR to estimate AGB of wetland vegetation species in Maungani wetland. The results have demonstrated that sentinel 2 has the capability to estimate the aboveground biomass of wetland vegetation. For instance, the combination of extracted spectral bands and derived vegetation indices outperformed the individual use or separation use of extracted spectral bands and derived vegetation indices in deriving aboveground biomass, producing high R^2, low RMSE, and low AIC. In this regard, results achieved in this study coincide with the finding of studies by Sibanda et al. (2015); Shoko and Mutanga, (2017); Thamaga and Dube, (2018). This might be attributed to more or an increase in variation of wetland vegetation species diversity. Moreover, the results obtained after implementing variable selection further improved the final model prediction accuracy for wetland vegetation species AGB, compared to those derived from all variables.

However, the individual use of derived vegetation indices produced weaker results when compared to the use of extracted spectral bands, and spectral bands slightly improved the estimation of wetland vegetation AGB. The weak performance of derived vegetation indices might be attributed by the saturation level reached on the dense vegetation, chlorophyll and water content. When canopy cover reaches 100%, the amount of red light that can be absorbed by vegetation reaches a peak while Near Infra-Red (NIR) reflectance continues to increase due to multiple scattering effects (Mutanga et al., 2012). This mismatch results in poor relationships between biomass and vegetation because most of the vegetation indices are computed from Red and NIR. The slightly improved results when estimating AGB using spectral bands might be attributed to the addition of new bands such as the red edge. The presence of this bands provide more opportunities and enabling the computation of different indices, which offer additional information for vegetation analysis, and potential for estimating wetland vegetation biomass (Addabbo et al., 2016; Shoko et al., 2018). This band provides a sensitive measurement of the red-edge reflectance.

Therefore, it strengthens the performance of sentinel 2 in measuring vegetation parameters (Mutanga et al., 2010; Shoko et al, 2017). In contrast to other bands, the blue, red, RE and Shortwave Infrared (SWIR) spectral regions played a critical role in enhancing spectral separability of wetland vegetation from other land cover types. The selection of these bands can be attributed to the improved and unique sensitivity to plant biophysical and chemical properties (Dube and Mutanga, 2015) and this relates to studying of Shoko et al (2018).

Outcomes of this study concur with previous studies highlighting the capability of using Sentinel-2 MSI in aquatic or vegetation mapping related studies (Dube et al., 2017; Shoko and Mutanga, 2017). The results indicated that sentinel 2 improved spatial and spectral resolution in mapping wetland plant species AGB provides critical information or input to the ecologist, and water resource managers, especially on wetland and threatened wetland plant species. In addition, this information gives a better understanding of wetland productivity, and configuration required for frequent monitoring, assessment level, sustainability, and management practices.

4.5. Conclusions

Sentinel-2 MSI indicated the capability to estimate and map vegetation species diversity in Maungani wetland which has been a challenge with other broadband multispectral sensors. The application of multilinear regression of combined spectral bands and vegetation indices was able to provide a subset of variables and improved prediction for mapping species diversity, better than the frequent use of individual vegetation indices and spectral bands. Hence, remotely sensed data and derived diversity indices can be used to model and predict wetland plant species diversity. The Maungani wetland is highly productive, thus, the development and implementation of local-scale conservation strategies are recommended to protect the threatened wetland and plant species of Maungani wetland and also to prevent a huge amount of carbon to release to the atmosphere upon the extinction. The study of spatial and temporal changes, Leaf water content and chlorophyll within the area is recommended in future studies.

5. CHAPTER FIVE

SYNTHESIS

5.1. Introduction

Wetlands are the most valuable ecosystem on the planet because they play a significant role in the water cycle, ecological functions, improve and maintain water quality and they recognized as biodiversity hotspots (Mitsch et al., 2015; Singh et al., 2017; Clarkson et al., 2004). In addition, wetland vegetation plays an important role in the functioning of wetlands (Adam et al., 2010), it slows down the flow of water and enhances water quality by trapping nutrients, pollutants, and sediments in downstream aquatic ecosystems (Sieben et al., 2014).

However, wetland vegetation is impacted by overharvesting and overgrazing which, results in their degradation and fragmentation. These impacts result in direct loss or extinction of the wetland ecosystems. Therefore, wetland vegetation requires frequent and consistent monitoring assessment because they continuously change over short and long periods of time (White et al., 2015). In this regard, the accurate and estimation techniques that can precisely depict information that is required for assessing and mapping wetland vegetation at a wetland scale. The traditional method for monitoring wetland vegetation relied on biological assessment techniques which are time-consuming and field intensive and costly (US EPA, 2002). Thus, quick cost and time effective methods are required for monitoring wetland vegetation.

Nevertheless, remote sensing tools provide the most cost and time-effective data. The use of satellite images such as Envisat, Quickbird, and worldview has been widely used for mapping and monitoring wetland vegetation, however, the sensors are expensive. Whereas multispectral sensors such as Landsat often persist with saturation problem (Lu and Batistella, 2005; Pandit et al., 2019), due to lack of strategic red edge bands. This has led to poor identification or mapping of wetland vegetation species resulting in poor management efforts or strategies in place.

Therefore, sentinel 2 sensor with more spectral bands and improved spatial resolution and the presence of red edge bands and is perceived to offer more opportunities for estimating AGB in tropical and subtropical regions (Pandit et al., 2019). Thus, this study aims to test the performance of freely available sentinel 2 sensors in estimating and mapping wetland vegetation AGB as an indicator of ecological productivity. The sensor was chosen based on technological advancements, such as an improved revisit interval (5days), improved spectral bands and refined spatial resolution. Consequently,

5.2. The objectives of the study were:

1. To identify and assess vegetation species diversity using in situ data and Sentinel 2 data in Maungani wetland.
2. To map wetland vegetation species biomass as an indicator of ecological productivity in Maungani wetland in Limpopo, South Africa.

5.2.1. To identify vegetation species that occur in a wetland.

The study identified fifteen (15) types of wetland vegetation in Maungani wetland, situated in Limpopo. The most dominating family was the Cyperaece with six types of species and followed by the Poaceae family with 3 types of species with *cyperus latifidius* occurring in 33/ 40 plots with 82.5% cover and the total of 1614 g/m² AGB

5.2.2. To estimate and map wetland vegetation species diversity using in situ data and high-resolution satellite in Maungani wetland, Limpopo, South Africa

Four widely used diversity indices namely, Pielou, Shannon Wiener, Simpson, and species richness and sentinel 2 remotely sensed data used to estimate species diversity within the study area. specifically, an analysis was done using multiple regression and combined spectral bands and vegetation indices. The model was able to provide a subset of variables and improved prediction for mapping species diversity, better than the frequent use of individual vegetation indices and spectral bands. In this regard, all the diversity indices performed better in predicting species when using combined spectral bands and diversity indices. However, Simpson outperformed all the diversity indices with an R^2 of 0.75, RMSE of 0.09 (9%) and AIC of -190.3. The model from the Simpson diversity index was used to derive the species diversity map within the study area. The outstanding performance of combined variables might be attributed to the increase in variation of wetland vegetation species. The Sentinel 2 sensor showed its capability for mapping species diversity

5.2.3. To assess and map wetland vegetation species aboveground biomass as an indicator of ecological productivity in Maungani wetland

Overall, all the variables showed considerable prospective in predicting wetland vegetation species AGB. The results obtained when estimating species AGB using vegetation indices were poor and slightly improved when using the image spectral bands as a stand-alone model dataset. The use of combined spectral bands and vegetation indices produced satisfactory results for estimating species AGB when compared to the use in separation of spectral bands and vegetation indices. Spectral bands improved prediction of species AGB might be caused by the addition of the red edge bands. These bands provide a sensitive measurement of the red-edge reflectance, therefore, it strengthens the performance of sentinel 2 in measuring vegetation parameters.

5.3. Conclusions

The aim of the study is to assess and map wetlands vegetation as an indicator of ecological productivity in Maungani wetland using remotely sensed data. The outcomes of the study indicated the capabilities of sentinel 2 in predicting and mapping species diversity and aboveground biomass of wetland vegetation. Based on the finding of the study, the following conclusions were drawn:

- Sentinel 2 indicated its capability in predicting and mapping wetland vegetation species diversity and aboveground biomass in Maungani wetland.
- The study demonstrated that the use of an integrated dataset (spectral bands and vegetation indices) can improve predictive accuracy than when a stand-alone dataset.
- The application of multiple linear regression of combined spectral bands and vegetation indices was able to provide a subset of variables and improved prediction for mapping species diversity and biomass, better than the frequent use of individual vegetation indices and spectral bands.
- Species diversity indices indicated more abundance than richness and thus it was concluded that area is less diverse because of the dominance of one species.
- The study revealed that Maungani wetland is high productivity but conservation has to be prioritized given the location of the wetland.

5.4. Recommendations

The results indicated that Sentinel 2 data's improved spatial and spectral resolution in mapping wetland plant species AGB provides critical information or input to the ecologist, and water resource managers, as well as wetland managers. In addition, this information gives a better understanding of wetland productivity, and spatially explicit data required for frequent monitoring, assessment level, sustainability, and management practices. The Maungani wetland is highly productive and abundant, and it is largely dominated by *Cyperus Latifidius* which is mostly harvested for creating crafts. The development and implementation of local-scale conservation strategies are thus recommended to protect the threatened wetland

and plant species of Maungani wetland. These initiatives can help to enhance carbon sequestration and biodiversity conservation of these eco-hydrological resources from continued degradation. There is also a need to assess the impacts of land use and land cover changes on wetland condition and health

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