ASSESSING THE EFFECTS OF WETLAND CONVERSION TO CROP FARMING ON WETLAND LOSS, WATER QUALITY AND PLANT FOLIAR NUTRIENTS IN THE LOWER UMFOLOZI FLOODPLAIN SYSTEM

BY

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ABSTRACT

Wetland ecosystems are regarded as very beneficial in the world. They provide key benefits to humans and the environment including attenuation of floods, filtering polluted water and are habitats for many flora and fauna. Despite their importance, wetland ecosystems are subjected to multiple stressors, which include but not limited to increases in food demand, growing populations, climate change and variability. From a resource management perspective, wetland agriculture (crop production) presents a fascinating conundrum. Crop production alters wetland ecosystems significantly and at an unprecedented rate, especially in developing countries but at the same time, wetlands are highly productive. Whilst wetland agriculture is recognised globally, in South Africa, there is a lack of information about spatiotemporal changes of wetland extents and water quality status. Furthermore, the water reticulation role by wetlands and crop production can negatively affect plant nutrients composition. In that regard, this study aimed to investigate the effects of crop production on the floodplain system. Small-scale cultivation is one of the most detrimental causes of wetlands loss.

First, the study sought to detect and map small-scale farms in wetlands areas using WordView-2 in the lower uMfolozi floodplain system (UFS). Second, the study investigated the changes in land use and land cover (LULC), how they contribute to wetland extent loss and test how best the geographic object-based image analysis (GEOBIA) approach and multitemporal Landsat data could be used to map the spatiotemporal dynamics of land use in the study area. Third, to assess the quality of water and soil from the effects of surface water discharged from irrigated agriculture. Fourth, to determine how accurate Sentinel-2 and the random forests algorithm were at predicting nitrogen, potassium, calcium, magnesium, phosphorus, sulphur, zinc, boron, and copper in wetland vegetation, as well as evaluate seasonal nutrient variations.

To achieve the study objectives, a combination of research methods were used including standard analytical, geographical information system (GIS) and remote sensing techniques for triangulation purposes. Remote sensing has a high potential as a source of spatiotemporal information urgently required in wetland agriculture. Standard analytical procedures have the potential to afford the generation of information that is precise and accurate for such systems. The findings revealed the success of WorldView-2 in detecting small-scale farms in diverse and heterogeneous environments. The findings further revealed a major conversion of wetland to agriculture, which was attributed to small-scale farms. GEOBIA can extract time-series variations in different LULC at high levels of precision, far beyond what conventional pixel-based supervised classification algorithms can achieve. Results showed that the sodium adsorption ratio, electrical conductivity, sodium, chloride, pH, and nitrate content were all above the South African agricultural water quality guidelines' allowable limits. Last, the results revealed that for the dry winter and rainy summer seasons, the average R^2 was 0.66 and 0.76, respectively. During the summer, however, copper, sulphur, and magnesium were poorly correlated (R^2, ≤ 0.5).

Overall, the results of this study are important because they indicate that the human agent is one of the key drivers of a persistent decline in wetland habitats. Key findings from the research imply that there is an urgent need to devise and introduce objectively informed initiatives to enhance the sustainability of the UFS and others. The findings argue the generation of sound data on land-use change and concerted efforts to regularly track the characteristics of water, soils and plants in these habitats. Therefore, researchers are urged to take advantage of the above-mentioned instruments and techniques for assessing the status quo of wetlands, especially floodplains.

PREFACE

Under the supervision of Prof Elhadi Adam and Dr George Chirima, the research work outlined in this thesis was carried out at the School of Geography, Archaeology and Environmental Studies, Witwatersrand University, Johannesburg, South Africa.

Mandla Dlamini Signed Date: 16 August 2021

We would like to declare that no other institution has ever submitted the research work discussed in this thesis in any way. Except where due acknowledgements are made, this work reflects the candidate's work.

Promoter

Prof Elhadi Adam Signed____________________ Date ______________

Co-promoter

Dr George Chirima Signed____________________ Date ______________

DECLARATION I - PLAGIARISM

I, **Mandla Dlamini**, declare that:

1. Except where otherwise stated, the research mentioned in this thesis is my original work.

2. This thesis was not submitted at any institution for any degree or examination.

3. This thesis does not contain the data, photographs, graphs or other material of any other person unless specifically acknowledged as having been sourced from other individuals,

4. This research does not include the writing of other individuals unless explicitly recognized as obtained from other scholars. Where it has cited other published sources, then:

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DECLARATION II-PUBLICATIONS AND MANUSCRIPTS

Publication 1

DLAMINI, M, ADAM, E & CHIRIMA, JG. 2016. Detecting and mapping small subsistence farms on floodplain wetlands using Worldview-2: comparison of support vector machine and maximum likelihood classifier algorithms. In *Proceedings* of Centenary Conference of the Society of South African Geographers: 25 – 28 September 2016 (pp, 288-300) Stellenbosch, South Africa.

Publication 2

DLAMINI, M, ADAM, E, CHIRIMA, JG & HAMANDAWANA, H. A remote sensing-based approach to investigate changes in land use and land cover in the lower uMfolozi floodplain system, South Africa. *Transactions of the Royal Society of South Africa*, 2021
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Publication 3

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Publication 4 (Under review)

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DEDICATION

To Sibongile Sithole, my late mother, I wish you were here to share my accomplishments with me.

To my grandmother, Doris Sithole after my mother passed on when I was still tender, you became a mother to me, thank you for prayers and love.

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CHAPTER 1
GENERAL INTRODUCTION

1. BACKGROUND

1.1. Wetland values and functions

Wetlands play a crucial role in local and global water cycles and are at the centre of water, food, energy links, and a challenge for society's sustainable development because of climate change driven variations in natural rainfall (Clarkson et al., 2013). Wetlands provide a wide range of economic, social (Verma and Negandhi, 2011, Moor et al., 2017), environmental and cultural benefits (Lantz et al., 2013). These services and benefits include maintenance of water quality and supply (Finlayson, 2007), regulation of greenhouse gases, carbon sequestration, shoreline protection, sustenance of unique indigenous biota, and the provisioning of cultural, recreational and educational services (Sahagian et al., 1997, Seyam et al., 2001, McCartney and Van Koppen, 2004, Junk et al., 2006a, Fisher et al., 2009). They form a critical component of a region's water resources, that occur at the interface between aquatic and terrestrial environments, as well as between surface and groundwater systems (Keddy, 2010). They are also highly productive ecosystems that provide critical habitats for many terrestrial animals (including birds, amphibians, mammals and reptiles), which utilise their supporting functions during different stages of their life cycles (Semlitsch, 2000, Keddy, 2010).

Although they are vital for the proper functioning of terrestrial ecosystems, they are becoming some of the most threatened natural ecosystems (Davidson, 2014, Marambanyika et al., 2016). In many parts of the world, their functions and existence are being threatened by wide-ranging natural factors such as global climate change (Ngetar, 2011) and human activities, such as intensified agriculture, industrial development, urbanization, pollution and conversion of land for settlements (Bassi et al., 2014).

1.2 Status of wetlands condition in South Africa

At present, 43% of southern Africa is either arid or semi-arid, while about 70% of people depend on rainfed farming and face food insecurity (Cai et al., 2017). In South Africa (SA), wetland ecosystems are threatened by several human practices, that include large and small scale crop cultivation (Nel et al., 2013). This is so because, a) SA is a country that is characterised by limited water resources, erratic rainfall distribution and annual precipitation of less than 500 mm (Zucchini and Nenadić, 2006), which is far below the world average of 860 mm (DWAF, 2002), b) it has a climate that is predicted to have negative impacts in the near future from the increasing incidence of frequent and prolonged droughts (Turral et al., 2011). These changes are expected to put more pressure on limited arable land and on the goods and services provided by wetland ecosystems services. The latter is of great concern when viewed in the context of it's impact on agricultural production and the vulnerability of wetland ecosystems whose sustainability is being undermined by adverse human interventions designed to counter the effects of reduced rainfall amounts and prolonged dry seasons by reclaiming wetlands for crop cultivation (Lwasa et al., 2009).

Globally, wetlands (in inland, coastal and marine habitats) are declining (Dixon et al., 2016, Davidson et al., 2018). For instance, in New Zealand, more than 90% of wetlands have been lost in the last 150 years (Ausseil et al., 2011) while in SA, they are among the most threatened and poorly managed habitat types (Driver et al., 2012). Although they occupy only 2.4% of the country's total area, 48% of them are critically endangered, 12% are endangered, 5% are vulnerable and only 35% are least threatened (Macfarlane et al., 2014). Recent research has indicated that 64% to 71% of SA's inland wetlands have been lost during the 20th century (Gardner et al., 2015, Davidson, 2014) and over 50% of the wetlands in some SA's catchment areas destroyed (DWAF, 2005).

1.3. Implications of crop farming on wetland ecosystems

SA's largest water user is irrigated agriculture, which consumes more than 60% of the country's available water. Eutrophication, the process of nutrient enrichment of water and the resulting excessive algal growth is one of the major threats to water quality in SA and around the world in areas where intensive agriculture is practised. Although several studies on eutrophication and water quality have been performed in SA, there is still a need to better understand and quantify the nutrient composition of surface water. Knowing the nutrient status of wetlands is useful because it indicates stressors that may have adverse physical, chemical, or biological effects. This knowledge is valuable because of the increasing conversion of wetlands to crop farming in arid and semi-arid regions. This conversion is evidenced by reliance on wetlands for cultivation by most communities for crop production in arid and semi-arid areas (Marambanyika et al., 2016). Although crop farming in these areas is vital for food security, it can contribute to the degradation of freshwater ecosystems by contaminating soils and polluting fresh water resources (Gordon et al., 2011, Nhiwatiwa et al., 2017). Water quality may degrade due to land use patterns within wetlands as human activities increase. Changes in land use and practices are critical in influencing the hydrological characteristics of wetlands by inducing changes in surface runoff and impairing water quality. This is mainly so because intensive agriculture tends to pollute water bodies and accelerate nutrient loading, sedimentation and eutrophication (Moomaw et al., 2018a). Land use/ land cover (LULC) changes especially those induced by human activities, are the most important non-natural stressors affecting wetlands (Fonji and Taff, 2014).

Clearing of the natural wetland vegetation for cultivation purposes can also compromise the ecological functioning of wetlands (Kanyiginya et al., 2010), by shifting water balances due to changes in infiltration rates and induced loss of water storage capacities (Scoones, 1991). Wetland cultivation practices have major impacts on wetland hydrology, which, is one of the critical determinants of wetland vegetation composition, diversity (Collins, 2005). Disturbance to wetlands by agricultural activities results in the elimination of native species and the introduction of opportunistic alien species associated with shifts in water regimes (Collins, 2005). These interventions and manipulations affect the composition of wetland species by causing a substantial decline in wetland biodiversity (Legesse, 2007). Cultivation affects self-organization in wetlands by impacting spatial soil pH patterns, nutrient concentrations and soil organic matter (SOM) content (Cohen et al., 2008). Cultivation can also lower the clay content by encouraging soil disintegration and the eventual accumulation of clay on the surface and finer particulate material in the upper layers (Tegene and Hunt, 2000, Mutyavaviri, 2006).

The process of converting a wetland into agricultural fields begins with the removal of vegetation, followed by soil manipulation to optimize crop development. Cutting natural vegetation (e.g., papyrus and sedges) and constructing ditches and ridges to drain excess water are common practices in areas where permanent wetlands exist. The natural vegetation cover and species composition are altered when land is cleared for cultivation, whether by direct cutting or burning. Wetland vegetation is important for reducing evaporation, capturing sediments, storing nutrients, slowing surface water flow, and promoting infiltration (Todd et al., 2010). As a result of land clearing, the hydrology of the wetland is altered, thereby reducing its capacity to provide ecosystem services such as moderation of flood regimes, surface water levels and water retention (Acreman and Holden, 2013). Farmers also cut and destroy wetland plant rhizomes and tubers to establish optimal soil conditions, which is detrimental because it undermines the recovery of unique native plant species in the cleared field. Digging (with hoes) or tillage (with ploughs) are used to exploit wetland soils. As such, the topsoil loosens and the soil structure is destroyed, raising the soil's susceptibility to erosion. Ultimately, the long term effects of soil erosion are manifested downstream in the form of siltation and elevated nutrient concentrations (Nahayo et al., 2016).

1.4. Monitoring the impacts of agricultural process on wetland characteristics

Traditional methods of wetland monitoring, such as visual analysis of maps and aerial photographs and instrumental ground-based measurements, have been used for a long time. However, they are prohibitively time-consuming and incapable of producing consistent information that is descriptive of vast areas at multiple temporal scales (Gilbertson et al., 2017). Apart from the reliance on these techniques, unevenly distributed observations make much of the information they provide of little use at the operational level; areas, where information is unavailable, are often covered only superficially by poorly representative averages. Other disadvantages of traditional methods include technical and practical impediments induced by the scarcity of accredited laboratories, the prohibitive cost of analysis, high level of expertise and equipment sophistication required, and the high costs of analysing large samples (Dallas and Day, 2004, Meinhardt, 2009). For example, in terms of soil quality, most published information on the state of agrochemicals in the aquatic wetland environments has been well documented internationally in developed countries but such studies are scarce in developing countries (Kwok et al., 2007). Wetland inventories were previously compiled using relatively complex methods such as map interpretation and digitization and by manual collection and analysis of ancillary data, which frequently resulted in incompatible and inconsistent results (Aires et al., 2013, Melton et al., 2013). These problems can be solved by using the latest remote sensing approaches. Remote sensing technology provides a realistic and cost-effective way to research changes in wetlands, especially over large areas. Remote sensing technology provides rich data repositories that can be used for systematic measurements at multiple spatial and temporal scales.

1.5. Research gaps and motivation

Globally, the importance of wetland agriculture is widely recognised (McCartney et al., 2010). However, few studies in Africa have quantitatively assessed spatial and temporal changes in wetlands (Isunju, 2016, Mwita, 2013). Furthermore, the paucity of long long-term data on water quality in wetlands remains an issue in SA South Africa (Matavire, 2015). However, the advent of remote sensing and advances in geographic information systems (GIS) have opened new opportunities to bridge these gaps by providing cost-effective ways to mapping and quantify spatial changes in wetland coverage over time (Ozesmi and Bauer, 2002, Adam et al., 2010, Mesta et al., 2014). These tools have become useful for natural resource management and research. Remote sensing's usefulness is enhanced by the fact that it can be linked to ground data (Mesta et al., 2014). For remote sensing products to be useful, they have to be validated and verified through ground-truthing (Grundling et al., 2013). Hence, remote sensing coupled with survey methods is critical for analysing changes in wetlands induced by human activities such as crop farming (Turyahabwe et al., 2013). To augment remotely sensed data, biophysical and chemical indicators, specifically vegetation, soil and water analyses, are vital in determining changes in wetlands that are not easily identifiable by using remote sensing.

Wetland agricultural practices are often a significant economic pursuit among rural communities because they provide suitable cultivation conditions for various crops such as rice, maize, sugarcane, and various vegetables. For example, wetland cultivation is critical in sub-Saharan countries that include Malawi, Zambia, Kenya, Tanzania and Ethiopia because it produces about 37% of food in these countries (Nyirenda, 2020) and 55 % of cash income per household (Msusa, 2011). Even though wetland agriculture can make crucial contributions to food and livelihood security in the short term, in the long term, there are concerns about the sustainability of this utilization and the maintenance of benefits that are derived from wetlands (Dixon and Wood, 2003).

Nutrient enrichment from agricultural activities may cause changes in the composition of vegetation species, resulting in a decrease in overall system species diversity. Therefore, it is becoming increasingly apparent that the resulting changes in wetland habitats compromise their ecological integrity and alter the provisioning of wetland services, leading to major effects on human well-being (Schuyt, 2005). Nutrient element levels provide information about plant nutrient conditions and quality. This type of data is particularly useful for tracking and managing the long-term stressors that may have physical, chemical or biological impacts on wetlands. The concentrations of foliar nitrogen, phosphorus, and potassium have been the subject of a significant investigation by using remote sensing to estimate the concentrations of biochemicals in plants (Kanke et al., 2012, Clevers and Gitelson, 2013, Mutanga et al., 2015, Delloye et al., 2018). Although foliar nitrogen, phosphorus, and potassium are fairly common nutrients that can be easily estimated by using remote sensing, the same cannot be said for the other equally essential nutrients.

In view of this and other considerations, it is apparent that SA needs to determine the nature and potential effects of agricultural impacts on wetlands and how wetlands can sustain related agricultural activities (McCartney et al., 2010). Understanding the nature and the extent of crop farming impacts on wetland environments is, therefore, an important initial step towards ensuring the sustainable productivity of subsistence and commercial farming in wetlands. Unfortunately, however, the basis for making decisions about the extent to which wetlands can be sustainably used for agriculture remains extremely weak (Rebelo et al., 2010). This deficiency argues for an effective monitoring system that can be used to enhance conservative use and management of the country's threatened wetlands. It is, therefore, crucial to make inventories of both historical and current changes in wetlands in terms of the extent to which agricultural activities pose threats to their sustainability and integrity (Scott et al., 2014).

This is particularly so because SA is one of the countries experiencing significant losses in wetland areas but information on catchment-scale changes is extremely limited (Begg, 1986, Van Niekerk and Turpie, 2012, Grundling et al., 2013). Although previous studies have been conducted in KwaZulu-Natal, in uMfolozi catchment for example (Roberts and Pyke, 1984, Begg and Carser, 1989, Grenfell et al., 2009, Perissinotto et al., 2013), they are fragmented to the extent that none of them has been able to provide useful insights on factors that influence crop farming in these environments and their aerial extent, quality of water and nutrient composition. Although such studies may be useful starting points for researchers interested in learning more about wetland use and management, spatial and temporal changes in wetlands are still poorly understood. Since the degree of vulnerability of wetlands to anthropogenic impacts is still largely unknown in most developing countries, assessing the overall state of wetlands using a holistic approach is important. This limitation provides a partial explanation of why this study was purposefully designed to investigate the impacts of human interventions in the UFS where vegetation is being cleared to provide land for crop farming. This understanding is critical for the sustainable utilisation and management of this valuable ecosystem.

This study investigated the effects of wetland conversion to crop farming on wetland loss, water quality and plant foliar nutrients in the lower UFS. The spatiotemporal aerial extent of encroachment activities were assessed using the GEOBIA technique on medium resolution Landsat remotely sensed data. In addition, based on land use/ land cover changes mapped in the study area, water and soil quality were assessed using standard analytical procedures. The characterisation and prediction of several nutrients in wetland plants foliar using random forests regression model and very high Sentinel-2 remotely sensed data was also done. Previous research findings, as well as the findings of this study, should be used to influence current and future floodplain wetland management and degradation mitigation efforts.

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1.6. Overall study aim and objectives

This study, therefore, aimed to assess the effects of cultivation on floodplain wetlands by using the uMfolozi floodplain system as a case study. This was done by using satellite data to reconstruct long-term changes in land cover that have been caused by crop cultivation and monitoring the effects of this activity on water quality and nutrient concentrations in different wetland plants. The specific objectives were to:

1. Compare the performance of the support vector machine and maximum likelihood classifier algorithms to detect and map small scale farms in heterogeneous landscapes using WorldView-2 data.

2.Quantify wetland area loss within the lower uMfolozi floodplain system (UFS) and relate observed land use land cover changes to wetland loss using Landsat data.

3.Assess the physico-chemical characteristics of surface water quality in the lower UFS.

4.Characterise the seasonal variations of wetland-plant nutrients using Sentinel-2 multitemporal data

1.7. Significance of the study

This study assessed the impacts of the agricultural activities on wetlands characteristics in the UFS, northern KwaZulu-Natal, SA. As floodplains habitats are reported by Blakey et al. (2017) and Skowno et al. (2018) to be threatened habitats, it is essential to know their status for better conservation and rehabilitative management as enshrined in the Sustainable Development Goals (SGDs) 6.6 and 15.1 on the protection and conservation of freshwater ecosystems. This study is, therefore, for a timely contribution to SA and other African countries at large (Van Asselen et al., 2013). While the development of wetlands is important for human survival, the environmental impacts of these interventions may be detrimental to wetland ecosystems, biodiversity, and the sustainable provisioning of wide-ranging ecosystem goods and services. Understanding the impacts of wetland conversion to farmlands requires quantitative analyses of spatiotemporal changes in the extent of wetlands and water quality. Such information is critical for the sustainable utilisation of these ecosystems. In addition, stressors that may have physical, chemical, or biological effects on wetlands may be early indicators of cryptic effects that are detrimental to the sustainability of these vital ecosystems. This study attempts to do this by providing a knowledge-based approach for wetland management and conservation that is informed by findings from a case study of the UFS.

1.8. Thesis outline

The remaining five chapters of this thesis (Chapters 2-6) are organised as follows.

Chapter 2 investigates the degradation effects of small scale farming on wetlands by using field-based monitoring to pinpoint the major problem issues. In this chapter, the utility of the remote sensing approach to detect and map small-scale farms in the wetlands areas was exhaustively investigated by Worldview 2 images to determine the classification accuracy of two techniques, i.e maximum likelihood classifier (MLC) and support vector machine (SVM). The findings of this investigation showed that SVM is capable of detecting small scale farms in wetlands with a user's and producer's accuracies of 73 % and 65 %, respectively. These findings are important because they demonstrate that a) remote sensing can be used to reliably characterise different land use and land cover types at appropriate spatial scales, b) quantitative inventorisation of spatial distributions of small scale farms can be used as a surrogate indicator of human impacts on wetland ecosystems, c) the information provided in this chapter offers an excellent scientific basis for informed formulation actionable interventions and sustainable management practices.

Chapter 3

Having noted the usefulness of remotely sensed data in detecting small scale farms in complex and heterogeneous landscapes, this chapter proceeds to interrogate the spatiotemporal impacts of agricultural land uses on wetlands. The goal of the was to understand land use and land cover (LULC) changes in the lower UFS and to relate these changes to wetland loss by using the geographic object-based image analysis (GEOBIA) approach and Landsat earth observation multitemporal data to map the spatial and temporal in land use and land cover (LULC). The results indicated that GEOBIA can reliably detect time-series variations in different LULC at high levels of details surpassing what is commonly achievable by using the traditional pixel-based supervised classification algorithms. The findings also revealed a significant conversion of wetland to small scale cultivation farms which is helpful because sheds light on the effects of cultivation on the water and soil quality of the UFS. The take-home message from this chapter is that there is an urgent need to formulate and implement objectively informed interventions that can be used to enhance the sustainability of this floodplain system and others elsewhere.

Chapter 4

Chapter 4 investigated the quality of water and soil of the lower UFS based on systematic characterization and assessment of the impacts of surface water discharged from irrigated agriculture. This characterization and assessment was purposefully structured to fill existing gaps in the availability of water quality datasets for wetlands in SA. The findings of this chapter revealed that the sodium adsorption ratio, electrical conductivity, sodium, chloride, pH and nitrate content were above the permissible limits specified by the South African agricultural water quality guidelines. These findings were translated into recommendations for future monitoring of water and soil quality in wetlands.

Chapter 5

This section chapter sought to assess the accuracy of Sentinel 2 images in predicting nitrogen, potassium, calcium, magnesium, phosphorus, sulphur, zinc, boron and copper in wetland vegetation and crops. The findings revealed that early degradation symptoms of wetland ecosystems can be detected in the vegetation. Because of this, it is, therefore, necessary to understand the nutrient compositions of wetland vegetation and equally important because the vegetation can indicate stressors that requiring timely implementation of informed interventions. The findings revealed that copper, sulphur, and magnesium were poorly correlated (R^2, ≤ 0.5) during the summer season.

Chapter 6

This is a conclusive and synthesis chapter that provides a comprehensive integration and summary of all findings of the study and, its limitations and recommendations for the way forward.

CHAPTER 2

Detecting and mapping small subsistence farms on floodplain wetlands using WorldView-2 data

This chapter is based on:
DLAMINI, M, ADAM, E & CHIRIMA, G. 2016. Detecting and mapping small subsistence farms in floodplain wetlands using Worldview-2 images: comparison of support vector machine and maximum likelihood classifier algorithms (pp, 288-300). In *Proceedings* of the Centenary Conference of the Society of South African Geographers: 25 – 28 September 2016 Stellenbosch, South Africa.

Abstract

Wetlands contribute in diverse ways to many people's livelihoods, yet human encroachment and intensified agricultural activities have threatened the existence and functions of wetland ecosystems. In particular, in this study area, subsistence and commercial agriculture in the form of banana and sugarcane are a threat to the wetland as both types of farming are dependent on a good water supply. Despite the assumed contribution of subsistence agriculture to wetland loss and degradation, few studies have quantitatively assessed the extent of impacts of agriculture on wetlands. Understanding the nature and extent of impacts of agricultural activities on wetland environments is an important initial step towards ensuring sustainable subsistence farming that aims to maximise farming activities and promote the productivity of wetlands. The need for an effective monitoring system for wetland conservation and management is required. However, detecting and mapping these small subsistence farms in wetland areas is difficult due to poor accessibility and is also costly and time-consuming using traditional field surveys. Remote sensing can be a powerful tool to monitor wetland changes, degradation as well as wetland losses. The main objective was to evaluate the performance of support vector machine (SVM) and maximum likelihood classifier (MLC) in detecting small subsistence farming operations in floodplain wetlands of the lower uMfolozi catchment in KwaZulu, Natal, South Africa using high spatial resolution Worldview-2 (WV-2). This study showed that the small subsistence farms in wetlands can be accurately mapped and detected using WorldView-2, support vector machine classifier (SVM) with a user and producer’s accuracies of 88% and 67 % respectively. These results provide a robust and accurate spatial framework to assist wetland managers in focussing their monitoring and control efforts on specific areas that are highly susceptible to agricultural impacts.

Keywords: floodplain wetlands; small subsistence farms; WorldView-2; support vector machine

2.1 INTRODUCTION

Wetlands contribute in diverse ways to the livelihoods of many people (Verma and Negandhi, 2011). Wetland ecosystems provide flood attenuation, maintenance of dry season flow, pollution control and detoxification, climate regulation, freshwater for drinking and domestic supply, agriculture, fibre and fuel, medicinal purposes and biodiversity support (Mailvaganam, 1994, Sahagian and Melack, 1998, Seyam et al., 2001, McCartney and Van Koppen, 2004, Emerton, 2005, Junk et al., 2006b). Wetlands can provide the retention, recovery and removal of excess nutrients and waste treatment (Finlayson et al., 2005). Wetlands act as sinks for greenhouse gases such as carbon dioxide, which influence local and regional weather patterns (Finlayson et al., 2005).

Despite the above important ecosystem services, wetlands are threatened (Adam et al., 2010, Thorburn et al., 2011, Turyahabwe et al., 2013). Most of the wetland ecosystems have been lost through anthropogenic activities such as water abstraction, agricultural practices and pollution (Frenken, 2005). Dams and water abstraction can reduce the amount of water available to support wetlands and river systems, altering water flowing downstream (Davies and Day, 1998). Farming practices, which use a lot of water for irrigation purposes, can cause changes in the catchment soil and vegetation conditions leading to disturbances of how precipitation is routed to wetland catchments. The latter leads to major disturbances of the wetland water budget or cycle (Voldseth et al., 2007). Discharge of waste and irrigation return flows from agriculture cause pollution to wetlands through eutrophication (Katukiza et al., 2014, Nyenje et al., 2014). SA is a water-scarce country receiving an average of less than 500 mm of rainfall per year (Breen and Begg, 1989, Schuyt and Brander, 2004) and almost all of its accessible freshwater has already been allocated for use, of which agriculture, industry and mining are the largest users (DWA, 2010). Approximately 85% of the coastal wetland area in KwaZulu-Natal has been transformed into sugarcane fields leaving a few scattered patches of wetlands (Begg, 1986).

Regardless of the above effects of crop farming activities on wetlands, agriculture plays a critical role in supporting rural economic development and ensuring food security (Masuku et al., 2017). Agriculture provides livelihoods for approximately 60% of Africa's rural population (Poulsen et al., 2015) .Subsistence agriculture is important in rural communities for providing better living and food security (Mashamaite, 2014). In rural areas of SA, agricultural development is more significant because it alleviates poverty and creates more job opportunities (Mugambiwa and Tirivangasi, 2017). Household or subsistence farming is mostly practised in rural areas because it is cost-effective compared to large scale farming (Tibesigwa and Visser, 2016). The cost-effectiveness is attributed to family labour and less need for educational knowledge (Mathebula et al., 2017).

The UFS is situated in the uMkhanyakude District municipality, which is one of SA's poorest and most underdeveloped municipalities (Hansen et al., 2015). The floodplain system is degrading as a result of ever-increasing human population demands, which have increased rapidly from the recent historical past to the present (McCracken, 2008), with approximately 60% of wetland area being converted to unsustainable agricultural activities in less than two decades by the early 1980s (Begg, 1988, Vivier et al., 2010). Given that the majority of residents in this region are unemployed and depend on subsistence crop cultivation for a living (Nustad, 2015), it is apparent that there is a pressing need to pay attention to how subsistence farms affect the wetland system for conservation purposes. Despite the fact that the study tends to be only tangentially involved in this system, the wetland is clearly under siege as a result of policy and community disputes. The official policy considers subsistence cultivation and other extractive uses as unsustainable intrusions (Nustad, 2015), while local communities consider free access to the wetland system and its services to be their birthright.

The need for an effective monitoring system, which can enhance wetland conservation and management, is required for SA. It is difficult to monitor wetland environments on a regional scale because of the high costs of surveys, time-consuming, and limited accessibility to wetlands (Ozesmi and Bauer, 2002, Adam et al., 2010). It is important to make inventories of both historical and current changes of wetlands in terms of the extent to which agricultural activities pose threats to the sustainability and integrity of wetlands (Scott et al., 2014). Remote sensing can be a strong and useful technique for monitoring changes and deterioration in wetland ecosystems in real-time,(Munyati, 2000, Ozesmi and Bauer, 2002) as well as mapping inaccessible wetland areas (Klemas, 2013). Wetland inventories in SA have been carried out on a large scale, resulting in the exclusion of many small scales, yet important and threatened wetland systems (van Deventer et al., 2016). Therefore, the effects of small-scale farms on wetland degradation can be overlooked because of the lack of detailed inventories at a scale that is appropriate for their assessments.

The classification of land use/land cover (LULC) is one of the most important applications in remote sensing (Roy and Giriraj, 2008). However, classification is a complicated task since many factors affect classification performance, including the spatial resolution of remotely sensed data, the availability of different data sources (e.g., field survey data), a suitable LULC classification system, the availability of classification software, and the analyst's experience (Lu and Weng, 2007). The difficulty in determining the best classification method for a given study often necessitates a comparative analysis of various classifiers in order to generate a satisfactory classification result (Rogan et al., 2008, Shao and Lunetta, 2012, Srivastava et al., 2012).

Traditional supervised classifiers, such as the Maximum Likelihood Classifier (MLC), have been widely used been used for land cover classification and land-use change monitoring, with overall high accuracies, mostly 80% (Shalaby and Tateishi, 2007). Various non-parametric classification algorithms have been developed over the last two decades in order to achieve more precise and reliable classifications (Huang and Lees, 2004, He et al., 2015). Neural Networks (NNs), Support Vector Machines (SVMs), and Random Forest (RF) are the most extensively studied and commonly used algorithms (Bahari et al., 2014, Lowe and Kulkarni, 2015), and they have been compared to MLC. In general, previous studies comparing the performance of these advanced classification approaches found that SVMs, outperformed traditional classification methods like MLC (Yu et al., 2012, Szuster et al., 2011). For example, Kumar et al. (2014) used compared SVM, and MLC for classifying land cover types on wetland environments, and found that SVM had higher classification accuracy and lower classification variability than MLC. These advanced classifiers have benefits that traditional classifiers do not. NNs, RFs, and SVMs, for example, make no statistical assumptions about the distribution of training data and can provide satisfactory classification results even when there are less or spectrally mixed training data (Waske et al., 2010).

Therefore, this study aims at evaluating the performance of support vector machine (SVM) and maximum likelihood classifier (MLC) in detecting and mapping small subsistence farming operations in the highly heterogeneous floodplain wetlands of the lower uMfolozi catchment in KwaZulu, Natal, SAusing high spatial resolution Worldview-2 (WV-2).

2.2. MATERIALS AND METHODS

2.2.1. Study area

The UFS is an extensive floodplain wetland system (Figure 1), which is approximately 19 000 hectares in extent (Ellery et al., 2011).

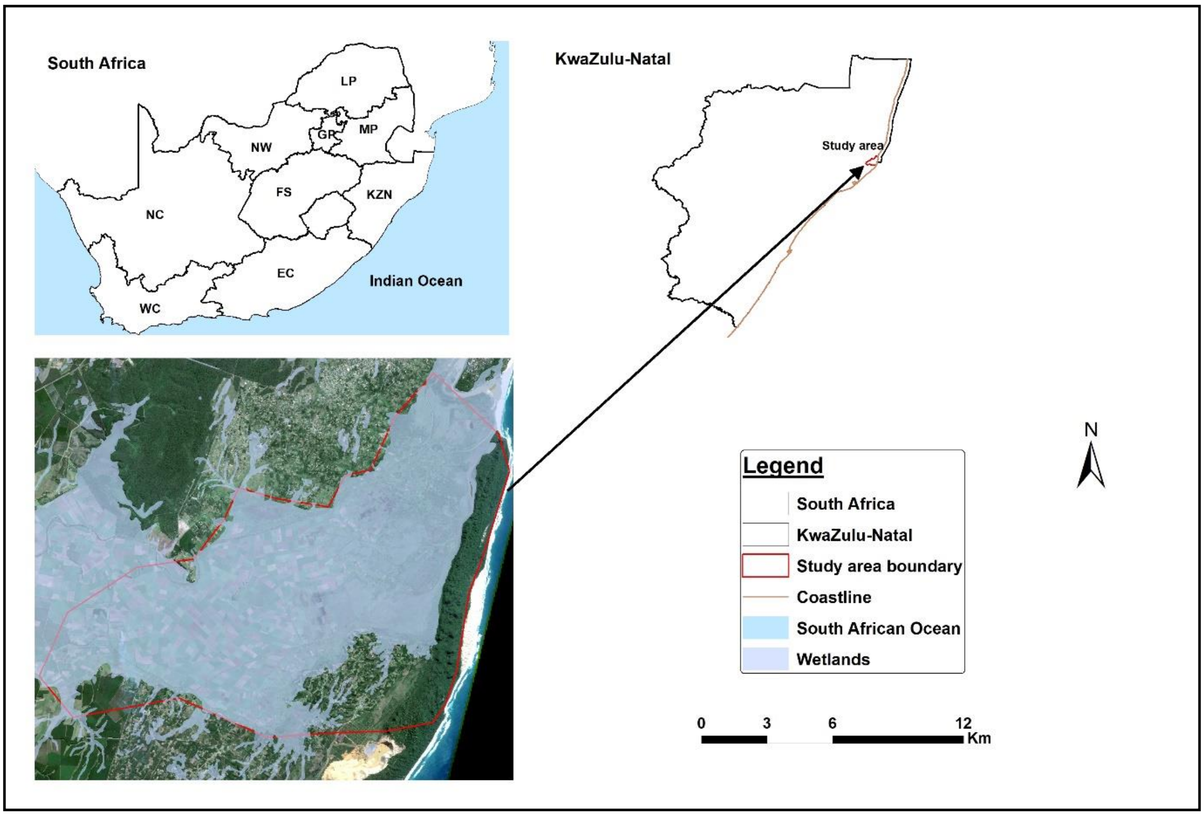

Figure 2.1. The location of the study area.

The upper two-thirds of the floodplain has been into sugarcane plantations (mostly) and *Eucalyptus* plantations but to a lesser extent. The remainder falls within the iSimangaliso Wetland Park but it has also been extensively cultivated by small-scale subsistence farmers (Grenfell et al., 2009). According to Grenfell et al. (2009), during the recent historical past, the floodplain was a mosaic of permanent and seasonal herbaceous wetland, with *Cyperus papyrus* and *Phragmites australis* as the dominant plant species. Where vegetation has not been cleared, *Ficus trichopoda* trees occur on the banks of abandoned and active channel courses. The uMfolozi River flows eastward along the northern part of the floodplain. A second river, the Msunduze River, drains a localized catchment, and flows along the southern margin before turning northward at the Maphelane dune cordon, and joining the uMfolozi River near its mouth. The region experiences a subtropical climate, with large seasonal variations in precipitation. Thus, despite subtropical temperatures, the inundation of the floodplain is seasonal. Rainfall in the region of the coastal uMfolozi floodplain averages 1090 mm/a, declining to 645 mm/a toward the upper catchment boundary. Potential evapotranspiration on the floodplain is 1805 mm/a (Schulze, 1997).

The UFS falls within the iSimangaliso Wetland Park (IWP). Around 39% of the people in this area are unemployed, relying on subsistence cultivation of *Ipomoea batatas*, *Musa acuminata*, and *Colocasia esculenta*, as well as small-scale vegetable production (cabbage, spinach, carrots, and so on), to supplement their income. Despite the fact that the UFS is a large wetland system covering approximately 19 000 hectares (Ellery et al., 2011), the majority of it has been converted to small-scale commercial sugarcane production and commercial forestry since 1911 (Keddy, 2010). Sugarcane farming and canalisation of the uMfolozi River to supply irrigation water to the sugarcane plantations have gradually increased since then, to the point that by 1960, more than half of the floodplain had already been changed by sugarcane farming and canalisation of the uMfolozi River (Vivier et al., 2010, Hansen et al., 2015). Spatial conflicts where fencing and punitive measures are put against local conservation transgressors are evident in the study area. The building of a fence, for example, has been criticized by tribal authority leaders in communities adjacent to the IWP as potentially restricting their access to natural resources that are vital for economic and traditional use (Sowman and Wynberg, 2014).

2.2.2. Image acquisition and pre-processing

A cloud-free WV-2 image of 11 June 2015 was used in this study. WV-2, launched in October 2009, is one of the first high-resolution 8-band multispectral commercial satellites. Operating at an altitude of 770 km, WorldView-2 provides images with spatial resolutions of 46 cm and 1.85 m in the panchromatic and multispectral bands respectively. Table 2.1 describes the temporal sequencing and characteristics of WV-2 images.

Table 2.1. Temporal sequencing and characteristics of the World View-2 satellite image used.

Resolution	Characteristics
Spatial resolution	1.85 meters
Temporal resolution	1.1 to 3.7 days
Bands (nm)	Band 1, coastal (400 to 450)
	Band 2, blue (450 to 510)
	Band 3, green(510 to 580)
	Band 4, yellow (585 to 625)
	Band 5, red (630 to 690)
	Band 6, red edge (705 to 745)
	Band 7, near-infrared 1 (770 to 895)
	Band 8,near-infrared 2 (860 to1040)
	Panchromatic (spatial resolution 0.46 meters)

Source: (www.satimagingcorp.com/satellite-sensors/worldview-2/)

Worldview 2 images were obtained from Digital Globe in a Tagged Image File Format (TIFF) files with D-WGS–1984 projections, which made it possible to export them to ENVI 5.3 and GIS processing software. The images were acquired orthorectified from source and atmospherically corrected using Flaash Standard Model on ENVI 5.3 software after which they were re-projected to UTM Zone 36S in ENVI 5.4.

2.2.3. Field collection of reference data

A pilot field survey was conducted in March 2016, during the rainy season. During this survey, the compilation of ground truth was guided by a thematic map that was prepared from the unsupervised classification of a footprint coverage of the study area obtained. The number of thematic information classes in this map was purposefully set at 15, with this limit being chosen because it was reasoned this number was large enough to accommodate most of the heterogeneously distributed vegetation and non-vegetation cover types in the study area. For each of the 15 thematic groups, three sample sites were systematically chosen, and their exact positions were calculated using a Garmin global positioning system (GPS) with a rated absolute positional accuracy of 4 m. Ground truth was compiled by classifying different cover types based on observed spatial distributions of (1) different vegetation, (2) land-use types, and (3) natural features. Following that, the data was compiled into ten separate land-cover types: (1) bareland and harvested fields, (2) forest, (3) grassland, (4) plantations, (5) subsistence farms, (6) sugarcane plantations, (7) waterbody, (8) wetland, (9) coastal sand, and (10) built-up areas. For each land cover class, a true colour composite band (5, 3, and 2) was generated based on field survey information for better identification of the listed training classes (Table 2.2). Signatures describing statistical characteristics of each land cover class were extracted using the Regions of Interest (ROI) tool in ENVI 5.3.

Table 2.2. Training and validation data sets for the land cover classes.

Land cover class	Code	Training data set	Validation data set	Total
Grassland	G	8628	1294	9922
Built-up areas	BUA	2441	230	2671
Coastal sand	CS	5317	979	6296
Indigenous forest	IF	7993	1115	9108
Plantations	P	2620	393	3013
Sugarcane plantations	SP	2462	369	2831
Subsistence farm	SF	7887	780	8667
Waterbody	WB	3744	395	4139
Wetland	WL	18111	1700	19811
Bareland & harvested fields	BHF	10966	1100	12066

2.2.4. Image classification

As discussed in the preceding sections, the maximum likelihood classifier (MLC) has been one of the most commonly used and reliable parametric image classifiers. Support vector machine (SVM) has also proven to be the most accurate and reliable non-parametric classifier. Consequently, this study compared the two classifiers to determine which one would be effective at identifying small-scale farms in the lower UFS. To reduce evaluation bias, MLC and SVM classifications used identical sets of training and validation samples.

- **Support vector machine**

The Support vector machines algorithm (SVM), developed by Vapnik and his colleagues in the late 1970s, is one of the most widely used kernel-based learning algorithms in a broad range of machine learning applications, especially image classification (Mountrakis et al., 2011). The primary aim of SVMs is to solve a convex quadratic optimization problem in order to achieve a globally optimal solution in principle, thereby avoiding the local extremum dilemma that plagues other machine learning techniques. SVM is a non-parametric supervised technique that is unaffected by the underlying data distribution. This is one of the advantages of SVMs over other statistical techniques like maximum probability, which involve prior knowledge of data distribution (Mather and Tso, 2016). SVM is a linear binary classifier that defines a single boundary between two groups in its most basic form by assuming that multi-dimensional data in the input space can be segregated linearly.

SVMs are particularly appealing in the field of remote sensing because they can effectively handle limited training data sets and often offer higher classification accuracy than traditional methods (Ghoggali et al., 2009, Ming et al., 2016, Ch et al., 2013). SVM is a high-dimensional space classifier that is especially useful in the field of remote sensing image processing, where dimensionality can be extremely high (Milgram et al., 2006, Mathur and Foody, 2008). Furthermore, only a subset of training data is needed for the decision-making process of appointing new members. As a consequence, SVM is one of the most memory-efficient techniques, as only a subset of the training data must be processed in memory (Wu et al., 2016).

In this study, true colour composite images (bands 5, 3 and 2) were used to classify small-scale farms and other land covers. For the ten land cover classes, trained polygons covering a number of pixels were generated. The one-against-one method was used in this analysis since it has been shown to work better than the one-against-all method (Platt et al. 2000). ENVI (ITT Visual Information Solution, US) was used for multiclass SVM classification using the pairwise classification strategy. The decision value of each pixel for each class in the SVM classification output is used for probability estimates. The radial basis function (RBF) kernel was used in this study, as suggested by (Hsu et al., 2003), with no changes to the default kernel function (0.143), penalty (100), pyramid levels (0), or classification likelihood threshold (0). The penalty parameter allows for some misclassification, which is especially useful for non-separable training sets. Finally, by separating classes based on an optimally defined hyperplane between class boundaries, a pixel-based SVM classification was performed.

- **Maximum likelihood classifier**

The Maximum Likelihood Classifier (MLC) is a pixel-based parametric classifier that assigns classes based on the likelihood of belonging to that class. Each class is represented by a single distribution (Gaussian is traditional, particularly in remote sensing software) generated from the training data. The class to which a pixel is allocated is the class with the greatest likelihood for that pixel (Mather and Tso, 2016). MLC has a sound theory and preferred parametric algorithm especially in land cover and land use monitoring approaches (Palaniswami *et al*., 2006 and Lillesand and Kiefer, 2004). It is available in many commercial image processing software and is, therefore, the most used technique (Palaniswami et al., 2006, Gao, 2009, Otukei and Blaschke, 2010, Lillesand et al., 2014). In this study, the original World View 2, true-colour composite image bands (5, 3 and 2) were used to classify small-scale farms and other land covers. For image classification, maximum-likelihood classification (MLC) was used by (1) defining features and selecting training areas based on field data provided in Table 2.1. MLC is based on two assumptions: (1) that the image data is normally distributed, and (2) that the statistical parameters (e.g., mean vector and covariance matrix) of the training samples correctly represent the corresponding land cover class. However, in dynamic and heterogeneous ecosystems such as wetlands, the image-derived parameters are not always normally distributed. Differential global positioning system (GPS) based reference samples were first superimposed on regular false-colour composites using the 7, 5, and 3 bands combination to search for class homogeneity across the sample points during the field visit. For each of the ten land cover groups, polygons covering various numbers of pixels were generated.

2.2.5. Classification accuracy assessment

Accuracy assessment determines the quality of the classification derived from remotely sensed data (Congalton and Green, 2008). Accuracy assessment was conducted for the classified image using the confusion matrix module on ENVI. A confusion matrix using a validation dataset of each land cover class was subsequently constructed to compute the overall accuracy, user's and producer's accuracies, and kappa statistic (Congalton and Green, 2008). An error of commission represents pixels that belong to another class but labelled as belonging to the class, whilst the error of omission represents pixels that were assigned to the incorrect class. The Kappa coefficient is an overall index that combines both errors of commission and omission. It demonstrates a measure of the reliability of the classification. Kappa ranges between 0 and 1 Landis and Koch (1977). The Kappa can be broken into six groupings for interpretation. Table 2.3 presents the Kappa Index of Agreement (KIA) statistic and the strength of agreement (Viera and Garrett, 2005). It is worth noting that even though there have been ongoing discussions about the meaninglessness of the Kappa index in terms of accuracy pointed by Pontius Jr and Millones (2011), it was still included in this analysis of this chapter.

Table 2.3. KIA statistic and strength of agreement (Presented after Viera and Garrett, 2005).

KIA	Strength of Agreement
< 0.00	Poor
0.21 – 0.20	Slight
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Substantial
0.81 – 1.00	Almost perfect - Perfect

2.3. RESULTS

2.3.1. Performance of SVM and MLC

The investigation's results are presented in the form of (1) a map depicting the spatial distributions of different cover types and (2) confusion matrixes that summarise the classification accuracies of the different classifiers that were used. Ten land cover classes including subsistence farms were obtained from the use of SVM and MLC (Figure 2.2). Both classifiers were able to detect subsistence farms in the floodplain system using the high-resolution WV-2 image. As shown in both maps, subsistence farms were heterogeneously distributed around indigenous forests, waterbodies, and wetlands.

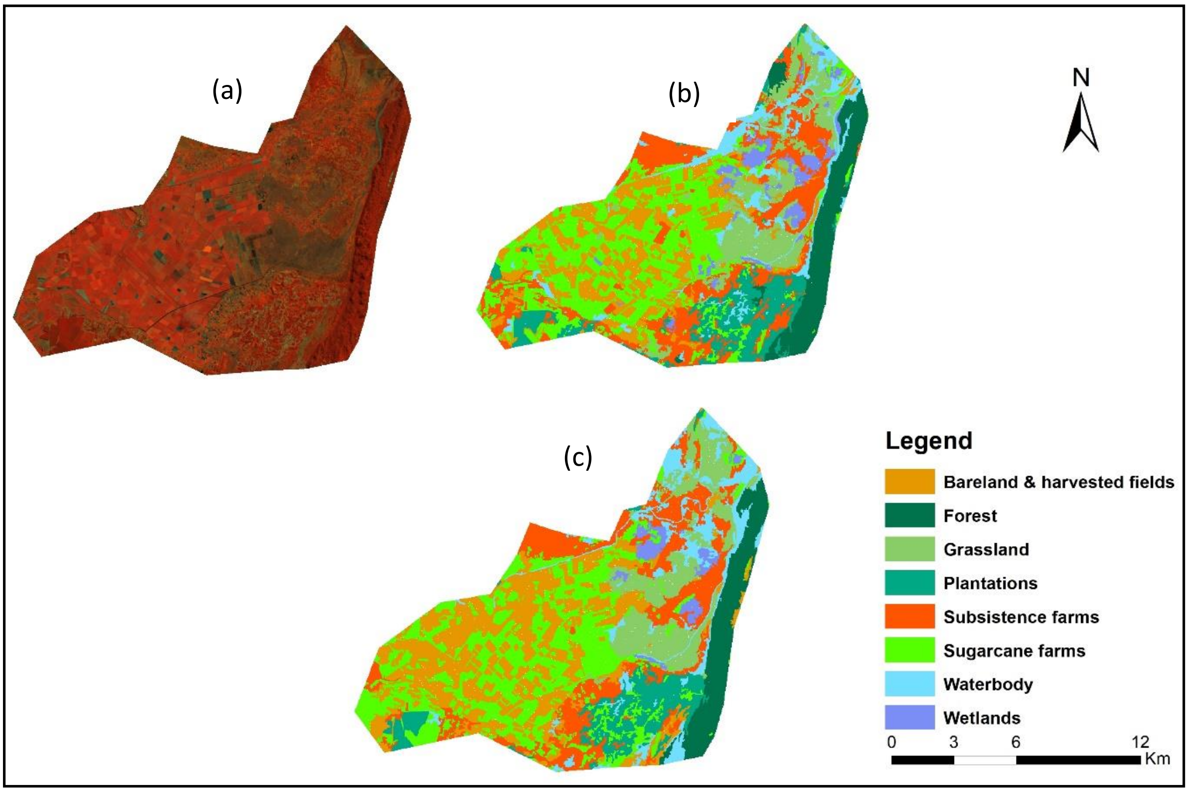

Figure 2.2. Mapping the small scales farms and other land use/ land cover classes based on the false colour composite WV-2 image using (A) support vector machine using (B) maximum likelihood classifier (C).

Classification accuracy assessment was performed for both the SVM and MLC classifiers to evaluate the prediction performance of the trained models using the independent test data set. Tables 2.4 and 2.5 show confusion matrices of the classification accuracies of SVM and MLC respectively.

Table 2.4. Confusion matrix and associated Maximum Likelihood classifier (MLC) accuracies based on independence test data set. The accuracies include overall accuracy (OA %), kappa statistic, user's accuracy (UA %), and producer's accuracy (PA %).

Class	G	BHF	FO	PL	SGF	SBF	WB	WL	**Row Total**	UA
G	2258	12	106	4	56	347	0	3270	**6080**	37
BHF	6	1080	2	0	0	156	0	8	**1252**	86
FO	203	142	19647	1299	1471	391	0	282	**23435**	83
P	3	36	313	1696	69	11	0	132	**2260**	75
SGF	0	7	698	88	7909	344	0	0	**9046**	87
SBF	326	151	771	43	341	3297	0	1062	**5991**	55
WB	0	3	0	0	0	5	8595	0	**8603**	99
WL	1016	123	503	2	7	453	0	6275	**8379**	75
Column Total	**3812**	**1554**	**22040**	**3128**	**9853**	**5004**	**8595**	**11029**	**65105**	
PA	59	69	89	54	80	66	100	56		
OA	77									
Kappa	0.76									

Table 2.5. Confusion matrix and associated Support Vector Machine (SVM) accuracies based on independence test data set. The accuracies include overall accuracy (OA %), kappa statistic, user's accuracy (UA %), and producer's accuracy (PA %).

Class	G	BHF	IF	P	SGF	SBF	WB	WL	**Row Total**	UA
G	3180	25	111	25	34	159	0	2573	**6107**	52
BHF	13	1897	6	25	34	159	0	72	**2206**	86
IF	8	87	5630	357	107	1047	0	177	**7413**	76
P	3	26	712	2146	111	276	0	79	**3353**	64
SGF	4	0	139	68	215	0	356	68	**850**	25
SBF	71	133	538	38	62	3777	0	582	**5201**	73
WB	0	1	47	186	0	0	3839	0	**4073**	94
WL	238	72	186	3	9	411	0	7288	**8207**	88
Column Total	**3517**	**2216**	**7369**	**2848**	**563**	**5829**	**4195**	**10839**	**37376**	
PA	90	86	76	75	38	65	92	67		
OA	75									
Kappa	0.74									

Key to acronyms: Grasslands (G), bareland and harvested fields (BHF)), forest (FO), plantations (PL), sugarcane farms (SGF), subsistence farms (SBF), waterbody (WB) and wetland (WL)

The MLC classifier had a higher overall accuracy (OA) of accuracy 77% and a kappa value (K) of 0.76 than the SVM classifier (OA = 75 %, K = 0.74). In both classifiers, waterbody, coastal sand, indigenous forest and bare-land and harvested sugarcane achieved high user and producer accuracies. MLC generated lower user and producer accuracies for grassland, sugarcane plantations, subsistence farms and built-up areas. However, the MLC classifier confused the class pixels for subsistence farms and wetlands possibly because of the open canopy nature of crops in subsistence farms. SVM also confused between sugarcane plantations and grasslands. Generally, although MLC had a higher overall accuracy than SVM, it was outperformed by SVM's higher user and producer accuracies for subsistence farms.

2.4. DISCUSSION

Detailed land cover mapping is now an important research topic in land change science and landscape planning. Anthropogenic activities are constantly changing land cover patterns and influencing biophysical processes (Li et al., 2014). To estimate agricultural extents, detailed and accurate land use and land cover (LULC) maps generated from high-resolution images are useful in the decision-making process and sustainable management of land resources. According to (Foody, 2002, Lu and Weng, 2007), the high costs and limited availability of remotely sensed data with appropriate spatial, spectral, and radiometric resolutions continue to impede their application in LULC mapping. Against this background, this study sought to determine the performance of the multispectral-sensor (Worldview-2) in mapping and detecting small subsistence on floodplain wetlands.

Classification results in this study demonstrated that Worldview-2 imagery using SVM and MLC classification techniques are valuable in mapping and detecting small-scale farms in heterogeneous landscapes. Using SVM and MLC, high classification accuracies were achieved (Tables 2.3 and 2.4). SVM and MLC successfully classified eight LULC classes and their results were compared. SVM performed better than MLC in classifying and detecting subsistence farms, which was the main aim of the current study. These results are in agreement with findings by Szuster et al. (2011) and Yu et al. (2012) examined and compared the performance of the SVM and MLC classification techniques in the tropical coastal zone and concluded that SVM is a better classifier. Deilmai et al. (2014) also applied SVM and MLC in Landsat data to extract land use and lover cover changes in Johor Malaysia and obtained results that showed that SVM gives higher accuracies than MLC.

The spatial and spectral characteristics of the WorldView-2 data set allowed us to successfully separate vegetated areas covered by sugarcane, plantations, indigenous forest and subsistence farms. In SA, attempts to separate these cover types using traditional multispectral data (SPOT and Landsat) have to date been unsuccessful (Fairbanks et al., 2000, Islam et al., 2008, Otukei and Blaschke, 2010, Cho et al., 2012). Diverse studies that have used VW-2 for predicting and mapping forest structural parameters, urban land cover mapping and discriminating commercial forest species have concluded that VW-2 data have considerably improved the classification and prediction accuracies compared to conventional sensors (Ozdemir and Karnieli, 2011, Zhou et al., 2012, Peerbhay et al., 2013).

Both SVM and MLC were unable to fully deal with the high spectral variation inherent in some LULC types such as sugarcane forest, and hence classification error on the LULC maps (Figures 2.2) which is consistent with (Adam et al., 2014). According to (Lu and Weng, 2007, Duro et al., 2012), the issue of high spectral variation inherent in some LULC types is a common problem when classifying heterogeneous landscapes using high spatial resolution based on per-pixel classification techniques.

The overall accuracies obtained in this study provide reliable information that can be used to assist wetland managers in focusing their existing monitoring and control efforts on specific areas that are susceptible to agricultural impacts. Therefore, this knowledge is critical in the management of our endangered and threatened wetland ecosystems in SA. Notwithstanding, the interpretation of these results can only be regarded as preliminary since further research is needed in using Worldview-2 in the study area. Given the user's and producer's accuracies achieved by MLC and SVM classifiers to detect small scale farms, further research is required to develop a technique to better identify these land cover types in wetlands. Random Forests (RF) can be used which are known to be more accurate on forests and globally on croplands (Pelletier et al., 2016). The use of object-based classification would have improved the results than pixel-based classification. Pixel-based classification only uses the spectral information in the image while object-based classification uses spectral, spatial, contextual, and textual information (Flanders et al., 2003, Leukert et al., 2004). In object-based classification, the image is segmented into objects that form the classification units, which improves classification accuracy (Manakos et al., 2000, Niemeyer and Canty, 2003).

2.5. CONCLUSION

The study sought to detect and map the small-scale farms in a complex floodplain wetland system using a multispectral sensor, WorldView 2 and was able to provide insights in the classification accuracies of SVM and MLC by discriminating small-scale farms from other land cover types in a heterogeneous coastal landscape. The results demonstrated similarities in the overall performance of SVM and MLC but SVM performed better in discriminating subsistence farms. As a result, future research should consider concentrating on the spatial and temporal distributions of small-scale farms, as well as their effects on wetlands. Subsequently, the use of alternative approaches such as random forests and object-based image algorithm should be further explored. Mapping exercises such as the one described in this study are useful for natural resources and wetland conservation planning exercises, such as water use planning, water quality assessment and wetland change detection.

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CHAPTER 3

A remote sensing-based approach to investigate changes in land use and land cover in the lower uMfolozi floodplain system, South Africa

This chapter is based on:

Mandla Dlamini, Elhadi Adam, George Chirima & Hamisai Hamandawana. (2021). A remote sensing-based approach to investigate changes in land use and land cover in the lower uMfolozi floodplain system, South Africa, *Transactions of the Royal Society of South Africa,* DOI:10.1080/0035919X.2020.1858365.

Abstract

The goal of this chapter was to understand land use and land cover (LULC) changes within the lowerUFS , SA, and relate those changes to wetland loss. Changes in LULC were assessed using a geographic object-based image analysis (GEOBIA) algorithm to classify multidate Landsat images into eight cover types over a period of 20 years, between 1997 and 2017. Post classification accuracy assessment of all map-outputs was conducted by compiling confusion matrixes and calculating producer, user, and global accuracies and kappa coefficients (K) for each map output. Levels of accuracy for all map-outputs were within acceptable limits, ranging between 79% and 88% (K = 0.76 and 0.86, respectively). Thereafter, paired t-tests were applied to determine whether the changes in LULC over the study period were significant. Results of this investigation showed a significant ($p< 0.01$) conversion of wetland to cultivation, by 14%. This finding is important because it demonstrates that in this environment, human agency is one of the major drivers of a persistent decrease in the wetland ecosystem. The major insight from this observation is that there is an urgent need to formulate and implement objectively informed interventions to enhance the sustainability of the UFS and that of others elsewhere.

Keywords: subsistence cultivation; wetland conversion; supervised classification; Landsat

3.1 INTRODUCTION

Wetlands provide a variety of ecosystem services that include water quality improvement, flood attenuation and protection, groundwater recharge and agricultural production (Bhatta et al., 2016). Despite the provision of these services, wetlands are widely threatened at regional, subregional and global scales by human activities that include hydrologic modifications, contamination by anthropogenic pollutants, eutrophication and conversion to a wide range of uses, notably agriculture and human settlement. These adverse effects are aggravated by changes in climate (Winter, 2000) that have far-reaching implications for the sustainability of these vital ecosystems. Evidence of these changes comes in the form of an extensive decrease in the wetland area, and persistent loss of vegetation (Xu et al., 2018). These adverse effects are a major cause of concern because of their established tendency to reinforce each other in inducing irreversible impairment of the natural balance in the functioning of these ecosystems (Banadda et al., 2009). This asseveration is supported by the reported decrease in the world's wetlands by 64–71% since 1900, largely because of encroachment by agriculture and other human land-use activities (Davidson, 2014).

Encroachment by human activities is now so widespread that it has come to be recognised not only as one of the major drivers of wetland degradation but also as a catalytic agent that amplifies the adverse effects of climate change. Human agency and climate change are further reinforced by a lack of routine monitoring, meaning the information needed to guide the formulation of environmentally friendly interventions is scarce (Driver et al., 2012). Information scarcity has far-reaching implications because it entails concomitant inaction. InSA, for example, only 15% of the country's varied wetland types remain in their near-natural ecological state, with floodplain wetlands recorded as presently having less than 5% of their total area under near-natural conditions (AUTHORITY, 2016, Skowno et al., 2018). This situation is bound to deteriorate unless concerted efforts are taken to reverse the rate at which wetlands are being degraded by the combined effects of human agency and climate change. Although wetlands continue to be degraded as a result of a conspicuous lack of interest in their sustainability, they still provide vital ecosystem goods and services that are essential for sizeable human populations whose livelihoods depend on what these shrinking resource niches provide. The range of provisions they offer is so wide that it should be obvious they must be safeguarded at all costs and without reservation. They support numerous ecological processes such as nutrient dynamics, energy flow, and movement of organisms and materials (Foley et al., 2005, Kareiva et al., 2007). They also serve as natural sinks for nutrients from terrestrial sources and provide (1) freshwater for multiple uses, (2) a wide variety of plants used for various purposes, (3) fall-back grazing during the dry seasons of all years, (4) nesting grounds and habitats for birds, (5) habitats and spawning grounds for multiple freshwater fish species and (6) aesthetically appealing environments in which to live and undertake non-extractive recreational activities (Hamandawana et al., 2020). The list is endless but, unfortunately, wetlands continue to be robbed and degraded by extractive and unsustainable human resource use practices. These exploitive uses are often aggravated by competing demands for wetlands' finite resources, which are continuously increasing, in tandem with similar changes in human populations. One source of these problematic demands is agriculture, which accounts for most of the observed loss in wetland area through the conversion of wetlands for crop production. Equally problematic are industrial and urban development, which add their share of the pressure by converting what is available to meet their requirements (Kingsford et al., 2006, Kingsford, 2015) and degrading most of these natural systems due to a lack of proper monitoring and enforcement of conservation regulations.

As human-induced pressures increase, climate change exacerbates this build-up by imposing externalities that are beyond the natural coping capacities of these ecosystems (Bate et al., 2016). Although the situation may appear irremediable, there is in fact tremendous room to respond appropriately by providing the information mentioned above, which is conspicuously lacking. Obtaining this information requires innovative techniques that are not only cost-effective but also capable of offering what is required at appropriate temporal and spatial scales. As explained in subsequent sections, remote sensing provides a viable means of bridging this information gap in ways that are potentially capable of providing lasting solutions to the information scarcity problem. An explanation is helpful here in demonstrating why the present study considers information critical in attempting to enhance the sustainability of our wetlands. Information is critical because apart from providing a reliable inventory of how wetland resources are being exploited and replenished, it is also the backbone of policy formulation, management decision-making and implementation of informed interventions. Inventory assessments are vital because they provide a reliable basis for monitoring what is happening and tracking disruptions that require immediate attention. Without this information, it is difficult to deploy conservation policies to protect wetlands, hence this example illustrates the usefulness of remote sensing because of its demonstrated capabilities to outperform conventional techniques by offering spatially explicit information at costs within the reach of many stakeholders. Because of the dynamic nature of processes that occur in wetland ecosystems, long-term profiling is needed to discriminate periodic reversible changes from those that may end up being irreversible. Reversibility is crucial because it determines whether interventions will be successful by imposing limits beyond which corrective interventions cannot reverse the undesirable effects of degradation. Although wetland monitoring has for a long time relied on traditional methods, that include visual interpretation of maps and aerial photographs, and instrumental ground-based measurements, these methods are prohibitively costly, time-consuming and incapable of providing consistent information that is representative of large areas at multiple temporal scales (Hoshino et al., 2012, Melton et al., 2013, Gilbertson et al., 2017). Besides the reliance on these methods, unevenly distributed observations render most of the information they provide of little use at the operational level; areas for which information cannot be provided are often superficially covered by poorly representative averages. These challenges can be addressed by fully exploiting what remote sensing offers.

Over the last few decades, remote sensing has become widely accepted as a viable means to provide usable information timeously. Some reasons for this recognition are: (1) the increasing availability of freely accessible images from the Landsat archives; (2) the long temporal coverage provided by the continuous Landsat data sets (48 years, from 1972 to the present), which makes it ideal for the investigation and detection of long-term change; (3) optimised spatial resolutions for reliable characterisation of informative land use and land cover (LULC) types (30 m for most bands); (4) immediate download access of required images from the United States Geological Surveys USGS data portal; and (5) dedicated and planned commitment to continue providing images into the future (Zhuet al., 2019). This scenario provides a convincing demonstration of the fact that for LULC monitoring at scales required for wetlands monitoring, access to raw data is indeed no longer one of the major obstacles confronting the policy–planning interface. What is lacking is an organised and collective effort by the scientific community to exploit fully the rich data sets that have become readily accessible. Although remote sensing has increasingly been used in many wetland research areas, notably LULC monitoring (Schmidt and Skidmore, 2003, Wang et al., 2004, Giri et al., 2011), vegetation quality and quantity assessment, and other areas that include hydrological processes (Li et al., 2009), its full potential remains to be meaningfully exploited.

While Landsat images have the above outlined potentials to bridge information gaps, radar data products could broaden the scope of investigative analysis because of their insensitivity to variable weather conditions and cloud cover. Unfortunately, however, their use is constrained by several limitations. First, there is a price tag on most of these images, which makes them inaccessible to most potential users, with this same limitation affecting other image types provided by most platforms. Second, their acquisition involves high energy utilisation on satellite platforms, which makes it difficult to provide optimum time series data sets for many regions of the world (Woodhouse, 2006). These limitations make Landsat images the mainstay of pixel-based LULC characterisation at multiple temporal and spatial scales (Grundling et al., 2013, Jia et al., 2014, Liu and Yang, 2015, Kumar and Acharya, 2016). This does not, however, imply that Landsat images do not have their own limitations. It is well known that Landsat images are incapable of supporting detailed discrimination of different vegetation species because of their coarse spatial resolutions (Gallant, 2015, Gómez et al., 2016). This limitation is noted by Adam et al. (2010) who report that Landsat's spatial and spectral resolutions are too coarse for reliable discrimination of wetland vegetation species.

While these limitations have been specifically raised as examples, these images are further affected by constraints similar to those associated with what other platforms provide. First, their utilisation is confounded by reliance on pixel-based classifications that are dependent on feature based brightness values (Blaschke et al., 2014). This brightness dependence entails its own limitations that arise from the elimination of effective exploration and utilisation of the robust spatial concepts of a neighbourhood, proximity and homogeneity analysis (Burnett and Blaschke, 2003). Added to this is their narrow spectral resolutions (McIver and Friedl, 2002) that render them incapable of discriminating heterogeneously distributed vegetation species with low interclass spectral separability (Bourgeau-Chavez et al., 2009, Gallant, 2015, Amani et al., 2017). Second, these limitations have substantial implications for biodiversity studies where the abundance of different species is considered to be a critical determinant of the stability and health of wetland ecosystems (Elliott et al., 2020). This valuation is premised on the fact that greater species richness is an uncompromisable characteristic of heathy wetland systems (Brose, 2008, Elliott et al., 2020). This connection implies that although high-resolution data sets are expensive, they are essential for the species-level characterisation of different vegetation types. Hence, the information they can provide is indispensable because it is the backbone of conservation-oriented interventions (Tockner et al., 1999). Although difficult to implement due to a lack of suitable information, the success of these interventions determines the availability of functional wetland systems for present and future generations.

To achieve this functionality, there is a need to explore innovative techniques of using what is available and readily accessible to secure the ability of these ecosystems to sustainably provide their valued goods and services (Tscharntke et al., 2005). With science at a crossroads because accessible data sets lack the required discrimination skills, while those with the requisite skills are not affordable, attempts to improve classification outputs from coarse resolution images by adding different vegetation indices have been explored by many (Peña-Barragán et al., 2011, Sahebjalal and Dashtekian, 2013). The emergence of this new thinking is demonstrated by pioneer initiatives to use the geographic object-based image analysis (GEOBIA) approach, which has many advantages compared to pixel-based classification. This approach is a category of digital remote sensing image analysis that segregates geographic entities by discretising image objects as fundamental primitives (Blaschke, 2010). Known advantages of this novel technique include its ability to extract sub-pixel information at higher levels of classification accuracy by using the spatial, and textural properties of individual objects as additional information to their reflectance characteristics (Liu and Xia, 2010). Although GEOBIA has been largely applied to high-resolution images, the algorithms on which it is based can be adapted to classify readily accessible medium-resolution images such as Landsat images. This avenue promises better change detection by providing tremendous scope to refine conventional pixel-based classification techniques (Lu et al., 2014).

The feasibility of the technique is demonstrated by recent studies Ai et al. (2020) that used GEOBIA-based methods and medium-resolution remote sensing data to monitor continuous LULC changes in heterogeneous environments. What this breakthrough suggests is that

GEOBIA can be used in synergy with different spectral indices to extract the unused information contained in Landsat's pixelised images. The spectral indices worth exploring include but are not limited to (1) the normalised difference vegetation index (NDVI); (2) the green normalised vegetation index (GNDVI); (3) the soil adjusted vegetation index (SAVI); and (4) the ratio vegetation index (RVI). It is possible to use these indices because they can deliver improved LULC classifications using the red, green and near-infrared bands of the electromagnetic spectrum (Dronova, 2015). Their usefulness can be illustrated by SAVI, whose capability to discriminate soil types on the basis of differences in brightness has been used to improve classifications of different vegetation types by fusing them with other vegetation indices (Xue and Su, 2017, Chen et al., 2019). This technique has also been found to be capable of improving mapping accuracy in heterogeneous landscapes like wetlands (Chen et al., 2018), and improving land cover discrimination in high density vegetation landscapes (Xue and Su, 2017). Although useful, as outlined above, indices like RVI and NDVI have compromised capabilities because of their sensitivity to soil brightness in sparsely vegetated areas (Xue and Su, 2017).

This limitation can, however, be addressed by using various machine learning classification algorithms, for example, support vector machine (SVM), which so far has been successfully implemented in GEOBIA (Mountrakis et al., 2011). SVM functions by using a decision surface (optimal hyperplane) that maximises separation margins between different information classes (Cortes and Vapnik, 1995, Veenman et al., 2002). This permutation enables it and the other vegetation based indices to produce higher accuracies compared to what is achievable using the pioneer conventional classifiers (Lin et al., 2013, Salehi et al., 2015). The challenges outlined above argue for tireless efforts to embrace responsible stewardship by routinely monitoring the remaining wetlands at our disposal. Given the difficulties confronting broad-based coverage of all systems, a bottom-up approach, in which the local informs the regional, promises to offer a viable compromise approach. This reasoning explains why we decided to focus on the UFS. Located in uMkhanyakude District Municipality, the UFS was also judged to be suitable for this investigation because it is found in one of the poorest and most underdeveloped local authorities in SA (Hansen et al., 2015). This unfavourable positioning is aggravated by persistent degradation induced by the ever-growing demands of human populations that have rapidly increased from the recent historical past to the present

(McCracken, 2008), with approximately 60% of wetland area being converted to unsustainable agricultural activities in less than two decades, by the early 1980s (Begg, 1988, Vivier et al., 2010).

Considering that most people in this area are unemployed standing residents whose livelihoods are largely dependent on subsistence crop cultivation (Nustad, 2015), it is apparent that there is an urgent need to focus attention on how this wetland can be conserved. Although research appears to be only distantly interested in this system, this wetland is clearly under siege because of conflicts between local communities and policy. While local communities consider free access to the UFS and its resources to be their birthright, official policy views subsistence cultivation and other extractive uses as unsustainable intrusions. As a result, the concept of a shared landscape is collapsing. Given the complex nature of the UFS, an innovative monitoring technique is needed to provide up-to-date information that can be used to guide the formulation and implementation of effective interventions. We attempt to approach the realisation of this objective by using the GEOBIA algorithm along with purposefully selected vegetation indices comprising NDVI, SAVI and RVI to quantify long-term LULC changes in this system. The goal of this initiative was to better understand the major drivers of the aforementioned changes in this environment to provide objectively informed recommendations on adoptable interventions that are potentially capable of enhancing the sustainability of this threatened ecosystem.

3.2. MATERIALS AND METHODS

3.2.1. Study area

The UFS is a floodplain wetland (Garden, 2008) situated in the small town of St Lucia (28°22'S, 32°25E'), in the uMkhanyakude District Municipality of SA (Figure 3.1).

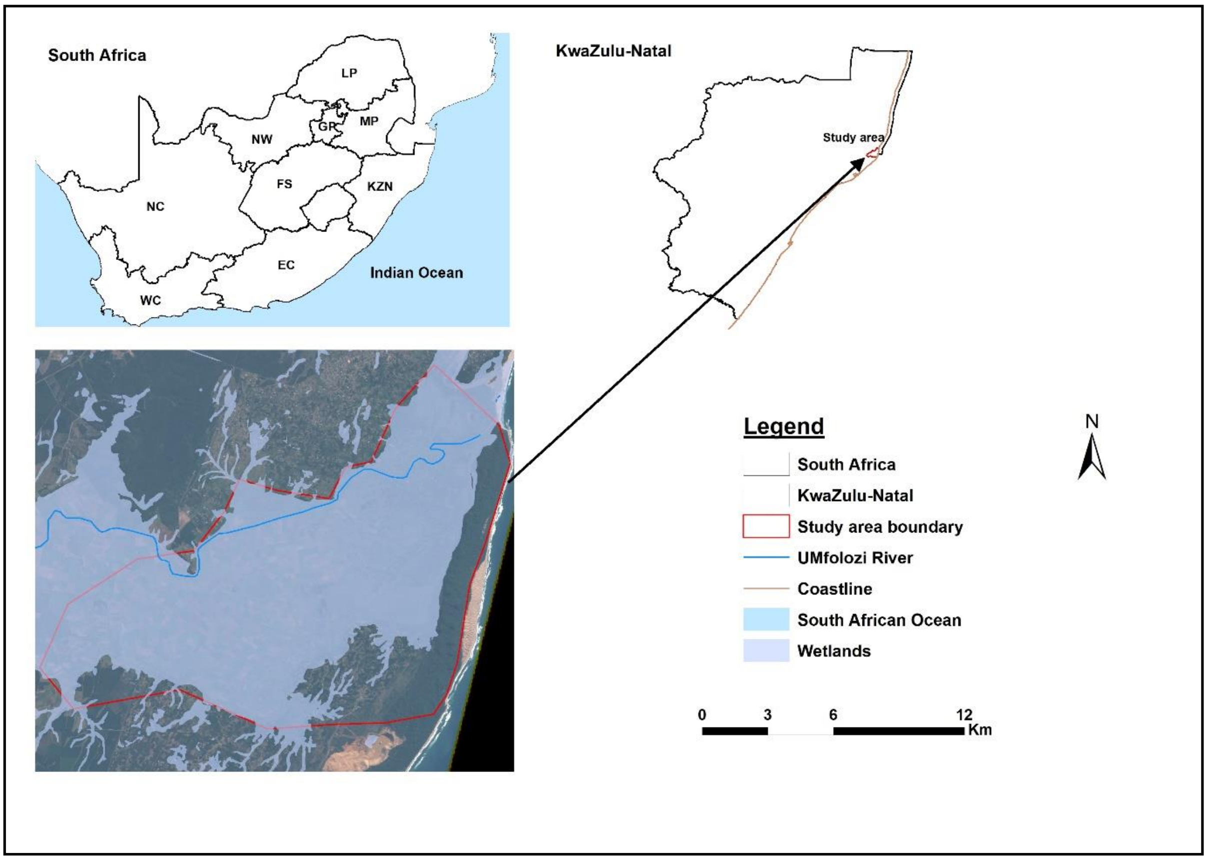


Figure 3.1. The geographical location of the study area.

This municipality is well known for being one of the country's poorest and most underdeveloped local authorities (Hansen et al., 2015). In terms of physiography, the floodplain is bound inland by deeply incised meanders of the uMfolozi River, which cuts its way through rhyolite rock formations of the Lebombo Mountains. After these mountains, it meanders downstream towards the Indian Ocean, within the confines of elevated landscapes in the southern and northern peripheries of Zululand and Maputaland (Garden, 2008). With an evolution dating back to ~18 000 yrs BP, the UFS originated from a dramatic loss of the river's confinement from a marginal width of ~950 m to > 6 km in less than 1.5 km before it enters the ocean (Garden, 2008). The surface geology of Maputaland, in which most of our study sites are situated, consists of conglomerates, limestone, calcareous rocks and clayey sands. Rainfall in this area is predominantly seasonal. Localities distant from the Indian Ocean experience a subtropical climate, with large seasonal variations in precipitation, which ranges between 671 mm/a and 1002 mm/a (Morgenthal et al., 2006). The coastal floodplain areas receive similar but less variable amounts, ranging between 645 and 1090 mm/a along a precipitation gradient in which the lowest amounts are confined to localities in the upper river's upper catchment areas. Throughout the entire area, however, most of the rainfall is confined to the summer months between October and March, with the highest amounts occurring between January and March (Morgenthal et al., 2006). This rainfall regime translates into seasonal inundation of the floodplain and evapotranspiration rates approximating 1805mm annually (Schulze, 1997).

Surface hydrology is dominated by (1) two main rivers – the uMfolozi River in the north and the Msunduze River in the south – that converge into a common mouth that marks their terminal entry into the Indian Ocean; and (2) shallow floodplain lakes, the largest of which are Lake Teza and Lake Futululu. Flow in these rivers is highly variable (Garden, 2008), and characterised by low base-flows and isolated occurrences of short-duration peak floods that mimic the seasonal distribution of rainfall. Although they are mostly short-lived, these flash floods have a profound influence on the floodplain's morphological characteristics (Grenfell and Ellery, 2009) that are characterised by repeated landform construction and destruction. The major vegetation types in this wetland include *Cyperus papyrus, Phragmites mauritianus, Phragmites australis and Ficus trichopoda* (Garden, 2008). About 39% of people in this area are unemployed, depending on subsistence cultivation of Ipomoea batatas, Musa acuminata and Colocasia esculenta and small-scale production of vegetables (cabbage, spinach, carrots, etc.) that provide supplementary livelihoods. Although the UFS is an extensive wetland system covering approximately 19 000 hectares (Ellery et al., 2011), most of it has been converted to small scale commercial sugarcane production and commercial forestry that date back to 1911 (Keddy, 2010). Since then, conversion has progressively increased, to the extent that by as early as 1960, more than 50% of the floodplain had already been modified by sugarcane farming and canalisation of the uMfolozi River to supply irrigation water to the sugarcane plantations (Vivier et al., 2010, Hansen et al., 2015). These exploitive and extractive uses have imposed a severe strain on the wetland's functional capacities.

3.2.2. Landsat data and field data collection

The data sets that were used include like-season Landsat 5 Thematic Mapper (TM) images from 1997, 2001, 2004 and 2008; a Landsat Enhanced Thematic Mapper (ETM) image from 2012; and a Landsat Operational Land Imager (OLI) image from 2017. Table 3.1 describes the temporal sequencing and characteristics of these images. These images were purposefully selected to provide cloud-free footprint coverage of the study area. Landsat images were preferred for this investigation because of (1) the demonstrated capability of their 30 m spatial resolution for land-cover characterisation, (2) their accessibility and the fact that they are free of charge, and (3) their long-term temporal coverage. Fieldwork was conducted during the wet-season months of February and March 2017, after a pilot survey in the same months of the previous year. The compilation of ground truth was guided by a thematic map that was prepared from the unsupervised classification of a footprint coverage of the study area, obtained by clipping the 2017 Landsat image. The number of thematic classes in this map was purposefully set at 18, with this upper limit being preferred because it was reasoned, this number was large enough to be capable of accommodating most of the different vegetation and non-vegetation cover types in the area due to limited heterogeneity in their distributions. Three sample sites were systematically selected for each of the 18 thematic classes, whose exact locations were identified with a Garmin geographical positioning system (GPS) with a rated absolute positional accuracy of ± 4 m. Ground truth was compiled by characterising different cover types based on spatial distributions in (1) different vegetation, (2) land-use types and (3) natural features that were observed. Thereafter, this information was summarised to produce eight land-cover types: (1) bare land and harvested fields, (2) forest, (3) grassland, (4) plantations, (5) subsistence farms, (6) sugarcane plantations, (7) water and (8) wetland. Although different woody and herbaceous species were present in different areas of the floodplain, species-level classification was not possible because of heterogeneous distributions and the inability of Landsat imagery's coarse 30- m spatial resolution (C-res) to discriminate sub-pixel-sized cover types. C-res misclassification occurs when a single pixel represents an integration of many smaller image objects that do not correspond to their real-world appearance. To overcome this limitation, broad information classes were created by merging field-observed features with close resemblance into contiguous cover types. For example, tree-size specimens of *Ficus sycomorus* (sycamore fig), *Hibiscus tilliaceus* (lagoon hibiscus), and other woody species that are common in floodplain wetland areas (van Deventer et al., 2017) were combined into a forest. This information was then segregated into two classes with 2/3 of the information compiled for each thematic class being reserved for supervised classification and the remaining 1/3 being reserved for classification accuracy assessment.

3.2.3. Image compilation and pre-processing

Pre-processing of the Landsat images in our database was performed in ENVI 5.4. The images were first clipped to provide footprint coverage of the study area. This was followed by using the layer-stack tool to select bands namely blue, green, red, near-infrared, short wave infrared and thermal infrared from the TM and ETM images and bands blue, green, red, near-infrared, short wave infrared 1 and short wave infrared 2 from the Landsat OLI image. Because the Landsat scenes were obtained in digital number (DN) format, they had to be converted to top-of-atmosphere (TOA) spectral radiances, which was accomplished using FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes), which is provided as a plug-in to ENVI 5.4. Thereafter, the same software's projection and transformation toolset was used to re-project all images to Universal Transverse Mercator zone 36 S. Since the Landsat scenes acquired after May 2003 have scan-line errors (stripes), the 2004 and 2008 images were corrected using the Landsat two-band gap-fill method provided in ENVI. Specific details on how the method works are provided elsewhere (Yin et al., 2017). Table 3.1 describes the temporal sequencing and characteristics of the Landsat images that were used.

Table 3.1. Temporal sequencing and characteristics of the images that were used.

Acquisition date	Scene product ID	Path/Row	Cloud cover (%)	Spatial resolution (m)	Quality rating
11/10/1997	LT51670801997284JSA00	167/080	25	30	*9
16/06/2001	LT51670802001167JSA00	167/080	0.00	30	9
21/04/2004	LT51670802004112JSA00	167/080	0.00	30	9
07/09/2008	LT51670802008251JSA00	167/080	0.00	30	9
21/05/2012	LE71670802012142ASN00	167/080	0.00	30	9
19/01/2017	LC81670802017019LGN01	167/080	0.01	30	9

*Image quality as rated by the USGS: 9 = excellent, 7–8 = good, 5–6=fair,1–2 = extremely poor. * This image was assigned a quality rating of 9 because the recorded 25% cloud cover did not obscure any part of the study area.*

3.2.4. Segmentation and image classification

We employed a multiresolution GEOBIA approach to segment images, which were then classified using a supervised SVM technique. Segmentation is the partitioning of an image into discrete non-overlapping units based on specific criteria (Hay et al., 2005). It is a bottom-up technique in which individual pixels are iteratively merged into larger objects (Baatz and Schäpe, 2000). This grouping increases the discrimination of spectrally similar land-cover types by using texture, shape and context features to determine the creation of objects from individual pixels (Burnett and Blaschke, 2003). There is no single perfect algorithm that is appropriate for all images (Muñoz-Huerta et al., 2013) In this study, multiresolution segmentation (MRS) in eCognition was preferred following recommendations provided by (Marpu et al., 2010). The MRS is a widely recommended technique for image segmentation, in which the size of segmented objects is controlled by user-defined scale parameters (Anders et al., 2011) whose selection is based on iterative screening and thresholding (Belgiu and Drăguţ, 2014). This segmentation was performed by weighting all bands 1 except the red and near-infrared, which were weighted 2 in order to discriminate vegetated surfaces. The scale parameter was kept at 50. The shape and compactness parameters were both set at 0.5 (Chen et al., 2012) (because the relationships of the spectrum versus the shape and compactness versus smoothness were unknown. The images that were produced from these segmentation procedures were then subjected to supervised classification by using the 60% of ground truth that was reserved for this purpose during field investigation. In performing the classifications, the number of training pixels was determined by reference to guidelines provided in the literature. Some authors suggest a minimum of 50 training pixels/class if the area covered is 500 km^2 and the number of classes is >12 (Bharatkar and Patel, 2013) while others suggest 30 pixels/class without providing limits on the number of classes or the size of the area covered (Mui et al., 2015).

Sample selection: Because the total number of classes in our study was eight and the area covered was <500 km^2 (19 000 hectares = 190 km^2), we decided to use the intermediate 30 pixels/class suggested by Mui et al. (2015). This translates into a recommended window of 6 × 5 pixels at Landsat's 30-m resolution (Lu and Weng, 2007, Mather and Koch, 2011, Myburgh and Van Niekerk, 2013). However, there were exceptions with classes that covered small proportions of the scenes (i.e. wetlands and grassland) because of MRS's ability to sample classes with spatial coverages below the specified window of 6 × 5 pixels. Sample objects were trained by supplementing field-compiled information with collateral ground truth from Google Earth images and contextual information that was obtained from (1) prior knowledge of the tone, shape and texture appearance of features like water and cultivated land-holdings; and (2) habitat preferences of individual vegetation species. From these examples, water is known to be irregularly shaped while cultivated plots usually have rectangular uniform appearances, and herbaceous species like *Cyperus papyrus*, *Phragmites mauritianus* and *Phragmites australis* were expected in the permanently flooded wetland areas. This additional information boosted the reliability of signature extraction because of the established usefulness of contextual information in aiding the minimisation of classification errors (Kalra et al., 2013). To enhance the accuracy of our classifications, SVM was selected to classify the images because of its superiority over conventional classification approaches (Oommen et al., 2008). SVM is a non-parametric algorithmic machine learning classification technique that is trained to find the optimal classification hyperplane by minimising the upper bounds of classification errors (Cortes and Vapnik, 1995, Mashao, 2004). In this study, SVM implementation was performed using the radial basis function (RBF) kernel as recommended by Hsu et al. (2003), without altering its default parameters on kernel function (0.143), penalty (100), pyramid levels (0) or classification probability threshold (0).

3.2.5. Classification accuracy assessment of the LULC classes

Classification accuracy assessment (CLACASS) is a common quantitative method that applies an error matrix derived from independent reference data sets (Stehman, 2000, Foody, 2002) to assess the quality of classified map outputs (Congalton and Green, 2008, Mui et al., 2015). In this study, CLACASS was accomplished by calculating overall accuracies and kappa coefficients (K) following procedures suggested by Campbell (2002) and by Congalton and Green (2008). Hamandawana (2012) provides an illustrated explanation of how these statistics can be calculated. Table 3.2 shows the overall percentage of accuracies and K coefficients that were obtained for each of the six map outputs. Even though there have been ongoing discussions about the meaninglessness of the Kappa index in terms of accuracy Pontius Jr and Millones (2011), it was still included in this analysis of this chapter.

Table 3.2. Overall accuracy for each satellite image.

Image	Overall accuracy (%)	Kappa Coefficient
1997	82	0.80
2001	81	0.79
2004	79	0.76
2008	84	0.82
2012	83	0.80
2017	88	0.86
Average	**83**	**0.81**

In Table 3.2, kappa values are interpreted as follows: (1) values ≥0.75 indicate excellent agreement beyond chance, (2) values ranging from ≥0.4 to <0.75 indicate fair to a good agreement beyond chance, and (3) values <0.4 indicate poor agreement beyond chance (Tana et al., 2013).

3.2.6. Object-based change detection analysis

After determining the accuracies of our map outputs, object-based change detection (OBCD) (Blaschke, 2005) was performed to quantify the changes in LULC in order to investigate observed patterns in spatial distributions of wetlands for the five-time slices (1997–2001, 2001–2004, 2004–2008, 2008–2012 and 2012–2017) between 1997 and 2017. The change detection analysis revealed and quantified expansion, contraction or no change in specific land cover classes relative to each other. This characterisation was preferred because apart from being one of the most commonly used, it allows the detection of transitional "from-to" changes in individual cover types (Yang and Lo, 2002, Yuan et al., 2005). We used this procedure to produce the initial map for 1997 and five change-detection maps for the above-listed time slices by performing post-classification comparisons in ArcGIS 10.6. Thereafter, these maps were overlaid to produce a matrix table that summarised all time-series in the 20 years between 1997 to 2017. Paired t-tests were then performed to determine whether there were significant differences in changes among agriculture, bare land and harvested fields, plantations, forest, sugarcane farms, wetlands, and subsistence farms.

3.3. RESULTS

Results of this investigation are presented in the form of (1) a table that summarises percentage compositions and percentage changes in the LULC types that were mapped from Landsat images (Table 3.3); (2) maps that show spatial distributions of these cover types (Figure 3.2); and (3) a graph that shows their percentage compositions from 1997 to 2017 (Figure 3.3).

Table 3.3. Temporal sequencing and characteristics of the images that were used.

Cover type	Percentage composition						Percentage change					
	1997	2001	2004	2008	2012	2017	1997-2001	2001-2004	2004-2008	2008-2012	2012-2017	1997-2017
BHF	23.01	20.49	24.67	32.80	38.65	25.56	-2.52	4.18	8.14	5.85	-13.09	2.55
FO	8.09	7.85	8.89	3.86	6.93	4.28	-0.24	1.04	-5.03	3.07	-2.65	-3.81
GR	4.45	5.90	6.47	2.45	6.45	6.60	1.45	0.57	-4.02	4.00	0.15	2.15
PL	12.67	16.87	16.63	9.61	14.46	7.25	4.21	-0.24	-7.02	4.85	-7.21	-5.42
SGF	27.52	28.95	25.03	30.36	22.22	45.63	1.43	-3.92	5.33	-8.13	23.41	18.11
WA	9.09	10.47	9.85	6.73	7.89	9.20	1.38	-0.61	-3.12	1.15	1.32	0.11
WE	15.17	9.47	8.46	14.20	3.41	1.49	-5.71	-1.00	5.73	-10.79	-1.92	-13.68
SBF	0.00	0.00	0.00	0.00	4.96	11.80	0.00	0.00	0.00	0.00	6.85	11.8

* Bareland & harvested fields (BHF), forest (FO), grassland (GR), plantations (PL), subsistence farms (SBF), sugarcane farms (SGF), waterbody (WA) and wetlands (WE)

The major long term changes that were observed include (1) a substantial decrease in wetland, by 13.68% ($p < 0.01$), and a marginal decrease in plantations and forest, by 5.42% and 3.81%, respectively; (2) a substantial increase in subsistence farms and sugar cane farms, by 11.8% ($p < 0.0001$) and 18.11% ($p < 0.01$), respectively, and a near-equal marginal increase in bare-land and harvested fields and grassland, by 2.55% and 2.15%, respectively; and (3) a negligible increase in water, by 0.11%.

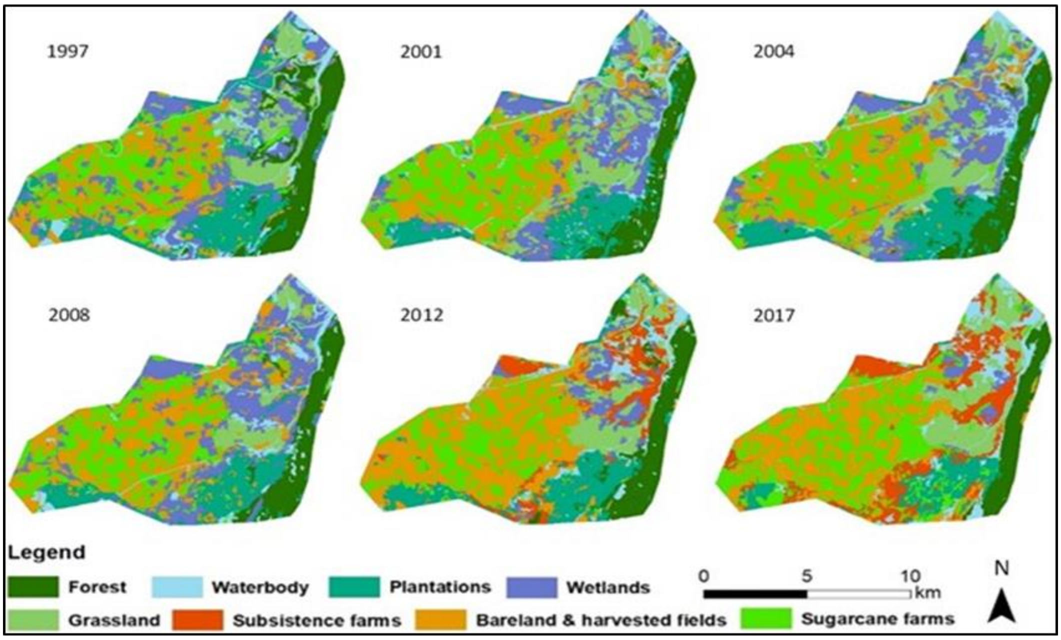
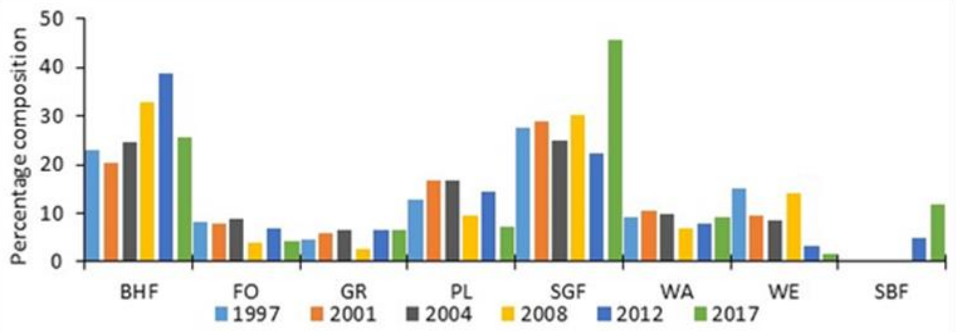


Figure 3.2. Spatial distributions of cover types that were mapped from Landsat images: 1997-2017.



Explanation: BHF = Bare land & harvested fields, FO = forest, GR = grassland, PL = plantations, SGF = sugarcane farms, WA = waterbody, WE = wetlands, SBF = subsistence farms

Figure 3.3. Percentage compositions of cover types that were mapped from Landsat images: 1997-2017.

The most striking observations include an abrupt emergence of subsistence farms in 2012 and a corresponding decrease in wetland areas. All cover types except subsistence farms exhibited periodic variations. The greatest long-term decrease (1997–2017) was in wetland aerial extent (Figure 3.2), which persistently decreased after 2008 as subsistence farms emerged and expanded rapidly (Figure 3.3).

3.4. DISCUSSION

The main goals of this chapter were to (1) provide a remote sensing-based approach to quantify long-term changes in LULC in the lower UFS over a period of 20 years between 1997 and 2017, (2) ascertain the major drivers of these changes, and (3) provide suggestions on what needs to be done to enhance the sustainability of this ecosystem. Eight LULC types were investigated, mapped and assessed, with subsistence farming only emerging after 2012 (Figure 3.2). Sugarcane farms, bare land and harvested fields, plantations and wetlands were distributed evenly over the whole study area. The observed contraction of wetland between 1997 and 2017 was investigated based on the "from-to" map output that was obtained from the SVM classification (Figure 3.2). The post-classification comparison revealed an expansion of subsistence farms in the final period between 2012 and 2017 and a corresponding decrease in the wetland, with wetland areas that were present in the UFS between 1997 and 2008 gradually disappearing after 2012 as subsistence farmland increased. This observation suggests that the long-term contraction of the wetland was largely the result of an inversely related expansion of subsistence farms.

The major insight from this finding is that GEOBIA is capable of teasing out time-series variations in different LULC types at high levels of detail that surpass what is commonly achievable using traditional supervised classification algorithms. This is because of the technique's ability to use spatial information on shape and texture to improve classification accuracy (Lu and Weng, 2007) in complex and heterogeneous landscapes. An additional strength of this algorithm arises from its inherent capability to reduce errors caused by spatial misregistration, which pixel-based methods are incapable of handling (McDermid et al., 2008). This assertion is supported by findings in which GEOBIA was successfully used to classify Landsat images in several studies that investigated long-term changes in different wetland ecosystems (Ramsey III and Laine, 1997, Munyati, 2000, Baker et al., 2007, Kiage et al., 2007, Tağil, 2007, Carreño et al., 2008, Frohn et al., 2011, Kassawmar et al., 2011, Thomas et al., 2011, Jia et al., 2014). In our investigation, the high average overall accuracy of 82.83%, K = 0.81 achieved by SVM (Table 3.2) demonstrates the ability of our methodology to accurately quantify long-term time-series LULC changes in heterogeneous floodplain ecosystems. This information is crucial for sensitive wetland ecosystems, where accurate maps are required for national biodiversity assessments (NBA), more so because of their widely reported deteriorating ecological conditions (Driver et al., 2012, Skowno et al., 2018). In SA, accurate characterisation of wetlands is more important than ever because they are ecologically vulnerable to climate change (Driver et al., 2012). Apart from providing ecosystem goods and services especially for rural livelihoods (Baker et al., 2006, Adekola and Mitchell, 2011, McCartney et al., 2011), wetlands also play an important role in moderating local weather conditions. Although the average overall accuracy was 82.83%, an overall accuracy of 88%, K = 0.86 was observed for 2017, further demonstrating the ability of our proposed methodology to produce higher levels of accuracy than the standard 85% recommended by other researchers for Landsat-based classifications (Anderson, 1976). Despite Pontius Jr and Millones (2011) opinion that the Kappa index is meaningless, many land use and land cover studies Rwanga and Ndambuki (2017) and Polykretis et al. (2020) still utilize it, hence it was included in this analysis. Comparative studies have also demonstrated that SVM produces superior, or at least comparable results for multispectral and hyperspectral image classifications relative to more commonly used maximum and minimum likelihood classification techniques (Pal and Mather, 2003, Foody and Mathur, 2004, Oommen et al., 2008, Szuster et al., 2011). Uncertainties and errors in change detection results are always present and often attributed to spectral characteristics and artefacts that affect classification overall accuracies. In this study, for example, forests, sugarcane farms and plantations are often easily confused due to similarities in their spectral characteristics. This limitation was adequately addressed by the object-oriented approach, which has demonstrated the ability to reduce most misclassification errors (Immitzer et al., 2012). However, our CRes Landsat data sets failed to detect subsistence farms in the period 1997 and 2008. This was not unexpected because similar findings were obtained elsewhere by Rebelo et al. (2017), exhibiting difficulties using historical Landsat images to produce accurate classifications of heterogeneous wetland cover types. Although these limitations have far-reaching implications, our goal was to quantify LULC and changes thereof to ascertain the major drivers of temporal variations in these cover types. The findings of our investigation point to a substantial 17% expansion of subsistence farms in the 5 years between the 2012 and 2017 periods and an inversely related long-term (1997-2017) decrease in the wetland area by 14% (Table 3.3); thus, it is not unreasonable to conclude that human agency has been one the major drivers of long-term LULC changes in this environment.

These observations are in agreement with Nustad (2015) who reported that smallholder farmers are destroying unique biodiversity in this area, and other studies elsewhere that report wetlands are decreasing because of encroachment by various human resource-use practices, especially crop farming (Davidson, 2014, Gardner et al., 2015, Li et al., 2015). Wetlands in the study area are regarded as the mainstay of local people's livelihoods, with cultivable land being one of the most important resources (Rebelo et al., 2010). Their importance is not only confined to SA. They are widely acknowledged for their life-supporting services in Kenya, where their sustainability is being threatened by inappropriate human practices of resource use (Ajwang'Ondiek et al., 2020). This is a major cause of concern; approximately 62% of all wetland vegetation was lost in Uganda between 2002 and 2014 through the conversion of wetlands to farmland (Isunju, 2016), and as much as 52% of SA's Ga-Mampa wetland was lost to farmland between 1996 and 2004 (Troy et al., 2007).

Significant differences ($p < 0.01$) were observed between wetland and non-natural human-introduced cover types including harvested fields, plantations and sugarcane. This suggests that sizeable proportions of wetland in the UFS are being converted extensively for agricultural activities. As mentioned, the area's population has increased over the past century, with this increase being accompanying by a high unemployment rate (39%). By implication, the wetland aerial extent in the lower UFS is expected to decrease as more land is converted to agriculture in order to increase food production (Wood et al., 2013, Feyissa et al., 2019). The conversion of wetlands to cultivated land can destroy their ecological integrity by disrupting the hydrological cycle and other functional processes (Galbraith et al., 2005).

Preservation of wetland ecosystems is vital for the continued provision of ecosystem services, including habitat for aquatic life, mitigation of floods, providing freshwater during prolonged droughts, supporting groundwater recharge, purifying water from different terrestrial sources, and supporting agriculture by providing fertile soils. However, wetlands continue to be threatened by wide ranging anthropogenic activities and the adverse effects of climate change. Conserving floodplain wetlands in SA and other areas worldwide is a formidable challenge that requires collective efforts. The challenges confronting their sustainability include resource over-extraction by unemployed populations and the negative attitude of farmers towards wetland conservation (Keys and McConnell, 2005, Assessment, 2005).

Despite these problems, the sustainability of wetlands should be safeguarded by embracing sound resource-use practices. However, it is not easy to strike a balance between the conservation of biodiversity and the pressing needs of socio-economic development. Policies, too, aggravate this situation by prescribing regulation without involving local communities. This explains why in this wetland, there is a conflict between state-led conservation agencies and local communities, with the former tending to perpetuate historical tenure insecurities that deprived local communities of access to cultivable land. This has compelled local communities to rely on over-exploitation of the limited resources at their disposal. Similarly, Pimbert and Pretty (1997) and Timmer (2004) reported that the degradation of wetlands tends to be pronounced when the local communities have not been granted secure usufruct rights over the natural resources. Moreover, when few local community members hold legal titles to land, they show little inclination to participate in natural resource conservation initiatives (Pagdee et al., 2006, Rudel, 2006, Le Bel et al., 2011). Community-based wetland management is therefore, recommended. Community involvement in such matters confers a sense of ownership and accountability. This is because local communities develop responsible stewardship if they are included in making decisions that affect their daily operations (Springer and Almeida, 2015).

3.5. CONCLUSION

From the overall research findings, the following conclusions can be drawn. Land-use information for the lower uMfolozi from 1997 to 2017 using Landsat data could be extracted with high accuracy by combining the GEOBIA method and SVM. GEOBIA demonstrated its ability to yield reliable estimates by providing outputs with overall accuracy levels approximating 83%. The dominant change that took place in the study area involved the conversion of wetlands to small-scale farms. In view of this observation, it recommended that community-based natural resource management (CBNRM) needs to be carefully reconsidered and prioritised as one of the potentially viable sustainable management strategies. This approach would (1) give the local communities opportunities to acquire rights to natural resources within their environment, (2) empower them to willingly embrace sustainable resource practices and (3) create viable income-generating opportunities that would go a long way to enhance sustainability by creating employment. Overall, CBNRM would promote wetland conservation by involving local communities in managing their own resources. We conclude by inviting those interested in the sustainability of these ecosystems to build on our initiative by making concerted efforts to fine-tune methodologies that can be used to cost-effectively provide reliable information on the nature, causes and extent of long-term changes in LULC affecting these ecosystems.

CHAPTER 4

Assessing the effects of land use on surface water quality in the lower uMfolozi floodplain system, South Africa

This chapter is based on:

Dlamini, M.; Chirima, G.; Jovanovic, N.; Adam, E. Assessing the effects of land use on surface water quality in the lower uMfolozi floodplain system, South Africa.2021 *Internatioanl. Journal. Environmental. Research. Public Health*, *18*, 561. https://doi.org/10.3390/ijerph18020561.

Abstract

This chapter investigated the impacts of cultivation on water and soil quality in the lower UFS in KwaZulu-Natal province,SA. We did this by assessing seasonal variations in purposefully selected water and soil properties in these two land-use systems. The observed values were statistically analysed by performing Student's paired t-tests to determine seasonal trends in these variables. Results revealed significant seasonal differences in chloride ,sodium concentrations , electrical conductivity (EC) and the sodium adsorption ratio (SAR) with cultivated sites exhibiting higher values. Most of the analyzed chemical parameters were within acceptable limits specified by the South African agricultural-water-quality (SAWQ) water quality guidelines for irrigation except for sodium adsorption ratio (SAR), chloride, sodium, pH, EC and nitrate content in cultivated sites. Quantities of glyphosate, ametryn and imidacloprid could not be measured because they were below detectable limits. The study concludes that most water quality parameters met SAWQ's standards. These results argue for concerted efforts to systematically monitor water and soil quality characteristics in this environment to enhance sustainability by providing timely information for management purposes.

Keywords: crop farming; chemical parameters; soil properties; seasonal variation

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4.1 INTRODUCTION

In southern Africa, wetlands play a significant role in the livelihoods of many people (Verma and Negandhi, 2011, Bhatta et al., 2016). The ability of wetlands to maintain dry season flow provides farmers in semi-arid areas with opportunities to grow crops all-year-round, thereby improving their food security and incomes. Besides crop production, wetlands provide other services that support people's livelihoods such as improving water quality, attenuating floods and climate change regulation (Maltby and Acreman, 2011, Barbier, 2013). Wetlands act as sinks for greenhouse gases such as carbon dioxide, which influence local and regional weather patterns (Moomaw et al., 2018b). They form a critical component of a region's water resources in the interface between aquatic and terrestrial environments, as well as between surface and groundwater systems (Smardon, 2014). Wetland ecosystems are extremely valuable not only because they are highly productive but also because they provide habitats for many wildlife and plant species (Semlitsch, 2000, Smardon, 2014) and non-material benefits such as spiritual enrichment, recreational and aesthetic services (Russi et al., 2013).

Despite the provision of the above valuable services and functions, wetlands are globally among the most threatened ecosystems. As in many parts of the world, the extent of South African wetlands continues to be reduced through conversion to croplands (Gardner et al., 2015). They are also adversely affected by the impacts of water extraction, urbanization, infrastructure development, pollution, poor farming practices, and climate change and variability (Zedler and Kercher, 2005, Finlayson et al., 2006, An et al., 2007, Junk et al., 2013, Russi et al., 2013, Bassi et al., 2014, Capon et al., 2015). In the arid and semi-arid areas, for example, wetlands have been severely degraded through conversion to croplands. This degradation has been aggravated by the persistent loss of ecosystem services, impairment of different functional processes, water quality, and loss of biodiversity. The trade-off between crop production and water quality is one of the most serious and challenging issues in modern agricultural landscapes (Bennett et al., 2009).

One of the main problems associated with wetland water quality management in SA is eutrophication due to nutrient enrichment by agricultural activities (Bwapwa, 2018), the most important of which include agrochemicals that are widely used to increase crop production.

However, the intensive application of agrochemicals can pollute water bodies through nutrient enrichment via surface runoff, leaching and sub-surface flow (McKergow et al., 2003, Munyika et al., 2014, Selemani et al., 2018). Fertilizers and a wide range of different agrochemicals affect the physico-chemical characteristics of soil, surface water and biota (Selemani et al., 2018). Nitrate pollution, for example, is common in agricultural regions throughout the world where eutrophication is increasingly becoming one of the major environmental problems (Matson et al., 1997) with water from farmed areas often exhibiting high nutrient loads (Heathwaite and Johnes, 1996). In these agricultural regions, crop production activities impose severe environmental stresses that affect functional processes in wetland ecosystems by (a) polluting potable water resources, (b) disrupting, natural nutrient cycling processes, soil nutrient retention and carbon sequestration and by (c) reducing biodiversity. In addition, environmental degradation through agricultural-related deforestation can also affect vegetation with irrigation infrastructure aggravating the situation by modifying surface and in-stream flows, infiltration patterns and overall water quantity.

Floodplain wetlands in many parts of the world have been used for agriculture because of their high fertility, which is sustained by flood-driven deposition of natural nutrients. This natural endowment renders wetland ecosystems susceptible to degradation by attracting a wide-ranging of resource extractive practices (Tockner et al., 2008). In SA, most wetlands are confronted by severe threats because of their suitability for agriculture and the numerous ecosystems goods and services they provide (SANBI, 2013). These scenarios are also evident in other African countries, with Nigeria, Rwanda and Ethiopia, for example, going as far as encouraging farmers to cultivate wetlands to mediate drought-induced food shortages (Taiwo, 2013). Although several studies in these countries have reported the importance of wetlands in supporting the production of rice, maize, and various vegetable crops for both subsistence and commercial use (Akpan-Idiok et al., 2001, Ojanuga et al., 2003, Nagabhatla and Brakel, 2010, Taiwo, 2013) their sustainability is being compromised by inappropriate human resource use practices.

The same threats are becoming increasingly evident in the UFS, which is situated in the northern peripheries of SA's KwaZulu-Natal province. This wetland resides in iSimangaliso Wetland Park, which is well known for being, a World Heritage site that has a scenic environmental layout, which supports local communities by attracting wide-ranging tourism activities. The same wetland also supports its inhabitants by sustaining commercial and subsistence crop farming activities. Having recognized the vital importance of this wetland to the livelihoods of local communities in this environment, we decided to assess water quality in this locality to ascertain how human interference is impacting this floodplain ecosystem. This motivation was inspired by a conscious acknowledgement of the fact that comprehensive wetland water quality monitoring is essential because it provides the vital information needed in formulating sound management practices for this threatened wetland ecosystem. In SA, water quality guidelines stipulate the target water quality range (TWQR) for different water use sectors such as agriculture (DWAF, 1996). The TWQR can be defined as the concentration levels at which certain constituents would cause adverse effects on the fitness of water for different consumptive and non-consumptive uses in a manner that does not compromise sustainability (EPA, 2020).

To the best of our knowledge, there is a paucity of long-term water quality datasets on wetlands in SA, although a monitoring protocol exists. Such data help to elucidate what constitutes good and bad water quality concerning anthropogenic activities and the natural environment. Therefore, providing valuable knowledge is important because this helps to inform the formulation of implementable management interventions. This realization prompted us to evaluate the environmental status of the lower UFS based on systematic characterization and assessment of the impacts of surface water discharged from irrigated agriculture on the wetland system's water quality. This evaluation was guided by the hypothesis that cultivated areas have higher concentrations of physico-chemical parameters such as nitrates, electrical conductivity (EC), sodium adsorption ratio (SAR) and other parameters, compared to uncultivated sites. The objectives were, 1) to assess the physico-chemical characteristics of water in the lower UFS wetlands based on South African water quality guidelines for agricultural water use in irrigation, and 2) to evaluate the seasonal impacts of irrigation agriculture on water quality.

4.2. MATERIALS AND METHODS

4.2.1. Study area background

The UFS is situated in the vicinity of St Lucia, a town located in uMkhanyakude District Municipality (28° 22′ S and 32° 25′ E), KwaZulu-Natal Province, SA (Figure 4.1).

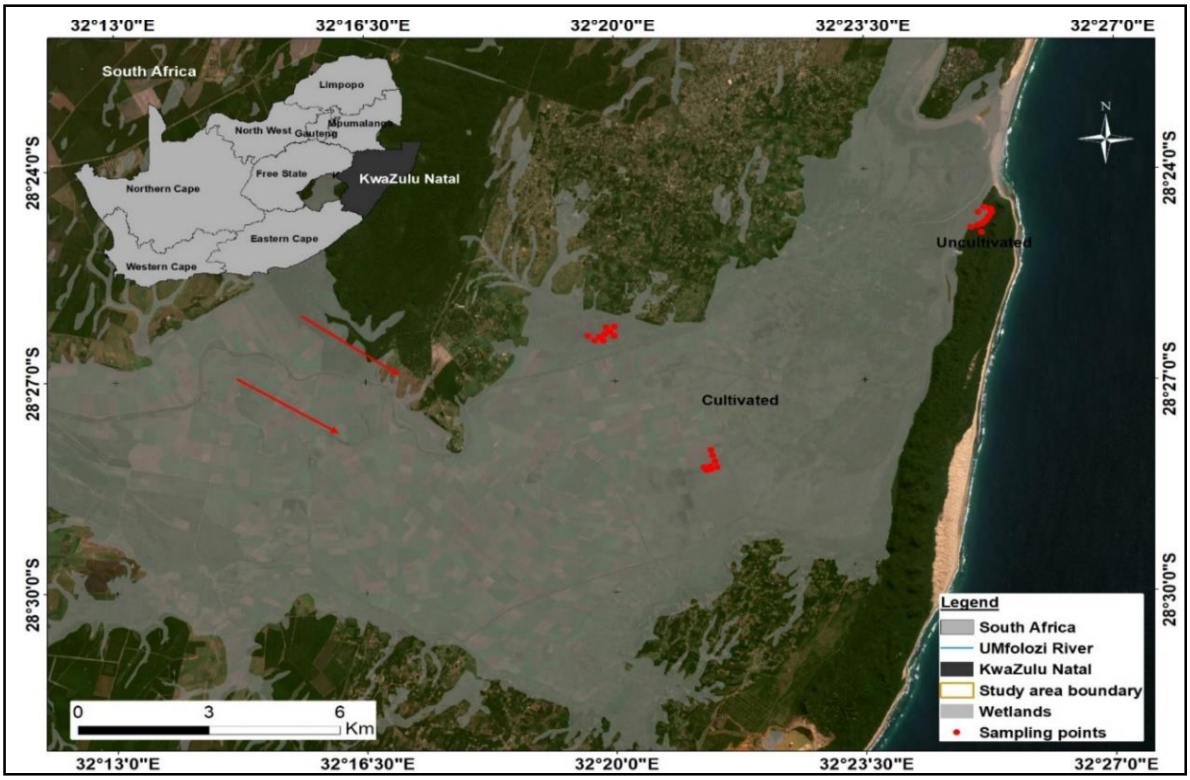


Figure 4.1. Study area: The uMfolozi floodplain in uMkhanyakude District Municipality. Red arrows show west to east water flow towards the Indian Ocean**.**

This municipality is one of the poorest and most underdeveloped local authorities in SA (Hansen et al., 2015. The UFS is approximately 19,000 hectares in extent (Hansen et al., 2015). Physiographically, the floodplain is bound inland by the incised meanders of the uMfolozi River. The river cuts through rhyolite rock of the Lebombo to the east by the Indian Ocean, to the south and north by Zululand and Maputaland formation rocks (Ellery et al., 2008). Maputaland, which covers most of the study area, comprises calcarenite, clayey sand, limestone and conglomerate. The region experiences a subtropical climate, with large seasonal variations in annual precipitation ranging between 671 and 1002 mm (Garden, 2008). Rainfall in the region of the coastal UFS averages 1090 mm/annum, declining to 645 mm/annum towards the upper catchment boundary. The region experiences summer rainfall, with January and March being the wettest months (Morgenthal et al., 2006). Table 4.1 shows the monthly average rainfall and maximum temperatures for the 2017 and 2018 periods. Therefore, the inundation of the floodplain is seasonal. Potential evapotranspiration on the floodplain is 1805 mm/annum (Schulze, 1997).

Table 4.1. Average monthly rainfall and maximum temperature for the 2017 and 2018 periods in Riverview, Mtubabatuba, KwaZulu-Natal weather station.

Months	Monthly average rainfall (mm)		Monthly maximum temperature (°C)	
	2017	2018	2017	2018
JAN	126.6	29.4	30	31
FEB	179.2	140.4	30.3	29.3
MAR	46.6	66.4	30.6	30.2
APR	18.2	59.6	28.8	28.9
MAY	314	205.4	27.4	26.5
JUN	36.2	40	25.7	25.4
JUL	10.8	3	25.4	25
AUG	3.8	48.4	25.7	25.3
SEP	39.4	40.6	27.3	27.6
OCT	64.4	96	27.5	26.7
NOV	122	40.2	28.1	27.6
DEC	87.6	107.4	28.6	29.3

Source: https://www.weathersa.co.za/

The surface hydrology is comprised of two major tributaries, the Black uMfolozi which originates in the north at elevations approximating 1500 m a.m.s.l. and the more southerly White uMfolozi which arises at an altitude of ~1620 m. The two rivers join approximately 50 km west of the uMfolozi River's mouth into the sea. The dominant vegetation types in the floodplain system include *Cyperus papyrus*, *Phragmites mauritianus*, *Phragmites australis* and *Ficus trichopoda*. The uMfolozi River has a highly variable flow regime (Garden, 2008), characterized by a low base-flow and a few large but brief floods each year. Floods are a feature of the river and they have a profound influence on the geomorphology of the floodplain (Grenfell and Ellery, 2009). Although infrequent and of short duration, these floods carry much of the annual river flow and it is during these times that most of the geomorphologic changes occur.

The major source of livelihood for the majority of people in this area is agriculture with sugarcane being the primary crop produced by most farmers. The clearance of land for the cultivation of sugarcane and commercial forestry dates back to 1911 (Keddy, 2010). By 1960, more than 50% of the floodplain had been converted to sugarcane farms whose establishment was made possible by the construction of canals, diversion of the uMfolozi River and the clearing of indigenous wetland vegetation (Vivier et al., 2010, Hansen et al., 2015). The floodplain also supports subsistence farming of other crops wherein the dominant ones include sweet potato (*Ipomoea batatas)*, banana (*Musa acuminate)*, and *amadumbe* (*Colocasia esculenta*). Land conversion takes place through direct clearance of vegetation by using the traditional slash and burn techniques, which date back to 2006. In 2009 the herbicide (imidacloprid) was first introduced in the study area (Searle, 2013) to suppress the pest called sugarcane Thrip (*Fulmekiola serrata*) which was identified in 2005 (Leslie and Moodley, 2009). In terms of fertilizer applications, sugarcane requires substantial quantities of nitrogen (N) and potassium (K) for optimum yields with N being applied through direct injection into the soil to depths of ~200 mm. These agricultural activities make the floodplain susceptible to pollution which compromises the livelihoods of local communities by adversely impacting the ecological integrity and health of the entire system.

4.2.2. Data collection

Three study sites (two with cultivation and one pristine uncultivated site) were selected in the floodplain wetland area (Figure 4.1). The two cultivated sites were approximately 3 km apart and are used for commercial and subsistence crop farming. The commercial site comprised sugarcane while the subsistence site consisted of sweet potato, amadumbe and banana. The sweet potato, amadumbe and banana are grown on land that is temporarily flooded. Subsistence crops are not irrigated while sugarcane is supplemented with sprinkler irrigation using water from the uMfolozi River. The uncultivated site (control site) was situated in Maphelane Nature Reserve (where there is controlled access), approximately 8 km away from the cultivated plots and closer to the ocean. Sampling sites were selected based on land use as well as on accessibility, safety, and the presence of surface water.

Four site visits were undertaken during 2017 and 2018. Surface water samples were selected and collected randomly based on the anthropogenic activity. Water samples were taken between 8 AM and 1 PM (Chigor et al., 2013) at a distance of ±100 m intervals. Water depth was 0.85 m during the wet season and ± 0.50 m during the dry season. The number of samples collected depended on the presence of surface water during the wet (March) and dry (July) periods. Therefore, the number of samples ranged between 13 and 17 from the cultivated sites and 10 from the uncultivated site. Water samples were collected using 100 mℓ acid pre-treated sampling bottles at every sampling point (APHA, 2005). Temperature, pH and electrical conductivity (EC) were measured on-site using a handheld multi-parameter, YSI professional plus (APHA, 2005). Accuracies for each probe were according to YSI Incorporated, 2011 standards (conductivity: 0.5% or 0.001 mS/cm, pH: ±0.2 and temperature: ±0.2 °C). Global positioning system (GPS) coordinates of each sampling point were recorded so that sampling could take place at the same points during subsequent field trips.

Soil samples were collected at the same locations as water samples in March and July of 2017 and 2018. The samples were collected to a depth of 50 cm at intervals of 0–10, 10–20, 20–30, 30–40 and 40–50 cm using a soil auger and following procedures suggested by Polese et al. (2002). Soil samples were mixed at each depth to form one composite sample. They were then transported to the laboratories and air-dried at room temperature for the chemical analyses. Once-off soil samples (July 2018) were collected from the same locations mentioned above for herbicide analysis.

4.2.3. Water and soil lab analyses

The water and soil properties were determined in the laboratory (chemical analyses) and used to assess the extent of environmental degradation due to agriculture via comparing cultivated and uncultivated sites. The concentrations of cations were determined by the ion chromatography method with a conductivity detector (Shimadzu, Tokyo, Japan). The environmental protection agency (EPA) method was used (Pfaff, 1993) to determine anion concentrations. A volume of 2–3 mL was injected into an ion chromatograph where ions of interest were separated and measured using a guard and the analytical column. Both anions and cations were determined using an ICPE-9000 spectrometer. Anions detection limits were as follows: boron (0.01), fluoride (0.030), nitrite (0.022), nitrate (0.060) and phosphate (0.109).

Soil pH was measured in a 1:2.5 soil/water ratio using a glass rod pH meter calibrated using buffer solutions of pH 4, 7 and 8. Cation exchange capacity (CEC) was determined following the extraction method where soil samples were also saturated with ammonium acetate buffered at pH 7 to displace the exchangeable bases (Silva et al., 2010). To determine N-NO_{3^-}, 1M HCl was used to extract nitrate from the soil mass to volume ratio of 1:10 and determined with a flow analyzer. The soil was saturated with deionized water for 8 hours and the filtrate analyzed for alkalinity and salinity. To analyze the organic matter, a known sample mass was dried at 100°C for 8 hours. The sample was then ashed at 6000°C and the organic matter percentage was calculated by employing loss on ignition (LOI). A CNS-2000 analyzer (Leco Corporation, Michigan, United States of America, USA) was used for total carbon+nitrogen determination in soil samples, based on the dry combustion principle. Soil samples were analyzed at combustion temperatures of 950°C (Wright and Bailey, 2001). The Bouyoucos-hydrometer method Orhan and Kılınç (2020) was used for soil texture determination.

Glyphosate, imidachloprid and ametryn were quantified using standard lab methods (SABS, 2019) with a liquid chromatography-mass spectrometer (LC-MS) while ametryn was quantified using a gas chromatography-mass spectrometer (GC-MS). The limit of quantification (LOQ) for imidachloprid and ametryn was 0.01 mg/kg, and 0.05 mg/kg for glyphosate.

4.2.4. Statistical analysis

Data were compared between cultivated and uncultivated sites to evaluate the impact of agriculture on soil and water quality. In addition, data collected in different seasons (dry and wet) were compared to determine seasonal variability of water and soil quality. Paired t-tests were performed in IBM SPSS Statistics version 26 (SPSS Inc, Chicago, USA) to determine if differences in water and soil parameters were statistically significant. The observed water parameters were compared to the South African water quality guidelines for agricultural water use in irrigation (DWAF, 1996) to determine the fitness of the wetland’s water for use. For this purpose, field recorded water parameters were compared to the accepted limits for each parameter (Table 4.2). The scientific information underpinning the specification of pollution limits can be found in (DWAF, 1996). Seasonal data for EC and sodium adsorption ratios (SAR) provided by Koegelenberg (2004)were ranked against the irrigation water classes for EC and SAR provided in Table 4.3. Hypothesis testing approaches (t-tests) were performed to determine the significance of deviations between field parameters that were measured to the South African water quality (SAWQ) guidelines for irrigation.

Table 4.2. SAWQ guidelines accepted limits for agricultural use: irrigation (DWAF, 1996).

Parameters	Accepted Limits Guideline
Ammonium (mg/l))	5
Boron (mg/l)	0.5
Chloride (mg/l)	100
Fluoride (mg/l)	2
Nitrate (mg/l)	5
Nitrite (mg/l)	5
pH	8.4
SAR	2
Sodium (mg/l)	70
EC (mS/m)	40

Table 4.3. Irrigation water classes for electrical conductivity and sodium adsorption ratio (Koegelenberg, 2004).

Constituents	Fitness for Use			
	Good	Fair	Marginal	Unacceptable
EC (mS/m)	0–40	40–90	90–270	>270
SAR	0–1.5	1.5–3.0	3.0–5.0	>5.0

4.3. RESULTS

4.3.1. Comparison of Water Quality Analyses between Cultivated and Uncultivated Sites and Seasonal Dynamics

The results of water quality analyses for cultivated and uncultivated are presented in the form of a table (Table 4.4).

Table 4.4. Water quality parameters based on the land use (cultivated and uncultivated) for 2017 and 2018 dry and wet periods.

Variables	Statistics	WET SEASON CULTIVATED			WET SEASON UNCULTIVATED			DRY SEASON CULTIVATED			DRY SEASON UNCULTIVATED		
		* Mar 17–** Mar 18 cult			* Mar 17–**Mar 18 uncult			* Jul 17–** Jul 18 cult			* Jul 17–** Jul 18 uncult		
		* N = 17	** N = 17	Avg	* N = 10	** N = 10	Avg	* N = 14	** N = 13	Avg	* N = 10	** N = 10	Avg
NH_4^+ (mg/L)	Mean	0.24	0.31	0.28	0.36	0.34	0.33	0.06	0.08	0.07	0.17	0.04	0.105
	Maximum	0.93	0.79	0.86	0.70	1.66	1.2	0.30	0.27	0.29	0.96	0.12	0.56
	Minimum	0.08	0.08	0.08	0.15	0.05	0.1	0.01	0.01	0.01	0.01	0.02	0.015
	Median	0.15	0.27	0.225	0.34	0.07	0.21	0.05	0.04	0.05	0.08	0.02	0.05
	SD	0.21	0.21	0.21	0.17	0.57	0.38	0.07	0.09	0.08	0.30	0.04	0.17
	p-value *		0.163						0.186				

	p*-value *		0.006						0.006				
B(mg/L)	Mean	0.05	0.07	0.06	0.02	0.06	0.04	0.04	< 0.01	0.025	0.04	< 0.01	0.025
	Maximum	0.15	0.10	0.125	0.04	0.07	0.06	0.05	< 0.01	0.03	0.06	< 0.01	0.035
	Minimum	0.03	0.05	0.04	0.00	0.03	0.02	0.02	< 0.01	0.015	0.02	< 0.01	0.015
	Median	0.04	0.06	0.05	0.02	0.06	0.04	0.04	< 0.01	0.025	0.04	< 0.01	0.201
	SD	0.03	0.01	0.02	0.02	0.01	0.02	0.01	< 0.01	0.01	0.01	< 0.01	0.01
	***p*-value ***		0.108						0.359			-	
	p*-value *		0.807						0.000			-	
Cl^- (mg/L)	Mean	310.36	435.36	265.28	30.07	67.30	38.99	397.71	273.88	335.8	172.87	166.61	169.74
	Maximum	417.18	857.59	373.1	50.98	84.50	52.90	622.49	303.30	462.9	221.82	183.78	202.8
	Minimum	26.4	337.43	109.2	20.27	40.14	27.75	188.91	159.12	174	123.70	123.20	123.45
	Median	349.5	377.26	275.75	23.9	71.13	36.85	379.85	284.05	332	179.68	170.66	175.2
	SD	107.70	134.55	121,13	12.63	16.66	14.65	153.83	41.24	97.5	32.73	18.26	25.495
	***p*-value ***		0.020						0.020				
	p*-value *		0.004						0.012				
NO_3- (mg/L)	Mean	1.57	0.83	1.19	0.18	0.20	0.19	1.05	< 0.060	0.555	0.71	< 0.060	0.385
	Maximum	5.96	3.27	4.49	0.36	0.50	0.43	3.44	< 0.060	1.75	2.88	< 0.060	1.471
	Minimum	0.05	0	0.03	0.06	0.06	0.06	0.10	< 0.060	0.08	0.14	< 0.060	0.1
	Median	0.67	0.65	0.60	0.16	0.09	0.15	0.57	< 0.060	0.315	0.37	< 0.060	0.215
	SD	1.88	0.78	1.33	0.10	0.18	0.14	1.12	< 0.060	0.59	0.88	< 0.060	0.47
	***p*-value ***		0.135						0.056			-	
	p*-value *		0.798						0.001			-	
NO_2− (mg/L)	Mean	8.69	< 0.022	4.46	1.05	0.23	2.76	< 0.022	< 0.022	0.022	< 0.022	< 0.022	0.022
	Maximum	24.10	< 0.022	12.16	2.77	0.93	1.85	< 0.022	< 0.022	0.022	< 0.022	< 0.022	0.022
	Minimum	0	< 0.022	0.111	0	0.00	0.00	< 0.022	< 0.022	0.022	< 0.022	< 0.022	0.022
	Median	9.90	< 0.022	5.061	0.85	0.00	0.43	< 0.022	< 0.022	0.022	< 0.022	< 0.022	0.022
	SD	7.60	< 0.022	3.91	1.16	0.35	0.76	< 0.022	< 0.022	0.022	< 0.022	< 0.022	0.022
	***p*-value ***		0.085						0.000				
	p*-value *		0.001						0.187				
PO_4^{3-}(mg/L)	Mean	0.93	1.46	1.17	0.15	0.49	0.33	2.05	< 0.109	1.08	1.90	< 0.109	1.00
	Maximum	8.01	4.25	6.15	0.24	0.87	0.57	4.00	< 0.109	2.06	3.65	< 0.109	1.88
	Minimum	0.00	0.00	0.00	0.05	0.18	0.13	0.86	< 0.109	0.49	0.43	< 0.109	0.27
	Median	0.12	1.26	0.58	0.17	0.46	0.34	1.71	< 0.109	0.91	2.12	< 0.109	1.11
	SD	2.05	1.44	1.75	0.07	0.24	0.16	0.85	< 0.109	0.48	0.99	< 0.109	0.55
	***p*-value ***		0.189						0.621			-	
	p*-value *		0.002						0.000				
F (mg/L)	Mean	0.53	0.56	0.55	0.64	0.58	0.61	0.44	< 0.030	0.24	0.28	< 0.030	0.16
	Maximum	1.24	1.22	1.21	0.80	0.76	0.78	1.26	< 0.030	0.65	0.41	< 0.030	0.22
	Minimum	0.21	0.27	0.24	0.43	0.41	0.41	0.15	< 0.030	0.09	0.13	< 0.030	0.08
	Median	0.50	0.51	0.51	0.63	0.58	0.59	0.35	< 0.030	0.19	0.31	< 0.030	0.17
	SD	0.29	0.26	0.28	0.12	0.13	0.13	0.28	< 0.030	0.16	0.10	< 0.030	0.07
	***p*-value ***		0.629						0.180			-	
	p*-value *		0.065						0.000				
pH	Mean	6.69	8.19	7.44	6.64	7.36	7	8.11	7.93	7.15	7.74	7.74	7.20
	Maximum	6.89	9.20	8.01	6.86	7.85	7.33	8.58	8.39	7.75	8.60	7.92	7.80
	Minimum	6.46	7.33	6.90	6.43	7.13	6.77	7.59	7.59	6.55	7.25	7.58	6.80
	Median	6.44	7.94	7.19	6.63	7.28	6.96	7.94	7.94	7.25	7.64	7.73	7.20
	SD	0.15	0.53	0.34	0.19	0.22	0.21	0.27	0.22	0.25	0.46	0.13	0.30
	***p*-value ***		0.038						0.305				
	p*-value *		0.100						0.048				
SAR	Mean	3.71	5.24	4.51	1.26	1.97	1.62	3.86	3.07	3.47	2.88	2.58	2.73
	Maximum	4.77	6.96	5.85	1.60	2.24	1.90	5.05	4.50	4.80	3.27	2.97	3.12
	Minimum	1.45	4.62	3.05	0.97	1.51	1.235	2.18	1.80	2.00	2.25	1.41	1.83
	Median	3.91	4.83	4.45	1.27	2.06	1.7	4.08	2.90	3.50	2.97	3.73	3.35
	SD	0.82	0.74	0.78	0.21	0.26	0.24	0.91	0.80	0.86	0.35	0.50	0.43
	***p*-value ***		0.014						0.009				
	p*-value *		0.014						0.020				
Na (mg/L)	Mean	132.63	216.73	176.42	27.84	47.90	37.87	158.67	107.1	132.90	83.57	73.65	78.65

	Maximum	192.27	329	260.65	35.85	54.90	45.4	252	159	205.50	102	86.80	94.4
	Minimum	27.74	192	109.85	24.66	35.20	29.95	78.40	52.80	65.60	67.50	38.50	53
	Median	142.87	201	172.45	25.59	49.80	37.4	162	101.50	131.75	83.20	76.25	79.85
	SD	41.17	36.16	38.67	3.88	7.37	5.63	61.32	29.60	45.46	10.46	14.82	12.64i
	***p*-value ***		0.017						0.033				
	p*-value *		0.031						0.014				
	Mean	44.20	150.87	97.54	9.13	43.88	26.51	92.92	94.44	93.65	74.07	66.84	70.45
	Maximum	54.10	229	141.55	14.20	49	31.6	143.10	119.70	131.40	84.80	72	78.4
	Minimum	28.60	135	81.8	5	38	21.5	52	60.70	56.35	55	54.10	54.55
EC (mS/m)	Median	47.10	143	95.05	9.50	44.50	27	90.50	94.40	92.45	81.60	68.25	74.95
	SD	7.55	23.67	15.61	3.02	4.02	3.52	32.22	13.83	22.92	12.75	5.81	9.28
	***p*-value ***		0.015						0.063				
	p*-value *		0.270						0.011				
	Mean	26.2	-		26.45	-		17.55	16.32	16.50	19.84	16.46	18.18
	Maximum	30	-		29.20	-		24.60	17.60	18.05	24.20	17.40	20.8
	Minimum	24.4	-		24.70	-		13.50	15.60	14.55	16.50	15.60	16.05
Temperature (°C)	Median	26.45	-		26.30	-		17.20	16.05	16.13	19.20	16.60	18
	SD	1.67	-		1.32	-		2.84	0.63	1.74	2.93	0.64	1.79
	***p*-value ***		-			-			0.008				
	p*-value *												

N = number of variables, * Cultivated, ** Uncultivated, *p*-value * (uncultivated vs. cultivated), *p*-value ** (seasonality, wet vs. dry period)

As shown in Table 4.4, chloride showed higher concentrations in cultivated sites (*p*, 0.020) compared to uncultivated sites. A similar pattern was observed for sodium adsorption ratios in both wet and dry periods (*p*, 0.014 and 0.009) with sodium, exhibiting higher values in the cultivated compared to the uncultivated sites (*p*, 0.017 and 0.003). Significant differences were also observed in the wet period for pH (*p*, 0.038) and electrical conductivity (EC) with higher concentrations being associated with the cultivated sites. The remaining parameters (ammonia, phosphate, nitrate and boron) did not show any significant differences between cultivated and uncultivated sites.

A comparison of water quality parameters between the two seasons (wet and dry) was explored. However, due to equipment failure in the field, analysis for pH, EC for March 2018 was done in the laboratory with no results for the temperature of the period. Water recordings indicated a clear seasonal change with an average temperature of 26.45 °C (higher) recorded in the wet summer season and 19.84 °C in the dry winter season. T-tests showed that the concentrations of water quality from the sampling seasons varied among the parameters. Ammonium showed significant differences between the seasons in both cultivated and uncultivated (*p*, 0.006) sites. In both cultivated and uncultivated sites, chloride ($p \leq 0.05$), sodium adsorption ratio ($p \leq 0.05$) and sodium also showed significant differences between the seasons. The significant difference (*p*, 0.011) for EC and pH (*p*, 0.048) between the seasons was observed only in the uncultivated sites.

4.3.2 Comparison of Water Quality with South African Water Quality (SAWQ) Guidelines for Irrigation

Figure 4.2 shows results from a comparative analysis of field derived samples and SAWQ guidelines for irrigation. The results correspond to the mean of the parameters using the error bars from the standard deviation values. Overlaps of the error bars show insignificant differences in parameters between cultivated and uncultivated.

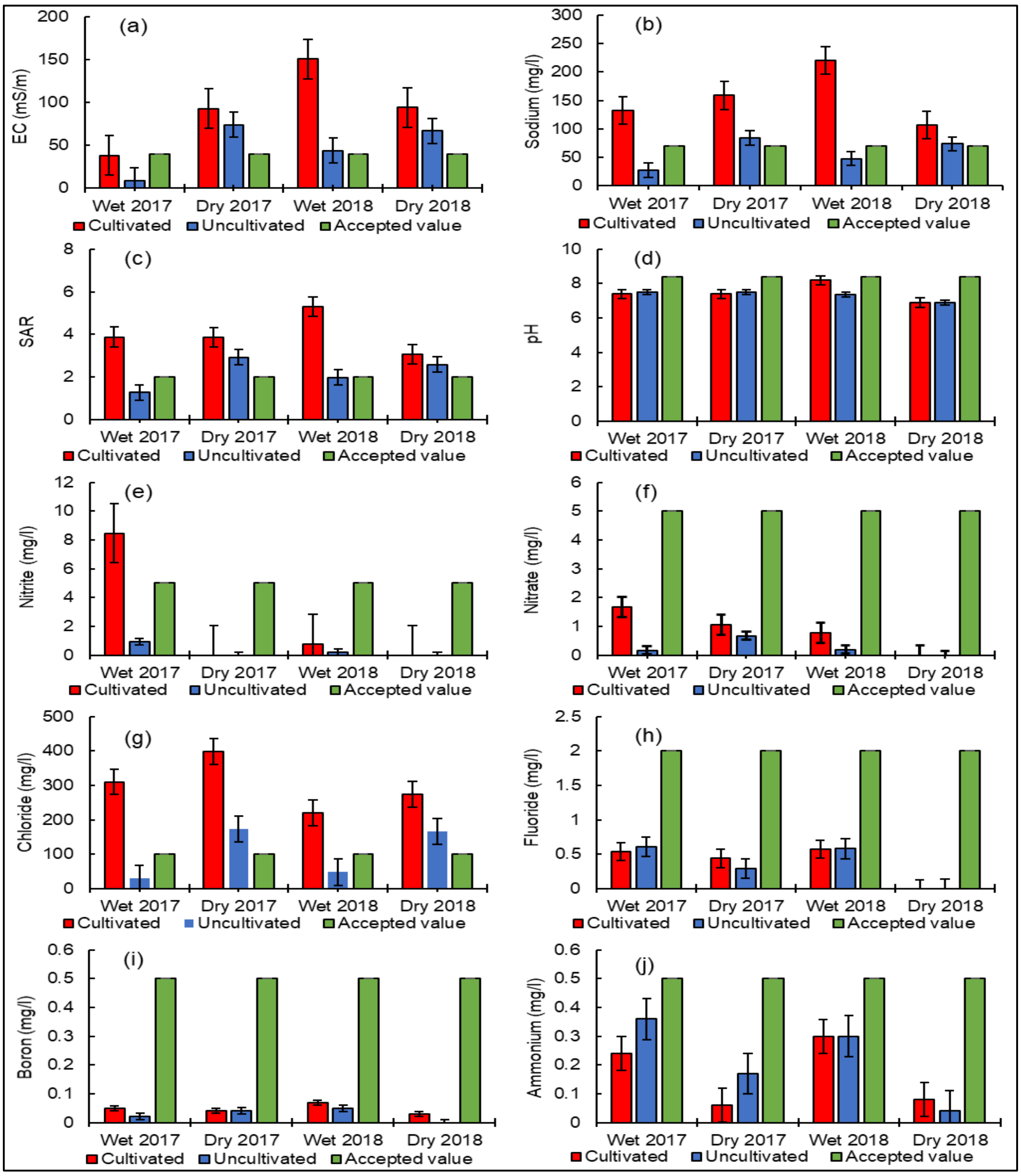


Figure 4.2. Comparison of water quality constituents recorded in wetlands (uncultivated and cultivated) with South African water quality (SAWQ) target values in wet and dry seasons of 2017 and 2018, (a) EC, (b) Na, (c) SAR, (d) pH, (e) NO2−, (f) NO3-, (g) Cl−, (h) F, (i) B and (j) NH_4^+.

As shown in Figure 4.2, the seasonal means of each parameter were compared against SAWQ target concentration levels for agricultural use (irrigation). It should be noted that not all the parameters analyzed in this chapter are found in the SAWQ guidelines and as explained earlier in section 3.1, EC and pH in the wet season of 2018 were measured in the laboratory because the instrument failed during field investigation. Most of the parameters were within the acceptable levels in both the cultivated or uncultivated sites, except for EC, SAR, sodium and chloride. It was observed with 95% confidence that the actual means of ammonium, boron, fluoride, pH, nitrate and nitrite from the fieldwork did not differ significantly from the values in the SAWQ guidelines (Table 4.2). Although nitrite concentrations were within the acceptable limits, a sharp spike of 8.7 mg/L was observed in the wet period in the cultivated site for March 2017, which exceeded the SAWQ guidelines. Nitrite is highly mobile (Rao and Puttanna, 2000), therefore it's high loading from the increased agricultural activities and high rainfall that occurs during wet seasons could be an important factor. As observed from the results, spikes of this nature were not seen for the dry season of the year 2017 and the rest of the study periods.

EC exceeded the target concentrations in July of 2017 and March of 2018 for both uncultivated and cultivated sites. For the periods that exceeded the limits, cultivated samples were more than 50% higher while the uncultivated samples were approximately 40% higher than the SAWQ targets. SAR exceeded the target concentrations for all periods in the cultivated sites, while the exceedance only occurred in the dry season (July) of 2017 and 2018 from the uncultivated site. SAR samples for the cultivated sites were more than 50% higher with less than 50% from the uncultivated site compared to the irrigation targets. Sodium and chloride exceeded the SAWQ guideline limits in cultivated sites for all the study periods. A similar pattern for SAR on sodium and chloride from the uncultivated sites was observed where exceedance only occurred in the dry periods. Sodium samples from the cultivated sites were two to three times higher and less than 10% higher from the uncultivated site compared to SAWQ guidelines limits. The chloride content in samples from the cultivated sites was three to four times higher whereas in the uncultivated sites they were almost two times higher than the SAWQ limits.

4.3.3. Cultivation and soil quality.

Table 4.5 shows the results of clay and sand content analysis.

Table 4.5. Soil texture for cultivated and uncultivated wetland sites.

Texture	Mean (%) ± Std. Deviation		p-value
	Cultivated	Uncultivated	
Sand	13.43 ± 15.32	73.63 ± 15.32	0.03
Silt	41.97 ± 10.42	17.02 ± 15.31	0.51
Clay	44.60 ± 14.58	9.35 ± 7.88	0.04

Clay and sand content of the soil samples analyzed using an independent two-sample t-test from uncultivated and cultivated sites were significantly different ($p \leq 0.05$), while silt content was not significantly different (Table 4.5). The cultivated site had a higher mean value of clay (44.60) than an uncultivated site (9.35). On the contrary, the cultivated site had a lower mean value of sand (13.43) than an uncultivated site (73.63). Considering the location of the uncultivated site in the vicinity of sand dune depositions (Figure 4.1), the sand content was expected to be high and the clay content to be low.In terms of the herbicides analysis, no detection of glyphosate, imidacloprid, ametryn in the soil samples was observed as all the herbicides were below the limit of quantification mentioned in section 4.2.3.

Table 4.6 shows results of soil physico-chemical analysis of samples that were obtained from cultivated and uncultivated sites.

Table 4.6. Soil physico-chemical properties of cultivated and uncultivated sites.

Parameters	Statistics	March 2017		July 2017		March 2018		July 2018	
		Cult	Uncult	Cult	Uncult	Cult	Uncult	Cult	Uncult
EC (mS/m)	N	17	10	14	10	17	10	13	10
	Mean	57.4	31.7	14.2	11.2	25	19.8	27.4	16.5
	Maximum	84	85	19	22	44	19.8	84	20
	Minimum	11	12	9	2	16	3	2	14
	Median	62	23	14	11.5	22.5	19.8	17.3	17.5
	SD	21.1	23.9	2.6	6.8	8.2	11.1	29.8	2.3
	p-value	0.30		0.54		0.33		<0.01	
CEC (cmol(+)/kg)	N	17	10	14	10	17	10	13	10
	Mean	25.9	31.2	29.7	25.9	19.8	32.8	22.1	37.8
	Maximum	43.2	44.2	37.8	36.8	19.8	39.9	32.4	49.6
	Minimum	3.1	9.2	11.7	12.9	3	15.5	5.6	31.4
	Median	27.5	32.9	30.7	28.6	19.8	33.6	30.8	36.2

	SD	13.9	11.4	7.1	8.3	11.1	6.9	7.1	5.5
	p-value	0.98		0.65		0.83		0.69	
pH	N	-	-	-	-	17	10	13	10
	Mean	-	-	-	-	0.36	0.37	0.34	0.34
	Maximum	-	-	-	-	0.36	0.40	0.38	0.37
	Minimum	-	-	-	-	0.32	0.36	0.32	0.31
	Median	-	-	-	-	0.37	0.37	0.33	0.34
	SD					0.07	0.01	0.02	0.02
	p-value					0.13		0.59	
Organic matter (%)	N	-	-	-	-	17	10	13	10
	Mean	-	-	-	-	6.2	5.7	6.6	5.8
	Maximum	-	-	-	-	6.2	6	6.9	6.1
	Minimum	-	-	-	-	4.8	4.8	6.3	5.5
	Median	-	-	-	-	5.9	5.7	6.2	5.8
	SD	-	-	-	-	1.1	0.36	0.23	0.22
	p-value	-		-		0.08		0.52	
$N\text{-}NO_3^-$ (mg/kg)	N	17	10	14	10	17	10	13	10
	Mean	9.5	7.4	6.4	5.5	8.9	11.5	8.5	11.7
	Maximum	23.1	19.2	8	7.2	8.9	12.5	10.8	12.9
	Minimum	11.2	1.2	4.1	3.4	4.9	9.9	6.1	10.4
	Median	5.6	5.9	6.2	5.2	10.1	11.6	10.2	11.8
	SD	8.1	5.9	1.2	0.9	1.86	0.89	1.16	0.86
	p-value	0.05		0.08		0.01		0.02	
Total carbon (%)	N	17	10	14	10	17	10	13	10
	Mean	4.6	5.1	5.5	6.4	14.3	8.3	12.6	9
	Maximum	7.5	8.8	7.2	8	36.7	34.5	33.5	26.8
	Minimum	1	1.2	3.4	4.1	0.3	2.6	0.23	4.1
	Median	5.3	4.5	5.2	6.2	13.5	7.5	12.4	8.1
	SD	2.2	2.3	0.9	1.2	10.8	5.7	9.4	4.6
	p-value	0.94		0.22		0.03		0.92	
Total nitrogen (%)	N	17	10	14	10	17	10	13	10
	Mean	0.07	0.10	0.09	0.15	1.5	2.8	1.5	2.6
	Maximum	0.12	0.13	0.13	0.73	2.4	3.9	2.9	3.8
	Minimum	0.04	0.05	0.01	0.07	0.6	1.6	0.03	1.2
	Median	0.07	0.10	0.09	0.11	1.5	2.6	0.1	2.6
	SD	0.02	0.03	0.02	0.16	0.5	0.6	0.07	0.7
	p-value	0.76		0.03		0.17		0.06	

Cult = cultivated; Uncult = uncultivated; N = number of samples; - = no data

As shown in Table 4.6, organic matter, cation exchange capacity, total carbon and nitrogen had higher values in the uncultivated site but there were no significant differences in all periods. Both pH and EC exhibited higher values in the cultivated sites but again there were no significant differences. Nitrate content was higher in the cultivated sites and differed significantly between the sites.

4.4. DISCUSSION

This chapter involved assessments of water quality to ascertain the impacts of surface water discharged from irrigated agriculture on wetlands water quality. Furthermore, the concentrations of chemical parameters were compared to agricultural guidelines of SA for fitness for use. Additionally, the study evaluated the impacts of cultivation on the water quality of the floodplain wetland during dry and wet periods. Parameters on the cultivated sites exhibited higher concentrations of salts throughout the study period compared to the uncultivated sites. These include chlorides, sodium, sodium adsorption ratio and EC. These findings are in agreement with observations by Verhoeven et al., (2006) who report higher nutrient loads in farmed areas in The Netherlands. This appears to be a regional and global concern over wetlands and water quality. Most of the chemical parameters assessed were within permissible limits for water quality for agricultural use, except for electrical conductivity (EC), sodium adsorption ratio (SAR), sodium and chloride. This has important implications for irrigators as it may cause the accumulation of salts (mainly sodium and chloride) and salinization of soils and water in the long run. In our study, a significant relationship existed between floodplain chemistry and season. For instance, ammonia, SAR, chloride and sodium showed significant differences within the seasons both in cultivated and uncultivated sites. This suggests that seasonal variations in both anthropogenic and natural processes such as precipitation influence the quality of wetlands water to different attributes between seasons.

A high EC can stress plants and cause productivity losses. In the present study, water conductivity ranged from 9 to 150 mS/m between the years 2017 and 2018 (Table 4.4). Obtained values were lower in the site with no cultivation as compared to the cultivated sites. An EC of 40 mS/m is accepted by SAWQ guidelines as a threshold concentration level for agriculture (irrigation). In this chapter, all the EC values from the cultivated marginally exceeded the guideline, while from the uncultivated site only values that fell under the dry season were above the limit (Figure 4.2). High salt concentrations in the water or soil can reduce the portability of water and adversely affect plant productivity (Morway and Gates, 2012). Furthermore, high EC can cause the inability of vegetation to compete for ions in water and soil causing toxicity of particular ions (La Mora-Orozco et al., 2018) such as chloride, sodium, etc. However, in terms of irrigation classes for fitness use (Koegelenberg, 2004) , EC fell between good and marginal values. Irrigated agriculture through water abstraction can reduce the dilution capacity as well as potentially add significant quantities of salt via return flows and the concentrating effect of increasing evapotranspiration. A significant difference between cultivated and uncultivated sites in EC in the wet season was found in the study.

This can be attributed to the surface runoff with dissolved ions in rain and floodwater. A different trend was reported in a study in India where EC was found to increase during the monsoon (Hussain et al., 2015). Shabalala et al. (2013)confirmed EC to be higher in the wet season than in the dry season in Bonsma Dam located in the southern Drakensberg, KwaZulu-Natal. This was attributed to the water bodies being recharged during the rainy season, with salts and nutrients being leached to the water table. On the other hand, Mmualefe and Torto (2011) reported dilution in the wet season. Furthermore, the increase in EC can be caused by factors such as geology and soils of the area Shabalala et al. (2013) as well as land use like agriculture. Elsewhere in Uganda, the increase in EC in a dry season was caused by the evaporation of water from the underground water channels which increased the concentrations of dissolved salts (Ngabirano et al., 2016). High concentrations of chloride which, was the case in this chapter area are typically associated with the magnitude and extent of manure use and soil infiltration (Lorenz et al., 2014) which are known to increase electrical conductivity (Acosta et al., 2011, Sainato et al., 2012). Therefore, the observed increase in EC from cultivated sites is a result of agricultural inputs and high evaporation, which lead to the concentration of salts.

The geology of the study area comprises calcarenite, clayey sand, limestone, conglomerate, and dune sand. Clay soils tend to have high EC as a result of the presence of salts that dissolve when washed into the water and are retained in the soils with inherently low hydraulic conductivity (EPA, 2018). This may explain the high conductivity of cultivated floodplain wetlands. Although this study did not investigate the origin of the salt in the study area, the literature confirms that EC is primarily affected by the geological soil and rock formations of the area through which water flows (Thilagavathi et al., 2012, Gamvroula et al., 2013). For example, freshwater ecosystems that run through areas with granite bedrock tend to have a lower EC as its composition has more inert materials that do not ionize (EPA, 2018). The tidal forcing effect is also a common feature in coastal environments, enhancing the extent of saltwater ingress particularly near the top of the water table (Davies, 2014). The mean concentrations of chloride were above the SAWQ limits in the cultivated sites and above the same limits in the uncultivated areas during the dry period. The possible source of chloride in this chapter could be attributed to the runoff water from agricultural fields and irrigation in which can increase chloride concentrations. This finding is consistent with observations by Chen et al. (2005) and Zhang et al. (2007) who report an increase in chloride concentrations from fertilizer applications in agricultural lands. The pH of most freshwater systems is predominantly determined by or dependent on atmospheric influences, the mineral content of the surrounding rocks, soils and other landforms. It often ranges from 6 to 8, which is ideal for aquatic life (Sampaio et al., 2010, CSIR, 2010). pH values ranging between 6.5 and 8.4 are considered acceptable by the SAWQ guidelines for agricultural use. A significant difference in pH concentrations between cultivated and uncultivated areas can be attributed to land clearing activities that induce salinity problems. In this study, water was alkaline (pH > 9). A high pH (7.44) in the wet season compared to 7.20 in the dry season (Table 4.4) could be attributed to the surface runoff of agricultural input. On the contrary, Brainwood et al. (2004) observed a different pattern of an increase in pH with a decrease in rainfall and an increase in water use for irrigation. The pH of water bodies can be affected by factors such as bedrock and soil composition through which water moves. Some rock types such as limestone can neutralise acidity, while others like granite do not affect the pH (Mosher et al., 2010). Most natural waters have a pH suitable for irrigation because it tends to be buffered by the soil under pristine conditions which is suitable for most crops that tolerate a reasonable pH range (Zaman et al., 2018).

Nutrients, mainly nitrogen and phosphorus, are applied to croplands in the form of fertilizers to promote crop growth. An excessive amount of these nutrients can cause water quality problems when entering water environments. In the current study, most ionic concentrations such as ammonium, boron, fluoride, nitrate, etc. were within the acceptable water quality range for agricultural use (irrigation) with the exception of sodium and chloride. Lower values of ammonium from the cultivated sites were attributed to the adsorption of clay minerals and therefore less mobile, while high nitrate in the cultivated sites was attributed to its high mobility. SAR determines the suitability of water for irrigation purposes because it is linked to the sodium hazard in soils (Gholami and Srikantaswamy, 2009). The set limit for SAR by

SAWQ guidelines is two. In this study, most of the SAR values exceeded the set limit (Figure 4.2); they fell between good and marginal classes (Table 4.3), indicating water of medium to high salinity. This suggests that water infiltration problems in this area are caused by the swelling of clay minerals which weakens the soil aggregates by closing soil pores (Van de Graaff and Patterson, 2001) may occur in this area in future. High sodium values with a corresponding increased level of SAR may be caused by the precipitation of magnesium and calcium as carbonates and bicarbonates leaving sodium in solution (Mandal et al., 2019). Rahman et al. (2013)reported high concentrations of calcium, chloride and magnesium due to seawater intrusion in Sundarbans coastal wetlands in Bangladesh. Our study area is situated in a similar environment along the coast and close to the ocean where nutrient inputs into coastal water may occur naturally through processes such as oceanic upwelling (Cloern et al., 2016).

Physico-chemical soil analyses including texture, organic matter, total carbon and nitrogen, cation exchange capacity (CEC) and nitrate were assessed in Table 4.6. Changes in soil properties through tillage can affect soil and water quality simultaneously. Nutrients mostly found in the topsoil can be transported through surface runoff, reaching water bodies such as wetlands. These nutrients are manifested in the degradation of surface water quality. Variations in the physico-chemical properties of soil and water between cultivated and uncultivated sites were observed in our study area. The results for the CEC showed higher values in the uncultivated sites, albeit not significantly different between the sites. Average CEC values for uncultivated sites ranged between 25.9 cmol (+)/kg and 37.8 cmol (+)/kg while in the cultivated sites they were between 19.8 cmol (+)/kg and 25.9 cmol (+)/kg. These findings concur with Bewket and Stroosnijder (2003) and Marzaioli et al. (2010) who found CEC to be higher in the undisturbed soils compared to the cultivated ones. The high CEC in the uncultivated sites could be explained by high organic matter (11. 5% and 11.7%) compared to the cultivated soil (8.5% and 8.7%) and related to land cultivation decreasing organic matter. Leaching and low vegetation cover in cultivated wetlands that expose the soil to direct contact with surface runoff is another reason for lower CEC content in cultivated sites (Tilahun, 2007, Minjibir, 2011). The pH was higher in the cultivated sites but differences were not significant. As observed by Mutyavaviri (2006), the removal of vegetation and exposure of soils to wind and sun could increase the aeration and temperature of the soil. This could facilitate the rapid decomposition of organic matter and prevent the accumulation of acids, thereby increasing pH (Mekonnen and Aticho, 2011, Dube and Chitiga, 2011). Lower pH values in the uncultivated soil could be attributed to the release of organic acids from organic matter decomposition. Concentrations of total nitrogen in the uncultivated sites differed from the cultivated ones, although not significantly. These differences were expected because of the high organic matter in the uncultivated sites which is the main source of nitrogen (Brady et al., 2008). A decrease in vegetation cover, soil preparation and wetland drainage can cause a decrease in the total nitrogen content. Previous studies have also shown similar results with the cultivation of wetland being associated with increased soil aeration and temperatures that accelerate rapid decomposition and mineralization of plant materials thereby lowering the nitrogen content (Dube and Chitiga, 2011, Liu and Xia, 2010). Crops in the surface soil can absorb and retain pollutants from cultivated land, thereby influencing water quality. Sodium, chloride, EC and SAR from water analyses were higher in the cultivated land and exceeded the SAWQ guideline limits. These results corresponded with findings of our soil analysis, which showed lower organic matter, CEC, total nitrogen and carbon in the cultivated sites with high EC and pH. The clearing, fertilization and tillage practices for cultivation purposes can increase nutrient concentrations in the soil. These nutrients are usually controlled and reduced by natural vegetation and grasslands, thereby regulating water quality.

4.5. CONCLUSION

In light of the set objectives and hypothesis, some important conclusions can be drawn. This chapter hypothesized that cultivated sites would exhibit higher concentrations of chemical parameters comprising nitrate, nitrite, boron, ammonia, pH and electrical conductivity (EC) compared to sites without cultivation. However, only a few water quality parameters like chloride, sodium adsorption ratio (SAR), nitrate and sodium showed significant differences in by land use type (cultivated and uncultivated) and seasonality. Most water quality parameters were within acceptable limits of fitness for agricultural use, except EC and SAR, which was attributed to anthropogenic inputs, seasonality and geological weathering. Regardless of their exceedance above guideline limits, water EC and SAR fell between good and marginal irrigation classes, suggesting moderate suitability for irrigation. Long-term issues of salinity and sodicity presented by SAR and EC may be expected and this needs to be monitored. These findings have demonstrated that the use of floodplain wetlands for commercial and subsistence crop farming can have minimal impacts on water quality as long as the degree of intensification, pesticide/herbicide and fertilizer use remains within limits.

The conditions of a water body fluctuate periodically. It is therefore recommended that future work should include sufficient surface and groundwater data by employing regular sampling and analysis. The quality and fitness of water vary in tandem with changes in land use, rainfall and farming activities. Therefore, their overall state should be investigated and evaluated.

This will aid in understanding surface and groundwater interaction to obtain a complete water resource assessment in the lower UFS. It will also be good to compare the study results with the current uMfolozi resource water quality targets other than with South African water quality guidelines for agriculture. However, there was no water quality data available for this catchment. Lastly, although the water quality in the lower uMfolozi is still in a good state, there is a possibility of deterioration in the future as a result of the increasing crop farming activities. A wetland monitoring programme for water quality by agronomists and ecologists is recommended. A monitoring protocol has been available for some years but there is a lack of systematic observation. Deploying an effective monitoring mechanism is therefore recommended in order to provide reliable information that can be used to guide policy formulation and the identification and implementation of appropriately informed management strategies. This will go a long way in enhancing the sustainability of this wetland for benefit of present and future generations.

CHAPTER 5

Seasonal wetland vegetation and crop leaf nutrients characterisation using Sentinel-2 MSI data

This chapter is based on:

Dlamini, M.; Chirima, JG.; Sibanda, M; Dube, T; Adam, E Seasonal Wetland Vegetation and crop leaf nutrients characterisation using Sentinel-2 MSI data. *Remote Sens.* **2021**, *13*, x

Abstract

In many arid environments of the world particularly in Africa and Asia, floodplain wetlands are a valuable agricultural resource. However, the water reticulation role by wetlands and crop production can negatively impact wetland plants. Knowledge of the foliar biochemical elements of wetland plants enhances understanding of the impacts of wetland agriculture in the context of wetland areas. This study used Sentinel-2 multispectral data to predict seasonal variations in the concentrations of nine elements in the leaves of key floodplain wetland vegetation types and crops in the uMfolozi floodplain system (UFS). Nutrient concentrations in different floodplain plant species were predicted using Sentinel-2 multispectral data derived vegetation indices in concert with the random forests regression. Results showed a mean R^2 of 0.66 and 0.76 for the dry winter and wet summer seasons, respectively. However, copper, sulphur, and magnesium were poorly correlated ($R^2 \leq 0.5$) with vegetation indices during the summer season. The average % RMSE's for plant types in summer and winter were 26.8 % and 20.8 %, respectively. There was a statistically significant difference in nutrient concentrations (p-value = 0.001) between the two plant types, (R^2 = 0.92 (crops), R^2 = 0.81 (vegetation). The red-edge band "740 mm" and the normalised difference vegetation index (NDVI) were the best nutrient predictors. These results demonstrate the usefulness of Sentinel-2 imagery and random forests regression in predicting seasonal, nutrient concentrations as well as the accumulation of chemicals in wetland vegetation and crops.

Keywords: crop production; multispectral data; random forests, vegetation indices; wetlands conservation

5.1. INTRODUCTION

Wetlands in South Africa (SA) cover about 2.9 million hectares and about 2.4 % of the country's land area (Driver et al., 2012). They are recognised as highly valuable natural resources that sustain the livelihoods of local communities by providing wide-ranging ecosystem goods and services that include, wild fruits, vegetables, rice and water purification (Kotze et al., 2009, Steven and Lowrance, 2011). They also mediate the adverse effects of extreme weather conditions (IPCC, 2014) by attenuating floods and slowing down the speed of water movement (Renaud et al., 2013). Despite their valued recognition, the rate of wetland degradation worldwide and in SA remains high (Gardner et al., 2015, Davidson et al., 2018).

In South Africa, wetlands are some of the most threatened ecosystems with ~50% of them in a critically endangered state (Driver et al., 2012). Although they are vital for the livelihoods of rural communities (Houghton et al., 1999), their sustainability is being threatened by the increasing incidence of climate change-driven droughts and frequent rainfall failures (Dai, 2013). In sub-Saharan countries including Ethiopia, Kenya, Malawi, Tanzania, and Zambia wetland cultivation is a recognised and common practice in arid environments (Nyirenda, 2020) that generates about 37% of consumed food and 55% of cash income per household (Msusa, 2011). Nyamadzawo et al. (2015) in Zimbabwe compared wetland gardens against upland fields and the study observed that more harvests from wetland gardens (2- 3 t ha^{-1}) compared to upland fields with less than (1t ha^{-1}). Despite these services, wetland ecosystems are highly modified by water extraction, urbanisation, infrastructure development, pollution, poor farming practices as well as droughts and climate variability. Given the high agricultural productivity, and the water reticulation role of wetlands, there is a need to identify effective and synoptic spatial explicit techniques for assessing and monitoring nutrient enrichment of wetlands. A study by (Zhu et al., 2014) noted that with an increase in foliar copper content, generally the mesophyll cells shrink and destroy the internal structure of a plant's leaves altering its physiological and structural characteristics. In this regard, understanding the foliar nutrient composition of vegetation and crops growing in wetlands could offer critical information on the status of nutrient enrichment as well as the accumulation of chemicals in a wetland's water and soils. Since vegetation links the physical environment and the upper levels of the food chain (Verkleij et al., 2009, Peralta-Videa et al., 2009) and considering that foliar nutrients, as well as the chemical elements, can be determined by the physiological traits of plant, monitoring wetland plant status. Therefore information is used as a proxy for assessing nutrient enrichment as well as the toxicity of crops produced in the wetlands.

Plants require at least fourteen mineral elements for adequate nutrition (Mengel et al., 2001), a lack of which reduces plant growth and (White and Brown, 2010). About six mineral elements, nitrogen (N), phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg), and sulphur (S), are required by plants in adequate amounts (White and Brown, 2010). Their presence at tolerable concentration levels in the plant can now be determined using remote sensing techniques (Kanke et al., 2012, Clevers and Gitelson, 2013, Özyiğit and Bilgen, 2013, Mutanga et al., 2015, Adjorlolo et al., 2014, Ramoelo and Cho, 2018, Mutanga et al., 2012, Li et al., 2019, Delloye et al., 2018, Ye et al., 2020). However, significant research advances and efforts have been exerted towards estimating the concentration of foliar nitrogen, phosphorus and potassium (Kanke et al., 2012, Clevers and Gitelson, 2013, Özyiğit and Bilgen, 2013, Mutanga et al., 2015, Adjorlolo et al., 2014, Ramoelo and Cho, 2018, Mutanga et al., 2012, Li et al., 2019, Delloye et al., 2018, Ye et al., 2020). However, the majority of the widely used techniques are point sample-based, destructive, time-consuming and expensive to conduct, despite the high accuracies associated with them. These include laboratory-based assaying methods. Meanwhile, remote sensing techniques have emerged as the most timely, effective, and spatially explicit technique suitable for evaluating foliar nutrient enrichment of wetland plants.

Nitrogen, phosphorus and potassium have been widely characterised using remote sensing techniques (Mahajan et al., 2017, ÖZYİĞİT and Bilgen, 2018, Siqueira et al., 2020). Although the literature indicates that these elements can be easily characterised using various techniques, other trace elements that are found in wetlands such as Magnesium (Mg), Copper (Cu), Boron (B) and Sulphur (S) are difficult to estimate and have not been widely explored in the context of remote sensing. In this regard, there is a need for assessing the utility of remotely sensed data sets in estimating the chemical concentrations of chemical elements such as Mg, Cu, B, and S. This limitation explains why several studies on nutrient concentrations have routinely coupled in situ remote sensing techniques such as spectroscopy with laboratory analysis (Zengeya et al., 2013, Li et al., 2020, George et al., 2019, Luo et al., 2016). For instance, Li et al (2020) used hyperspectral data and laboratory to estimate and understand nitrogen and phosphorus in wetland plants. The majority of these studies have mostly focused on grassland and indigenous species (Ramoloe et al.,2015a). Less effort has been exerted towards foliar nutrients like Cu, B, and S in wetland settings (Van Asselen et al., 2013, Ramoelo et al., 2015a). Furthermore, the traditional laboratory methods are mostly used to provide the information that is required to guide wetland conservation and management (Barker and Pilbeam, 2015), however, these methods require intensive field sampling and laboratory chemical analysis. The chemical analysis methods are reported to be labour intensive, time-consuming, and costly (Chhabra et al., 2010, Gilbertson et al., 2017).

Meanwhile, the high spectral resolution associated with hyperspectral sensors has proven to exhibit better prospects in the detailed characterisation of wetland plant nutrient concentrations (i.e. nitrogen and phosphorus) (Luo et al., 2016). Previous research has also widely indicated the major setbacks associate with hyperspectral data. Hyperspectral data is often affected by high dimensionality also known as the Hughes phenomenon, coverage of small spatial extents as well as exorbitant acquisition costs. To adequately monitor nutrient concentrations in wetland plants, a monitoring system that can be applied over optimum spatial and temporal scales is required. The use of freely available satellite imagery is a viable option as it enables cost-effective mapping and monitoring of inaccessible and extensive wetland areas (Lee and Yeh, 2009, Held et al., 2003). Overall, the literature underscores the potential of the medium to high spatial resolution sensors such as the WorldView-2, 3 and Sentinel-2 (S-2) in detecting variations in plant nutrient concentrations (Wood et al., 2013, Driver et al., 2012, Ollis et al., 2013, Fennessy et al., 2004). Despite the optimal performance of very high-resolution (VHR) sensors such as WorldView, their high acquisition costs and limited spatial coverages undermine their ability to characterise vegetation traits over large areas (Dube et al., 2016).

Although launched in 2015, S-2 has already proven to be highly useful for monitoring vegetation quality particularly macronutrients such as nitrogen and phosphorus (Sibanda et al., 2015, Otunga et al., 2019, Chemura et al., 2018). The S-2 has a high revisit period of 5-days, a spatial resolution of 10-60 m, coupled with a systematic global acquisition and open access policy which makes it ideal for local-level real-time plant nutrient monitoring. In addition to the visible and near-infrared (NIR) wavelengths, the S-2 includes three bands in the red edge region centred at 705, 740, and 775 nm, which have attracted a lot of interest in the characterisation of various plant traits and vegetation monitoring including macronutrients (Delloye et al., 2018, Clevers et al., 2017, Clevers and Gitelson, 2013, Chemura et al., 2018, Gao et al., 2020). For instance, S-2 has been used to characterise the seasonal and spatial variations of the nitrogen and phosphorus ratio in alpine grasslands of China at optimal accuracies (R^2 of 0.49 and 0.59, as well as a root, mean square error (RMSE) of 2.27 and 3.11 for the dry and wet seasons, respectively) (Gao et al., 2020). Specifically, S-2 has 13 spectral bands comprising, of four bands with a 10 m spatial resolution (centred at 496 nm, 560 nm, 665 nm, and 835 nm), six bands with a 20 m resolution (centred at 703 nm, 740 nm, 783 nm, 865 nm, 1610 nm, and 2202 nm), and three bands with a 60 m spatial resolution at 443 nm, 945 nm, and 1373 nm (Frampton et al., 2013). Because S-2 data can be accessed free of charge from the Copernicus Open Access Hub (https://scihub.copernicus.eu/), has greater prospects in mapping and monitoring vegetation micro and macronutrients, especially in countries with limited spatial data sources and financial resources. However, most of the studies that have sought to characterise nutrients using S-2 remotely sensed mainly concentrated on the macronutrients (N, P, and K) whereas a gap still exists in assessing its capability, efficiency and robustness in detecting and mapping micronutrients nutrients such as Mg, Cu, B and S, particularly in wetland areas. Hence, there is a need to assess the ability of S-2 in detecting plant macronutrients in relation to micronutrients in wetland areas as a proxy for evaluating nutrient enrichment in wetlands.

The evaluation of the nutritional conditions in plants at high spatial resolution is becoming a common practice due to the increasing availability of robust spectral data sources such as S-2 in concert with robust algorithms (Hernández-Clemente et al., 2019, Gao et al., 2020). Selected examples include Random Forests ensemble (RF), principal component analysis (PCA), stepwise multiple linear regression (SMLR), (Zhai et al., 2013, Min and Lee, 2005, Gao et al., 2020) and machine learning algorithms (MLAs) (Pham et al., 2019, Wu et al., 2019, Wolanin et al., 2019). The use of MLAs in predicting nitrogen is a fairly new advancement that involves a fusion of several spectral vegetation indices in mapping leaf nutrient variations (Prado Osco et al., 2019).

Although there is no machine learning method that is universally appropriate for estimating vegetation quality, several studies have evaluated the performance of the random forests regression model (RF) in predicting leaf nitrogen content of wetland vegetation (Liang et al., 2018, Ramoelo et al., 2015a). RF has been demonstrated to be more robust in estimating plant traits compared to the support vector machine (SVM) (Polikar, 2006, Breiman, 2001, Burai et al., 2015, Doktor et al., 2014, Ghimire et al., 2010). Hence RF was utilised in this study to predict calcium, magnesium, sulphur, zinc, boron copper and other nutrients with the intent of identifying key spectral variables, which are suitable for reliable estimation of leaf nutrient content. The study's specific objectives were to, a) test the usefulness of the RF model and S-2 data in predicting the concentrations of N, K, Ca, Mg, P, S, Zn, B, and Cu nutrients, b) determine the key wavelengths that are important predictors of these nutrients and, c) characterise seasonal variations in wetland plants leaf nutrient content.

5.2 MATERIALS AND METHODS

5.2.1 Study area description

The uMfolozi floodplain system is located in St Lucia, a town located in Mtubatuba Local Municipality, South Africa (28° 22 'S and 32° 25 E'). The uMfolozi River consists of two main tributaries, the Black uMfolozi that rises at around 1500 m asl. in the north and the White uMfolozi that rises at an altitude of 1620 m. Around 50 km west of the mouth of the uMfolozi river, these two tributaries converge on the sea. Since the catchment falls within the uMfolozi-Hluhluwe Nature Reserve, the bulk of the catchment consists of natural vegetation cover. Grasslands are about 60% of the remaining natural vegetation, 21% of thickets and bushes and 15% of natural woods and forests. Just less than a quarter of the uMfolozi catchment, apart from natural vegetation, comes under agriculture, much of which is small-scale subsistence and commercial forestry. The floodplain itself is predominantly used for sugar cane cultivation (65%), while the rest falls within the iSimangaliso Park (previously known as St. Lucia Wetlands Park).

The uMfolozi River catchment drains a portion of 11 068 km^2 of northern KwaZulu-Natal on Southern Africa's eastern seaboard. The river consists of Lebombo rhyolite rock in the east and Zululand and Maputaland rocks (calcarenite, calcareous sand, limestone, and conglomerate) to the north and south of the Indian Ocean (Garden, 2008). About 80% of the rainfall occurs, precipitation is mainly limited to the summer months, peaking between November and April (Morgenthal et al., 2006). Mean annual catchment precipitation ranges from 1288 mm in the coastal town of St. Lucia, to 667 mm/a in the mid-upper catchment of the uMfolozi Game Reserve, and 914 mm/a in the upper catchment in Nongoma. Mean annual evapotranspiration potential is normally more than double that of precipitation, with average atmospheric demands of approximately 1800 mm/a (Schulze, 1997).

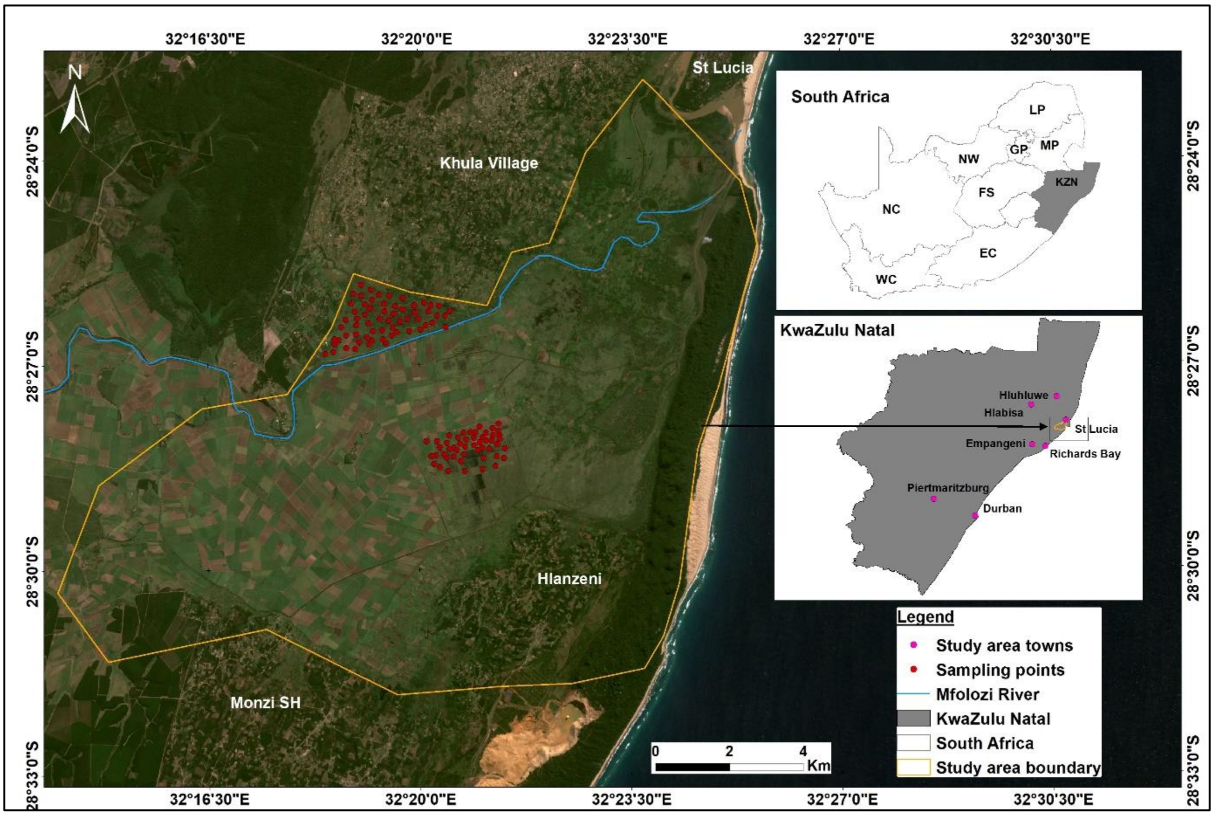


Figure 5.1. The geographical location of the study area.

5.3 Field data collection

5.3.1 Plant species leaf sampling

The datasets comprised leaf samples of major crops (*Musa acuminate*, *Ipomoea batatas*, sugarcane and *Colocasia esculenta*) and dominant wetland vegetation species (*Phragmites australis*, *Cyperus papyrus* and *Cynodon dactylon*). Sampling points were randomly generated to cover the area within the wetland guided by the accessibility of sampling sites. Then Purposive sampling of leave was utilised in identifying the leaves for collection. Leaf samples were collected on the 12 March 2017 (wet season) and 22 July 2017 (dry season), hereafter referred to as summer and winter, respectively. Upon arrival at each sampling point within the wetland, the plants (trees and crops) were identified and recorded along with the location of the sampling point. A Garmin Montana global positioning system (GPS) with a rated positional accuracy of ± 3 meters, was used to measure the location of each plant where leaves were harvested. Then, leaf samples were randomly collected from different crown levels (top, middle, and bottom) to avoid biases. A total number of 76 leaf samples (38 for crops and 38 for vegetation) were collected in summer and 85 samples (40 for crops and 45 for vegetation) were collected in winter. About 150 g of leaf material was collected from each crop/ plant. Sampled leaves were packed in ziplock plastic bags, which were properly labelled and stored in a cooler box to preserve them during transportation to the laboratory. In the laboratory, the samples were oven-dried at 70 ˚C for at least 24 hours and milled to particle sizes of < 0.5 mm.

5.3.2 Chemical analyses

In this study, six major elements required in large amounts by plants (nitrogen, phosphorus, potassium, calcium, magnesium and sulphur) (White and Brown, 2010) and three micronutrient elements required as trace amounts (boron, zinc and copper) (Öztürk et al., 2010) were chosen. The dry oxidation (Dumas) method was used to determine nitrogen (Morgenthal et al., 2006) by igniting each leaf sample in oxygen at 950 ˚C to produce carbon dioxide, nitrogen gas and oxides of nitrogen. These gases were passed through silvered cobalt oxide and a column of copper at 650 ˚C to reduce the oxides of nitrogen to nitrogen gas by removing excess O_2. After removal of water vapour and CO_2 by traps, the N_2 gas was finally separated from other gases using gas chromatography, based on a helium carrier gas and detected by a thermal conductivity detector. The instrument is calibrated against the pure compound of known composition. The compound chosen for calibration standard is Phenylalanine which contains 8.48% N.

An aliquot of the digest solution was used for the Inductively Coupled Plasma Optical Emission Spectrometric (ICP-OES) instrument for the determination of K, Ca, Mg, P, S, Zn, B and Cu (Gardner and Finlayson, 2018). This is an Agilent 725 (700 series) simultaneous instrument where all the elements and wavelengths are determined simultaneously. Thus, several of the elements may be determined at more than one wavelength allowing confirmation of the values with no increase in analysis time or consumption of digest solution. However, sulphur (S) was determined separately from the other elements after purging the optics of the instrument with argon (Ar) gas. This is due to the low wavelengths (below 190 nm) used for detecting S and the problems caused by oxygen in the air at these very low wavelengths if the system is not purged. Each element was measured at one or two appropriate emission wavelengths that were chosen for their high sensitivity and lack of spectral interferences.

5.3.3 Image compilation and pre-processing

Table 5.1 describes the characteristics of the S-2 images that were used and the numbers of sample sites from where leaf samples were collected during the wet (12 /03/2017) and dry (22/07/2017) seasons.

Table 5.1. Sentinel-2 images acquisition and field samples.

Season	Image acquisition date	Collection date of samples	Scene ID	Cloud cover (%)	No of samples
Wet	27/03/2017	12 /03/2017	S2A_MSIL1C_20170327T074231 _N0204_R049_T36JVP	0.4	76
Dry	18/07/2017	22/07/2017	S2A_MSIL1C_20170718T075211 _N0205_R092_T36JVP	0	85

Source: *https://www.sentinel-hub.com/develop/documentation/eo_products/Sentinel2EOproducts*.

The S-2 images were utilised because of their optimum spatial and spectral resolutions for leaf-nutrient characterisation, as well as the expansive tiles that covered the study area. As shown in Table 1, the difference in the number of days between collection dates of samples and image acquisition dates for wet and dry periods were 15 and 4, respectively. The images were atmospherically corrected to surface reflectances using the Sen2Cor plug-in tool provided in the Sentinel Application Platform (SNAP) toolbox as illustrated in literature (Muller-Wilm et al., 2013, Farahmand and Sadeghi, 2020, Van Passel et al., 2020). Thereafter, the 20 m bands were resampled into 10 m to match the first five bands VISNIR bands. Meanwhile, bands 1, 9, and 10 were excluded in this study because they are not suitable for vegetation applications. Vegetation indices were then computed and used with the spectral bands to predict nutrient concentrations in vegetation and crops growing in a wetland by using several red edge based indices (Table 5.2).

All the processes of the study methodology are summarized in figure 5.2. This begins with satellite image data and field data collection. These two were put together to perform a random forests regression model.

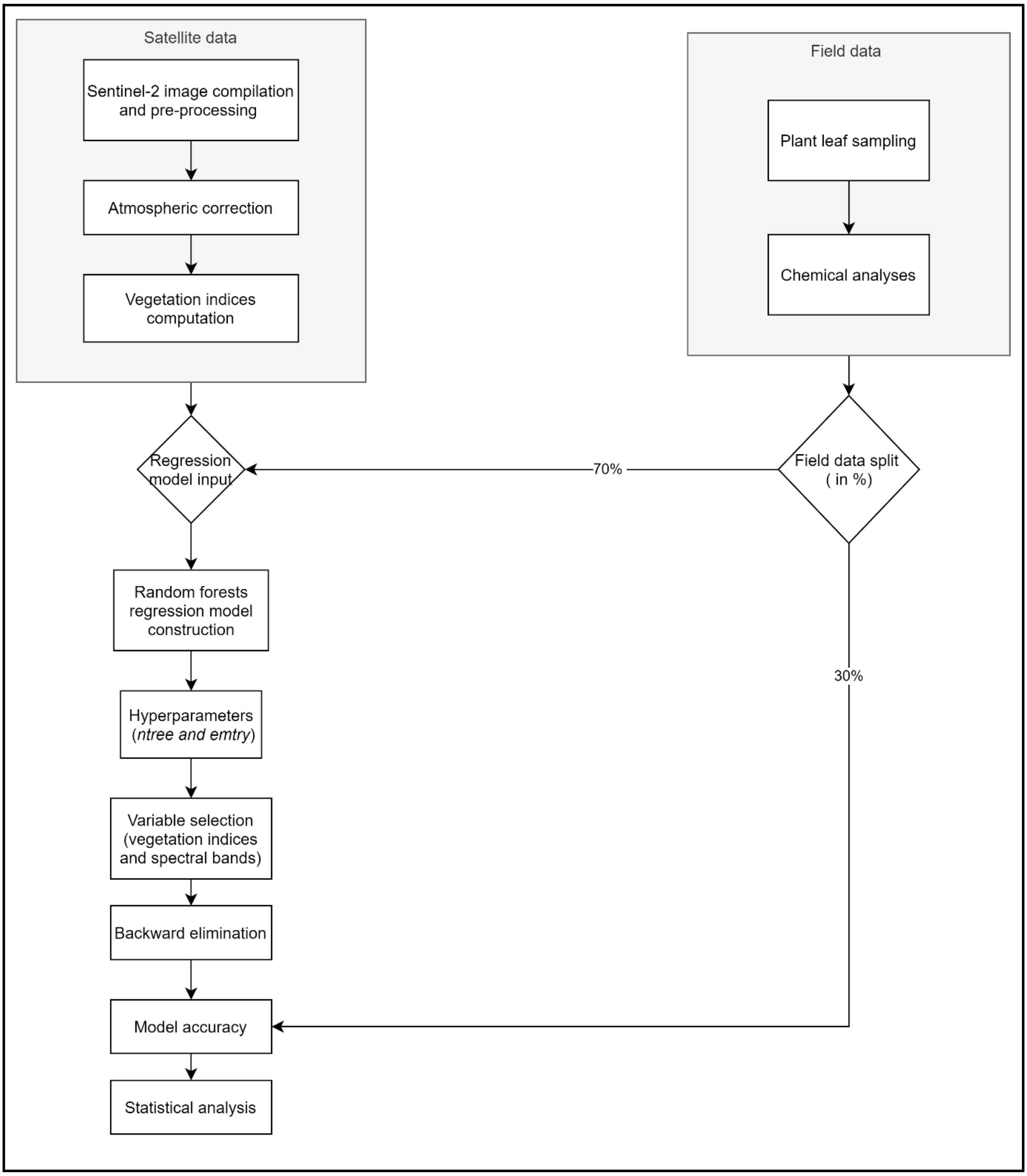


Figure 5.2 The flow chart summarizes the overall methods for the study.

Table 5.2. Various vegetation cover and chlorophyll content-related remote sensing indices.

Name	Equation	References
Normalized Difference Vegetation Index (NDVI)	(NIR - R)/(NIR + R)	(Jordan, 1969)
Simple Ratio (SR)	NIR/R	(Jordan, 1969)
Red Edge 1	$(R_1 - R)/2$	(Barnes et al., 2000, Clevers and Gitelson, 2013)
Red Edge 2	$R_2 – R_1)/2$	(Barnes et al., 2000, Clevers and Gitelson, 2013)
Red Edge 3	$(R_3. R_2)/2$	(Barnes et al., 2000, Clevers and Gitelson, 2013)
Chlorophyll Red Edge ($CI_{red-edge}$)	(R_3/R_2) -1	(Clevers and Gitelson, 2013)
Chlorophyll Green (CI_{green})	$(R_3$/green) -1	(Gitelson et al., 2003, Gitelson et al., 2006)
The MERIS Terrestrial Chlorophyll Index (MTCI)	(NIR- $R_2/R_{705})/(R_2$-R)	(Dash and Curran, 2004)

5.4. Prediction of nutrient concentrations using random forests regression

RF was performed in the R statistical package to predict the concentration of nutrients in crops and wetland vegetation. RF is a blended model that is characterised by an enormous number of trees (Ishwaran, 2015, Breiman, 2001). The model works by repeatedly splitting each tree (remotely sensed data in this study) into increasingly homogenous subsets at each node to produce a series of terminal nodes. In this study, the training of the regression was based on 70% of the ultimate data and new predictions determined by sensing the input down the tree and taking the means of the response variables (nutrient contents). The remaining 30% was used in model accuracy assessment.

Each regression tree in the RF algorithm is built using a subset of training samples that are independently selected by replacement of the original samples (Ok et al., 2012). A subset of a few variables was randomly selected to determine the split in order to increase the robustness of the model by increasing diversity amongst trees and avoiding overfitting the model (Ok et al., 2012) and the RF predictor finally constructed by taking the average overall trees. The samples that are not utilised to grow the tree are referred to as Out of the Bag (OOB) data (Breiman, 2001) which the algorithm uses to estimate accuracy by using the difference in the mean square errors to compute the OOB error estimate (Muller-Wilm et al., 2013). The explanatory power of each variable is determined by a Gini coefficient which measures the total decrease in node impurity (weighted by the probability of reaching that node) averaged across all trees. In this regard, two hyperparameters were used in this study to tune the models, that is the number of trees (*ntree*) and the number of variables randomly sampled as candidates at each split (*mtry*). It has to be pointed out that the adjustment of these hyperparameters did not significantly change the results hence these were held constant for various models considering the variability in the number of samples in stages 1 to 3 illustrated in Table 5.3.

Variable selection of the most important model parameters needed for accurate nutrient prediction was accomplished by implementing the backward feature elimination method (Sandri and Zuccolotto, 2006, Hapfelmeier and Ulm, 2013). The variable importance in RF determines various measures such as the frequency with which the variable is studied, such as the Gini coefficient and permutation coefficient. The variation method is considered superior to other approaches because it uses out-of-of-bag assessments (Breiman, 2001). The RF can assess the large factors by the decrease in accuracy mean significance. Increased mean variability indicates a greater significance for that particular variable, while low mean values indicate a lower significance. The method works by generating all the variables of the input predictor and gradually removing input predictor variables with the least relative effect. Table 5.3 describes the experiments that were performed with S-2 MSI data to predict nutrient concentrations on crops and wetland vegetation. More details on the RF regression ensemble are detailed in the literature (Grömping, 2009, Breiman, 2001, Gao et al., 2020, Otgonbayar et al., 2019).

Table 5. 3. Experiments for predicting heavy metal concentrations in crops and wetland vegetation.

Analysis	Data manipulation	Spectral data used
1	separate plant functional types and seasons	bands and vegetation indices
2	pooled based on plant functional types and both seasons	bands and vegetation indices
3	pooled based on nutrient types across all plant types	bands and vegetation indices

In the first analysis stage, nutrient concentrations were predicted using the chlorophyll green, chlorophyll red edge, red edge position (REP), ratio index, normalized difference vegetation index, MERIS terrestrial chlorophyll index and S-2 MSI bands for the wet (March) and the dry (July) season. The objective of this analysis was to determine the ability of S-2 MSI data to detect seasonal concentrations of different nutrients in different plant types at different seasons. In the second stage, the seasonal data were pooled to detect and characterise the year-round nutrient concentrations. The third analysis pooled the wet and dry season datasets into one dataset in order to assess the robustness of S-2 MSI data in detecting and characterising nutrient concentrations across all plant functional types. All prediction models were evaluated by using the explained mean squared residual (MSR) variance (Var Expl (%), root mean square error (RMSE) and, relative root mean square error (RMSE %). The RMSE% and the R^2 are both scaled between 0 and 100. To compute the RMSE%, all RMSEs from each model were normalised using the mean of each variable and then expressed as a percentage (Shcherbakov et al., 2013, Richter et al., 2012). The RMSE% has been widely used in literature to compare different variable predictions (Richter et al., 2012, Karl et al., 2017, Chen et al., 2017) hence it was adopted and used in this study. The accuracies (RMSE % and in some instances with R^2) of the training datasets were presented and used to conduct the Mann-Whitney U and the Student t's Tests. The Mann-Whitney U independent samples test was then used to test whether there were significant differences (α= 0.05) between the prediction accuracies (R^2 and RMSE%) derived during the summer in relation to those derived from the winter for crop and wetland vegetation, respectively (Table 5.4). The Mann-Whitney U Tests was used following the data's significant deviation from the normal distribution (α= 0.05) based on the Kolmogorov-Smirnov Test. Similarly, a Student's t-test of independent samples was then used to assess whether the prediction accuracies derived in crops were significantly different (α= 0.05) from those derived from wetland vegetation in this study (Table 5.6). The Student's t-test was used because the data did not significantly deviate from the normal distribution based on the Kolmogorov-Smirnov Test.

The raster calculator tool in ArcGIS 10.6 was used to map the spatial and temporal distribution of nutrients utilizing RF regression model outputs and essential variables (NDVI, REP1, and band 7) for characterizing studied nutrients.

5.5 RESULTS

5.5.1 Dry and wet season crop and vegetation nutrient prediction

Tables 5.4 and 5.5 show seasonal levels of accuracy (R^2 and RMSE %) for different nutrients that were investigated. For both vegetation and crops, high R^2 accuracies and low RMSE% were observed for all nutrients in winter (Tables 5.4 and 5.5). Nutrient concentration predictions for crops were lowest for magnesium (R^2, 0.38) which had the highest summer RMSE% of 47 (Table 5.4). Weak vegetation regressions for sulphur (R^2, 0.28) and copper (R^2, 0.39) were observed in summer (Table 5). Higher R^2 averages were observed in vegetation compared to crops in the winter season but the differences between the winter and summer mean R^2 values for crops (*p*, 0.17) and vegetation (*p*, 0.28) were not statistically significant. The summer-winter RMSE percentages were higher in crops compared to vegetation and the differences in average values for both were statistically significant i.e. *p*, 0.031 for crops and *p*, 0.04 for vegetation (Table 5.6).

Table 5. 4. Dry and wet season nutrient concentration prediction accuracies for crops.

Period	Element	MSR	Var Expl %	RSq	RMSE	RMSE %
Summer	N%	0.477223	68	0.9	0.73506	24
	K (mg/kg)	60233470	41	0.68	8457.83	35
	Ca (mg/kg)	289507814	57	0.74	9284.56	12
	Mg (mg/kg)	333.0564	89	0.38	1879.82	47
	P (mg/kg)	78.95824	90	0.54	624.611	25
	S (mg/kg)	386031.1	62	0.55	936.065	33
	Zn (mg/kg)	139.7284	37	0.59	7.23155	24
	B (mg/kg)	598.4158	44	0.78	10.5662	29
	Cu(mg/kg)	25.71765	42	0.54	4.78946	24
Winter	N %	0.226328	74	0.7	0.54962	24
	K (mg/kg)	28543675	78	0.7	3894.2	22
	Ca (mg/kg)	2857320	77	0.71	1475.83	24
	Mg (mg/kg)	429935.8	80	0.8	572.577	19
	P (mg/kg)	239896.9	74	0.59	326.662	15
	S (mg/kg)	217700.9	73	0.57	376.378	18
	Zn (mg/kg)	61.92744	60	0.79	5.23155	18
	B (mg/kg)	76.79981	64	0.87	4.52707	26
	Cu (mg/kg)	3.887578	70	0.76	1.60895	21

Table 5.5 Dry and wet season nutrient concentration prediction accuracies for wetland vegetation.

Period	Element	MSR	Var Expl %	R^2	RMSE	RMSE %
Summer	N%	0.188858	62	0.75	0.49749	22
	K (mg/kg)	15624853	45	0.75	2232.95	16
	Ca (mg/kg)	7996152	40	0.89	1492.64	28
	Mg (mg/kg)	5527032	41	0.82	961.09	28
	P (mg/kg)	425870.3	72	0.75	467.523	22
	S (mg/kg)	783215.5	11	0.28	973.06	29
	Zn (mg/kg)	76.493	58	0.7	12.141	28
	B (mg/kg)	159.1755	78	0.87	9.47249	29
	Cu(mg/kg)	3.086087	65	0.39	5.62771	29
Winter	N %	0.338176	67	0.53	0.673354	23
	K (mg/kg)	5754312	67	0.89	4198.11	19
	Ca (mg/kg)	5912891	61	0.82	1355.96	24
	Mg (mg/kg)	1091054	64	0.79	726.721	20
	P (mg/kg)	123812.6	75	0.82	300.969	13
	S (mg/kg)	32246433	35	0.82	629.213	23
	Zn (mg/kg)	23.21096	81	0.84	5.23262	17
	B (mg/kg)	32.66435	64	0.82	3.2020	28
	Cu (mg/kg)	2.596388	75	0.84	1.59787	22

Tables 5.6, 5.7 and 5.8 show a) seasonal mean comparisons of R^2 and RMSE % nutrient estimates for different functional types, b) Seasonal nutrient prediction accuracies for crops and vegetation and c) descriptive statistics for R^2 values and RMSE% for plant types using pooled data respectively.

Table 5.6. Comparisons of nutrient prediction accuracies (RMSE %) between the summer and winter seasons in crops and vegetation, respectively.

		RMSE%	
Plants	Statistics	Summer	Winter
Crops	Rank Sum	110	61
	p-value (α= 0.05)	0.031	
Vegetation	Rank Sum	107.5	63.5
	p-value (α= 0.05)	0.04	

Table 5.7. Seasonal nutrient prediction accuracies for crops and vegetation.

Plant Type	Nutrient	MSR	Var Expl		RMSE	
			%	R^2	RMSE	%
	N	0.246383	64.77	0.92	0.51	20
	K	7636615	82.84	0.84	8807.97	44
	Ca	2321326	73.59	0.86	3890.30	60
Wetland vegetation	Mg	328410.8	79.31	0.7	2536.48	78
	P	299893.7	72.54	0.67	1693.25	60
	S	492032.1	31.44	0.84	347.54	14
	Zn	16.25276	87.22	0.84	5.99	18
	B	134.3053	70.24	0.75	11.08	63
	Cu	0.980854	87.2	0.83	2.88	36
	N	0.203769	83.65	0.93	0.40	16
	K	14020623	88.51	0.95	3201.65	16
	Ca	17702853	56.75	0.91	1553.11	22
Crops	Mg	1503814	67.27	0.92	555.95	16
	P	100539.7	83.96	0.93	292.50	13
	S	158620.3	83	0.9	391.87	16
	Zn	20.36852	87.04	0.93	3.97	13
	B	156.9875	75.54	0.91	7.18	27
	Cu	5.985723	80.56	0.86	2.01	21

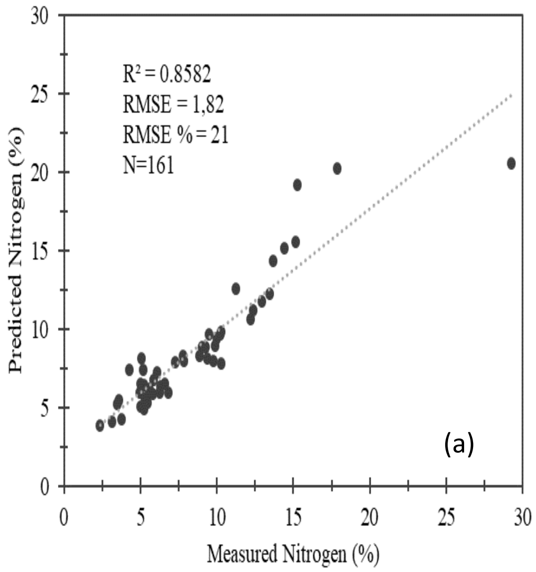
Table 5.8. Descriptive statistics for R^2 values and RMSE% for plant types using pooled data.

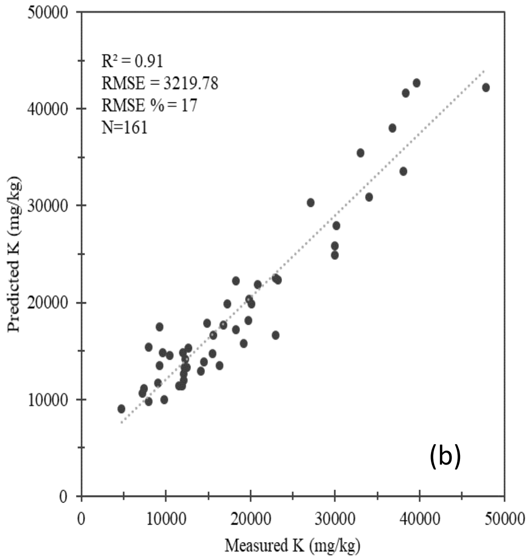
Accuracy unit	Statistics	Vegetation	Crops
R^2	Mean	0.92	0.81
	Maximum	0.95	0.92
	Minimum	0.86	0.67
	Median	0.92	0.84
	St deviation	0.03	0.08
	p-value		0.001
RMSE %	Mean	43.7	17.8
	Maximum	78	27
	Minimum	14	13
	Median	44	16
	St deviation	23	4.6
	p-value		0.004

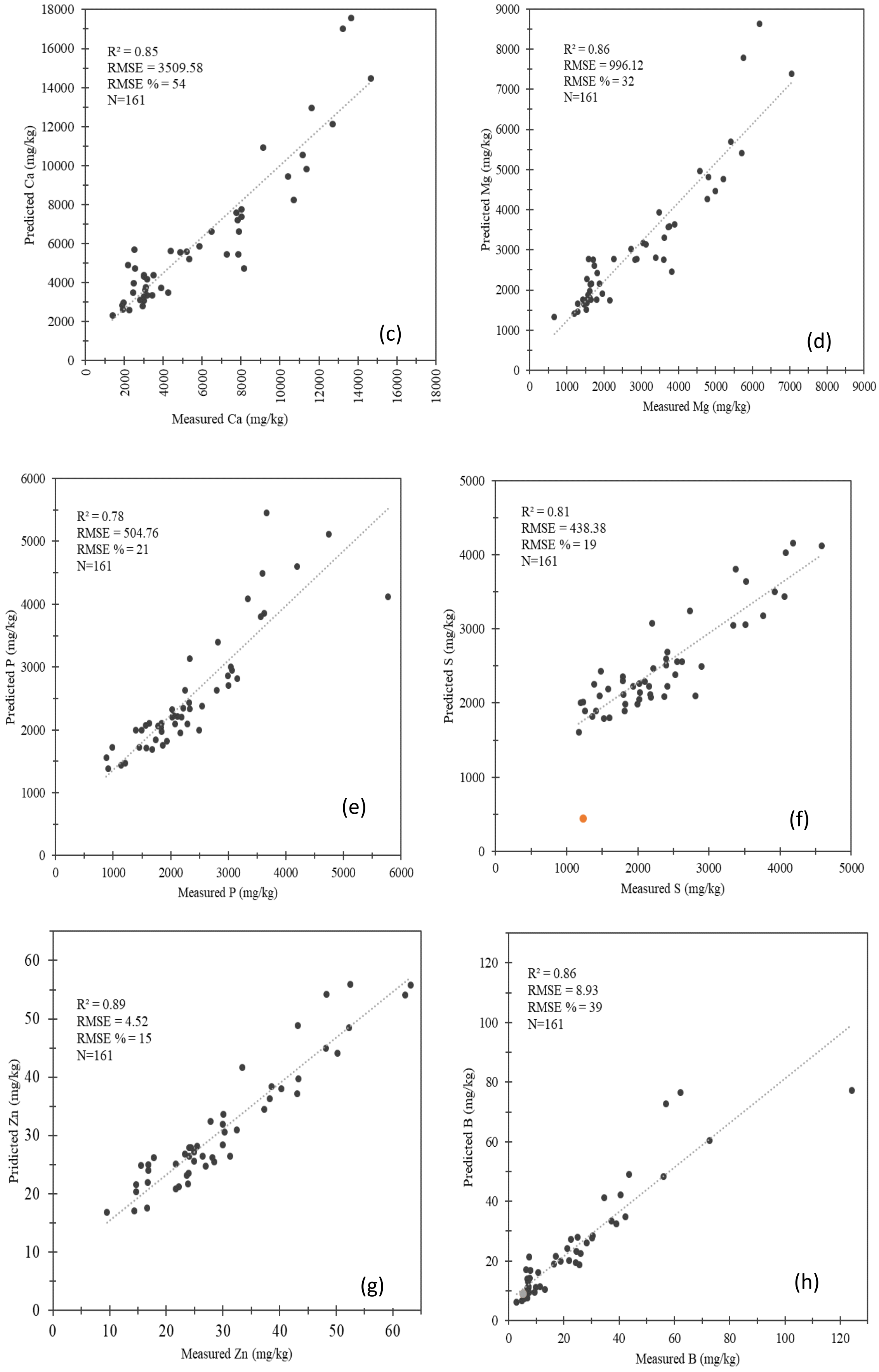
5.5.2 Dry and wet season crop and vegetation nutrient prediction using pooled data

In addition, the annual predictions of nutrient concentrations presented in Table 5.7 were used to calculate the statistics provided in Table 5.8. A higher mean R^2 accuracy for nutrients across plant types was observed for vegetation (0.92) compared to a mean R^2 of 0.81 for crops (Table 5.8). Differences in these mean R^2 values were statistically significant (*p*, 0.001). A higher percentage of RMSE (43.7) was observed for vegetation compared to what was observed for (17.8). The difference between these vegetation types and crop RMSE values was statistically significant (*p*, 0004). In all cases, measured and predicted nutrient concentrations were strongly correlated with R^2 ranging from 0.91 for potassium to 0.78 for magnesium. Although boron and magnesium showed a good correlation, both had high RMSE percentages.

Figure 5.3 is a composite summary of the performance of the statistical models that were used to relate foliar nutrients measured from the laboratory and data from S-2 images. Figure 5.3 shows the best fits for the model (in terms of R^2 and RMSE %) arranged by performance. As can be seen, the studied nutrients' prediction performances were strong and very consistent, with R^2 values ranging from 0.78 to 0.91. The nutrients, on the other hand, showed the polar opposite of variability in terms of RMSE%. It's worth noting that lower RMSE values suggest a better model prediction fit. The RMSE percentages for different nutrients ranged from 15% to 54 %. Zinc, potassium, sulphur, copper, phosphorus, and nitrogen were found to have low RMSE percents ranging from 15% to 21%. The RMSE of calcium, boron, and magnesium were all greater, with calcium having the highest at 54 percent. The overall findings revealed that several nutrients, such as calcium, boron, and magnesium, are poorly predicted, as evidenced by the RMSE percent values.







R² = 0.85
RMSE = 3509.58
RMSE % = 54
N=161
Predicted Ca (mg/kg)
Measured Ca (mg/kg)
(c)
R² = 0.86
RMSE = 996.12
RMSE % = 32
N=161
Predicted Mg (mg/kg)
Measured Mg (mg/kg)
(d)
R² = 0.78
RMSE = 504.76
RMSE % = 21
N=161
Predicted P (mg/kg)
Measured P (mg/kg)
(e)
R² = 0.81
RMSE = 438.38
RMSE % = 19
N=161
Predicted S (mg/kg)
Measured S (mg/kg)
(f)
R² = 0.89
RMSE = 4.52
RMSE % = 15
N=161
Predicted Zn (mg/kg)
Measured Zn (mg/kg)
(g)
R² = 0.86
RMSE = 8.93
RMSE % = 39
N=161
Predicted B (mg/kg)
Measured B (mg/kg)
(h)

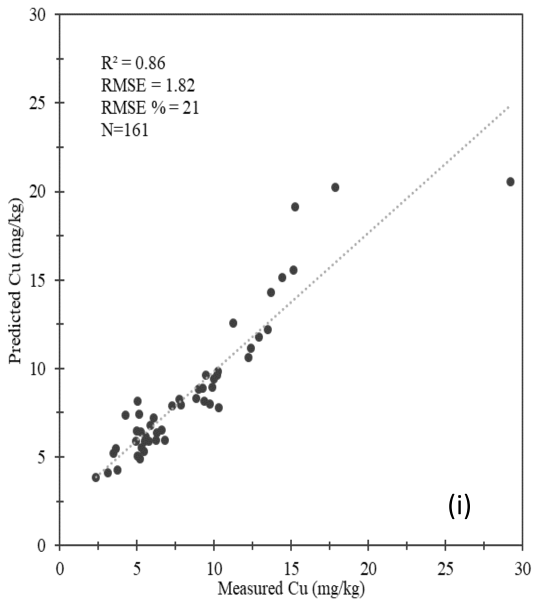
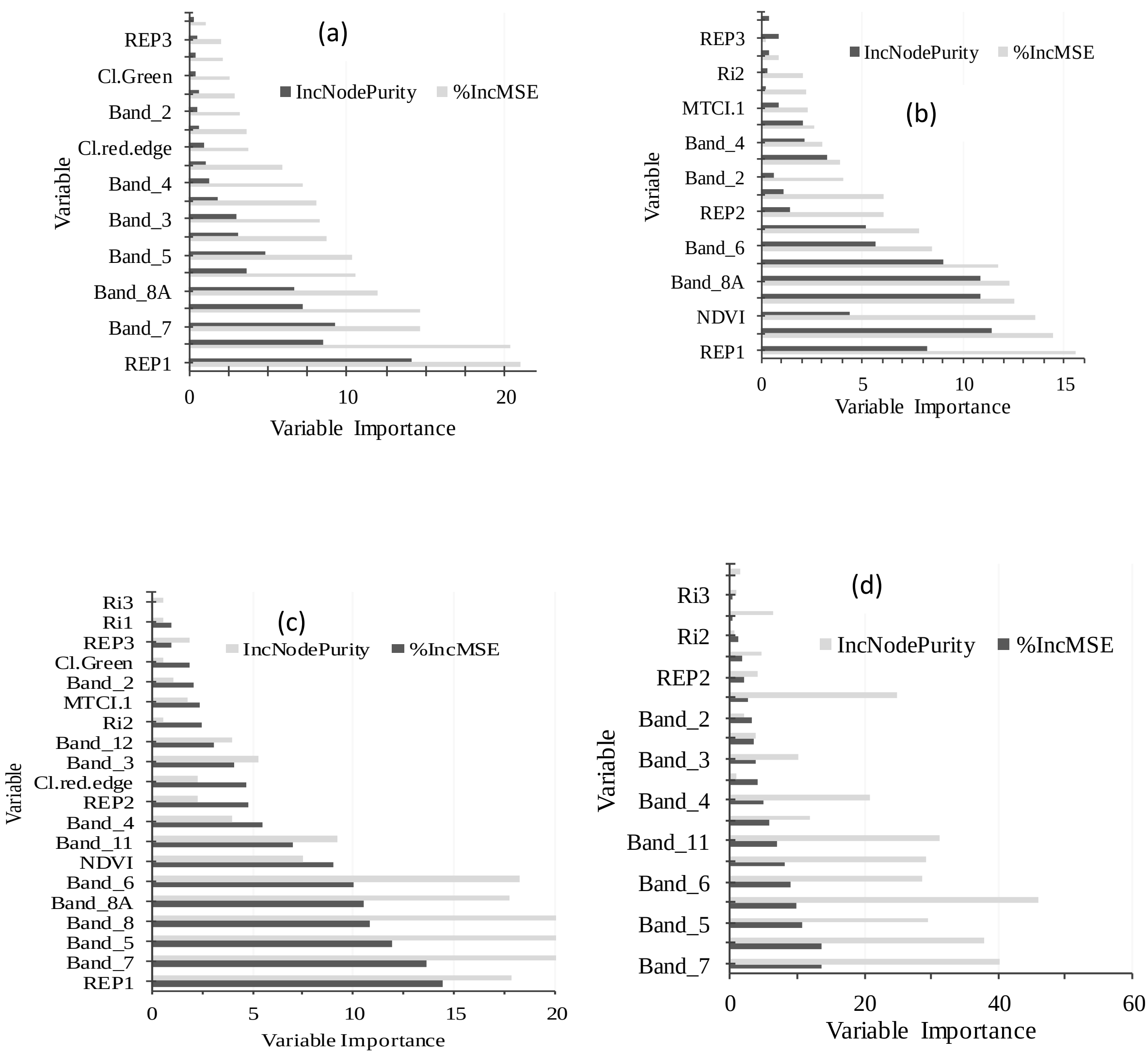


Figure 5.3 Accuracies derived in predicting N, K, Ca, Mg, (P, S, Zn, B, Cu concentrations using S-2 MSI data.

5.5.3 Variable importance selection

The RF model was able to explore and rank the variables by their importance in yielding the best prediction capability. The relationship between different nutrient predictions was determined by plotting their regression values. Figure 5.4 shows important variables derived in predicting studied nutrients namely, N, K, Ca, Mg, (P, S, Zn, B and Cu. Few of the variables contributed noticeably to the prediction of nutrients, namely spectral bands (2, 7, 5, 8A and 12) and vegetation indices (REP1 and NDVI). Red edge bands and REP1 were high % IncMSE and common variables for predicting nutrients.


(a)
IncNodePurity
%IncMSE
REP3
Cl.Green
Band_2
Cl.red.edge
Band_4
Band_3
Band_5
Band_8A
Band_7
REP1
Variable
0
10
20
Variable Importance
(b)
IncNodePurity
%IncMSE
REP3
Ri2
MTCI.1
Band_4
Band_2
REP2
Band_6
Band_8A
NDVI
REP1
Variable
0
5
10
15
Variable Importance
(c)
IncNodePurity
%IncMSE
Ri3
Ri1
REP3
Cl.Green
Band_2
MTCI.1
Ri2
Band_12
Band_3
Cl.red.edge
REP2
Band_4
Band_11
NDVI
Band_6
Band_8A
Band_8
Band_5
Band_7
REP1
Variable
0
5
10
15
20
Variable Importance
(d)
IncNodePurity
%IncMSE
Ri3
Ri2
REP2
Band_2
Band_3
Band_4
Band_11
Band_6
Band_5
Band_7
Variable
0
20
40
60
Variable Importance

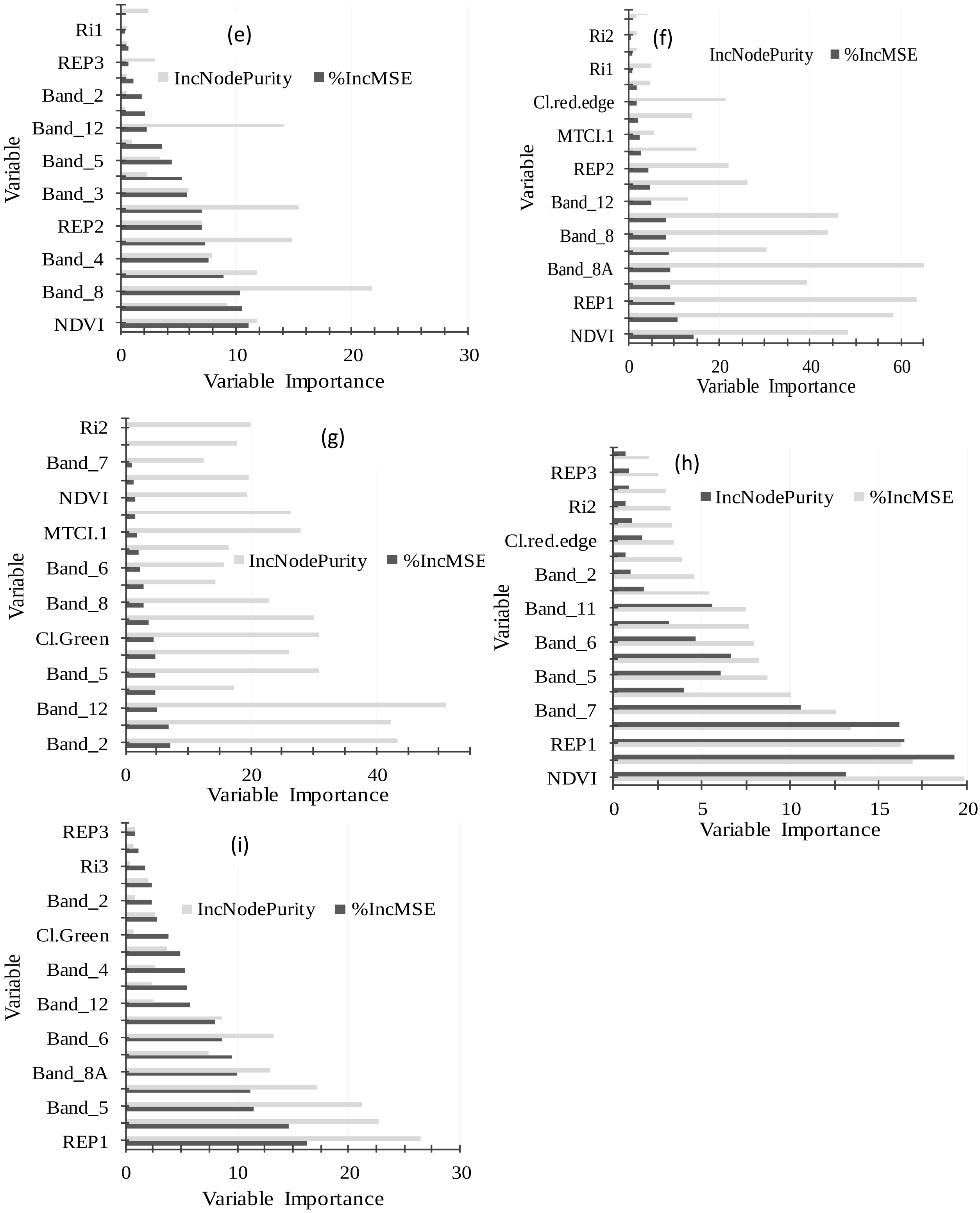


Figure 5. 4 Importance of variables that were used to predict (a), N, (b), K, (c), Ca, d, (Mg), (e), P, (f), S, (g), Zn, (h), B and (i), Cu by using S-2 MIS data.

Explanation: Mean decrease accuracy (%IncMSE) and Mean decrease gini (IncNodePurity),red edge position (REP), chlorophyll green (Cl. Green), ratio index (Ri), MERIS Terrestrial Chlorophyll Index (MTCI) and normalized difference vegetation index (NDVI).

Few of the variables contributed noticeably to the prediction of nutrients, namely spectral bands (2, 7, 5, 8A and 12) and vegetation indices red edge position 1 and Normalized

Difference Vegetation Index (REP1 and NDVI). Red edge bands and REP1 were high % IncMSE and common variables for predicting nutrients.

Figure 5.5 shows the spatial distribution of nutrients (sulphur, potassium, magnesium, copper, nitrogen, phosphorus, zinc and boron) in relation to important variables (NDVI, REP1 and band 7) presented in Figure 5.4 to develop a relationship between the nutrients variation and land use land cover types. The lowest values correspond to areas with crop farming (dark red for waterbodies), higher values (dark green) represent the most developed vegetation (forest and grassland). Except for magnesium, which showed a distinct trend of having high concentrations in sugarcane farms, the LULC-nutrient effect variation was shown to be consistent. This is due to the antagonistic effects of (Ca and Mg) and K in sugarcane, where soils with high Ca and Mg can lower leaf K and vice versa.

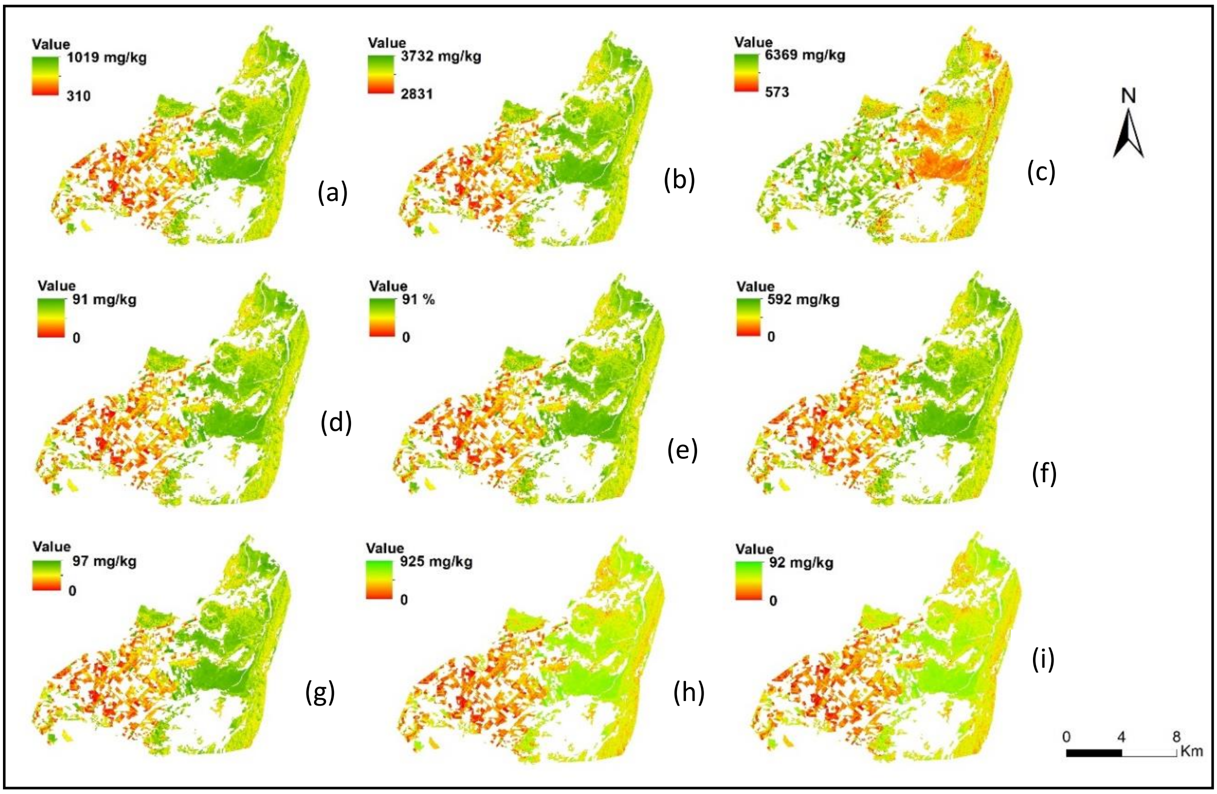


Figure 5.5 Spatial distribution of nutrients a) S, b) K, c) Mg, d) Cu, e) N, f) P, g) Zn, h) Ca and i) B.

5.6 DISCUSSION

In this study, we used the RF algorithm and S-2 on both wetlands vegetation and crops and across seasons to predict the concentrations of N, K, Ca, Mg, P, S, Zn, B and Cu. Results show that: (a) RF model using S-2 can predict foliar concentration across several nutrients and (b) S-2 can predict nutrients across plant types and seasons. Derived S-2 vegetation indices such as NDVI and bands 2 and 7 performed well in showing important variables for nutrient prediction. Seasonal characterisation of nutrients was also successful which could be attributed to the variability of photosynthetic pigments such as chlorophyll (Ramoelo et al., 2015a). However, the RF model performed poorly in the prediction of magnesium, and sulphur in the summer season. Also, across the seasons, the model performed poorly in predicting calcium, magnesium, phosphorus and boron in wetland vegetation returning high RMSE %. This can be attributed to easy leaching and increased mobility of these nutrients that might have caused the decrease of their concentration during the period of high rainfall, thereby weak correlation with S-2. Phenology is also an important factor in this result, considering the fact that most vegetation indices such as NDVI, especially red edge-based indices, rely on the vigour and greenness of the vegetation. Osco et al. (2020) also found nutrients like Mg, S, P, K and Ca presented inferior performances compared to nutrients such as nitrogen, zinc etc. Another contribution of this work is that it was possible to identify wavelengths and spectral regions that most contributed to predicting studied nutrients.

As outlined above, the infusion of vegetation spectral indices proved to be important in the evaluation of the most studied nutrient, nitrogen (Shah et al., 2019, Huang et al., 2017, Kalacska et al., 2015). Different indices and bands that were key wavelengths in predicting nutrient concentrations include red edge position, NDVI and band 2 (Figure 5.4) implying that different nutrients could be predicted by the different variables. In this study, the key variable that was important in predicting most of the nutrients including nitrogen, potassium, calcium, boron and copper was the red edge position 1 computed from the near-infrared (NIR) and red edge position bands followed by normalized difference vegetation index (NDVI) for predicting phosphorus and sulphur. Similar findings were observed in North American forests where canopy nitrogen was correlated to both the NIR spectral region as well as NIR-based vegetation indices including NDVI (Lepine et al., 2016, Wang et al., 2016).

The sensitivity of red edge bands to potassium, calcium, copper and nitrogen was not surprising since studies conducted by other researchers confirm the strong correlation between nitrogen concentrations. This relationship is corroborated by (Kanke et al., 2012, Abdel-Rahman et al., 2013, Frampton et al., 2013, Ramoelo et al., 2015b) who observed the same trend for nitrogen content. The study by (Cho et al., 2007) also proved a consistent performance by red edge based indices (NDVI) in estimating herbaceous biomass. The red edge is considered as the surrogate measure of vegetation chlorophyll content (Raper and Varco, 2015, Frampton et al., 2013, Schlemmer et al., 2013). Therefore, in this study, an expectation of the magnesium concentration to be strongly predicted in the red edge bands (band 7) was not questionable. Magnesium is located in the central of the chlorophyll molecule and it is regarded as the activator of some enzymes in plants (Marschner, 1995). The results by (Ferwerda and Skidmore, 2007, Mutanga et al., 2004) found the NIR region to be the best in estimating magnesium concentrations. NDVI computed from red and NIR bands showed to be the key variable in predicting phosphorus and sulphur concentrations. Similar to this is Pinheiro Lisboa et al. (2018) who found NDVI to be a useful tool in predicting nitrogen and phosphorus concentrations in sugarcane crops. Several studies have used these indices (NIR spectral region and NDVI) to study heavy metals in plants (van Deventer and Cho, 2014, Martinez et al., 2015, Rathod et al., 2015).

5.6.1 Prediction of nutrients using the RF model

This study has shown the utility of the RF model using S-2 in predicting concentrations of N, K, Ca, Mg, P, S, Cu, Zn and B. The technique yielded high coefficients determination ranging between 0.78 and 0.91. The technique also exhibited low RMSE% with an exception of magnesium (32%), boron (39%) and calcium (54%), implying the unsuitability of the model to predict these nutrients. RF regression successfully predicted sugarcane leaf nitrogen levels from Hyperion images (Abdel-Rahman et al., 2013). Multiple studies have demonstrated that RF models often perform remarkably well in different fields of scientific research (Freeman et al., 2012, Freeman et al., 2016, Cutler et al., 2007, Verikas et al., 2011). These studies also concluded that the RF model is capable of predicting nitrogen content. In this study, fusing spectral vegetation indices, NIR spectral region and NIR based vegetation indices (NDVI) with RF proved to be a suitable approach for predicting the studied nutrients.

5.6.2 Crops and vegetation nutrients seasonal predictions

Most nutrients exhibited significant relationships (R^2 <0.7) between measured and predicted concentrations across seasons and plant types with few that showed a weak relationship (R^2 >0.5) i.e. calcium, magnesium, phosphorus and boron). This implies that S-2 has the potential in predicting concentrations of selected chemical elements across the seasons and plant types. Generally, with the R^2 accuracies on predicting foliar nutrient concentrations, there were no significant differences within nutrients from crops ($p > 0.05$) and vegetation ($p > 0.05$) between the summer and winter seasons.

Similar findings by Gama et al. (2019) confirmed a weak relationship between leaf reflectance and concentrations of phosphorus, potassium and calcium. Poor prediction of magnesium, copper and sulphur in summer were observed which implies difficulties in predicting such nutrients in a wet season. Magnesium, copper and sulphur are micronutrients that are highly affected by the processes of reduction and oxidation (redox) in concert with the shifting water levels which determine their levels of concentration in the wetland's soils and water, seasonally. Subsequently, their poor detection in this study could be explained by the seasonal variations in the amount of available water which regulates the redox processes thereby regulating their concentration levels in soil and water as well as in the plant systems (Lu et al., 2016, Olivie-Lauquet et al., 2001, Ribeiro et al., 2019). For instance, a related study (Olivie-Lauquet et al., 2001) also noted and concluded that seasonally occurring processes such as redox and shifting in water abundance regulate the type and amount of trace elements that are available in the water, which was similar to the findings of this study.

Moreover, high RMSE % suggesting the poor performance of the model across the seasons was also observed in calcium, magnesium, phosphorus and boron in wetland vegetation. Season-specific analyses showed that dry season models performed better than the wet ones with the coefficient determinants of means of 0.76 in winter and 0.66. This might be attributed to the higher reflectance in the visible spectrum (bands 2, 3 and 4) in the dry season compared to the wet season. Plants in dry seasons are generally less green with lower moisture content and less chlorophyll which leads to lower energy absorption and greater reflection. Contrary, Ramoelo et al. (2012); Cho et al. (2013) and Skidmore et al. (2010) found models such as random forests to perform better in the wet season compared to the dry one.

5.6.3 Implications of remote sensing on wetland plant nutrients

Over the past years, several studies (Oliveira et al., 2019, Mahajan et al., 2014) have used remote sensing and chemical analyses in predicting foliar nutrient concentrations in plants. However, these studies mostly concentrated on estimating only nitrogen, grasses and in a particular season. Predicting wetland plant nutrient concentrations with viable technology options is the first step towards monitoring and managing the sustainability of agricultural resources. These technologies have facilitated a great opportunity for understanding vegetation health which has been previously regarded as a complex research area (Mutanga et al., 2016). Although limited in geographical reach, our findings show that S-2 imagery could be a significant additional source of data to improve the situation.

This study has demonstrated that RF using S-2 can be useful for monitoring and predicting various plant nutrients quantities and quality for floodplain wetlands. S-2 images found a significant relationship between nutrient contents, NIR spectral region and NIR based vegetation indices (NDVI). S-2 also provided an opportunity to seasonally characterize the studied nutrients. The findings of this study present a great opportunity and technique for mapping and monitoring nutrient enrichment in wetlands beyond the characterization of plant macronutrients (NPK) across both crops and natural vegetation species. The study provided models that still need to be evaluated in other wetlands for accuracy and robustness. This is a step towards a time-efficient and cheap technique for mapping and monitoring wetlands from local to regional scales based on S-2's optimal spatial resolution and swath widths.

A method of performing chemical analysis in plants in the laboratory is spatially limited for many reasons. Since our approach returned high coefficient determinants for most of the nutrients in crops and vegetation, it is safe to conclude that remotely sensed data make up for shortcomings of the traditional methods with the advantages of real-time and rapid observations. As a result, this information would be useful in estimating plant health conditions and nutritional status.

5.7 CONCLUSION

This study demonstrated immense potentials for S-2 data to be used for predicting leaf nitrogen, potassium, calcium, magnesium, phosphorus, sulphur, zinc, boron and copper concentrations. Different vegetation indices and bands including red edge position, NDVI and band 2 can be important in predicting different nutrients across the seasons even though foliar prediction using S-2 did not show a strong relationship in predicting leaf magnesium, copper and sulphur in a wet season. The major conclusion of this work is that the RF model was able to provide and predict nutrients with reasonable accuracies. The study, therefore, recommends that researchers elsewhere can use the methodology provided in this article as a tool in assessing and monitoring the quality of plants/vegetation in floodplain wetlands.

CHAPTER 6

SYNTHESIS, OVERALL CONCLUSIONS AND RECOMMENDATIONS

6.1 SYNTHESIS OF THE FINDINGS

The role of wetlands and their ecosystem services is widely acknowledged on a global scale. However, only a few studies have quantified the changes in wetland extent over time (Isunju, 2016, Mwita, 2013). Furthermore, in SA, a lack of long-term data on water quality in wetlands continues to be a concern (Matavire, 2015). Therefore, the effect of converting natural floodplain wetlands in "northern KwaZulu-Natal" to farming lands on wetland aerial extents, water/soil quality, and vegetation nutrients was investigated in this study. Remote sensing and geographic information system (GIS) advancements have made it possible to cost-effectively map and measure changes in wetland coverage at appropriate temporal and spatial scales (Ozesmi and Bauer, 2002). For natural resource management and research, these resources have become indispensable. The fact that remote sensing can be connected to ground data adds to its utility (Mesta et al., 2014). Ground-truthing must be used to validate and verify remote sensing products before they can be used (Grundling et al., 2013). As a result, remote sensing in combination with survey methods, which include biophysical and chemical indicators such as vegetation and water samples, were essential in this study to assess changes in floodplain wetlands.

Knowing the status of wetlands is critical for gaining insight not only for their ecosystem services but also for sustainable development and management. Occupying 6.5 % of the land surface in the world (Tooth et al., 2002), wetlands have a wide range of ecological services, which include the provision of water for livestock and domestic use and the production of wild foods and medicinal plants. Wetlands provide regulating services, which include carbon sequestration, flood attenuation, groundwater replenishment, trapping pollutants and regulation of pests and pathogens (Mitsch and Gosselink, 2000). Wetlands are also important for cultural values and heritage and recreational use (Turpie, 2010). In addition, wetlands are a source of livelihood, especially for rural communities, particularly in southern Africa (Frenken and Mharapara, 2002). Wetlands are the most vulnerable of all habitats in SA, with 48% of them being classified as critically endangered (SANBI, 2013). However, due to growing human population growth, the increasing demand for these ecosystems' threatened resources has resulted in their overuse and degradation. Explicit information on a broader picture on land cover changes, water and soil quality, nutrient composition of wetland ecosystems is limited in SA. Therefore, the objectives of this study were to:

1. Compare the performance of the support vector machine and maximum likelihood classifier algorithms in detecting and mapping subsistence farms in heterogeneous landscapes using WorldView-2 data.
2. Quantify wetland area loss within the lower uMfolozi floodplain system (UFS) and relate observed land use land cover changes to wetland loss using Landsat data.
3. Assess the physico-chemical characteristics of surface water in the lower UFS.
4. Seasonally characterise the plant and crop leaf nutrients in UFS using Sentinel-2 imagery.

6.2. The comparison of the support vector machine and maximum likelihood classifier Detecting and mapping small subsistence farms on floodplain wetlands using WorldView-2

Subsistence agriculture is critical in rural populations because it provides them with better living and food security (Mashamaite, 2014). Agricultural development is important in rural areas of most African countries because it helps to alleviate poverty while increasing the number of jobs (Mugambiwa and Tirivangasi, 2017) and Srivastava et al. (2012). This study used the UFS situated in uMkhanyakude District Municipality as a case study from which the findings can be applied to other wetlands elsewhere. The major results revealed an urgent and pressing need to pay attention to how subsistence farms affect the sustainability of wetlands. The official policy regarding subsistence farming practices and other extractive uses in the uMfolozi floodplain need to be viewed as unsustainable intrusions. Methods for capturing the effects of crop production on wetlands are critical; however, the effectiveness of such methods depends on numerous factors including the size of individual landholdings/farms. Field surveys of wetlands can provide spatially accurate and detailed characterisations of these ecosystems by tapping on interrogative techniques that can provide useful information on hydroperiods, water, soil and vegetation soil characteristics. This is especially so because field surveys are becoming prohibitively expensive and practically incapable of supporting regional and countrywide characterisations. The use of remote sensing has provided unique opportunities to address this limitation by offering temporally robust datasets at multiple spatial scales. Although remotely sensed imagery like Landsat and

SPOT have been routinely used in the mapping of small-scale wetlands, they are generally confounded by their limited spatial resolutions. Although remotely sensed data is mainly used in two ways comprising visual interpretation or image classification with the latter being the most accurate, several factors affect image classification. These include but are not limited to the spatial resolution of remote sensing data, different types of vegetation targeted for investigation and availability and affordability of software tools needed for this purpose and user's experience (Lu and Weng, 2007).

The difficulty in choosing a classification method also implies problematic formulation of classifiers capable of timely providing reliable classifications were reported by Rogan et al. (2008), Shao and Lunetta (2012). Chapter 2 attempted to address this limitation by providing a comparative assessment of the performance of parametric (maximum likelihood classifier) and non-parametric (support vector machine) classifiers in characterising LULC types in a heterogeneous landscape. The Maximum Likelihood Classifier (MLC) and Support Vector Machine (SVM) were capable to do this at acceptable levels of classification accuracies. This capability was demonstrated by evaluating the performance of these algorithms in detecting small subsistence farms and other similarly scaled LULC types in the lower UFS. The major finding from this initiative was that Worldview-2 imagery can be used with SVM and the MLC classifier to cost-effectively provide high-resolution products that are suitable for use for different stakeholders interested in enhancing the sustainability of wetland ecosystems. The superiority of these algorithms over-simplistic pixel-based classification techniques is demonstrated by the fact that SVM performed better in discriminating subsistence farms. These findings are important because they create space for the formulation of spatially comprehensive monitoring frameworks and robust wetland inventories.

6.3. The utility of geographic object-based image analysis and Landsat data to determine land use land cover changes

An understanding of land-use and land-cover changes (LULC) helps to establish successful strategies that can be used to mitigate the degradation of wetland ecosystems. This investigation (Chapter 3) demonstrated that is possible by mapping LULC) changes in the lower UFS over a period of twenty-years (1997-2017) by linking these changes to wetland loss.

The study revealed that changes in LULC variations have been shown in the literature to be important and indeed the major drivers of wetland degradation in the UFS as reported by other researchers in many studies under similar environmental conditions. With freely available images from the Landsat archives, the emergence of the spatial object-based image analysis (GEOBIA) approach could provide a better understanding of land use and land cover changes in wetlands. Compared to conventional pixel-based classification, GEOBIA overcomes geographic limitations imposed on coarse resolution datasets because of its ability to discretize image objects into fundamental primitives (Blaschke, 2010). As demonstrated in Chapter 3, The SVM was able to discriminate fragmented LULC types with all its outputs falling in the ranges of acceptable classification accuracies (OA = 79 %, K= 0.76 and OA = 88 %, K= 0.86). Long-term changes that were observed include (i) a 13.68 % decrease in wetlands (p = 0.01), marginal decreases in plantations and forest by 5.42 % and 3.81 %, respectively, (ii) a significant increase in subsistence farms and sugar cane farms, by 11.8 % (p =0.0001) and 18.11 % (p= 0.01) respectively, and the near equal marginal increases in plantations and forest, by 5.42 % and 3.81%, respectively. The results presented in Chapter 3 demonstrate that GEOBIA and SVM techniques can reliably discriminate different land use/cover information classes from Landsat data by yielding average accuracies in the range of ± 83 %.

6.4. Surface water quality assessment in the floodplain system

It was critical to assess the water quality of the system impacted by crop farming activities, mostly subsistence farms, using the main findings in Chapter 4 whose aim was to better understand the effects of cultivation on the lower uMfolozi wetland floodplain's water and soil quality by comparing uncultivated and cultivated sites on a seasonal basis and using the South African agricultural-water-quality guidelines. The findings revealed significant seasonal variations in chloride and sodium concentrations, as well as electrical conductivity (EC) and sodium adsorption ratio (SAR) at cultivated sites, with higher values at cultivated sites. Sites with cultivation had higher chloride concentrations (p, 0.020) compared with uncultivated areas. We observed substantial variations in the adsorption ratio (p =0.014 and 0.009) and sodium (p =0.017 and 0.003) for both wet and dry seasons due to similar patterns. The variations in electrical conductivity (p =0.054) and pH (p =0.038) between the cultivated and uncultivated sites were also evident. In terms of nitrate and phosphate, there were no major variations between the uncultivated and cultivated locations.

Most of the analysed chemical parameters were within the permissible limits specified by the South African water quality (SAWQ) water quality guidelines for irrigation, except (SAR), chloride, sodium, and EC. The EC's in the cultivated sites were 50 % higher than the target values, while the uncultivated samples were about 40 % higher than the targets, compared to the SAWG targets. In contrast to SAWG targets, SAR samples were found to be 50% lower in uncultivated sites and 50% higher in cultivated sites. When compared to SAWQ targets, sodium concentrations in the cultivated sites were twice to three times higher in the cultivated sites and 10% higher in the uncultivated sites. In contrast to the SAWQ limits, the chloride content in the cultivated sites was 3 to 4 times higher and nearly two times higher in the uncultivated sites. In terms of soil quality, the herbicides glyphosate, imidacloprid, and ametryn were found to be below the level of quantification in none of the samples examined. The uncultivated sites had higher cation exchange capacity, organic matter, total carbon, and nitrogen, but no major differences were found between the sites. Despite the fact that the pH and EC values in the cultivated site were higher, the difference in averages was negligible. The cultivated sites had higher nitrate concentrations, which varied significantly between them (p = 0.05). The results of this chapter show that commercial and subsistence farming in the floodplain of wetlands has no negative impact on water quality as long as pesticides, herbicides, and fertilizers are used in a reasonable amount. These findings point to the need for coordinated efforts to manage and enhance the water and soil characteristics of wetlands by monitoring as part of a long-term plan to ensure their long-term viability. The findings of this study have revealed that to ensure the floodplain's survival and crop farming, hazards linked to salinity and sodicity must be addressed.

6.5. Characterisation of seasonal wetland plant leaf nutrients using Sentinel-2 MSI data

Given the importance of wetlands in water reticulation and the regular human disruption from agricultural contaminants, this chapter (Chapter 5) was intended to evaluate the suitability of wetland areas for agricultural practices (crop production) based on the concentrations of different chemicals in different plants. The results of this chapter show that using Sentinel 2 to run a random forests model (RF) can help track and evaluate the quantity and quality of different plant nutrients in floodplain wetlands. It was discovered that nutrient content, NIR spectral area, and NIR based vegetation indices (NDVI) have a significant relationship. S-2 also allowed us to characterize the nutrients under study on a seasonal basis. The findings of this characterisation provide tremendous scope for further use of these images for wetland plant monitoring at different spatial scales. The results of this study demonstrated the importance of continuing to investigate new topics in order to determine the nutrient composition that determines plant stress in fragile wetland ecosystems. The results further demonstrate that Sentinel 2 data be used for reliable and timely monitoring of wetland ecosystems.

6.6 CONCLUSIONS

This work was primarily aimed at evaluating the effects of the conversion of wetlands to agricultural lands. The use of the long term and relatively new multispectral datasets and image processing techniques, integrated with standard analytical methods could accurately improve the information on the potential effects of cultivation practices on wetlands. This is necessary in order to enhance the sustainable utilisation of SA's threatened wetlands. Based on the findings in different chapters of this thesis, the following was concluded:

1) Small subsistence farms can accurately be detected and mapped using the support vector (SVM) machine image classification algorithm.

2) Organised utilisation of GEOBIA and, long term medium-resolution Landsat datasets and SVM could enable meaningful understanding of the dynamics of wetland systems.

3) Standard analytical methods can be powerful in assessing the impacts of cultivation on water and soil characteristics of wetlands.

4) The freely new generation sensor i.e. Sentinel 2 and random forest machine learning algorithm have demonstrable abilities to predict/estimate the concentrations of several nutrients in different wetland vegetation types on a seasonal basis.

Overall, the findings of the present study demonstrated the importance of earth observation tools in investigating the impacts of cultivation in heterogeneous environments (wetlands).

The study recommends the use of multi-source remotely sensed data for monitoring wetlands under different environmental settings.

Area of future research

The findings of this work demonstrate the importance of knowing the status of wetlands for monitoring and management and management purposes. We conclude by recommending that future research should:

1. Further studies should continue to explore the potential usefulness of non-parametric classifiers such as random forest, k-Nearest Neighbour (kNN).
2. GEOBIA needs to be seriously considered because it yielded high levels of overall accuracy.
3. Explore innovative techniques through which communities can be motivated to sustainably use their wetland resources. Further studies should also focus on the short term seasonal and inter-annual variations in nutrient circulations.
4. Should continue to develop new models that will enable full utilisation of the different types of remote sensing data that are becoming increasingly available.
5. When analysing and comparing classification accuracy, researchers are advised to present a set of simple measurements and associated outputs such as estimates of per-class accuracy and the confusion matrix, rather than using the kappa coefficient.
6. Cloudiness posed a severe barrier for the study's use of S-2 images, limiting the availability of excellent quality photographs and requiring only one scene to be used per season. Complementary technologies, such as the employment of an unmanned aerial vehicle (UAV) with multispectral cameras, are required.

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